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# Vector Quantization Pretraining for EEG Time Series with Random Projection and Phase Alignment

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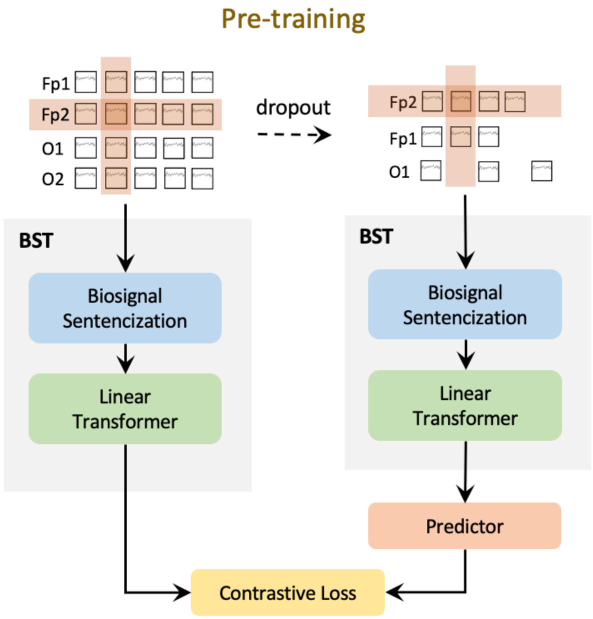
# Representations of the EEG data

**Self-Supervised Models**: Using proxy tasks to get the representations of EEG data



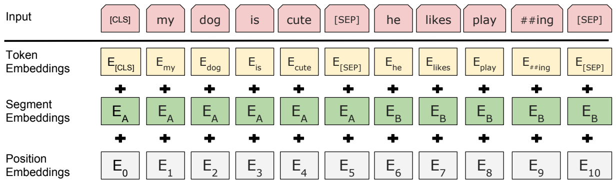

Contrastive-loss-based Self-supervised learning model[1]

**Cons**: Hard to construct the positive/negative pairs； Unable to be scalable

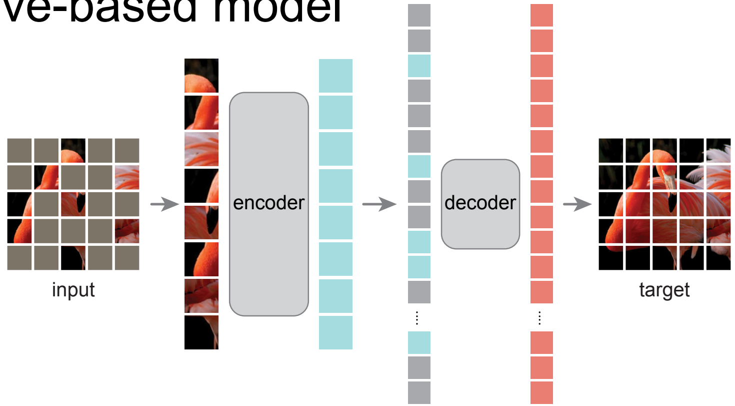
[1]BIOT: Cross-data Biosignal Learning in the Wild

# Semantic Units

## **Self-Supervised Models**: Reconstructive-based model




Treat words as basic semantic units




Treat patched figures as semantic units

- The significance of semantic units has been extensively studied in Natural Language Processing (NLP) and Computer Vision (CV), demonstrating their crucial role during the pre-training stage.
- Easily scalable.
- How can we define a well-defined semantic unit in EEG data?

