# **Recent Advances in Speech Language Models: A Survey**

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#### **Abstract**

Large Language Models (LLMs) have recently garnered significant attention, primarily for their capabilities in text-based interactions. However, natural human interaction often relies on speech, necessitating a shift towards voice-based models. A straightforward approach to achieve this involves a pipeline of "Automatic Speech Recognition (ASR) + LLM + Text-to-Speech (TTS)", where input speech is transcribed to text, processed by an LLM, and then converted back to speech. Despite being straightforward, this method suffers from inherent limitations, such as information loss during modality conversion and error accumulation across the three stages. To address these issues, Speech Language Models (SpeechLMs)-end-toend models that generate speech without converting from text—have emerged as a promising alternative. This survey paper provides the first comprehensive overview of recent methodologies for constructing SpeechLMs, detailing the key components of their architecture and the various training recipes integral to their development. Additionally, we systematically survey the various capabilities of SpeechLMs, categorize the evaluation metrics for SpeechLMs, and discuss the challenges and future research directions in this rapidly evolving field.

# 1 Introduction

Large Language Models (LLMs) have demonstrated remarkable capabilities in generating text and performing a wide array of natural language processing tasks [Achiam et al., 2023; Dubey et al., 2024a; Zhang et al., 2022b], serving as powerful foundation models for AI-driven language understanding and generation. Their success has also spurred numerous applications in various other domains, yet the reliance solely on text-based modalities presents a significant limitation. This leads to the development of speech-based generative models, which allow to interact with humans more naturally and intuitively. The inclusion of speech not only facilitates real-time voice

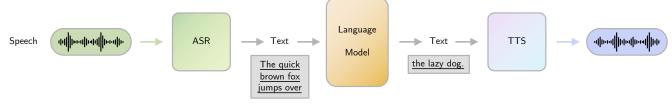
interactions but also enriches communication by combining both text and speech information [Nguyen *et al.*, 2023b; Nguyen *et al.*, 2024].

Given the extensive mutual information between text and speech, it is natural to modify existing LLMs to enable speech interaction capabilities. A straightforward approach is to adopt an "Automatic Speech Recognition (ASR) + LLM + Text-to-Speech (TTS)" framework (Figure 1a) [Huang et al., 2024]. In this setup, the user's spoken input is first processed by the ASR module, which converts it into text. The LLM then generates a text response based on this transcription. Finally, the TTS module transforms the text response back into speech, which is played back to the user. However, this naive solution mainly suffers from the following two problems. 1) Information loss. Speech signals not only contain semantic information (i.e., the meaning of the speech) but also paralinguistic information (e.g., pitch, timbre, tonality, etc.). Putting a text-only LLM in the middle will cause the complete loss of paralinguistic information in the input speech [Zhang et al., 2023a]. 2) Cumulative error. A staged approach like this can easily lead to cumulative errors throughout the pipeline, particularly in the ASR-LLM stage [Fathullah et al., 2024]. Specifically, transcription errors that occur when converting speech to text in the ASR module can negatively impact the language generation performance of the LLM.

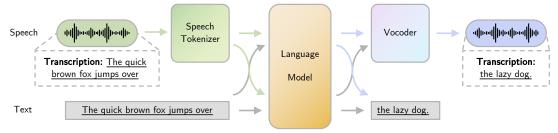
The limitations of the naive ASR + LLM + TTS framework have led to the development of Speech Language Models (SpeechLMs, Figure 1b). Unlike the naive framework, SpeechLMs directly encode speech waveforms into discrete tokens, capturing essential features and information from audio (section 3.1). Although individual speech tokens may not carry word-level semantic meaning, they capture the semantic information of speech utterances and retain valuable paralinguistic information, which prevents the information loss. SpeechLMs then model these tokens autoregressively, without solely relying on text input, which allows them to use the additional paralinguistic information to generate more expressive and nuanced speech (section 3.2). Finally, the generated tokens are synthesized back to speech (section 3.3). By working directly with the encoded speech tokens, SpeechLMs effectively mitigate the cumulative errors, as their training is integrated with the speech encoding, whereas the training of LLMs (language modeling) is completely independent of the ASR (speech recognition) module

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(a) Illustration of the "ASR + LLM + TTS" framework.



(b) Illustration of the architecture of a SpeechLM.

Figure 1: Architectures of the "ASR + LLM + TTS" framework and a SpeechLM. We emphasize that, for SpeechLM, the same content can be used across both speech and text modalities, meaning that any input modality will yield any output modality of the same results. This intentional repetition of input/output contents in the figure highlights this point.

in the naive framework.

Beyond basic conversational abilities, SpeechLMs hold the potential to undertake more complex tasks, such as encoding speaker-specific information and emotional nuances (Figure 2). This capability allows SpeechLMs to distinguish between different speakers during a conversation and to comprehend and generate speech imbued with specific emotional tones. Such advancements are crucial for applications in areas like personalized assistants, emotion-aware systems, and more nuanced human-computer interaction scenarios. Furthermore, SpeechLMs can be designed to enable real-time voice interaction, where the model can be interrupted by humans or choose to speak while the user is still speaking, which resembles the pattern of human conversations more closely.

In this survey, we present the first comprehensive overview of recent endeavors in constructing SpeechLMs. We explore the various components that constitute their architecture (section 3) and the training recipes (section 4) involved in their development. we aim to elucidate the current state of the field by analyzing these models from the above perspectives. Additionally, we survey the downstream applications of SpeechLMs (section 5), classify metrics to evaluate SpeechLMs (section 6), discuss the challenges encountered in this rapidly evolving area, and outline promising future research directions that could drive further advancements in SpeechLM technology (section 7). Our contributions are summarized as follows:

- We present the first survey in the field of SpeechLMs.
- We propose a novel taxonomy (Figure 3) of classifying SpeechLMs from the underlying components and the training recipes.
- We propose a novel classification system for the

evaluation methods for SpeechLMs.

