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Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 45(45)

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Publication Date
2023

Peer reviewed

User-independent Emotion Classification based on Domain Adversarial Transfer Learning

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Abstract

EEG-based emotion recognition is one of the hot research directions in the field of human-computer interaction. The traditional user-dependent models have had remarkable success. However, due to the individual differences, the generalization performance of traditional models is poor for user-independent emotion recognition. Therefore, this work proposes a two-step domain adversarial transfer learning based on typical subjects (TS-DATL) framework with pre-training and domain adversarial training. Pre-training is to find out several typical representative subjects in the training dataset and mark the data most similar to the target domain as the source domain. Domain adversarial training is to narrow the mapping gap between the source domain and the target domain on the common feature space. Experiments were conducted on a public dataset DEAP. The results show that TS-DATL framework successfully reduces the difference of EEG signals across subjects, and effectively improves the prediction accuracy of two emotional dimensions.

Keywords: emotion classification; EEG; domain adaptation; GAN; transfer learning;

Introduction

In the field of human-computer interaction, in order to achieve accurate and natural interaction, computers and robots must have the ability to process emotions. From facial images, gestures, and voice signals to other physiological signals, methods of emotion recognition vary accordingly. Electroencephalogram (EEG), which is directly generated by brain neurons, is spontaneous and not affected by subjective consciousness, and has special advantages in some application scenarios. Many scholars have done a lot of research on EEG emotion recognition. Recently, many researchers have achieved accuracy of over 85% in user-dependent models (Koelstra et al., 2012; Zheng & Lu, 2015; Katsigiannis & Ramzan, 2017) on EEG-based emotion recognition.

However, psychological studies have shown that there are significant differences in the way individuals feel and express emotions (Jayaram et al., 2016). Traditional user-dependent models don't consider the particularity of individuals, and can't adapt to new individuals in practical application. For example, the recognition accuracy of the model proposed by Petrantonakis & Hadjileontiadis (2012) can reach 94.40% for the user-dependent scenes but 62.58% for the user-independent one. Fortunately, recent years have seen new efforts to classify emotions across subject.

Transfer learning is a promising method to solve this problem. One solution is to apply instance-based transfer learning. In order to make the probability distribution of the training data similar to that of the testing data, a few samples are purposefully selected from the labeled source domain data. Then, the emotion classification is performed using the traditional model. For example, X. Zhang et al. (2019) used the maximum mean discrepancy (MMD) (Gretton et al.,2012) to measure the similarity between individuals, and then constructed a target personalized emotion model with the labeled EEG data of similar individuals using the TrAdaBoost (Wenyuan Dai et al., 2007). The method achieves average accuracies of 66.1% and 66.7% for valence and arousal respectively in subject-independent experiment on DEAP (Koelstra et al., 2012) dataset.

Another transfer learning approach that has been successfully applied in emotion recognition is the feature-based one, whose idea is to map the features of two domains into a common feature space where the marginal probability distributions of the two domains are similar. To find this common feature space, various domain adaptive methods have been developed. Zheng & Lu (2016) compared the performance of transfer component analysis (TCA) (Pan et al.,2010), kernel principle component analysis (KPCA) (Schölkopf & Müller, 1998), and transductive parameter transfer (TPT) on SEED dataset, and found that TPT had the best classification effect. J. Li et al. (2019) applied style transfer mapping (STM) (Zhang & Liu, 2011) to EEG-based emotion recognition across subjects, which also achieved a good test result. Another way to find the public space is to take advantage of the transferability of deep neural networks. Li et al. (2018) proposed to replace the deep layer of neural network with the multikernel MMD(MK-MMD) to adapt the source domain and target domain to narrow the differences between domains, achieving a higher accuracy than traditional transfer learning methods. J. Li et al. (2019) also offered another efficient solution. Considering joint distributed adaptation (JDA) (Long et al.,2013) and generative adversarial network (GAN) (Gulrajani et al.,2017), they used adversarial training to adapt the marginal distribution in the shallow layer of the network, and collaborative reinforcement to adapt conditional distribution in the deep layer of the network, and achieved success on SEED and DEAP datasets.

