Deep Representation Learning for Affective Speech Signal Analysis and Processing

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I. Introduction

Speech emotion recognition (SER) is an important research area with direct impacts in applications of our daily life spanning education, healthcare, security and defense, entertainment, and human-computer interaction (HCI). The advances in many other speech signal modeling tasks such as *automatic speech recognition* (ASR), *text-to-speech synthesis* (TTS), and *speaker identification* (SID) have led to the current proliferation of speech-based technology. Incorporating SER solutions into existing and future systems can take these voice-based solutions to the next level. Speech is a highly non-stationary signal with dynamically evolving spatial-temporal patterns. It often requires sophisticated representation modeling framework to develop algorithms that can handle real-life complexities. Most of the variability in a speech signal comes from the interplay between lexical, para-linguistic, idiosyncratic, and many other contextual information, which are simultaneously conveyed in the speech signal. In particular, emotion directly affects the speech production process, modulating the acoustic signal with expressive characteristics in a subtly complex manner. Many of the traditional signal processing methods are designed based on psycho-acoustical knowledge to characterize these fine-grained patterns of the affect-related acoustic modulation [1]. Researchers in the field of SER have empirically derived standard feature sets accompanied with open toolboxes to obtain an off-the-shelf emotion recognizer [2], [3]. However, there is inevitable information

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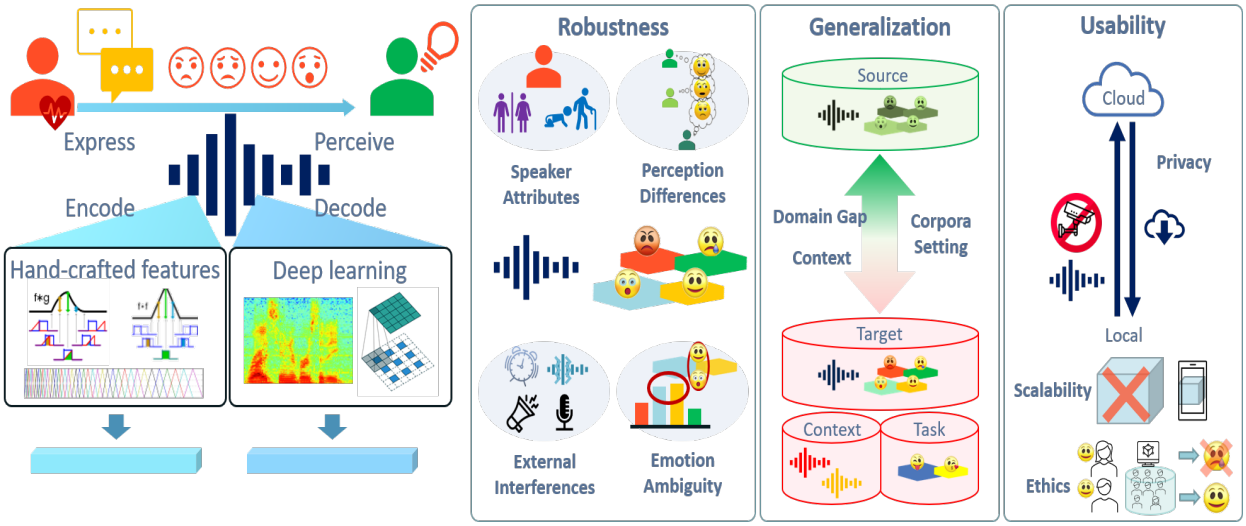

Fig. 1. The overview of deep representation learning scheme for SER and the three real-world modeling challenges: robustness, generalization and usability

loss due to the knowledge-driven, as compared to data driven process in computing these hand-crafted features, which can underestimate the complexity in modeling the affective speech signal in real life.

With the continuous advancement in the deep representation algorithms, the modeling challenges around deploying SER solutions in our daily life are being addressed across three core dimensions using deep networks for affective speech modeling:

- **Robustness**: How do we learn speech representations that can be robust against settings of signal acquisition and the nature of emotion manifestation to achieve robustness?
- **Generalization**: How do we learn speech representations that can handle source-target domain mismatch in cross-context application scenarios to achieve generalization?
- **Usability**: How do we learn speech representations that can be practical during deployment, handling privacy and ethical concerns to achieve usability?

These modeling challenges are critical in leading SER technology into an integrative component of our daily life. Our aim in this paper is to provide the readers easy-to-follow materials that demonstrate the use of deep representation learning approaches in addressing these affective speech signal processing and analysis tasks. Our focus is mostly on the modeling part (i.e., back-end), rather than on the feature extraction part (i.e., front-end), emphasizing deep learning strategies that are appropriate solutions for these challenges. For a detailed review of representation learning at the front-end of SER, the readers are referred to the work of Alisamir and Ringeval [4].

II. THREE MODELING CHALLENGES

Robustness, generalization, and usability are the three major affective signal modeling goals in deploying SER in the real world. Fig. 1 provides an overview, highlighting key issues that can be addressed with deep representation learning methods for each of the three modeling goals. These three challenges are all interconnected. For example, a complex architecture might be more robust against noise in real-world situation with better generalization to different conditions, but its computation power, memory requirement and even privacy concerns may prevent it from deploying this system in actual applications. For sake of presentation, however, we discuss each of them in separate sections. In terms of *robustness*, current available databases and models hardly cover the possible emotional speech variability space. To develop a speech emotion recognition system, we rely on affective speech samples collected in predetermined contexts or scenarios, where the ground truths are often derived from manually-annotated labels collected with perceptual evaluations. A key source of variability is the differences in the situated data acquisitions. Differences in microphones and in their placement create wide variations of affective speech data. Environmental noises also modulate emotion perception, reducing speech intelligibility [5]. Another source of variability is the individual's personal traits in expressing and perceiving emotions. The subjective differences in emotion perception affects the labels used to train the models, as raters may perceive different emotions from the same speech [2]. Furthermore, the boundary between emotional categories are blurred for emotional expressions observed in daily interactions, introducing variations in the labels [6]. These uncontrollable factors are embedded within the collected speech signals and create additional technical difficulty in handling the expanded speech variability space to achieve robust SER.

In terms of *generalization*, an important modeling goal in SER is to learn representations that can handle cross domain mismatches, which result from data with different languages, labeling protocols, speaker traits, and interaction settings [7], [8]. The available representation models trained with data from a source domain should be able to maintain their emotion discriminatory power in a target domain, even when both domains may have inevitable mismatches. This goal is often difficult due to insufficient labeled samples in the target domain, vast distributional emotional differences between target and source domain, and inconsistent emotional descriptors. Directly using source speech representations on the target domain would result in significant degradation in performance, often due to inadequate generalization capability. Technically, there is a tradeoff between model performance and generalizability. Without a careful design, insufficient training and fine-tuning can lead to negative transfer and domain shift problems [3], [9]. We can facilitate improving SER toward generalization by tackling the source-target mismatch on both speech features and emotion labels using deep learning approaches.

In terms of *usability*, practical issues in deploying SER need to be considered such as model compactness, sensitive attribute masking, and fair representation. Real-world SER solutions often follow a cloud-local architecture to handle large-scale training and inferences. Current SER models tend to utilize deep architectures to achieve both robustness and generalization. However, edge devices only allow limited computation, storage, and memory access [10]. This constraint creates technical issues in learning SER to attain high efficiency. Privacy leakage during cloud-local transmission can also threat the trustability of the SER model. Relying exclusively on edge computing would limit the model capacity. A better handling of the tradeoff between achieving high performance and addressing privacy issues is key for deploying a trustable SER system [11]. Another practical issue that should be carefully avoided is the exclusion of a target user demographic while building the representation. The collected affective speech databases can introduce ethics concerns such as unconscious inclusion of stereotypical bias and unfair representations. The protocol in data collection and speech feature would likely come under scrutiny as the SER model is rapidly being deployed and utilized as decision-making aid in our daily life.

Most studies addressing speech representation learning focus on advancement of deriving unified front-end representations that can be applied to downstream speech tasks [12], [13]. In contrast, we will discuss about using deep representation learning to overcome these three key modeling challenges to enable SER in real-world applications: *robustness*, *generalization*, and *usability*. We will first highlight the use of deep representation learning for each of the three associated affective speech modeling tasks. Then, we will identify the up-to-date effective approaches in addressing these issues.