• We identify several challenges in building SpeechLMs.

#### 2 Problem Formulation

In this section, we provide a formal definition of Speech Language Models. A Speech Language Model (SpeechLM) is an autoregressive foundation model that processes and generates speech data, utilizing contextual understanding for coherent sequence generation. It supports both speech and text modalities, such as speech-in-text-out, text-in-speech-out, or speech-in-speech-out, enabling a wide range of tasks with context-aware capabilities. We note that the concept of SpeechLM is in contrast to traditional text-based language models, such as LLM, where the only modality being processed within the model is text. Therefore, to avoid confusion, we call those text-based language models TextLMs throughout this survey.

We offer a unified framework in which SpeechLMs can process and generate speech data, text data, or even interleaved speech and text data. Specifically, an audio waveform  $\mathbf{a}=(a_1,a_2,\ldots,a_Q)$  consists of a sequence of audio samples  $a_i\in\mathbb{R}$  of length Q, where  $1\leq q\leq Q$ . Similarly, a text span  $\mathbf{t}=(t_1,t_2,\ldots,t_K)$  consists of a sequence of text tokens  $t_j$  (word, subword, character, etc.) of length K. Let  $\mathbf{M}=(M_1,M_2,\ldots,M_N)$  denote a multimodal sequence of length N, where each element  $M_i\in\{a_i,t_j\}$ . We define  $\mathbf{M}^{\text{in}}=(M_1^{\text{in}},M_2^{\text{in}},\ldots,M_{N_{\text{in}}}^{\text{in}})$  as the input multimodal sequence and  $\mathbf{M}^{\text{out}}=(M_1^{\text{out}},M_2^{\text{out}},\ldots,M_{N_{\text{out}}}^{\text{out}})$  as the output multimodal sequence, where  $N_{\text{in}}\geq 0$  and  $N_{\text{out}}\geq 0$ . Then, A SpeechLM parameterized by  $\theta$  can then be represented as:

$$\mathbf{M}^{\text{out}} = SpeechLM(\mathbf{M}^{\text{in}}; \theta). \tag{1}$$

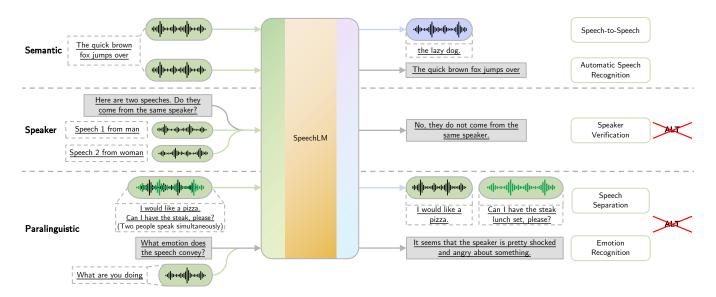


Figure 2: Applications of a SpeechLM. We use ALT to represent the "ASR + LLM + TTS" framework.

# 3 Components in SpeechLM

There are three main components within a SpeechLM, namely speech tokenizer, language model, and token-tospeech synthesizer (vocoder), as illustrated in Figure 1. The fundamental reason for such a three-staged design pattern is to use the language modeling architecture (e.g., decoder-only transformer) to model speech autoregressively in the format of audio waveforms. Since both the input and output of a language model are discrete tokens, additional modules need to be attached to the language model to handle the I/O format. Specifically, the speech tokenizer first transforms continuous audio waveforms into discrete tokens to serve as input to the language model, then the language model performs the nexttoken prediction based on the input speech tokens. Finally, the vocoder transforms the discrete tokens outputted by the language model back into audio waveforms. We note that our focus here is on how the three components are grouped together to form a SpeechLM rather than a comprehensive overview of each component. Therefore, for speech tokenizer and vocoder, we mainly summarize the methods used in existing SpeechLMs. Table 1 summarizes the popular choices of the three components in various SpeechLM papers.

#### 3.1 Speech Tokenizer

Speech tokenizer is the first component in SpeechLMs, which encodes continuous audio signals (waveforms) into latent representations and then converts the latent representations into discrete tokens (or sometimes called speech units). This conversion allows the audio input to be effectively processed by a language model for tasks such as speech recognition or synthesis. Speech tokenizer aims to capture essential features of the audio while reducing its dimensionality, facilitating the subsequent modeling and analysis of speech patterns. In this section, we categorize speech tokenizers based on their focus on modeling different aspects of the raw audio.

#### **Semantic Understanding Objective**

Speech tokenizers designed with a semantic understanding objective aim to convert speech waveforms into tokens that accurately capture the content and meaning of the speech. These tokenizers focus on extracting semantic features from the waveforms, which enhances tasks like ASR.

A semantic understanding speech tokenizer typically comprises a speech encoder and a quantizer, where the speech encoder encodes the essential information from the waveform and the quantizer discretizes continuous representations into discrete tokens. Let  $f_E(\cdot)$  denote the speech encoder parameterized by  $\theta_{f_E}$ , we have  $\mathbf{v} = f_E(\mathbf{a}; \theta_{f_E})$ , where  $\mathbf{v} = (v_1, v_2, \ldots, v_P)$  represents the encoded representations. Since  $\mathbf{v}$  is still continuous, a quantizer  $d(\cdot)$  is utilized to discretize the representation. Depending on different design choices, the discrete speech tokens  $\mathbf{s} = (s_1, s_2, \ldots, s_P)$  can either be derived from  $\mathbf{a}$  or  $\mathbf{v}$ . Therefore, we have  $\mathbf{s} = d(\mathbf{v}; \theta_d)$  or  $\mathbf{s} = d(\mathbf{a}; \theta_d)$ . After that,  $\mathbf{s}$  can be used to train the speech tokenizer as a target label (such as masking  $\mathbf{a}_{\text{mask}} \subset \mathbf{a}$  and reconstructing its corresponding label  $\mathbf{s}_{\text{mask}} \subset \mathbf{s}$  [Hsu et al., 2021]) or to train the following language model.

