

BELT-2: BOOTSTRAPPING EEG-TO-LANGUAGE REPRESENTATION ALIGNMENT FOR MULTI-TASK BRAIN DECODING

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ABSTRACT

The remarkable success of large language models (LLMs) across various multi-modality applications is well established. However, integrating large language models with humans, or brain dynamics, remains relatively unexplored. In this paper, we introduce BELT-2, a pioneering multi-task model designed to enhance both encoding and decoding performance from EEG signals. To bolster the quality of the EEG encoder, BELT-2 is the first work to innovatively 1) adopt byte-pair encoding (BPE)-level EEG-language alignment and 2) integrate multi-task training and decoding in the EEG domain. Inspired by the idea of *Bridging the Brain with GPT*, we further connect the multi-task EEG encoder with LLMs by utilizing prefix-tuning on intermediary output from the EEG encoder. These innovative efforts make BELT-2 a pioneering breakthrough, making it the first work in the field capable of decoding coherent and readable sentences from non-invasive brain signals. Our experiments highlight significant advancements over prior techniques in both quantitative and qualitative measures, achieving a decoding performance with a BLEU-1 score of 52.2% on the ZuCo dataset. Furthermore, BELT-2 shows a remarkable improvement ranging from 31% to 162% on other translation benchmarks. Codes can be accessed via the provided anonymous link¹.

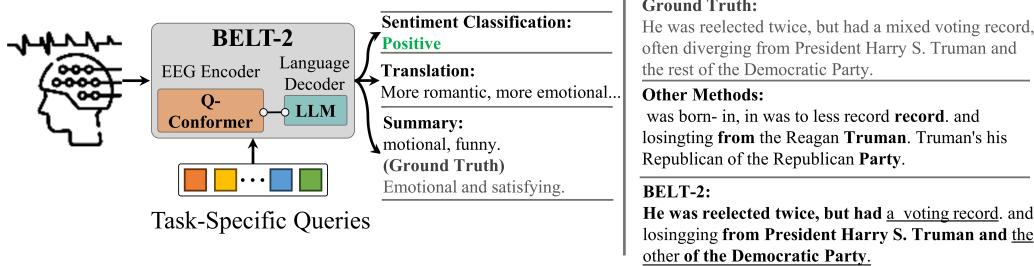


Figure 1: Overview of BELT-2. The first work of multi-task brain decoding by bridging the Q-Conformer EEG encoder and LLMs. Provided samples also suggest BELT-2 is the first to achieve fluent sentence decoding results from noninvasive brain signals.

1 INTRODUCTION

Recently, the emergence of large language models (LLMs) has spurred efforts to integrate them with various modalities, such as VisualLLMs (Liu et al., 2023b; Oquab et al., 2023), and Robotics (Driess et al., 2023). These methods achieved remarkable improvement in various task settings. Yet, an important topic, the direct combination of LLMs with human intention remains relatively unexplored. Nonetheless, the inherent subject-wise non-stationary characteristics of Electroencephalography (EEG) signals, coupled with rigorous experimental protocols, make the task of decoding words or sentences exceptionally challenging.

¹<https://anonymous.4open.science/r/BELT-2-0048>

Explorations on brain-to-text and brain-to-speech decoding in the earlier stage (Herff et al., 2015; Makin et al., 2020; Panachakel & Ramakrishnan, 2021; Nieto et al., 2021) mostly perform decoding on a closed word-level set, which still has notable restrictions on vocabulary size and limitations to more intricate application scenarios. For the brain-to-language decoding, EEG-to-Text (Wang & Ji, 2022) introduced the open-vocabulary decoding of EEG signals with an initial performance baseline. DeWave (Duan et al., 2023) improved decoding performance by introducing a discrete encoder for EEG. BELT (Zhou et al., 2023a) which boosted decoding performance by leveraging language supervision. However, these methods are limited to single-task settings and have not achieved multi-task decoding from brain signals to natural languages. An extensive **related works** is provided in Appendix A due to space limit.

In this paper, we propose BELT-2, the first EEG-language learning framework to bridge the modality gap and effectively exploit LLM’s generative capacity for EEG decoding. BELT-2 enhances three key aspects of brain decoding research. 1) It is the first to introduce **BPE-level contrastive learning** for EEG-to-language alignment. 2) It first introduces a **prompt-based multi-task encoder** for EEG research. 3) It proposes a cost-effective solution for connecting an EEG encoder with a large language model (LLM).

More specifically, we introduce a novel discrete querying conformer (Q-Conformer) as the EEG encoder to improve encoding capacity and enable multitasking (Figure 5). Unlike previous single-task EEG encoders (Zhou et al., 2023a; Duan et al., 2023), Q-Conformer is able to extract task-specific contexts according to a given query prompt. For the training of Q-Conformer, we propose the BPE-level EEG-language contrastive learning (BPE-CL) to bootstrap the learning of language-aligned EEG representation. After training, we bridge the Q-Conformer and an LLM decoder by prefix-tuning with both models frozen. To improve the performance of the bridging, we further propose a technique called speculative augmentation (SA) to improve the training efficiency. The main contributions of BELT-2 could be concluded in four aspects.

- This paper presents a novel framework capable of decoding fluent open-vocabulary sentences, facilitating multi-task EEG decoding including EEG translation, sentiment classification, and summarization.
- The Q-Conformer is proposed to improve the encoding ability and the scalability for multi-tasking while the BPE-level contrastive learning establishes a firm alignment between EEG and language representations.
- This paper provides a cost-effective bridging method for connecting LLMs with brain encodings by turning virtual-prefix. A speculative augmentation method is introduced to further improve the bridging performance.
- Experimental results suggest that the proposed BELT-2 exceeds SOTA performance on different EEG decoding tasks. For EEG translation, BELT-2 achieves 52.59 BLEU-1, 17.85 BLEU-4, and 40.1 Rouge-1 Precision, which significantly outperforms the previous baseline by 31%, 162% and 26% respectively. On sentiment classification, BELT-2 achieves 74.62% accuracy without further assistance from additional classifiers or external datasets. BELT-2 is also the first work that achieves EEG summarization with a SOTA 31.17 BLEU-1 score.

2 BELT-2

BELT-2 introduces the Q-Conformer which enhances both the capacity to encode EEG information and the extendibility to multi-task. To bridge the modality gap between EEG and language, we boost EEG-to-Language representation learning through two learning stages: (1) the EEG-to-language alignment learning stage for learning the Q-Conformer EEG encoder. (2) a prefix-tuning stage for bridging Q-Conformer with LLM.

2.1 Q-CONFORMER AS EEG ENCODER

The overall structure of the Q-Conformer is illustrated in Figure 5 which consists of a discrete conformer, a Context Transformer (C-Former), and a query prompt. The discrete conformer functions as a discrete EEG tokenizer that captures primitive patterns from the input EEG embeddings. The C-Former extracts mid-layer coding (MLC) that contains context information specific to a given task given by the learnable query prompt.

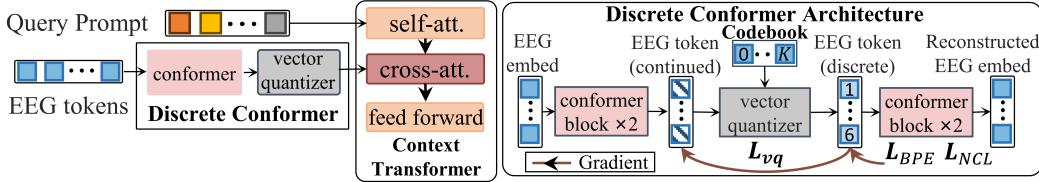


Figure 2: The overall structure of the Q-Conformer. It consists of a discrete conformer, a context transformer (C-Former), and a query prompt. The input EEG embeddings (EEG embed) are first processed by the conformer into continuous EEG tokens. A vector quantizer is then used to discretize the EEG tokens. Then, a query prompt interacts with the discrete EEG token via the cross-attention layer from in the C-Former to extract task-specific context information from the discrete EEG tokens.