In this study, combining the above two approaches, we proposed a two-step domain adversarial transfer learning based on typical subjects（TS-DATL）framework. This framework flexibly uses source domain information (i.e. EEG data of subjects in the training set) for emotion recognition in the target domain. Typical subjects were selected according to the applicability of each user-dependent model on the other subjects' data in the training set. Only the typical subject's domain data that best matched the target domain were used to the domain adaptation on the target. On DEAP dataset, the framework achieved 71.89% and 60.42% classification accuracy in valence and arousal scales respectively. The results suggest that this framework is a promising technique towards user-independent EEG emotion recognition.

The remainder of this paper is organized as follows. The next section details the two parts of the TS-DATL framework. Then, we present the details and results of the experiments on DEAP dataset. Finally, discussion is given.

Methods

The proposed TS-DATL framework consists of two parts, namely pre-training and domain adversarial training as illustrated in Fig. 1.

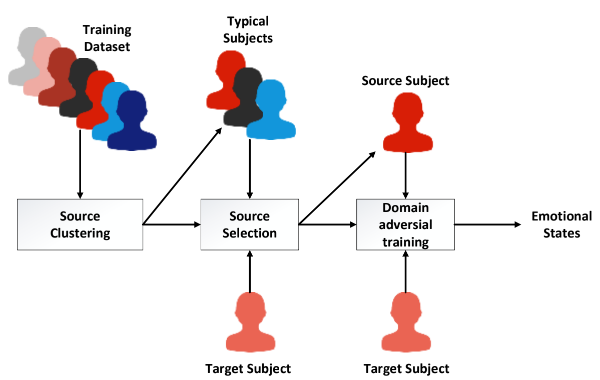


Figure 1: The proposed TS-DATL framework.

The pre-training is instance-based transfer learning. First, several typical representative subjects were identified in the training data. Then, the data most similar to the target domain were marked as the source domain. The domain adversarial training is a feature-based transfer learning based on Wasserstein GAN, which is an improved stable version of traditional GAN. Through adversarial training, the distance of the marginal probability distribution between domains is reduced.

Pre-training

Emotional EEG activities are specific, and it is difficult to cluster subjects directly by traditional clustering algorithm. Pre-training attempts to find several typical subjects to achieve clustering effect indirectly. Studies (Zhang, X. et al., 2018) have shown that EEG based biometric recognition is highly reliable. Hence, the accuracy of user-independent classification was taken as an indicator of the similarity between subjects, that is, a classifier trained by one subject's EEG data was applied to another subject. Specifically, for the total number of M subjects in the training set, each subject can obtain $M-1$ user-independent classification accuracy, and then the subject with the highest accuracy is marked as a typical subject. Compared with other user-dependent models, that model trained from the data of typical subjects has better generalization performance. In this way, the subjects in the training set are assigned to typical subjects, and the subjects belonging to the same typical subjects set naturally form a source cluster, as Figure 2. The number of clusters n is the number that is not identical among the 31 typical subjects selected. All typical subjects were encoded from 0 to n, and the IDs were taken as the labels to train a 4-layer feedforward neural network on the training set as the target cluster selector. In this way, EEG variation between subjects is reduced by using data from the most similar typical subject and a "negative transfer" of the whole framework is ensured on the target.

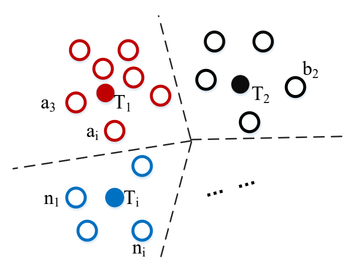


Figure 2: Visualization of source clustering results. Circles denotes subjects of training set. Subjects of the same color are consistent with their most similar subjects. T_1 to T_i represent all selected typical subjects.