# Representations of the EEG data

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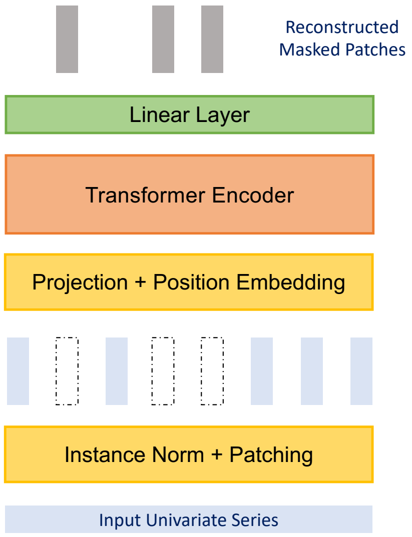


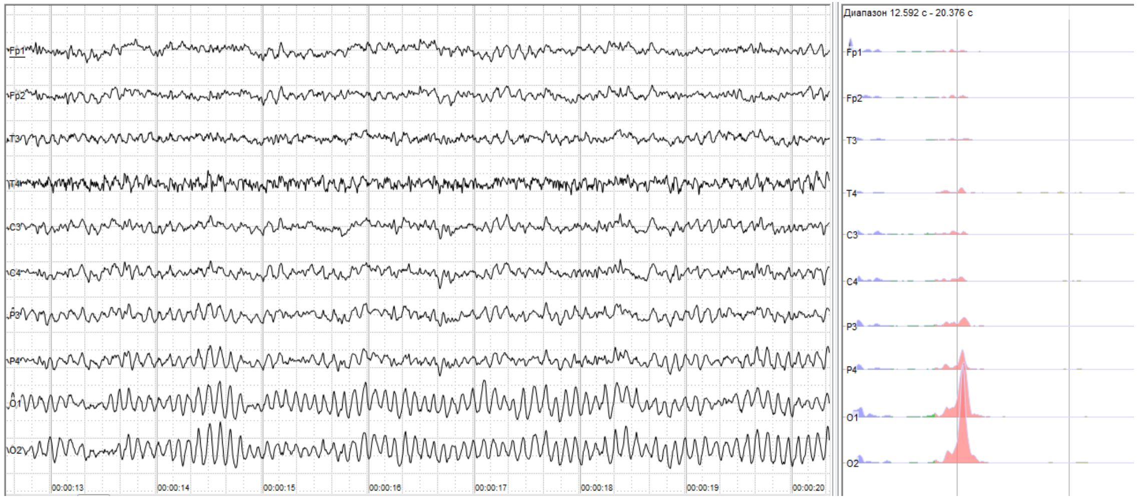

Reconstruct-based Self-supervised Learning model[1]

