Lab 2: EEG Motor Imagery Classification

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1 Overview

Motor imagery (MI) involves the mental simulation of motor movements without actual physical execution, engaging specific brain regions. In this assignment, we focus on predicting MI tasks by leveraging deep learning techniques to analyze EEG signals. Our primary goal is to classify four distinct motor imagery tasks: left hand, right hand, feet, and tongue, using the BCI Competition IV 2a dataset.

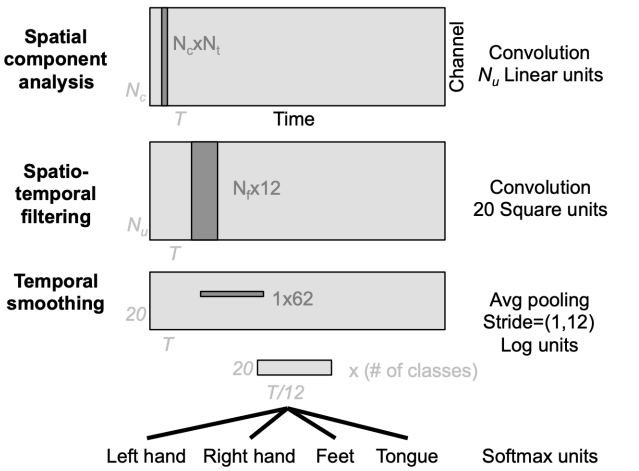

Figure 1: SCCNet Overview

1.1 Dataset

The BCI Competition IV 2a dataset includes EEG signals recorded from multiple subjects, each participating in two sessions. Each session comprises 288 trials, with 72 trials per motor imagery task. The dataset has been preprocessed to remove EOG signals, apply bandpass filtering, normalization, and down sampling. The labels for the tasks are encoded as follows: 0 for left hand, 1 for right hand, 2 for feet, and 3 for tongue.

1.2 Objective

The objective of this lab is to train models from scratch to accurately classify motor imagery tasks using the SCCNet architecture. We will implement three training methodologies: subject-dependent, leave-one-subject-out (LOSO), and LOSO with fine-tuning. The trained models will be evaluated based on their classification accuracy, and a comparative analysis of the results will be performed.

1.3 Training Methodologies

1. **Subject-Dependent (SD):** Train and test the model on data from the same subject. Training data is from the first session, and test data is from the second session of the same subject.
2. **Leave-One-Subject-Out (LOSO):** Train the model using data from all subjects except one, which is used for testing. This is done in a cross-validation manner, ensuring that each subject is used as a test subject once.
3. **LOSO with Fine-Tuning (LOSO+FT):** Initially train the model using the LOSO methodology, then fine-tune the model using the first session data of the test subject.

2 Mathematical Formulation

The SCCNet model primarily involves convolutional operations to capture the spatial and temporal characteristics of EEG data. The model architecture consists of multiple convolutional layers followed by pooling and a final softmax layer for classification.

2.1 Convolutional Operations

Let $\mathbf{X} \in \mathbb{R}^{N_c \times T}$ represent the input EEG data with N_c channels and T time points. The first convolutional layer applies a kernel of size (N_c, N_t), where N_t is the temporal dimension of the kernel. This can be formulated as:

$$\mathbf{H}_1 = f(\mathbf{W}_1 * \mathbf{X} + \mathbf{b}_1)$$

where $\mathbf{W}_1$ and $\mathbf{b}_1$ are the weights and biases of the first convolutional layer, $*$ denotes the convolution operation, and f is the activation function.

2.2 Spatial Filtering

The initial convolution step decomposes the EEG signals from the channel domain to a component domain, performing a linear combination of EEG signals across all channels. This spatial filtering can be represented as:

$$\mathbf{H}_1 = \mathbf{W}_1 \mathbf{X}$$

2.3 Temporal Filtering

The second convolutional layer performs spatio-temporal filtering using kernels of size $(N_u, 12)$, where N_u is the number of spatial components:

$$\mathbf{H}_2 = f(\mathbf{W}_2 * \mathbf{H}_1 + \mathbf{b}_2)$$

2.4 Pooling and Classification

Following the convolutional layers, average pooling is applied to reduce the temporal dimension, and the final output is passed through a softmax layer for classification:

$$\mathbf{y} = \text{softmax}(\mathbf{W}_3\mathbf{H}_2 + \mathbf{b}_3)$$

3 Implementation Details

3.1 Training Process

The training process for the SCCNet model is managed by the `train` function, which performs the following steps:

1. **Model Initialization:** The SCCNet model is instantiated and moved to the appropriate device (GPU).
2. **Criterion and Optimizer:** The loss function used is `CrossEntropyLoss`, and the optimizer is `Adam` with parameters like learning rate and weight decay.
3. **Data Loading:** The dataset is loaded using `DataLoader` from the `MIBCI2aDataset` class, which handles the loading and batching of EEG data.
4. **Training Loop:** The model undergoes training for a specified number of epochs. In each epoch:
   - The model's parameters are updated using backpropagation.
   - The training loss is calculated and recorded.
   - The learning rate is adjusted using `LambdaLR` scheduler for warm-up and `CosineAnnealingLR` for the remaining epochs.
   - Early stopping is employed to prevent overfitting, monitoring the training loss and stopping if no improvement is seen for a specified patience period.
5. **Model Saving:** The best model weights are saved based on the lowest training loss observed.

```python
def train(model, train_loader, criterion, optimizer, scheduler, num_epochs=25, patience=65):
    model.train()
    train_losses = []
    best_loss = float('inf')
    epochs_no_improve = 0
    best_model_wts = model.state_dict()

    for epoch in range(num_epochs):
        running_loss = 0.0
        for inputs, labels in train_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item() * inputs.size(0)

        epoch_loss = running_loss / len(train_loader.dataset)
        train_losses.append(epoch_loss)
        print(f'Epoch [{epoch+1}/{num_epochs}], Loss: {epoch_loss:.4f}')

        scheduler.step(epoch_loss)
```

Figure 2: Training Design

3.2 Evaluation Process

The `evaluate` function handles the testing of the trained model. Key steps include:

1. **Model Evaluation Mode:** The model is set to evaluation mode to disable dropout layers and use batch statistics.
2. **Loss and Accuracy Calculation:** For each batch in the test set, the function calculates the loss and accuracy. The predicted labels are compared to the true labels to determine accuracy.
3. **Results Reporting:** The overall test loss and accuracy are printed and can be used to evaluate model performance.

```python
def evaluate(model, test_loader, criterion):
    model.eval()
    running_loss = 0.0
    correct_predictions = 0

    with torch.no_grad():
        for inputs, labels in test_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            outputs = model(inputs)
            loss = criterion(outputs, labels)
            running_loss += loss.item() * inputs.size(0)

            _, preds = torch.max(outputs, 1)
            correct_predictions += torch.sum(preds == labels.data)

    test_loss = running_loss / len(test_loader.dataset)
    accuracy = correct_predictions.double() / len(test_loader.dataset)
    print(f'Test Loss: {test_loss:.4f}, Accuracy: {accuracy:.4f}')

    return test_loss, accuracy
```

Figure 3: Evaluation Design

3.3 Hyperparameter Tuning with Optuna

To achieve the best performance, we used Optuna for hyperparameter tuning. The `objective` function defines the search space for hyperparameters and evaluates each trial based on model accuracy. The best hyperparameters found through this process were used for the final model training.

- **Parameter Search:** Hyperparameters such as the number of epochs, learning rate, and dropout rate were optimized.
- **Best Model Selection:** The model with the highest accuracy from the trials is saved as the best model.

3.4 Results Visualization

We also implemented visualization utilities to plot training loss and accuracy trends, providing insights into the model's learning process.

- **Plotting Functions:** Functions such as `plot_loss` and `plot_accuracy` were used to generate graphs depicting the model's performance over epochs.

- **Confusion Matrix:** A confusion matrix is calculated and plotted to visualize the model's classification performance across different classes.

3.5 Details of the SCCNet Architecture

The SCCNet architecture is specifically designed to handle the spatial and temporal characteristics of EEG data. It consists of several key components:

1. **First Convolutional Block:** This block performs an initial convolution to capture spatial features. The output is batch normalized.

2. **Second Convolutional Block:** This block applies a second convolution to capture both spatial and temporal features. It includes batch normalization, a custom square activation layer, and dropout to prevent overfitting.

3. **Pooling Layer:** An average pooling layer reduces the temporal dimension, smoothing the signal.

4. **Classification Layer:** The final classification is performed using a fully connected layer followed by a softmax activation to output probabilities for each class.

