An Eye Opener Regarding Task-Based Text Gradient Saliency

Anonymous ACL submission

Abstract

Eye movements in reading reveal humans' cognitive processes during language understanding. As such, the time a reader's eyes dwell on a token has been utilized as a measure for the visual attention paid to that word, or the importance of that word to the reader. This study investigates the alignment of the importance attributed to input tokens by language models (LMs) on the one hand and humans, in the form of fixation durations, on the other hand. While previous research on the internal processes of LMs have employed the models' attention weights, recent studies have argued in favor of gradient-based methods. Moreover, previous approaches to interpret LMs' internals with human gaze have neglected the tasks readers performed during reading, even though psycholinguistic research underlines that reading patterns are task-dependent. We thus introduce a novel approach that employs a gradient-based saliency method designed to emulate task-specific human reading strategies to align model and human importance, and we find that task specificity plays a crucial role in this alignment.

1 Introduction

Human eye movements during reading reflect cognitive processes involved in language processing (Just and Carpenter, 1980; Rayner, 1998): the fixation duration on a word correlates with reading comprehension (Rayner, 1977; Malmaud et al., 2020a). As such, fixation duration has been employed as proxy of the relative importance of a word to a reader (Hollenstein and Beinborn, 2021).

The introduction of neural attention mechanisms (Bahdanau et al., 2014) and the Transformer architecture (Vaswani et al., 2017), which relies on self-attention to compute input and output representations, has given fresh impetus to research into how language models (LMs) process language. Attention mechanisms assign dynamic weights to input tokens, offering a method to understand a model's internal functioning and decision-making processes (Wang et al., 2016; Ghaeini et al., 2018).

Recent research has compared model and human language comprehension by aligning model attention weights with human reading metrics, such as fixation durations (Sood et al., 2020; Eberle et al., 2022; Bensemann et al., 2022), presuming model attention effectively signifies the relative importance of input tokens. However, research on attention (Jain and Wallace, 2019; Serrano and Smith, 2019; Brunner et al., 2019) has questioned the reliability of attention weights in accurately reflecting token significance, labeling attention as a contentious issue in interpretability discussions (Bastings and Filippova, 2020). Alternative approaches like gradient-based saliency (Simonyan et al., 2014; Li et al., 2016), which assess the impact of input tokens on model predictions through gradients, are proposed for better assessing token importance. Building on this, Hollenstein and Beinborn (2021) incorporated a saliency method by correlating gradient saliencies, obtained through iterative token masking and gradient computation, with human fixation durations. However, the output space of this approach comprises tens of thousands of tokens, which makes gradient-based saliency methods uninformative (Yin and Neubig, 2022). Moreover, the model and the humans did not partake in the same task when processing the text, which is a crucial discrepancy, as psycholinguistic studies show that human reading strategies vary with the task and differ from normal reading (Shubi and Berzak, 2023; Mézière et al., 2023; Malmaud et al., 2020b).

To address this, we propose a novel gradient-based saliency approach that replicates the classification tasks humans perform during task-specific reading to better align the importance LMs and humans assign to tokens. Additionally, we expand our analysis to include decoder-based LMs, which, due to their auto-regressive nature, align more closely with the incremental nature of human processing.

2 Related Work

Model attention and human attention Research comparing model attention to human visual attention, using fixation locations and durations as proxies, has produced mixed findings. Sood et al. (2020) observed distinct differences between transformer LM attention patterns and human fixation patterns. Conversely, studies by Eberle et al. (2022) and Bensemann et al. (2022) found strong correlations between early transformer layer attention weights, like those in BERT (Devlin et al., 2019), and human visual attention, contrasting with earlier results. This discrepancy can be attributed to methodological differences in processing attention weights: Sood et al. (2020) analyzed maximum attention values from the last layer's sub-word tokens, while Bensemann et al. (2022) averaged attention across sub-word tokens in the first layer.

