PARSE: Pairwise Alignment of Representations in Semi-Supervised EEG Learning for Emotion Recognition

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Abstract—We propose PARSE, a novel semi-supervised architecture for learning strong EEG representations for emotion recognition. To reduce the potential distribution mismatch between the large amounts of unlabeled data and the limited amount of labeled data, PARSE uses pairwise representation alignment. First, our model performs data augmentation followed by label guessing for large amounts of original and augmented unlabeled data. This is then followed by sharpening of the guessed labels and convex combinations of the unlabeled and labeled data. Finally, representation alignment and emotion classification are performed. To rigorously test our model, we compare PARSE to several state-of-the-art semi-supervised approaches which we implement and adapt for EEG learning. We perform these experiments on four public EEG-based emotion recognition datasets, SEED, SEED-IV, SEED-V and AMIGOS (valence and arousal). The experiments show that our proposed framework achieves the overall best results with varying amounts of limited labeled samples in SEED, SEED-IV and AMIGOS (valence), while approaching the overall best result (reaching the second-best) in SEED-V and AMIGOS (arousal). The analysis shows that our pairwise representation alignment considerably improves the performance by reducing the distribution alignment between unlabeled and labeled data, especially when only 1 sample per class is labeled.

1 Introduction

Human emotions are encountered and experienced by humans on a daily basis, and significantly influence our behaviors, interactions, and perceptions of the world. It is therefore critical to develop algorithms capable of recognizing different human emotions from behaviour measures and physiological signals to assist computers in better responding to human needs and interactions. As a result, affective computing, a discipline that aims to develop data-driven computational models capable of recognizing human emotional states [1], has become a popular field of research in recent years.

Emotions can be detected and quantified using a variety of different human-generated signals, including facial expressions [2], speech [3], and bio-signals such as electrocardiogram (ECG) [4], electrodermal activity [5], photoplethysmogram [6], Electroencephalogram (EEG) [7] and others. While each modality comes with a unique set of advantages and disadvantages (e.g., wearability, cost, accuracy, etc.), EEG is highly regarded as an informative and viable option for affective computing given its direct relation to the central nervous system.

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Deep learning models have become increasingly popular in recent years due to the significant advancements in deep neural networks, computational power, and abundance of collected data. Such methods have shown great promise in dealing with various challenges encountered in EEG, including high dimensionality, non-stationarity, and high susceptibility to noise and the linear mixing effect [8], [9]. The majority of these methods, however, are fully supervised and rely heavily on large amounts of 'labeled' training samples. On the other hand, labeling EEG signals is challenging, time-consuming, expensive, and often requires annotation experts. Many EEG-based works in the area, for example, require diverse emotion annotation methods such as pre-stimulation selfassessment, post-experiment self-assessment, and numerous expert evaluations to acquire accurate labels [10]-[13]. When only very small portions of training samples are labeled, most existing fully supervised learning solutions often suffer from performance degradation. To address this challenge, we propose a novel Semi-Supervised Learning (SSL) pipeline by efficiently leveraging large amounts of unlabeled EEG samples and very few labeled ones.

Problem statement. (1) The field of SSL has witnessed interesting progress in recent years, most notably in the computer vision domain [14]-[19]. Nonetheless, very few works have adopted these state-of-the-art methods in the field of EEG representation learning, and fewer so have proposed novel SSL frameworks to learn EEG for emotion recognition or otherwise. (2) In most recent SSL methods, the distribution of unlabeled samples plays a critical role in the performance of the model. In particular, when pseudo-labels are generated (guessed) for unlabeled samples, existing methods often consider the confidence of the model on the estimated pseudo-labels to accept or reject unlabeled samples for which low-confidence pseudo-labels cannot be guessed [18], [19]. While this approach is logically viable and practically effective, the confidence threshold set is often dataset-specific and requires trial and error. In particular, this would be a significant challenge given the distribution differences between different datasets in the context of EEG. (3) In addition to the internal distribution of unlabeled samples, the closeness of the distribution of unlabeled samples with respect to labeled samples also plays a key role in SSL methods. Should the distribution of labeled and unlabeled samples be far from each other, the quality of the generated pseudo-labels for the unlabeled samples may be compromised due to the lack of generalizability in the model. While this issue has not been addressed in most SSL methods [17]-[19], we believe that this problem needs to be addressed especially in the context of semi-supervised EEG representation learning given the vast distribution differences often found within different datasets.

Contributions. In this paper, we propose a novel semi-supervised EEG learning framework for emotion recognition. Our model, entitled PARSE (Pairwise Alignment of Representations for Semi-Supervised EEG Learning), first augments the labeled and unlabeled EEG data. A classifier is then used to make predictions on the original, weakly augmented, and strongly augmented unlabeled data. Then, we average these three predictions as the guessed label for each unlabeled sample. Next, we apply convex combinations between labeled and unlabeled data followed by representation alignment by training a domain discriminator on the interpolated set. A classifier is also trained simultaneously to perform emotion recognition. An overview of our method is presented in Figure 1. We test PARSE on four publicly available datasets SEED [10], SEED-IV [11], SEED-V [12], and AMIGOS [13], considering the following criteria: i) including discrete (e.g., sad, happy, neutral) and continuous emotions (e.g., arousal); (ii) including binary and multi-class classification tasks (2, 3, 4, or 5 classes); (iii) including both balanced and imbalanced datasets.

To fully evaluate our method, we also implement and adopt several SSL methods from other domains (computer vision), with which to compare our method. In particular, we implement and compare our method with varying amounts of few labeled samples (1,3,5,7,10,25) labeled samples per class) against three cuttingedge methods MixMatch [17], FixMatch [18], and AdaMatch [19], in addition to five classical SSL methods, Π -model [14], temporal assembling [14], mean teacher [15], convolutional autoencoders [20], and pseudo-labeling [21]. Our experiments show that PARSE achieves overall best results in SEED, SEED-IV and AMIGOS (valence), and approaches the best results in SEED-V (0.3\%) difference) and AMIGOS (arousal). We also perform an analysis on the impact of our pairwise representation alignment module. The study shows that the alignment consistently improves our method's performance with a varying number of labeled samples across all datasets. Our analysis also shows that the alignment helps reduce the distance between the distributions of labeled and unlabeled data, particularly when only one sample per class is available. This finding is further demonstrated by the effective performance of our model in the scarcely supervised scenario (1) labeled sample per class).

In summary, our contributions in this paper are as follows: (1) We propose a novel SSL approach for EEG representation learning. Our method performs pairwise representation alignment between labeled and unlabeled samples and generalizes well across a varying number of scenarios with few labeled samples across four large public datasets. (2) We perform extensive experiments and compare our method to several recent and classical SSL methods. The study shows that our approach obtains strong results, outperforming most other methods. (3) We also carry out a detailed ablation study to demonstrate the impact of our pairwise representation alignment component.

The rest of this paper is organized as follows. Section 2 discusses the related work in emotion recognition with EEG, semi-supervised learning, as well as semi-supervised EEG representation learning for emotion recognition. Section 3 describes our proposed semi-supervised solution for EEG learning. Section 4 presents the dataset, EEG preprocessing, and feature extraction. We also describe the evaluation protocol, implementation details, and SSL benchmarks. In section 5, we present and analyze the experiments and results, including the ablation study performed to

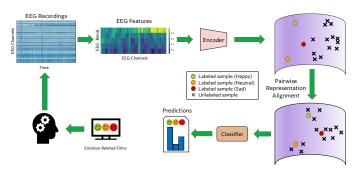


Fig. 1. An overview of our proposed semi-supervised EEG learning with pairwise representation learning, PARSE, in the training phase is presented.

investigate the impact of the pairwise representation alignment. Additionally, we further analyze the effect of various hyperparameter settings on the model's performance. Finally, we summarize our work and provide the concluding remarks.