Discrete Conformer: The discrete conformer consists of a conformer model and a vector quantizer. After preprocessing, the raw EEG waveform is segmented into windows using eye-tracking information. Then a frequency domain transform converts EEG segments into fix-size EEG embeddings $\mathbf{e} \in \mathbb{R}^{L \times N \times D}$. L is the maximum length of the embedding sequence, N denotes the number of EEG channels, and D denotes the embedding size. The conformer model consists of 2 conformer blocks which follow the structure manifested in (Gulati et al., 2020). The conformer model $E(\cdot)$ converts the EEG embeddings \mathbf{e} into continuous EEG tokens $\mathbf{h} \in \mathbb{R}^{L \times N \times d}$, where d denotes the size of the continuous EEG tokens.

We then convert \mathbf{h} to a set of discrete tokens \mathbf{b} by a vector quantizer (VQ) that looks up the nearest discrete code \mathbf{v}_k , $k = \{0, 1, \dots, K\}$ from the codebook \mathcal{V} (Razavi et al., 2019). The quantization process $\mathbf{z}_q(\mathbf{h})$ can be written as Equation 1.

$$\mathbf{z}_q(\mathbf{h}) = \{\mathbf{z}_q(\mathbf{h}_i)\}_{i=0}^L, \quad \mathbf{z}_q(\mathbf{h}_i) = \mathbf{v}_k, \quad k = \arg \min_j \|\mathbf{h}_j - \mathbf{v}_j\|_2^2 \quad (1)$$

We use L_{vq} (Equation 2) to train the discrete codebook. The L_{vq} is a weighted summation of 4 loss terms. The first two terms are the codebook loss and the commitment loss. They are used to update the codebook by minimizing the information loss between the input and the output discrete tokens Van Den Oord et al. (2017). The third term encourages the balanced use of all entries in the codebook and prevents codebook collapse during training (Dieleman et al., 2018). The last term is a reconstructive loss that ensures the information passed to the VQ is sufficient to describe the EEG signal.

$$\mathcal{L}_{vq} = \|\text{sg}[\mathbf{h}] - \mathbf{z}_q(\mathbf{h})\|_2^2 + \|\mathbf{h} - \text{sg}[\mathbf{z}_q(\mathbf{h})]\|_2^2 + \frac{1}{|\mathcal{V}|} \sum_{k=0}^{|\mathcal{V}|} p_k \log p_k + \|\mathbf{e} - \hat{\mathbf{e}}\|_2^2 \quad (2)$$

, where $\text{sg}[\cdot]$ stands for the stop-gradient operator which is an identity at the forward pass while having zero gradients during the backward pass. $|\mathcal{V}|$ denotes the size of the discrete codebook and p_k denotes the softmax probability of the codebook entry k being used in each batch. $\hat{\mathbf{e}}$ denotes the reconstructed EEG embedding from $\mathbf{z}_q(\mathbf{h})$ using 2 conformer blocks.

C-Former and Query Prompt We create a set number of learnable query embeddings (query prompt) as input to the C-Former. The C-Former is composed of self-attention layers and cross-attention layers arranged in consecutive order. After feeding the query prompts and the discrete EEG tokens into the C-Former, the query prompts interact with each other through the self-attention layers and further interact with the discrete EEG tokens through the following cross-attention layer. A new query prompt will be initialized when training the Q-Conformer for a specific task. After training on a specific task, the query prompts learn to act as the instruction of the current task that guides the C-Former to extract MLC as the task-specific context from the EEG modality.

This querying mechanism enables a more flexible adaptation of the pretrained Q-Conformer to a new downstream task by adding a new set of query prompts. It also allows the reusing of knowledge learned from previous training tasks. In our experiment setup, we initialize the C-Former with the pre-trained weights of BART_{large} (Lewis et al., 2019). We employ a query prompt of 20 learnable tokens for a specific, with each query possessing a dimensionality of 1024.

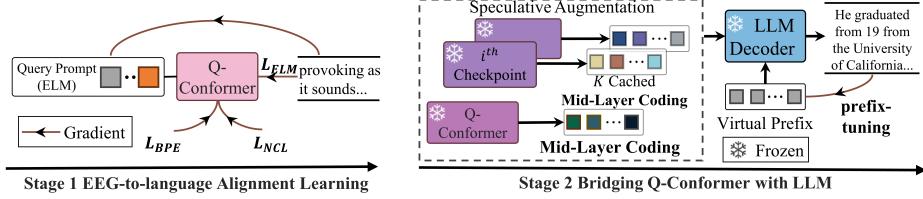


Figure 3: BELT-2’s two-stage training schema. For EEG-to-language alignment learning (**left**), we jointly optimize three objectives that firmly establish the EEG-to-language alignment and enforce the query prompt to extract the EEG context most relevant to a task. For bridging of Q-Conformer and LLM (**right**), connect a frozen EEG model (Q-Conformer) and a frozen LLM by tuning the continuous virtual prefix using the prefix-tuning method. Speculative augmentation is used to boost the performance of the prefix-tuning process.

2.2 EEG-TO-LANGUAGE ALIGNMENT LEARNING

In the EEG-to-language alignment learning stage, we train the Q-Conformer and align the encoded EEG tokens to the language modality. To achieve EEG-to-Language alignment, we combine two contrastive objectives and a pretraining objective to the VQ objective in Equation 2. The two contrastive objectives include (1) BPE-level contrastive learning (BPE-CL), and (2) Negative Contrastive learning (NCL). We further pretrain the Q-Conformer to achieve a task-specific query prompt by the EEG-to-Language matching (ELM) objective, which guides the C-Former to extract MLC that contains the most relevant EEG contexts in the specific task.

BPE-level contrastive learning (BPE-CL) learns to align the discrete EEG tokens with BPE subword embeddings by maximizing their mutual information. Unlike the BELT-1 model (Zhou et al., 2023a) where contrastive learning is only performed at the word level, we perform EEG-language alignment in the BPE subword level to improve EEG-language alignment. Given the limited size of EEG-language pairs in the training set, this method enforces stronger semantic guidance to the EEG representation while enhancing the matching of subword units that are out-of-training vocabulary.

The sampling strategy of the BPE-CL is illustrated in Figure 4. We commence by converting words into BPE tokens $w \in \mathcal{W}$, e.g., converting “Visually” into [“Vis”, “ually”]. The embeddings of these BPE tokens serve as positive targets for the EEG token corresponding to “Visually” while BPE tokens other words are viewed as negative targets. We uniformly sample 1 positive target and K negative targets for each discrete EEG token in a training batch. The learning objective L_{bpe} for the discrete EEG tokens and the BPE embeddings is formulated as:

$$\mathcal{L}_{bpe} = -\log \frac{\exp(\mathbf{z}_q(\mathbf{h})^\top \mathbf{w}^+)}{\exp(\mathbf{z}_q(\mathbf{h})^\top \mathbf{w}^+) + \sum_{i=1}^K \exp(\mathbf{z}_q(\mathbf{h})^\top \mathbf{w}^-)}, \quad (3)$$

, where \mathbf{w}^+ is the sampled embedding of the positive BPE token and \mathbf{w}^- is the negative ones.