Limitations of attention-based interpretation The inconsistent results outlined above challenge the usefulness of methods based on model attention to investigate the internals of LMs. Indeed, Brunner et al. (2019) emphasize the lack of token identifiability as one moves to higher layers of a model, and Abnar and Zuidema (2020) show that distinct attention patterns are only found in earlier layers, while in higher layers the attention weights approximate a uniform distribution. Moreover, Jain and Wallace (2019) question whether attention weights can reliably identify the relative importance of inputs to the entire model, showing that different attention distributions yield equivalent model predictions. Similarly, Serrano and Smith (2019) find attention weights to be very noisy indicators of importance. Finally, an analysis of BERT's (Devlin et al., 2019) attention (Clark et al., 2019) reveals a significant focus on the [SEP] token, which does not affect model outputs when its attention is altered, suggesting a "no-op" operation. Similarly, research on attention heads (Voita et al., 2019; Michel et al., 2019) finds that many of them can be pruned with minimal impact, further indicating the potential redundancy or non-operational nature of certain attention mechanisms.

Saliency-based methods for analyzing LMs with human gaze As saliency-based methods are arguably more suited than methods based on attention (Bastings and Filippova, 2020) for model analysis, Hollenstein and Beinborn (2021) extract token importance by iteratively masking each input token, computing the L2 norm of the gradient for the correct output with respect to each token, and then summing all saliency scores for each input token. However, while they do emulate the LM's pre-training objective, this does does not necessarily align with human processing: whereas the model "sees" the input only partially, and as many times as there are tokens, the readers see the input fully and only once. Moreover, the gaze data used in their study was, in parts, recorded while participants were completing a task, such as sentiment analysis and relation extraction (i.e., task-specific reading). In our approach, we thus compute gradients by having the model perform the same kind of classification task that humans performed during reading. Thereby the token importance attributed by both humans and the model refers to the importance within the constraint of a specific task, and the model sees the input only once, and fully.

3 Method

Consider an input sentence, formalized as $\mathbf{x} = \langle x_1, \ldots, x_N \rangle$ of N tokens, where x_j is the j^{th} token (word) in the sentence, and two corresponding token importance vectors of the same length: the *human importance* vector $\mathbf{h} = \langle h_1, \ldots, h_N \rangle$ and the *model importance* vector $\mathbf{m} = \langle m_1, \ldots, m_N \rangle$, where h_j and m_j are the human and model importance attributed to token x_j. We obtain the mean Spearman correlation between model and human importance by computing the by-token Spearman correlations between the vectors $\mathbf{m}$ and $\mathbf{h}$ for all sentences $\mathbf{x}$, then dividing the sum of these correlations by the number of sentences $\mathbf{x}$.

Extracting model importance: gradient-based saliency The *model importance* vector $\mathbf{m}$ consists of gradient saliency values m_j for each input token x_j of the sentence $\mathbf{x}$. "Saliency" refers to neural network interpretation methods that assign an importance distribution over the input in order to analyse a network's prediction (Ding and Koehn, 2021). In other words, saliency methods aim at explaining how sensitive the decision of a model is to changes in the input. The most common method of assigning this importance distribution is by means of the gradient (Simonyan et al., 2014). Given a parametrized language model f_θ, we compute the gradient g with respect to an input token $x_j \in \mathbf{x}$ as

