**Time-generalized multivariate analysis of EEG responses reveals a cascading
architecture of semantic mismatch processing**

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Abstract:

Event-related brain potentials have a strong impact on neurocognitive models, as they inform about the temporal sequence of cognitive processes. Nevertheless, their value for deciding among alternative cognitive architectures is partly limited by component overlap and the possibility of ambiguity regarding component identity. Here, we apply temporally-generalized multivariate pattern analysis – a recently-proposed machine learning method capable of tracking the evolution of neurocognitive processes over time – to constrain possible alternative architectures underlying the processing of semantic incongruity in sentences. In a spoken sentence paradigm, we replicate established N400/P600 correlates of semantic mismatch. Time-generalized decoding indicates that early vs. late mismatch-sensitive processes are (i) distinct in their neural substrate, arguing against recurrent or latency-shifted single process architectures, and (ii) partially overlapping in time, inconsistent with predictions of strictly serial models. These results are in accordance with an incremental-cascading neurocognitive organization of semantic mismatch processing. We propose time-generalized multivariate decoding as a valuable tool for neurocognitive language studies.

Keywords: EEG; ERP; semantic mismatch; N400; P600; multivariate pattern analysis; generalization across time decoding

Statement of significance: We apply a recently developed method supporting the functional interpretation of EEG/MEG activation patterns: time-generalized multivariate pattern decoding. We demonstrate how this method can complement traditional ERP approaches to constrain for possible neurocognitive architectures of language processing. Using semantic violations, our results indicate an incremental-cascading nature of the language system.

1. Introduction

Research in cognitive neuroscience has inspired a number of competing proposals concerning the cognitive architecture of the human language system (e.g., Bornkessel & Schlesewsky, 2006; Bornkessel-Schlesewsky & Schlesewsky, 2009; Brouwer, Fitz, & Hoeks, 2012; Friederici & Gierhan, 2013; Friederici, 2002; Hagoort, 2003; Kuperberg, 2007). These neurocognitive models not only address the question of where in the brain the various sub-components of language are represented, but in particular also focus on the temporal sequence in which the different cognitive as well as neural component processes of the language system are recruited. In the domain of sentence processing, neurocognitive models typically propose a hierarchical sequence of increasingly more abstract computations (e.g., analysis, integration, or reanalysis of phonologic, semantic, or syntactic representations), each of which can, ideally, be mapped onto specific (combinations of) brain systems. Such proposed architectures include (i) mostly serial models (e.g., Friederici, 2002), where processes occur in a strictly sequential order, (ii) parallel and recurrent models, where processes reoccur or operate simultaneously, possibly on different types of information (e.g., Hagoort, 2003a), and (iii) cascading architectures (Bornkessel-Schlesewsky & Schlesewsky, 2009; McClelland, 1979), where processes occur in order, but not necessarily in a strictly sequential manner, so that a higher-order process can start on incomplete information, i.e., before the previous stage has terminated.

Thus, controversy exists not only regarding the functional specificity of the different brain systems involved in language processing, but also with respect to the specific temporal sequence of involved cognitive processes. Electroencephalography (EEG) and event-related brain potentials (ERPs) are particularly well-suited tools for addressing such questions due to their precise temporal resolution, in the order of a few milliseconds. Indeed, a number of different ERP effects are known to consistently occur during sentence comprehension, most prominently the N400. This vertex-negative potential, peaking around 400 ms post word-onset, is elicited by semantic incongruence between word meaning and sentence context (Kutas & Hillyard, 1980). The P600, a later, vertex-positive component of the ERP, was first observed

for syntactic violations (e.g., Hagoort & Brown, 2000; Hagoort Wassenaar, & Brown, 2003b; Kaan, Harris, Gibson & Holcomb, 2000; Osterhout, 1997, Osterhout, Allen, McLaughlin & Inoue, 2002) and for a long time exclusively associated with late integrative processes in the domain of syntax (e.g., Friederici, 2011; Swaa, Ledoux, Camblin, & Boudewyn, 2012). More recently, it was shown that salient semantic violations (Szewczyk & Schriefers, 2011), including semantically induced thematic violations (Kim & Osterhout, 2005; Kuperberg, Sitnikova, Caplan, & Holcomb, 2003) and semantic reversal anomalies (Kolk, Chwilla, Van Herten, & Oor, 2003; van Herten, Kolk, & Chwilla, 2005), also elicit robust P600 effects. Appearance of the semantic P600 also often depends on the nature of participants' behavioural task (e.g., Kuperberg, 2007; for more reviews on the semantic P600 see Bornkessel-Schlesewsky and Schlewsky, 2008; Brouwer, Crocker, Venhuizen, and Hoeks, 2017). Recent research also showed that N400 and P600 often occur as a biphasic brain response (e.g., van de Meerendonk, Kolk, Vissers, & Chwilla, 2010). Recent theorizing has thus associated the P600 also with processes of conflict monitoring and domain-independent sentence reanalysis (Shen, Fiori-Duharcourt & Isel, 2016; van de Meerendonk et al, 2010) and/or integration (Brouwer et al., 2017).

The temporal differences between distinct language-sensitive ERP effects have provided the primary constraints for neurocognitive models of the timing of language processes. However, despite their excellent temporal resolution, ERPs are nevertheless limited in addressing certain questions about cognitive architectures. Most importantly, due to the fact that ERPs typically evolve over 10s or 100s of milliseconds and typically have no clear boundaries, they cannot unambiguously track the temporal evolution of neurocognitive processes over time. Accordingly, univariate statistical analysis of ERPs can identify time windows at which stimulus processing differs, but cannot directly distinguish between serial vs. cascading cognitive architectures as introduced above. This limitation is further complicated by the fact that temporal filters (often used to smooth the noisy EEG signal) can introduce spurious components into the ERP: For example, filtering a late positive component

with a strong high pass filter will induce a spurious earlier negative component (Molinaro, Barber, Caffarra & Carreiras, 2015; Tanner & Van Hell 2014; Tanner, 2015).