The key design choices lie in how to effectively encode and quantize the speech into discrete tokens. Wav2vec 2.0 [Baevski et al., 2020] uses a convolutional encoder followed by a product quantization module [Jegou et al., 2010] to discretize the continuous waveform. Then, a portion of the quantized representations is masked and modeled using a contrastive loss. W2v-BERT [Chung et al., 2021] is built upon wav2vec 2.0 and proposes to use Masked Language Modeling (MLM) loss [Devlin, 2018] in addition to contrastive loss. Similarly, HuBERT [Hsu et al., 2021] uses the k-means algorithm to cluster the speech utterances into a certain number of hidden units, and then perform MLM to predict the target hidden units from the masked speech utterances. To better align the representation of text and speech modalities, Google USM [Zhang et al., 2023c] utilizes text-injection loss [Chen

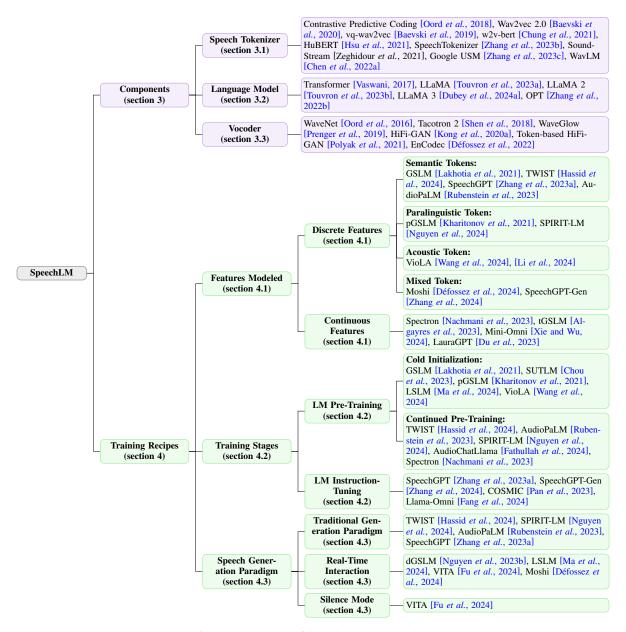


Figure 3: Taxonomy of Speech Language Models.

et al., 2022b] at the second pre-training stage to improve the performance and robustness of the downstream tasks. WavLM [Chen et al., 2022a] adds the speech denoising objective during pre-training. While the majority of speech tokenizer studies focus on semantic-related tasks such as ASR and TTS, WavLM shows that speech denoising can boost the performance of non-semantic tasks such as speaker verification and speech separation. A full list of downstream tasks is listed in section 5.

### **Acoustic Generation Objective**

Speech tokenizers with an acoustic generation objective focus on capturing the acoustic features necessary for generating high-quality speech waveforms. These tokenizers prioritize the preservation of essential acoustic characteristics over semantic content, making them suitable for speech synthesis tasks.

To generate high-quality speech waveforms, acoustic generation speech tokenizers employ a speech synthesis or speech reconstruction objective. To achieve this, the architecture typically includes an encoder, a quantizer, and a decoder. Same as before, the encoder  $f_E(\cdot)$  and quantizer  $d(\cdot)$  transform the original waveform into discrete tokens. After that, the decoder  $f_D(\cdot)$  reconstructs these tokens back into speech waveforms. This process is represented by  $\hat{\mathbf{a}} = f_D(\mathbf{s}; \theta_{f_E})$ , where  $\hat{\mathbf{a}}$  is the generated or reconstructed waveform.

Neural audio codecs are very suitable for and are primarily employed as acoustic generation speech tokenizers. These codecs utilize the advanced modeling capabilities of deep neural networks to compress audio signals into a compact representation, typically in the form of quantized tokens. For example, both SoundStream [Zeghidour *et al.*, 2021] and En-Codec [Défossez *et al.*, 2022] use convolution blocks as the encoder and use Residual Vector Quantization (RVQ) [Zeghidour *et al.*, 2021] as the quantizer. This mechanism allows for codecs to efficiently transmit or store audio with minimal loss in quality. Since the output of codecs is in discrete format, they can also be leveraged by SpeechLM to autoregressively generate speech.

#### **Mixed Objective**

Speech tokenizers with a mixed objective aim to balance both semantic understanding and acoustic generation. Currently, the development of these tokenizers is in its early stages. Most existing mixed speech tokenizers primarily adopt the architecture of acoustic generation speech tokenizers and focus on distilling information from semantic tokenizers into the acoustic tokenizer. SpeechTokenizer [Zhang et al., 2023b] utilizes the RVQ-GAN [Défossez et al., 2022; Zeghidour et al., 2021] architecture, distilling semantic information from HuBERT [Hsu et al., 2021] to the first layer of RVQ. Building on SpeechTokenizer, Mimi [Défossez et al., 2024] employs a single vector quantizer (VQ) to extract information from WavLM [Chen et al., 2022a] and incorporates another RVQ module to learn the acoustic information.