**Cons**: Prone to be corrupted; Noise is also encoded into the representations

[1] A Time Series is Worth 64 Words: Long-term Forecasting with Transformers

# Semantic Units

## Well-defined Semantic Unit

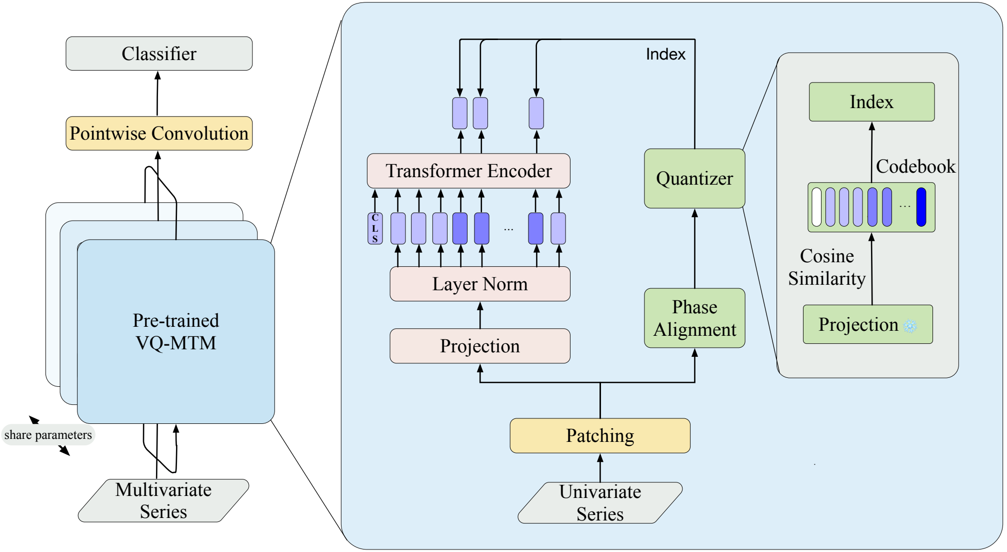



Features of EEG Signals:
- Low signal-to-noise ratio
- Periodic nature

Possible Problems:
- Data corruption
- Small lag or shift in the semantic units

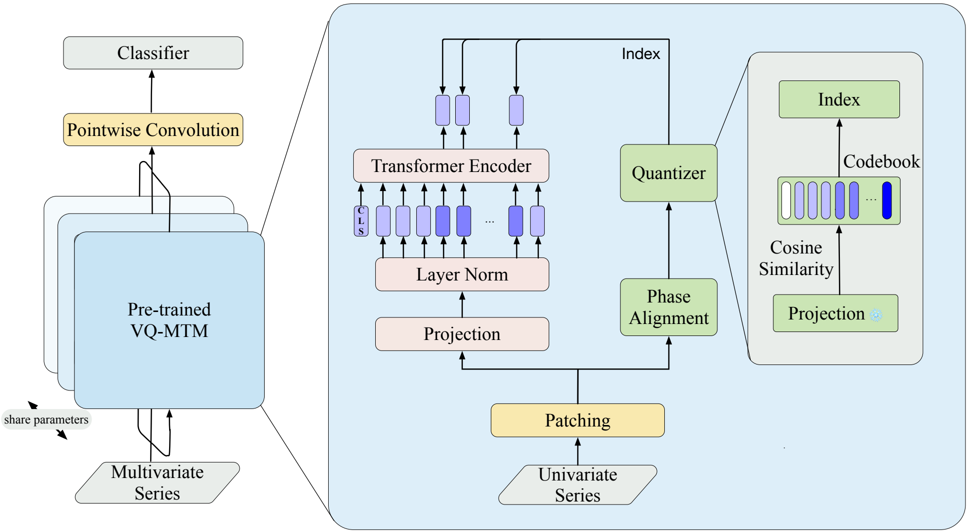
# Representations of the EEG data

**Our Method**: Adding a Phase-Alignment module and a Quantization module to obtain well-defined semantic units.




The pipeline of the pre-training stage of VQ-MTM.

# Overview of the VQ-MTM




Two existing challenges:

- High noise ratio
- Shifting or small lag in the semantic units

Solutions

- Quantization Module
- Phase-Alignment Module

## Quantization Module

To solve the problem of high noise ratio, we introduce the quantization module, which is not sensitive to noise due to its quantization mechanism.

However, the Quantization Module will introduce some problems:
- Determining how to obtain labels in the absence of explicit labels.
- Establishing a method to measure the distance between semantic units.

Thus, we propose the following solutions:
- We calculate the similarity of tokens with pre-defined (randomly initialized) tokens to generate the corresponding labels.
- Drawing from the concept of correlation, we use cosine similarity as the metric to calculate the distance between semantic units.

## Random Projection

**Problems**: The representation dimensions of template units might not match the length of the semantic units

**Key Points (JL-Lemma)**:

$$\Pr\left[|\langle \mathbf{v}_i, \mathbf{v}_j \rangle - \langle \mathbf{u}_i, \mathbf{u}_j \rangle| \leq \epsilon\right] \geq 1 - \frac{2}{n},$$

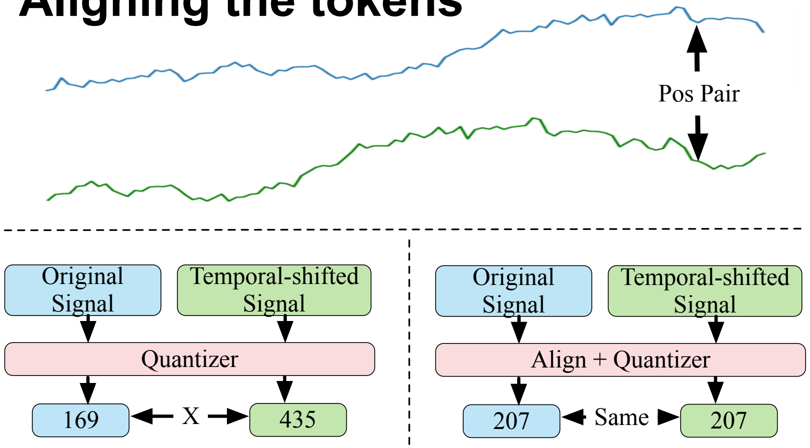
where $\mathbf{v}_i = \mathbf{A}\mathbf{u}_i$