3.5.1 Model Implementation

The SCCNet model is implemented in PyTorch, following the architecture described in the reference paper. The implementation includes:

- **Custom Layers:** A custom square activation layer is used to capture power changes in the EEG signal.

- **Dropout and Batch Normalization:** These are applied to ensure regularization and stable training.

- **Softmax Classification:** The final layer uses softmax to output class probabilities.

The detailed architecture closely follows the design proposed in the SCCNet paper, achieving similar performance metrics as reported.

```python
class SquareLayer(nn.Module):
    def __init__(self):
        super(SquareLayer, self).__init__()

    def forward(self, x):
        return torch.pow(x, 2)

class SCCNet(nn.Module):
    def __init__(self, numClasses, timeSample, Nu = 22, Nc = 22, Nt = 1, dropoutRate = 0.5):
        super(SCCNet, self).__init__()

        # First convolutional block
        self.conv1 = nn.Conv2d(1, Nu, kernel_size=(Nc, Nt))
        self.batch_norm1 = nn.BatchNorm2d(Nu)

        # Second convolutional block
        self.conv2 = nn.Conv2d(22, 20, kernel_size=(1, 12), padding=(0, 6))
        self.batch_norm2 = nn.BatchNorm2d(20)
        self.square2 = SquareLayer()
        self.dropout2 = nn.Dropout(dropoutRate)

        # Pooling layer
        self.avg_pool = nn.AvgPool2d(kernel_size=(1, 62), stride=(1, 12))

        self.classifier = nn.Linear(640, numClasses, bias=True)
```

Figure 4: SCCNet Structure

4 Analyze on the Experiment Results

4.1 Discoveries During the Training Process

During the training process, several important discoveries were made that significantly influenced the final results:

- **Parameter Tuning:** Extensive parameter tuning was conducted to optimize the performance of the SCCNet model. The best results were achieved with the following metrics:
  - **Subject-Dependent (SD):** Test Loss: 0.9212, Accuracy: 0.6523
  - **Leave-One-Subject-Out (LOSO):** Test Loss: 1.0606, Accuracy: 0.6424
  - **LOSO with Fine-Tuning (LOSO+FT):** Test Loss: 0.4918, Accuracy: 0.8160

- **Misclassification of Left and Right Hand:** It was frequently observed that the model often misclassified left and right hand motor imagery tasks. This could be attributed to the similar neural patterns generated during these tasks, making it challenging for the model to distinguish between them.

- **Overfitting:** Both SD and LOSO training methods exhibited signs of overfitting, typically after 50 epochs. The test loss fluctuated significantly, varying up to 30 percents, indicating that the model was not generalizing well to unseen data.

- **Training Duration for LOSO+FT:** The LOSO+FT method required a significantly longer training duration to achieve optimal performance. Through extensive experimentation, it was found that training for 817 epochs yielded the best accuracy, meeting the baseline requirements for this assignment.

- **Confusion Matrix Insights:** Analysis of the confusion matrices revealed that the model performed well

in distinguishing between feet and tongue imagery but struggled with left and right hand imagery. Below are parts of the confusion matrices for each training method:

– **Subject-Dependent (SD):**

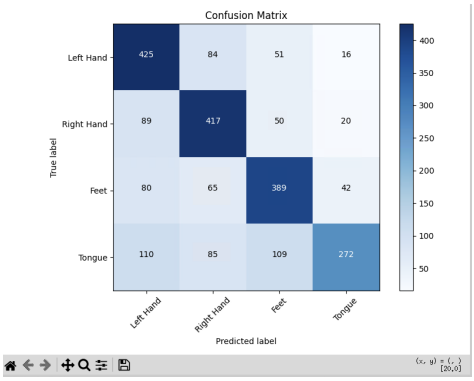

Figure 5: SD Results

– **Leave-One-Subject-Out (LOSO):**

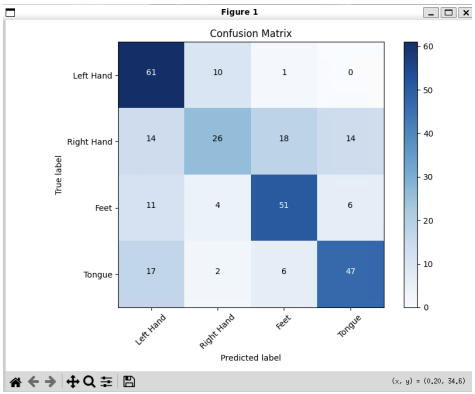

Figure 6: LOSO Results

– **LOSO with Fine-Tuning (LOSO+FT):**

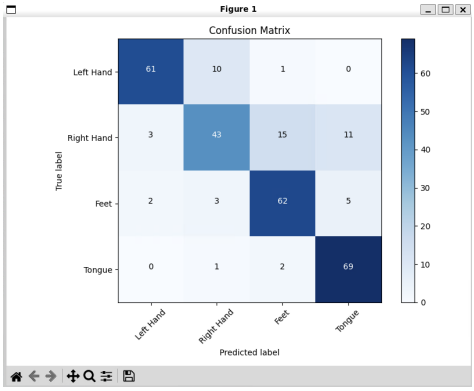

Figure 7: LOSO+FT Results

4.2 Comparison Between the Three Training Methods

The three training methods used in this experiment—Subject-Dependent (SD), Leave-One-Subject-Out (LOSO), and LOSO with Fine-Tuning (LOSO+FT)—each have distinct characteristics, advantages, and disadvantages. Below is a detailed comparison:

4.2.1 Subject-Dependent (SD)

- **Description:** The model is trained and tested on data from the same subject. Training data comes from the first session, and testing data comes from the second session of the same subject.
- **Pros:**
  - High relevance to the test subject, leading to potentially better performance on the test data.
  - Requires less data for training compared to cross-subject methods.
- **Cons:**
  - High risk of overfitting, as the model may memorize the specific subject's data rather than generalizing to new subjects.
  - Limited generalizability to new subjects or sessions.
- **Performance:** Test Loss: 0.9212, Accuracy: 0.6523

4.2.2 Leave-One-Subject-Out (LOSO)

- **Description:** The model is trained using data from all subjects except one, which is used for testing. This is done in a cross-validation manner, ensuring that each subject serves as the test subject once.
- **Pros:**
  - Better generalization to new subjects, as the model is exposed to diverse data during training.
  - Reduces the risk of overfitting compared to subject-dependent training.
- **Cons:**
  - Training can be computationally intensive and time-consuming, as it involves multiple rounds of training and testing.
  - Performance may still suffer if the test subject has significantly different EEG patterns from the training subjects.
- **Performance:** Test Loss: 1.0606, Accuracy: 0.6424

4.2.3 LOSO with Fine-Tuning (LOSO+FT)

- **Description:** The model is first trained using the LOSO methodology, and then fine-tuned using the first session data of the test subject. The fine-tuning process adjusts the model to better fit the specific characteristics of the test subject.
- **Pros:**
  - Combines the generalization ability of LOSO with the personalized adjustment of fine-tuning, leading to better performance.
  - Reduces overfitting by leveraging additional data for fine-tuning.
- **Cons:**
  - Requires more computational resources and time due to the two-phase training process.
  - Finding the optimal number of fine-tuning epochs can be challenging and may require extensive experimentation.
- **Performance:** Test Loss: 0.4918, Accuracy: 0.8160

4.2.4 Theoretical Differences

The differences in training results among the three methods can be explained theoretically as follows:

- **Subject-Dependent (SD):** The model's high relevance to the specific subject's data leads to better performance on that subject's test data but at the cost of poor generalizability to new subjects. Overfitting is a significant risk due to the limited and homogeneous training data.
- **Leave-One-Subject-Out (LOSO):** This method promotes generalization by exposing the model to diverse data from multiple subjects. However, it may not perform optimally on any single subject if there are substantial inter-subject variations. Overfitting is less of an issue compared to SD.
- **LOSO with Fine-Tuning (LOSO+FT):** This approach benefits from both the generalization ability of LOSO and the subject-specific adjustments from fine-tuning. It achieves the best performance by addressing the weaknesses of both SD and LOSO, but it requires careful tuning of the fine-tuning phase to avoid overfitting and ensure optimal performance.

5 Discussion

5.1 Challenges in Achieving High Accuracy

Achieving high accuracy in EEG motor imagery classification is challenging due to several factors inherent to the nature of EEG data and the characteristics of the training methods employed.