A further problem for deriving conclusions about cognitive architectures based on the timing of ERP effects stems from the lack of a clear baseline: An ERP positivity can, e.g., result from a positive effect in one or a negative effect in the other condition – which again introduces ambiguity in neurocognitive models that specify the order of cognitive processes and their underlying neural mechanisms. Finally, the scalp topographical distributions of ERP effects – also often used for identification of ERP components or effects – are similarly confounded. For example, calculating a baseline during a time window in which some component differs between experimental conditions can introduce spurious effects such that the resulting topography in fact often corresponds to an interaction between the topography in the baseline and the topography in the time window of interest (Steinhauer & Drury, 2012). Conversely, the lack of an ERP effect cannot provide evidence for the absence of a cognitive process, as it might simply be masked by a second ERP component (e.g., Schwartz, Kutas, Butters, Paulsen, & Salmon, 1996).

As a consequence, ERP patterns like the semantic N400-P600 can result from a range of possible cognitive architectures and multiple possible neural implementations. One pattern that can be excluded immediately based on the biphasic nature of the ERP effect is that of a single neuro-cognitive process that is consistently more active in one condition than in the other. Such an architecture – which we might refer to as a ‘naïve recurrent’ architecture – could not result in a biphasic ERP response, as the simulation in Fig. 1A (rows 1 and 2) shows. Effects like the N400-P600 complex imply a sequence of distinct neurocognitive component processes (as suggested, e.g., by Friederici, 2002). However, such an ERP pattern would be compatible both with a strictly serial sequential model, where two distinct cognitive processes are more active for one condition than for the other, with the second only becoming involved once the first has terminated its processing (Fig. 1B, rows 1 and 2), as well as with a cascading sequential model, where the second of two subcomponents already starts processing the input while the first is still active (Fig. 1C). Published serial models of language (e.g., Friederici,

2002) are not explicit concerning the strict seriality of involved cognitive processing stages (in the sense of a modular architecture as proposed by, e.g., Fodor, 1983), and so often do not explicitly exclude cascading processes at the implementational level.

Fig. 1: Simulation of possible cognitive architectures and resulting ERPs and decoding patterns.

Simulation of different cognitive architectures in terms of the sequence of involved cognitive processing stages per condition (first row), their associated difference ERPs (second row), temporal (MVPA) decoding time courses for classifiers that were trained during the time window of the respective cognitive process and tested at all time points - which parallels the time course of activity of different neurocognitive processes (third row; cf. also King & Dehaene, 2014), and resulting idealized generalization across time (GAT) matrices (fourth row). The simulation (see https://github.com/heikele/GAT_n4-p6/ for code) assumes identical transfer functions between the activation time course of cognitive processes (row 1) and the resulting difference ERPs (row 2), as well as between cognitive processes and their multivariate decoding (rows 3 and 4), for all modelled architectures. Specifically, it is assumed that processes 1 and 2 elicit distinct spatial patterns, but project to the displayed sensor (second row) to a similar extent. (A) 'Naïve recurrent' cognitive architecture assuming a single process in the critical condition; its EEG response results in one ERP component and a sustained GAT pattern (both of which is incompatible with the biphasic N400/P600 pattern). (B) Strictly serial cognitive architecture, with a sequence of two temporally non-overlapping processing stages yielding a biphasic ERP pattern. Critically, strict seriality implies the absence of any MVPA generalization to the time window of the respective other process. (C) Cascading serial architecture. The temporally overlapping processing stages elicit a biphasic ERP difference wave that is virtually indistinguishable from the strictly serial model. Nevertheless, GAT decoding recovers the temporal overlap of involved processes: in the time window where both processes are active, early and late classifiers simultaneously show above-chance decoding. (D) Latency-shifted single process model, according to which the same cognitive process is activated in both conditions, however earlier in the easier (congruent) than in the

difficult (incongruent) condition. This configuration of cognitive processes again results in almost identical difference ERPs between the two conditions. However, generalization across time MVPA decoding shows a pronounced pattern reversal between the two patterns: above-chance decoding within the time window in which the respective MVPA classifier was trained, but below-chance results in the time window of the respective other ERP effect. For colour Fig., please refer to the digital version of this article.

Another account would attribute the biphasic N400-P600 pattern to a single process that appears in both conditions, however with different latencies depending on the different cognitive demand (latency shift model; Fig. 1D, rows 1 and 2). Applied to the N400/P600 pattern, this was e.g. suggested by Curran, Tucker, Kutas and Posner (1993), who interpreted the biphasic pattern of negativity and positivity as a latency shifted positive-going ERP that appears first in the semantically congruous and then in the incongruous condition. The N400, in this work, was characterized as "... an interval of minimal topographic differentiation prior to the development of a delayed [late positive component] ..." (Curran et al., 1993, p. 206). As visualized in the simulation in Fig. 1D (rows 1 and 2), this latency shift model can result in a virtually identical biphasic ERP pattern as serial and cascading architectures.

To summarize, with respect to the above-discussed cognitive architectures of language, i.e., serial vs. cascading vs. latency-shifted, the order of (neuro-) cognitive processes and their separability cannot be resolved to a satisfactory degree on the basis of univariate analyses of the ERP. In the present study, we use a novel analysis approach – time-generalized multivariate pattern analysis (MVPA) – to achieve this. MVPA methods have in the last years been applied successfully in functional neuroimaging for decoding brain states that are not directly identifiable using traditional univariate statistics (e.g., Haxby et al., 2001; Haynes & Rees, 2006). In EEG research, multivariate pattern classification algorithms are trained on patterns of electrophysiological signals across multiple measured scalp sensors, to classify single trials as belonging to one of two or more psychological states (Parra et al., 2001). Most recently, King and Dehaene (2014) introduced time-generalized decoding to characterize the evolution of psychological states over time based on scalp-measured neurophysiological data. Here, multivariate pattern classifiers are not only applied to determine

whether or not EEG or MEG brain states differ at a specific point in time, but are also applied to *different* time points in the trial to examine whether an identified brain state generalizes across time. Thus, if a classifier trained at time point t_0 can continue to classify trials based on electrophysiological signals elicited at subsequent time points t_{0+x} , one can conclude that neural activation patterns (and, by inference, in cognitive processes) persist or re-occur over time. If this is not the case, this indicates a different underlying neurocognitive architecture.

