UNet-HCRF Integration for Sequence Labeling on EEG Data

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Overview

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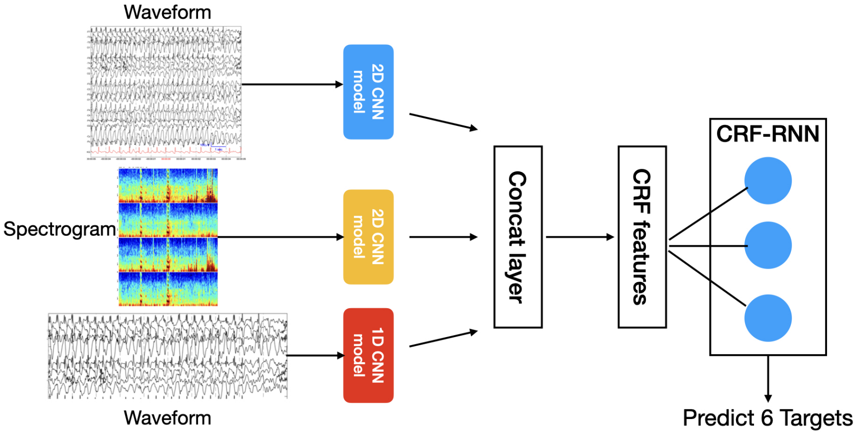
Introduction

- Electroencephalography (EEG) pattern recognition tasks are crucial for healthcare, where accurate and timely data classification can significantly impact patient outcomes.
- Deep learning has recently emerged as a powerful tool for sequence labeling.
- Conditional random fields (CRFs) have been employed for modeling label dependencies, demonstrating promising results.

Framework



Waveform
Spectrogram
Waveform
2D CNN model
2D CNN model
1D CNN model
Concat layer
CRF features
CRF-RNN
Predict 6 Targets

Overview

CNN-HCRF Model Structure

- Given the feature of the input data $\mathbf{I}$ learned by CNN, i.e. $\mathbf{x} = \mathbf{F}(\mathbf{I})$, its corresponding hidden part states $\mathbf{h}$, and the class label y, a hidden conditional random field (HCRF) has the exponential form:

$$\mathbb{P}(y, \mathbf{h} | \mathbf{x}; \theta) = \frac{\exp\left(\Phi(y, \mathbf{h}, \mathbf{x}; \theta)\right)}{\sum_{y' \in Y} \sum_{\mathbf{h} \in H^N} \exp\left(\Phi(y', \mathbf{h}, \mathbf{x}; \theta)\right)},$$

  where θ is the model parameter, H^N denotes the set of all possible hidden part states of N hidden parts, and $\Phi(y, \mathbf{h}, \mathbf{x}; \theta)$ refers to potential function depending on the feature $\mathbf{x}$.

- The probability of class label y for the given feature $\mathbf{x}$ is:

$$\mathbb{P}(y|\mathbf{x}; \theta) = \sum_{\mathbf{h} \in H^N} \mathbb{P}(y, \mathbf{h} \mid \mathbf{x}; \theta) = \frac{\sum_{\mathbf{h} \in H^N} \exp\left(\Phi(y, \mathbf{h}, \mathbf{x}; \theta)\right)}{\sum_{y' \in Y} \sum_{\mathbf{h} \in H^N} \exp\left(\Phi(y', \mathbf{h}, \mathbf{x}; \theta)\right)}.$$

CNN-HCRF Model Structure (cont.)

The jointly probability distribution of the HCRF model is:

$$\Phi(y, \mathbf{h}, \mathbf{x}; \theta) = \underbrace{\sum_{j \in \nu} \phi(h_j, x_j; \omega) + \sum_{i \neq j} \psi(h_i, h_j, x_i, x_j; \eta)}_{\text{Measures log-likelihood } \log \mathbb{P}(\mathbf{h}|\mathbf{x}; \theta)}$$

$$+ \underbrace{\sum_{j \in \nu} \varphi(y, h_j, x_j; \delta) + \vartheta(y, x_0; \varpi)}_{\text{Measures log-likelihood } \log \mathbb{P}(y|\mathbf{h}, \mathbf{x}; \theta)},$$

where:

- Unary potential $\phi(h_j, x_j; \omega)$: Measures the likelihood of the local feature x_j is assigned as the hidden part state h_j, with parameter ω is learned by end-to-end CNN-UNet structure.

CNN-HCRF Model Structure (cont..)

- Binary potential $\psi(h_i, h_j, x_i, x_j; \eta)$: Balances the hidden label compatibility of the neighboring pixels p on the feature $\mathbf{x}$:

$$\psi(h_i, h_j, x_i, x_j; \eta) = \mu(h_i, h_j)\left[\omega_1 \exp\left(-\frac{|p_i - p_j|^2}{2\eta_\alpha^2} - \frac{|x_i - x_j|^2}{2\eta_\beta^2}\right) + \omega_2 \exp\left(-\frac{|p_i - p_j|^2}{2\eta_\gamma^2}\right)\right],$$

where $\mu(h_i, h_j)$ is a label compatibility function, ω_1 and ω_2 are linear combination weights of different kernels, and the parameters η_α, η_β and η_γ control the influence of the corresponding feature spaces.