2 RELATED WORK

2.1 Emotion Recognition with EEG

The general approach to emotion recognition with EEG consists of preprocessing EEG recordings, followed by feature extraction, and finally a classifier to learn the extracted features [9], [22]. In the preprocessing step, many approaches such as frequency filtering and blind signal separation are used to remove noise and artefacts from EEG data [10], [11], [13]. Following, well-known features such as logarithm Power Spectral Density (PSD) and Differential Entropy (DE) are extracted from the decomposed signals in several dominant EEG frequency bands (e.g., alpha, beta, gamma) [10]–[13]. Successive to feature extraction, various classification algorithms for emotion recognition have been developed [10]–[13]. For instance, K-nearest neighbor [10], support vector machines [10]–[13], logistic regression [10], random forest [23], and naive Bayes [13] have been employed to learn the non-linear output information from the extracted features.

Recently, various deep learning techniques have been used to improve recognition performance due to their capabilities in learning more task-relevant and dominant information from extracted features or automatically learned representations. For example, deep belief networks [10] and deep neural networks [11] have been used to learn higher level features using multiple hidden layers. Recurrent deep neural architectures such as long shortterm memory networks [24] and spatial-temporal recurrent neural networks [25] have been used to exploit dependencies among features extracted from sequential data. A convolutional neural network framework was employed to discover spatial-temporal information [26]. Graph neural networks were used to learn topological structure information of EEG channels through graph connections [27], [28]. All of the deep learning-based frameworks listed above outperform conventional machine learning classifiers, many of them achieving state-of-the-art performance in various emotion recognition tasks.

2.2 Semi-supervised Learning

2.2.1 Unsupervised Pre-training

When very few labeled data are available for training, deep learning networks may not perform very well due to overfitting,

slow convergence, and the random initialization of the neural networks [29]. To tackle this problem, unsupervised pre-training, for instance using Stacked Auto-Encoders (SAE) and Deep Belief Networks (DBN), has been proposed [30]. In the pre-training stage, SAE or DBN is trained on unlabeled data to update the weights of each layer and capture a better latent representation of inputs while minimizing the unsupervised training loss. Then, the pre-trained network (e.g., encoder) followed by a classifier is fine-tuned using labeled data in a supervised manner [30]. In [29], [30], the unsupervised pre-training stage was claimed as a regularization and was shown to be capable of guiding the model toward a better local minima in the fine-tuning stage. This unsupervised pre-training strategy has been successfully used to improve performance on small labeled training sets in computer vision, natural language processing, and EEG learning [29], [31]— [33].

2.2.2 Pseudo-Labeling

Pseudo-labeling is another semi-supervised approach that encourages the model to obtain lower entropy predictions on the unlabeled data [21]. To do so, in the first step, a model is trained using labeled data. The trained model is then used to obtain confident predictions on the unlabeled samples (also called pseudo-labels). Finally, the model is retrained using the entire data with true labels and pseudo-labels together [21]. This efficient semi-supervised paradigm outperformed many supervised techniques with small amounts of labeled training samples [21].

2.2.3 Consistency Regularization

Consistency regularization claims that a label should remain consistent even after a perturbation or augmentation is applied on its data [16]. This approach has been widely used in semi-supervised learning [14]-[16]. The most common regularization approaches that can be applied on both unlabeled and labeled data are stochastic augmentations (e.g., Gaussian noise) imposed on inputs and a dropout layer applied in the network. Π-model proposed in [14], for example, first applies two different augmentations on the same input. It then trains the network with dropout, on the two augmented inputs, and enforces consistency by reducing the distance between the corresponding two network outputs in an unsupervised manner. The supervised term is simply the crossentropy calculated between labeled data and the ground truth. Π model outperformed pseudo-labeling in multiple vision datasets with small amounts of labeled data [16]. Π-model, however, trains slowly because it trains on each input twice. Furthermore, because of the single evaluation in each training epoch, the network outputs may be noisy or unreliable [14].

Temporal ensembling was later proposed as an improved version of the Π -model to train the network only once on each input and aggregate the predictions from earlier training epochs [14]. As a result, when compared to the Π -model, temporal ensembling requires less training time. Moreover, consistency regularization is applied between the current network output and the aggregated output which is more reliable [14], [16]. However, due to the slow update of aggregating the network predictions (once per training epoch), temporal ensembling may not be able to provide promising results when the dataset is too large [15].

In [15], a more enhanced version of temporal ensembling, called mean teacher, was proposed. Mean teacher aggregates the model weights more frequently from each previous training batch rather than the ensemble of model predictions from past training

epochs. Afterwards, the consistency regularization is applied by minimizing the distance between the two outputs of the network with and without the ensemble model weights (e.g., using an exponential moving average). Mean teacher has obtained better results than the Π -model and temporal ensembling in a few computer vision datasets [15], [16].

2.2.4 Holistic Approaches

Recently, a few complex pipelines, also known as 'holistic' approaches, have been proposed by combining various elements of the SSL ideas described above. For example, MixMatch [17] has been built upon two SSL core concepts, namely consistency regularization applied in [14]-[16] and label entropy minimization used in pseudo-labeling [21]. Specifically, in the first step, data augmentations are applied to both labeled and unlabeled data. In the second step, the augmented unlabeled data are fed forward to a model to obtain the predictions, with no gradients propagated during this step. Following this, the predictions are averaged to obtain the guessed labels. The entropy of the guessed labels' distributions is then minimized using a sharpening method. In the third step, a powerful data augmentation method, named MixUp [34], is employed to combine the augmented labeled data with ground truth, and the augmented unlabeled data with the guessed labels into a new set [17]. In the last step, the model is trained by minimizing the cross-entropy loss between the predictions on the labeled data and labels, as well as the L2 loss between the predictions on the unlabeled data and the guessed labels from the new mixed set. MixMatch outperformed Π -model, mean-teacher, and pseudo-labeling in multiple vision datasets given a few labeled examples [17].

FixMatch, a more accurate SSL pipeline, was proposed in [18]. In comparison to MixMatch [17], FixMatch combines consistency regularization and pseudo-labeling in a much simpler manner. Specifically, FixMatch first applies weak and strong augmentations to unlabeled data, as well as a weak augmentation to labeled data. Following, the weakly augmented unlabeled data are fed to a model to obtain pseudo-labels. The model is then trained on strongly augmented unlabeled data by minimizing cross-entropy loss between the model's prediction and the pseudo-labels, rather than reducing their squared difference which was used in the previous SSL methods [14]-[17] as the unsupervised loss. Next, a user-defined threshold is employed to ensure that pseudo-labels are only used for unsupervised loss update when the model is confident in its predictions on the unlabeled data. The supervised loss term employs cross-entropy between model predictions on weakly augmented labeled data and the ground truth. FixMatch achieved better performance than the related works discussed above when only a small number of samples were labeled [18].

AdaMatch, a very recent cutting-edge SSL framework, was proposed in [19] to tackle the issue of SSL performance degradation when the class distribution differed between the labeled and unlabeled sets. This problem could ideally be solved by requiring that pseudo-labels of the unlabeled data to have the same class distribution as the actual unlabeled data. However, because the real class distribution of unlabeled data is often unknown, AdaMatch estimates it using the class distribution of labeled data. To do so, AdaMatch first acquires the class distribution of a model's prediction on weakly augmented labeled data. Similarly, it obtains the predicted class distribution of the model's prediction on weakly augmented unlabeled data. Following that, it calculates the ratio of labeled data class distribution to the *expected* unlabeled

data class distribution. This ratio is then used to modify the model's prediction on unlabeled data so that the adjusted class distribution of the unlabeled data would follow the labeled data class distribution. AdaMatch also proposes a relative confidence threshold that is not only based on a user-defined value suggested in FixMatch [18], but also depends on the model's confidence in its predictions on weakly labeled data. The unsupervised term of AdaMatch is quite similar to the one used in FixMatch [18]. Compared to the supervised term used in FixMatch [18], AdaMatch employs an additional cross-entropy loss between the model's prediction on strongly augmented labeled data and ground truth. AdaMatch outperformed other approaches, including FixMatch, on various computer vision datasets and achieved state-of-the-art results [19].

