Deep Representation Learning in Speech Processing: Challenges, Recent Advances, and Future Trends

Siddique Latif1,2, Rajib Rana1, Sara Khalifa2, Raja Jurdak2,3, Junaid Qadir4, and Björn W. Schuller5,6

1University of Southern Queensland, Australia
2Distributed Sensing Systems Group, Data61, CSIRO Australia
3Queensland University of Technology (QUT), Brisbane, Australia
4Information Technology University, Punjab, Pakistan
5Imperial College London, UK
6University of Augsburg, Germany

Abstract—Research on speech processing has traditionally considered the task of designing hand-engineered acoustic features (feature engineering) as a separate distinct problem from the task of designing efficient machine learning (ML) models to make prediction and classification decisions. There are two main drawbacks to this approach: firstly, the feature engineering being manual is cumbersome and requires human knowledge; and secondly, the designed features might not be best for the objective at hand. This has motivated the adoption of a recent trend in speech community towards utilisation of representation learning techniques, which can learn an intermediate representation of the input signal automatically that better suits the task at hand and hence lead to improved performance. The significance of representation learning has increased with advances in deep learning (DL), where the representations are more useful and less dependent on human knowledge, making it very conducive for tasks like classification, prediction, etc. The main contribution of this paper is to present an up-to-date and comprehensive survey on different techniques of speech representation learning by bringing together the scattered research across three distinct research areas including Automatic Speech Recognition (ASR), Speaker Recognition (SR), and Speaker Emotion Recognition (SER). Recent reviews in speech have been conducted for ASR, SR, and SER, however, none of these has focused on the representation learning from speech—a gap that our survey aims to bridge. We also highlight different challenges and the key characteristics of representation learning models and discuss important recent advancements and point out future trends. Our review can be used by the speech research community as an essential resource to quickly grasp the current progress in representation learning and can also act as a guide for navigating study in this area of research.

I. INTRODUCTION

The performance of machine learning (ML) algorithms heavily depends on data representation or features. Traditionally most of the actual ML research has focused on feature engineering or the design of pre-processing data transformation pipelines to craft representations that support ML algorithms [1]. Although such feature engineering techniques can help improve the performance of predictive models, the downside is that these techniques are labour-intensive and time-consuming.

To broaden the scope of ML algorithms, it is desirable to make learning algorithms less dependent on hand-crafted features. A key application of ML algorithms has been in analysing and processing speech. Nowadays, speech interfaces have become widely accepted and integrated into various real-life applications and devices. Services like Siri and Google Voice Search have become a part of our daily life and are used by millions of users [2]. Research in speech processing and analysis has always been motivated by a desire to enable machines to participate in verbal human-machine interactions. The research goals of enabling machines to understand human speech, identify speakers, and detect human emotion have attracted researchers’ attention for more than sixty years [3]. Researchers are now focusing on transforming current speech-based systems into the next generation AI devices that react with humans more friendly and provide personalised responses according to their mental states. In all these successes, speech representations—in particular, deep learning (DL)-based speech representations—play an important role. Representation learning, broadly speaking, is the technique of learning representations of input data, usually through the transformation of the input data, where the key goal is yielding abstract and useful representations for tasks like classification, prediction, etc. One of the major reasons for the utilisation of representation learning techniques in speech technology is that speech data is fundamentally different from two-dimensional image data. Images can be analysed as a whole or in patches but speech has to be studied sequentially to capture temporal contexts.

Traditionally, the efficiency of ML algorithms on speech has relied heavily on the quality of hand-crafted features. A good set of features often leads to better performance compared to a poor speech feature set. Therefore, feature engineering, which focuses on creating features from raw speech and has led to lots of research studies, has been an important field of research for a long time. DL models, in contrast, can learn feature representation automatically which minimises the dependency on hand-engineered features and thereby give better performance in different speech applications [4]. These deep models can be trained on speech data in different ways.

Email: siddique.latif@usq.edu.au
such as supervised, unsupervised, semi-supervised, transfer, and reinforcement learning. This survey covers all these feature learning techniques and popular deep learning models in the context of three popular speech applications [5]: (1) automatic speech recognition (ASR); (2) speaker recognition (SR); and (3) speech emotion recognition (SER).

Despite growing interest in representation learning from speech, existing contributions are scattered across different research areas and a comprehensive survey is missing. To highlight this, we present the summary of different popular and recently published review papers Table 1. The review article published in 2013 by Bengio et al. [1] is one of the most cited papers. It is very generic and focuses on appropriate objectives for learning good representations, for computing representations (i.e., inference), and the geometrical connections between representation learning, manifold learning, and density estimation. Due to an earlier publication date, this paper had a focus on principal component analysis (PCA), restricted Boltzmann machines (RBMs), autoencoders (AEs) and recently proposed generative models were out of the scope of this paper. The research on representation learning has evolved significantly since then as generative models like variational autoencoders (VAEs) [10], generative adversarial networks (GANs) [11], etc., have been found to be more suitable for representation learning compared to autoencoders and other classical methods. We cover all these new models in our review. Although, other recent surveys have focused on DL techniques for ASR [7], [9], SR [12], and SER [8], none of these has focused on representation learning from speech. This article bridges this gap by presenting an up-to-date survey of research that focused on representation learning in three active areas: ASR, SR, and SER. Beyond reviewing the literature, we discuss the applications of deep representation learning, present popular DL models and their representation learning abilities, and different representation learning techniques used in the literature. We further highlight the challenges faced by deep representation learning in the speech and finally conclude this paper by discussing the recent advancement and pointing out future trends. The structure of this article is shown in Figure 1.

II. BACKGROUND
A. Traditional Feature Learning Algorithms

In the field of data representation learning, the algorithms are generally categorised into two classes: shallow learning algorithms and DL-based models [13]. Shallow learning algorithms are also considered as traditional methods. They aim to learn transformations of data by extracting useful information. One of the oldest feature learning algorithms, Principal Components Analysis (PCA) [14] has been studied extensively over the last century. During this period, various other shallow learning algorithms have been proposed based on various learning techniques and criteria, until the popular deep models in recent years. Similar to PCA, Linear Discriminant Analysis (LDA) [15] is another shallow learning algorithm. Both PCA and LDA are linear data transformation techniques, however, LDA is a supervised method that requires class labels to maximise class separability. Other linear feature learning methods include Canonical Correlation Analysis (CCA) [16], Multi-Dimensional Scaling (MDS) [17], and Independent Component Analysis (ICA) [18]. The kernel version of some linear feature mapping algorithms are also proposed including kernel PCA (KPCA) [19], and generalised discriminant analysis (GDA) [20]. They are non-linear versions of PCA and LDA, respectively. Another popular technique is Non-negative Matrix Factorisation (NMF) [21] that can generate sparse representations of data useful for ML tasks.

Many methods for nonlinear feature reduction are also proposed to discover the non-linear hidden structure from the high dimensional data [22]. They include Locally Linear Embedding (LLE) [23], Isometric Feature Mapping (Isomap) [24], T-distributed Stochastic Neighbour Embedding (t-SNE) [25], and Neural Networks (NNs) [26]. In contrast to kernel-based methods, non-linear feature representation algorithms directly learn the mapping functions by preserving the local information of data in the low dimensional space. Traditional representation algorithms have been widely used by researchers of the speech community for transforming the speech representations to more informative features having low dimensional space (e.g., [27], [28]). However, these shallow feature learning algorithms dominate the data representation learning area until the successful training of deep models for representation learning of data by Hinton and Salakhutdinov in 2006 [29]. This work was quickly followed up with similar ideas by others [30], [31], which lead to a large number of deep models suitable for representation learning. We discuss the brief history of the success of DL in speech technology next.

B. Brief History on Deep Learning (DL) in Speech Technology

For decades, the Gaussian Mixture Model (GMM) and Hidden Markov Model (HMM) based models (GMM-HMM) ruled the speech technology due to their many advantages including their mathematical elegance and capability to model time-varying sequences [32]. Around 1990, discriminative training was found to produce better results compared to the models trained using maximum likelihood [33]. Since then researchers started working towards replacing GMM with a feature learning models including neural networks (NNs), restricted Boltzmann machines (RBMs), deep belief networks (DBNs), and deep neural networks (DNNs) [34]. Hybrid models gained popularity while HMMs continued to be investigated.

In the meanwhile, researchers also worked towards replacing HMM with other alternatives. In 2012, DNNs were trained on thousands of hours of speech data and they successfully reduced the word error rate (WER) on ASR task [35]. This is due to their ability to learn a hierarchy of representations from input data. However, soon after recurrent neural networks (RNNs) architectures including long-short term memory (LSTM) and gated recurrent units (GRUs) outperformed DNNs and became state-of-the-art models not only in ASR [36] but also in SER [37]. The superior performance of RNN architectures was because of their ability to capture temporal contexts from speech [38], [39]. Later, a cascade of convolutional neural networks (CNNs), LSTM and fully connected (DNNs) layers were further
shown to outperform LSTM-only models by capturing more discriminative attributes from speech \cite{40, 41}. The lack of labelled data set the pace for the unsupervised representation learning research. For unsupervised representation from speech, AEs, RBMs, and DBNs were widely used \cite{42}.