Negative contrastive learning (NCL) aims to further improve the distinctions between the discrete EEG tokens by randomly sampling K negative EEG tokens as distractors for each discrete EEG token in a training batch, which is defined as:

$$\mathcal{L}_{neg} = -\log \frac{1}{\sum_{i=1}^K \exp(\mathbf{z}_q(\mathbf{h})^\top \mathbf{z}_q(\mathbf{h})^-)}, \quad (4)$$

, where $\mathbf{z}_q(\mathbf{h})^-$ are sampled negative tokens from the batch and $\mathbf{z}_q(\mathbf{h})$ is defined in Equation 1. This objective enlarges the distinction among EEG tokens that are indistinguishable upon reading different words, easing the decoding effort.

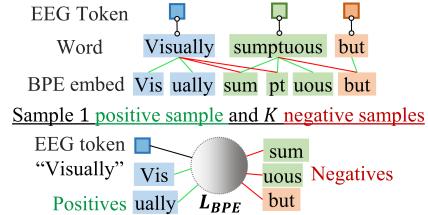


Figure 4: The illustration of BPE-level contrastive learning.

EEG-to-language matching (ELM) aims to function as the pretraining task for learning the initial task-specific query prompt, which in terms is used to instruct the C-Former to extract task-specific context from the EEG tokens. We use a sequence-to-sequence machine translation loss similar to previous works Zhou et al. (2023a); Wang & Ji (2022); Duan et al. (2023) as the objective function. Given the word-level EEG embedding sequence and text sentence pair $\langle \mathcal{E}, \mathcal{S} \rangle$, we maximize the probability of the decoded sentence $p(\mathcal{S}|\mathcal{E})$ produced by the Q-Conformer. The learning objective is a machine translation term L_{tr} , which could be written as follows:

$$\mathcal{L}_{elm} = - \sum_l^L \log p(s_l \in \mathcal{S} | \mathbf{q}) \quad (5)$$

, where L is the total length of the target text sequence, $s_l \in \mathcal{S}$ denotes the decoded tokens from the C-Former and \mathbf{q} denotes the query prompt.

2.3 BRIDGING Q-CONFORMER WITH LLM

We propose to bridge the frozen Q-Conformer and a frozen LLM to leverage both models effectively for EEG-to-Language tasks by tuning a set of virtual prefixes added to the output embeddings of the Q-Conformer, in order to achieve stronger performance at a lower training cost.

Prefix-tuning To achieve a proper prefix prompt that can steer the LLM to decode the MLC without changing the LLM’s parameters, we adopt the prefix-tuning (Li & Liang, 2021) method to only train a set of virtual prefix tokens as prompts to the LLM. In particular, we concat the virtual prefix and the MLC from the Q-Conformer as input to the subsequent frozen LLM. Please refer to Appendix C.3 for more details on prefix-tuning.

Speculative Augmentation (SA) Despite the use of the lightweight prefix-tuning method, the size and diversity of training samples are still lacking. This is because while the Q-Conformer learns to extract task-specific context, it also learns to ignore task-irrelevant information. This would be a well-anticipated perk for an EEG encoder if we choose to directly decode language output from the EEG encoder. However, it also significantly reduces the diversity of training samples, making the learning of a good prefix difficult.

Our BELT-2 framework solves this issue by proposing the SA method to sample MLC from a total of $K+1$ Q-Conformer checkpoints to provide more diverse prefix-tuning samples. In particular, we randomly sample K model checkpoints other than the best-performing checkpoint to produce MLC for the prefix-tuning. During the forward process, a speculative ratio r is defined to determine whether to use best checkpoint or one of the K suboptimal checkpoints. To reduce the cost of memory, we cache the output MLCs of these K model checkpoints during the training of Q-Conformer to avoid actually loading the checkpoints in the prefix-tuning stage.

In our experiment, we set $K = 15$ for a balance of performance and training costs to achieve a $6\times$ larger and more diverse training sample set for the tuning of the LLM Decoder.

2.4 EXTENDING DECODING TO MULTI-TASK

Translation: Our definition of the EEG-to-Text translation task follows previous works on this topic (Wang & Ji, 2022). Given the word-level EEG embedding sequence and text sentence pair $\langle \mathcal{E}, \mathcal{S} \rangle$, we maximize the probability of the decoded sentence $p(\mathcal{S}|\mathcal{E})$ produced by our model. The training objective L_{tr} for the translation task could be written as follows:

$$p(\mathcal{S}|\mathcal{E}) = \prod_{l=1}^L p(s_l|\mathcal{E}, s_{<l}), \quad \mathcal{L}_{tr} = - \sum_l^L \log p(s_l \in \mathcal{S}) \quad (6)$$

where L is the total length of the target text sequence and $s_l \in \mathcal{S}$ denotes the word tokens produced by our model.

Summary: We propose the first EEG-to-text summarization task by creating a summary dataset from the Zuco datasets. Human attention lingers around keywords and pivotal concepts during reading (Ding et al., 2022). Consequently, we hypothesize that the extraction of key concepts could be a more direct way to facilitate the transmission of neural information and the understanding of a

person’s intention. As such, our nuanced summarization task not only enhances our understanding of EEG data but also opens up exciting possibilities for advancing research in cognitive science.

We kickstart by constructing the prompt “*Rewrite the sentence by summarizing its main idea using {T} words from the sentence, and keep the summarized sentence similar to the original sentence: {s}*” with $\{s\}$ being each ground truth sentence from the ZuCo dataset and attain the initial summarization targets for each sentence. We set $T = 8$ in our experiment and use the LLAMA2 model (Touvron et al., 2023) to generate the initial summarization targets. Afterwards, manual inspection and rectification are carried out to improve the dataset’s reliability and informativeness. The word-level EEG embedding sequence and summary pair are denoted by $\langle \mathcal{E}, \hat{\mathcal{S}} \rangle$. To extend the Q-Conformer for summarization task, a new query prompt for summarization will be added. The training objective for generating summaries is similar to Equation 6, with the sole alteration being the substitution of \mathcal{S} with $\hat{\mathcal{S}}$. For multi-task training, we train all tasks simultaneously by randomly sampling tasks for each update iteration.

Sentiment Classification: We could further extend the Q-conformer to perform the sentiment classification task by adding another query prompt for the Q-Conformer and using the last output token from the Q-conformer as the CLS token. In particular, we use the EEG-sentiment label pair $\langle \mathcal{E}, c \rangle$. Unlike Wang & Ji (2022), we don’t need to use external sentiment classification datasets or learn an additional classifier. The training objective for sentiment classification is as follows:

$$\mathcal{L}_{st} = - \sum_{i=1}^{|C|} c_i \log p(\hat{c} | \mathcal{E}_i), \quad (7)$$

, where $|C|$ is the number of the sentiment categories and \hat{c} is the sentiment prediction.

3 EXPERIMENT AND RESULTS

3.1 EXPERIMENT SETUP AND IMPLEMENTATION DETAILS

We use the ZuCo datasets (Hollenstein et al., 2018; 2019) for the training and evaluation of the proposed BELT-2 framework. The ZuCo datasets contain EEG data recorded during natural reading tasks with eye-tracking data for word-level EEG segmentation. Reading material is collected from movie reviews (Socher et al., 2013) and Wikipedia articles. We split the dataset into train, val, and test subsets (80%, 10%, 10%). In this cross-sentence setting, sentences will not overlap among any two subsets. In addition, cross-subject performance is also evaluated. We evaluate translation and summary performance using the BLEU scores (Papineni et al., 2002) and ROUGE-1 scores Lin (2004). We use **P**, **R**, **F1**, and **Acc** to denote precision, recall, F1-score, and accuracy respectively.

