Use Physiological Data To Fine-tune Language Model

Predict Physiological Signals By Using BERT

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Introduction

How the human brain processes language has been a central topic in cognitive neuroscience and psycholinguistic research. A typical approach to study this topic is to learn a model to predict brain activity when a subject is doing language tasks. We present some stimuli - words, phrases, sentences, etc., to a subject while collecting their physiological data - EEG, MEG, fMRI. The theory underlying this computational model is that the neural basis of the language representation is related to the distributional properties of those in a broadly based corpus of the language. The limitation of learning such predictive models is that most machine learning models require a lot of data. However, it is difficult to obtain sufficient physiological data in practice. In this study, we leverage the advantages of the pre-trained language model - **BERT**, a recent widely used pre-trained language model, to mitigate the constrain of insufficient data. In recent years, pre-trained language models have greatly promoted all aspects of NLP research. Benefit from the pre-trained model, almost all NLP downstream tasks have reached the SOTA performance. A language model learns to predict the probability of a sequence of words. A **pre-trained language model** is that train by using a large corpus such as Wikipedia so that it encodes broad and general language properties. The pre-trained language model can then be used in downstream NLP tasks by fine-tuning through a small amount of task-specific data sets. The results demonstrate that EEG and some gaze features are predictable by using BERT and fine-tuned BERT. This study confirms the connection between the NLP pre-trained language models and the human. It also opens a window for the related research.

Main Objectives

Gaze features including: gaze duration **(GD)**, total reading time **(TRT)**, first fixation duration **(FFD)**, single fixation duration **(SFD)**, go-past time **(GPT)**, the sum of all fixations prior to progressing to the right of the current word **(nFixations)** and mean pupil size **(MPS)**. This study utilizes multi-modal physiological data (EEG and Gaze features) to fine-tune BERT to investigate the following questions:

1. Does fine-tuning BERT to predict the physiological data enables the BERT to encode the human-related language information?
2. Does human-related language information learned by fine-tuning BERT can be transfer among subjects?

GLUE Tasks

General Language Understanding Evaluation benchmark (GLUE) is a collection of natural language understanding (NLU) tasks for model evaluation, comparison, and analysis. It includes nine sentence or sentence-pair language understanding tasks. Using GLUE tasks to fine-tune the pre-trained BERT will empower it to generate language encoding suitable for the specific task.

Corpus	Task	Domain
	Single-Sentence Tasks	
CoLA	acceptability	misc.
SST-2	sentiment	movie reviews
	Similarity and Paraphrase Tasks	
MRPC	paraphrase	news
STS-B	sentence similarity	misc.
QQP	paraphrase	social QA questions
	Inference Tasks	
MNLI	NLI	misc.
QNLI	QA/NLI	Wikipedia
RTE	NLI	news, Wikipedia
WNLI	coreference/NLI	fiction books

Table 1: Nature Language Processing Tasks Used in Fine-tune BERT

Model Architecture

Training Strategy

- Train the linear layer only.
- Train the entire model.