2.3 Semi-supervised EEG Emotion Recognition

Semi-supervised learning has been very rarely studied in the context of EEG-based emotion recognition. Recently, in [35], we proposed a deep semi-supervised architecture with an attention-based recurrent autoencoder for EEG learning. We also re-implemented several popular SSL pipelines equipped with deep learning techniques, namely unsupervised pre-training [29], pseudo-labeling [21], Π-model [14], temporal ensembling [14] and mean teacher [15], which were all originally proposed in the field of computer vision. We compared our framework to the aforementioned SSL methods on a large-scale EEG emotion dataset, SEED. Very lately, in [36], we adapted and implemented three recent stateof-the-art holistic SSL methods, MixMatch [17], FixMatch [18], and AdaMatch [19] for EEG representation learning. We also compared these three holistic SSL techniques to the other five classical SSL methods, Π-model [14], temporal ensembling [14], mean teacher [15], convolutional autoencoder [20], and pseudolabeling [21] on two popular emotion recognition datasets, SEED and SEED-IV. Our study demonstrated the great potential for semi-supervised EEG-based emotion recognition, and motivated this study to develop novel semi-supervised methods designed for the field of EEG representation learning.

3 Proposed Solution

3.1 Problem Setup

For a classification problem with k emotion categories, let us denote $\mathcal{D}_l = \{(x_i^l, y_i^l)\}_{i=1}^M, \mathcal{D}_u = \{x_i^u\}_{i=1}^N, \mathcal{D}_v = \{(x_i^l, y_i^l)\}_{i=1}^I,$ and \mathcal{D} as the labeled, unlabeled, validation, and overall training sets, where $\mathcal{D}_l \cup \mathcal{D}_u \cup \mathcal{D}_v = \mathcal{D}$ and $\mathcal{D}_l \cap \mathcal{D}_u \cap \mathcal{D}_v = \emptyset$. \mathcal{D}_l is formed by m samples per class selected from \mathcal{D} ($M = m \times k$). Our goal is to propose a robust pipeline to improve the model's performance on emotion recognition by leveraging large amounts of \mathcal{D}_u when limited \mathcal{D}_l are available. We are interested in multiple few labeled scenarios when $M \ll N$, including a barely supervised scenario, where **only one** sample per class is labeled (m = 1).

3.2 Solution Overview

We aim to propose a novel SSL architecture for EEG-based emotion recognition, while reducing the distribution mismatch between large unlabeled and small labeled data. To achieve this, we first apply two types of augmentations (strong and weak) on both labeled and unlabeled EEG data. Following that, we compute the model's averaged predictions on both the original and

augmented unlabeled data. To reduce the entropy of the averaged prediction, we further employ a sharpening process and use the sharpened prediction as guessed labels for all the unlabeled data. Next, we apply convex combinations between pairwise labeled and unlabeled data to form a new set. After that, we simultaneously perform emotion recognition and pairwise representation alignment by training an emotion classifier and a domain discriminator (labeled vs. unlabeled) on the new interpolated set. The overview of our proposed solution is shown in Figure 2. In the following subsections, we describe each step for the proposed method in detail.

3.3 Our Approach

In order to efficiently train using the entire large set of unlabeled data (\mathcal{D}_u) together with the small amounts of labeled data (\mathcal{D}_l) , we first replicate \mathcal{D}_l by $\lfloor N/M \rfloor$ times to obtain the same size as \mathcal{D}_u . Then we separate both labeled and unlabeled data with equal proportions into training batches (B) as $\mathcal{D}_l = \{(x_b^l, y_b^l); b \in (1, ..., B)\}$ and $\mathcal{D}_u = \{x_b^u; b \in (1, ..., B)\}$. Next, we perform data augmentation as described below.

3.3.1 Data Augmentation

We first apply strong and weak augmentations on both labeled and unlabeled data. For each x_b^l and x_b^u in the training batch of D_l and D_u , we generate the augmented data as $\mathcal{A}_{s/w}(x_b) = x_b + \mathcal{N}(\mu,\sigma)$, where $x_b \sim [0,1]$ is the normalized input, and \mathcal{N} is a Gaussian distribution with $\mu = 0.5$. The strength of the augmentation can be tuned by changing σ . We choose 0.8 and 0.2 as σ in the additive Gaussian noise for strong (\mathcal{A}_s) and weak (\mathcal{A}_w) augmentations respectively, as suggested in [26], [37]. Following data augmentation, label-guessing is required to obtain pseudolabels for both the original and augmented unlabeled data, which we describe below.

3.3.2 Label-Guessing

After data augmentation, we enlarge the unlabeled set of data by concatenating the original (x_b^u) , weakly $(\mathcal{A}_w(x_b^u))$, and strongly $(\mathcal{A}_s(x_b^u))$ augmented unlabeled samples. We then pass-forward the enlarged unlabeled data to an encoder (G) and a classifier (C) to generate pseudo-labels (p_b) by averaging the predictions as:

$$p_b = \frac{1}{3} \sum_{1}^{3} \operatorname{softmax}(p_m(y \mid x_b^{u,r}; \theta_G, \theta_C)), \tag{1}$$

where $x_b^{u,r}$ for r=1,2,3, denotes x_b^u , $A_w(x_b^u)$, and $A_s(x_b^u)$, respectively. Here, p_m represents the model prediction, and θ_G and θ_C denote the model parameters for the encoder and classifier, respectively. Then, to minimize the entropy of the pseudo-labels, we apply a sharpening operation by

$$p_b^u = p_b^{1/T} / \sum_{1}^{k} (p_b^{1/T}),$$
 (2)

where T=1 is the temperature hyper-parameter used to adjust the entropy level of the pseudo-labels (p_b) , as suggested in [17].

In addition to emotion pseudo-labels, we also assign binary domain labels (z^u) to the unlabeled set (G_u) as:

$$G_u = \{ (\langle x_b^u \cup \mathcal{A}_s(x_b^u) \cup \mathcal{A}_w(x_b^u) \rangle, \langle p_b^u \cup p_b^u \cup p_b^u \rangle, z^u) \}, (3)$$

where \langle , \rangle denotes the concatenation of two or more sets.

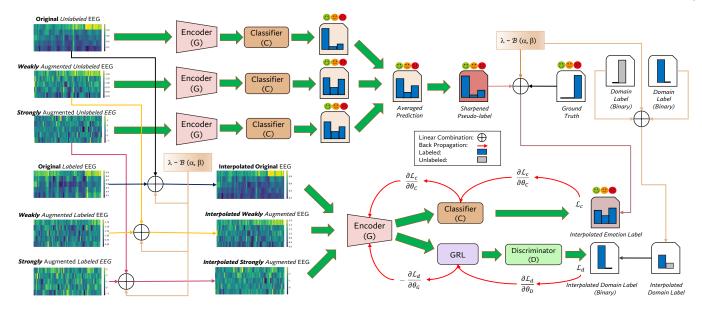


Fig. 2. The architecture of our proposed semi-supervised framework with pairwise representation alignment, PARSE, for emotion recognition.

Similarly, we enlarge the labeled data as the concatenation of the original (x_b^l) , weakly $(\mathcal{A}_w(x_b^l))$, and strongly $(\mathcal{A}_s(x_b^l))$ augmented labeled data. Since the augmentation should not alter the labels of the data, we employ the ground truth of the original labeled data as labels for the weakly and strongly augmented labeled data. Moreover, similar to the unlabeled set (G_u) , we also assign binary domain labels (z^l) to the labeled set (G_l) as:

$$G_l = \{ (\langle x_h^l \cup \mathcal{A}_s(x_h^l) \cup \mathcal{A}_w(x_h^l) \rangle, \langle y_h^l \cup y_h^l \cup y_h^l \rangle, z^l) \}, \quad (4)$$

where $z^l \neq z^u$ and $|z^l| = |z^u| = 3|y_b^l|$ (|.| denotes the size of a set). The data and corresponding labels from both G_l and G_u are then used for pairwise convex combinations, which will be discussed in the following.