Nowadays, there has been a significant interest in three classes of generative models including VAEs, GANs, and deep auto-regressive models \cite{43, 44}. They have been widely being employed for speech processing—especially VAEs and GANs are becoming very influential models for learning speech representation in an unsupervised way \cite{45, 46}. In speech analysis tasks, deep models for representation learning can either be applied to speech features or directly on the raw waveform. We present a brief history of speech features in the next section.

C. Speech Features

In speech processing, feature engineering and designing of models for classification or prediction are often considered as separate problems. Feature engineering is a way of manually designing speech features by taking advantage of human ingenuity. For decades, Mel Frequency Cepstral Coefficients (MFCCs) \cite{47} have been used as the principal set of features for speech analysis tasks. Four steps involve for MFCCs extraction: computation of the Fourier transform, projection of the powers of the spectrum onto the Mel scale, taking the logarithm of the Mel frequencies, and applying Discrete Cosine Transformation (DCT) for compressed representations. It is found that the last step removes the information and destroys spatial relations; therefore, it is usually omitted, which yields the log-Mel spectrum, a popular feature across the speech community. This has been the most popular feature to train DL networks.

| Paper | Focus | Representation Learning | ASR | SR | SER | Deep Learning | Details |
|-------|-------|------------------------|-----|----|-----|---------------|---------|
| Bengio et al. 2013 | Speech | ✓ | ✓ | ✓ | ✓ | ✓ | This paper reviewed the work in the area of unsupervised feature learning and deep learning, it also covered advancements in probabilistic models and autoencoders. It does not include recent models like VAE and GANs. |
| Zhong et al. 2016 \cite{6} | Speech | ✓ | ✓ | ✓ | ✓ | ✓ | In this paper, the history of data representation learning is reviewed from traditional to recent DL methods. Challenges for representation learning, recent advancement, and future trends are not covered. |
| Zhang et al. 2018 | Speech | ✓ | ✓ | ✓ | ✓ | ✓ | This paper provides a systematic overview of representative DL approaches that are designed for environmentally robust ASR. |
| Swain et al. 2018 | Speech | ✓ | ✓ | ✓ | ✓ | ✓ | This paper reviewed the literature on various databases, features, and classifiers for TIR system. |
| Nassif et al. 2019 | Speech | ✓ | ✓ | ✓ | ✓ | ✓ | Has paper presented a systematic review of studies from 2006 to 2018 on DL based speech recognition and highlighted the on the trends of research in ASR. |
| Our paper | Speech | ✓ | ✓ | ✓ | ✓ | ✓ | Our paper covers different representation learning techniques from speech, DL models, discusses different challenges, highlights recent advancements and future trends. The main contribution of this paper is to bring together scattered research on representation learning of speech across three research areas: ASR, SR, and SER. |

Fig. 1: Organisation of the paper.
The Mel-filter bank is inspired by auditory and physiological findings of how humans perceive speech signals [48]. Sometimes, it becomes preferable to use features that capture transpositions as translations. For this, a suitable filter bank is spectrograms that captures how the frequency content of the speech signal changes with time [49]. In speech research, researchers widely used CNNs for spectrogram inputs due to their image like configuration. Log-Mel spectrograms is another speech representation that provides a compact representation and became the current state of the art because models using these features usually need less data and training to achieve similar or better results.

In SER, feature engineering is more dominant and a minimalistic sets of features like GeMAPs and eGeMAPs [50] are also proposed based on affective physiological changes in voice production and their theoretical significance [50]. They are also popular being used as benchmark feature sets. However, in speech analysis tasks, some works [51], [52] show that the particular choice of features is less important compared to the design of the model architecture and the amount of training data. The research is continuing in designing such DL models and input features that involve minimum human knowledge.

D. Databases

Although the success of deep learning is usually attributed to the models’ capacity and higher computational power, the most crucial role is played by the availability of large-scale labelled datasets [53]. In contrast to the vision domain, the speech community started using DNNs with considerably smaller datasets. Some popular conventional corpora used for ASR and SR includes TIMIT [54], Switchboard [55], WSJ [56], AMI [57]. Similarly, EMO-DB [58], FAU-AIBO [59], RECOLA [60], and GEMEP [61] are some popular classical datasets. Recently, larger datasets are being created and released to the research community to engage the industry as well as the researchers. We summarise some of these recent and publicly available datasets in Table II that are widely used in the speech community.

E. Evaluations

Evaluation measures vary across speech tasks. The performance of ASR systems is usually measured using word error rates (WER), which is the fraction of the sum of insertion, deletion, and substitution divided by the total number of words in the reference transcription. In speaker verification systems, two types of errors—namely, false rejection (fr), where a valid identity is rejected, and false acceptance (fa), where a fake identity is accepted—are used. These two errors are measured experimentally on test data. Based on these two errors, a detection error trade-offs (DETs) curve is drawn to evaluate the performance of the system. DET is plotted using the probability of false acceptance ($P_{fa}$) as a function of the probability of false rejection ($P_{fr}$). Another popular evaluation measure is the equal error rate (EER) which corresponds to the operating point where $P_{fa} = P_{fr}$. Similarly, the area under curve (AUC) of the receiver operating curve (ROC) is often found. The details on other evaluation measures for the speaker verification task can be found in [71]. Both speaker identification and emotion recognition use classification accuracy as a metric. However, as data is often imbalanced across the classes in naturalistic emotion corpora, the accuracy is usually used as so-called unweighted accuracy (UA) or unweighted average recall (UAR), which represents the average recall across classes, unweighted by the number of instances by classes. This has been introduced by the first challenge in the field—the Interspeech 2009 Emotion Challenge [72] and has since been picked up by other challenges across the field. Also, SER systems use regression to predict emotional attributes such as continuous arousal and valence or dominance.

III. APPLICATIONS OF DEEP REPRESENTATION LEARNING

Learning representations is a fundamental problem in AI and it aims to capture useful information or attributes of data, where deep representation learning involves DL models for this task. Various applications of deep representation learning have been summarised in Figure 2.

![Fig. 2: Applications of deep representation learning.](image)

A. Automatic Feature Learning

Automatic feature learning is the process of constructing explanatory variables or features that can be used for classification or prediction problems. Feature learning algorithms can be supervised or unsupervised [73]. Deep learning (DL) models are composed of multiple hidden layers and each layer provides a kind of representation of the given data [74]. It has been found that automatically learnt feature representations are given enough training data – usually more efficient and repeatable than hand-crafted or manually designed features which allow building better faster predictive models [6]. Most importantly, automatically learnt feature representation is in most cases more flexible and powerful and can be applied to any data science problem in the fields of vision processing [75], text processing [76], and speech processing [77].

B. Dimension Reduction and Information Retrieval

Broadly speaking, dimensionality reduction methods are commonly used for two purposes: (1) to eliminate data redundancy and irrelevancy for higher efficiency and often increased performance , and (2) to make the data more understandable and interpretable by reducing the number of input variables [6]. In some applications, it is very difficult to analyse the high dimensional data with a limited number of training samples.
TABLE II: Speech corpora and their details.

| Application          | Corpus          | Language | Mode    | Size                  | Details                                                                 |
|----------------------|-----------------|----------|---------|-----------------------|-------------------------------------------------------------------------|
| Speech and Speaker Recognition | LibriSpeech [62] | English   | Audio   | 1,000 hours of speech of 2,844 speakers | Designed for speech recognition and also used for speaker identification and verification. |
|                      | VoxCeleb1 [63]  | English   | Audio-Visual | 1,200 hours of audio and video | This corpus is extracted from videos uploaded to YouTube and is used for speaker identification and verification. |
|                      | TED-LIUM [64]   | English   | Audio    | 180 hours of speech | This corpus is extracted from TED Talks for ASR. |
|                      | THCHS-30 [65]   | Chinese   | Audio    | 10 hours of speech from 30 speakers | This corpus is recorded for Chinese speech recognition. |
|                      | ASHELL [66]     | Mandarin  | Audio    | 310 hours of speech from 400 speakers | An open-source Mandarin ASR corpus. |
|                      | Tuda-De [67]    | German    | Audio    | 347 hours of speech from 147 speakers | A corpus of German utterances was publicly released for distant speech recognition. |
|                      | EMD-DIE [68]    | German    | Audio    | 10 sessions, 409 utterances | Speech of German teachers which are widely used in everyday communication. |
|                      | SEMAINE [69]    | English   | Audio-Visual | 315 paragraphs and 129 conversations | An induced corpus collected to build sensitive multimodal agents that can engage a person in a natural and emotionally coloured conversation. |
|                      | EMOCAP-ES [70]  | English   | Audio-Visual | 12 hours of speech from 10 speakers | To collect this data, an interactive setting was set up with authentic emotions and create a larger emotional corpus to study multimodal interactions. |
|                      | MSP-IMPROVE [71]| English   | Audio-Visual | 1 hour of audiovisual data of 12 speakers | This corpus is included from audiovisual interactions of actors for study emotions. |

Therefore, dimension reduction becomes imperative to retrieve important variables or information relevant to the specified problems. It has been validated that the use of more interpretable features in a lower dimension can provide competitive performance or even better performance when used for designing predictive models [79].