III. Affective Speech Modeling: Robustness

Robustness is an important consideration while modeling speech for emotion recognition. SER systems should be robust against signal-based and emotional-based variabilities. Figure 2 shows a general overview of robustness challenges in the SER field. Signal-based variations are typically related to differences in the way we express emotions (e.g., inter-speaker, gender and phonetic variability), and presence of external interferences (e.g., noise, channel variability, reverberation and far-field speech). Emotional-based variations are associated with the natural perceptual ambiguity between subjects in interpreting emotions, which affects the labels. Recent SER formulations have addressed signal-based and emotional-based variations with model formulations, providing important insights for researchers working on this area. In this section, we mostly focus on discussing these formulations based on deep representation approaches.

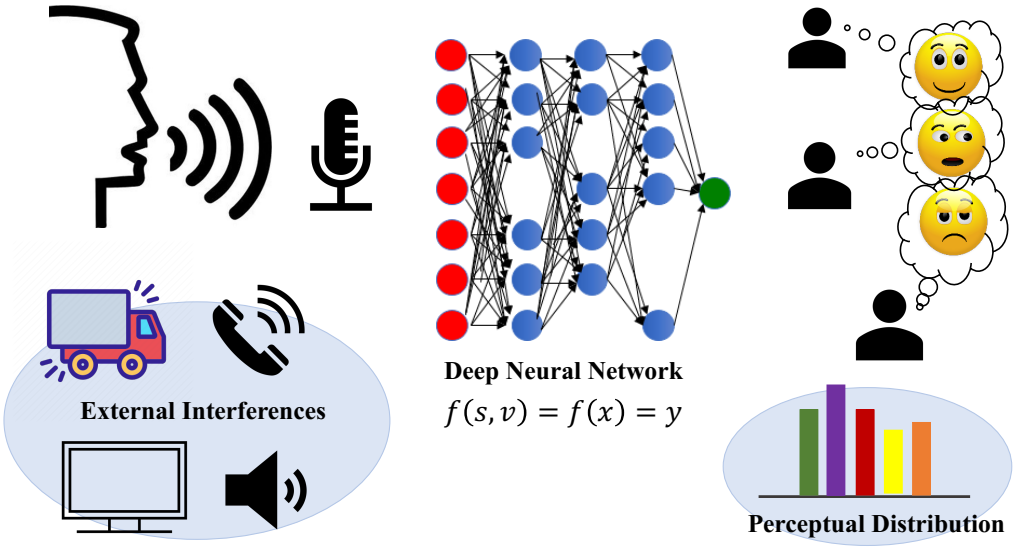

Fig. 2. An overview of robustness challenges for SER. It is generally divided into signal-based and emotional-based variations. Modeling these variations by deep learning approaches are recent popular research trends in SER field.

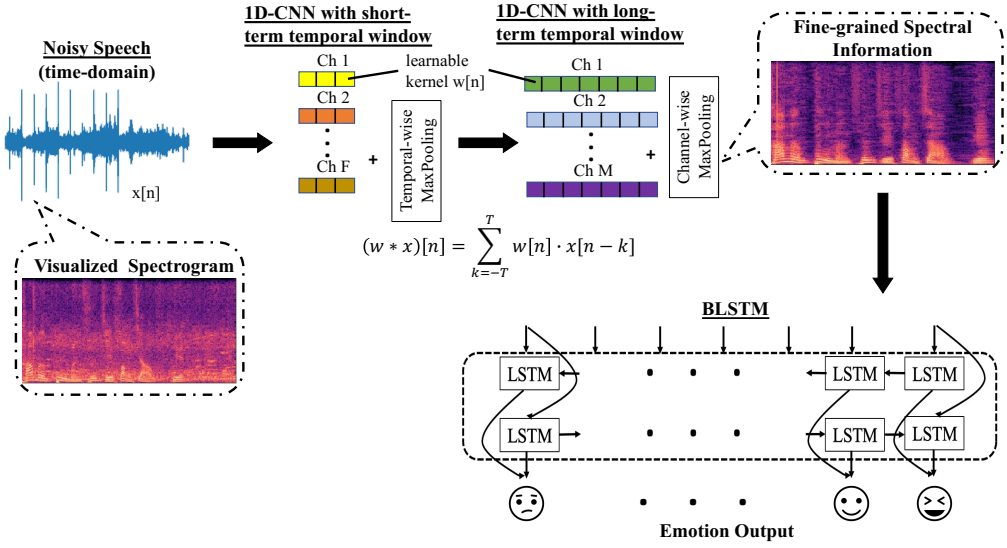

Fig. 3. An example of an SER architecture proposed to learn deep emotional speech representation to deal with signal-based variations in an end-to-end framework [14].

A. *Signal-Based Variations*

Signal-based variations of affective speech can be represented with Equation 1. The input audio signal $x[n]$ is transformed by the function $f(\cdot)$ into a vector, from where we can predict its emotional label y. This target output can represent either emotional categories (e.g., happy, neutral or anger) or emotional attributes (e.g., arousal, valence, or dominance). In this study, we consider cases when function $f(\cdot)$ is

implemented with a deep learning model.

$$f(x[n]) = y \tag{1}$$

$$x[n] = s[n] + v[n] \tag{2}$$

When solving the issues of signal-based variations, we can further decompose the input audio signal $x[n]$ as the sum of a clean raw speech $s[n]$ and external interferences $v[n]$ (Eq. 2). The term $v[n]$ is a general term that includes different interference during the data acquisition such as environment, background noise (e.g., stationary and non-stationary noise), and recording conditions (e.g., reverberations, far-field speech, microphone settings). Likewise, the speech production of an individual varies with speaker traits such as vocal tract length and vocal fold size. Researchers have proposed to solve these two components by utilizing deep learning approaches [5], [15].

1) Noisy Speech Enhancement: Ambient noises severely affect both the time-domain and frequency-domain structures of a signal, distorting the acoustic representation for a SER system. Various approaches have been proposed to resolve this issue including data augmentation, feature compensation, and extraction of robust acoustic features. A complementary approach to these methods is to apply a *speech enhancement* (SE) algorithm prior to implement a SER model to attenuate the influence of the external interference $v[n]$. This approach is recommended, since it is a straightforward and effective pre-processing step. For example, Triantafyllopoulos *et al.* [5] introduced a spectrogram-based SE network as a preprocessing module for a SER model. The SE network was independently trained from the SER by optimizing the *mean square error* (MSE) between the magnitude spectrum of the enhanced signal $|\hat{X}(t,w)|$, and the magnitude spectrum of the clean signal $|X(t,w)|$ (Eq. 3).

$$\mathcal{J} = \frac{1}{TW}\sum_{t}\sum_{w}(|\hat{X}(t,w)| - |X(t,w)|)^2 \tag{3}$$

The original noisy input audio $x[n]$ is first enhanced by the trained SE system to output $\hat{x}[n]$, which is the inverse of the *short-time Fourier transform* (STFT). The enhanced vector $\hat{x}[n]$ is then feed into the SER model. Since the $v[n]$ term in the enhanced signal is attenuated, the modeling power of the SER model to capture emotional-relevant features improves under different noisy environments, increasing its robustness against external interference. The evaluation on the Emo-DB corpus showed that the approach improved the *unweighted average recall* (UAR) from 14.73% to 20.75% on the -5dB *signal to noise ratio* (SNR) condition, and from 18.05% to 26.85% on the 0dB SNR condition [5]. Another elegant alternative is to jointly learn the speech enhancement and SER tasks. The enhancement model is embedded

in the intermediate layers of an end-to-end SER framework [14]. This strategy allows the model to remove background noise or music, while preserving important speech emotional cues. Notice that while integrating SE techniques in SER tasks can effectively improve the system robustness, it also increases the complexity of the entire framework.

Example: Robustness of SER against environment noise

Figure 3 illustrates an example of a network implementation of an end-to-end SER system that is robust against noise interference. We follow the approach presented by Trigeorgis *et al.* [14]. Generally, the network consists of two parts.