3.2 IMPLEMENTATION DETAILS

The code could be assessed through an anonymous link ². For the word-level EEG embeddings, the total length of an embedding sequence is $L = 56$ and the embedding size is $d = 840$. The discrete conformer has 8 attention heads with the feed-forward dimension size of 2048 and a discrete codebook with 1024 entries with a latent size of 1024. The number of querying tokens used for The Q-Conformer is 20. We train the Q-Conformer with a learning rate of $5e^{-06}$ for 60 epochs during EEG-to-language alignment learning using AdamW (Loshchilov & Hutter, 2017). For the bridging stage, we use 8 virtual prefix and set the speculative augmentation factor K to 15 with a speculative ratio of 0.3. We use pre-trained BART and T5 models from the huggingface platform to initialize the Q-conformer and the LLM decoder. We also conducted experiments of massive size LLAMA2 model ³ in Section 3.5. Due to the limitation of space, refer to Appendix C for more details.

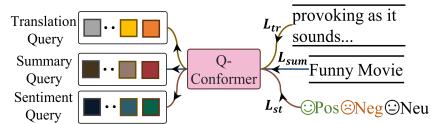


Figure 5: For multi-task training, we train three tasks simultaneously by randomly sampling tasks for each training iteration. Each task-specific query prompt learns to provide task-specific instructions by training on the corresponding task-specific objective function.

²<https://anonymous.4open.science/r/BELT-2-0048>

³<https://huggingface.co/meta-llama/Llama-2-7b>

3.3 TRANSLATION PERFORMANCE

Quantitative Results We show quantitative results in Table 1. Compared to previous methods, e.g., EEG-to-Text (Wang & Ji, 2022), Dewave (Duan et al., 2023), and BELT-1 (Zhou et al., 2023a) When only using EEG Encoder, We observe that the introduction of BPE-level contrastive learning bootstrapped a significant improvement (row 4 compared to row 5), achieving the SOTA EEG decoding BLEU-{1, 2, 3, 4} scores of 43.06, 25.57, 15.16, and 9.17, which outperform DeWave by 1.71, 1.42, 1.24, and 0.95. By further connecting with the LLM decoder, BELT-2 further achieves the BLEU-{1, 2, 3, 4} scores of 52.59, 36.32, 25.21, and 17.85, which brings additional 9.66, 10.96, 10.16, and 8.76 BLEU score improvements. The increase of the metrics is more significant for longer phrases (+162% for 4-gram and +99% for 3-gram) compared to the baseline EEG-to-Text method. Additionally, we present ablation results that analyze the influence of VQ and the BPE-CL within our model, revealing that the utilization of BPE-CL significantly contributes to the enhancement of performance. However, multitask training did not bring a significant improvement to the translation result, which is elaborated in the Appendix F.

Table 1: Quantitative Results on Brain-to-Language Translation on the ZuCo Datasets.

Model	Vector Quantizer	BPE-CL	Enable Multi-Task	Prefix Tuning	BLEU-N (%)				ROUGE-1 (%)		
					N=1	N=2	N=3	N=4	R.	P.	F1
EEG-to-Text	✗	✗	✗	✗	40.12	23.18	12.61	6.80	28.8	31.7	30.1
Dewave	✓	✗	✗	✗	43.35	24.15	13.92	8.22	28.82	33.71	30.69
BELT-1	✓	✗	✗	✗	42.31	25.26	14.81	8.73	29.86	36.06	32.57
BELT-2	✓	✓	✓	✗	43.06	25.57	15.05	9.09	30.28	34.12	31.99
BELT-2+LLM(T5)	✓	✓	✓	✓	52.38	36.28	25.28	17.95	36.08	39.47	37.59
BELT-2 Ablations											
BELT-2	✓	✗	✓	✓	41.57	24.02	13.80	8.06	29.35	32.46	30.74
BELT-2	✗	✓	✓	✗	41.90	24.57	14.2	8.28	29.60	34.03	31.54

Table 2: Qualitative results on unseen EEG signals. The **bold** denotes an exact match between the ground truth and our prediction. underline denotes a fuzzy match with similar semantic meanings.

(1)	Target	He is a prominent <u>member</u> of the Bush family, the younger brother of President George W. Bush and the second son of former President George H. W. Bush and Barbara Bush.
	Others	was a former member of the American <u>family</u> , and first <u>brother</u> of President George W. Bush.
	Ours	the father <u>son</u> of President President George H. W. Bush. his Bush.
	Target	He was great member <u>member</u> of the American <u>family</u> , and <u>younger</u> brother of President George H. Bush
	Ours	and the younger cousin of President President George H. W. Bush. the Bush.
(2)	Target	Adolf Otto Reinhold Windaus (December 25, 1876 - June 9, 1959) was a significant German chemist.
	Others	rian Hitler,hardt,eren18 18, 1885 – January 3, 18) was a German figure- and
	Ours	Adolf Hitlero vonhard voner (J 15, 1875 - January 15, 1945) was a German German industrialpacist
(3)	Target	It just doesn't have much else... especially <u>in</u> a moral <u>sense</u> .
	Others	was so's work the to and not the country <u>sense</u> .
	Ours	It just doesn't work the of going except in the a way <u>sense</u> .
(4)	Target	He was reelected twice, but had a mixed <u>voting record</u> , often diverging from President Harry S. Truman and the rest of the Democratic Party.
	Others	was a- in, never to less record <u>record</u> , and losintg from his Reagan Truman . Truman's his Republican of the Republican Party.
	Ours	He was reelected twice, but had <u>voting record</u> , and losingg from President Harry S. Truman and the other of the Democratic Party.
(5)	Target	Following the 1980 presidential election, Bush and his family moved to Miami-Dade County, Florida.
	Others	the deaths <u>election</u> , the was his wife moved to California, Dade County, Florida.
	Ours	After his election <u>presidential election</u> , Reagan and his family moved to Miami,Dade County, Florida.

Cross-Subject Results As cross-subject performance is of vital importance for practical usage, we further report translation performance in cross-subject settings where we leave one subject out for evaluation and train the model using other subjects. Figure 6 shows the cross-subject translation performance for a total of 10 subjects compared to the cross-sentence result we achieved in the cross-sentence setting (Table 1). The radar charts in Figure 6 denote the performance is stable across different subjects with subjects achieving BLEU-1 scores ranging from 48.04 to 51.41.

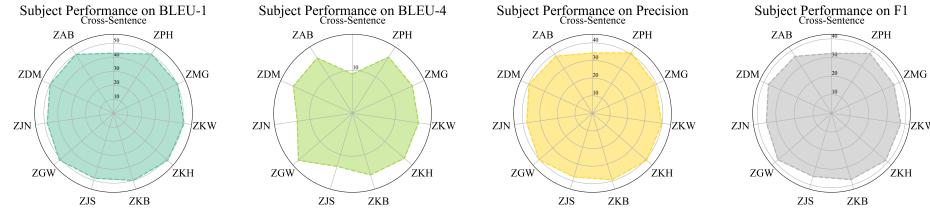


Figure 6: The cross-subjects performance for translation task.

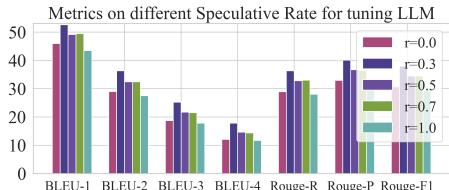


Figure 7: Ablation on speculative ratio.

Model	BLEU (%)		Rouge-1		
	N=1	N=3	P.	R.	F1
EEG-to-Text	25.14	0	10.37	7.30	8.49
BELT-2 w/o Pretrained	26.87	2.08	9.84	11.06	10.34
BELT-2 w/ Pretrained	31.17	5.09	12.73	13.26	12.91

Table 3: Quantitative Results of Summary Task

Qualitative Evaluation We showcase the generated text alongside the established approach from Wang & Ji (2022) in Table 2. We observe that BELT-2 generates more fluent sentences with greater grammatical coherence. Notably, our model adeptly captures subject-predicate relationships while other methods miss the subject and predicate. This is demonstrated by the accurate decoding of phrases like “*He was*” vs. “*He is*”, “*It just doesn’t work*” vs. “*It just doesn’t have*”. Furthermore, for sentence structures involving quoted dates, such as “(January 15, 1875 - January 15, 1945)” vs. “(December 25, 1876 - June 9, 1959)”, were also consistently deciphered.