CNN-HCRF Model Structure (cont...)

- Unary potential $\varphi(y, h_j; \delta)$: Measures the compatibility between global class label y and the hidden local state h_j:

$$\varphi(y, h_j; \delta) = \sum_{a \in Y} \sum_{b \in H} \delta_{a,b} \cdot \mathbb{1}(y = a) \cdot \mathbb{1}(h_j = b),$$

  where $\mathbb{1}(\cdot)$ is a indicator function, and $\delta_{a,b}$ denotes the likelihood of class label $y = a$ containing a joint with hidden state $h_j = b$, learned during training.

- Global potential $\vartheta(y, x_0; \varpi)$: Measures the likelihood of the global feature x_0 is assigned as the action label y, with parameter ϖ learned during training process.

Variational Inference of HCRF

- The mean-field varepsilon family approximation of $\log P(\mathbf{h} \mid y, \mathbf{x}, \theta)$ is expressed as $\mathbb{Q}(h) = \prod_{i=1}^{N} q_i(h_i)$.
- The evidence lower bound (ELBO) under the mean-field family is:

$$
\begin{aligned}
\mathrm{ELBO}(\mathbb{Q}) &= \mathbb{E}_{\mathbb{Q}(\mathbf{h})} \log \mathbb{P}(y, \mathbf{h} | \mathbf{x}; \theta) - \mathbb{E}_{\mathbb{Q}(\mathbf{h})} \log q(\mathbf{h}) \\
&= \sum_{i=1}^{N} \mathbb{E}_{q_i(h_i)} \left[\phi(h_j, x_j; \omega) + \varphi(y, h_j, x_j; \delta) \right] \\
&+ \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{l,l'} \mathbb{1}_{\{i \neq j\}} \mathbb{Q}(h_i = l) \mathbb{Q}(h_j = l') \mu(l, l') \\
&\left[\omega_1 \exp\left(-\frac{|p_i - p_j|^2}{2\eta_\alpha^2} - \frac{|\mathbf{F}_i(\mathbf{I}) - \mathbf{F}_j(\mathbf{I})|^2}{2\eta_\beta^2} \right) + \omega_2 \exp\left(-\frac{|p_i - p_j|^2}{2\eta_\gamma^2} \right) \right] \\
&- \sum_{i=1}^{N} \mathbb{E}_{q_i} \log q_i(h_i) + \vartheta(y, \mathbf{x}; \varpi).
\end{aligned}
$$

- By the coordinate ascent variational inference (CAVI) algorithm, fixing $q_j(h_j), \forall j \neq i$, the optimal $q_i(h_i)$ that maximizes $\mathrm{ELBO}(q_i(h_i))$ is:

$$\mathbb{Q}(h_i) \propto \exp\{\mathbb{E}_{\mathbb{Q}(\mathbf{h}_{-i})} \log \mathbb{P}(y, h_i, \mathbf{h}_{-i} \mid \mathbf{x}; \theta)\}.$$

- The explicit form of $q_i(l)$ is derived as follows:

$$q_i(l) = \frac{1}{Z_i} \exp \Bigg\{ \phi(h_j, x_j; \omega) + \varphi(y, h_j, x_j; \delta) + \sum_{j \neq i} \sum_{l'} q(l')\mu(l, l')$$
$$\left[\omega_1 \exp\left(-\frac{|p_i - p_j|^2}{2\eta_\alpha^2} - \frac{|\mathbf{F}_i(\mathbf{I}) - \mathbf{F}_j(\mathbf{I})|^2}{2\eta_\beta^2} \right) + \omega_2 \exp\left(-\frac{|p_i - p_j|^2}{2\eta_\gamma^2} \right) \right] \Bigg\},$$

where Z_i is the normalization constant.

Mean Field Inference in HCRF

Algorithm 1: Mean-field inference in fully-connected CRF

Input: $Q_i(h_i) \leftarrow U_i(h_i),\ i = 1, 2, \ldots, N$ `// Initialize` $Q(h)$

while *not reach max iteration number* **do**

- $\hat{Q}_i^{(m)}(h_i) \leftarrow \sum_{j \neq i} k^{(m)}(f_i, f_j) Q_j(h_i)$ for all m `// Message Passing`;
- $\tilde{Q}_i^{(m)}(h_i) \leftarrow \sum_{l \in \mathcal{L}} \mu^{(m)}(h_i, l) \sum_m \omega^{(m)} \hat{Q}_i^{(m)}(l)$ `// Compatibility Transform`;
- $Q_i(h_i) \leftarrow \exp\{\phi(h_j, x_j; \omega) + \varphi(y, h_j, x_j; \delta) - \tilde{Q}_i(x_i)\}$ `// Local Update`;
- Normalize $Q_i(h_i)$;