Domain Adversarial Training

Conventional GANs have a wide range of applications and are proven to produce a lot of " realistic" data. Through the feature space transformation in the generator, the noise is made more similar to real data in the continuous adversarial training, which is what we are hoping for. Therefore, we treat source data as the real data of GANs and target data as the noise of GANs. The generator ensures the source data can be able to fool the domain discriminator and have better adaptability to the emotion classifier. Considering the feature space of the source is fixed, we add a source generator to transform the source feature space for improving the flexibility, shown in Figure 3. In addition, in order to deal with the problems of conventional GANs in hyperparameter tuning and convergence, we replace the traditional Jensen-Shannon divergence with Wasserstein distance to train the GANs (WGAN-GP). Adversarial-training consists of two parts:

Source Domain Training A 7-layer feedforward neural network is used as the user-dependent emotion classification model, which was fed with the source data $\boldsymbol{X_s}$, referring the source dataset labels $\boldsymbol{Y_s}$, to minimum cross entropy loss optimization. Normally, when the network layer is relatively shallow, the extracted feature will not have a strong characteristic, which refers to the representation of the features to the original data. When the network layer is deep, the features extracted by the model will have strong representativeness. So, the first 4 shallow layers of neural network, acting as the source generator $\boldsymbol{\psi_s}$, generate more generalization features. As emotion classifier $\boldsymbol{C}$, the last 3 deep layers focus on more detailed EEG emotion classification information. The loss function of emotion classifier is formulated in formula (1):

$$min_{\theta_s,\theta_c} L_C(X_s, Y_s) = -\mathrm{E}_{(x_s,y_s)\sim(X_s,Y_s)}\left[\sum_{h=1}^{H} \mathrm{I}(y_s = h) \boldsymbol{log C}\left(\psi_s(x_s)\right)\right] \quad (1)$$

where H is the number of emotion states. θ_s and θ_c are fixed after the source-training step, and θ_c is also fixed for the final target emotion prediction.

Target Domain Training Fed with the target data $\boldsymbol{X_t}$, alternately train the domain discriminator $\boldsymbol{D}$ and the target generator $\boldsymbol{\psi_t}$. To be specific, first maximize the D-Loss of the domain discriminator with the target fixed generator, then minimize the G-Loss of the target generator with the fixed domain discriminator as following:

$$\begin{aligned} max_{\theta_d} L_D(\boldsymbol{X_s}, \boldsymbol{X_t}) = {} & \mathrm{E}_{x_s\sim X_s}\left[D\left(\psi_s(x_s)\right)\right] \\ & - \mathrm{E}_{x_t\sim X_t}\left[D\left(\psi_t(x_t)\right)\right] \\ & - \lambda \mathrm{E}_{\hat{x}\sim\hat{X}}\left[(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2\right] \end{aligned} \quad (2)$$

$$min_{\theta_t} L_G(\boldsymbol{X_t}) = -\mathrm{E}_{x_t\sim X_t}\left[D\left(\psi_t(x_t)\right)\right] \quad (3)$$

where $\boldsymbol{\lambda}$ is a hyperparameter of controlling gradient penalty, and $\hat{\mathbf{x}}$ denotes the data sampled from the distributions of $\boldsymbol{X_s}$ and $\boldsymbol{X_t}$.

Repeat the above steps until the domain discriminator cannot distinguish between the target generated data $\mathrm{X_t}'$ and the source generated data $\mathrm{X_s}'$. In this case, D-loss converges, and the marginal distributions of $\mathrm{X_t}'$ is approximate to the marginal distribution of $\mathrm{X_s}'$. Assuming that the conditional distributions of two domains are also similar, we input $\mathrm{X_t'}$ into the emotion classifier derived from source domain training to obtain higher recognition accuracy, as shown in formula (4) and (5):

$$P(\boldsymbol{X_s}') \approx P(\boldsymbol{X_t}') \quad (4)$$

$$P(\boldsymbol{Y_s}|\boldsymbol{X_s}') \approx P(\boldsymbol{Y_t}|\boldsymbol{X_t}') \quad (5)$$

In addition, $\theta_{\boldsymbol{s}}$ is fixed after pre-training and used to initialize θ_t to ensure that the distribution of $\boldsymbol{X_t}'$ is relatively close to $\boldsymbol{X_s}'$ (Luo et al.,2018). Otherwise, it is difficult for generators and discriminators to achieve Nash equilibrium. θ_t are optimized in the alternating procedure.