3.4 MULTI-TASK PERFORMANCE

Sentiment Classification As shown in Table 4, previous works need to train an LLM classifier using an external Stanford Sentiment Treebank dataset (around 11,000 sentences) (Socher et al., 2013) and a new EEG encoder due to poor performance when training directly on the ZoCo dataset (Row 1-3). In contrast, an EEG encoder incorporating external classifiers (row 4-7) demonstrated improved performance (Wang & Ji, 2022). Our proposed Q-Conformer Encoder, achieve the state-of-the-art sentiment classification accuracy of 74.62% on the ZuCo dataset. We also observe that our method could effectively leverage pretrained knowledge from the translation task to improve performance (row 8-9).

Summarization We compare the summarization performance of the BELT-2 model with the EEG-to-Text model as the baseline. As shown in Table 3, the EEG-to-Text struggles to generate summarization while the proposed BELT-2 model exhibited better generative capacity, especially in longer phrases. Compared to using a newly initialized encoder (row 2), our BELT-2 exhibits a remarkable capacity to utilize the pretrained knowledge to increase the performance for the summarization task (row 3). Generally, it attains the BLEU-{1, 2, 3, 4} scores of 31.17, 15.7, 8.91, 5.09, outperforming the baseline method.

3.5 ABLATION STUDY

Bridging Q-Conformer Encoder with different LLMs Table 1 shows the result of bridging our Q-Conformer encoder with the T5 (Raffel et al., 2020). In Table 5, we conduct a comprehensive investigation of bridging LLM decoders with the Q-Conformer model, including the LLAMA2, T5, and the PEGASUS (Zhang et al., 2020) models. Results show that T5 LLMs consistently outperform other variants and boost the decoding performance. We attribute this superiority to T5’s denoising training objectives. However, the sheer scale of the LLM decoder does not necessarily lead to enhanced decoding performance. For example, PEGASUS and LLAMA2 did not yield much improvement in the translation performance.

Table 4: Quantitative Results of Sentiment Classification

EEG Encoder	Additional CLS Model	Additional Dataset	Acc.	P.	R.	F1
MLP	None	None	31.8	32.8	33.6	27.5
Bi-LSTM	None	None	30.9	27.5	33.6	17.4
Transformer	BERT	None	36.6	23.7	34.5	27.2
EEG2Text	BART	SST	55.30	62.40	56.50	55.60
BELT-1	BART	SST	65.13	63.67	63.34	62.45
BELT-1	Albertv2	SST	60.09	61.63	60.03	59.56
BELT-1	XLNet	SST	67.32	66.55	65.71	65.02
BELT-2 w/o Pretrained	None	None	59.74	57.67	57.63	57.11
BELT-2 w/ Pretrained	None	None	74.62	75.34	73.84	73.31

Table 5: Ablation study of bridging Q-Conformer Encoder with different LLMs

LLM	Type	BLEU-N (%)				ROUGE-1 (%)		
		N=1	N=2	N=3	N=4	P.	R.	F1
LLAMA2	7B	21.40	6.96	3.38	2.21	12.23	13.20	12.61
PEGASUS	google/pegasus-x-base	37.67	18.90	9.68	5.21	26.43	31.06	28.38
	google/pegasus-xsum	40.82	23.70	13.39	7.61	30.25	33.94	31.86
T5	t5-small	51.02	33.44	22.41	15.42	34.91	37.80	36.15
	t5-base	51.36	33.75	22.74	15.63	35.09	38.19	36.41
	t5-large	52.59	36.32	25.21	17.85	36.32	40.10	38.00
	google/flan-t5-base	50.01	33.09	21.77	14.49	32.97	36.64	34.54
	google/flan-t5-large	49.85	33.08	22.07	14.84	33.11	36.61	34.59

Speculative Augmentation We further conduct ablation experiments on the effect of different speculative ratios in Figure 7. We observe that the introduction of speculative augmentation at $r = 0.3$ has a significantly better impact on the decoding performance across all evaluated metrics.

LIMITATIONS

While BELT-2 achieved remarkable translation improvements by combining Q-Conformer with LLMs, it is worth noting that the accuracy still lags behind traditional language-to-language translation. Also, it is noted that the experiments were conducted on publicly available neural reading datasets with the help of eye-tracking markers. As a result, BELT-2 has not realized everyday communication such as ‘silent speech’ or ‘reading mind’. The vision of communication or controlling devices directly from brain dynamics remains a challenging task for follow-up research.

4 CONCLUSION

This paper introduces BELT-2, a pioneering EEG-language learning framework for bridging brain signals to LLMs. Our framework achieves EEG-to-language alignment by incorporating the novel BPE-CL objective and proposed an effective method for bridging a frozen Q-Conformer EEG Encoder and a frozen LLM to leverage their generative capacity. The multi-task extendibility of the Q-Conformer also establishes BELT-2 as the first work to achieve a multi-task decoding model in EEG research. Extensive experiments were conducted to evaluate the performance of BELT-2 quantitatively and qualitatively. Especially, this work provides the first study investigating the feasibility of using frozen pretrained LLM to process EEG contexts exemplified by a wide range of LLMs. Our experimental result shows that the BELT-2 framework represents a significant step forward in integrating human brain signals with LLMs, opening up exciting new avenues for research and development in cognitive neuroscience and brain-computer interfaces. We hope that this work will inspire further exploration and innovation in this exciting and rapidly evolving field.

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SUPPLEMENTARY MATERIAL FOR BELT-2: BOOTSTRAPPING EEG-TO-LANGUAGE REPRESENTATION ALIGNMENT FOR MULTI-TASK BRAIN DECODING

A RELATED WORKS

EEG decoding Prior brain studies demonstrated the potential to decode speech (Anumanchipalli et al., 2019) and language signals (Anumanchipalli et al., 2019) from the human brain using invasive neuro-sensors, but the risks make it impractical for most people. More recently, a surge of efforts was made to extract rich information from noninvasive brain signals through advanced representation learning techniques, opening the door to a wide array of innovative tasks based on brain signals, such as image reconstruction (Singh et al., 2023) and movement prediction (Zhou et al., 2023b). Nonetheless, Many of these efforts have limitations, including vocabulary size and decoding performance, hindering their suitability for complex practical scenarios. Our work focuses on open-vocabulary sentence decoding from noninvasive brain signals with fluent decoding performance and versatile multi-task adaptability, making it a promising solution for a diverse range of applications.

EEG-Language representation alignment A crucial step for most cross-modality tasks is the acquisition of aligned multi-modal representations (Liu et al., 2023a; Mokady et al., 2021; Rombach et al., 2022). Achieving this involves an alignment step following the acquisition of unimodality pretrained models (Li et al., 2023). Yet, the formidable challenge persists due to the limited scale and sparse EEG dataset annotations, as we strive to create a semantically coherent and universally adaptable EEG encoder, akin to visual counterparts (Dosovitskiy et al., 2020; Radford et al., 2021).