### 3.2 Language Model

Due to the success of TextLMs [Achiam et~al., 2023; Team et~al., 2023; Dubey et~al., 2024a], most SpeechLMs follow their architectures. They primarily employ transformers [Vaswani, 2017] or decoder-only architectures (such as OPT [Zhang et~al., 2022b], LLaMA [Touvron et~al., 2023a]) to generate speech in an autoregressive manner. To formally define it, given  $|V_t|$  as the vocabulary size and h as the hidden dimension, a typical text-based decoder-only transformer language model consists of an embedding matrix  $E_t \in \mathbb{R}^{|V_t| \times h}$ , a sequence of L transformer decoder blocks  $\mathbf{De} = \{De_1, De_2, \ldots, De_L\}$ , and an output embedding matrix  $E_t' \in \mathbb{R}^{h \times |V_t|}$ . Therefore, the language model (LM) can be represented as

$$\mathbf{t}^{\text{out}} \sim \text{LM}(\mathbf{t}^{\text{in}}, (E_t, \mathbf{De}, E_t')).$$
 (2)

To adapt the language model to generate speech, the original text tokenizer is changed to the speech tokenizers illustrated in section 3.1.  $E_t \in \mathbb{R}^{|V_t| \times h}$  is thus changed to a speech embedding matrix  $E_s \in \mathbb{R}^{|V_s| \times h}$ , where  $|V_s|$  represents the vocabulary size of the speech tokenizer. The output embedding matrix is also changed from  $E_t' \in \mathbb{R}^{h \times |V_t|}$  to  $E_s' \in \mathbb{R}^{h \times |V_s|}$ . As a result, the language model in an SpeechLM is represented as

$$\mathbf{s}^{\text{out}} \sim \text{LM}(\mathbf{s}^{\text{in}}, (E_s, \mathbf{De}, E_s')).$$
 (3)

Because the language model architecture of SpeechLMs is borrowed from TextLMs, it is natural that the resulting model can jointly model both text and speech modalities [Nguyen et al., 2024; Zhang et al., 2023a]. To achieve this, a naive and most adopted approach is to expand the vocabulary of

the original TextLM to incorporate both text and speech tokens. Specifically, the speech embedding matrix is usually appended to the end of the text embedding matrix, resulting in a larger embedding matrix  $E_m \in \mathbb{R}^{(|V_t|+|V_s|)\times h}$ . Let  $\mathbf{m}$  be a token sequence containing both speech and text tokens, the resulting language model becomes

$$\mathbf{m}^{\text{out}} \sim \text{LM}(\mathbf{m}^{\text{in}}, (E_i, \mathbf{De}, E_i')).$$
 (4)

By doing so, the model can generate both text and speech in a single sequence, enabling much more diverse applications (see section 5).

## 3.3 Token-to-Speech Synthesizer (Vocoder)

After the tokens have been autoregressively generated by the language model component, a token-to-speech module, often known as vocoder, is utilized to synthesize all the speech tokens back into speech waveforms. This process involves converting the linguistic and paralinguistic information represented by the generated speech tokens into audio waveforms that can be heard. This can be seen as a reverse process to the speech tokenizer and therefore can be represented as

$$\mathbf{a} = V(\mathbf{s}; \theta_V), \tag{5}$$

where V is the vocoder model parameterized by  $\theta_V$ .

The pipeline of the SpeechLM vocoder can vary depending on the underlying vocoder model. There are two main pipelines: Direct synthesis and input-enhanced synthesis. Direct synthesis is the pipeline where the vocoder directly converts speech tokens generated by the language model into audio waveforms. For example, [Polyak et al., 2021] adapts the HiFi-GAN [Kong et al., 2020a] architecture and takes discrete tokens as inputs. In contrast, inputenhanced synthesis employs an additional module to transform the tokens into a continuous latent representation before they are fed into the vocoder [Anastassiou et al., 2024; Betker, 2023]. The main reason for using this pipeline is that vocoders typically require intermediate audio representations, such as mel-spectrograms [Kumar et al., 2019; Kong et al., 2020a; Lee et al., 2022], as input. When comparing the two pipelines, direct synthesis is generally simpler and faster than Input-Enhanced Synthesis. However, the choice of pipeline depends on the type of tokens used as input. Tokens from acoustic generation tokenizers contain sufficient acoustic information, making them suitable for sirect aynthesis. Conversely, tokens from semantic understanding tokenizers provide rich semantic information but lack fine acoustic details, particularly in higher frequencies. Therefore, these tokens are better enhanced into an acoustic-rich representation, such as mel-spectrograms, before synthesizing the final

Vocoders can be categorized by their architectural choice. In the following sections, we summarize vocoders that are mostly adopted in the development of SpeechLMs.

### **GAN-based Vocoder**

Generative Adversarial Network (GAN) is the most adopted architecture of the vocoders [Kumar *et al.*, 2019; Kong *et al.*, 2020a; Polyak *et al.*, 2021; Kim *et al.*, 2021; Lee *et al.*, 2022]. It is well known for its fast and high-fidelity generation in