- Part I: The input of an end-to-end framework is a time-domain audio waveform. The raw signal might contain noisy background including music or other interferences that impact the performance of a SER system. Therefore, the first part of the network is two 1D-*convolutional neural network* (CNN) layers that perform short-term and long-term temporal convolution on the raw signal, respectively. The short-term convolution aims to extract fine-scale spectral information from the high sampling rate signal following by a temporal-wise max pooling operation. The long-term convolution intends to extract more higher-level, abstract features from the speech signal by intentionally increasing the kernel size for the second 1D-CNN. Finally, the information is aggregated with a channel-wise max pooling operation.
- Part II: After the CNN-based network, a recurrent-based network (i.e., BLSTM) is concatenated to serve as the emotional discriminator. The optimization object is shared across the CNN and the BLSTM networks, jointly updating learnable weights to form the end-to-end training framework. The CNN network is considered as a feature extractor which has noise reduction ability to remove undesired noises, while preserving important emotional cues for the BLSTM discriminator. The choice of the object function depends on the recognition task, where the cross-entropy loss is often used for emotional category tasks (i.e., classification problem) and the *concordance correlation coefficient* (CCC) is often used for emotional attribute prediction tasks (i.e., regression problem).

2) Robustness Against Speaker Variability: We express emotion differently due to idiosyncratic or physical variations that are reflected in the speech signal. Gender and phonetic variabilities are also important speaker-dependent traits included in $s[n]$. Approaches in SER aims to remove or adapt idiosyncratic speaker information that is contained in $s[n]$ to improve robustness of a SER model for unseen speakers. Conventional methods include speaker normalization, domain adaptation or data selection.

Recent advances in deep neural learning offer powerful adversarial schemes to achieve the goal of removing speaker characteristics. For example, Li *et al.* [15] proposed an adversarial training network for SER to disentangle the speaker and emotional characteristics. In addition to the cross entropy loss ($\mathcal{L}_{Emo}$) for the primary SER task, they incorporated an entropy loss (H_{Spk}) in the cost function, as shown in Equation 4. This term in the cost function encourages the model to increase the uncertainty or randomness of another independently trained *speaker classifier* (SC) output, forming a multi-task setting to train the model.

$$\mathcal{L} = \lambda \mathcal{L}_{Emo} - (1 - \lambda)\mathcal{H}_{Spk} \tag{4}$$

The maximization of the entropy term during the training is achieved by implementing a gradient reversal layer. Since the SER model is trained to remove speaker traits, the approach reduces the sensitivity toward acoustic variability due to physical differences across individual speakers. This approach improved the performance of a SER system built without considering speaker variations, increasing the UAR from 57.45% to 59.91%, using the recordings of the IEMOCAP corpus. A limitation of performing adversarial learning is typically the optimization of a minimax problem, which might lead to unstable convergence issues.

3) Robustness Against Sentences of Different Lengths: Another practical problem that can increase variability is the duration of a sentence. The varying durations of each utterance are common in SER databases. The SER model should maintain robust recognition performance regardless of the duration of the signal. However, SER models typically are not capable to handle long sequences [16], which may even include dynamic emotional changes within a sentence (i.e., non-uniform emotion expressions over time). Given the fixed structure in the network, sentences are often zero padded or truncated to reach a target duration. These approaches affect the robustness of the SER model, leading to severe performance degradation. For instance, Lin and Busso [16] showed that the absolute CCC values across emotional attributes for long sentences (i.e., eight to eleven seconds) were between 3% and 14% lower than the corresponding performances for short sentences (i.e., less than five seconds). A simple but effective approach to address this problem it to split a sentence of arbitrary length T_i into a fixed number of segments or chunks with the same duration [16]. This goal is achieved by dynamically adjusting the step size Δc_i between chunks for different duration inputs. Equation 5 gives the step size for that sentence, where w_c is the fixed length of the chunks (e.g., $w_c = 1$ sec), and C is the fixed number of desired chunks (e.g., $C = 10$, assuming the maximum duration of the sentences is 10 sec).

$$\Delta c_i = \frac{T_i - w_c}{C - 1} \tag{5}$$

Since the method creates chunks with a fixed duration, it is straightforward to extract acoustic representations using methods such as *long-short term memory* (LSTM) or *convolutional neural networks* (CNNs) with fixed structures. Since the number of chunks is also fixed, it is easy to aggregate the temporal information. For example, we can combine chunk-level information with attention models. The attention weights can effectively capture the emotionally salient regions within a speech regardless of its duration, resulting in robust performance toward sentences of different length. Furthermore, the model is highly parallelizable leading to a computationally effective SER implementation. The experimental results systematically showed significant improvements in CCC with absolute gain between 2% and 8% by using the adjusted step size approach for different models (e.g., LSTM, CNN) across different emotional attributes (i.e., arousal, dominance and valence).

B. Emotional-Based Variations

A second source of variability is the subjective nature of human's emotional expression and perception. The ground truth labels of emotion are often derived from human perceptual evaluations. As depicted in Figure 2, individuals may perceive different emotional content despite listening to the exact same audio clips. The perceptual variability leads to low inter-evaluator agreements in the labels, resulting in noisy emotional labels that directly influence the robustness of machine learning based SER systems. Studies have proposed strategies to deal with this problem with either label-based or model-based solutions.

1) Joint Hard-Soft Emotional Label Learning: The most straightforward way to incorporate the differences in emotional perception in SER tasks is to train the model with soft-labels. For example, if a speech recording is perceived as happiness by two raters, anger by one rater, and sadness by one rater the model is trained with the vector [0.5, 0.25, 0.25, 0], where the dimensions represent the emotions happiness, anger, sadness and neutral, respectively. This approach explicitly includes label variation/noise (i.e., perception variabilities) into the optimization process while training the SER system. Instead of training a SER model solely based on the consensus ground truth (e.g., the majority or average of annotations), Chou and Lee [2] introduced a framework that jointly learns both consensus assignment (hard label) and emotion distribution (soft label). Equation 6 shows the softlabel $q(c_k)$, which indicates the class probability for the k-th emotional class. The variable K refers to the total number of emotion classes and $\mathbb{1}_k^{(n)}$ is an indicator that is one when the n-th annotator selects the k-th class, and zero otherwise.

$$q(c_k) = \frac{\alpha + \sum_n \mathbb{1}_k^{(n)}}{\alpha K + \sum_{k'} \sum_n \mathbb{1}_{k'}^{(n)}} \tag{6}$$

The novelty in the softlabel definition is the use of a smoothing coefficient α, which controls the *sharpness* of the output label distribution. Therefore, the model not only encourages learning a single emotional target, but also captures the label uncertainty reflected by the spread of the soft distribution. As a result, the trained SER model typically achieves higher recognition performance, since it explicitly considers the natural variations of the emotional labels.

Other methods to leverage the difference in perception across evaluators are (1) finding trends across labels, (2) applying oversampling techniques that take into account the distribution of the labels provided to the samples, and (3) modeling uncertainty directly from the labels.

2) Model Uncertainty Prediction: An alternative approach to deal with emotional variability is to capture uncertainty in the model prediction as part of the learning process. In addition to recognizing emotions, the SER system also estimates the confidence in its predictions. This information can be valuable for practical applications, especially in human-in-the-loop scenarios, where ambiguous cases can be further reviewed. Sridhar and Busso [17] presented a model-level approach to deal with label uncertainty. They designed a SER model with a reject option to recognize categorical emotions, enabling the model to abstain from providing a classification result when the confidence of the prediction falls below a certain threshold. The performance of a reject option is measured by reporting the accuracy of the system as a function of the test coverage, which is defined as the percentage of the test set over which the system provides a prediction. As the model rejects more samples, the SER performance is expected to increase, since the most ambiguous samples are removed from the test set. The confidence in the results was estimated with two alternative criteria. The first criterion was to minimize the empirical risk of the selective classifier, while maintaining the test coverage as high as possible. The second criterion was to compute the difference between the two highest classes predicted by the DNN model. If the difference is above a certain threshold, the model is confident to make a prediction. Otherwise, it rejects the sample. This approach effectively improves the recognition accuracy without compromising much the test coverage. Another approach to capture model uncertainty is with *Monte Carlo* (MC) dropout. MC dropout provides a way to calculate the intractable posterior distribution of the predictions by approximating variational inference using deterministic neural networks with dropout regularization. Dropout needs to be applied both during training and testing stages. During training, dropout effectively samples a smaller network at every iteration in a tractable and feasible manner. This approach is also computationally effective. Sridhar and Busso [6] used this approach to quantify uncertainty in the predictions of emotional attributes. The