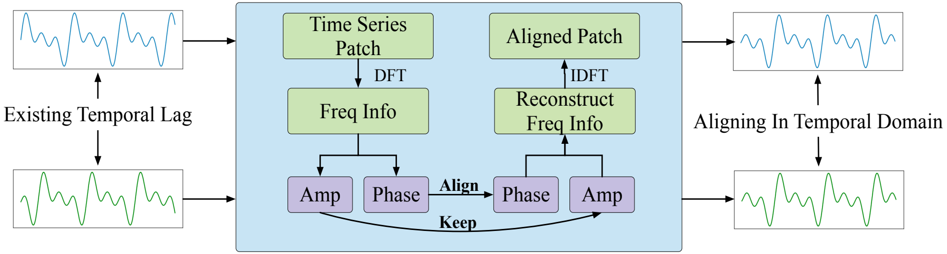
**Pros**: Introducing minimal additional computation costs since the added parameters are all frozen

* The problem can be solved by leveraging the Johnson-Lindenstrauss Lemma, using a randomly initialized mapping from the semantic unit's length to the template unit's representation.

# Phase Alignment Module

## Aligning the tokens




**Problems**: Inability to maintain consistency of variant labels.

**Goals**: Aligning the variations in the raw data.

**Formula**:

$$\hat{\mathbf{z}} = \mathrm{DFT}(\mathbf{z}),$$

$$\hat{\mathbf{z}}_{\mathrm{aligned}} = \mathrm{PhaseAlign}(\hat{\mathbf{z}}),$$

$$\mathbf{z}_{\mathrm{aligned}} = \mathrm{IDFT}(\hat{\mathbf{z}}_{\mathrm{aligned}}).$$

**Key Points in Phase Alignment**:

$$\theta_k = \arg(\hat{z}_k) - k \cdot \arg(\hat{z}_1),$$

$$\hat{\mathbf{z}}_{\mathrm{aligned}} = \left[ |\hat{z}_k| e^{i\theta_k} \right]_{k=0}^{N-1}.$$

# Experiments

## Experiment results on TUSZ dataset

| Model | Seizure Detection AUROC | | Seizure Classification Weighted F1-Score | |
|---|---|---|---|---|
| | 12-s | 60-s | 12-s | 60-s |
| DCRNN | 0.836 | 0.753 | 0.603 | 0.478 |
| TimesNet | 0.845 | 0.713 | 0.504 | 0.475 |
| MAE | 0.799 | 0.747 | 0.592 | 0.585 |
| PatchTST | 0.866 | 0.834 | 0.607 | 0.554 |
| SimMTM | 0.653 | 0.637 | 0.491 | 0.455 |
| VQ-MTM | **0.887** | **0.904** | **0.620** | **0.615** |
| Improvement(%) | 2.42 | 8.39 | 2.14 | 5.13 |

## Computation cost during the pre-training stage

| Model | SimMTM | BIOT | MAE | VQ-MTM |
|---|---|---|---|---|
| Flops | 1.78G | 7.84G | 0.15G | 0.12G |
| Params | 0.53M | 1.74M | 2.50M | 0.20M |

## Conclusion

Phase-Alignment Module

- Avoids mislabeling
- Ensures that data variations are projected onto the same template

Quantization Module

- Generates pseudo labels for the raw data

Delivers better performance compared to previous methods, while maintaining comparable computational efficiency.