Information retrieval is a process of finding information based on a user query by examining a collection of data [80]. The queried material can be text, documents, images, or audio, and users can express their queries in the form of a text, voice, or image [81], [82]. Finding a suitable representation of a query to perform retrieval is a challenging task and DL-based representation learning techniques are playing an important role in this field. The major advantages of using representation learning models for information retrieval is that they can learn features automatically with little or no prior knowledge [83].

C. Data Denoising

Despite the success of deep models in different fields, these models remain brittle to the noise [84]. To deal with noisy conditions, one often performs data augmentation by adding artificially-noised examples to the training set [85]. However, data augmentation may not help always, because the distribution of noise is not always known. In contrast, representation learning methods can be effectively utilised to learn noise-robust features learning and they often provide better results compared to data augmentation [86]. In addition, the speech can be denoised such as by DL-based speech enhancement systems [87].

D. Clustering Structure

Clustering is one of the most traditional and frequently used data representation methods. It aims to categorise similar classes of data samples into one cluster using similarity measures (e.g., Euclidean distance). A large number of data clustering techniques have been proposed [88]. Classical clustering methods usually have poor performance on high-dimensional data, and suffer from high computational complexity on large-scale datasets [89]. In contrast, DL-based clustering methods can process large and high dimensional data (e.g., images, text, speech) with a reasonable time complexity and they have emerged as effective tools for clustering structures [89].

E. Disentanglement and Manifold Learning

Disentangled representation is a method that disentangles or represents each feature into narrowly defined variables and encodes them as separate dimensions [1]. Disentangled representation learning differs from other feature extraction or dimensionality reduction techniques as it explicitly aims to learn such representations that aligns axes with the generative factors of the input data [90], [91]. Practically, data is generated from independent factors of variation. Disentangled representation learning aims to capture these factors by different independent variables in the representation. In this way, latent variables are interpretable, generalisable, and robust against adversarial attacks [92].

Manifold learning aims to describe data as low-dimensional manifolds embedded in high-dimensional spaces [93]. Manifold learning can retain a meaningful structure in very low dimensions compared to linear dimension reduction methods [94]. Manifold learning algorithms attempt to describe the high dimensional data as a non-linear function of fewer underlying parameters by preserving the intrinsic geometry [95], [96]. Such parameters have a widespread application in pattern recognition, speech analysis, and computer vision [97].

F. Abstraction and Invariance

The architecture of DNNs is inspired by the hierarchical structure of the brain [98]. It is anticipated that deep architectures might capture abstract representations [99]. Learning abstractions is equivalent to discovering a universal model that can be across all tasks to facilitate generalisation and knowledge transfer. More abstract features are generally invariant to the local changes and are non-linear functions of the raw input [100]. Abstraction representations also capture high-level continuous-valued attributes that are only sensitive to some very specific types of changes in the input signal. Learning such sorts of invariant features has more predictive power which has always been required by the artificial intelligence (AI) community [101].

IV. REPRESENTATION LEARNING ARCHITECTURES

In 2006, DL-based automatic feature discovery was initiated by Hinton and his colleagues [29] and followed up by other researchers [30], [31]. This has led to a breakthrough in representation learning research and many novel DL models have been proposed. In this section, we will discuss these
models and highlight the mechanics of representation learning using them.

A. Deep Neural Networks (DNNs)

Historically, the idea of deep neural networks (DNNs) is an extension of ideas emerging from research on artificial neural networks (ANNs) [102]. Feed Forward Neural Networks (FNNs) or Multilayer Perceptrons (MLPs) [103] with multiple hidden layers are indeed a good example of deep architectures. DNNs consist of multiple layers, including an input layer, hidden layers, and an output layer, of processing units called “neurons”. These neurons in each layer are densely connected with the neurons of the adjacent layers. The goal of DNNs is to approximate some function $f$. For instance, a DNN classifier maps an input $x$ to a category label $y$ by using a mapping function $y = f(x; \theta)$ and learns the value of the parameters $\theta$ that result in the best function approximation. Each layer of a DNN performs representation learning based on the input provided to it. For example, in case of a classifier, all hidden layers except the last layer (softmax) learn a representation of input data to make classification task easier. A well trained DNN network learns a hierarchy of distributed representations [74]. Increasing the depth of DNNs promotes reusing of learnt representations and enables the learning of a deep hierarchy of representations at different levels of abstraction. Higher levels of abstraction are generally associated with invariance to local changes of the input [1]. These representations proved very helpful in designing different speech-based systems.

B. Convolutional Neural Networks (CNNs)

Convolutional neural networks (CNNs) [104] are a specialised kind of deep architecture for processing of data having a grid-like topology. Examples include image data that have 2D grid pixels and time-series data (i.e., 1D grid) having samples at regular intervals of time to create a grid-like structure. CNNs are a variant of the standard FNNs. They introduce convolutional and pooling layers into the structure of DNNs, which take into account the spatial representations of the data and make the network more efficient by introducing sparse interactions, parameter sharing, and equivariant representations. The convolution operation in the convolution layer is the fundamental building block of CNNs. It consists of several learnable kernels that are convolved with the input to compute the output feature map. This operation is defined as:

$$ (h_k)_{ij} = (W_k \otimes q) + b_k, \quad (1) $$

where $(h_k)_{ij}$ represents the $(i, j)^{th}$ element for the $k^{th}$ output feature map, $q$ is the input feature maps, $W_k$ and $b_k$ represent the $k^{th}$ filter and bias, respectively. The symbol $\otimes$ denotes the 2D convolution operation. After the convolution operation, a pooling operation is applied, which facilitates nonlinear downsampling of the feature map and makes the representations invariant to small translations in the input [73]. Finally, it is common to use DNN layers to accumulate the outputs from the previous layers to yield a stochastic likelihood representation for classification or regression.

In contrast to DNNs, the training process of CNNs is easy due to fewer parameters [105]. CNNs are found very powerful in extracting low-level representations at the initial layers and high-level features (textures and semantics) in the higher layers [106]. The convolution layer in CNNs acts as data-driven filterbank that is able to capture representations from speech [107] that are more generalised [108], discriminative [106], and contextual [109].

C. Recurrent Neural Networks (RNNs)

Recurrent neural networks (RNNs) [110] are an extension of FNNs by introducing recurrent connections within layers. They use the previous state of the model as additional input at each time step which creates a memory in its hidden state having information from all previous inputs. This makes RNNs to have stronger representational memory compared to hidden Markov models (HMMs), whose discrete hidden states bound their memory [111]. Given an input sequence $x(t) = (x_1, ..., x_T)$ at the current time step $t$, they calculates the hidden state $h_t$ using the previous hidden state $h_{t-1}$ and outputs a vector sequence $y = (y_1, ..., y_T)$. The standard equations for RNNs are given below:

$$ h_t = H(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \quad (2) $$

$$ y_t = (W_{xh}x_t + b_y), \quad (3) $$

where $W$ terms are the weight matrices (i.e., $W_{xh}$ is a weight matrix of an input-hidden layer), $b$ is the bias vector, and $H$ denotes the hidden layer function. Simple RNNs usually fail to model the long-term temporal contingencies due to the vanishing gradient problem. To deal with this problem, multiple specialised RNN architectures exist including long short-term memory (LSTM) [112] and gated recurrent units (GRUs) [111] with gating mechanism to add and forget the information selectively. Bidirectional RNNs [113] were proposed to model future context by passing the input sequence through two separate recurrent hidden layers. These separate recurrent layers are connected to the same output to access the temporal context in both directions to model both past and future.

RNNs introduce recurrent connections to allow parameters to be shared across time which makes them very powerful in learning temporal dynamics from sequential data (e.g., audio, video). Due to these abilities, RNNs especially LSTMs have had an enormous impact in speech community and they are incorporated in state-of-the-art ASR systems [114].

D. Autoencoders (AEs)

The idea of an autoencoding network [115] is to learn a mapping from high-dimensional data to a lower-dimensional feature space such that the input observations can be approximately reconstructed from the lower-dimensional representation. The function $f_0$ is called the encoder that maps the input vector $x$ into feature/representation vector $h = f_0(x)$. The decoder network is responsible to map a feature vector $h$ to reconstruct the input vector $\hat{x} = g_0(h)$. The decoder network parameterises

This work is the extended version of paper accepted in IEEE Transactions on Affective Computing 2021.

https://ieeexplore.ieee.org/document/9543566
the decoder function \(g_0\). Overall, the parameters are optimised by minimising the following cost function:

\[
\mathcal{L}(x, g_0(f_0(x))) = \|x - \hat{x}\|_2^2.
\]

(4)

The set of parameters \(\theta\) of the encoder and decoder networks are simultaneously learnt by attempting to incur a minimal reconstruction error. If the input data have correlated structures; then, the autoencoders (AEs) can learn some of these correlations \(\mathcal{J}_{\theta}\). To capture useful representations \(h\), the cost function of Equation (4) is usually optimised with an additional constraint to prevent the AE from learning the useless identity function having zero reconstruction error. This is achieved through various ways in the different forms of AEs, as discussed below in more detail.