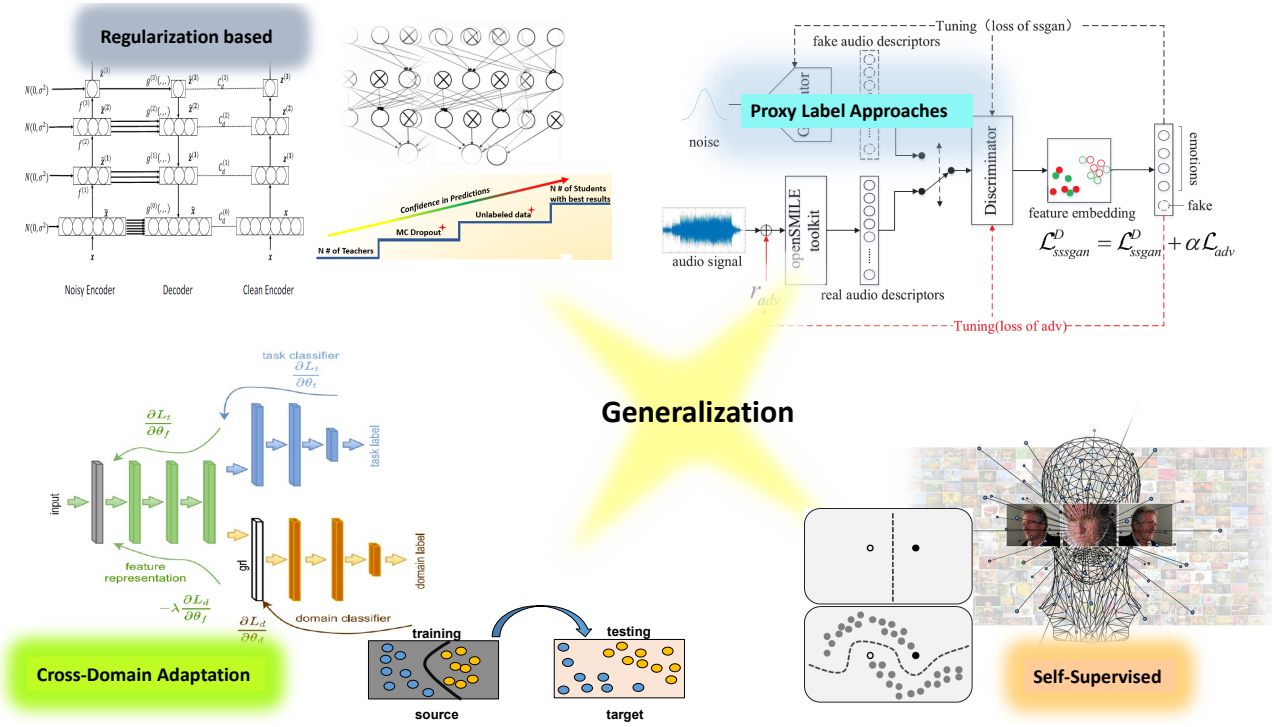

Fig. 4. Generalization can be achieved through different strategies - **Regularization-based methods** such as DNN architectures which layer reconstruction and MC dropout techniques, **Cross-Domain Adaptation** where DNN models are adapted efficiently to reduce domain mismatches, **Self-Supervised learning methods** to derive supervision from the data itself without additional labels that improve generalization and **Proxy Label approaches** that produce pseudo labels for unlabeled data to improve generalization in DNNs.

study found that sentences with extreme values for valence, arousal and dominance were predicted with less uncertainty, whereas more ambiguity was observed among neutral samples. While this approach is beneficial for modeling prediction uncertainties in SER, it requires multiple inference steps to calculate meaningful uncertainties. Also, a DNN with MC dropout is still dependent on the dropout and activation hyper-parameters, which can modify the calculated uncertainty.

IV. Affective Signal Modeling: Generalization

Generalization is the ability of a system to respond to novel situations not observed in the training data. Generalizing SER systems to adapt to new conditions is an important problem with the increasing presence of speech-based systems across multiple domains such as healthcare, security and defense, and education. It is difficult to learn acoustic representations that capture general trends across multiple unseen scenarios. Factors that affect the generalization of the SER system are scarcity of emotionally rich and balanced databases, accurate and consistent ground truth labels, and differences in the interaction settings. Studies

in SER have demonstrated that it is possible to circumvent several factors hindering generalization by employing machine learning approaches such as dropout [7], early stopping, data augmentation [18], [19], l_1 and l_2 weight regularization, and use of a speaker-independent hold-out set to test the models. Figure 4 gives a broad perspective on different ways to achieve generalization. This section describes promising approaches to improve the generalization of the SER models, focusing on regularization-based methods, cross-domain adaptation approaches, self-supervised learning methods and proxy label approaches.

A. Regularization-based methods

DNNs often have millions of parameters which are extremely hard to optimize, especially when the train and test conditions are mismatched. This mismatch can be due to factors such as acquisition conditions, acoustic and emotion distributions, and even merely the types of human interactions. Reducing co-dependencies between layers of a DNN can help in learning more generic trends across input instances, leading to better performance on unseen instances and improving generalization. We describe some of the recent and promising regularization techniques that have been used to achieve this goal.

1) Regularization with Layer Reconstruction: An approach to regularize a DNN is with reconstruction losses of intermediate layers, which are added to the main supervised problem. The most common formulations for this task are autoencoders and noisy autoencoders. The benefits of these auxiliary tasks is that they do not require emotional labels, so unlabeled data from the target domain can be used to reduce the mismatch between train and test sets. An appealing approach to achieve this goal is to use ladder networks. In contrast to simple autoencoders, the ladder network architecture uses skip connections between the encoder and decoder layers, attenuating the information overload from encoder to the decoder layers. Parthasarathy and Busso [20] explored this architecture, using *multi-task learning* (MTL) as a regularization. The prediction of emotional attributes (arousal, valence, and dominance) was the primary task, and the reconstruction of feature representations at various layers in a DNN was the auxiliary task. By simultaneously solving the primary and auxiliary tasks, the models were regularized by finding more general high-level feature representations that are discriminative for the primary task. The unsupervised nature of the auxiliary task (i.e., reconstruction of intermediate feature representations) helped the SER system to improve its generalization by adding more unlabeled data from the target domain.

$$\mathcal{C}_{Lad+MTL} = \alpha\mathcal{C}_{aro} + \beta\mathcal{C}_{val} + (1-\alpha-\beta)\mathcal{C}_{dom} + \sum_{l} \lambda_l \mathcal{C}_d^{(l)} \tag{7}$$

The implementation of this approach is fairly straightforward with the loss function shown in Equation 7. The overall MTL loss of the ladder network consists of $\mathcal{C}_{aro}$, $\mathcal{C}_{val}$ and $\mathcal{C}_{dom}$, which are the individual

losses for the prediction of arousal, valence, and dominance, respectively. The loss function also includes $\mathcal{C}_d^{(l)}$, which is the reconstruction loss at layer l in the network. α, β and λ_l are hyper-parameters to weigh these losses with $(\alpha, \beta) \in [0, 1]$ and $\alpha + \beta \leq 1$.

2) Regularization with Monte Carlo Dropout: A powerful approach to regularize a model is with dropout, where nodes in the network are randomly removed during training in each epoch. Dropout helps regularize a DNN by training thinner networks at each iteration, avoiding co-adaptations between nodes of the network. Co-adaptation appears when different hidden units in a neural network have highly correlated behavior. It is better for computational efficiency and the models ability to learn a general representation if hidden units can independently detect features of each other. Therefore, these co-adaptation between nodes are detrimental to the models. Dropout is an effective approach to avoid these co-adaptations. Studies on SER have used dropout in a *monte carlo* fashion to develop generalizable models for SER. Sridhar and Busso [7] used knowledge distillation to learn acoustic representations under a teacher-student paradigm to improve consistency in the predictions, generalizing the models to diverse input conditions. In this approach, an ensemble of teacher models were created with *Monte Carlo* (MC) dropout. The study used multiple teacher models implemented with different dropout rates to increase the diversity of the ensemble. The learned feature embeddings of the teachers were used to train an ensemble of student models. This approach was found to increase the consistency of the models by decreasing the uncertainty in the prediction of emotional attributes provided by the student ensemble.