$$g(x_j) := \frac{\partial f_\theta^c}{\partial x_j}(\mathbf{x}), \tag{1}$$

	BERT *base*	BERT *large*	RoBERTa	DistilBERT	GPT-2 *base*	GPT-2 *large*	OPT
				Sentiment Analysis (SA)			
fine-tuned	0.61$_{0.010}$	*0.57*$_{0.011}$	*0.47*$_{0.012}$	*0.53*$_{0.011}$	0.49$_{0.011}$	0.55$_{0.010}$	*0.43*$_{0.012}$
pre-trained (0-shot)	0.55$_{0.011}$	0.59$_{0.010}$	0.45$_{0.012}$	0.52$_{0.012}$	0.4$_{0.014}$	0.48$_{0.012}$	0.42$_{0.013}$
random init. (0-shot)	0.24$_{0.013}$	0.22$_{0.013}$	0.04$_{0.014}$	0.21$_{0.013}$	0.2$_{0.014}$	0.19$_{0.014}$	0.15$_{0.015}$
				Relation Extraction (RE)			
fine-tuned	*0.53*$_{0.010}$	0.52$_{0.009}$	0.42$_{0.010}$	0.45$_{0.010}$	0.46$_{0.010}$	0.52$_{0.009}$	0.5$_{0.011}$
pre-trained (0-shot)	0.51$_{0.010}$	0.47$_{0.011}$	0.37$_{0.011}$	0.49$_{0.010}$	0.37$_{0.011}$	0.45$_{0.011}$	0.42$_{0.011}$
random init. (0-shot)	0.08$_{0.011}$	0.07$_{0.011}$	0.04$_{0.012}$	0.09$_{0.011}$	0.16$_{0.013}$	0.16$_{0.013}$	0.14$_{0.014}$

Table 1: We report mean Spearman correlations and standard errors between model and human importance for all models in their *fine-tuned*, *pre-trained (0-shot)*, and *randomly initialized (0-shot)* version, for both tasks SA and RE. The difference in correlations is significant in all cases except for the ones indicated in italic.

where c indexes the true class y in the model's output, and f_θ^c refers to the predicted output logit for the true class y. We then follow Li et al. (2016) by defining the gradient saliency m_j of token x_j as the L1 norm of its gradient $m_j := |g(x_j)|$. Since different LMs employ different tokenization methods which split tokens into sub-word tokens (Sennrich et al., 2016; Song et al., 2021), we pool gradients back to token level by summing up the sub-word token-level gradient norms. We then normalize the token-level saliencies by dividing them by the sum of all saliency values in the sentence.

Extracting human importance: relative fixation duration To obtain the *human importance* vector $\mathbf{h}$, we first extract raw total fixation durations $t_{j,r}$ for each token $x_j \in \mathbf{x}$, which is the sum of the durations of all fixations on that token by a reader r. However, due to variations in reading speed across readers and sentences, these raw durations can vary significantly between instances. We thus normalize them by dividing them by the sum of durations across all tokens within a sentence, resulting in *relative fixation durations* $d_{j,r} = t_{j,r}/\sum_j t_{j,r}$ for each token x_j. These relative durations are then averaged across all readers to bypass individual differences and to obtain a more robust signal, resulting in aggregated relative fixation durations $h_j = \sum_r d_{j,r}/\,|\text{readers}|$ for each token x_j.

4 Experiments[1]

Datasets The eye-tracking part of the *Zurich Cognitive Language Processing Corpus* (ZuCo; Hollenstein et al., 2018) comprises two task-specific readings: in the sentiment analysis (SA) reading, participants were presented with a subset from the *Stanford Sentiment Treebank* (SST; Socher et al., 2013) that consists of movie reviews, based on which they had to rate the movies; in the relation extraction (RE) reading, they performed relation extraction on a subset of sentences from the *Wikipedia relation extraction corpus* (Culotta et al., 2006).

Models and fine-tuning We include both encoder models and decoder models, as well as models from the same family but different in size. Encoders include BERT (Devlin et al., 2019) *base* and *large*, RoBERTa (Liu et al., 2019), and DistilBERT (Sanh et al., 2019); decoders include GPT-2 (Radford et al., 2019) *base* and *large*, and OPT (Zhang et al., 2022). As the models perform classification — ternary for SA, and 9-class for RE —, we utilize the architecture variants implemented for sequence classification in Huggingface (Wolf et al., 2019). For SA, we fine-tune the models on the SST dataset and for RE on the *Wikipedia* dataset (Culotta et al., 2006) , excluding the sentences used for ZuCo SA and RE, respectively.[2]

Baselines. We include two sets of baseline models: the above-mentioned models randomly initialized (*random* (0-shot)), and the models pre-trained but not fine-tuned (*pre-trained* (0-shot)).