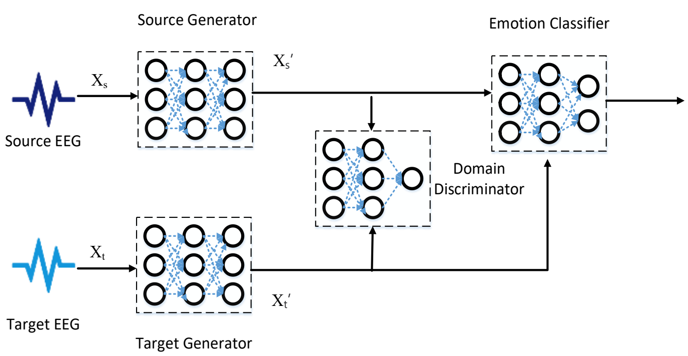


Figure 3: Illustration of domain adversarial training, which consists of four parts: the source generator and the target generator map two raw domain data to new feature spaces, the domain discriminator distinguishes source and target generated data, and the emotion classifier predicts emotion states.

Experiments

Materials

In order to evaluate the effectiveness of TS-DATL framework, we conducted experiments on DEAP, which is a well-known multimodal physiological database. The database collected 32 subjects' emotional data induced by music videos, including 32 channels of EEG signals and 8

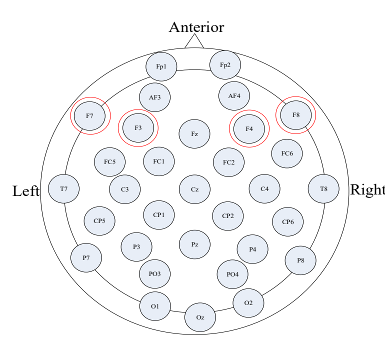


Figure 4: International 10-20 system on DEAP dataset.

Table 1: DEAP Dataset.

	Shape
Data	32×40× 32 ×8064 (Subjects × Videos × Channels × ($Second$ × Samples))
Labels	32×40× 2 (Subjects × Videos × ($Valence$, Arousal))

channels of other physiological signals. These electrodes' arrangement is based on the internationally recognized 10-20 system, as shown in Figure 4. Each subject watched 40 one-minute music videos and filled in the Self-assessment manikins (SAM), which rated Arousal, Valence, Dominance and Liking respectively. Each of these scale from 1 to 9. In our experiments, raw EEG data is sampled down to 128 Hz in order to filter out irrelevant signals. Arousal and Valence are divided into two categories: if the score is greater than or equal to 5, the label is set to high; otherwise, it is set to low.

Methods

Data segmentation A 1-second EEG segment is considered a basic unit of emotion. Thus, excluding the silent part, the records of each subject were divided into 2400 (40 videos ×60 seconds) samples. Sample labels are the same as that of original trials. In order to verify the subject independence of this framework, all samples of one subject were divided into testing set, and samples of the other 31 subjects were divided into the training set. Cross-validation is performed to eliminate randomness.

Feature extraction Based on the knowledge of neuroscience and the hypothesis of individual frontal asymmetry (Cao et al., 2022), we use the left-right frontal region difference as the feature. First, silent signals were used to calibrate the stimulus signals to exclude the influence of experimental environment and other external factors during EEG acquisition. The mean value of the 3-second silent signals was used as the baseline signal of each trial, and the deviation between the stimulus signal and the baseline signal reflected the actual emotional state. The specific expression is as follows:

$$emotion\_v_j = stimulus\_v_j - \frac{1}{3}\sum_{k=1}^{3} silent\_v_k \quad (6)$$

Where $emotion\_v_j$, $stimulus\_v_j$ and $silent\_v_k$ are 128-demension vectors. $stimulus\_v_j$ denotes raw EEG stimulus data vector of the j-th second on each music segment. $silent\_v_k$ is raw EEG silent data vector of the j-th second on each music segment. $emotion\_v_j$ refers to the actual emotional data vector of the j-th second on each music segment.