The approach from Sridhar and Busso [7] used MC dropout as a technique to implement variational inference within a Bayesian deep learning framework to tackle the SER problem and achieved significant performance gains. This approach also points to a new direction of research for SER, where Bayesian learning approaches can be successfully used.

B. Cross-Domain Adaptation

Cross-corpora evaluation of SER models often leads to a decrease in performance due to the poor generalization across different conditions. The challenge of source-target mismatch is best solved by training models on large amounts of labeled data from the target domain. However, obtaining large labeled datasets is expensive and time consuming. Learning domain invariant representations is a viable direction that helps in increasing the SER performance.

1) Fine-tuning a front-end network: Another approach for achieving generalization in SER is by fine-tuning the representations learned by a front-end network to model the emotional content of a target corpus. Lu *et al.* [21] used this approach instead of transfer learning between emotional corpora. To avoid the expensive human annotation process and cover a wide range of information, a speech front-end

network, referred to as AV-SpNET, was trained with large-scale media data collected in the wild, which includes multiple languages across different domains. To assign pseudo labels to this unlabeled data, Lu *et al.* [21] proposed a rule-based method to assign arousal labels based on prosodic information. Valence scores were derived from transcription of the recordings using sentiment analysis. The AV-SpNET is built with a MTL structure using CNN, where the primary task is to recognize the pseudo labels ($\mathcal{L}_{emo}$) and the secondary task is to reconstruct the inputs with an autoencoder ($\alpha\mathcal{L}_{auto}$). The model is optimized by using a combination of reconstruction and proxy label recognition losses, as shown in Equation 8. Once the model is trained, the parameters of the AV-SpNET network are frozen. The outputs of this network are then used as the input of an SER system built for the target domain problem. Therefore, this approach is implemented in two steps. While this approach needs no labeled data from the source and target domains, it requires huge amount of data to achieve better generalization.

$$\mathcal{L} = \alpha\mathcal{L}_{auto} + (1-\alpha)\mathcal{L}_{emo} \tag{8}$$

2) Domain Adversarial Training: Domain adaptation is another approach to reduce the mismatch between train and test conditions. Abdelwahab and Busso [9] used a MTL framework with gradient reversal to achieve generalization. The auxiliary task is to create a domain classifier that recognizes whether the speech is either from the source or target domains. A shared feature representation between domains is learned, which preserves discriminative information for the SER task. This approach is implemented by using a gradient reversal layer where the gradient produced by the domain classifier is reversed and propagated to the shared layers such that the model learns an indistinguishable representation for both domains. An added benefit of this approach is that no labeled data from the target domain is necessary to train the domain classifier. $\mathcal{L}_y$ and $\mathcal{L}_d$ are the losses related to the attribute prediction task and domain classification task, respectively. The overall cost function can be obtained using Equation 9,

$$E(\theta_f, \theta_y, \theta_d) = \frac{1}{n}\sum_{i=1}^{n}\mathcal{L}_y^i(\theta_f, \theta_y) - \lambda(\frac{1}{m}\sum_{i=1}^{m}\mathcal{L}_d^i(\theta_f, \theta_d)) \tag{9}$$

where θ_f, θ_y and θ_d represent the parameters of the shared layers, layers related to the main prediction task, and the layers of the domain classifier, respectively. The variable n is the number of labeled samples and m is the number of the labeled and unlabeled data samples. The model is trained with a minmax objective with λ controlling the tradeoff between the two losses. The optimal setting is achieved when the prediction accuracy for the SER task is maximized and the performance for the domain classifier is at chance (i.e., the feature representation does not distinguish between source and target domains).

Another example is the study from Chao *et al.* [3], which focused on learning an encoder to derive speech representations between domains that would mitigate the issue of emotional semantic inconsistency (i.e., the difference in the emotion labeling between two different domains). Specifically, Chao *et al.* [3] designed an adversarial discrepancy learning strategy. This strategy involves an iterative minmax approach. First, they trained two source emotion regressor networks that would result in a maximal recognition difference in the target domain while using a fixed source speech representation encoder. Then, they minimized such a recognition difference by updating the source speech representation encoder while keeping these trained regressors fixed. This process then iterates until convergence. This particular strategy of minimizing the maximum difference does not simply learn an encoder to obtain common speech representation between domains, but also encourages such an encoded space to minimize the potential emotional semantic distortion between source and target.

While domain adversarial training techniques are very successful for generalization, the minmax nature of the losses used during training makes these approaches unstable and sensitive to hyperparameter tuning.

3) Manifold Subspace Learning: Transfer learning can be effective to minimize mismatches between source and target domains. Zhang *et al.* [8] used an approach inspired on manifold and subspace learning to transfer knowledge from domains in a cross-corpus SER evaluation. The approach constructs a neighbor graph that can measure the differences in the feature distributions between the source and target datasets by preserving the geometrical structure of the data. During training, they learn a corpus-invariant projection matrix that aligns features from different corpora into a common discriminative subspace, which leads to improvements in SER performance. This is a joint framework that combines a discriminative subspace learning, a graph-based distance metric and a feature selection method. It is not completely unsupervised, which helps the model to avoid learning irrelevant feature representations that may not be discriminative for the SER classifier. However, this approach is implemented in an iterative manner and needs to tune several hyper-parameters. The approach also uses the $l_{2,1}$-normalization, which combines in a single function the l_1 and l_2 constraints. This optimization is implemented in an iterative manner, first the l2 l_2 constraint and then l_1 constraint, which makes it computationally expensive.

4) Generative Models: Another approach that has been recently used to improve the generalization of the models is with generative models, especially with *generative adversarial network* (GAN). GAN uses an adversarial approach between a generator that creates synthetic samples matching a target distribution, and a discriminator that determines whether the samples are real or created by the generator (i.e., fake). The key idea in using generative models is to create rich representations, especially when the training data is limited. Sahu *et al.* [22] used a model relying on GAN to classify emotions based on the low dimensional feature bottleneck layer of an autoencoder. The lower dimensional encoding space is matched

with a simple prior distribution p_z by using a GAN formulation. They used samples from this lower dimensional subspace as input to the decoder of the autoencoder to obtain synthetic feature vectors, which were further used for SER. The authors developed three different variations of this autoencoder-GAN framework: (1) a GAN framework is used to match the encoding space to p_z, (2) an additional GAN to match the output of the decoder (synthetic features) to the real feature vectors (input features), and (3), a similar framework to the first two approaches, but conditioning the GAN with an emotion class label. They trained the models with the MSE loss as the reconstruction loss to update the autoencoder weights, cross-entropy loss for the GAN, and an additional mutual information loss for the conditional GAN. This approach was evaluated with cross-corpus experiments with low-resource conditions on the training data, demonstrating the improvement in generalization by adding synthetic samples. The study trained SER models with very few samples from the source corpus. They progressively added more synthetic samples, observing higher improvements in recognition accuracy on the target corpus as they added more synthetic data.

Bao *et al.* [19] presented another study that uses a generative model to address the problem of data scarcity in SER. This study used CycleGAN to generate synthetic feature representations that aim to reduce the distance between synthetic and real data and increase the emotional discrimination of the feature representation. CycleGAN can map the source and target domains without paired training data. The CycleGAN implements a bi-directional mapping between the source and target domains where an adversarial discriminator generates synthetic samples indistinguishable from the real samples. A classifier is added to discriminate emotions between the generated data to learn a generalized distribution from real source samples, avoiding that the model only reconstructs the original data. The overall loss function is given by Equation 10,

$$\mathcal{L} = \sum_i \mathcal{L}_i^{GAN} + \lambda^{cyc} \sum_i \mathcal{L}_i^{cyc} + \lambda^{cls} \mathcal{L}^{cls} \tag{10}$$

where $\mathcal{L}_i^{GAN}$ is the minmax GAN loss for each emotional class i, $\mathcal{L}_i^{cyc}$ is the cycle consistency loss, and $\mathcal{L}^{clc}$ is the softmax cross-entropy loss of the classifier added to the model. The cycle consistency loss accounts for translating back the synthetic data from the target to the source domain, calculating the MSE between real and generated samples. The weights λ^{cyc} and λ^{cls} are hyper-parameters of the model.

