Decoding Semantic Content from EEG

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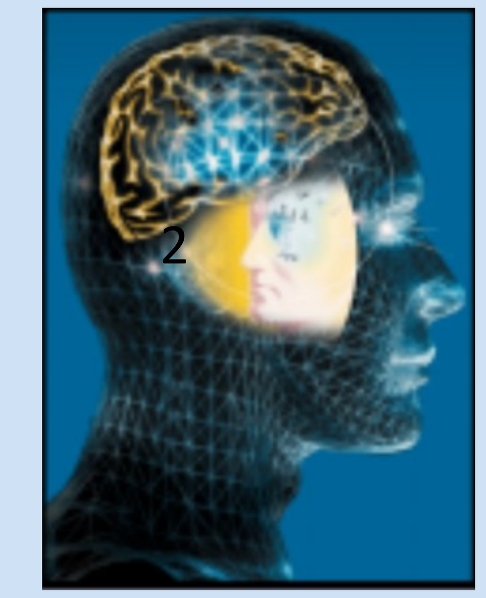


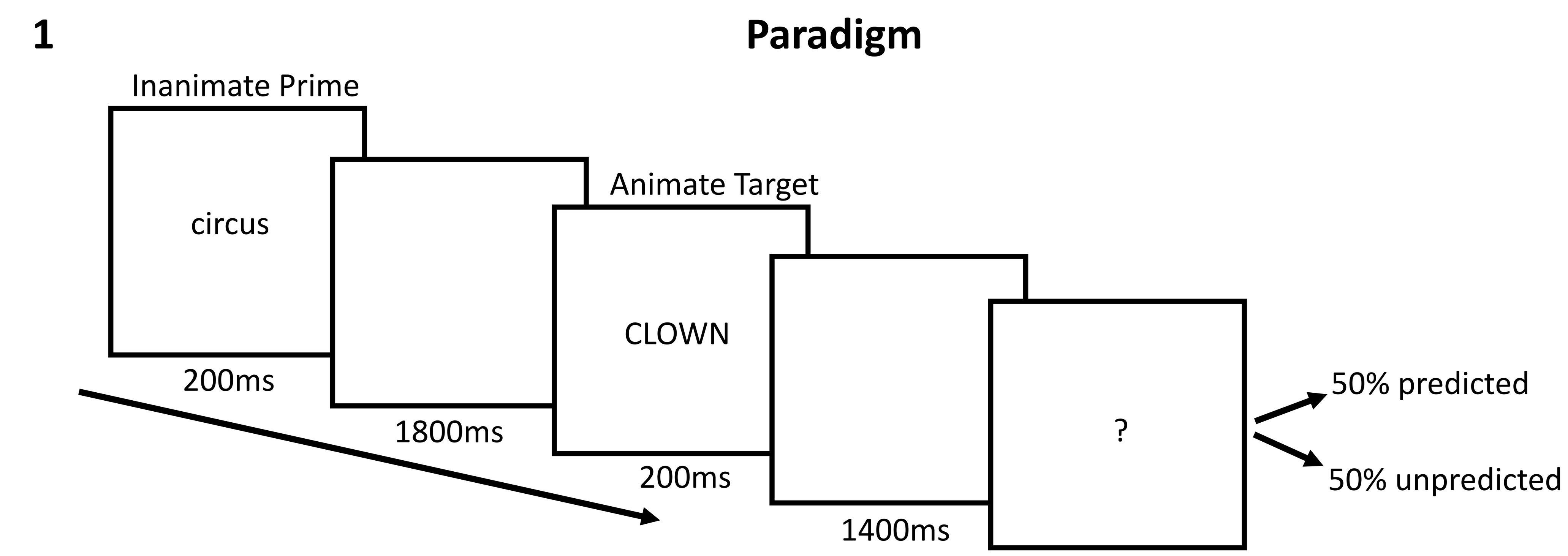
Introduction

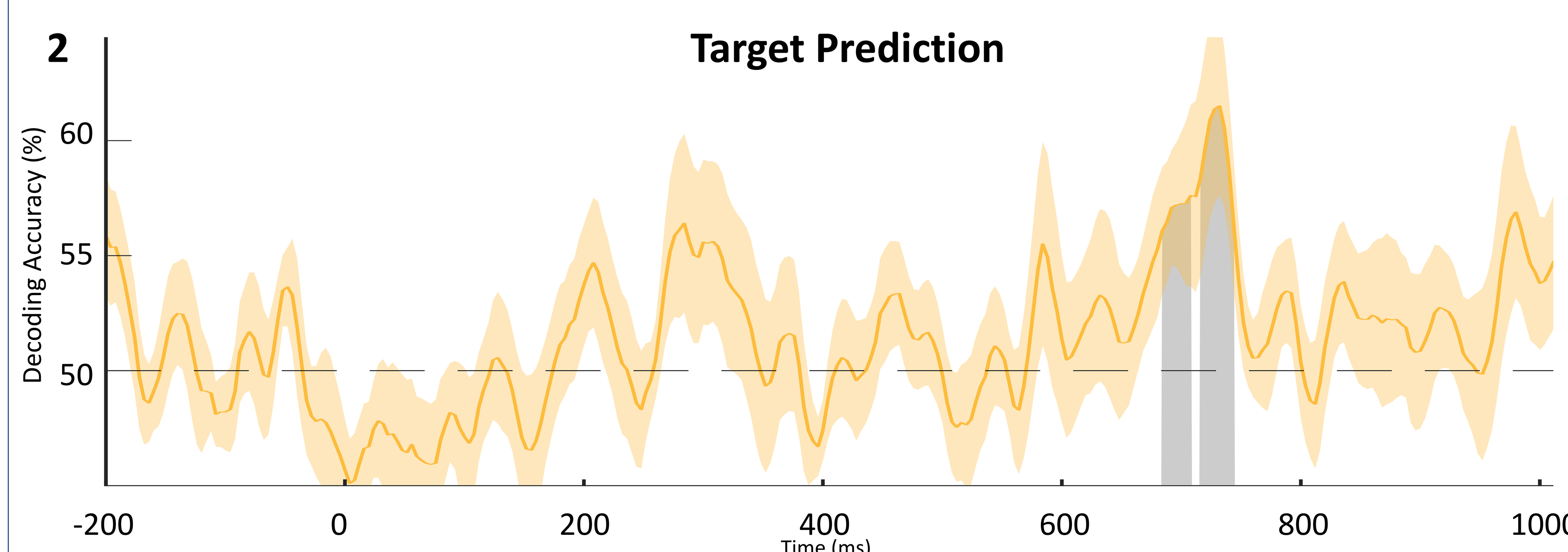
Traditional univariate analysis of EEG and ERP data have provided many insights in the dynamic neural computations that underlie visual word recognition (Grainger & Holcomb, 2009). But it is difficult to infer the linguistic content of these computations using these traditional analysis methods. Recent developments in machine-learning classification have provided a promising tool to analyze the content of computations in the EEG signal (Bae & Luck, 2018, 2019; Hong et al., 2020), but little is known about their application to studies of word recognition. In the present study, EEG data from a visual ERP prediction accuracy priming paradigm (Brothers et al, 2016) were used to examine if an adaptation of a Support Vector Machine (SVM)-based classification analysis method (Bae & Luck 2018) could reliable categorize the EEG signal along two dimensions: 1) the prediction accuracy of the target words, and 2) the animacy of the prime and target words.