3.3.3 MixUp

The generalization performance of a model could degrade due to the adversarial examples whose model predictions could be easily altered by small perturbations (e.g., Gaussian noise used for our previous data augmentations) [38], [39]. To tackle this problem, we encourage convex combinations between pairs of samples, as inspired by a powerful method called MixUp [34]. Specifically, we generate a new training set by applying convex combinations between the *labeled* and *unlabeled* set (G_l, G_u) , according to:

$$\lambda \sim \mathcal{B}(\alpha, \beta),$$
 (5)

$$\tilde{x}_b = \lambda \langle x_b^l \cup \mathcal{A}_s(x_b^l) \cup \mathcal{A}_w(x_b^l) \rangle + (1 - \lambda) \langle x_b^u \cup \mathcal{A}_s(x_b^u) \cup \mathcal{A}_w(x_b^u) \rangle, \tag{6}$$

$$\tilde{y}_b = \lambda \langle y_b^l \cup y_b^l \cup y_b^l \rangle + (1 - \lambda) \langle p_b^u \cup p_b^u \cup p_b^u \rangle, \tag{7}$$

$$\tilde{z}_b = \lambda z_b^l + (1 - \lambda) z_b^u, \tag{8}$$

where \mathcal{B} is the Beta distribution with α, β of 0.25 and $\lambda \in [0, 1]$. We choose α and β with the same value, as suggested in [17], [34], [40]. The new combined set $(\tilde{x}_b, \tilde{y}_b, \tilde{z}_b)$ will next be used in our pairwise representation alignment step.

3.3.4 Pairwise Representation Alignment

Following MixUp, we align the distribution of the pairwise labeled and unlabeled embeddings. These embeddings are obtained by training the encoder using the new interpolated set $(\tilde{x}_b, \tilde{y}_b, \tilde{z}_b)$. To measure the distribution divergence between labeled and unlabeled data, we use:

$$d_{H} = 2\{1 - \min\left[\frac{1}{|\tilde{x}_{b}|} \sum_{i}^{|\tilde{x}_{b}|} \arg\max(p_{m}(z \mid x_{i}; \theta_{G}, \theta_{D})) \neq z_{i}\right]\},$$
(9)

based on [40], [41], in which $x_i \in \tilde{x}_b$ and $z_i \in \lfloor \tilde{z}_b \rfloor$. θ_D is the model parameters for the discriminator (D). We minimize this distribution divergence in order to encourage the encoder (G) to align the EEG representations of labeled and unlabeled data as:

$$\min_{G} d_{H} = \max_{G} \min_{H} \left[\frac{1}{|\tilde{x}_{b}|} \sum_{i}^{|\tilde{x}_{b}|} \arg \max(p_{m}(z \mid x_{i}; \theta_{G}, \theta_{D})) \neq z_{i}] \right].$$

$$(10)$$

As suggested in [40], [41], we optimize this max-min problem by adding a Gradient Reverse Layer (GRL) before the D in order to reverse the gradient in G, as shown in Figure 2. Specifically, GRL is used to reverse the sign of the gradients during back-propagation so that the discriminator loss can be directly minimized using the existing optimization algorithms (e.g., Adam [42]) [43]. Finally, we train both the emotion classifier and the domain discriminator by minimizing the emotion classification loss:

$$\mathcal{L}_c = ||\tilde{y}_b - \operatorname{softmax}(p_m(y \mid \tilde{x}_b; \theta_G, \theta_C))||_2^2$$
 (11)

and domain discriminator loss

$$\mathcal{L}_d = \mathcal{H}(|\tilde{z}_b|, p_m(z \mid \tilde{x}_b; \theta_G, \theta_D)), \tag{12}$$

where $\mathcal{H}(p,q) = -\sum p(x)\log q(x)$ represents cross-entropy. We use an adversarial training strategy to minimize the distance between the labeled and unlabeled representations.

3.3.5 Total Loss Function

Our total loss function comprises three parts. The first term is a supervised loss $\mathcal{L}_s = \mathcal{H}(y_b^l, p_m(y \mid x_b^l; \theta_G, \theta_C))$ that has

been commonly used in many SSL literature. We adopt the unsupervised loss L_u used in [18] as the second term, as follows:

$$\mathcal{L}_u = \mathcal{H}(y_h^u, p_m(y \mid \mathcal{A}_s(x_h^u); \theta_G, \theta_C)), \tag{13}$$

where $y_b^u = \arg\max(p_m(y \mid \mathcal{A}_w(x_b^u); \theta_G, \theta_C))$. Consequently, we update the total loss as:

$$\mathcal{L}_{total} = \mathcal{L}_s + \eta \mathcal{L}_u + \delta(\lambda \mathcal{L}_c + \mathcal{L}_d), \tag{14}$$

where $\delta=1.0$. Instead of using a pre-defined threshold τ [18] that may need to be tuned for each dataset individually, we apply a warm-up function η on the unsupervised loss, similar to [19], as follows:

$$\eta(t) = \frac{1}{2} - \cos(\min(\pi, 2\pi t/T))/2,$$
(15)

where t and T are the current and the maximum iterations. The warm-up function is used to slowly increase the weight of the unsupervised loss when the model is being trained further as well as being more confident on its predictions. The third term is the sum of the classification and discriminator losses trained on the interpolated set as mentioned earlier.

3.4 Architecture Details

Here we describe the architecture details of the different modules, namely encoder, classifier, and discriminator, used in our proposed method, as shown in Table 1. The encoder consists of two 1-D convolutional blocks, where each block contains a 1-D convolutional layer followed by a 1-D batch normalization layer and a LeakyReLU activation. The classifier and discriminator share the same architecture containing two fully connected layers with a dropout rate of 0.5. The encoder is used to transform EEG inputs into a learned embedding, while the classifier is used for identifying emotion categories, and the discriminator is used to determine whether the input data are labeled or unlabeled. In Table 1, s denotes the total number of EEG features and k is the number of emotion categories.

4 EXPERIMENTAL SETUP AND SETTINGS

4.1 Datasets

We use the following four datasets in our study. In all the dataset mentioned below, the EEG electrodes were placed using $10-20\,$ system.

4.1.1 SEED

The SEED dataset was built by Zheng and Lu [10]. 15 film clips with three emotions (neutral, positive and negative) were chosen and used as stimuli in the experiments. The studies were completed by a total of 15 participants, consisting of 8 females and 7 males. Each participant completed the experiment twice, with each experiment consisting of 15 trials. Each trial has a 4-step pipeline: 5 seconds of start hint before the film clip, 4 minutes of the clip as emotion stimulus, 45 seconds of self-assessment, and finally 15 seconds of break. EEG was recorded from 62 electrodes at a sampling rate of 1000Hz.

TABLE 1
Architectural details of our proposed model.

Module	Layer details	Output shape
Input	-	(1, s)
Encoder	Conv1D, kernel(3), output channels(5) BatchNorm1D, output channels(5) LeakyReLU, slope(0.3)	(5, s-2)
Elicotei	Conv1D, kernel(3), output channels(10) BatchNorm1D, output channels(10) LeakyReLU, slope(0.3)	(10, s-4)
Embedding	Flatten	$10 \times (s-4)$
Classifier		(k)
Discriminator	Linear, 64 ReLU, — Dropout, 0.5 Linear, 2	(2)

4.1.2 SEED-IV

Zheng et al. developed the SEED-IV dataset, which was initially used in [11]. As stimuli, 72 film clips with four emotions (sad, fear, happy and neutral) were selected. The experiments were completed by 15 individuals, consisting of 8 females and 7 males. Each participant repeated the experiment three times, with completely different stimuli each time. Each experiment has a total of 24 trials (6 trials for each emotion). Each trial has three stages: 5 seconds of start hint, 2 minutes of film clip, followed by 45 seconds of self-assessment. 62 EEG recordings were collected at a sampling frequency of 1000Hz.

4.1.3 SEED-V

The SEED-V dataset was developed by Liu et al. [12]. As stimuli, 45 short videos with five emotions (happy, fear, neutral, sad, and disgust) were chosen. The studies were completed by a total of 16 participants, 10 females and 6 males. Each participant repeated the experiment three times, with completely different stimuli each time. Each experiment includes 15 trials (3 trials for each emotion). Each trial has three stages: 15 seconds of start hint, 2-4 minutes of film clip, and 15 or 30 seconds of self-assessment. In total, 62 EEG recordings were collected with a sampling frequency of 1000Hz.