King and Dehaene (2014) discuss in a comprehensive way how the results of generalization across time decoding exclude or support certain underlying cognitive architectures. Applying this logic allows us to predict different patterns of MVPA decoding for the three possible cognitive architectures we have laid out above – i.e., serial vs. cascading vs. latency-shifted: The non-overlapping processes of the strictly serial model would predict successful but independent decoding of semantic congruency vs. incongruency in the N400 and in the P600 time window, without any generalization or temporal overlap between the two (Fig. 1B, third and fourth row). Alternatively, if the underlying cognitive architecture is cascading in the sense that a process is first triggered and prior to its culmination a second processing stage is already initiated, then in addition an intermediate period should emerge where both early and late classifiers score above chance, reflecting a period of simultaneous activation of the two distinct neurocognitive processes (Fig. 1C, row 3 and 4). Finally, the latency-shift model predicts an entirely different MVPA decoding pattern: Due to the temporally shifted activation of the identical process in both conditions, a classifier trained on the early time window (here identifying the EEG pattern for the easier condition) would provide negative evidence for this condition in the later time window (where the identical pattern is present in the other experimental condition), and vice-versa for the later time window (Fig. 1D, rows 3 and 4).

In sum, strictly serial vs. cascading vs. latency-shifted single process cognitive architectures predict virtually indistinguishable biphasic ERP responses, but qualitatively and quantitatively distinguishable decoding time courses when applying MVPA with generalization across time. In the present study, we thus apply this novel statistical approach to EEG data

from a typical semantic violation paradigm, with the aim of tracking the temporal evolution of neuro-cognitive systems underlying the processing of semantic violations during spoken sentence comprehension. We do not intend to contribute to on-going discussions about the functional roles of the involved ERP components, e.g., concerning the role of late positivities in semantic/combinatoric problems. Instead, we employ a new method to traditional experiments to address long-standing questions in the neurocognition of language. This approach complements univariate ERP analysis by circumventing many of its shortcomings (e.g., w.r.t. overlapping patterns), thereby extending the range of questions that can be addressed with EEG research in our field. Here, we apply this method to more directly constrain the possible cognitive architectures underlying the processing of semantically coherent and incoherent language.

2. Methods:

2.1 Participants:

Forty-five native speakers of German (age range 18-42 years) were recruited from the Goethe University of Frankfurt campus, and compensated with course credit. All participants gave informed consent according to protocols approved by the local ethics committee and reported no history of neurological or psychiatric disorders. Four participants were excluded from the analyses due to a high number of rejected trials, and one due to not being a native speaker of German, leaving a final sample of 40 participants (7 male, 33 female, age mean = 22, SD = 4.6).

2.2 Stimuli and procedure:

Participants were asked to sit in front of a screen (distance: 65 cm) in a semi-lit room and to listen to sentences played at a comfortable loudness using two speakers. A trial consisted of a visual fixation cross at the centre of the screen and, after a 400-600 ms delay, by the onset of auditory sentence presentation. Directly after the sentence, a probe appeared

on the screen asking participants to judge by button press whether or not the sentence they just heard was synonymous with the immediately preceding sentence. Wrong answers were indicated by a loud beep. We chose this task to ensure that participants processed sentence *meaning*, without explicitly making semantic *congruence* task-relevant. Participants could self-induce a pause if they felt tired or lack of attention. Prior to EEG recording, participants conducted a training run with thirteen sentences, the ninth being a synonymous sentence.

The experiment consisted of a total of 350 German sentences, of which 80 were the critical stimuli for the present study, containing congruent vs. incongruent target words (40 per condition). In addition, 230 sentences were included that served as fillers and contained different manipulations not analysed here, and 40 synonymous sentences used for the judgment task; in total, 25.71% of sentences contained a violation. The critical sentences for the present experiment contained target words with very high cloze probability (mean: 90.99%, SD: 5.51%). Cloze probability indicates how well the target word fits into the preceding sentence context (Kutas & Federmeier, 2011) – i.e., corresponding closely to how predictable it is. The stimulus set consisted of six sentences from the Potsdam Sentence Corpus (Kliegl, Grabner, Rolfs & Engbert, 2004), 31 from Freunberger and Roehm (2016), and 43 sentences developed in our lab. For the latter, cloze ratings were empirically determined as the relative frequency of occurrence of a given word in a written sentence completion task ($n = 20$).

The 80 critical sentences were 4-16 words in length (mean = 8); 44 target nouns were in the sentence final position, 19 in pre-final, 8 in the third, 8 in the fourth, and 1 in the fifth-to-last position. Target words had an average spoken length of 444 ms (SD = 111ms) and on average 6.3 letters (SD = 2.11). Semantically incongruent sentences were created by replacing target words with morpho-syntactically matched words from other stimulus sentences used in this experiment. Two non-overlapping lists were created with 40 congruous and 40 incongruous sentences, so that each version of a sentence was presented to 50% of subjects. An example of a high cloze congruent sentence is: 'Mona wird morgens vom Schnurren ihrer [Katze] geweckt' (English translation: 'Mona is awakened in the morning by the purring of her [cat]'). An example of a high cloze incongruent sentence is: 'Bevor er die Straße überqueren

konnte, musste er auf das Grün-Signal der [Sonne] warten' (English translation: 'Before he could cross the street, he had to wait for the green signal from the [Sun]'). In both examples the target words are in square brackets.

Sentences were spoken and recorded by a male, native speaker of German with clear pronunciation in a sound proof chamber using a WH20CLR microphone (Shure Inc., Illinois, US) and Audacity software (Team Audacity, 2015). Recordings were cut into separate waveform audio format (wav) files and target word onsets were calculated relative to the start of the sentence, using the Munich AUtomatic Segmentation tool (Kisler, Schiel & Sloetjes, 2012). Stimuli were presented in randomized order (but synonymous sentences always followed their corresponding antecedents) using PsychoPy (Peirce, 2007; 2008).