Su *et al.* [18] proposed a novel approach to achieve cross-corpus emotion recognition. They trained a CycleGAN with two generators to learn a bi-directional mapping between the source (S) and the target (T) corpora with a goal of generating synthetic source domain samples that are target-aware. They used labeled data from the source domain and unlabeled data from the target domain. To achieve their objective,

they conditioned the generator to learn the mapping from the target to the source domain ($G_{T\rightarrow S}$) on the emotional labels from the source domain. They enforced two regularization constraints: the identity loss and the cycle consistency loss. The identity loss maintains the source domain information after transformations. This objective is achieved by transforming the source samples using the transformation $G_{T\rightarrow S}$ back to the source domain. Then, the loss function imposes that the transformed samples should be similar to the actual source samples. This loss also ensures that samples in the target domain that are similar to the samples in the source domain are not heavily transformed. The cycle consistency loss ensures that the samples undergoing bi-directional transformation ($G_{S\rightarrow T}$ to $G_{T\rightarrow S}$) are identical to the original samples.

The approaches presented by Sahu *et al.* [22], Bao *et al.* [19] and Su *et al.* [18] need a two stage training procedure, where, first, the generator of the GAN is trained to generate fake samples, and, second, the augmented samples are used to train the SER classifier. Another disadvantage is the use of the minmax loss function, which makes the GAN training very unstable and sensitive to hyper-parameter tuning.

C. Self-Supervised Learning Methods

An appealing approach to improve the generalization of the SER models is the use of self-supervised learning, where the key idea is to derive labels for auxiliary tasks directly from the data. The aim of this formulation is that by solving these auxiliary tasks, the model has to extract general patterns from the data, which leads to feature representations that generalize better for the main task. An example of self-supervised learning in other domains includes masking a word in a sentence, expecting that the network would predict the missing word. The label here is the missing word which is freely available. Another example in natural language processing is changing a word in a sentence for a random word and asking the neural network to identify the mistake. In SER, this approach can be used with predictive and contrastive models.

1) Predictive models: A class of self-supervised models are predictive models, where the loss function is computed in the output space by estimating performance between predicted and ground truth labels. The losses include the self-supervised tasks or the main target task. An example of predictive models in SER was proposed by Pascual *et al.* [12]. This study developed a *problem-agnostic speech encoder* (PASE) to learn general speech representations to tackle different downstream supervised tasks (e.g., SER or speaker recognition). They designed a single neural encoder followed by several small subnetworks to jointly solve multiple self-supervised tasks. These subnetworks consist of self-supervised tasks, including reconstruction of the waveform and acoustic features such as *Mel-frequency cepstral coefficients* (MFCC)

and prosody features. The general representations created with these self-supervised tasks are used for SER and other speech tasks by either freezing the encoder or fine-tuning the encoder and task classifier.

2) Contrastive models: Another self-supervised approach is to use contrastive losses in the feature representation space. An approach to achieve this goal is by adding data perturbations to create different views from the data, and training the network to minimize the mismatches between the views. The concept of "views" in this context comes from the multi-view training strategy, where multiple inputs are used to train a system. The inputs could be perturbations of a single modality (e.g., adding noise, adversarial changes through gradient reversal, and speech rate manipulations) or different features extracted from the signal (e.g., extracting features from statistics over frame level features, spectral features, and temporal features). Using information from different views can significantly improve the model performance. Multi-view learning aims to learn one function to model each view and jointly optimizes all the functions to improve the generalization performance. Combining contrastive and reconstruction losses has been shown to be an effective technique in SER tasks.

Jiang *et al.* [13] used different views of the input data by introducing augmentations such as random pitch shift, speed perturbation, room reverberation, and additive noise to the raw speech waveforms and spectrograms. They learned speech representations using encoders. For a given input sample, they used two different augmentations to provide two correlated views of the sample and learned an encoded representation by simultaneously training two encoders. They used the MSE loss between the encoded representations and the input raw feature. The encoders were built using the transformer layers. By maximizing agreement between the learned feature representations of the two augmented samples via a contrastive loss in the latent space, they extracted meaningful feature representations for a SER downstream task. The contrastive loss objective used here is called the *normalized temperature-scaled Cross Entropy Loss* (NT-Xtent). Equation 11 shows this loss, where $sim(z_i, z_j)$ represents the cosine similarity between the encoded feature representations. The function $\mathbb{1}_{[k=i]} \in [0, 1]$ is an indicator function that is one if $k \neq i$ and zero otherwise. The variable τ denotes a temperature parameter. Equation 11 represents the loss function for a positive pair of examples (i, j). The final loss is computed across all positive pairs (both (i, j) and (j, i)) within a mini-batch.

$$\mathcal{L}_{i,j} = -\log \frac{\exp(sim(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(sim(z_i, z_k)/\tau)} \tag{11}$$

D. Proxy Label Approaches

Proxy label approaches are a particular class of *semi-supervised learning* (SSL) algorithms that focus on producing pseudo labels on unlabeled data, augmenting the training set. These proxy labels are produced

by the model itself, or variants of it, without any additional supervision. Some of the prominent SSL methods relying on proxy label include self-teaching, self-ensembling, and multi-view training.

1) Generative Modeling with Label Smoothing: Zhao *et al.* [23] proposed a *semi-supervised generative adversarial network* (SSGAN) with proxy labels to learn powerful feature representations to achieve state-of-the-art results on publicly available emotional corpora. In addition to classifying the inputs as real or fake, the SSGAN discriminator is also able to predict the emotional class of a sample if they are real. They used a divergence probability measure to smooth the conditional label distribution given the inputs using adversarial and virtual adversarial training methods. This distribution smoothing process using virtual labels for the unlabeled set serves as a proxy label to train the model.

Example: *Domain Adversarial Neural Network* (DANN) for SER

DANN is trained with labeled data from the source domain and unlabeled data from the target domain. The network consists of a shared feature representation layer followed by two pathways for the domain classifier and SER task. There is a gradient reversal layer in between the feature representation layers and the domain classifier. A concise illustration of the network architecture is shown in the bottom left corner of Fig 4. The implementation of this approach follows these steps:

- Step I: Train the network with labeled data from the source domain (database A) and unlabeled data from the target domain (database B). For example, database A can be a speech emotional corpus, and database B can be spontaneous recordings collected from the domain where the SER system will be used.
- Step II: The main task classifier is trained with labeled data from the source domain. This can be a categorical emotion classification task or an emotional attribute prediction task. The domain classifier is trained with data from both the source and target domains. Emotional labels are not needed for this auxiliary task.
- Step III: Both the main task and the domain classifiers are trained in parallel using the objective function described in Equation 9. With the minmax nature of the loss function, the feature representations learned will be effective across the source and target domains.
- Step IV: The training of a network with an adversarial loss function using a gradient reversal layer may be unstable if the hyper-parameters are not properly adjusted, especially λ which combines both losses (Eq.9). A recommended approach is to initialize λ to zero for the first 10 epochs, and slowly increasing its value till it reaches $\lambda = 1$ by the end of the training. Therefore, the models will be properly initialized before introducing the gradient reversal layer.