4.1.4 AMIGOS

The AMIGOS dataset was developed by Correa et al. [13]. 37 participants (12 females and 25 males) completed experiments with both 16 short and 4 long video clips as stimuli. Experiments with short video stimuli consist of three stages: 5 seconds of baseline recording, a few minutes of video clips of varying duration (less than 250 seconds), and self-assessment of arousal, valence as well as other affective states. Experiments with long video stimuli also consist of three stages: 45 seconds of initial selfassessment of several affective states including arousal and valence, two video clips of varying lengths (more than 14 minutes), and another 45 seconds of self-assessment. Videos of participants during experiments were cropped to display the face and then segmented into continuous 20-second clips. Three annotators assigned valence and arousal scores (between [-1,1]) to each of these 20-second video snippets. A threshold of (0.0) was used to transform continuous scores into binary classes (positive and negative). 14 EEG channels were recorded at a sampling rate of 128Hz.

4.2 Preprocessing

EEG preprocessing is often dataset-dependent due to the various collection equipment, as well as experimental conditions and protocols. It often contains downsampling, artefact removal, and noise filtering.

4.2.1 Downsampling

In all three SEED-series datasets, EEG signals were downsampled from 1000~Hz to 200~Hz. In AMIGOS dataset, EEG data were already recorded at a low sampling rate of 128~Hz and were not further downsampled to avoid aliasing effect.

4.2.2 Artefact Removal and Noise Filtering

EEG signals are often contaminated by Electrooculogram (EOG) and Electromyogram (EMG) [10], [44]. EOG signals, which reflect the ocular activities such as eye movements and eye blinks, are most active below 4Hz [44]. EMG signals reflect the muscular activities around the face and are dominant above 30Hz [44]. Both EOG and EMG have high overlap with EEG, which is dominant in 0.3 - 50Hz [10]. To minimize the aforementioned artefacts, in SEED, the EEG signals were visually checked by experts, and those recordings being identified as highly contaminated by EOG and EMG were then discarded [10]. To remove artefacts, a linear dynamic system, principal component analysis, and blind source separation were used to remove the artefacts from EEG in SEED-IV [11], SEED-V [12], [45], and AMIGOS [13], respectively. A band-pass filter was applied to each dataset to filter the noise and artefacts outside the dominant EEG frequency ranges according to [10]–[13].

4.3 Feature Extraction

Following preprocessing, we use pre-defined EEG segments proposed in the respective dataset publications [10]-[13], for feature extraction. In each of the SEED series datasets, EEG data were divided into segments of the same length with no overlap between adjacent segments. The lengths of EEG segments were set to 1 second for SEED and 4 seconds for SEED-IV and SEED-V, respectively [10]–[12]. For AMIGOS, EEG signals corresponding to each video clip were separated into 20-second segments. The first and last segments were selected from the EEG data corresponding to the initial and final 20 seconds of the video clips. Next, following the first 5 seconds of video clips, EEG data were divided into non-overlapping 20-second segments, yielding 340 EEG segments for each participant [13]. It should be noted that the features extracted (described below) from the five EEG bands are further scaled into the range of [0, 1] with min-max normalization before being fed to our proposed framework.

4.3.1 Differential Entropy

In SEED-series datasets, DE features were extracted from five EEG bands, notably delta (1-4Hz), theta (4-8Hz), alpha (8-14Hz), beta (14-31Hz), and gamma (31-50Hz). A total of $62\times 5=310$ features were extracted. We assume that the signals have a Gaussian distribution, and thus DE is calculated as follows:

$$DE = \frac{1}{2}\log 2\pi e\sigma^2. \tag{16}$$

4.3.2 Power Spectral Density

In AMIGOS dataset, the logarithm of PSD features were computed from five EEG bands, namely theta (3-7Hz), slow alpha (8-10Hz), alpha (8-13Hz), beta (14-29Hz), and gamma (30-47Hz). In addition, the logarithm of PSD asymmetry between 7 symmetric pairs of EEG channels (e.g., F7 and F8) were also extracted as features. As a result, a total of $(14+7)\times 5=105$ features were extracted. The PSD is calculated as:

$$S_{xx}(\omega) = \lim_{T \to \infty} E\left[|\hat{X}(\omega)|^2\right]. \tag{17}$$

4.4 Evaluation Protocols

To evaluate our proposed pipeline, we strictly follow the same evaluation protocols that have been used for emotion recognition in the original articles that were published with these public datasets [10]-[13]. In SEED, we use the first 9 trials as training data (each emotion class with three trials) and the rest 6 trials as the testing data in each experiment, as defined in [10]. In SEED-IV, we employ the pre-defined first 16 trials (each emotion class with four trials) as the training set, and the remaining 8 trials as the testing set. In SEED-V, 15 trials were split into three groups, where each pre-defined group contains 5 trials with all 5 emotions. We concatenate the first group from each of the three experiments to form a new fold of 15 trials. Similarly, we form the other two folds by concatenating the second and third groups from each of the three experiments. Following that, we perform a 3-fold cross-validation as performed in [12]. The class distributions are almost balanced in the SEED-series datasets, where the accuracy is adopted as the evaluation metric [10]-[12]. In AMIGOS, we adopt the same leave-one-participant-out protocol for training and testing data splits, as used in [13]. The ratios of negative/positive classes are 0.721/0.279 and 0.805/0.195 for valence and arousal, respectively [13], [46]. Therefore, as the class distribution is very imbalanced, we use the F1-score (mean F1-score for both classes) as the evaluation metric as suggested in [13].

4.5 Implementation Details

We use a batch size of 8 for the datasets with subject-dependent evaluation (SEED, SEED-IV and SEED-V) and 64 for the dataset with subject-independent evaluation (AMIGOS). We adopt the Adam algorithm [42] with a default learning rate of $1e^{-3}$ for optimization. We apply a total of 30 training epochs for all the experiments. Our experiments have been implemented using PyTorch on a pair of NVIDIA GeForce RTX 2080 Ti GPUs.

Similar to other semi-supervised studies [17]–[19], we evaluate PARSE with a varying number of labeled samples per class (m), where $m \in \{1,3,5,7,10,25\}$. For those comparison methods using a dataset-specific hyper-parameter τ , we perform a smart search in the range of [0.0-1.0] with a step size of 0.1 on the validation set (not the test set) to find the optimum hyper-parameter (τ) . Specifically, in FixMatch, we set $\tau=0.9$ for SEED and SEED-IV, $\tau=0.7$ for SEED-V and $\tau=0.6$ for AMIGOS. In AdaMatch, we set $\tau=0.6$ for SEED and AMIGOS, $\tau=0.5$ for SEED-IV, as well as $\tau=0.9$ for SEED-V.

4.6 SSL Benchmarks

For comparison and evaluation of our work, we adapt, implement, and necessary modify three cutting-edge SSL methods, MixMatch [17], FixMatch [18], and AdaMatch [19], in addition to five

classical SSL methods, Π -model [14], temporal assembling [14], mean teacher [15], convolutional autoencoders [20], and pseudolabeling [21], for EEG representation learning. We employ the same convolutional encoder and classifier in these benchmarks as in the one used in our proposed method. For the decoder component of the convolutional autoencoder benchmark, we use two transposed convolutional 1-D blocks. In each block, a 1-D transposed convolutional layer is followed by a 1-D batch normalization layer and ReLU activation. We implement the Π -model, temporal ensembling, mean teacher, pseudo-labeling, and convolutional autoencoder with the same algorithm settings (e.g., loss function, unsupervised weight, etc.) used in [35].

5 RESULTS AND DISCUSSIONS

We compare our proposed framework to the other existing methods when only very few training samples per class are labeled $(m \in \{1,3,5,7,10,25\})$. This experimental protocol is in accordance to recent state-of-the-art studies on SSL [17]–[19]. Each method is evaluated **five** times for all 6 few labeled scenarios, each time with a different random seed for the selection of D_l . Table 2, 3, 4 and 5 show the averaged results (mean and standard deviation) for SEED, SEED-IV, SEED-V and AMIGOS (valence and arousal) across 5 different random seeds, respectively. In the following sections, we discuss the obtained results.