2.3 Data acquisition and pre-processing:

EEG data was recorded using 64 active Ag/AgCl electrodes (ActiCAP; Brain Products GmbH, Gilching, Germany) arranged in an extended 10-20 layout (cf. Fig. 2) using either a brainAmp amplifier or an actiChamp amplifier (both Brain Products GmbH, Gilching, Germany); sampling rate of 1000Hz; low-pass filter of 500Hz; time constant of 10s; left earlobe as ground. (Note that descriptive and statistical control analyses of both univariate and MVPA pipelines indicated equivalent results between the two recording setups.) EEG data analysis was conducted in MNE-Python (Gramfort et al., 2013; 2014), and the code for all analyses is available at https://github.com/heikele/GAT_n4-p6/. All analyses were conducted with linked mastoids as reference. To speed up processing of the highly computationally expensive MVPA analyses, and given that N400 and P600 ERPs are low-frequency components, data were down-sampled to 100Hz with a high-pass filter of 0.1Hz and a low-pass filter of 30Hz. Data were segmented into epochs of 1600 ms length (-300 to 1300 ms relative to the onset of the target word) and baseline-corrected using the interval of -300 to 0 ms. Eye movements and muscle artefacts were corrected by using an independent component analysis (Jung et al, 2000), followed by an automated trial rejection/repair method (Jas, Engemann, Bekhti, Raimondo, & Gramfort., 2017). After pre-processing, reference channels and the four peri-

ocular electrodes (SO1, SO2, FP1, FP2) were discarded, so that all further analysis are based on 58 EEG electrodes.

2.4 Univariate analysis:

ERPs were calculated by averaging trial epochs per condition for each participant. For statistical analysis, the mean amplitudes were calculated for two non-consecutive time windows of 200 ms length, defined a-priori as reflecting the N400 (300-500ms; e.g., Van Berkum, Zwitterlood, Hagoort & Brown, 2003) and the P600 (600-800ms; e.g., Van Herten et al., 2005; Vissers, Chwilla, Egger & Chwilla, 2013; Verhees, Chwilla, Tromp & Vissers, 2015). These time windows were also used for the statistical evaluation of decoding performance (see below). While our selected time window for the P600 has been used in previous papers, other papers have used earlier starting points (e.g. 500 ms) and/or longer time windows. The current definition was chosen because it provides an equal number of time points for both effects (in particular to avoid imbalanced variances across conditions). Also, we reasoned that a possible bias towards overlapping decoding performance is reduced by inserting a temporal ‘buffer’ between the time windows of interest. Averaged amplitudes (μV) were submitted to a $2 \times 2 \times 2$ repeated measures ANOVA using congruency (congruent vs. incongruent) as well as nested Regions of Interest/ROIs with anteriority (anterior/posterior) and laterality (left/right) as fixed effects. The ROIs (see Fig. 2) consisted of anterior (left: F3, F5, F7, FC1, FC3, FC5; right: F4, F6, F8, FC2, FC4, FC6) and posterior electrodes (left: P3, P5, P7, CP1, CP3, CP5; right: P4, P6, P8, CP2, CP4, CP6). The choice of ROIs was analogous to previous studies investigating N400 as well as early and late positivities in semantic processing (e.g. Bornkessel-Schlesewsky et al., 2015; Freunberger & Roehm, 2016), but took into account the higher number of electrodes in our study. Only significant interaction effects ($p < 0.05$) will be resolved.

2.5 Multivariate pattern analysis and generalization across time:

In order to track the unfolding of the neurophysiological incongruence effect (i.e., incongruent vs. congruent target word) over time, a multivariate pattern analysis (MVPA) was implemented on the epoched EEG data. Independently for each subject, a Ridge Classifier (Tikhonov, Arsenin & John, 1977), as implemented in scikit-learn (Pedregosa et al, 2011) with default parameters (regularization term: $\alpha = 1$), was trained to classify trials as being congruent or incongruent. Classifiers were trained separately on EEG activity at each of 160 time points (i.e., sampling rate of 100Hz for epochs from -300 to 1300 ms). A 5-fold stratified cross-validation procedure (e.g., Marti, King & Dehaene, 2015) with balanced classes (i.e., equal number of congruent vs. incongruent trials per fold) was used: Each participant's epochs were split into five equal-sized folds and for each fold, trial type (incongruent vs. congruent) was predicted by a classifier trained on the other four folds. See also Supplementary Fig. S1 for a visualization of these procedures. The accuracies of these predictions correspond to the *classifier score* (see *Statistical Analyses* below). A Ridge classifier was chosen a priori because it is a linear model that is relatively fast to fit and apply. We also tested a Support Vector Machine (Friedman, Hastie & Tibshirani, 2001; default penalty parameter $C = 1.0$) using both a linear and non-linear (radial basis function) kernel but results did not differ qualitatively.

In order to investigate the temporal sequence of neural processing stages initiated by the processing of the incongruent target word, a generalization across time approach (King & Dehaene, 2014; see also Supplementary Fig. S1) was used: I.e., each classifier is not only tested at the time point it was trained on, but also at every other time point in the EEG epoch. This results in a generalization across time matrix (cf. Fig. 3A) that shows training times on the y-axis against testing times on the x-axis. The diagonal of this matrix represents training and testing at the same time point. Off-diagonal entries show pattern persistence or re-occurrence – that is, time points t_{+x} where a classifier trained at time point t can still successfully classify trials, indicating shared EEG patterns (and thus, by inference, shared cognitive processes) across both time points (see King & Dehaene, 2014, for further discussion). We determined whether clusters in the generalization across time matrix were significantly different from

chance using Threshold-Free Cluster Enhancement (Smith & Nichols, 2009) as implemented in MNE Python, with parameters $\text{extent} = 0.1$ and $\text{height} = 0.1$. Remember that the different cognitive architectures discussed above predict different decoding patterns in the generalization across time matrix (which are depicted in an idealized fashion in the bottom row of Fig. 1).