For reducing the impact of poor electrode contact or postural movement, de-trending was carried out to eliminate signal trend items. Previous studies generally divided EEG into four bands, namely θ (4 ~ 8 Hz), α (8 ~ 13 Hz), β (13 ~ 30hz), δ (30 ~ 45 Hz), and we used a 4 ~ 13 Hz band-pass eight order Butterworth filter for filtering after experiment. Finally, the relevant channels that are more closely related to the frontal region are selected. For DEAP database, as seen from figure 4, left frontal channels (F3, F7) and right frontal channels (F4, F8) are selected. It is defined as $final\_v_j = left\_v_j - right\_v_j$, where $final_{v_j}$ represents the final EEG feature, $left\_v_j$ and $right\_v_j$ represents the left frontal data and the right frontal data of the j-th second on each music segment respectively. In order to remove the redundant items in these feature, PCA algorithm was used to reduce the dimension to 128.

Implementation details Three contrast experiments were designed to verify the superiority of the proposed TS-DATL framework from a perspective of subject independence. In the first experiment, we compared MMD method, standard Euclidean method, the SVM, personal identification method and the pre-training method. The first two methods were use MMD distance and standard Euclidean distance as the metric to select similar individuals. The personal identification was to encode the id of 31 subjects in the training set from 0 to 31, and used the SVM model as the identity recognizer. The data of the most similar subjects selected by the above five methods were used to train the SVM model. In the second experiment, the 32nd subject was the target, and the other 31 subjects were the source respectively. The baseline accuracy of SVM model, the accuracy of 7-layer fully-connected network and the accuracy after domain adversarial training were compared. The third experiment was to verify the superiority of the TS-DATL framework, which took the similar individuals selected from the pre-training as the source domain of the domain adversarial training. The source generator, target generator, domain discriminator and emotion classifier in domain adversarial training were set as four-layer neural network. The number of 4-layer source generator's and target generator's neurons were 128, 128, 256, 256 respectively. The number of the emotion classifier's neurons were 256, 128, 128, 2. The number of domain discriminator's neurons were 256, 256, 128,1. All activation in the middle layers were ReLU. Each of the above methods were independently performed for 5 times, and retained the average as the final results.

Results

In the first experiment, we used accuracy and F1-score as a performance metric to verify the reliability of the pre-training method in selecting similar individuals. Table 2 shows that the pre-training method achieves 4.4% and 1.05% improvements respectively in valence and arousal dimensions. Since using all data of 31 subjects directly to train a SVM model, the baseline has a good performance with long consuming time. Standard Euclidean just fight to a draw with the baseline while shortening the training time. The personal identification method only plays a role in the valence dimension.

Table 2: The first experiment.

Method	Valence(%)		Arousal(%)	
	accuracy	F1-score	accuracy	F1-score
Baseline (SVM)	66.5	61.47	56.8	**47.02**
MMD	59.21	46.78	41.64	27.42
Standard Euclidean	66.74	64.12	56.68	44.48
Personal Identification	67.85	67.80	54.82	45.36
Pre-training	**70.91**	**71.58**	**57.85**	45.04

In the second experiment, we evaluated the performance of domain adversarial training and showed the average accuracy of the three models in Figure 5. In addition, a pair of subjects were randomly selected as source domain and target domain, and their data distributions were plotted in Figure 6. Clearly, in these two point of view， domain confrontation training has performed well, and the data transformed by both generators is of high quality. It can be seen that, for different distributions of data from source domains, the SVM models fluctuate greatly and the generalization performance is not strong. However, the 7-layer feedforward neural network is more stable and can discover more popular emotional characteristics. Domain adversarial training is not only stable, but also more suitable to the specific target domain with more great accuracy. The same conclusion can be drawn from two-dimensional visualizations of the distributions. The data distributions of the original source domain and the target domain are different. The data distribution of source domain is similar to the scattered star distribution, while that of target domain is more standard circular distribution. And some red emotional data points in the source domain are more exotic than other data. After the feature space transformation by the source generator and the target generator, the data distributions of both domains are similar to the fan distribution. We also have orange data points in the target domain to fit the red data in the source domain. Clearly, the gap between two domains is narrowed.