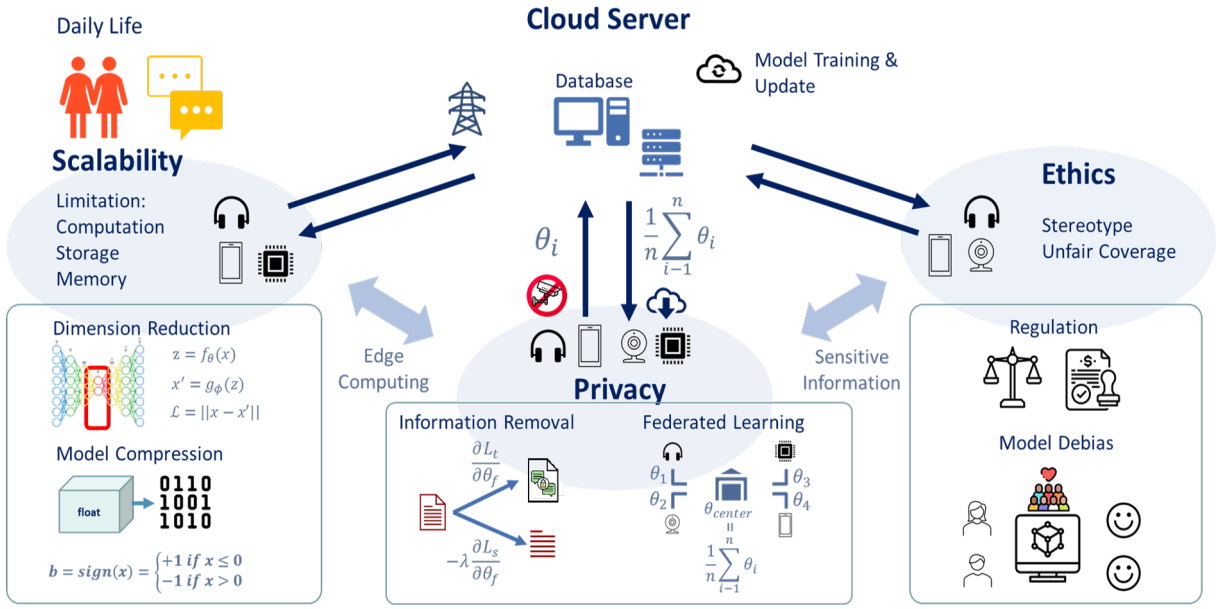

Fig. 5. The overview of the SER usability challenges and current solutions

This approach does not need to include complex architectures. Abdelwahab and Busso [9] implemented each of the three blocks (feature representation layers, domain classifier, and task classifier) with a two-layer DNN, each of them with 256 nodes.

V. Affective Speech Modeling: Usability

Performance should not be the only metric considered when deploying SER systems for real-world applications. There are also major usability constraints that need to be addressed, including scalability, privacy, and ethics requirements, where representation learning methods can be used to mitigate potential issues associated with these considerations. Current application systems are often set up as cloud servers with local end users as shown in Figure 5. Several issues arise when providing SER services with this setting. For example, transferring local data over internet may result in delayed responses, or even worse, in leakage of private information. If we decide to perform model prediction in the local devices (e.g., edge computing), we need to dramatically condense the model and data representation. Another related problem is how to train or adapt the model in the server when new information is available from the local users. Another usability issue is unintentional bias in SER systems, which can result in important negative societal consequences. Biased results may reflect issues related to imbalanced representation in the data or underlying social stereotypes reflected on the labels. This section discusses some of the representation learning approaches intended to mitigate these usability issues for SER systems.

A. Scalability with Compact Representation

State-of-the-art representation learning frameworks utilize various forms of reconstruction loss optimization methods to minimize the difference in the response of a full original model and a squeezed model. The goal is to fit the high dimensional DNN into a light network that can be used in a local mobile device. Several studies have proposed techniques to simultaneously take care of both the recognition performance and the model complexity [10], [24]. This section discusses two directions to address this issue: dimension reduction and model compression.

1) Reducing the dimension of the feature representation: The techniques of dimensional reduction have been used for years since hand-crafted acoustic representations used in early works in SER tasks led to over-expanded dimension problems. Studies have proposed more targeted feature sets rooted on the externalization of expressive speech. A prominent work is the eGeMAPS feature set [1], which is a minimal selected acoustic set for paralinguistic tasks based on psychoacoustic knowledge and statistical results. Besides manual selection approaches to reduce the feature dimension, studies have widely used traditional statistical feature selection algorithms such as *principal component analysis* (PCA) and *forward feature selection* (FFS) as a pre-processing step to reduce the feature dimension. With DNN, feature reduction can be effectively implemented with autoencoders using a bottleneck layer trained with either supervised or unsupervised strategies. The autoencoder aims to reconstruct input features at the output layer, and, therefore, preserves meaningful information in the latent space. Autoencoder can be considered as a non-linear generalization of PCA. Advanced networks cast the problem as a latent distribution modeling problem and solve it with generative models such as *variational autoencoder* (VAE), *adversarial autoencoder* (AAE), and GAN. These networks add different loss functions to constrain the latent layer to follow a given distribution. Studies have reported that these low dimensional latent representations can not only reduce memory consumption, but also improve the robustness by mitigating the overfitting problem [24]. An important observation is that there is a tradeoff between model compactness and system performance. An open challenge is to balance this tradeoff achieving a useful system with reasonable performance.

2) Model Compression: A straightforward approach to reduce the model complexity is by squeezing a complex model into a light architecture with a small number of parameters. Training approaches such as the teacher-student model can be very effective, where the objective for the light model (i.e., student) is to mirror the representation response of the full model (i.e., teacher). A light model not only requires less computational resources, but also less memory, which can be an important requirement for edge computing. Another direction to compress the model is to focus on the architecture itself by pruning the

number of deep network nodes or layers to fundamentally reduce the memory usage. Specifically, several studies have designed low-rank layers, 1×1 convolutional filters, or pooling mechanisms to shrink the node numbers in deep network layers. These models often achieve comparable performance than the full model.

An alternative approach to reduce the memory requirement is to quantize the network weights, compressing the size of every neural network node unit. Zhao *et al.* [10] proposed to binarize the weights of the SER model, successfully achieving prominent compression rate. The method uses the sign function to perform the binarization. The idea is to minimize the l_2 loss computed between the float-value weight matrix and the binarized target matrix with a scaling factor. Take convolutional layer as an example. The weights W and inputs I_s are processed with a binarized layer with $H = sign(W)$ and $B = sign(I_s)$. The optimized objective function is expressed as:

$$\alpha^*, \beta^* = \underset{\alpha,\beta}{\operatorname{argmin}} ||\mathbf{I_s^T W} - \alpha\beta\mathbf{H^T B}||. \tag{12}$$

We can regard $\alpha^*\mathbf{H}$ and $\beta^*\mathbf{B}$ as the binarized approximation of $\mathbf{I_s}$ and $\mathbf{W}$. After back-propagation with the recognition loss, we obtain the optimized rescaling factors α and β. We represent the original model with these binarized parameters which significantly reduce each value into only 1 bit. The experimental results using the binarized convolutional recurrent neural network achieved only 1% loss in accuracy in two SER databases with a model that was 26 times smaller in memory requirement.

B. Privacy-Aware Speech Representation

Privacy concerns have rapidly emerged with the growing integration of SER into everyday life. Speech representation is known to contain sensitive personal attributes. From acoustic features, it is possible to infer personal information such as identity, gender, and age. Developing methods to preserve users privacy is an important usability goal. Studies have focused on two major directions: 1) securing communication between cloud service and edge devices, where the inference happens in the cloud, and the edge device only needs to upload the feature and wait for the prediction output from the cloud service, and 2) training approaches without collecting sensitive information from edge-based devices, where the inference directly happens at the edge device. This Section discusses these two scenarios.

1) Cloud-Edge Service (Inference on the Cloud Service): In deploying SER as a cloud service, a user's private information is exposed to risk during the communication between the edge and the cloud. In this scenario, studies have proposed representation learning approaches to mask sensitive attributes. The approaches are often based on adversarial training with gradient reversal layer and regularized

optimization. These methods can be used to handle a single or few sensitive attributes, where the model is built with parallel paths, one for the main SER task, and another for the sensitive attribute that we want to mask (identity, gender, age, or even the location). The model essentially erases sensitive attributes using the reverse gradient layer [25] or flexibly aligns the privacy attribute in a specific order through a layered dropout mechanism [11] when deriving the representation, while maintaining high accuracy for the main SER task. If the loss function for the main task is $\mathcal{L}_t$, the loss function for the sensitive attributes task is $\mathcal{L}_s$, and the current parameters of the network is θ_f, the gradient that is back-propagated (Δw_{total}) is computed in Equation 13. The parameter λ weighs the loss of the gradient reversal layer to control the tradeoff between privacy preservation and the main task performance.

$$\Delta w_{total} = \frac{\partial L_t}{\partial \theta_f} + (-\lambda \frac{\partial L_s}{\partial \theta_f}) \tag{13}$$

An alternative approach is to use regularized optimization, where we can introduce a loss to guide the model to remove sensitive information from the user. For example, we can preserve privacy-related attributes by exploiting contrastive losses. Arora and Chaspari [26] proposed a training strategy using the Siamese network that creates uniform random pairing for multiplicative perturbation of the data. The approach repeatedly applies the Gombertz function, which is a non-linear transformation that can prevent the inversion of the sensitive information (i.e., speaker information in this study), and limits the growth of the input space. The use of the contrastive loss maximizes the emotion-related discriminative distance and effectively reduces the growth rate of the input sensitive attribute information by a repeated Gombertz function in the learned representation.