For each sample point of each trial in the testing data set of a given cross-validation fold, the classifier trained on one sample point of EEG data from the remaining four folds (see above) generates a dichotomous prediction of belonging to the congruent vs. the incongruent category. Assessing the quality of the predictions - i.e., correctly vs. incorrectly labelled trials - yields the classifier's accuracy and constitutes its *score*, conceptually corresponding to the strength of the neural pattern. To obtain these scores, non-parametric effect sizes were generated in the form of an area-under-the-curve/AUC computed from the receiver operative curves/ROC (ROC-AUC; Friedman et al, 2001), representing true positive (e.g., a trial was correctly predicted as congruent) against false positive (e.g., a trial was incorrectly predicted as congruent) predictions, for various levels of confidence/probability (as quantified by each data point's distance to the decision surface of the classifiers' hyperplane). Thus, the ROC-AUC represent how often (in terms of proportion) trials were correctly classified (with 1 being a perfect prediction score of a classifier predicting the correct condition 100% of the time, 0.5 being equivalent to guessing, and scores below 0.5 corresponding to worse than guessing, i.e., systematically guessing the wrong category). These ROC-AUC scores were subsequently averaged across all testing folds.

Time-generalized decoding scores were statistically evaluated in the two time windows introduced above, i.e., N400 vs. P600, thereby tracking over the time course of the entire epoch the classification accuracy scores of classifiers trained on data from these two time windows. Specifically, the performance of N400 vs. P600 classifiers over time was evaluated by (i) averaging the accuracy scores of all classifiers that were trained within the respective time windows (i.e., 300-500ms and 600-800ms), (ii) inferential testing their classification accuracy against chance (0.5) at all other time points (i.e., generalization across time for the entire 1600

ms of the EEG epoch) using a non-parametric signed-rank test ($\alpha = 0.05$), and then (iii) correcting for multiple comparisons with the false discovery rate method (FDR; Benjamini & Hochberg, 1995). As a final step, the averaged N400 classifier performance was subtracted from the averaged P600 classifier performance at each time point across the trial epoch. To test this difference for significance, a signed-rank test ($\alpha = 0.05$) was used and FDR was applied to correct for multiple comparisons. All inferential tests are two-sided.

3. Results

3.1 Behavioural results:

Behavioural performance on the 1-back synonymity task was calculated to make sure that the task was not too difficult and that participants were attending to the sentences. On average, participants made one error out of 40 synonymous trials (range 0-3), indicating that participants understood the meaning of the sentences well.

Fig. 2: Event related-brain potentials (ERPs) for congruent and incongruent trials. Grand-average ERPs for congruent (black) and incongruent (red) target words for each region of interest (ROI), i.e., (A) left anterior (electrodes F3, F5, F7, FC1, FC3, FC5), (B) right anterior (electrodes F4, F6, F8, FC2, FC4, FC6), (C) left posterior (electrodes P3, P5, P7, CP1, CP3, CP5), and (D) right posterior (electrodes P4, P6, P8, CP2, CP4, CP6). ROIs are shown on the electrode layout displayed in the center. Variance corridors represent bootstrapped 95% confidence intervals. (E) Depicts the topographic difference between trials (incongruent-congruent) at specific time points in the grand-averaged ERP. For colour Fig., please refer to the digital version of this article.

3.2 Event-related brain potentials

ERPs are visualized in Fig. 2, indicating a clear N400 between ~200 and 500 ms after target onset and a somewhat weaker late positivity with left posterior focus for incongruous relative to congruous target words, starting between 600 and 700 ms after onset of the target word. The ANOVA in the a-priori defined N400 time window (300-500ms) revealed a reliably more negative-going ERP for incongruent as compared to congruent target words, mean = -2.43, SD = 1.96, $F(1, 39) = 59.65$, $p < 0.001$. The effect of congruency varied as a function of anteriority, $F(1, 39) = 21.28$, $p < 0.001$, and resolving this interaction by means of paired t-tests revealed that the effect of congruency was more pronounced at posterior (mean = -3.14, SD = 2.41, $t(39) = -8.158$, $p < 0.001$) than anterior (mean = -1.72, SD = 1.95, $t(39) = -5.502$, $p < 0.001$) electrodes. A significant interaction between laterality and congruency was observed, $F(1, 39) = 16.51$, $p < 0.001$, and resolving this by means of paired t-test revealed that the effect of congruency was more pronounced over the right hemisphere (mean = -2.88, SD = 2.28, $t(39) = -7.898$, $p < 0.001$) than left (mean = -1.98, SD = 1.87, $t(39) = -6.620$, $p < 0.001$). No three-way interaction was observed for the N400 time window ($F(1, 39) = 0.538$, $p = 0.468$, respectively).

The ANOVA in the a-priori defined P600 time window (600-800ms) showed no consistent main effect of congruency, mean = 0.06, SD = 2.48, $F(1, 39) = 0.023$, $p = 0.880$, but there was a significant interaction between congruency and laterality, $F(1, 39) = 28$, $p < 0.001$. Resolving this interaction according to hemisphere, by means of paired t-tests revealed no congruency effect over left (mean = 0.64, SD = 2.76, $t(39) = 1.452$, $p = 0.154$) or right-hemisphere (mean = -0.52, SD = 2.37, $t(39) = -1.377$, $p = 0.176$) electrodes. However, when resolving by congruency condition, within the incongruent conditions the left hemisphere showed significantly more positive-going ERPs than the right hemisphere (mean = 0.71, SD = 1.18, $t(39) = 3.733$, $p < 0.001$). The hemispheric difference observed in the congruent condition was borderline significant (mean = -0.46, SD = 1.43, $t(39) = -1.983$, $p = 0.054$). No significant interaction with anteriority and no three-way interaction was observed ($F(1, 39) = 0.687$, $p = 0.412$ and $F(1, 39) = 0.02$, $p = 0.887$, respectively).