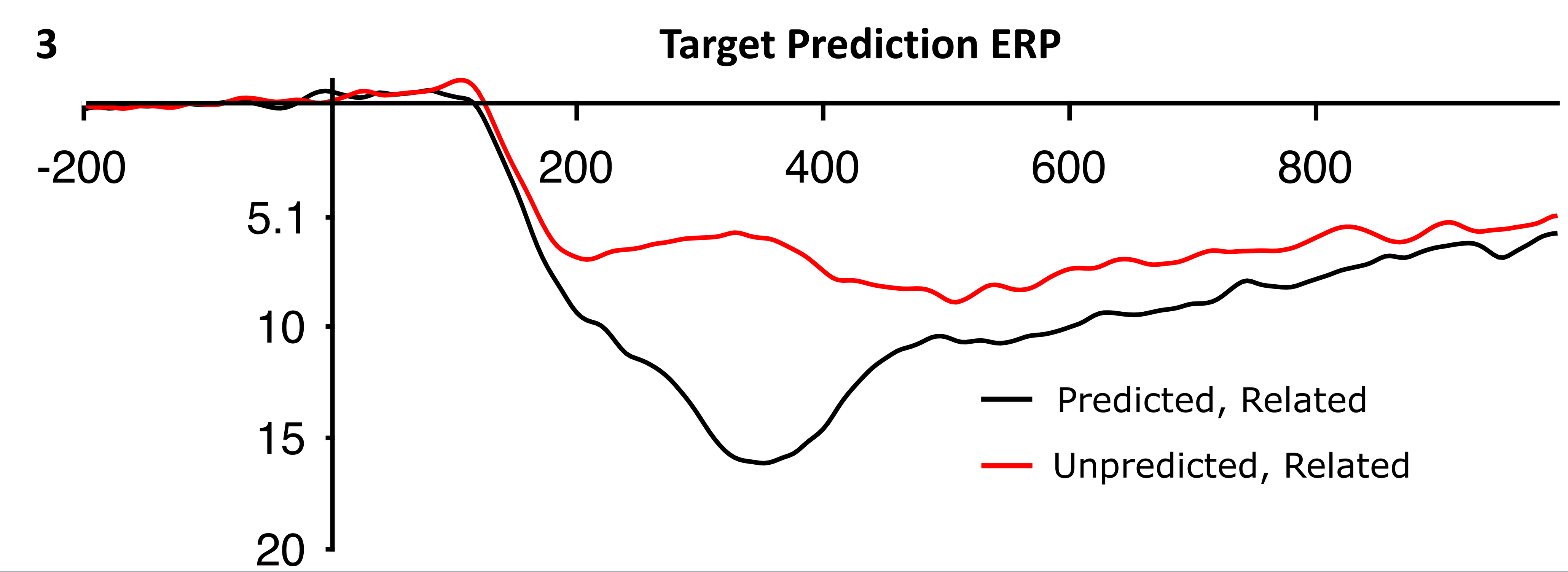
Methods: Paradigm

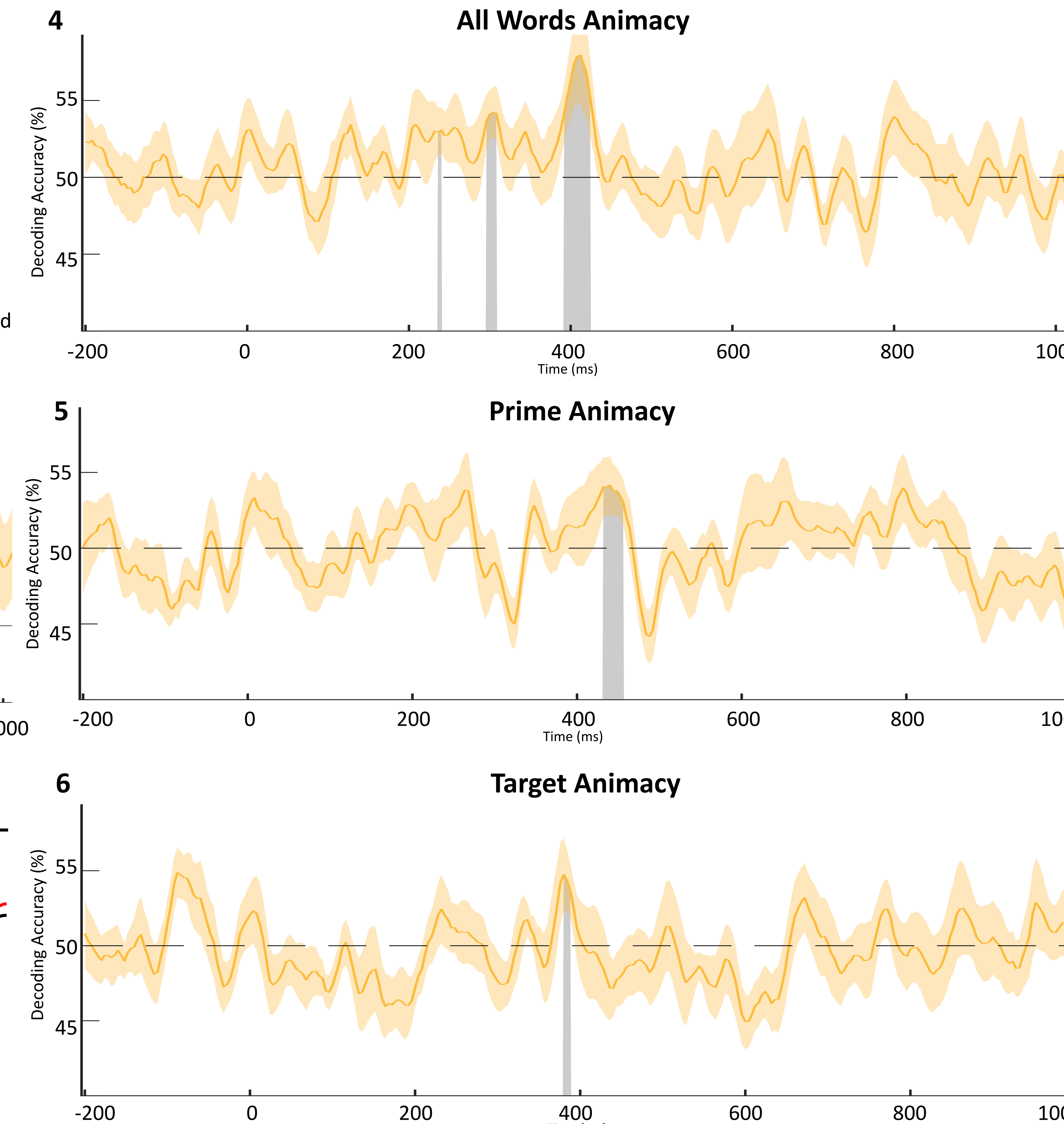
Figure 1. Participants (N=13) read 320 related (circus – CLOWN) and 160 unrelated word pairs (table – CLOWN). Related word pairs had a forward association strength of 0.5 (range = 0.4-0.6). Target words were the same across all lists. The task was to actively predict the target word and to indicate with a button press if the target word had been accurately predicted or not. Words were labeled according to animacy post-hoc. Animate words consisted of people, animals, and titles (manager). Inanimate words consisted of objects and abstract words (worry).

Figure 3. We assessed the magnitude of the lexical ERP effects for prediction (predicted-related, unpredicted-related).









Methods: Decoding

The SVM method classified 500 time points across the -200 – 1800ms stimulus-locked interval according to either animacy or prediction. Machine learning was performed over 10 iterations using 3-fold cross validation. In each iteration, trials were separated into 3 blocks (2 training; 1 testing) and were rotated. This allowed each data point to be used for both training and testing. Decoding accuracy (chance level = 50%) was calculated across all iterations for each subject and then averaged across subjects. To keep an equal number of trials across conditions, each iteration used a random sampling of the larger condition. Statistical significance was determined using a permutation method (Bae & Luck, 2019). This allowed for multiple comparison correction and accounted for autocorrelation in the EEG data.

Results & Discussion

Decoding for prediction accuracy (figures 2,3): The decoder reliably categorized (significantly above chance) EEG trials according to prediction accuracy of the targets in two epochs; both were within 650 – 800ms.

Decoding for animacy (figures 4,5,6): The decoder reliably categorized (significantly above chance) EEG trials according to animacy of the targets in three epochs; all were within 200 – 500ms.

These results indicate the SVM-based method was able to reliably classify EEG data according to the 1) prediction accuracy of target words in a priming paradigm and 2) whether words were animate or not. In future studies we aim to examine if we can decode in the EEG signal the exact nature of the information that is anticipated during word processing.

References

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