Results As depicted in Table 1, the more similar the model's training is to the human task, the more aligned are the model and human importance vectors. There exist medium to strong correlations between the fine-tuned *model importance* and *human importance* vectors, exemplified by correlations of 0.61 by BERT *base* or 0.55 by GPT-2 *large* for SA. Additionally, most *fine-tuned* models produce significantly higher correlations than the *pre-trained* baselines, and the pre-trained models all have significantly higher correlations than their randomly initialized counterparts. Encoder models, on average, achieve higher correlations than decoders, despite variability within both types. Additionally, SA task model importance correlates more strongly on average than for RE.

[1]Our code is available at `anonymous-link`.

[2]For training and implementation details as well as classification test results, see Appendix A.

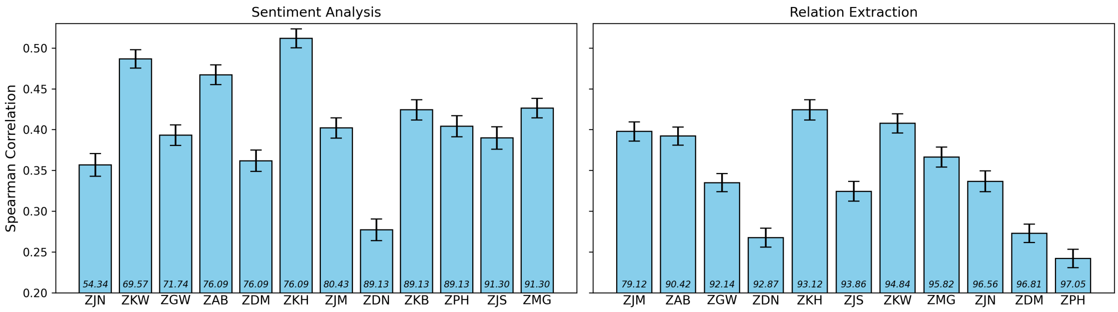

Figure 1: Mean Spearman correlations between relative fixation durations and gradient saliencies for fine-tuned BERT *base* are depicted at the participant level, with error bars denoting the standard error. Participants are arranged according to task accuracy, with their average task accuracies presented at the bottom of each bar.

5 Participant-level analysis

To investigate whether the models correlate more with certain participants, we perform an additional participant-level analysis in which we compute correlations between the model-extracted saliency values and relative fixation durations for each participant individually. We also extract the participants' response accuracies for both their SA and RE, averaged over sentences. The underlying intuition is that the models possibly correlate more with participants that have a higher task accuracy.

Results The juxtaposition of correlations on participant level and participants' accuracies reveals no discernible pattern, as exemplified by BERT *base* in Figure 1. The correlation coefficients between participants exhibit great variability in both tasks. Participants' task accuracies are distributed across a wide range for SA but exhibit a ceiling effect for RE. Moreover, averaging the participant-level correlations yields lower correlation values than using the aggregate relative fixation durations, e.g., the group-level correlation with BERT *base* is 0.61 and the average on participant-level is 0.41.[3]

6 Discussion and Conclusion

The experimental results find medium to strong correlations between model importance vectors, derived from gradient saliencies, and human importance vectors, indicated by relative fixation durations, particularly when language models (LMs) are fine-tuned for tasks mirroring those undertaken by readers: task-specific fine-tuned models demonstrate notably stronger correlations than pre-trained zero-shot baselines. The discrepancy between the pre-trained and randomly initialized models suggests an initial understanding for human importance attribution acquired during pre-training. These findings underline the importance of matching tasks between models and humans for accurate gaze analysis, with task-specificity influencing reading behavior but remaining largely ignored in NLP (Shubi and Berzak, 2023). We further find that SA tasks show consistently higher correlations than RE, possibly due to the complexity introduced by more output classes affecting model predictions. Moreover, initial observations suggest encoders outperform decoders in correlation, potentially due to decoders' unsuitability for classification tasks. Yet, this distinction may be incidental, influenced by factors like pre-training data or model architecture. Surprisingly, BERT *base* yields the highest correlation, while BERT *large* and RoBERTa, who achieve higher test accuracies than BERT, produce lower correlations. This indicates that emulating human importance attribution is neither a function of model parameters nor does it necessarily imply better model performance. The participant-level analysis reveals no distinct pattern, indicating that the models do not mirror the token importance attribution of more proficient humans. Moreover, averaging correlations across individual participants results in a lower correlation value compared to when participant fixation durations are aggregated across sentences. This implies both that by-participant aggregation of relative fixation durations produces a more robust signal, and that models correlate more with average human language processing than with subject-level idiosyncracies.