3.3 Multivariate pattern analysis and generalization across time decoding

The generalization across time matrix (Fig. 3A) shows decoding performance for the MVPA categorization into trials with congruent vs. incongruent target words (5-fold cross-validation; cf. Methods section 2.5 for further details) over the entire trial epoch (testing time: x-axis), for classifiers trained at each sample point in the trial epoch (training time: y-axis). Consistent with the ERP results, significant decoding performance along the diagonal of the across-time matrix (Fig. 3A and B) demonstrates that congruent and incongruent trials indeed elicited reliably different EEG patterns starting at around 270 ms post target word onset and including our a-priori defined time windows of interest, i.e., 300-500ms as well as 600-800ms.

Fig. 3: Generalization across time decoding results. Decoding semantic congruency with multivariate pattern analysis (MVPA) and generalization across time (GAT), relative to the onset of the target word at 0 ms. (A) GAT decoding matrix for the subject-averaged classifier performance. Contours outline statistically significant clusters (above or below chance) identified by TFCE ($p < 0.01$; cf. Methods section for details). (B) MVPA decoding performance along the diagonal of the GAT matrix (i.e., representing MVPA classifiers trained and tested at the same time), corresponding to the dashed line in panel A. Significant above chance ($>50\%$) diagonal decoding was observed between 270 and 940

and intermittently from 980 to 1270 ms ($p < 0.05$, FDR corrected). (C) GAT decoding performance for selected time windows of interest representing the N400 (300-500 ms; green) and P600 (600-800 ms; dark blue). Performance time-courses represented here reflect the average of performance time-courses of all classifiers trained in the respective time window, i.e., an average of all rows of the GAT matrix shown in (A) within that time window. The N400-time window classifier showed significant above chance decoding from 140 to 770 ms ($p < 0.05$, FDR corrected), and the P600-window classifier showed significant above chance decoding between 360 and 1270 ms ($p < 0.05$, FDR corrected); overlap (i.e., simultaneous significant decoding of both classifiers) is observed from 360 to 770 ms. (D) Difference between N400 classifier and P600 classifier performance across time. The N400 classifier performed significantly better than the P600 classifier from 180 to 410 ms ($p < 0.05$, FDR corrected) while the P600 classifier performed significantly better than the N400 classifier from 590 to 1300 ms ($p < 0.05$, FDR corrected). Variance corridors represent 95% bootstrapped confidence intervals. Horizontal lines index time points of significance (thick lines for $p < 0.01$; thin lines for $p < 0.05$). For colour Fig., please refer to the digital version of this article.

To examine the separability of neural processes reflected in these two time windows, we averaged the performance time-courses of all classifiers trained between 300 and 500 ms ('N400 classifier') and of all classifiers trained between 600 and 800 ms ('P600 classifier'). Fig. 3C shows the temporal evolution of the N400 and P600 classifier performances across the entire trial epoch. Decoding performances were clearly separable between N400 and P600 classifiers. After FDR correction ($p < 0.05$), we observed significant decoding performance for the classifier trained in the N400 window (i.e., 300-500ms) between 140 and 770 ms. For the P600 classifier (trained at 600-800ms), we observed significant decoding performance from 360 to 1270 ms. Thus, both classifiers generalized within certain limits beyond their narrow window of training and showed an overlap of significance from 360 to 770 ms (see Fig. 3C).

To examine the temporal specificity of the N400 vs. P600 classifiers – and thus the independence of underlying neural processes - we subtracted the averaged N400 classifier performance per time point from the averaged P600 classifier performance per time point (Fig. 3D). The N400 decoder performed significantly better than the P600 decoder from 180 to 410 ms ($p < 0.05$; FDR corrected) while the P600 decoder performed significantly better than the N400 decoder from 590 to 1300 ms ($p < 0.05$; FDR corrected). Between 410 and 590, both classifiers performed significantly above chance and neither classifier performed significantly better than the other (see Fig. 3D). Using different time windows for the P600 classifiers, i.e.,

500-700ms, 700-900ms, 800-1,000ms, 600-1000ms, had no qualitative impact on the results (see Supplementary Analysis 1 in the Supplementary Materials).

Fig. 4: Control analysis for between-subjects variability in timing of ERP components. Single subject decoding performance time courses, stacked and sorted by mean decoding score in the time window in which the respective decoder was trained. (A) Results for classifiers trained on the N400 time window, and (B) results for classifiers trained on the P600 time window. Above this heatmap, regression coefficient time series (blue line) plus confidence intervals are shown, representing the degree of correlation between activity in the sorting window and the respective time point in the trial. For details, see the text. For colour Fig., please refer to the digital version of this article.

Finally, we conducted an additional analysis to rule out that the observed overlap was the spurious result of non-overlapping effects that, however, might vary temporally between participants. To that end, we plotted single-subject time courses of decoder performance, sorted by decoding performance in the respective time window in which the classifiers were trained (i.e., N400: Fig. 4, left panel; P600: Fig. 4: right panel). If the overlap of N400 and P600 patterns is present at the level of the individual participant (i.e., if the overlap is not a spurious result due to averaging non-overlapping but – between subjects – temporally variable effects), then there should be a statistically reliable correlation between decoding strength in the training time window and time-generalized decoding strength in the overlap window, for both components. To test this, we conducted regression analyses predicting, at each time point, decoding strength (outcome variable) based on the rank order of decoding strength averaged

over the training window (predictor variable). This analysis was also done for both time windows. The blue line in Fig. 4 represents the time course of these regression coefficients, together with the 95% confidence interval. We find that, as expected under the cascading architecture, heatmaps of single subject decoding scores showed a vertical gradient both in the sorting and in the overlap window. We also observe statistically reliable positive regression scores (with confidence intervals excluding zero) to the right of the N400 time window (left panel) and to the left of the P600 time window (right panel), spanning the full overlap window (i.e., 500-600ms). This indicates that the observed temporal overlap of N400 and P600-based decoding does not result from temporally dissociable but jittered sequential processes. For further single-trial based evidence against temporally jittered effects, see Supplementary Analysis 1 in the Supplementary Materials.