Diverging from the conventional fully-supervised paradigm, infusing natural language supervision enriches non-language modalities representation with semantics and zero-shot generalization (Desai & Johnson, 2021). Previous studies in unimodal vision tasks show that a large vision encoder, trained directly with language supervision, can match performance compared to learning from massive datasets (Joulin et al., 2016). Recent works incorporating language-guided learning also support the value of additional semantics for non-language representation generalization (Wang et al., 2023; Elizalde et al., 2023). Inspired by their successes, our work endeavors to bootstrap the learning of an Encoder that aligns EEG and language representation through natural language supervision.

B MATHEMATICAL SYMBOLS USED IN THIS PAPER

In Table 6 we show a list of mathematical symbols used in this paper.

Table 6: List of mathematical symbols used in this paper

Symbol	Description	Symbol	Description
$\langle \mathcal{E}, \mathcal{S} \rangle$	Word-level EEG embedding sequence and text sentence pair	$\langle \mathcal{E}, c \rangle$	Word-level EEG embedding sequence and sentiment label pair
$\langle \mathcal{E}, \hat{\mathcal{S}} \rangle$	Word-level EEG embedding sequence and text summary pair	$w \in \mathcal{W}$	BPE text token's embeddings
$c \in \mathcal{C}$	Sentiment label	$e \in \mathcal{E}$	EEG embedding vector
		$v \in \mathcal{V}$	Discrete codebook embeddings

C IMPLEMENTATION DETAILS

C.1 IMPLEMENTATION DETAILS FOR THE Q-CONFORMER

The Q-Conformer is implemented using the configuration detailed in Table 7. The detailed structures for the convolution module are shown in Table 8. We use the same Conformer block for the encoder and decoder, each with 2 Conformer blocks. We trained All models are trained on Nvidia A40 GPUs.

Table 7: Detailed configuration of the conformer block

Layer	Hidden Size	Activation Function	Number of Heads
Layer Norm	840	-	-
Feed Forward Module	840	GELU	-
LayerNorm	840	-	-
Multi-Head Self Attention	840	-	8
Convolution	840	-	-
Module	840	-	-
Layer Norm	840	-	-
Feed Forward Module	840	GELU	-
LayerNorm	840	-	-

Table 8: Detailed configuration of the convolution module

Layer	Kerrnel	Stride	In Channel	Out Channel
Layer Norm	-	-	840	840
Pointwise Convolution	1	1	840	2×840
Depthwise Convolution	31	1	840	840
Batch Norm	-	-	840	840
Pointwise Convolution	1	1	840	840
Dropout	-	-	-	-

C.2 TRAINING DETAILS FOR EEG-TO-LANGUAGE ALIGNMENT LEARNING

To train the Q-Conformer during the EEG-to-language alignment learning, we use a weighted summation of all the following loss terms:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{vq} + \lambda_2 \mathcal{L}_{bpe} + \lambda_4 \mathcal{L}_{elm} + \lambda_3 \mathcal{L}_{neg}, \quad (8)$$

λ_1 to λ_4 are coefficients for each loss term. We set λ_1 to λ_4 as [1, 10, 10, 0.001]. The main reason for such a setting is the aim to prioritize the learning of achieving EEG-to-language alignment and the training of the query prompt specific to the ELM task. To avoid collapse in training, we implemented the gradient normalization method to normalize the scale of the loss function and stabilize the training process.

C.3 TRAINING VIRTUAL PREFIX FOR BRIDGING Q-CONFORMER AND LLM

The prefix-tuning method used in our paper closely follows the implementation in Li & Liang (2021), the objective function (\mathcal{L}_{bridge}) is defined as a modified loss function tailored to guide the selective of continuous virtual prefix prompts. We use θ to denote the matrix that stores the virtual prefix. Using the machine translation loss \mathcal{L}_{tr} as an example, the objective function can be expressed as:

$$\mathcal{L}(\theta_{\text{bridge}}) = \mathcal{L}_{tr}(\hat{\mathcal{S}}, \mathcal{S}) \quad (9)$$

In this example, the prefix prompts to learn properly describe the EEG-to-Language translation task to the subsequence frozen LLM, utilizing the generation capacity of the LLM models to improve translation performance.

C.4 TRAINING DETAILS FOR MULTI-TASK LEARNING

To extend our model to multi-task decoding, we simultaneously train the model in three EEG decoding tasks including translation, summary, and sentiment classification task. We randomly sample a task for each batch during the training epochs. The loss function for translation task \mathcal{L}_{tr} and sentiment classification tasks \mathcal{L}_{st} are illustrated in Equation 6 and Equation 7 respectively.

For learning the summary task, the loss function could be written as follows:

$$\mathcal{L}_{sum} = - \sum_l^{|\hat{\mathcal{S}}|} \log p(s_l \in \hat{\mathcal{S}}) \quad (10)$$

, where $p(s_l)$ denotes a model predicting the word token for the next location. The final multi-task objective \mathcal{L} is written as follows:

$$\mathcal{L}_{mt} = \mathcal{L}_{tr} + \mathcal{L}_{sum} + \mathcal{L}_{st} \quad (11)$$

D IMPROVED Q-CONFORMER EEG ENCODER

We observed a noteworthy trend when utilizing a relatively larger learning rate of $1e - 4$, as opposed to the optimal learning rate of $5e - 6$ for the top-performing Q-Conformer Encoder, as indicated in Figure 8. This variance in learning rates led to a remarkable performance by the Q-Conformer Encoder on the training dataset, resulting in notably high BLEU Scores. Specifically, the BLEU-1 and BLEU-4 scores soared to remarkable levels, reaching 93.03 and 92.69 respectively. In stark contrast, the EEG-to-Text baseline method significantly lagged behind, registering only BLEU-1, 4 scores of 38.98 and 6.82 during our replicated training, highlighting the superior EEG encoding capabilities of the Q-Conformer Encoder.

It's also worth noting that the BLEU-1 performance of the Q-Conformer encoder experienced a decline from 42.43 to 35.48 during the testing phase, we interpret this as a minor setback. Such a reduction in performance can often be attributed to the challenges of generalization, which frequently happen in the context of training on a relatively small dataset.

Furthermore, it's worth highlighting that within this setting, the Q-Conformer still achieved a testing BLEU-4 score of 9.3, surpassing the baseline EEG-to-Text method's training set BLEU-4 score. This outcome serves as a compelling testament to the enhanced encoding capacity conferred by our Q-Conformer Encoder.

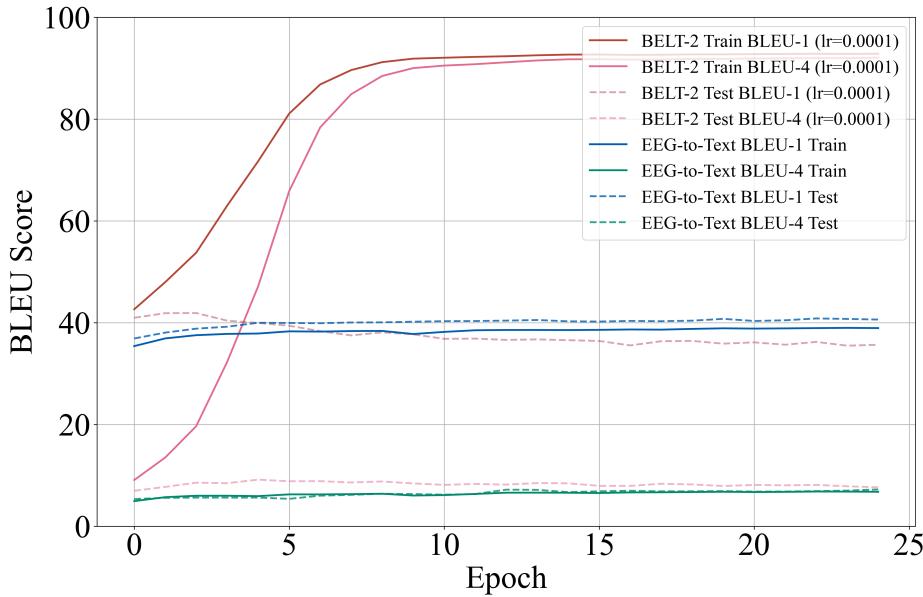


Figure 8: EEG encoder performance comparison

E COMPARISON WITH BELT-2 WITHOUT BPE-LEVEL CONTRASTIVE LEARNING

In Figure 9(a) and Figure 9(b), we present a comprehensive comparison of the learning curves and BLEU-1 curve of the baseline EEG-to-Text model (Cruttenden, 2014), the Q-Conformer encoder without applying the BPE-level contrastive learning (BELT-2 w/o BPE-CT) and the Q-Conformer