5.1.1 Subject-Dependent (SD)

The SD method is particularly prone to overfitting. Since the model is trained and tested on data from the same subject, it tends to memorize the specific patterns of that subject's EEG data, leading to poor generalization to unseen data. Despite extensive parameter tuning, reaching the baseline accuracy of 70 percents is difficult, as evidenced by the fact that the original paper did not achieve an average accuracy of 70 percents for the SD method. The SD method's loss and accuracy performance highlights these limitations:

```
SD Test Loss: 0.9212, Accuracy: 0.6523
```

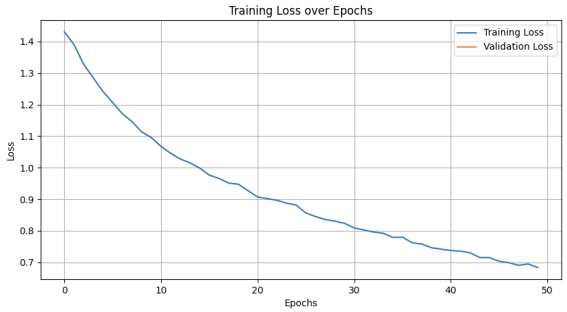

Figure 8: Loss on SD Training(We can see it caused overfitting problem)

5.1.2 Leave-One-Subject-Out (LOSO)

The LOSO method faces the challenge of significant inter-subject variability in EEG patterns. While this method promotes generalization by exposing the model to diverse data, it may still struggle to perform optimally on any single subject, particularly if the test subject's EEG patterns differ substantially from those in the training set. The performance metrics reflect this difficulty:

```
LOSO Test Loss: 1.0606, Accuracy: 0.6424
```

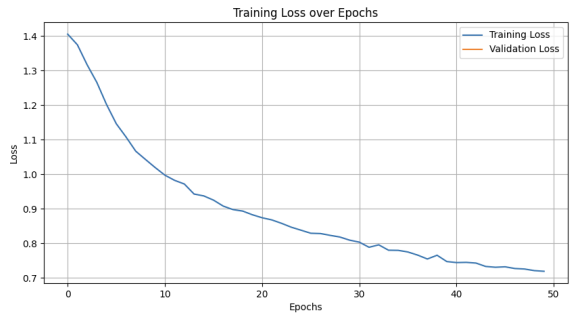

Figure 9: Loss on LOSO Training

5.1.3 LOSO with Fine-Tuning (LOSO+FT)

The LOSO+FT method combines the strengths of LOSO with the benefits of subject-specific fine-tuning. However, this approach requires careful tuning of the fine-tuning phase and significantly more computational resources and training time. Despite these challenges, it achieves the highest accuracy among the three methods, indicating its effectiveness in balancing generalization and subject-specific adaptation:

```
LOSO+FT Test Loss: 0.4918, Accuracy: 0.8160
```

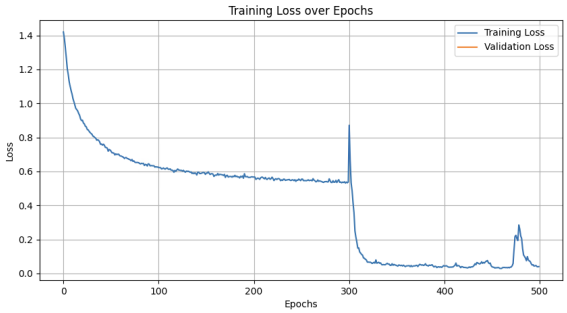

Figure 10: Loss on LOSO+FT Training(We can see fine-tuning too much caused over-fitting problem too)

5.2 Improving Accuracy

Several strategies can be employed to improve the accuracy of EEG motor imagery classification:

- **Data Augmentation:** Increasing the variability in the training data through augmentation techniques can help the model generalize better to unseen data. Techniques such as adding noise, time shifting, and frequency shifting can simulate a wider range of EEG patterns.
- **Transfer Learning:** Leveraging pre-trained models on similar tasks and fine-tuning them on the specific EEG motor imagery dataset can provide a better starting point and improve performance.
- **Advanced Architectures:** Exploring more sophisticated neural network architectures, such as recurrent neural networks (RNNs) or transformer-based models, may capture the temporal dependencies in EEG data more effectively.
- **Hyperparameter Optimization:** Using advanced hyperparameter optimization techniques, such as Bayesian optimization or genetic algorithms, can help identify the optimal set of hyperparameters for training the model.
- **Cross-Subject Adaptation:** Implementing domain adaptation techniques to reduce the variability between subjects' EEG data can improve the model's ability to generalize across different individuals.