4. Discussion:

In the present study, we applied a novel approach to the analysis of EEG data – time-generalized multivariate pattern decoding (King & Dehaene, 2014) – to decide between different possible cognitive architectures underlying the processing of semantic congruency violations during sentence comprehension. Consistent with previous research (Bornkessel-Schlesewsky & Schlewsky, 2006; Brouwer et al., 2017; Kuperberg, 2007), our sentence processing paradigm elicited a biphasic ERP pattern with a centrally distributed N400, followed by a late positivity for incongruous relative to congruous target words. This late positivity shows an enlarged squared-decoding profile demonstrated in previous reports on decoding late positivities, e.g., King et al. (2013), compatible with a sustained component active over long stretches of time.

The observed biphasic ERP pattern can – in principle – result from multiple alternative underlying cognitive architectures, including a strictly serial sequence of at least two cognitive processes, a cascading sequence of at least two distinct cognitive processes that overlap in time, or the latency-shifted activation of a single process in both experimental conditions.

Decomposition of the semantic mismatch N400/P600 with Generalization Across Time MVPA resulted in a pattern consistent with the predictions derived from the cascading model, as laid out in Fig. 1, which suggests the temporally overlapping activation of two cognitive processes that are distinguishable at the neurophysiological level. Specifically, MVPA classifiers that were trained in an a-priori defined N400 time window to distinguish EEG patterns elicited by congruent vs. incongruent target words did not generalize throughout the entire time window of the late positivity, and vice versa. Rather, there was only partial overlap between the two EEG effects. This decoding pattern is consistent with the widely shared assumption that at least two distinct neuro-cognitive processes are activated after encountering a semantically incongruent word (Bornkessel-Schlesewsky & Schlewsky, 2009; Kuperberg, 2007).

However, both EEG patterns (i.e., N400 and P600) could be recovered from 360 to 770 ms post stimulus onset, which supports the simultaneous presence of both neural activation patterns (and thus, by inference, for the simultaneous activation of two cognitive processes). We interpret this result as strong support for a cascading cognitive architecture of semantic mismatch processing, as it indicates that the second neuro-cognitive process was initiated before the termination of the first process. In the following, we will discuss the theoretical implications of this result for neurocognitive models of language processing, followed by a critical consideration of the value of the multivariate generalization across time decoding method for neurocognitive studies of language processing.

4.1 Implications for neurocognitive models of sentence processing

Most neurocognitive models of language comprehension share the assumption of sequential activation of different processing stages, but are often underspecified with respect to the precise timing of this processing sequence. For example, a prominent model of sentence comprehension (Friederici, 1995; 2002) postulates a temporal sequence of (i) first pass syntactic structure building, followed by subsequent stages of (ii) semantic and thematic integration as well as – if necessary – by additional processes of (iii) syntactic reanalysis and repair. Following the discovery of semantic P600 effects (Kim & Osterhout, 2005), models

inspired by this three-stage architecture proposed a more general role for the late ERP positivity - e.g., corresponding to the integration between linguistic information in a narrow sense, and other, more general sources of information that may inform sentence meaning (Bornkessel-Schlesewsky & Schlesewsky, 2009). Similarly, an influential model of speech processing by Hickok and Poeppel (2007) assumes that early phonological analysis is followed by lexical, semantic, and combinatorial-syntactic processing of the speech signal in the form of a processing stream from posterior to anterior brain areas. These and similar models can accommodate a strictly serial as well as a temporally overlapping (cascading) sequence of processes, as they make no explicit claims concerning whether or not an individual process has to be finalized before the subsequent processing stage can be initiated.

Our results support such models as they provide evidence for the presence of distinguishable cognitive processing stages, which rules out the theoretical possibility of the occurrence of a latency shifted single process (e.g., Curran et al., 1993) as generator of the biphasic ERP pattern. In principle, our results are also compatible with the possibility that a single, unified computational process is applied to distinct types of linguistic information at different times and, importantly, at different locations of the brain or in different cortical networks (thereby eliciting distinguishable neurophysiological activation patterns). One such possibility is the proposal by Hagoort (2005; see also, e.g., Hagoort, 2017) that sentence processing relies upon a general combinatorial process (i.e., unification) applied to linguistic units at multiple different levels of representation (e.g., phonologic, semantic, syntactic).

The present data provide evidence for the cascading, temporally overlapping activation of the involved cognitive processes. Cascading models have originally been proposed to capture the benefits of sequential models - e.g., their simplicity and strictness - while accommodating for experimental findings that question the strict independence of different processing stages (such as the lack of blocking effects in certain contexts; Bornkessel-Schlesewsky & Schlesewsky, 2009). Cascading architectures are also computationally efficient in that processing stages are not in danger of running idle while a previous stage works, and are thus more robust to processing difficulties during on-line processing of

congruent speech - which is assumed to be incremental in the sense that processing of each element starts immediately when it becomes available, instead of being postponed (Knoeferle, Crocker, Scheepers & Pickering, 2005).

The temporal overlap of activation of distinct processing stages can also be interpreted as not just reflecting simultaneously active processes, but as actually interacting processes – which in turn may be a necessary component of information transfer between brain systems. Thus, it is possible that the time-window of temporal overlap corresponds precisely to the time window where different cognitive processes exchange information. If the simultaneous activation of neurocognitive systems is indeed a pre-condition for information transfer between these cognitively distinct processing stages, an interesting avenue for future research would be to investigate patterns of cortical information flow specifically in time windows of simultaneous pattern activation. With this, our results provide a potentially interesting starting point for future examinations of the behavioural relevance of temporally overlapping cognitive processes. For example, it might be worthwhile to explore whether individual differences in the duration of pattern overlap (or, for that matter, also in the duration of activation of the different processes themselves) impact behavioural performance - e.g., because cross-domain information flow is more effective.