encoder with BPE-level contrastive learning (BELT-2 w/ BPE-CT)g. The visualized learning curves include the BLEU-1 score and loss values for 30 epochs on the test split. Comparing the EEG-to-Text model and the BELT-2 model, it’s evident that BELT-2 offers a significant reduction in loss values with or without BPE-level contrastive learning, indicating the proposed model architecture is more efficient in capturing EEG patterns. However, a notable observation arises after epoch 8. Without the BPE-contrastive learning (orange curves), the BLEU-1 score fluctuates and drops significantly. On the contrary, the introduction of BPE-level loss helps stabilize the model’s performance, particularly on unseen EEG data. This highlights the substantial enhancement brought about by our proposed BPE-contrastive learning framework.

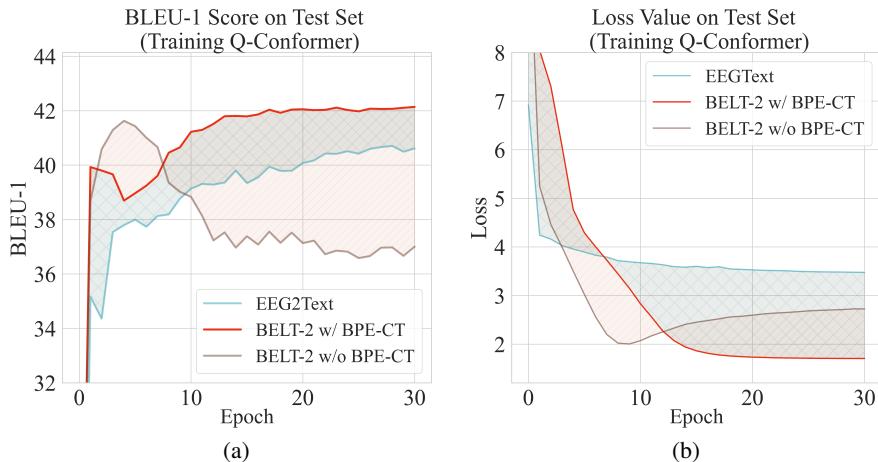


Figure 9: Ablation Study on Different Settings

F MULTI-TASK TRAINING RESULTS

We show the performance of translation, summary, and sentiment classification on the test set during the multitask training learning phase of BELT-2 in Table 10. In Table 10(a), we can observe that without the use of pretrained weights, all tasks are learned from scratch. In this case, the translation BLEU-1 score starts from 4.06 BLEU-1 score and rises to only reaches 41.47 and the summarization BLEU-1 score reaches 28.72. Also, the sentiment classification accuracy gradually increased to 59%. However, the use of Q-Conformer pretrained on translation tasks could improve the training stability and performance of both the sentiment classification task and the summarization task. Due to the pretrained weights, we observed that in Table 10(b), the BLEU-1 score of the summarization performance and sentiment achieved 23.0 BLEU-1 score after the first training epoch. Then continued to increase to 31.17. The accuracy for sentiment classification also reaches 79.86% at its peak and stabilizes at around 74%. However, the performance of the translation task slightly decreased. This is an expected phenomenon in multi-task training. Nonetheless, this ethernet still shows the multi-task learning capacity and extensibility of our BELT-2 framework.

G GENERATED SUMMARIZATION RESULTS

We created the summarization dataset with the prompt "Rewrite the sentence by summarizing its main idea using 8 words from the sentence and keep the summarized sentence similar to the original sentence: $\{s\}$ " where $\{s\}$ is the original sentence from the dataset. Table 9 showcases summary and prediction samples generated by the BELT-2 model. We could see those summary ground truths cover the key ideas of the original sentence and are within the maximum summarization word limit. On the training set, our BELT-2 model could learn and precisely generate a summary of the EEG signal, such as "film with twists" vs. "film with twists.". However, this summarization capacity did not generalize well on unseen test and validation data. We consider the lack of training data as one of the major reasons for this problem. Another reason is that our current model lacks higher-level

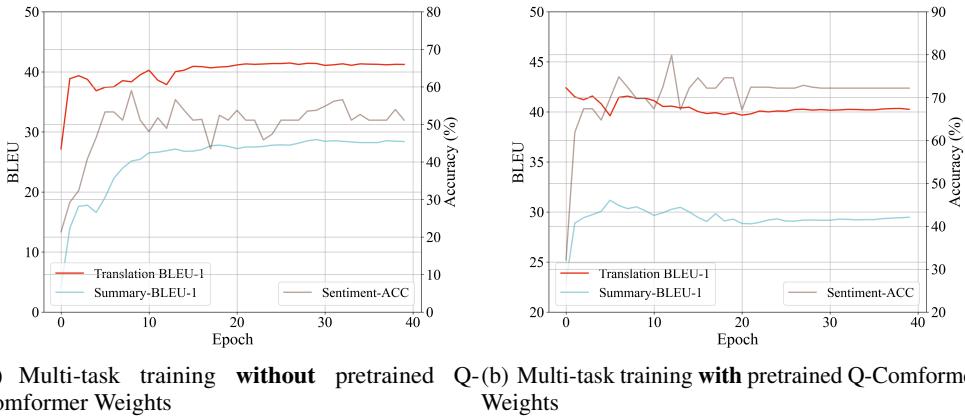


Figure 10: Ablation study on multitask learning and effect of our pretrained weights

skill that requires additional reasoning and abstraction skills beyond the mere translation of the brain signal, which leaves room for future improvements.

H ABLATION EXPERIMENTS ON HYPER-PARAMETERS

We conducted an ablation study on different hyper-parameters including the learning rate, batch size, frequency of the inserted cross-attention layer in the context layer of the Q-Conformer, and the number of querying prompts. The evaluation metrics can be found in Figure 11. We observe that the introduction of BPE-contrastive learning consistently improves training stability and model performance in different hyper-parameter settings. This result shows that the learning performance of BELT-2’s EEG encoder is not easily affected by the change of training parameters and is relatively easy to reproduce.

I AUGMENTATION EFFECT OF SPECULATIVE AUGMENTATION

The limitation of unique sentence from the training dataset also limits the diversity of the MLC context outputted by the Q-Conformer. The training set we used in our cross-sentence setting contains only 790 unique sentences as target for prefix-tuning when bridging Q-Conformer and LLM. For the Q-Conformer, predicts around 900 uniques MLC throughout the training dataset. This lack of training inputs makes the training for a good virtual prefix difficult. To solve this problem, our speculative augmentation method reuse cached MLC from the training stage of Q-Coformer. When using MLC from $K = 15$ checkpoints, we achieve a total of 5107 samples for prefix-tuning.

J EXTENSIVE EXAMPLES OF GENERATED TRANSLATION OUTPUTS

We provide extensive translation outputs from our BELT-2 model compared with the baseline EEG-to-Text model and the ground truth in Table 10. It shows that for some samples, the BELT-2 model still has insufficient performance, which indicates room for future improvements.