end

Overview

Harmful Brain Activity Classification Dataset

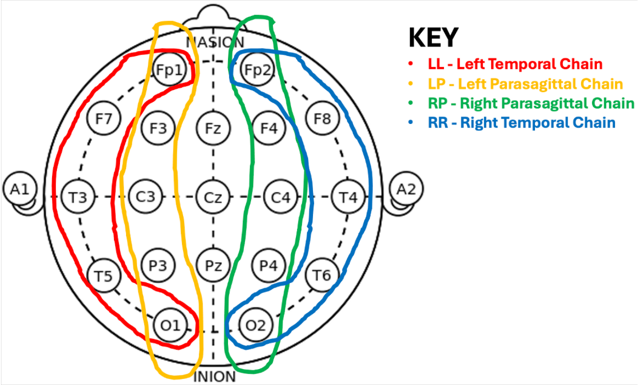
- The dataset contains 50-second long EEG samples covering a 10-minute window as well as spectrograms matching each sample.
- The EEG samples were labeled by expert annotators to determine which of the six features each spectrogram belonged to.
- The longer 10-minute window allows for the model to pick up on further insights regarding the nature of the brain activity.

Data Preparation

- Extract 10-minute long spectrograms centered at the midpoint time, where the expert ratings (Global EEGs) were provided.
- Convert the 50-second long EEG waveforms into spectrograms.

Make Spectrogram from EEG

- Bipolar Montage combines multiple EEG electrode signals by calculating the difference between adjacent electrodes, yielding signals representing specific brain regions.



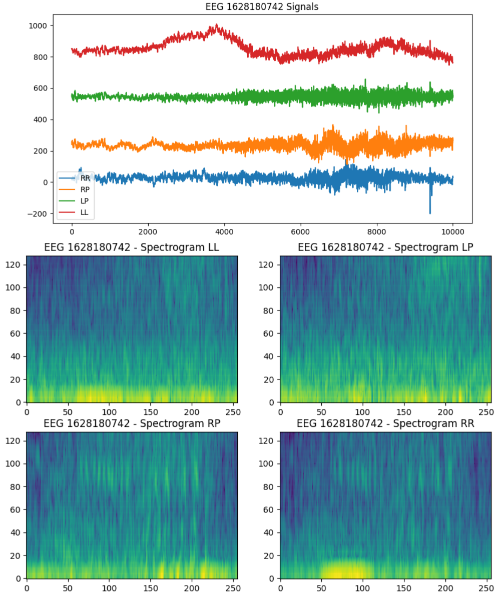
Make Spectrogram from EEG (cont.)

- A single time series signal is required to generate a spectrogram. To create four spectrograms from the dataset's 19 EEG time series signals, we employ Bipolar Montage to combine them into four representative signals.

$$\text{LL Spec} = \frac{1}{4}\left[spec(Fp1 - F7) + spec(F7 - T3) + spec(T3 - T5) + spec(T5 - O1)\right],$$
$$\text{LP Spec} = \frac{1}{4}\left[spec(Fp1 - F3) + spec(F3 - C3) + spec(C3 - P3) + spec(P3 - O1)\right],$$
$$\text{RP Spec} = \frac{1}{4}\left[spec(Fp2 - F4) + spec(F4 - C4) + spec(C4 - P4) + spec(P4 - O2)\right],$$
$$\text{RR Spec} = \frac{1}{4}\left[spec(Fp2 - F8) + spec(F8 - T4) + spec(T4 - T6) + spec(T6 - O2)\right],$$

where $spec(\cdot)$ is a custom function implemented using the `pywt` and `librosa` packages for signal transformation.

Make Spectrogram from EEG (cont..)



Training Schedule

The loss function was designed as Kullback-Leibler (KL) divergence.

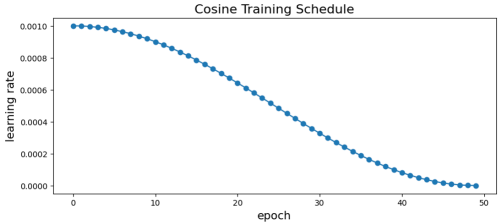


Figure 1: Pre-train UNet learning rate schedule.

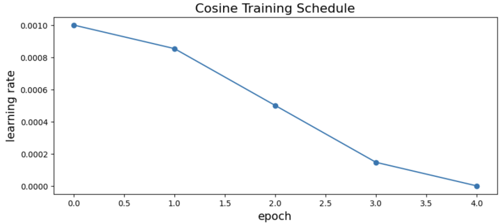


Figure 2: Fine tuning HCRF learning rate schedule.

Overview

Results

We evaluate our model by 5 fold cross-validation.

- Our model achieves a **0.4992** KL-divergence.
- The baseline model from Kaggle using EfficientNet obtains a 0.59 cross-validation KL-divergence.

However, there still are many teams on Kaggle have achieved even lower KL-divergence scores (0.2-0.3) by leveraging the power of large models like Vision Transformers (ViT).

Conclusion

- We build a Hidden Conditional Random Fields for EEG based Spectrograms image classification.
- The latent CRF layer is desgined to capture the latent segmentation information of the output of Neural Networks.
- A variational mean-field inference scheme is used to address the posterior distribution.
- We integrate the Unet and HiddenCRF into an end-to-end training structure. The Neural Networks feature learning and variational inference can be accelerated jointly by GPUs.