EE798R
Enhancing Self-Supervised ECG Representation Learning

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November 13, 2024

Abstract

This document presents an improvement to a self-supervised learning model for ECG signal representation by incorporating residual connections into the convolutional neural network architecture.

1 Proposed Improvement: Residual Connections

I propose incorporating **Residual Connections** [1] into the convolutional neural network. Residual connections allow the network to learn residual functions with reference to the layer inputs, improving representation learning.

2 Mathematical Formulation

A standard convolutional block without residual connections is defined as:

$$\mathbf{y} = \mathcal{F}(\mathbf{x}, \mathcal{W}), \tag{1}$$

where $\mathbf{x}$ is the input, $\mathcal{F}(\mathbf{x}, \mathcal{W})$ represents the transformation function, and $\mathcal{W}$ denotes the layer weights.

In a residual block, a shortcut connection allows:

$$\mathbf{y} = \mathbf{x} + \mathcal{F}(\mathbf{x}, \mathcal{W}), \tag{2}$$

enabling the block to learn the residual mapping $\mathcal{F}(\mathbf{x}, \mathcal{W}) = \mathbf{y} - \mathbf{x}$.

When dimensions differ, a linear projection $\mathcal{W}_s$ aligns them:

$$\mathbf{y} = \mathcal{W}_s\mathbf{x} + \mathcal{F}(\mathbf{x}, \mathcal{W}), \tag{3}$$

where $\mathcal{W}_s$ (often a 1×1 convolution) adjusts $\mathbf{x}$ to the required size.

3 Benefits of Residual Connections

- **Mitigating Vanishing Gradients:** Residual connections allow gradients to flow directly through the network, reducing the vanishing gradient problem and enabling the training of deeper models.
- **Learning Identity Mappings:** They provide a path for inputs to bypass convolutional layers, helping the network learn identity mappings and preserve important features if needed.
- **Improved Training Dynamics:** Residual connections simplify optimization, allowing faster convergence and better performance for networks.

```
Input
 │
 ├── Residual Conv Block 1
 │       ├── Conv1D
 │       ├── Activation
 │       └── Add Input (Residual Connection)
 │
 ├── Max Pooling
 │
 ├── Residual Conv Block 2
 │       ├── Conv1D
 │       ├── Activation
 │       └── Add Input (Residual Connection)
 │
 ├── Max Pooling
 │
 ├── Residual Conv Block 3
 │       ├── Conv1D
 │       ├── Activation
 │       └── Add Input (Residual Connection)
 │
 ├── Global Average Pooling
 │
 └── Dense Layers for Tasks
```

Figure 1: Modified Model with Residual Connections

4 Experiments and Results

Experiments to evaluate the impact of adding residual (skip) connections to different convolutional layers of our self-supervised ECG representation learning model. The configurations tested were:

1. **No Skip Connections**: The baseline model without any residual connections.
2. **Skip Connection in First Convolutional Block**: Adding a residual connection only in the first convolutional block.
3. **Skip Connections in First and Second Convolutional Blocks**: Adding residual connections in both the first and second convolutional blocks.
4. **Skip Connections in All Convolutional Blocks**: Adding residual connections in the first, second, and third convolutional blocks.

4.1 Training Time and Accuracy

For each configuration, the model was trained till it converged and measured the total training time and the accuracy achieved on the validation set. The results are summarized in Table 1.

Table 1: Comparison of Training Time and Accuracy for Different Configurations of Skip Connections

Configuration	**Training Time (hours)**	**Arousal**		**Valence**	
		Acc.	F1	Acc.	F1
No Skip Connections	~ 1.3	80.1	80.05	79.9	80.2
Skip Connection in First Block	~ 1.1	79.6	79.1	79.8	79.9
Skip Connections in First and Second Blocks	~ 1.1	81.5	81.5	81.3	81.1
Skip Connections in All Blocks	~ 1.05	82.8	82.9	82.4	82.8

4.2 Performance Improvements

Incorporating residual connections led to:

- Faster convergence during training.
- Improved accuracy on self-supervised transformation prediction tasks.

Other approach tried

4.3 Proposed Improvement: Contrastive Learning Approach

4.4 Attention-Based Dynamic Feature Selection

References

[1] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. *Deep Residual Learning for Image Recognition.* In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.