5.1 SEED

As shown in Table 2, classical SSL methods generally show inferior performance in all 6 designated few labeled scenarios. Convolutional autoencoder consistently outperforms the other classical approaches and slightly outperforms FixMatch. In all of the few labeled scenarios, AdaMatch consistently outperforms FixMatch and all the classical SSL approaches by achieving the second best result (shown with underline). AdaMatch also outperforms MixMatch only except when 5 samples per class are labeled. In the meantime, convolutional autoencoder and MixMatch achieve the third best results when $m \in \{1,25\}$ and $m \in \{3,7,10\}$, respectively. PARSE consistently achieves the best (shown in bold) performance. In particular, our proposed architecture consistently outperforms the second best methods by more than 3.0% across all the few labeled scenarios, demonstrating its superiority in the absence of sufficient labeled samples.

5.2 SEED-IV

As shown in Table 3, when compared to other more recent solutions, traditional SSL methods achieve lower performance. Temporal ensembling and convolutional autoencoder have comparable performances and produce the best two results among classical approaches. MixMatch, FixMatch, and AdaMatch nearly outperform all the classical methods, across all 6 few labeled scenarios. In particular, when only 1 sample per class is labeled, PARSE achieves the second best result (0.5787 \pm 0.1809), approaching the best method obtained by AdaMatch with only 0.43% difference. Our method obtains the best results when more labeled samples are given $(m \in \{3,5\})$. Especially when 3 samples per class are labeled, our method outperforms the second best result (AdaMatch) by 2\%. When even more labeled samples are provided, our method approaches the highest performance with very a small difference (0.15%, 0.16%) and 0.88% when $m \in \{7, 10, 25\}$).

5.3 SEED-V

As shown in Table 4, the classical methods are generally outperformed by other recent techniques, except for temporal ensembling which achieves the second best result when m=1 and convolutional autoencoder which closely approaches the third best result when m=10. Furthermore, FixMatch and AdaMatch have similar performance across all the few labeled scenarios. Our proposed architecture achieves the best results of 0.3942 ± 0.0979 and 0.5566 ± 0.1272 when 1 and 3 labeled samples per class are provided, respectively. When more than 3 labeled samples are available ($m \in \{5,7,10,25\}$), MixMatch obtains the best results despite its poor performance at the barely supervised scenario (m=1). In the meantime, PARSE consistently obtains the second best results ($m \in \{5,7,10,25\}$).

5.4 AMIGOS

5.4.1 Valence

As shown in Table 5 (Valence), among the classical approaches, mean teacher consistently achieves the highest performance, followed by temporal ensembling. When only 1 sample per class is labeled, mean teacher achieves the best result of 0.5254 ± 0.0772 , followed by our proposed method. PARSE achieves the best result when $m \in \{3,7,10,25\}$ and approaches the best result at m=5 with less than 1% difference. MixMatch achieves the best result for 5 labeled samples per class and the second best when more samples are labeled ($m \in \{7,10\}$).

5.4.2 Arousal

As displayed in Table 5 (Arousal), similar to valence, mean teacher consistently achieves the highest results, followed by temporal ensembling among all the classical SSL methods. Especially, mean teacher achieves the best result of 0.5095 ± 0.0724 when only 1 sample per class is labeled, and obtains the second best results among all the methods when more labeled samples are given $(m \in \{3,5,7\})$. MixMatch achieves the second best result in the barely supervised scenario and obtains the best results in the remaining few labeled scenarios. It can be observed that for estimating arousal in the AMIGOS, our method does not perform the best in any of the cases, yet obtains competitive performances all around.

5.5 Overall Performance

In Figure 3, we compare the average performance (across $m \in$ $\{1,3,5,7,10,25\}$) for all the SSL methods as well as a baseline supervised-only method. The supervised method trains an encoder and classifier with the same architecture used in the SSL methods only on labeled data (without any unlabeled data). We observe that for SEED, our method achieves the best results of 0.8731 ± 0.0917 , followed by AdaMatch (0.8347 ± 0.1007) and MixMatch (0.8199 \pm 0.1078). In SEED-IV, our method achieves the best results of 0.6855 ± 0.1651 , followed by MixMatch (0.6783 ± 0.1592) and AdaMatch (0.6713 ± 0.1628) . In SEED-V, MixMatch achieves the best results of 0.6087 ± 0.1232 , very closely followed by our method of 0.6058 ± 0.1280 . FixMatch obtains the third best results of 0.5761 ± 0.1272 . In AMIGOS (valence), our method achieves the best results of 0.5447 ± 0.1062 , followed by mean teacher (0.5380 ± 0.0710) and MixMatch (0.5268 ± 0.1442) . In AMIGOS (arousal), MixMatch achieves the best result of 0.5583 ± 0.1664 , followed by our method (0.5339 ± 0.0959) and mean teacher (0.5335 ± 0.0633) .

TABLE 2
The performance of PARSE in comparison to other semi-supervised methods on SEED dataset.

Method	1 label	3 labels	5 labels	7 labels	10 labels	25 labels
П-model [14]	0.6025 ± 0.0957	0.6787 ± 0.1014	0.7243 ± 0.1132	0.7494 ± 0.1084	0.7635±0.1093	0.7787 ± 0.1088
Temporal Ens. [14]	0.5922 ± 0.0902	0.6995 ± 0.0907	0.7380 ± 0.0978	0.7715 ± 0.0957	0.7980 ± 0.0953	0.8383 ± 0.0873
Mean Teacher [15]	0.5397 ± 0.0824	0.6275 ± 0.0998	0.6642 ± 0.0946	0.6990 ± 0.1132	0.7148 ± 0.0898	0.7709 ± 0.0966
Conv. AutoEnc. [20]	0.7139 ± 0.1220	0.8003 ± 0.1169	0.8286 ± 0.1089	0.8474 ± 0.0970	0.8546 ± 0.0977	0.8734 ± 0.0896
Pseudo-Label [21]	0.6802 ± 0.1320	0.7811 ± 0.1202	0.7957 ± 0.1078	0.8221 ± 0.1103	0.8411 ± 0.0979	0.8532 ± 0.0938
MixMatch [17]	0.6897 ± 0.1393	0.8089 ± 0.1280	0.8394 ± 0.1030	0.8546 ± 0.0964	0.8584 ± 0.0924	$0.8688 {\pm} 0.0878$
FixMatch [18]	0.6636 ± 0.1384	0.7626 ± 0.1156	$\overline{0.7904\pm0.1068}$	0.8179 ± 0.1056	0.8314 ± 0.0998	0.8444 ± 0.0909
AdaMatch [19]	0.7403 ± 0.1178	0.8259 ± 0.1026	0.8362 ± 0.1084	0.8584 ± 0.0969	0.8671 ± 0.0909	0.8802 ± 0.0880
PARSE (ours)	0.7777 ± 0.1205	0.8652 ± 0.1002	$0.8838 {\pm} 0.0909$	0.8955 ± 0.0862	0.9050 ± 0.0774	0.9114 ± 0.0752

TABLE 3
The performance of PARSE in comparison to other semi-supervised methods on SEED-IV dataset.

Method	1 label	3 labels	5 labels	7 labels	10 labels	25 labels
П-model [14]	0.4993 ± 0.1230	0.5465 ± 0.1466	0.5765 ± 0.1436	0.5879 ± 0.1477	0.6014 ± 0.1514	0.6192±0.1530
Temporal Ens. [14]	0.5276 ± 0.1315	0.5976 ± 0.1448	0.6300 ± 0.1435	0.6526 ± 0.1407	0.6592 ± 0.1371	0.6725 ± 0.1363
Mean Teacher [15]	0.4703 ± 0.1184	0.5156 ± 0.1235	0.5505 ± 0.1327	0.5660 ± 0.1291	0.5666 ± 0.1178	0.5797 ± 0.1300
Conv. AutoEnc. [20]	0.5319 ± 0.1858	0.5952 ± 0.1813	0.6301 ± 0.1674	0.6483 ± 0.1575	0.6640 ± 0.1726	0.6596 ± 0.1662
Pseudo-Label [21]	0.5231 ± 0.1793	0.5808 ± 0.1676	0.6036 ± 0.1792	0.6084 ± 0.1759	0.6213 ± 0.1903	0.6271 ± 0.1836
MixMatch [17]	0.5608 ± 0.1592	0.6503 ± 0.1579	0.6942 ± 0.1631	0.7092 ± 0.1602	0.7231 ± 0.1627	0.7320 ± 0.1519
FixMatch [18]	0.5337 ± 0.1733	0.6357 ± 0.1557	0.6343 ± 0.1626	0.6462 ± 0.1557	0.6650 ± 0.1591	0.6854 ± 0.1558
AdaMatch [19]	$0.5830 {\pm} 0.1595$	0.6652 ± 0.1658	0.6912 ± 0.1645	0.6811 ± 0.1580	0.6931 ± 0.1687	0.7143 ± 0.1604
PARSE (ours)	0.5787 ± 0.1809	0.6853 ± 0.1634	$0.6966 {\pm} 0.1596$	0.7077 ± 0.1647	0.7215 ± 0.1608	0.7232 ± 0.1615

TABLE 4
The performance of PARSE in comparison to other semi-supervised methods on SEED-V dataset.