In the third experiment, we integrated pre-training with domain adversarial training. In a best-case scenario, our framework reaches averaged accuracy of 71.89% and 60.42% on arousal and valence respectively across 32 subjects, respectively, higher than other methods. Compared with feeding the pre-training data into SVM models, the accuracy of domain adversarial training is continuously increased by 1% in valence and 2.6% in arousal dimension. The above phenomena suggest that there is no mutually exclusive effect between the two parts, instead there is a progressive relationship.

Finally, we provided a comparison with existing state of the art, shown Table 4. Some studies construct a model for each subject, such as Cao et al. Using single subject's previous EEG data, a good classification effect was obtained. Li et al. also used a domain adaptation approach to improve the accuracy and reliability of emotion recognition across users and sessions.

Table 3: The third experiment.

Method	Valence (%)		Arousal (%)	
	accuracy	F1-score	accuracy	F1-score
Baseline (SVM)	66.5	61.47	56.8	47.02
KNN	61.22	55.83	54.03	54.28
XGBoost	69.77	69.56	54.63	54.07
Pre-training	70.91	71.58	57.85	45.04
Ours (TS-DATL)	**71.89**	**72.28**	**60.42**	**67.09**

Table 4: Compare with state-of-the-art works.

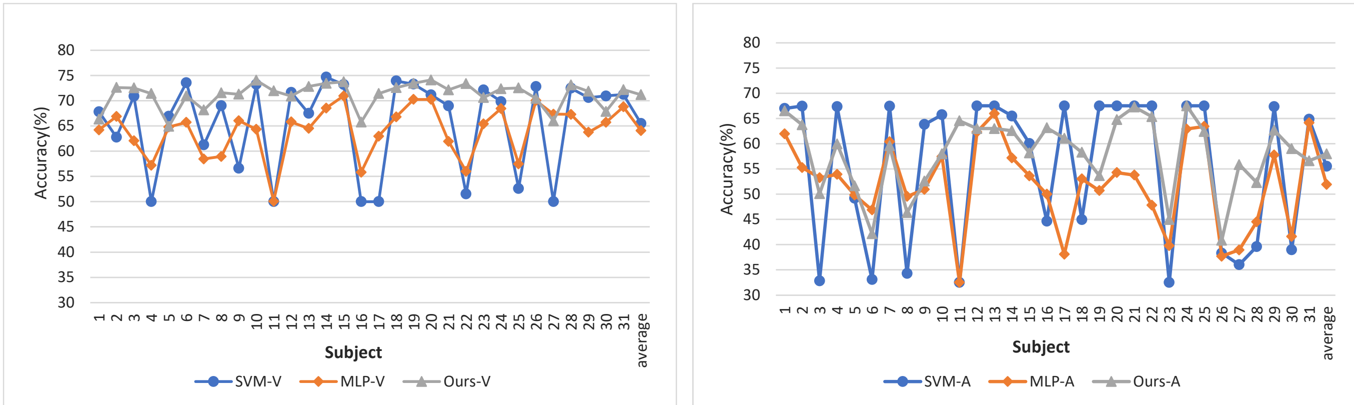
Method	Valence(%)	Arousal(%)
Cao et al.	74.6	67.7
Li et al.	52.54	62.66
Ours (TS-DATL)	71.89	60.42

Discussion

In order to solve the problem brought by individual differences in affective computing, this work introduces generative adversarial network and domain adaptation of the transfer learning. We proposed a two-step domain adversarial transfer learning based on typical subjects（TS-DATL）framework, and conducted comparative experiments on the two parts of the framework separately and completely. The results show that the framework can obtain much better performance in the EEG emotion classification of user-independent scenario. Although the accuracy of EEG emotion recognition has improved compared with user-dependent methods, it still needs to be improved. In addition to probability distribution adaptive task, the generated adversarial network can also decouple information. This framework simply regards the first 4 layers and the last 3 layers of the 7-layer feedforward neural network as the public part and the private part. The public part guarantees the success of the transfer learning, while the private part enhances the learning effect in a specific field. It is expected that more domain common and domain specific features can be learned through decoupling in the future, so as to further improve the accuracy of EEG emotion recognition.