4.2 Potential of MVPA decoding across time for neurocognitive language research

Beyond the current demonstration for semantic violations, MVPA with generalization across time (King & Dehaene, 2014) can be fruitfully applied to many further questions in the neurocognitive study of language processing. First and foremost, this concerns addressing problems that are inherent to the univariate ERP method, such as component overlap or ambiguous component identity. For example, future studies could use MVPA with generalization across time to investigate to which extent semantic P600 and syntactic P600 cross-decode between semantic and syntactic violations (i.e., whether or not pattern classifiers trained to identify a P600 elicited by syntactic violations can identify semantic violations in the P600 time window as well, and vice versa), or whether P600 effects induced by syntactic errors

vs. syntactic complexity (e.g., Friederici, 2011, p. 1382) are instances of the same or of different processes. Similarly, the Left-Anterior Negativity/LAN, particularly in the context of a biphasic LAN/P600 pattern, has elicited controversial discussion due to inconsistencies across studies concerning both its topography and its elicitation in different contexts (e.g., Molinaro, Barber & Carreiras, 2011; Molinaro et al., 2015; Tanner & Van Hell, 2014; Tanner, 2015). MVPA analyses can resolve such open issues concerning the specificity (for language or for specific domains of language) of established language-related ERP components, and thereby further constrain the range of plausible candidates for the neurocognitive architecture of language processing. Its capability of identifying overlapping components is for example demonstrated in the present study, as it could quantitatively demonstrate the simultaneous activation of a late positivity and a long-lasting N400 component.

MVPA with generalization across time potentially offers a solution to problems like these. First, it is, by and large, a reference-free method and largely independent of specific filter settings. As long as the information (i.e., a specific neurophysiological activation pattern) is present in the signal, MVPA will pick up on it, insensitive to the specific electrodes at which effects will appear. In its ability to aggregate over multiple sensors and thereby, if required, reduce the analysis to a single time course, temporal decoding also prevents the potential problem that important electrodes showing the effect of interest may unintentionally be omitted, as Tanner (2015) cautions. Second, time-generalized MVPA is more robust against individual differences in the specific morphology of activation patterns (which may, e.g., vary due to differences in the neuroanatomy of the generator regions). For example, persistence of a pattern in (or generalization across) time should only be observable if within individual subjects, the same pattern occurs at different time points – even if its scalp topography differs between persons. In the case of univariate ERP analysis, in contrast, effects can result from the averaging of heterogeneous participants that are arbitrarily different from those of any individual participant (see also our control analyses reported in the Supplementary Materials). Third, cross-decoding of ERP components (i.e., trying to explain ERP patterns with MVPA classifiers trained on other time windows of the data set or on independent datasets) can

directly address the relationship between a specific ERP difference and established ERP components such as the N400 and the P600. For example, if - as Tanner (2015) speculates - some LAN effects indeed stem from the overlay between an N400 and a P600, then MVPA decoders trained on an N400 effect, but also decoders trained on a P600 effect should show above-chance accuracy when applied to activity in the LAN time window. Conversely, decoders trained on the LAN effect in question should show some success in cross-decoding to N400 and P600 components.

4.3 Potential Limitations

Consideration of inter-individual differences, as discussed by Tanner (2015), also highlights some limitations of temporal decoding. While MVPA is trained within subjects, the grand-mean visualization and across-subjects statistical tests of decoding accuracies will still be sensitive to some forms of between-subject variance. E.g., if some subjects only show an N400, others only show a P600, and none show both, then the grand mean MVPA result will likely result in significant – though weaker – decoding in both the N400 and P600 time windows. Similarly, temporal variability of component latency within subjects may influence decoding results. E.g., if the two EEG patterns investigated here were in fact strictly serial, but the onset of the first component would differ substantially from trial to trial, averaging across trials might introduce a result similar to the component-overlap we report in the present study. However, in the analysis summarized in Fig. 4 -- and in addition, in the Supplementary Materials accompanying the present study -- we report control analyses that render this possibility highly unlikely.

Also, while many potential problems of EEG/ERP analysis are circumvented by MVPA, some issues remain. For example, just as ERP effects are usually interpreted regarding the differences between conditions (Luck, 2005), MVPA is typically applied to decode a condition contrast. Just as it is not trivial to assign a component to either one of the conditions (e.g., a positivity in one or a negativity in the other), a pattern identified by MVPA can stem from either of the two conditions. Thus, like any other method, MVPA is still fallible and requires careful

experimental design as well as descriptive data analysis. It is also in principle affected by some of the filtering issues known in EEG/MEG research, insofar as filters can shift, compress, or extend components in time. However, the effects of filtering are predictable. Low pass filters remove patterns that change quickly from time point to time point, and thus bear the danger of inducing spurious effects of generalization across time. High pass filters remove patterns that are stable across longer time spans, and thus remove generalization across time. Here, using a .1 -30Hz filter provides a conservative choice where the filter thresholds are sufficiently far removed from the observed signal so that filtering can be excluded as a substantial source of contamination. Nevertheless, particularly when applied in a complementary manner with univariate analysis, it can circumvent many problems, and open up new avenues of investigation. MVPA is thus not a universal inference engine, but an additional tool for experimentalists.

4.4 Conclusion

To our knowledge, this is the first application of time-generalized MVPA (King & Dehaene, 2014) to EEG data from sentence processing experiments. We have demonstrated the usefulness of this novel method for investigating specific aspects of the neurocognitive architecture of language processing that cannot be resolved using ERPs alone, or with other methods like functional MRI. For the present case of semantic mismatch processing, we provide evidence in accordance with the predictions we derived for a cascading architecture involving a temporally overlapping sequence of two distinguishable cognitive processes. We discussed possible implications of this finding, including temporal overlap in activation as a possible mechanistic basis for information exchange between the involved neurocognitive processes. We propose that MVPA decoding across time is an interesting, novel technique that can be fruitfully applied to a range of further research questions in the neurocognition of language.

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Competing Interests Statement

The authors declare no competing financial interests.

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