2) On-Edge Service (Inference on the Edge Device): In the scenario of edge-based applications, the goal is to evaluate the SER model on the edge device without transmitting raw data. This on-device training approach directly prevents private information leakage during transmission. The paradigm is referred to as *federated learning* (FL) [27], which enables the system to locally derive a representation, sending only model information from edge devices that are aggregated on the cloud. During inference, the network parameters are distributed back to edge devices, so the local models can perform as well as equivalent models trained with all the data.

We assume that we have n local users $\{E_1, E_2, \ldots, E_n\}$ training locally machine learning models with their own data $\{D_1, D_2, \ldots, D_n\}$. Conventionally, the most common approach is to train a final model M_{all} by using the union of all the data $\mathcal{D} \in \{D_1 \cup D_2 \cup D_3 \cup \ldots \cup D_n\}$. However, studies have developed federated learning approaches to train a model without sharing the data, addressing privacy issues. The ultimate goal is to have a performance similar to the performance of a model trained with all the data.

Each edge device learns a lightweight representation locally trained using data collected on the edge. The cloud model only needs either the estimated gradients or the parameters of the edge models without the need of the original data or the learned representation. Equations 14 and 15 show the averaged federated learning variables, where Δw_i stands for the gradient of the model i, and θ_i stands for the parameters of the model i. The final cloud model is updated with these aggregated gradients or parameters. The edge devices received the updated model during inference.

$$\theta_{center} = \frac{1}{n}\sum_{i=1}^{n}\theta_i \tag{14}$$

$$\Delta w_{center} = \frac{1}{n}\sum_{i=1}^{n}\Delta w_i \tag{15}$$

There are three commonly used types of federated learning approaches: *horizontal federated learning* (HFL), *vertical federated learning* (VFL), and *federated transfer learning* (FTL). The selection of these algorithms depends on the target scenario. We discuss HFL in more detail, which is the most common FL approach. HFL corresponds to the case when the tasks and input features used across edge devices are both the same, but the set of users are different (e.g., device A and device B both predict emotional categories through acoustic features, but each device belongs to different users). It is often implemented with the averaging integration approach, where the parameters of the model in the cloud are updated according to the average encrypted gradients from the edge devices [28].

Federated learning provides a privacy-preserving approach to locally build a robust and strong model. FL has the advantage of facilitating the integration of edge users data without privacy infringement. By aggregating the parameters or gradients, this approach can still achieve similar performance than conventional methods trained with all the data, without the risk of data leakage, since the local data is never shared with the cloud. These advantages are appealing for SER, given the applications that are relevant to this area (e.g., healthcare). Recently, Latif *et al.* [28] has demonstrated that FL is an effective approach in SER tasks. A limitation of using FL is the increase of the computation consumption imposed on the edge devices. This approach also requires more memory. These limitations will be mitigated as more powerful portable devices are introduced in the market.

Example: federated learning algorithm for SER

We provide an example on how to implement a federated learning solution for SER. We focus on horizontal federate learning. Figure 6 illustrates the process, where E_i represents the device of user i. We assume that each user is using the SER service on the device. This iterative strategy consists of

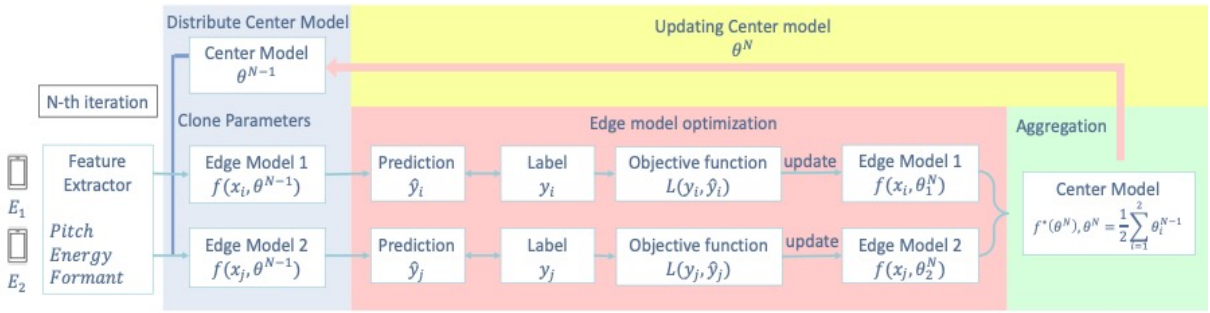

Fig. 6. The flow chart of federated learning algorithm example, E_n is the edge device of user n, then f means the local model distributed from center model, and θ, x is the model parameters and features respectively. Further, L is the loss function, and in this example we assume it as cross-entropy loss function.

four steps: distributed center model, edge model optimization, aggregation and center model update.

- Step I: The first step is distributed center model, where each device directly clones the parameter from the cloud service model. Therefore, the edge models are identical at the beginning.
- Step II:

  The second step is edge model optimization, where the edge models predict the emotion output of each utterance. The edge models compute the cross-entropy loss and directly optimize the local models. Note that each model is different at this stage, as dictated by the local data used in each device.
- Step III:

  The third step is aggregation, where the cloud service averages all the parameters from the edge models optimized with local data (Equations 14 and 15).
- Step IV:

  The fourth step is center model update, where the SER model in the cloud is updated with the aggregated model parameters.

By repeating these four steps, the center model is optimized without getting data from edge devices, properly preventing the disclosure of private information.

C. Ethical Considerations in Building Speech Representation

Another important usability issue is ethical considerations that have to be addressed during SER deployment. While there is still an active discussion about the definition of privacy, the data protection scheme for service providers, and the modification and creation of new regulations [29], we can make actionable changes in building representation learning algorithms for SER to attenuate potential ethical issues.

1) Reducing Bias in the SER Models: The data used to train a model can be affected by unintentional bias, which will be reflected on the models. The bias appears due to poor representation of under-represented groups in the data or by social stereotypes reflected on the labels collected with perceptual evaluations. An interesting and immediate approach to attenuate bias in the models is by building representation learning approaches that intentionally compensate for known unbalance representation. Domain adaptation is an appealing approach, where the auxiliary task is the recognition of an attribute that we aim our model to correct for bias. For example, Gorrostieta *et al.* [30] integrated the concept of "equality of odds" to define the fairness of the model, which means the distribution of sensitive predictions should be equally distributed. The study formulated the protected variable (e.g., gender or age) as an adversary task and trains a main model, which considers the adversarial loss of the protected attributes. The study showed that the proposed adversary representation learning approach was able to explicitly reduce unwanted bias that exists in a given dataset. These approaches address the fairness in the learned speech representation space when modeling the affective speech signal. This is a critical problem since emotion recognition systems have become a key component in decision making processes that impact our lives.

VI. Conclusions

The growing body of SER research in using deep representation learning approaches has opened up the possibility of wide deployment of speech solutions across domains, where we expect rapid into-life adoption of SER technology. SER can be readily *plugged into* a variety of human-centered and service-oriented industries, such as finance, entertainment, sales, marketing, healthcare, and education, where spoken interaction plays a major role. This paper provided a comprehensive summary on three major affective speech signal modeling challenges that are needed to be addressed to deploy successful SER solutions: robustness, generalization, and usability. This study presented effective deep representation learning architectures that are suitable to address these issues. The deep representation learning methods covered in this study provide appealing solutions to build robust SER systems against unwanted signal and natural human perceptual variations. The solutions improve, in a principled way, the generalization of speech representations that are agnostic to contexts, settings, and domains. The solutions consider usability constraints while learning speech representation to improve scalability and trustworthiness, while deploying SER technology. The complexity involved in realizing the value of SER in our everyday life requires continuous scientific and technical endeavor in modeling and representing emotional speech signal. Affective speech processing formulations with carefully designed deep neural networks to address

these key challenges will undoubtedly provide a core module to deploy SER algorithms built on the laboratory into ubiquitous SER services in the market.

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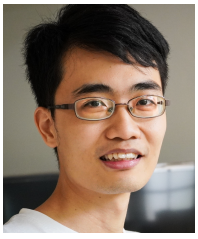

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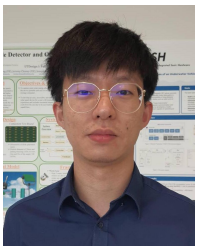

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