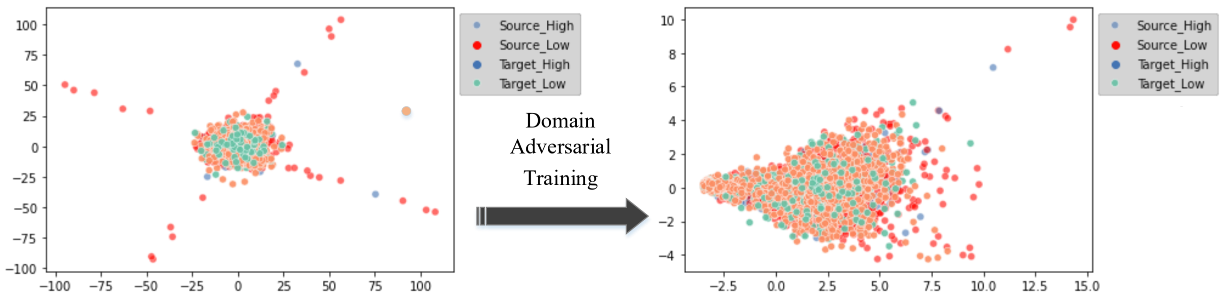
Acknowledgments

This work was supported by the Natural Science Foundation of China (61974109).



（a） Valence （b） Arousal

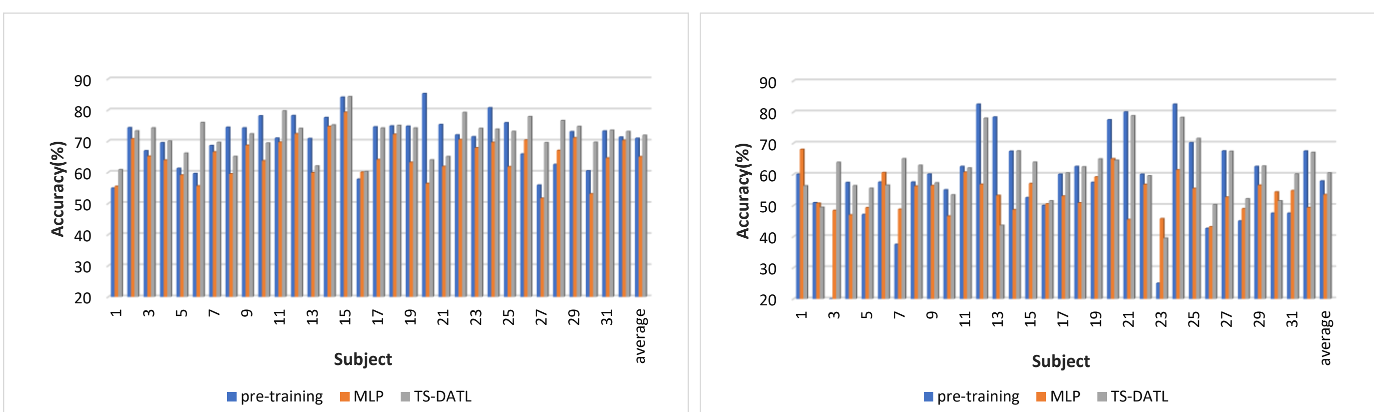
Figure 5: Accuracy of 3 models in the second experiment.



X_t
(a)

X_t'
(b)

Figure 6: Two-dimensional visualizations of the distributions of two subjects' data before and after the source generator and the target generator. While data points with red and blue colors represent two emotions states of source domain in arousal, respectively, data points with orange and green colors represent two emotions states of target domain.



（a） Valence （b） Arousal

Figure 7: Accuracy of 3 models in the third experiment.

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