Method	1 label	3 labels	5 labels	7 labels	10 labels	25 labels
П-model [14]	0.3673 ± 0.0817	0.4307 ± 0.1047	0.4739 ± 0.1104	0.4809 ± 0.1132	0.4919 ± 0.1158	0.5187 ± 0.1280
Temporal Ens. [14]	0.3909 ± 0.0863	0.4868 ± 0.1052	0.5470 ± 0.1219	0.5688 ± 0.1275	0.5945 ± 0.1268	0.6257 ± 0.1237
Mean Teacher [15]	0.3613 ± 0.0784	0.4260 ± 0.0899	0.4634 ± 0.1027	0.4591 ± 0.1093	0.4838 ± 0.1094	0.5079 ± 0.1116
Conv. AutoEnc. [20]	0.3608 ± 0.1212	0.5030 ± 0.1487	0.5838 ± 0.1467	0.6094 ± 0.1512	0.6547 ± 0.1536	0.6763 ± 0.1548
Pseudo-Label [21]	0.3259 ± 0.1213	0.4904 ± 0.1433	0.5175 ± 0.1629	0.5613 ± 0.1599	0.5962 ± 0.1620	0.6170 ± 0.1624
MixMatch [17]	0.3482 ± 0.0914	0.5476 ± 0.1250	$0.6304{\pm}0.1309$	0.6796 ± 0.1317	$0.7040{\pm}0.1300$	0.7427 ± 0.1302
FixMatch [18]	0.3862 ± 0.1074	0.5228 ± 0.1240	0.5928 ± 0.1300	0.6211 ± 0.1392	0.6547 ± 0.1318	0.6792 ± 0.1308
AdaMatch [19]	0.3746 ± 0.1129	0.5263 ± 0.1380	0.5967 ± 0.1423	0.6277 ± 0.1534	0.6508 ± 0.1508	0.6803 ± 0.1597
PARSE (ours)	0.3942±0.0979	$0.5566{\pm}0.1272$	0.6240 ± 0.1319	0.6576 ± 0.1304	0.6873 ± 0.1400	0.7150 ± 0.1405

In comparison, the supervised-only model achieves 0.7468 ± 0.1132 , 0.6015 ± 0.1628 , 0.5617 ± 0.1445 , 0.4697 ± 0.0974 , 0.4682 ± 0.0809 in SEED, SEED-IV, SEED-V, AMIGOS (valence) and AMIGOS (arousal), respectively. For both balanced (SEED, SEED-IV, and SEED-V) and imbalanced (AMIGOS valence and arousal) datasets, our proposed method outperforms the supervised-only model by considerable margins. It should be pointed out, however, that unlike PARSE, not all SSL methods consistently outperform the supervised-only approaches. Moreover, a general observation is that the performance of most SSL methods is quite dataset-dependant, and while our performance also varies across different datasets, we obtain more consistent results. This demonstrates the superiority of our method when faced with a scarcity of labeled samples across different datasets.

5.6 Ablation and Analysis

We perform an ablation study to investigate the impact of the pairwise representation alignment step in our method. Figure 4 shows the performance (mean and standard error) of our proposed method with and without pairwise representation alignment for SEED, SEED-IV, SEED-V, and AMIGOS (valence and arousal). In all these cases, we find that our model performs consistently

better with pairwise representation alignment than without it, across all the 6 few labeled scenarios. Specifically, when the class distribution of dataset is balanced, the alignment improves PARSE by approximately 5.0%, 4.8%, and 3.0% in SEED, SEED-IV, and SEED-V, respectively. Moreover, when the class distribution is imbalanced, the representation alignment boosts the performance by around 3.5% and 3.7% in AMIGOS (valence and arousal), respectively.

Following, we explore the learned EEG embeddings for both labeled and unlabeled data to better understand the impact of the representation alignment step in our model. To this end, we use t-distributed Stochastic Neighbor Embedding (t-SNE). Figure 5 shows a comparison between learned EEG embeddings with and without alignment for the different numbers of labeled samples in SEED-V (containing 5 emotion classes) as examples. We observe in Figures 5 (A) and (G) that when only 1 labeled sample per class is available, the learned embeddings of the unlabeled data are far apart from the labeled data in the absence of pairwise representation alignment. However, we observe that when alignment is performed, these embeddings (unlabeled and labeled) are brought closer to each other. This is a desired property as it means that the output class information for the labeled samples can confidently

TABLE 5
The performance of PARSE in comparison to other semi-supervised methods on AMIGOS dataset (valence and arousal).

	Valence						
Method	1 label	3 labels	5 labels	7 labels	10 labels	25 labels	
Π-model [14]	0.4201 ± 0.0932	0.4614 ± 0.0714	0.4558 ± 0.0703	0.4606 ± 0.0781	0.4699 ± 0.0728	0.4631±0.0657	
Temporal Ens. [14]	0.4514 ± 0.0811	0.4924 ± 0.0793	0.4962 ± 0.0701	0.5127 ± 0.0659	0.5210 ± 0.0670	0.5161 ± 0.0628	
Mean Teacher [15]	$0.5254 {\pm} 0.0772$	0.5314 ± 0.0760	0.5405 ± 0.0681	0.5384 ± 0.0755	0.5446 ± 0.0651	0.5475 ± 0.0643	
Conv. AutoEnc. [20]	0.3969 ± 0.1081	0.4592 ± 0.1014	0.4820 ± 0.0982	0.4873 ± 0.0968	0.4953 ± 0.1055	0.5302 ± 0.0989	
Pseudo-Label [21]	0.4069 ± 0.0818	0.4434 ± 0.0935	0.4516 ± 0.0925	0.4683 ± 0.0991	0.4603 ± 0.0915	0.4768 ± 0.0986	
MixMatch [17]	0.4581 ± 0.2008	0.5056 ± 0.1690	$0.5432 {\pm} 0.1381$	0.5386 ± 0.1403	0.5558 ± 0.1122	0.5594 ± 0.1045	
FixMatch [18]	0.4001 ± 0.0875	0.4548 ± 0.1134	0.4617 ± 0.1015	0.4796 ± 0.1082	0.4841 ± 0.1048	0.5010 ± 0.0969	
AdaMatch [19]	0.4356 ± 0.1110	0.4967 ± 0.1083	0.5043 ± 0.1053	0.5090 ± 0.1050	0.5353 ± 0.1089	0.5653 ± 0.1065	
PARSE (ours)	0.4753 ± 0.0946	0.5502 ± 0.1268	0.5343 ± 0.1091	0.5618 ± 0.1015	$0.5592{\pm}0.0972$	$\overline{0.5877 \pm 0.1080}$	
	Arousal						
Method	1 label	3 labels	5 labels	7 labels	10 labels	25 labels	
П-model [14]	0.4312 ± 0.1017	0.4466 ± 0.0658	0.4512±0.0707	0.4631±0.0677	0.4687 ± 0.0708	0.4736 ± 0.0647	
Temporal Ens. [14]	0.4649 ± 0.0682	0.4937 ± 0.0623	0.5052 ± 0.0681	0.5098 ± 0.0570	0.5110 ± 0.0584	0.5078 ± 0.0544	
Mean Teacher [15]	0.5095 ± 0.0724	0.5285 ± 0.0703	0.5338 ± 0.0671	0.5405 ± 0.0609	0.5427 ± 0.0523	0.5461 ± 0.0568	
Conv. AutoEnc. [20]	0.4078 ± 0.1005	0.4679 ± 0.0917	0.4745 ± 0.0739	0.4858 ± 0.0845	0.4947 ± 0.0903	0.5068 ± 0.0908	
Pseudo-Label [21]	0.4327 ± 0.0762	0.4519 ± 0.0785	0.4573 ± 0.0782	0.4648 ± 0.0726	0.4703 ± 0.0735	0.4832 ± 0.0894	
MixMatch [17]	0.4876 ± 0.2242	$0.5373 {\pm} 0.1916$	0.5670 ± 0.1684	0.5713 ± 0.1618	0.5911 ± 0.1297	$0.5958 {\pm} 0.1229$	
FixMatch [18]	0.4049 ± 0.1061	0.4507 ± 0.0857	0.4768 ± 0.0720	0.4808 ± 0.0748	0.4890 ± 0.0822	0.5034 ± 0.0866	
AdaMatch [19]	0.4009 ± 0.1024	0.4928 ± 0.1135	0.5092 ± 0.1076	0.5220 ± 0.1030	0.5344 ± 0.1096	0.5850 ± 0.1004	
PARSE (ours)	0.4846 ± 0.1047	0.5263 ± 0.1021	0.5251 ± 0.0944	0.5377±0.0991	0.5521 ± 0.0885	0.5776 ± 0.0866	