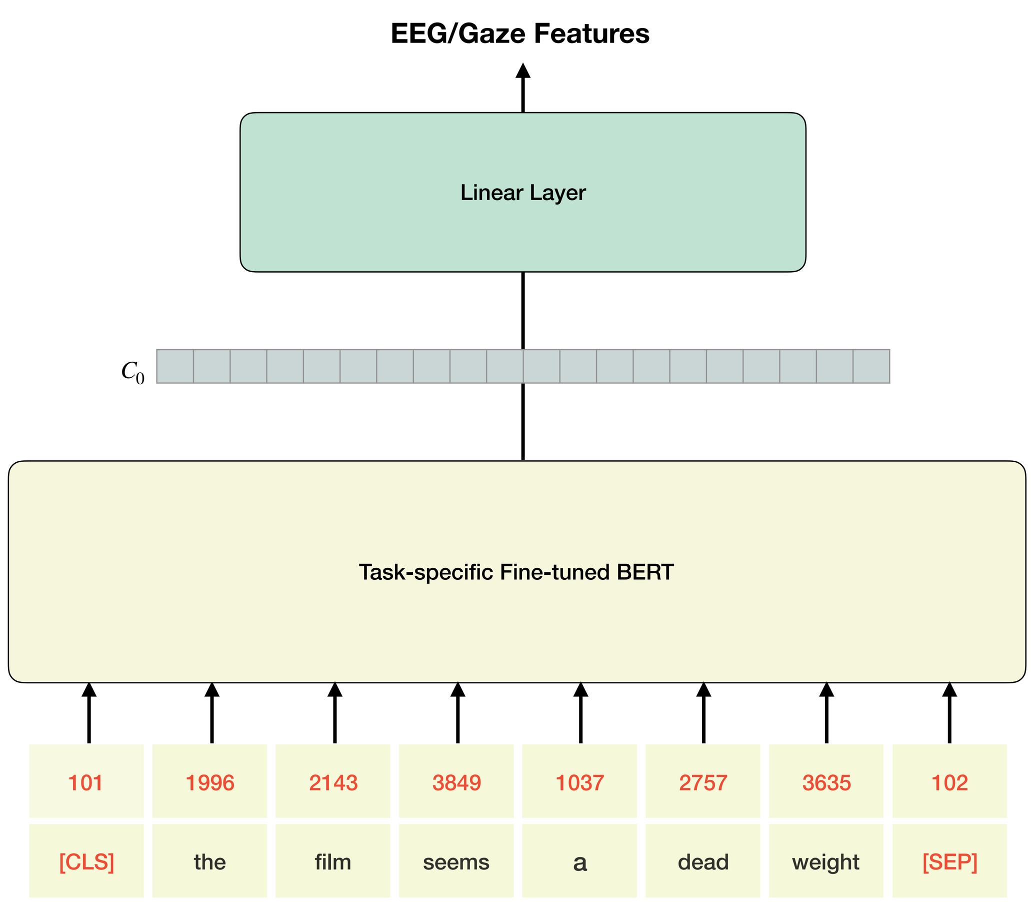

Figure 1: Model Architecture

Results

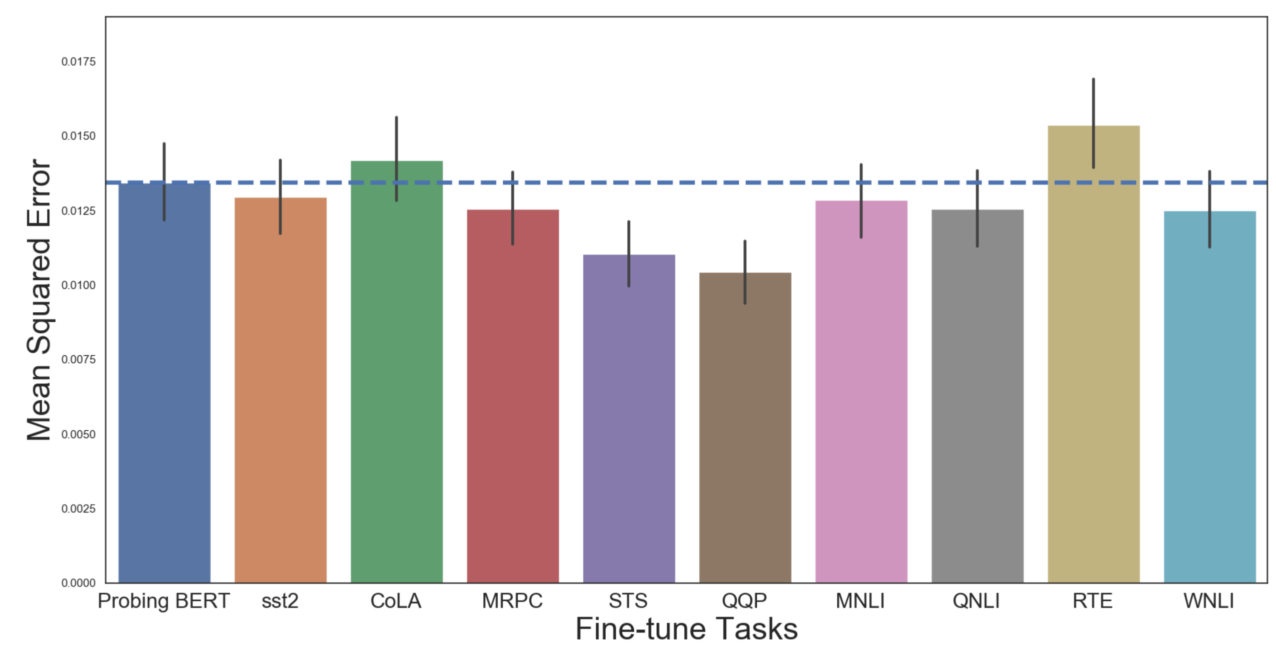

Figure 2: MSE performance, dashed blue reference line is the performance of pre-trained BERT (Probing BERT), the remaining are GLUE tasks fine-tuned BERT.