Approach	Speech Tokenizer	Language Model	Vocoder
Moshi [Défossez et al., 2024]	Mimi (SeaNet [Tagliasacchi et al., 2020] + Residual Vector Quantizer [Zeghidour et al., 2021])	Transformer*	Mimi
VITA [Fu et al., 2024]	CNN + Transformer + MLP [Fu et al., 2024]	Mixtral [Jiang et al., 2024]	Text-to-Speech Toolkit [Fu et al., 2024]
LSLM [Ma et al., 2024]	vq-wav2vec [Baevski et al., 2019]	Decoder-Only Transformer [Vaswani, 2017]	UniVATS [Du et al., 2024a]
SPIRIT-LM [Nguyen et al., 2024]	HuBERT, VQ-VAE, speechprop	LLaMA 2 [Touvron et al., 2023b]	HiFi-GAN [Kong et al., 2020a; Polyak et al., 2021]
TWIST [Hassid et al., 2024]	HuBERT [Hsu et al., 2021]	OPT [Zhang et al., 2022b], LLaMA [Touvron et al., 2023a]	HiFi-GAN
VOXTLM [Maiti et al., 2024]	HuBERT	OPT [Zhang et al., 2022b]	HiFi-GAN
Voicebox [Le et al., 2024]	EnCodec [Défossez et al., 2022]	Transformer* [Vaswani, 2017]	HiFi-GAN
VioLA [Wang et al., 2024]	EnCodec	Transformer*	Codec Decoder [Défossez et al., 2022]
FunAudioLLM [SpeechTeam, 2024]	SAN-M [Gao et al., 2020]	Transformer*	HiFTNet [Li et al., 2023]
AudioChatLlama [Fathullah et al., 2024]	Conformer layers [Gulati et al., 2020]	LLaMA 2	-
Wav2Prompt [Deng et al., 2024]	Conformer*	LLaMA-2, Vicuna [Chiang et al., 2023]	-
SpeechVerse [Das et al., 2024]	WavLM Large [Chen <i>et al.</i> , 2022a], Best-RQ [Chiu <i>et al.</i> , 2022]	Flan-T5-XL [Chung et al., 2024]	-
SpeechGPT-Gen [Zhang et al., 2024]	SpeechTokenizer [Zhang et al., 2023b]	LLaMA 2	SpeechTokenizer decoder [Zhang et al., 2023b]
LauraGPT [Du et al., 2023]	Conformer*	Qwen [Bai et al., 2023]	Transformer + Codec Decoder
Spectron [Nachmani et al., 2023]	Conformer*	PaLM 2* [Anil et al., 2023a]	WaveFit [Koizumi et al., 2023]
AudioLM [Borsos et al., 2023]	w2v-BERT [Chung et al., 2021]	Decoder-Only Transformer*	SoundStream* [Zeghidour et al., 2021]
UniAudio [Yang et al., 2023b]	EnCodec, Hifi-codec [Yang et al., 2023a], Improved RVQGAN [Kumar et al., 2023]	Transformer*	Codec Decoder
VALL-E [Wang et al., 2023a]	EnCodec	GPT-3 [Brown et al., 2020]	Codec Decoder
LTU [Gong et al., 2023]	Audio Spectrogram Transformer [Gong et al., 2021]	Vicuna	-
Llama-Omni [Fang et al., 2024]	Whisper [Radford et al., 2023]	Llama-3.1 [Dubey et al., 2024b]	HiFi-GAN
SALMONN [Tang et al., 2024]	Whisper, BEATs [Chen et al., 2023]	Vicuna	-
Mini-Omni [Xie and Wu, 2024]	Whisper + ASR Adapter [Xie and Wu, 2024]	Qwen2 [Yang et al., 2024]	TTS Adapter [Xie and Wu, 2024]
COSMIC [Pan et al., 2023]	Whisper	LLaMA-2	-
SpeechGPT [Zhang et al., 2023a]	HuBERT	LLaMA	HiFi-GAN
DLM [Nguyen et al., 2023b]	HuBERT	Dialogue Transformer [Nguyen <i>et al.</i> , 2023b]	HiFi-GAN
SUTLM [Chou et al., 2023]	HuBERT	Transformer*	-
dGSLM [Nguyen et al., 2023b]	HuBERT	Transformer*	HiFi-GAN
pGSLM [Kharitonov et al., 2021]	HuBERT	MS-TLM [Kharitonov et al., 2021]	HiFi-GAN
GSLM [Lakhotia et al., 2021]	HuBERT, CPC [Oord <i>et al.</i> , 2018], Wav2vec 2.0 [Baevski <i>et al.</i> , 2020]	Transformer*	Tacotron-2 + Waveglow [Shen <i>et al.</i> , 2018; Prenger <i>et al.</i> , 2019]

Table 1: Summarization of the architectural choice of speech tokenizer, language model, and vocoder in popular SpeechLMs. "-" represents non-existence or not indicated, \* means the architecture is mainly based on the written one, "A, B" means the authors experimented with both A and B as the component, and "A + B" means "A" and "B" are combined to serve as the component.

speech synthesis tasks. The architecture of GAN includes a generator and a discriminator. Specifically, the generator creates realistic audio waveforms from random noise or input features, while the discriminator evaluates the authenticity of the generated audio against real audio samples.

To utilize GAN to synthesize high-fidelity speech, various training objectives are designed, focusing on different aspects. First, **GAN loss** is utilized as the fundamental objective for the operation of the generator and the discriminator. Specifically, the typical choice GAN loss for the generator (G) and discriminator (D) is to use the least squares loss function. The GAN loss for the generator  $(\mathcal{L}_{\text{GAN}}(G; D))$  and the discriminator  $(\mathcal{L}_{\text{GAN}}(D; G))$  are

$$\mathcal{L}_{GAN}(G; D) = \mathbb{E}_{ms} \left[ \left( D(G(ms)) - 1 \right)^2 \right]$$
 (6)

and

$$\mathcal{L}_{GAN}(D;G) = \mathbb{E}_{(x,ms)} \left[ (D(x) - 1)^2 + (D(G(ms)))^2 \right],$$
(7)

respectively. In these loss functions, x represents the ground truth audio and ms represents its mel-spectrogram. Second, most GAN-based vocoders synthesize speech waveform

from mel-spectrograms, so **mel-spectrogram loss** is proposed to align the mel-spectrogram synthesized by the generator and the mel-spectrogram transformed from the ground-truth waveform, in order to improve the fidelity of the generated speech. Mel-spectrogram loss  $(\mathcal{L}_{\text{Mel}}(G))$  works by minimizing the L1 distance between the two versions of mel-spectrograms mentioned above. Its formula is shown below:

$$\mathcal{L}_{Mel}(G) = \mathbb{E}_{(x,ms)} [\|\phi(x) - \phi(G(ms))\|_{1}], \qquad (8)$$

where  $\phi(\cdot)$  is the function to transform a waveform into the corresponding mel-spectrogram. Third, to further enhance the generation fidelity, **feature matching loss**  $(\mathcal{L}_{FM}(G;D))$  is proposed to align the discriminator-encoded features of the ground truth sample and the generated sample with L1 distance, which has the following formula:

$$\mathcal{L}_{FM}(G; D) = \mathbb{E}_{(x, ms)} \left[ \sum_{i=1}^{T} \frac{1}{N_i} \| D^i(x) - D^i(G(ms)) \|_1 \right],$$
(9)

where  $D^i(\cdot)$  and  $N_i$  denote the features and the number of features in the *i*-th layer of the discriminator, respectively.