1) Undercomplete Autoencoders (AEs): One way of learning useful feature representations \(h\) is to regularise the autoencoder by imposing constraints to have a low dimensional feature size. In this way, the AE is forced to learn the salient features/representations of data from high dimensional space to a low dimensional feature space. If an autoencoder uses a linear activation function with the mean squared error criterion; then, the resultant architecture will become equivalent to the PCA algorithm, and its hidden units will learn the principal components of input data \(\mathcal{V}\). However, an autoencoder with non-linear activation functions can learn a more useful feature representation compared to PCA \(\mathcal{H}\).

2) Sparse Autoencoders (AEs): An AE network can also discover a useful feature representation of data, even when the size of the feature representations is larger than the input vector \(x\). This is done by using the idea of sparsity regularisation \(\mathcal{J}_{\theta}\) by imposing an additional constraint on the hidden units. Sparsity can be achieved either by penalising hidden unit biases \(\mathcal{J}_{\theta}\) or the outputs’ hidden unit, however, it hurts numerical optimisation. Therefore, imposing sparsity directly on the outputs of hidden units is very popular and has several variants. One way to realise a sparse AEs is to incorporate an additional term in the loss function to penalise the KL divergence between average activation of the hidden unit and the desired sparsity \(\rho\). Let us consider \(a_j\) as the activation of a hidden unit \(j\) for a given input \(x_i\); then, the average activation \(\hat{\rho}\) over the training set is given by:

\[
\hat{\rho} = \frac{1}{n} \sum_{i=1}^{n} \left[ a_j(x_i) \right],
\]

(5)

where \(n\) is the number of training samples. Then, the cost function of a sparse autoencoder will become:

\[
\mathcal{L}(x, g_0(f_0(x))) + \lambda \sum_{i=1}^{n} KL_1(\hat{\rho} || \rho)
\]

(6)

where \(\mathcal{L}(x, g_0(f_0(x)))\) is the cost function of the standard autoencoder. Another way to penalise a hidden unit is to use \(l_1\) as penalty by which the following objective becomes:

\[
\mathcal{L}(x, g_0(f_0(x))) + \lambda \|z\|_1.
\]

(7)

Sparseness plays a key role in learning a more meaningful representation of input data \(\mathcal{J}_{\theta}\). It has been found that sparse AEs are simple to train and can learn better representation compared to denoising autoencoders (DAE) and RBMs \(\mathcal{J}_{\theta}\). In particular, sparse encoders can learn useful information and attributes from speech, which can facilitate better classification performance \(\mathcal{J}_{\theta}\).

3) Denoising Autoencoders (DAEs): Denoising autoencoders (DAEs) are considered as a stochastic version of the basic AE. They are trained to reconstruct a clean input from its corrupted version \(\mathcal{J}_{\theta}\). The objective function of a DAE is given by:

\[
\mathcal{L}(x, g_0(f_0(\tilde{x}))),
\]

(8)

where \(\tilde{x}\) is the corrupted version of \(x\), which is done via stochastic mapping \(\tilde{x} \sim q_{D}(\tilde{x}|x)\). During training, DAEs are still minimising the same reconstruction loss between a clean \(x\) and its reconstruction from \(h\). The difference is that \(h\) is learnt by applying a deterministic mapping \(f_0\) to a corrupted input \(\tilde{x}\). It thus learns higher level feature representations that are robust to the corruption process. The features learnt by a DAE are reported qualitatively better for tasks like classification and also better than RBM features \(\mathcal{H}\).

4) Contractive Autoencoders (CAEs): Contractive autoencoders (CAEs) proposed by Rifai et al. \(\mathcal{J}_{\theta}\) with the motivation to learn robust representations are similar to a DAEs. CAEs are forced to learn useful representations that are robust to infinitesimal input variations. This is achieved by adding an analytic contractive penalty to Equation (4). The penalty term is the Frobenius norm of the Jacobian matrix of the hidden layer with respect to the input \(x\). The loss function for a CAE is given by:

\[
\mathcal{L}(x, g_0(f_0(x))) + \lambda \sum_{i=1}^{m} \|\Delta x z_i\|^2,
\]

(9)

where \(m\) is the number of hidden units, and \(z_i\) is the activation of hidden unit \(i\).

E. Deep Generative Models

Generative models are powerful in learning the distribution of any kind of data (audio, images, or video) and aim to generate new data points. Here, we discuss four generative models due to their popularity in the speech community.

1) Boltzmann Machines and Deep Belief Networks: Deep Belief Networks (DBNs) \(\mathcal{J}_{\theta}\) are a powerful probabilistic generative model that consists of multiple layers of stochastic latent variables, where each layer is a Restricted Boltzmann Machine (RBM) \(\mathcal{J}_{\theta}\). Boltzmann Machines (BM) are a bipartite graph in which visible units are connected to hidden units using undirected connections with weights. A BM is restricted in the sense that there are no hidden-hidden and visible-visible connections. A RBM is an energy-based model whose joint probability distribution between visible layer \(v\) and hidden layer \(h\) is given by:

\[
P(v, h) = \frac{1}{Z} \exp(-E(v, h)).
\]

(10)

\(Z\) is the normalising constant also known as the partition function, and \(E(v, h)\) is an energy function defined by the following equation:

\[
E(v, h) = -\sum_{i=1}^{D} \sum_{j=1}^{k} W_{ij} v_i h_j - \sum_{i=1}^{D} b_i v_i - \sum_{j=1}^{k} a_j h_j.
\]

(11)

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where \(v_i\) and \(h_i\) are the binary states of hidden and visible units. \(W_{ij}\) are the weights between visible and hidden nodes, \(b_i\) and \(a_j\) represent the bias terms for visible and hidden units respectively.

During the training phase, an RBM uses Markov Chain Monte Carlo (MCMC)-based algorithms [121] to maximise the log-likelihood of the training data. Training based on MCMC computes the gradient of the log-likelihood, which poses a significant learning problem [123]. Moreover, DBNs are trained using layer-wise training that is also computationally inefficient. In recent years, generative models like GANs and VAEs have been proposed that can be trained via direct back-propagation and avoid the difficulties of MCMC based training. We discuss GANs and VAEs in more detail next.

2) Generative Adversarial Networks (GANs): Generative adversarial networks (GANs) [11] use adversarial training to directly shape the output distribution of the network via backpropagation. They include two neural networks—a generator, \(G\), and a discriminator, \(D\), which play a min-max adversarial game defined by the following optimisation program:

\[
\min_{G} \max_{D} \mathbb{E}_{x}[\log(D(x))] + \mathbb{E}_{z}[\log(1 - D(G(z)))].
\] (12)

The generator, \(G\), maps the latent vectors, \(z\), drawn from some known prior, \(p_z\) (e.g., Gaussian), to fake data points, \(G(z)\). The discriminator, \(D\), is tasked with differentiating between generated samples (fake), \(G(z)\), and real data samples, \(x\), (drawn from data distribution, \(p_{data}\)). The generator network, \(G(z)\), is trained to maximally confuse the discriminator into believing that samples it generates come from the data distribution. This makes the GANs very powerful. They have become very popular and are being exploited in various ways by speech community either for speech synthesis or to augment the training material by generated feature observations or speech itself. Researchers proposed various other architectures on the idea of GAN. These models include conditional GAN [126], BiGAN [127], InfoGAN [128], etc. These days, GAN based architectures are widely being used for representation learning not only from images but also from speech and related fields.

3) Variational Autoencoders (VAEs): Variational Autoencoders (VAEs) are probabilistic models that use a stochastic encoder for modelling the posterior distribution \(q(z|x)\), and a generative network (decoder) that models the conditional log-likelihood \(\log p(x|z)\). Both of these networks are jointly trained to maximise the following variational lower bound on the data loglikelihood:

\[
\log p(x) \geq \mathbb{E}_{q(z|x)}\log p(x|z) - KL(q(z|x)||p(z)).
\] (13)

The first term is the standard reconstruction term of an AE and the second term is the KL divergence between the prior \(p(z)\) and the posterior distribution \(q(z|x)\). The second term acts as a regularisation term and without it, the model is simply a standard autoencoder. VAEs are becoming very popular in learning representation from speech. Recently, various variants of VAEs are proposed in the literature, which include \(\beta\)-VAE [129], InfoVAE [130], PixelVAE [131], and many more [132].

All these VAEs are very powerful in learning disentangled and hierarchical representations and are also popular in clustering multi-category structures of data [132].

4) Autoregressive Networks (ANs): Autoregressive networks (ANs) are directed probabilistic models with no latent random variables. They model the joint distribution of high-dimensional data as a product of conditional distributions using the following probabilistic chain-rule:

\[
p(x) = \prod_{i=1}^{n} p(x_i|x_{<i}, \theta),
\] (14)

where \(x_t\) is the \(t^{th}\) variable of \(x\) and \(\theta\) are the parameters of the AN model. The conditional probability distributions in ANs are usually modelled with a neural network that receives \(x < t\) as input and outputs a distribution over possible \(x_t\). Some of the popular ANs includes PixelRNN [43], PixelCNN [133], and WaveNet [44]. ANs are powerful density estimators and they capture details over global data without learning a hierarchical latent representation unlike latent variable models such as GANs, VAEs, etc. In speech technology, WaveNet is very popular and has powerful acoustic modelling capabilities. They are used for speech synthesis [44], denoising [134], and also in unsupervised representation learning setting in conjunction with VAEs [135].