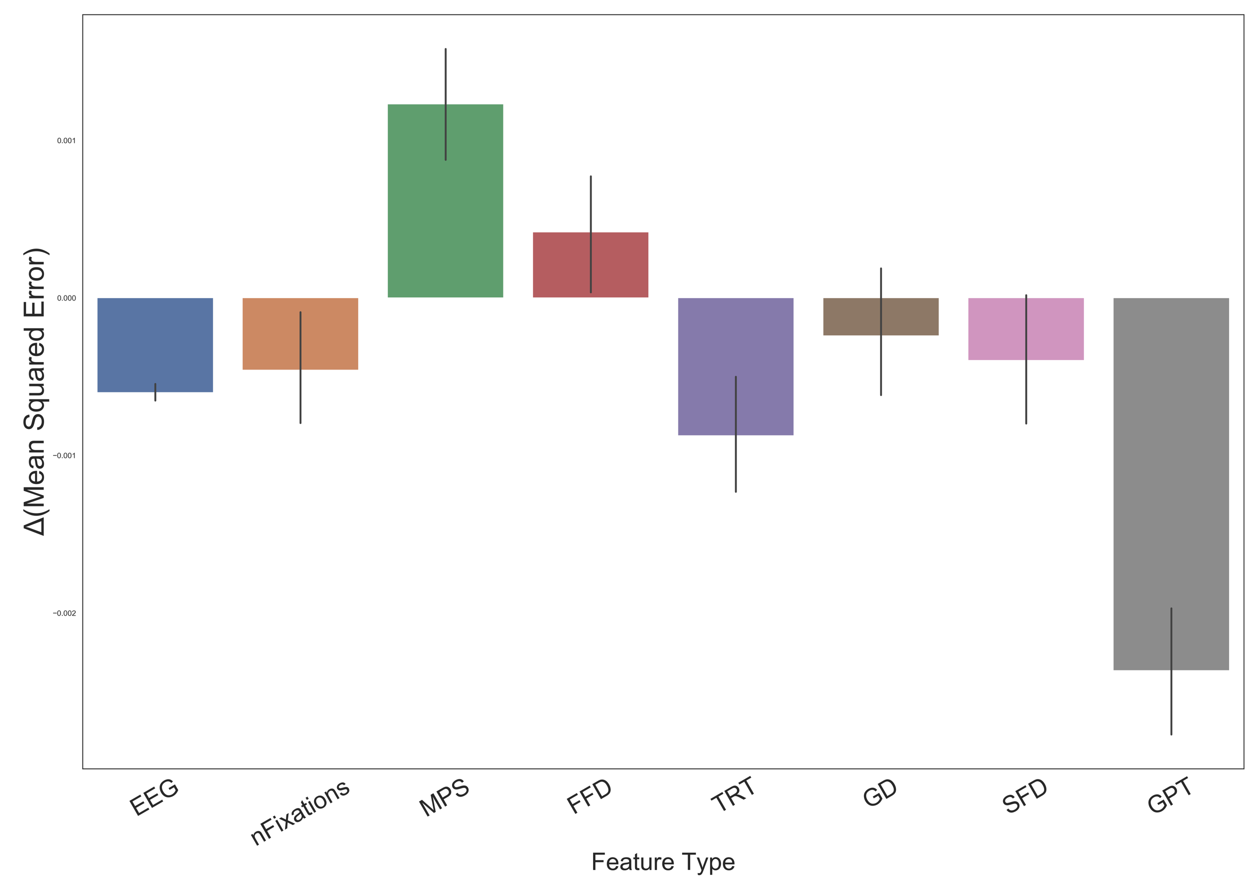

Figure 3: For various physiological signals, the MSE difference between training linear layer only and training the entire model.

- Using pre-trained language models (BERT) can better learn a model that predicts the EEG/Gaze features (Figure 2).
- The BERT fine-tuned by the GLUE task yields various performances. Except for CoLA and RTE, the performance of most GLUE-adjusted BERT is better than the original BERT (Figure 2).
- Using EEG/Gaze features fine-tune BERT will yield better performance except for mean pupil size and first fixation duration (Figure 3).
- With minor adjustments, the predictive model learned on one subject can be applied to another subject. (Not reflected on this poster).

Conclusions

- BERT learns something from the text that share the same parallel with human physiological signals.
- GLUE experiment suggests that human physiological signals sensitive to various language tasks.
- Fine-tune BERT by mean pupil size or first fixation duration does not improve the performance; it suggests the BERT structure might be too complicated for the two signals or requires more data.
- The model can cross subjects, which shows that the model can learn the commonality of human physiological data. The influence of individual differences on the model can be eliminated to some extent, which provides a basis for learning a large, general cross-subject model.

References

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