For architectural choices, GAN-based vocoders focus on injecting inductive biases to generate audio waveforms. Mel-

GAN [Kumar et al., 2019] adds residual blocks with dilations in the generator to model the long-range correlation among the audio time steps and proposes a multi-scale architecture for the discriminator to model the different frequency ranges of the audio. Based on the idea of the multi-scale discriminator, HiFi-GAN [Kong et al., 2020a] proposes a multi-period discriminator to model the diverse periodic patterns within the audio waveforms. To preserve high-frequency content, Fre-GAN [Kim et al., 2021] employs the Discrete Wavelet Transform (DWT) to downsample and learn spectral distributions across multiple frequency bands. Unlike traditional approaches like Average Pooling (AP), DWT efficiently decomposes the signal into low-frequency and high-frequency sub-bands. BigVGAN [Lee et al., 2022] introduces a periodic activation function called snake function along with an antialiased representation to reduce the high-frequency artifacts in the synthesized audio.

#### **GAN-based Neural Audio Codec**

Given that many neural audio codecs employ a GAN architecture, they can be effectively discussed within the context of GAN-based vocoders. Similar to its role as a tokenizer, although the primary objective of neural audio codecs is for audio compression, the encoded compact token sequences capture the essential information buried in the audio waveforms and therefore can be leveraged as a vocoder in SpeechLMs. EnCodec [Défossez et al., 2022] uses a GAN architecture and proposes a novel generator including an encoder, a quantizer, and a decoder. The compressed audio representations are outputted by the quantizer by using Residual Vector Quantization (RVQ). Polyak et al. utilizes HiFi-GAN [Kong et al., 2020a] as the vocoder backbone and proposes to disentangle the input features of a vocoder into distinct properties [Polyak et al., 2021], which include semantic tokens, pitch tokens, and speaker embeddings. Such a design choice enables the codec to better perform on pitch and speaker-related tasks such as voice conversion and  $F_0$  manipulation.

#### Other Types of Vocoder

The variety of vocoders is not restricted to the ones mentioned earlier, as those are the ones commonly employed in SpeechLMs. This section briefly outlines other potential vocoder types that are seldom explored as a component in SpeechLMs.

**Pure Signal Processing Vocoder.** Pure signal processing vocoders are traditional methods that rely on deterministic algorithms rather than deep learning models to synthesize speech [Griffin and Lim, 1984; Morise *et al.*, 2016]. However, this kind of vocoders introduces noticeable artifacts in the synthesized audio and is thus rarely used.

Autoregressive Vocoder. Autoregressive vocoders generate audio waveforms one sample at a time, with each sample conditioned on the previously generated samples [Oord *et al.*, 2016]. This approach allows for high-quality audio synthesis due to its sequential nature and the ability to capture intricate temporal dependencies within the audio signal. However, the sequential generation process can be computationally expensive and time-consuming, making autoregressive models less efficient compared to parallelized methods like GAN-based vocoders.

**Flow-based Vocoder.** Flow-based vocoder aims to establish a series of invertible transformations that map a simple distribution, such as a Gaussian, to the complex distribution of audio samples. This mechanism allows for efficient sampling and density evaluation, enabling the model to synthesize audio in parallel rather than sequentially, which significantly enhances both speed and quality [Prenger *et al.*, 2019]. Compared to GAN-based vocoders, Flow-based vocoders typically need more parameters and memory to train the model, which hinders them from being effectively utilized [Kumar *et al.*, 2019].

**VAE-based Vocoders.** Variational Autoencoders (VAEs) are powerful generative models that learn to encode input data into a compressed latent space while allowing for the reconstruction of the original data [Van Den Oord *et al.*, 2017; Huang *et al.*, 2019]. However, VAE is seldom explored as the underlying architecture of vocoders.

**Diffusion-based Vocoder.** Diffusion models have emerged in recent years as a powerful class of generative models that can be used for high-fidelity speech synthesis. They work by gradually adding noise to the input data (e.g. audio waveforms) to create a sequence of increasingly noisy representations, then learning to reverse this process to generate new samples [Kong *et al.*, 2020b; Chen *et al.*, 2020; Lee *et al.*, 2021]. For instance, DiffWave [Kong *et al.*, 2020b] uses Denoising Diffusion Probabilistic Models (DDPM) to synthesize audio. Additionally, CosyVoice [Du *et al.*, 2024b] introduces a Conditional Flow-Matching (CFM) model that serves as a vocoder in TTS systems.

# 4 Training Recipes

In this section, we categorize and summarize the commonly used training recipes found in recent SpeechLM papers. This includes an overview of the types of features modeled in SpeechLMs, the various training stages along with the techniques employed in each stage, and the different paradigms for generating speech.

#### 4.1 Features Modeled

The features modeled refer to the types of features outputted by the speech tokenizer and modeled by the language model component within a SpeechLM. These features play a crucial role in determining the capabilities and performance of SpeechLMs. Different features model the speech waveforms from different aspects. Based on recent developments, we can categorize the features modeled by SpeechLMs into two main types, including discrete features and continuous features.