In conclusion, we have developed a gradient saliency-based method to analyze LMs with human gaze that does not neglect task-specificity and found that mirroring tasks yields higher correlations.

[3]An overview of all by-participant accuracies and correlations, for all models can be found in Table 3 in Appendix B.

Limitations

First of all, the number of sentences in the eye gaze dataset is quite low, as is the number of readers (which are all L1 English readers based in Zurich, and are not experts in sentiment analysis or relation extraction), which does not make for a representative sample of the population at large.

Relatedly, for a more extensive evaluation of our task-specific approach, one would have to apply it to the same sentences that contain eye movements from natural reading instead of task-specific reading. We leave it to future work to extend the data from ZuCo with eye movements from natural reading.

Moreover, while the studies outlined in Section 2 underline the superiority of gradient-based over attention-based methods, they might still not be the state-of-the-art for explainability methods and one might employ methods such as Integrated Gradients or Layer-wise Relevance Propagation.

Ethics Statement

Working with human data requires careful ethical considerations. The eye-tracking dataset utilized in this study follows ethical standards and has been approved by the responsible ethics committees. It is licensed under the Creative Commons Attribution 4.0 International Public License (CC BY 4.0).

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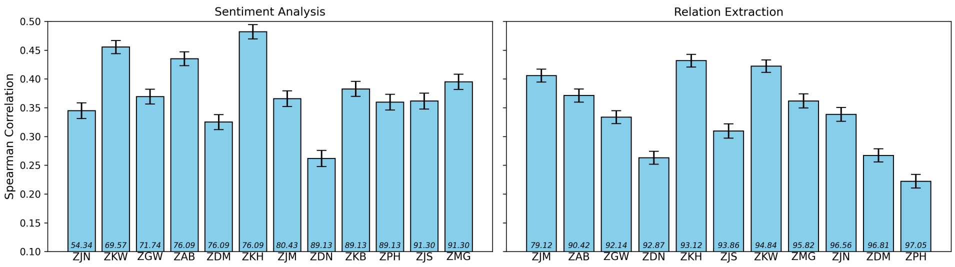
A Fine-Tuning Details

We fine-tune the models outlined in Section 3 on the SST (Socher et al., 2013) dataset for ternary sentiment classification, excluding the sentences used for ZuCo SA, and on the *Wikipedia* dataset (Culotta et al., 2006) for 9-class relation classification, excluding the sentences used for ZuCo RE. After excluding sentences from ZuCo SA and RE, we are left with 5211 sentences allocated for SA and 889 sentences allocated for RE. Subsequently, we implement an 80/20 split for training and validation. For testing, there are 400 sentences from ZuCo SA and 335 sentences from ZuCo RE [4]. We train the models for 10 epochs, with an early stopping patience of 3 epochs, using the AdamW (Loshchilov and Hutter, 2019) optimizer, a learning rate of $2 * 10^{-5}$, and a batch size of 16. All models are implemented in PyTorch (Paszke et al., 2019).