In this section, we have discussed DL models that use representation learning of speech. In Table III we highlight the key characteristics of DL models in terms of their representation learning abilities. All these models can be trained in different ways to learn useful representation from speech, which we have reviewed in the next section.

V. TECHNIQUES FOR REPRESENTATION LEARNING FROM SPEECH

Deep models can be used in different ways to automatically discover suitable representations for the task at hand, and this section covers these techniques for learning features from speech for ASR, SR, and SER. Figure 3 shows the different learning techniques that can be used to capture information from data. These techniques have different important attributes that we highlight in Table IV.

A. Supervised Learning

Deep learning (DL) models can learn representations from data in both unsupervised and supervised manners. In the supervised case, features representations are learnt on datasets by considering label information. In the speech domain, supervised representation learning methods are widely employed
for feature learning from speech. RBMs and DBNs are found
very capable in learning features from speech for different
tasks including ASR [52], [136], speaker recognition [137],
[138], and SER [139]. Particularly, DBNs trained in a greedy
layer-wise training [121] can learn useful features from the
speech signal [140].

Convolutional neural networks (CNNs) [104] are another
popular supervised model that is widely used for feature
 extraction from speech. They have shown very promising
results for speech and speaker recognition tasks by learning
more generalised features from raw speech compared to ANNs
and other feature-based approaches [107], [108], [141]. After
the success of CNNs in ASR, researchers also attempted to
exploit them for SER [41], [106], [142], [143], where they
used CNNs in combination with LSTM networks for modelling
long term dependencies in an emotional speech. Overall, it has
been found that LSTMs (or GRUs) can help CNNs in learning
more useful features from speech [40], [144].

Despite the promising results, the success of supervised
learning is limited by the requisite of transcriptions or labels
for speech-related tasks. It cannot exploit the plethora of freely
available unlabelled datasets. It is also important to note that
the labelling of these datasets is very expensive in terms of time
and resources. To tackle these issues, unsupervised learning
comes into play to learn representations from unlabelled data.
We are discussing the potentials of unsupervised learning in
the next section.

B. Unsupervised Learning

Unsupervised learning facilitates the analysis of input data
without corresponding labels and aims to learn the underlying
inherent structure or distribution of data. In the real world,
data (speech, image, text) have extremely rich structures
and algorithms trained in an unsupervised way to create
understandings of data rather than learning for particular tasks.
Unsupervised representation learning from large unlabelled
datasets is an active area of research. In the context of speech
analysis, it can exploit the practically available unlimited
amount of unlabelled corpora to learn good intermediate
feature representations, which can then be used to improve the
performance of a variety of supervised tasks such as speech
emotion recognition [145].

Regarding unsupervised representation learning, researchers
mostly utilise variants of autoencoders (AEs) to learn suitable
features from speech data. AEs can learn high-level semantic
content (e.g., phoneme identities) that are invariant to con-
founding low-level details (pitch contour or background noise)
in speech [135].

In ASR and SR, most of the studies utilised VAEs for
unsupervised representation learning from speech [135], [140].
VAEs can jointly learn a generative model and an inference
model, which allows them to capture latent variables from
observed data. In [46], the authors used FHVAE to capture
interpretable and disentangled representations from speech
without any supervision. They evaluated the model on two
speech corpora and demonstrated that FHVAE can satisfactorily
extract linguistic contents from speech and outperform an i-
vector baseline speaker verification task while reducing WER
for ASR. Other autoencoding architectures like DAEs are also
found very promising in finding speech representations in an
unsupervised way. Most importantly, they can produce robust
representation for noisy speech recognition [147]–[149].

Similarly, classical models like RBMs have proved to be
very successful for learning representation from speech. For
instance, Jaitly and Hinton used RBMs for phoneme recognition
in [52], and showed that RBMs can learn more discriminative
features that achieved better performance compared to MFCCs.
Interestingly, RBMs can also learn filterbanks from raw
speech. In [150], Sailor and Patil used a convolutional RBM

This work is the extended version of paper accepted in IEEE Transactions on Affective Computing 2021.

https://ieeexplore.ieee.org/document/9543566
(ConvoRBM) to learn auditory-like sub-band filters from the raw speech signal. The authors showed that unsupervised deep auditory features learnt by ConvoRBM can outperform using Mel filterbank features for ASR. Similarly, DBNs trained on features such as MFCCs \cite{151} or Mel scale filter banks \cite{140} create high-level feature representations.

Similar to ASR and SR, models including AEs, DAEs, and VAEs are mostly used for unsupervised representation learning. In \cite{152}, Ghosh et al. used stacked AEs for learning emotional representations from speech. They found that stacked AE can learn highly discriminative features from the speech that are suitable for the emotion classification task. Other studies \cite{153, 154} also used AEs for capturing emotional representation from speech and found they are very powerful in learning discriminative features. DAEs are exploited in \cite{155, 156} to show the suitability of DAEs for SER. In \cite{79}, the authors used VAEs for learning latent representations of speech emotions. They showed that VAEs can learn better emotional representations suitable for classification in contrast to standard AEs.

As outlined above, recently, adversarial learning (AL) is becoming very popular in learning unsupervised representation form speech. It involves more than one network and enables the learning in an adversarial way, which enables to learn more discriminative \cite{157} and robust \cite{158} features. Especially GANs \cite{159}, adversarial autoencoders (AAEs) \cite{160} and other AL \cite{161} based models are becoming popular in modelling speech not only in ASR but also SR and SER.

Despite all these successes, the performance of a representation learnt in an unsupervised way is generally harder to compare with supervised methods. Semi-supervised representation learning techniques can solve this issue by simultaneously utilising both labelled and unlabelled data. We discuss semi-supervised representation learning methods in the next section.

C. Semi-supervised Learning

The success in DL has predominately been enabled by key factors like advanced algorithms, processing hardware, open sharing of codes and papers, and most importantly the availability of large-scale labelled datasets and pre-trained networks on these, e.g., ImageNet. However, a large labelled database or pre-trained network for every problem like speech emotion recognition is not always available \cite{162, 163}. It is very difficult, expensive, and time-consuming to annotate such data as it requires expert human efforts \cite{165}. Semi-supervised learning solves this problem by utilising the large unlabelled data, together with the labelled data to build better classifiers. It reduces human efforts and provides higher accuracy, therefore, semi-supervised models are of great interest both in theory and practice \cite{166}.

Semi-Supervised learning is very popular in SER and researchers tried various models to learn emotional representation from speech. Huang et al. \cite{167} used CNN in semi-supervised for capturing affect-salient representations and reported superior performance compared to well-known hand-engineered features. Ladder network-based semi-supervised methods are very popular in SER and used in \cite{168, 169, 170}. A ladder network is an unsupervised DAE that is trained along with a supervised classification or regression task. It can learn more generalised representations suitable for SER compared to the standard methods. Deng et al. \cite{171} proposed a semi-supervised model by combining an AE and a classifier. They considered unlabelled samples from unlabelled data as an extra garbage class in the classification problem. Features learnt by a semi-supervised AE performed better compared to an unsupervised AE. In \cite{165}, the authors trained an AAE by utilising the additional unlabelled emotional data to improve SER performance. They showed that additional data help to learn more generalised representations that perform better compared to supervised and unsupervised methods.

In ASR, semi-supervised learning is mainly used to circumvent the lack of sufficient training data by creating features fronts ends \cite{172}, by using multilingual acoustic representations \cite{173}, and by extracting an intermediate representation from large unpaired datasets \cite{174} to improve the performance of the system. In SR, DNNs were used to learn representations for both the target speaker and interference for speech separation in a semi-supervised way \cite{175}. Recently, a GAN based model is exploited for a speaker diarisation system with superior results using semi-supervised training \cite{176}.

D. Transfer Learning

Transfer learning (TL) involves methods that utilise any knowledge resources (i.e., data, model, labels, etc.) to increase model learning and generalisation for the target task \cite{177}. The idea behind TL is “Learning to Learn”, which specifies that learning from scratch (tabula rasa learning) is often limited, and experience should be used for deeper understanding \cite{178}. TL encompasses different approaches including multitask learning (MTL), model adaptation, knowledge transfer, covariance shift, etc. In the speech processing field, representation learning gained much interest in these approaches of TL. In this section, we cover three popular TL techniques that are being used in today’s speech technology including domain adaptation, multi-task learning, and self-taught learning.

1) Domain Adaptation: Deep domain adaptation is a sub-field of TL and it has emerged to address the problem of unavailability of labelled data. It aims to eliminate the training-testing mismatch. Speech is a typical example of heterogeneous data and a mismatch always exists between the probability distributions of source and target domain data, which can degrade the performance of the system \cite{179}. To build more robust systems for speech-related applications in real-life, domain adaptation techniques are usually applied in the training pipeline of deep models to learn representations that explicitly minimise the difference between the source and target domains.