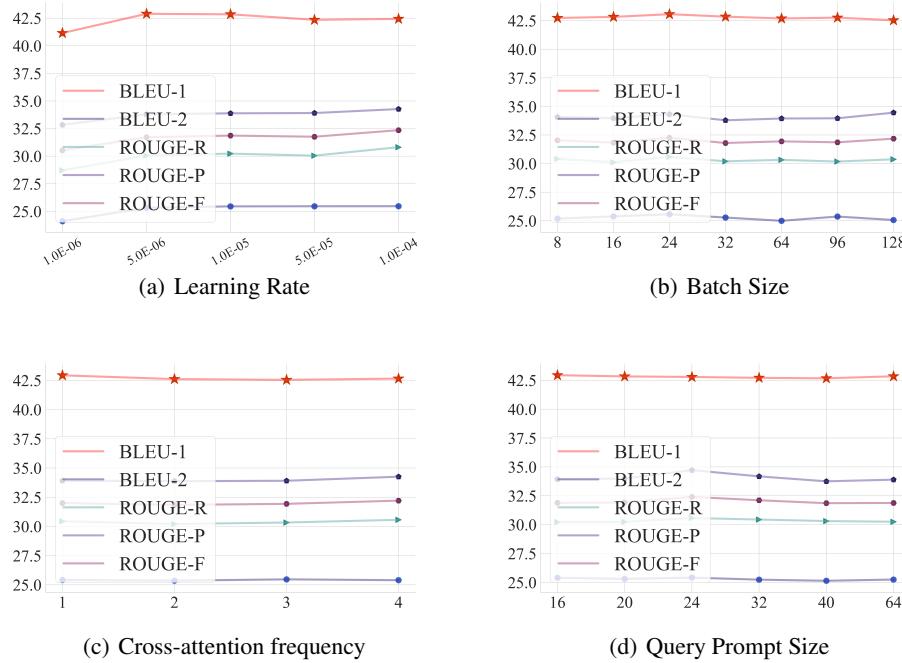


Figure 11: Ablation study on hyper-parameters.

Table 9: Summarization examples and generated results on the train set. The **bold** denotes an exact match between the ground truth and our prediction. underline denotes a fuzzy match with similar semantic meanings.

Training		
(1)	Sentence	Beautifully crafted, engaging filmmaking that should attract upscale audiences hungry for quality and a nostalgic, twisty yarn that will keep them guessing.
	Summary GT	High-quality film with twists.
	Prediction	-quality film with twists.
(2)	Sentence	Slow, silly and unintentionally hilarious.
	Summary GT	Silly, slow comedy .
	Prediction	inger, slow movie .
(3)	Sentence	The movie is for fans who can't stop loving anime, and the fanatical excess built into it.
	Summary GT	Anime fans will love excessive movie.
	Prediction	imated fans will love this gore.
(4)	Sentence	But here's the real damn: It isn't funny, either.
	Summary GT	Funny, but not really .
	Prediction	unny, smart not really .
(5)	Sentence	Everything was as superficial as the forced New Jersey lowbrow accent Uma had.
	Summary GT	Uma's accent was fake .
	Prediction	ma's accent was fake .
(6)	Sentence	Feels like nothing quite so much as a middle-aged moviemaker's attempt to surround himself with beautiful, half-naked women.
	Summary GT	Filmmaker surrounds himself with beautiful women .
	Prediction	mmakers imagined himself with beautiful women .
(7)	Sentence	He died in Springport, New York in 1815.
	Summary GT	Man passed away in Springport .
	Prediction	passed away in Springport .
Test and Validation		
(1)	Sentence	A richly imagined and admirably mature work from a gifted director who definitely has something on his mind.
	Summary GT	Director's mature work reflects deep thoughts.
	Prediction	's debut film. his empathy.
(2)	Sentence	An amateurish, quasi-improvised acting exercise shot on ugly digital video.
	Summary GT	Ugly video showcases poor acting .
	Prediction	ma., ugly acting .
(3)	Sentence	Warm Water Under a Red Bridge is a quirky and poignant Japanese film that explores the fascinating connections between women, water, nature, and sexuality.
	Summary GT	Japanese film explores women, water, nature, sexuality poignantly.
	Prediction	actor, themes's love, and. love.eticsancy.
(4)	Sentence	It just doesn't have much else... especially in a moral sense.
	Summary GT	Limited moral compass
	Prediction	role compass .
(5)	Sentence	It's solid and affecting and exactly as thought-provoking as it should be.
	Summary GT	Thought- provoking and solid.
	Prediction	inful provoking film funny.
(6)	Sentence	The art direction is often exquisite, and the anthropomorphic animal characters are beautifully realized through clever makeup design, leaving one to hope that the eventual DVD release will offer subtitles and the original Italian-language soundtrack.
	Summary GT	Beautiful animal characters, DVD subtitles.
	Prediction	iful, inter. funny experience.

Table 10: Extensive examples of generated translation outputs from unseen EEG signals in the test set. The **bold** denotes an exact match while underline denotes a fuzzy match with similar semantic meanings.

(1)	Target	It's not a particularly good film, but neither is it a monsterous one .
	Others	was a a bad good story, but it is it bad bad. one.
	Ours	It's not a bad bad movie, but it is it kinda good bad one .
(2)	Target	It's solid and affecting and exactly as thought- provoking as it should be .
	Others	was a, it, it what it.provoking as it is be.
	Ours	It's , believable, is what - provoking as the sounds be .
(3)	Target	Co-writer/director Jonathan Parker's attempts to fashion a Brazil-like, hyper-real satire fall dreadfully short.
	Others	operfounder of director of Dem is novel to make a film-themed film but-realistic of flatfully short of
	Ours	Theenstarrings director John Dem hass films to make a new-style film -realisticromre are flatareadfully flat.
(4)	Target	After World War II , Kennedy entered politics (partly to fill the void of his popular brother, Joseph P. Kennedy , Jr., on whom his family had pinned many of their hopes but who was killed in the war).
	Others	the War II, the was the andasly as serve the void left a father father , John Kennedy. Kennedy , who.) who the he father had been their of his hopes). never was never in the war).
	Ours	After the War II , became politics,andy to fulfill the void left his father father, John Kennedy . Kennedy, who.,who the Kennedy family had placedbased their of their hopes). had had in Battle.
(5)	Target	It's solid and affecting and exactly as thought- provoking as it should be.
	Others	was a, it, it what it.outoking as the sounds be.
	Ours	It's , logical, is what - provoking as the sounds be.
(6)	Target	Too much of this well-acted but dangerously slow thriller feels like a preamble to a bigger, more complicated story, one that never materializes.
	Others	bad of a is-known, not over- is like a film-ble to a more, more dramatic story. which that will quiteizes.
	Ours	Too much drama is-made, unly un-. like a -ble to a much, more serious,. one that' quiteizes.
(7)	Target	In 1923 he was awarded the inaugural Bôcher Memorial Prize by the American Mathematical Society.
	Others	the, married born the Nobel Pulitzercentne Prize Medal for the French Academyical Society.
	Ours	In 1815,he was awarded the Pulécher Prize Prize , the Royal Academyematical Society.
(8)	Target	He later became an educator, teaching music theory at the University of the District of Columbia; he was also director of the District of Columbia Music Center jazz workshop band.
	Others	was became a actor and and at and the University of California Arts of Columbia. and also also a of the University of Columbia 's School. department..
	Ours	He later became associate at and at at at the University of California West of Columbia and and he also of the English' Columbia ' Department. department.
(9)	Target	Fans of the TV series will be disappointed, and everyone else will be slightly bored.
	Others	of the film show " remember familiar to however the will will be happy amused.
	Ours	Fans of the movie series will be , as the who will be left disappointed.