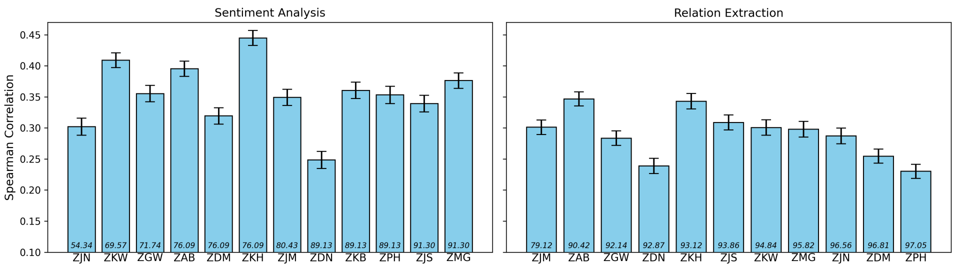
	BERT *base*	BERT *large*	RoBERTa	DistilBERT	GPT-2 *base*	GPT-2 *large*	OPT
SA	75.3	76.5	82.8	75.0	71.8	77.8	73.8
RE	57.9	61.2	57.9	60.9	53.1	56.1	55.2

Table 2: We report the accuracy of fine-tuning the models on the SST (Socher et al., 2013) for sentiment analysis (SA) and on the *Wikipedia* dataset (Culotta et al., 2006) for relation extraction (RE). In both cases, the ZuCo SA and RE sentences are excluded from the training data; the models are tested on the ZuCo sentences for SA and RE.