Researchers have attempted different methods of domain adaptation using representation learning to achieve robustness under noisy conditions in ASR systems. In \cite{179}, the authors used DNN based unsupervised representation method to eliminate the difference between the training and the testing data. They evaluate the model with clean training data and noisy test data and found that relative error reduction is achieved due to the elimination of mismatch between the

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distribution of train and test data. Another study [180] explored
the unsupervised domain adaptation of the acoustic model by
learning hidden unit contributions. The authors evaluated the
proposed adaptation method on four different datasets and
achieved improved results compared to unadapted methods. Hsu
et al. [46] used a VAE based domain adaptation method to learn
a latent representation of speech and create additional labelled
training data (source domain) having a distribution similar
to the testing data (target domain). The authors were able to
reduce the absolute word error rate (WER) by 35% in contrast
to a non-adapted baseline. Similarly, in [181] domain invariant
representations are extracted using Factorised Hierarchical
Variational Autoencoder (FHVAE) for robust ASR. Also,
some studies [182], [183] explored unsupervised representation
learning-based domain adaptation for distant conversational
speech recognition. They found that a representations-learning-
based approach outperformed unadapted models and other
baselines. For unsupervised speaker adaptation, Fan et al. [184]
used multi-speaker DNNs to take advantage of shared hidden
representation and achieved improved results.

Many researchers exploited DNN models for learning
transferable representations in multi-lingual ASR [185], [186].
Cross-lingual transfer learning is important for the practical
application, and it has been found that learnt features can be
transferred to improve the performance of both resource-limited
and resource-rich languages [172]. The representations learnt
in this way are referred to as bottleneck features and these
can be used to train models for languages even without any
transcriptions [187]. Recently, adversarial learning of representa-
tions for domain adaptation methods is becoming very popular.
Researchers trained different adversarial models and were
able to improve the robustness against noise [188], adaptation
of acoustic models for accented speech [189], [190], gender
variations [191], and speaker and environment variations
[192]–[195]. These studies showed that representation learning
using the adversarially trained models can improve the ASR
performance on unseen domains.

In SR, Shon et al. used DAE to minimise the mismatch
between the training and testing domain by utilising out-of-
domain information [196]. Interestingly, domain adversarial
training is utilised by Wang et al. [197] to learn speaker-
discriminative representations. Authors empirically showed that
the adversarial training help to solve dataset mismatch problem
and outperform other unsupervised domain adaptation methods.
Similarly, a GAN is recently utilised by Bhattacharyya et al.
[198] to learn speaker embeddings for a domain robust end-to-
end speaker verification system. They achieved significantly
better results over the baseline.

In SER, domain adaptation methods are also very popular
to enable the system to learn representations that can be used
to perform emotion identification across different corpora and
different languages. Deng et al. [199] used AE with shared
hidden layers to learn common representations for different
emotional datasets. These authors were able to minimise the
mismatch between different datasets and able to increase
the performance. In another study [200], the authors used a
Universe AE for cross-corpus SER. They were able to
learn more generalised representations using the Universe
AE, which achieves promising results compared to standard
AEs. Some studies exploited GANs for SER. For instance,
Wang et al. [197] used adversarial training to capture common
representations for both the source and target language data.
Zhou et al. [201] used a class-wise domain adaptation method
using adversarial training to address cross-corpus mismatch
issues and showed that adversarial training is useful when the
model is to be trained on target language with minimal labels.
Gideon et al. [202] used an adversarial discriminative domain
generalisation method for cross-corpus emotion recognition
and achieved better results. Similarly, [163] utilised GANs in
an unsupervised way to learn language invariant, and evaluated
over four different language datasets. They were able to
significantly improve the SER across different language using
language invariant features.

2) Multi-Task Learning: Multi-task learning (MTL) has led
to successes in different applications of ML, from NLP [203]
and speech recognition [204] to computer vision [205]. MTL
aims to optimise more than one loss function in contrast to
single-task learning and uses auxiliary tasks to improve on the
main task of interest [206]. Representations learned in MTL
scenario become more generalised, which are very important
in the field of speech processing, since speech contains multi-
dimensional information (message, speaker, gender, or emotion)
that can be used as auxiliary tasks. As a result, MTL increases
performance without requiring external speech data.

In ASR, researchers have used MTL with different auxiliary
tasks including gender [207], speaker adaptation [208], [209],
speech enhancement [210], [211], etc. Results in these studies
have shown that learning shared representations for different
tasks act as complementary information about the acoustic
environment and gave a lower word error rate (WER). Similar to
ASR, researchers also explored MTL in SER with significantly
improved results [165], [212]. For SER, studies used emotional
attributes (e.g., arousal and valance) as auxiliary tasks [213]–
[216] as a way to improve the performance of the system.
Other auxiliary tasks that researchers considered in SER are
speaker and gender recognition [165], [217], [218] to improve
the accuracy of the system compared to single-task learning.

MTL is an effective approach to learn shared representation
that leads to no major increase of the computational power,
while it improves the recognition accuracy of a system and also
decreases the chance of overfitting [219], [165]. However, MTL
implies the preparation of labels for considered auxiliary tasks.
Another problem that hinders MTL is dealing with temporality
differences among tasks. For instance, the modelling of
speaker recognition requires different temporal information
than phenom recognition does [219]. Therefore, it is viable
to use memory-based deep neural networks like the recurrent
networks—ideally with LSTM or GRU cells—to deal with this
issue.

3) Self-Taught Learning: Self-taught learning [220] is a new
paradigm in ML, which combines semi-supervised and TL. It
utilises both labelled and unlabelled data, however, unlabelled
data do not need to belong to the same class labels or generative
distribution as the labelled data. Such a loose restriction on
unlabelled data in self-taught learning significantly simplifies
learning from a huge volume of unlabelled data. This fact

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differentiates it from semi-supervised learning.

We found very few studies on audio based applications using self-taught learning. In [221], the authors used self-taught learning and developed an assistive vocal interface for users with a speech impairment. The designed interface is maximally adapted using self-taught learning to the end-users and can be used for any language, dialect, grammar, and vocabulary. In another study [222], the authors proposed an AE-based sample selection method using self-taught learning. They selected highly relevant samples from unlabelled data and combined with training data. The proposed model was evaluated on four benchmark datasets covering computer vision, NLP, and speech recognition with results showing that the proposed framework can decrease the negative transfer while improving the knowledge transfer performance in different scenarios.

E. Reinforcement Learning

Reinforcement Learning (RL) follows the principle of behaviourist psychology where an agent learns to take actions in an environment and tries to maximise the accumulated reward over its lifetime. In a RL problem, the agent and its environment can be modelled being in a state \( s \in S \) and the agent can perform actions \( a \in A \), each of which may be members of either discrete or continuous sets and can be multi-dimensional. A state \( s \) contains all related information about the current situation to predict future states. The goal of RL is to find a mapping from states to actions, called policy \( \pi \), that picks actions \( a \) in given states \( s \) by maximising the cumulative expected reward. The policy \( \pi \) can be deterministic or probabilistic. RL approaches are typically based on the Markov decision process (MDP) consisting of the set of states \( S \), the set of actions \( A \), the rewards \( R \), and transition probabilities \( T \) that capture the dynamics of a system. RL has been repeatedly successful in solving various problems [223]. Most importantly, deep RL that combines deep learning with RL principles. Methods such as deep Q-learning have significantly advanced the field [224].

Few studies used RL-based approaches to learn representations. For instance, in [225], the authors introduced DeepMDP, a parameterised latent space model that is trained by minimising two tractable latent space losses including prediction of rewards and prediction of the distribution over the next latent states. They showed that the optimisation of these two objectives guarantees the quality of the embedding function as a representation of the state space. They also show that utilising DeepMDP as an auxiliary task in the Atari 2600 domain leads to large performance improvements. Zhang et al. [226] used RL for learning optimised structured representation learning from text. They found that an RL model can learn task-friendly representations by identifying task-relevant structures without any explicit structure annotations, which yields competitive performance.

Recently, RL is also gaining interest in the speech community and researchers have proposed multiple approaches to model different speech problems. Some of the popular RL-based solutions include dialog modelling and optimisation [227], speech recognition [229], and emotion recognition [230]. However, the problem of representation learning of speech signals is not explored using RL.

F. Active Learning and Cooperative Learning

Active Learning aims at achieving improved accuracy with fewer training samples by selecting data from which it learns. This idea of cleverly picking training samples rather than random selection gives better predictive models with less human effort for labelling data [231]. An active learner selects samples from a large pool of unlabelled data and subsequently asks queries to an oracle (e.g., human annotator) for labelling. In speech processing, accurate labelling of speech utterances is extremely important and time-consuming. It has larger abundantly available unlabelled data. In this situation, active learning can help by allowing the learning model to select the samples from it learns, which leads to better performance with less training. Studies (e.g., [232], [233]) utilised classical ML-based active learning for ASR with the aim to minimise the effort required in transcribing and labelling data. However, it has been showed in [234], [235] that utilisation of deep models for active learning in speech processing can improve the performance and significantly reduce the requirement of labelled data.