#### **Discrete Features**

Discrete features refer to quantized representations of speech signals that can be represented as distinct, countable units or tokens. These features are typically derived from speech signals through various encoding and quantization processes, resulting in a finite set of possible values. Discrete features are the most used features by SpeechLMs as they can be represented as tokens and be modeled exactly the same as the text tokens within a TextLM. The majority of speech tokenizers produce discrete tokens that better model the *semantic information* within a speech waveform (semantic understanding

Dataset	Type	Phase	Hours	Date
LibriSpeech [Panayotov et al., 2015]	ASR	Pre-training	1k	2015
LibriLight [Kahn et al., 2020]	ASR	Pre-training	60k	2019
People dataset [Galvez et al., 2021]	ASR	Pre-training	30k	2021
VoxPopuli [Wang et al., 2021]	ASR	Pre-training	1.6k	2021
Gigaspeech [Chen et al., 2021]	ASR	Pre-training	40k	2021
Common voice [Ardila et al., 2019]	ASR	Pre-training	2.5k	2019
WenetSpeech [Zhang et al., 2022a]	ASR	Pre-training	22k	2022
LibriTTS [Zen et al., 2019]	TTS	Pre-training	0.6k	2019
CoVoST2 [Wang et al., 2020]	S2TT	Pre-training	2.8k	2020
CVSS [Jia et al., 2022]	S2ST	Pre-training	1.9k	2022
Spotify podcasts [Clifton et al., 2020]	Podcast	Pre-training	47k	2020
Fisher [Cieri et al., 2004]	Telephone conversation	Pre-training	2k	2004
SpeechInstruct* [Zhang et al., 2023a]	Instruction-following	Instruction-tuning	-	2023
InstructS2S-200K* [Fang et al., 2024]	Instruction-following	Instruction-tuning	-	2024

Table 2: A summary of popular datasets used in the pre-training and instruction-tuning phase of SpeechLMs. \* means it is the speech version of the text dataset synthesized using TTS. S2ST and S2TT represent speech-to-speech translation and speech-to=text translation, respectively.

speech tokenizers, section 3.1), such as [Chung *et al.*, 2021; Hsu *et al.*, 2021]. This is because they primarily use understanding objectives such as MLM to model the contextual information of the waveforms when training the tokenizer. We refer to them as *semantic tokens* here.

Most SpeechLMs only employ semantic tokens to represent speech. GSLM [Lakhotia et al., 2021], the firstever SpeechLM, compares three tokenizers, which include Contrastive Predictive Coding (CPC) [Oord et al., 2018], wav2vec 2.0 [Baevski et al., 2020], and HuBERT [Hsu et al., 2021]. It concludes that HuBERT performs the best on various tasks such as speech resynthesis and speech generation. A large number of works follow this setting and use HuBERT as the speech tokenizer [Hassid et al., 2024; Nguyen et al., 2024; Zhang et al., 2023a]. AudioPaLM [Rubenstein et al., 2023] experiments the choice between w2v-bert [Chung et al., 2021], USM-v1 [Zhang et al., 2023c], and USM-v2 [Rubenstein et al., 2023] (which is a modified version of USM-v1), and it concludes that USM-v2 is the best-performing speech tokenizer on ASR and Speech Translation (ST) tasks.

Although semantic tokens excel at generating semantically meaningful speech because of the modeling of the contextual information within speech waveforms, researchers find out that the speech generated solely upon semantic tokens lacks expressive information such as prosody and different pitches or timbres [Nguyen et al., 2023a; Nguyen et al., 2024]. To conquer this limitation, paralinguistic tokens can be integrated into the modeling process to capture expressive information with speeches. Specifically, pGSLM [Kharitonov et al., 2021] proposes to use the fundamental frequency (F0) and unit duration as prosody features to complement the Hu-BERT semantic tokens, and trains a multi-stream transformer language model to predict the semantic tokens, pitch (F0), and unit duration separately. Similarly, SPIRIT-LM [Nguyen et al., 2024] complements the HuBERT semantic tokens with pitch and style tokens [Duquenne et al., 2023]. This incorporation of extra acoustic tokens allows SpeechLMs to more effectively capture expressive elements without significantly compromising semantic understanding [Nguyen et al., 2024].

Another type is *acoustic tokens*, which are tokens aiming to capture the essential acoustic features to reconstruct high-fidelity speech, primarily obtained from neural audio codec models (see section 3.1). Codec models aim to learn the compressed representation of audio, so it is anticipated that both the semantic and acoustic information present in a speech waveform can be encoded in the representation. Some studies attempt to directly model the codec tokens in an autoregressive manner. VALL-E [Wang *et al.*, 2023b] utilizes codec tokens to achieve zero-shot TTS. It encodes a 3-second audio clip using EnCodec [Défossez *et al.*, 2022] as a prompt, enabling the TTS system to synthesize speech that matches the timbre information of the prompt. Viola [Wang *et al.*, 2024] uses codec tokens in a SpeechLM capable of performing ASR, TTS, and Machine Translation (in text).

**Discussion.** Different types of tokens influence the speech quality of SpeechLMs in different ways, often resulting in trade-offs [Borsos et al., 2023]. For example, while semantic tokens align well with text and excel in producing semantically coherent speech, the generated speech often lacks acoustic details, such as high-frequency information. Recovering and enhancing these details typically requires postprocessing, like a diffusion model, which significantly increases the model's latency. Conversely, acoustic tokens can facilitate the generation of high-fidelity audio but often struggle with inaccuracies in content generation [Zhang et al., 2023b]. Researchers have tried two ways to balance these trade-offs. The first involves combining semantic and acoustic tokens into a single sequence. AudioLM [Borsos et al., 2023] proposes a hierarchical modeling scheme that first models semantic tokens from w2v-bert [Chung et al., 2021] and then uses these tokens to predict acoustic tokens from SoundStream [Zeghidour et al., 2021], which ultimately generates speech. However, this kind of approach increases sequence length, which increases modeling complexity. The second strategy leverages mixed tokens (see section 3.1) to jointly model semantic and acoustic information, showing promising results in Moshi [Défossez *et al.*, 2024] and SpeechGPT-Gen [Zhang *et al.*, 2024].

