Supplementary material

The ERP response to the amount of information conveyed by words in sentences

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1 Models’ linguistic accuracy

Figure 1 displays how the models’ linguistic accuracy develops as the models are trained on an increasingly large data set (for RNN and PSG models) or as the order $n$ increases (for $n$-gram models). There are 10,000 word types in the selected BNC training corpus, so a model with no knowledge of the language would have a linguistic accuracy of $\log(1/10,000) = -9.21$. For the parts-of-speech models, this baseline is $\log(1/45) = -3.81$.

Fig. 1: Linguistic accuracy (average $\log P(w_{t+1}|w_1...t)$ over experimental sentences) of each language model, defined over words (top row) or parts-of-speech (bottom row). ‘Training data subset 10’ refers to the full training corpus (i.e., subset 9) presented twice to the RNN model.
2 Correlation between baselines and ERP amplitudes

Table 1 presents the coefficients of correlation between each ERP’s baseline and component amplitude, for different cut-off frequencies of the additional high-pass filter.

Table 1: Correlations between ERP baselines and component amplitudes, for different high-pass filters.

<table>
<thead>
<tr>
<th>Filter freq. (Hz)</th>
<th>ELAN</th>
<th>LAN</th>
<th>N400</th>
<th>EPNP</th>
<th>P600</th>
<th>PNP</th>
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<tbody>
<tr>
<td>(none)</td>
<td>.796</td>
<td>.522</td>
<td>.538</td>
<td>.756</td>
<td>.620</td>
<td>.583</td>
</tr>
<tr>
<td>0.25</td>
<td>.265</td>
<td>.360</td>
<td>.291</td>
<td>.419</td>
<td>.255</td>
<td>.160</td>
</tr>
<tr>
<td>0.33</td>
<td>.190</td>
<td>.295</td>
<td>.228</td>
<td>.352</td>
<td>.159</td>
<td>.087</td>
</tr>
<tr>
<td>0.50</td>
<td>.089</td>
<td>.190</td>
<td>.138</td>
<td>.248</td>
<td>.022</td>
<td>−.018</td>
</tr>
</tbody>
</table>

3 Exploratory analysis results

Each of the four Figures 2 to 5 shows the fit to ERP amplitudes of one of the four information measures: word surprisal, PoS surprisal, word $\Delta H$, and PoS $\Delta H$, respectively. Plotted are the $\chi^2$-statistics for individual language models as a function of each model’s linguistic accuracy. Negative values indicate effects in the negative direction. Dotted lines indicate $\chi^2 = \pm3.84$, the critical value at the $\alpha = .05$-level, which must not be taken as an indication of statistical significance because of the exploratory nature of these results.
Fig. 2: Fits of all models’ word surprisal to the amplitudes of different ERP components.
Fig. 3: Fits of all models' PoS surprisal to the amplitudes of different ERP components, over and above word surprisal under a 4-gram model trained on the full BNC corpus.
Fig. 4: Fits of RNN models’ word entropy reduction (for different levels of the lookahead distance $k$) to the amplitudes of different ERP components, over and above word surprisal under a 4-gram model trained on the full BNC corpus.
Fig. 5: Fits of RNN models' PoS entropy reduction (for different levels of the lookahead distance $k$) to the amplitudes of different ERP components, over and above word surprisal under a 4-gram model trained on the full BNC corpus.