Cooperative learning [235], [236] combines active and semi-supervised learning to best exploit available data. It is an efficient way of sharing the labelling work between human and machine which leads to reduce the time and cost of human annotation [237]. In cooperative learning, predicted samples with insufficient confidence value are subjected to human annotations and other with with high confidence values are labelled by machines. The models trained via cooperative learning perform better compared to active or semi-supervised learning [235]. In speech processing, a few studies utilised ML-based cooperative learning and showed its potential to significantly reduce data annotation efforts. For instance, [238], authors applied cooperative learning speed up the process of annotation of large multi-modal corpora. Similarly, the proposed model in [235] achieved the same performance with 75% fewer labelled instances compared to the model trained on the whole training data. These finding shows the potential of cooperative learning in speech processing, however, DL-based representation learning methods need to be investigated in this setting.

G. Summarising the Findings

A summary of various representation learning techniques has been presented in Table IV. We segregated the studies based on the learning techniques used to train the representation learning models. Studies on supervised learning methods typically use models to learn discriminative and noise-robust representations. Supervised training of models like CNNs, LSTM/GRU RNNs, and CNN-LSTM/GRU-RNNs are widely exploited for learning of representations from raw speech.

Unsupervised learning is to learn patterns in the data. We covered unsupervised representation learning for three speech applications. Autoencoding networks are widely used in unsupervised feature learning from speech. Most importantly,
DAEs are very popular due to their denoising abilities. They can learn high-level representations from speech that are robust to noise corruption. Some studies also exploited AEs and RBM based architectures for unsupervised feature learning due to their non-linear dimension reduction and long-range of features extraction abilities. Recently, VAEs are becoming very popular in learning speech representation due to their generative nature and distribution learning abilities. They can learn salient and robust features from speech that are very essential for speech applications including ASR, SR, and SER.

Semi-supervised representation learning models are widely used in SER because speech corpora have smaller sizes compared to ASR and SR. These studies tried to exploit additional data to improve the performance of SER. The popular models include AE-based models [165], [171] and other discriminative architectures [167], [239]. In ASR, semi-supervised learning is mostly exploited for learning noise-robust representations [240], [241] and for feature extraction [172], [173], [242].

Transfer learning methods—especially domain adaptation and MTL—are very popular in ASR, SR, and SER. The domain adaptations methods in ASR, SER, and SR are mainly used to achieve adaptation by learning such representations that are robust against noise, speaker, and language and corpus difference. In all these speech applications, adversarially learnt representations are found to better solve the issue of domain mismatch. MTL methods are most popular in SER, where researchers tried to utilise additional information available (e.g., speaker, or gender) in speech to learn more generalised representations that help to improve the performance.

VI. CHALLENGES FOR REPRESENTATION LEARNING

In this section, we discuss the challenges faced by representation learning. The summary of these challenges is presented in Figure 4.

![Fig. 4: Challenges of representation learning.](image)

A. Challenge of Training Deep Architectures

Theoretical and empirical evidence show the deep models usually have superior performance over classical machine learning techniques. It is also empirically validated that deep learning models require much more data to learn certain attributes efficiently [339]. For instance, adding top-5 layers in the network on the 1000-class ImageNet dataset trained network has increased the accuracy from ~84% [104] to ~95% [340]. However, training deep learning models is not straightforward; it becomes considerably more difficult to optimise a deeper network [341], [342]. For deeper models, network parameters become very large and tuning of different hyper-parameter is also very difficult. Due to the availability of modern graphics processing units (GPUs) and recent advancement in optimisation [343] and training strategies [344], [345], the training of DNNs considerably accelerated; however, it is still an open research problem.

Training of representation learning models is a more tricky and difficult task. Learning high-level abstraction means more non-linearity and learning representations associated with input manifolds becoming even more complex if the model might need to unfold and distort complicated input manifolds. Learning such representation which involves disentangling and unfolding of complex manifolds requires more intense and difficult training [1]. Natural speech has very complex manifolds [46] and inherently contains information about the message, gender, age, health status, personality, friendliness, mood, and emotion. All of this information is entangled together [347], and the disentanglement of these attributes in some latent space is a very difficult task that requires extensive training. Most importantly, the training of unsupervised representation learning models is much more difficult in contrast to supervised ones. As highlighted in [1], in supervised learning, there is a clear objective to optimise. For instance, the classifiers are trained to learn such representations or features that minimise the misclassifications error. Representation learning models do not have such training objectives like classification or regression problems do.

As outlined, GANs are a novel approach for generative modelling, they aim to learn the distribution of real data points. In recent years, they have been widely utilised for representation learning in different fields including speech. However, they also proved difficult to train and face different failure modes, mainly vanishing gradients issues, convergence problems, and mode collapse issues. Different remedies are proposed to tackle these issues. For instance, modified minimax loss [11] can help to deal with vanishing gradients, the Wasserstein loss [348] and training of ensembles alleviate mode collapse, and noise addition to the discriminator inputs [349] or penalising discriminator weights [350] act as regularisation to improve a GAN’s convergence. These are some earlier attempts to solve these issues; however, there is still room to improve the GANs training problems.

B. Performance Issues of Domain Invariant Features

To achieve generalisation in DL models, we need a large amount of data with similar training and testing examples. However, the performance of DL models drops significantly if test samples deviate from the distribution of the training data. Learning speech representations that are invariant to variabilities in speakers, language, etc., are very difficult to capture. The performance of representations learnt from one corpus do
not work well to another corpus having different recording conditions. This issue is common to all three applications of speech covered in this paper. In the past few years, researchers have achieved competitive performance by learning speaker invariant representations [210], [351]. However, language invariant representation is still very challenging. The main reason is that we have speech corpora covering only a few languages in contrast to the number of spoken languages in the world. There are more than 5,000 spoken languages in the world, but only 389 languages account for 94% of the world’s population[4]. We do not have speech corpora even for 389 languages to enable across language speech processing research. This variation, imbalance, diversity, and dynamics in speech and language corpora are causing hurdles to designing generalised representation learning algorithms.

C. Adversary on Representation Learning

DL has undoubtedly offered tremendous improvements in the performance of state-of-the-art speech representation learning systems. However, recent works on adversarial examples pose enormous challenges for robust representation learning from speech by showing the susceptibility of DNNs to adversarial examples having imperceptible perturbations [86]. Some popular adversarial attacks include the fast gradient sign method (FGSM) [352], Jacobian-based saliency map attack (JSMA) [353], and DeepFool [354]; they compute the perturbation noise based on the gradient of targeted output. Such attacks are also evaluated against speech-based systems. For instance, Carlini and Wagner [355] evaluated an iterative optimisation-based attack against DeepSpeech [356] (a state-of-the-art ASR model) with 100% success rate. Some other attempts also proposed different adversarial attacks [357], [358] and against speech-based systems. The success of adversarial attacks against DL models shows that the representations learnt by them are not good [359]. Therefore, research is ongoing to tackle the challenge of adversarial attacks by exploring what DL models can also pollute the speech signal. Although studies use ‘noise injection’ techniques to avoid overfitting, this works for moderately high signal-to-noise ratios [360]. This has been

TABLE V: Review of representation learning techniques used in different studies.

| Learning Type         | Applications | Aim                                           | Models                                              |
|-----------------------|--------------|-----------------------------------------------|-----------------------------------------------------|
| Supervised            | ASR          | To learn discriminative and robust representation | DNNs ([323], [324], RNNs ([325]–[327]), AL ([190]) |
|                       |              |                                               | DBNs ([140], [141]), CNNs ([124], [125], [252]), GANs ([255]) |
|                       | SR           |                                               | DBNs ([141], [140], RNNs ([259], [258]), CNNs ([257]) |
|                       |              |                                               | DBNs ([323], [324], RNNs ([259], [258]), CNNs ([257]) |
|                       |              |                                               | DBNs ([323], [324], RNNs ([259], [258]), CNNs ([257]) |
|                       | SER          | To learn representation from raw speech       | CNNs ([107], [108], [110], AEs ([313]), GANs ([314]) |
|                       |              |                                               | DBNs ([140], [141]), CNNs ([124], [125], [252]), GANs ([255]) |
| Unsupervised          | ASR          | To learn speech feature and noise robust representation. | DBNs ([136], [137], [300], CNNs ([301]), LSTM ([302]), AE ([183]) |
|                       | SR           |                                               | DBNs ([136], [137], [300], CNNs ([301]), LSTM ([302]), AE ([183]) |
|                       | SER          | To learn feature from raw speech.             | RBMs ([150], AEs ([151]), GANs ([159]) |
| Semi-Supervised       | ASR          | To learn speech feature representations in semi-supervised way. | DBNs ([142], [143]), CNNs ([315]) |
|                       | SR           |                                               | DBNs ([142], [143]), CNNs ([315]) |
|                       | SER          |                                               | DBNs ([142], [143]), CNNs ([315]), AEs ([171]), AAEs ([165]) |
| Domain Adaptation     | ASR          | To learn representation to minimise the acoustic mismatch between the training and testing conditions. | DBNs ([215], [216], CNNs ([151]), AL ([191]), AEs ([171]), AAEs ([165]) |
|                       | SR           |                                               | DBNs ([215], [216], CNNs ([151]), AL ([191]), AEs ([171]), AAEs ([165]) |
|                       | SER          |                                               | DBNs ([215], [216], CNNs ([151]), AL ([191]), AEs ([171]), AAEs ([165]) |
| Multi-Task Learning   | ASR          | To learn common representations using multi-objective training. | DBNs ([323], [324], RNNs ([332], [331]), CNN-LSTM ([353]), LSTM ([313]), AL ([338]), GANs ([157]) |
|                       | SR           |                                               | DBNs ([323], [324], RNNs ([332], [331]), CNN-LSTM ([353]), LSTM ([313]), AL ([338]), GANs ([157]) |
|                       | SER          |                                               | DBNs ([323], [324], RNNs ([332], [331]), CNN-LSTM ([353]), LSTM ([313]), AL ([338]), GANs ([157]) |
an active research topic and in the past few years, different DL models have been proposed that can learn representations from noisy data. For instance, DAEs [119] can learn a representation of data with noise, imputation AE [361] can learn a representation from incomplete data, and non-local AE [362] can learn reliable features from corrupted data. Such techniques are also very popular in the speech community for noise invariant representation learning and we highlight this in Table V. However, there is still a need for such DL models that can deal with the quality of data not only for speech but also for other domains.