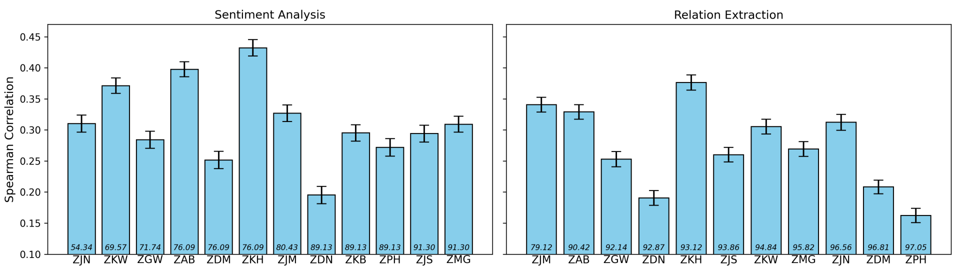
B Participant-Level Analysis



(a) BERT *large*

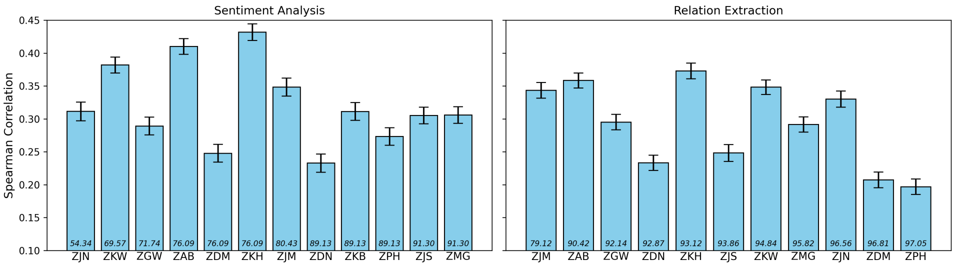


(b) DistilBERT

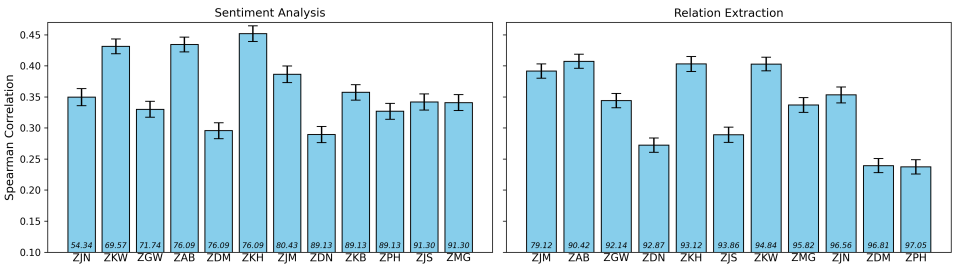


(c) RoBERTa

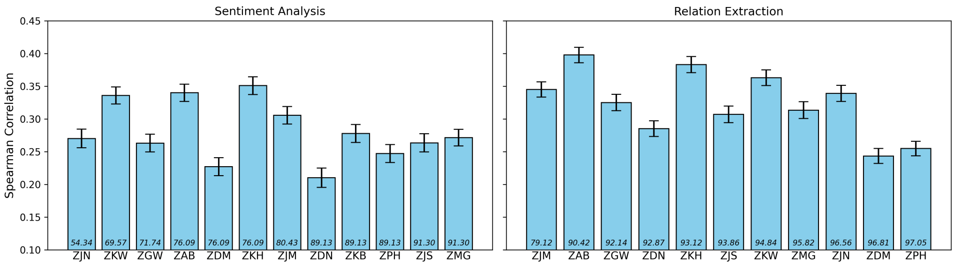
[4] Out of the original 407 sentences in ZuCo RE, we retain only 335 sentences that contain a specific relation.



(d) GPT-2 *base*



(e) GPT-2 *large*



(f) OPT

Figure 1: Spearman correlations between relative fixation durations and gradient saliencies for various models are depicted at the participant level, including standard error. Participants are arranged according to task accuracy, with their accuracy values presented at the bottom of each bar.

	ZAB	ZDM	ZDN	ZGW	ZJM	ZJN	ZJS	ZKB	ZKH	ZKW	ZMG	ZPH	avg
						Sentiment Analysis (SA)							
Task acc	76.09	76.09	89.13	71.74	80.43	54.34	91.3	89.13	76.09	69.57	91.3	89.13	79.53
BERT *base*	0.47	0.36	0.28	0.39	0.40	0.36	0.39	0.42	0.51	0.49	0.43	0.40	0.41
BERT *large*	0.44	0.33	0.26	0.37	0.37	0.34	0.36	0.38	0.48	0.46	0.39	0.36	0.38
DistilBERT	0.40	0.32	0.25	0.36	0.35	0.30	0.34	0.36	0.44	0.41	0.38	0.35	0.35
RoBERTa	0.4	0.25	0.2	0.28	0.33	0.31	0.29	0.3	0.43	0.37	0.31	0.27	0.31
GPT-2 *base*	0.41	0.25	0.23	0.29	0.35	0.31	0.31	0.31	0.43	0.38	0.31	0.27	0.32
GPT-2 *large*	0.43	0.3	0.29	0.33	0.39	0.35	0.34	0.36	0.45	0.43	0.34	0.33	0.36
OPT	0.34	0.23	0.21	0.26	0.31	0.27	0.26	0.28	0.35	0.34	0.27	0.25	0.28
						Relation Extraction (RE)							
Task acc	90.42	96.81	92.87	92.14	79.12	96.56	93.86	95.33	93.12	94.84	95.82	97.05	93.16
BERT *base*	0.39	0.27	0.27	0.34	0.40	0.34	0.32	–	0.42	0.41	0.37	0.24	0.34
BERT *large*	0.37	0.27	0.26	0.33	0.41	0.34	0.31	–	0.43	0.42	0.36	0.22	0.34
DistilBERT	0.35	0.25	0.24	0.28	0.30	0.29	0.31	–	0.34	0.30	0.30	0.23	0.29
RoBERTa	0.33	0.21	0.19	0.25	0.34	0.31	0.26	–	0.38	0.31	0.27	0.16	0.27
GPT-2 *base*	0.36	0.21	0.23	0.30	0.34	0.33	0.25	–	0.37	0.35	0.29	0.20	0.29
GPT-2 *large*	0.41	0.24	0.27	0.34	0.39	0.35	0.29	–	0.4	0.4	0.34	0.24	0.33
OPT	0.4	0.24	0.29	0.33	0.35	0.34	0.31	–	0.38	0.36	0.31	0.25	0.32

Table 3: The participants' task accuracy and their Spearman correlations with the LMs are reported. There is a lack of correlations for one participant in the RE task because of a pre-processing issue with the eye-tracking data.