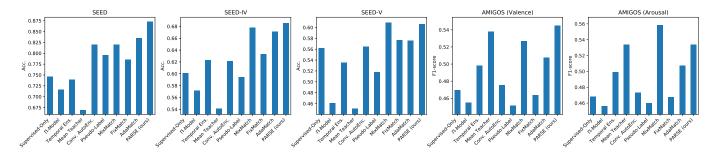


Fig. 3. Average performance of PARSE in comparison to other SSL methods as well as supervised learning for SEED, SEED-IV, SEED-V, and AMIGOS (valance and arousal), across all 6 few labeled scenarios ($m \in \{1, 3, 5, 7, 9, 10, 25\}$).

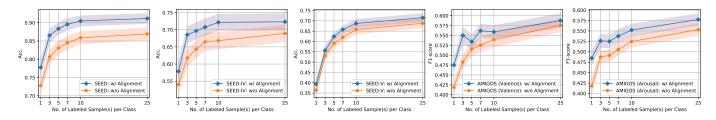


Fig. 4. The performance of PARSE with and without representation alignment, across varying number of labeled samples per class $(m \in \{1, 3, 5, 7, 9, 10, 25\})$ in SEED, SEED-IV, SEED-V and AMIGOS (valance and arousal).

be used to guess the labels for the unlabeled samples. We observe a similar, but less significant improvement when more labeled samples are available ($m \in \{3,5,7,10,25\}$), (see Figures 5 (B) through (F) vs. (H) through (L)). To provide quantitative evidence for this experiment, we employ the Maximum Mean Discrepancy (MMD) to measure the distance between the learned EEG representation of labeled and unlabeled sets. MMD values with and without pairwise representation alignment are compared across all 6 few labeled scenarios. As depicted in Figure 6, MMD is 0.0138 and 0.5853 with and without alignment when only 1 labeled sample per class is available, highlighting the importance of representation alignment in the scarcely supervised

situation. When more labeled samples are provided, however, MMD without alignment falls to 0.0726 at m=3 but remains nearly constant thereafter (e.g., MMD of 0.0650 at m=5). In all the few labeled scenarios except for the barely supervised scenario ($m \in \{3,5,7,10,25\}$), MMD values with alignment are consistently around $10\times$ lower than MMD values without it. Our proposed method with pairwise representation alignment brings the labeled and unlabeled data closer to each other, particularly in the barely supervised scenario, resulting in consistent and improved performance.

We perform further experiments to evaluate the effect of different hyper-parameter values on our model's performance. As

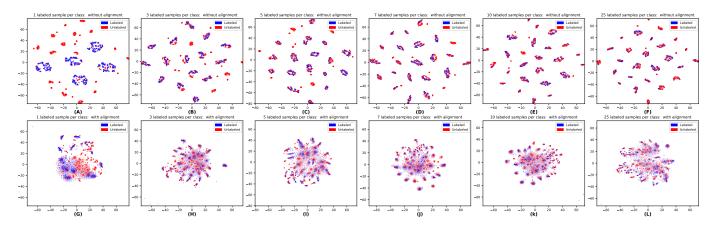


Fig. 5. Visual comparison, using t-SNE, between learned EEG embeddings without representation alignment $(1^{st}$ row) and with representation alignment $(2^{nd}$ row) when a varying number of labeled samples per class are used $(m \in \{1, 3, 5, 7, 9, 10, 25\})$. Here, the size of labeled and unlabeled sets are the same due to the replication process applied to the labeled set to increase their size (see Section 3.3). We observe stronger overlaps between the labeled and unlabeled samples when representation alignment is applied in PARSE, which will eventually result in more confident guessed labels for the unlabeled samples.

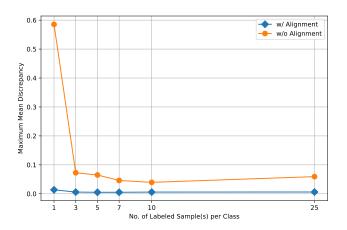


Fig. 6. Quantitative evaluation of the distances between labeled and unlabeled representations with and without alignment when a varying number of labeled samples ($m \in {1,3,5,7,9,10,25}$) are provided. MMD is used to calculate the distances

described earlier (Eq. 15), we use a warm-up function to gradually increase the weight η applied to the unsupervised term. Here we evaluate the impact of this parameter in the final performance. While our warm-up function only selects η values in the range of 0 to 1, manually selecting higher values is possible. Accordingly, we conduct our experiment by selecting $\eta=0.1,1.0,5.0$, and compare them to ours. As illustrated in Figure 7 (A), PARSE shows little sensitivity to this parameter, and while small variations are observed by selecting different values, the warm-up function does provide the best results.

Another parameter used in our model is δ , which is the weight applied on the pairwise representation alignment loss term (Eq. 14). To evaluate the impact of this parameter, we compare the performance of our method for different values of δ by setting it to 0.1, 0.5, 1.0, 5.0. As shown in Figure 7 (B), similar to η , δ does not have a significant impact on the performance of our model. Nonetheless, $\delta=1.0$ does achieve the best performance, which we select for our model.

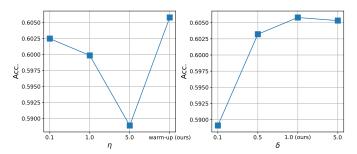


Fig. 7. The impact of different hyperparameters, η (A) and δ (B), on the performance of PARSE averaged across all 6 few labeled scenarios.

6 Conclusions

In this research, we propose a novel semi-supervised method for EEG-based emotion recognition. Our model relies on data augmentation, label guessing, convex combinations of unlabeled and labeled sets, and pairwise representation alignment between the distributions of unlabeled and labeled data. We conduct extensive experiments against a number of other methods, where only 1, 3, 5, 7, 10, and 25 samples per class are labeled, and evaluate the performance on four large publicly available datasets, SEED, SEED-IV, SEED-V and AMIGOS (valence and arousal). Our proposed framework achieves average best results across all 6 labeled scenarios in SEED, SEED-IV and AMIGOS (valence), and closely approaches the best result with only 0.3% difference in SEED-V. Our method also reaches the second-best result in AMIGOS (arousal). In addition, we show the impact of the pairwise representation alignment on our proposed method, with the varying number of labeled samples across all the datasets. We perform further analysis showing our pairwise representation alignment considerably reduces the distance between labeled and unlabeled representations, especially in the barely supervised scenarios. The results also show that our framework consistently outperforms the supervised-only method, addressing the challenge of scarcity of labeled EEG data.

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