VII. RECENT ADVANCEMENTS AND FUTURE TRENDS

A. Open Source Datasets and Toolkits

There are a large number of speech databases available for speech analysis research. Some of the popular benchmark datasets including TIMIT [54], WSJ [56], AMI [57], and many other databases are not freely available. They are usually purchased from commercial organisations like LDC, ELRA, and Speech Ocean. The licence fees of these datasets are affordable for most of the research institutes; however, their fee is expensive (e.g., the WSJ corpus license costs 2500 USD) for young researchers who want to start their research on speech, particularly for researchers in developing countries. Recently, a free data movement is started in the speech community and different good quality datasets are made free for the public to invoke more research in this field. VoxForge and OpenSLR are two popular platforms that contain freely available speech and speaker recognition datasets. Most of the SER corpora are developed by research institutes and they are freely available for research proposes.

Another important progress made by researchers of the speech community is the development of open-source toolkits for speech processing and analysis. These tools help the researchers not only for feature extraction, but also for the development of models. The details of such tools is presented in a tabular form in Table VI. It can be noted that ASR — as the largest field of activity — has more open source toolkits compared to SR and SER. The development of such toolkits and speech corpus is providing great benefits to the speech research community and will continue to be needed to speed up the research progress on speech.

B. Computational Advancements

In contrast to classical ML models, DL has a significantly larger number of parameters and involves huge amounts of matrix multiplications with many other operations. Traditional central processing units (CPUs) support such processing, therefore, advanced parallel computing is necessary for the development of deep networks. This is achieved by utilisation of graphics processing units (GPUs), which contain thousands of cores that can perform exceptionally fast matrix multiplications. In contrast to CPUs and GPUs, advanced Tensor Processing Units (TPUs) developed by Google offer 15-30 \times 10^{15} higher processing speeds and more advanced super-watt [373]. A recent paper [374] on quantum supremacy using programmable superconducting processor shows amazing results by performing computation a Hilbert space of dimension $(253 \approx 9 \times 1015)$ far beyond the reach of the fastest supercomputers available today. It was the first computation on a quantum processor. This will lead to more progress and the computational power will continue to grow at a double-exponential rate. This will disrupt the area of representation learning from a vast amount of unlabelled data by unlocking new computational capabilities of quantum processors.

C. Processing Raw Speech

In the past few years, the trend of using hand-engineered acoustic features is progressively changing and DL is gaining popularity as a viable alternative to learn from raw speech directly. This has removed the feature extraction module from the pipeline of the ASR, SR, and SER systems. Recently, important progress is also made by Donahue et al. [159] in audio generation. They proposed WaveGAN for the unsupervised synthesis of raw-waveform audio and showed that their model can learn to produce intelligible words when trained on a small vocabulary speech dataset, and can also synthesise music audio and bird vocalisations. Other recent works [375], [376] also explored audio synthesis using GANs; however, such work is at the initial stage and will likely open new prospects of future research as it transpired with the use of GANs in the domain of vision (e.g., with DeepFakes [377]).

### Table VI: Some popular tools for speech feature extraction and model implementations.

| Toolkit          | Programming Language | Trained Models |
|------------------|----------------------|----------------|
| CMU Sphinx [366] | Java, C, Python, and others | English plus 10 other languages |
| Kaldi [367]      | C++, Python           | English         |
| Julius [368]     | C, Python             | Japanese        |
| ESPnet [369]     | Python                | English, Japanese, Mandarin |
| HTK [370]        | C, Python             | None            |

- Speech Recognition Toolkits
- Feature Extraction Tools

https://www.ldc.upenn.edu/
http://catalog.elra.info/
http://www.voxforge.org/
http://www.openslr.org/

This work is the extended version of paper accepted in IEEE Transactions on Affective Computing 2021.
D. The Rise of Adversarial Training

The idea of adversarial training was proposed in 2014 [11]. It leads to widespread research in various ML domains including speech representation learning. Speech-based systems—principally, ASR, SR, and SER systems—need to be robust under environmental acoustic variabilities arising from environmental, speaker, and recording conditions. This is very crucial for industrial applications of these systems.

GANs are being used as a viable tool for robust speech representation learning [255] and also speech enhancement [279] to tackle the noise issues. A popular variant of GAN, cycle-consistent Generative Adversarial Networks (CycleGAN) [378] is being used for domain adaptation for low-resource scenarios (where a limited amount of target data is available for adaptation) [379]. These results using CycleGANs on speech are very promising for domain adaptation. This will also lead to designing such systems that can learn domain invariant representation learning, especially for zero-resource languages to enable speech-based cross-culture applications.

Another interesting utilisation of GANs is learning from synthetic data. Researchers succeeded in the synthesis of speech signals also by GANs [159]. Synthetic data can be utilised for such applications where large label data is not available. In SER, larger labelled data is not available. Learning representation from synthetic data can help to improve the performance of system and researchers have explored the use of synthetic data for SER [160], [380]. This shows the feasibility of learning from synthetic data and will lead to interesting research to solve the problems in the speech domain where data scarcity is a major problem.

E. Representation Learning with Interaction

Good representation disentangles the underlying explanatory factors of variation. However, it is an open research question that what kind of training framework can potentially learn disentangled representations from input data. Most of the research work on representation learning used static settings without involving the interaction with the environment. Reinforcement learning (RL) facilitates the idea of learning while interacting with the environment. If RL is used to disentangle factors of variation by interacting with the environment, a good representation can be learnt. This will lead to faster convergence, in contrast, to blindly attempting to solve given problems. Such an idea has recently been validated by Thomas et al. [381], where the authors used RL to disentangle the independently controllable factors of variation by using a specific objective function. The authors empirically showed that the agent can disentangle these aspects of the environment without any extrinsic reward. This is an important finding that will act as the key to further research in this direction.

F. Privacy Preserving Representations

When people use speech-based services such as voice authentication or speech recognition, they grant complete access to their recordings. These services can extract user’s information such as gender, ethnicity, and emotional state and can be used for undesired purposes. Various other privacy-related issues arise while using speech-based services [382]. It is desirable in speech processing applications that there are suitable provisions for ensuring that there is no unauthorised and undisclosed eavesdropping and violation of privacy. Privacy preserved representation learning is a relatively unexplored research topic. Recently, researchers have started to utilise privacy-preserving representation learning models to protect speaker identity [383], gender identity [384]. To preserve users’ privacy, federated learning [385] is another alternative setting where the training of a shared global model is performed using multiple participating computing devices. This happens under the coordination of a central server, however, the training data remains decentralised.

VIII. Conclusions

In this article, we have focused on providing a comprehensive review of representation learning for speech signals using deep learning approaches in three principal speech processing areas: automatic speech recognition (ASR), speaker recognition (SR), and speech emotion recognition (SER). In all of these three areas, the use of representation learning is very promising, and there is an ongoing research on this topic in which different models and methods are being explored to disentangle speech attributes suitable for these tasks. The literature review performed in this work shows that LSTM/GRU-RNNs in combination with CNNs are suitable for capturing speech attributes. Most of the studies have used LSTM models in a supervised way. In unsupervised representation learning, DAEs and VAEs are widely deployed architectures in the speech community, with GAN-based models also attaining prominence for speech enhancement and feature learning. Apart from providing a detailed review, we have also highlighted the challenges faced by researchers working with representation learning techniques and avenues for future work. It is hoped that this article will become a definitive guide to researchers and practitioners interested to work either in speech signal or deep representation learning in general. We are curious whether in the longer run, representation learning will be the standard paradigm in speech processing. If so, we are currently witnessing the change of a paradigm moving away from signal processing and expert-crafted features into a highly data-driven era—with all its advantages, challenges, and risks.

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This work is the extended version of paper accepted in IEEE Transactions on Affective Computing 2021.

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