#### **Continuous Features**

Continuous features, in contrast to discrete features, are unquantized, real-valued representations of speech signals that exist on a continuous scale. These features capture finegrained, nuanced aspects of speech that may be lost in discretization processes. Continuous features can include spectral representations like mel-spectrograms or latent representations extracted from neural networks. The exploration of leveraging continuous features to condition SpeechLMs is still in its infancy. Spectron [Nachmani et al., 2023] performs speech continuation by predicting the spectrograms frameby-frame. However, the generation of speech spectrograms still needs to be conditioned on text transcripts, which is not an end-to-end speech generation approach. Mini-Omni [Xie and Wu, 2024] extracts intermediate representations from a frozen Whisper encoder as input for the SpeechLM, whereas LauraGPT [Du et al., 2023] employs an audio encoder trained alongside the SpeechLM to derive latent representations from input speech.

## **4.2** Training Stages

Training a SpeechLM involves training the three main components: speech tokenizer, language model, and vocoder. Similar to TextLMs, the key to training SpeechLMs lies in effectively modeling speech continuation, which is primarily the responsibility of the language model. The speech tokenizer and vocoder usually rely on established methods and are trained using distinct training datasets specific to each SpeechLM approach. Therefore, This section reviews the main techniques used to train the language model component.

Following TextLMs, the training process for SpeechLMs can be divided into three stages: pre-training, instruction-tuning, and alignment. However, to our knowledge, there is currently no research specifically focused on the alignment process following instruction tuning. Therefore, we only discuss the works related to the pre-training and instruction-tuning stages of SpeechLMs.

#### **Language Model Pre-training**

The pre-training of the language model in SpeechLMs is a critical phase that significantly influences the model's ability to generate coherent and contextually relevant speech. This phase typically involves training the language model to autoregressively predict the next token on a large corpus of speech tokens. The primary objective during this stage is to learn the statistical patterns and dependencies inherent in the speech data, enabling the model to predict the next token in a sequence based on the preceding context. Table 2 includes popular datasets used in pre-training stage of SpeechLMs.

**Training data.** SpeechLMs pre-training mainly leverages large-scale open-sourced speech data. Commonly used datasets include those for ASR [Panayotov *et al.*, 2015; Kahn *et al.*, 2020; Galvez *et al.*, 2021; Wang *et al.*, 2021], TTS [Zen *et al.*, 2019], ST [Jia *et al.*, 2022; Wang *et al.*, 2021], podcasts [Clifton *et al.*, 2020], and dialogues [Cieri *et al.*, 2004]. Some datasets consist solely of speech data, while

others include both speech and corresponding text transcripts. The inclusion of text transcripts can enhance the model's representation by allowing it to learn the relationship between spoken language and its written form, which will be discussed later.

Cold Initialization. Some SpeechLMs use cold initialization during the pre-training phase, where model parameters are initialized randomly. The pioneering SpeechLM—GSLM [Lakhotia et al., 2021]—trained a transformer [Vaswani, 2017] from scratch to serve as the language model. This study demonstrated the effectiveness of the SpeechLM pipeline and compared performance across various speech tokenizer options. They found that HuBERT [Hsu et al., 2021] outperformed CPC [Oord et al., 2018] and wav2vec 2.0 [Baevski et al., 2020] in understanding speech content and generating natural speech. SUTLM [Chou et al., 2023] also uses a transformer as the language model. They studied the critical problem of jointly modeling speech and text tokens by comparing four different modeling methods: speech-only, text-only, concatenated speech-text, and alternating (interleaving) speechtext. They showed that the setting of alternating speech-text performs the best in cross-modal evaluations. Table 3 illustrates the four modeling methods.

Some works leverage a different architecture from the standard transformer. Since there are no existing checkpoints for those self-proposed architectures, it is necessary to train them from scratch. For example, pGSLM [Kharitonov et al., 2021] proposes a multi-stream transformer language model (MS-TLM) that takes multiple streams of input and predicts multiple streams of output to generate speech units, duration, and pitch embeddings simultaneously. dGSLM [Nguyen et al., 2023b] introduced a dialogue transformer language model (DLM) to jointly model the dialogue speech data from the two speakers. To enable the listening ability of SpeechLMs while speaking, LSLM [Ma et al., 2024] proposes to attach a streaming self-supervised learning (SSL) Encoder to an autoregressive token-based TTS Model. Viola [Wang et al., 2024] introduced a multi-task auto-regressive codec language model to autoregressively generate codec tokens instead of speech unit tokens.

Continued Pre-Training. In contrast to cold initialization, continued Pre-Training involves initializing the language model with pre-trained weights from a TextLM and then adapting it to handle speech tokens. This approach leverages the linguistic knowledge embedded in TextLMs, allowing for more efficient and effective training of SpeechLMs. Research by [Hassid et al., 2024] found that starting with a textually pre-trained language model (OPT [Zhang et al., 2022b] and LLaMA [Touvron et al., 2023a]) can enhance the model's convergence rate and significantly improve its speech understanding capabilities. They also demonstrated that while training from text-pretrained checkpoints outperforms cold initialization, training from image-pretrained checkpoints yields poorer results compared to cold initialization. This indicates that not all pre-trained checkpoints are equally effective. Additionally, AudioPaLM [Rubenstein et al., 2023] trained the SpeechLM using PaLM and PaLM-2 [Chowdhery et al., 2023; Anil et al., 2023b], showing that the SpeechLM benefits from both an increased size of the pre-

Modeling Method	Example	Explanation
Speech-only	[SPEECH] S12 S34 S33 S11 S59	Only the speech sequence is provided.
Text-only	[TEXT] A quick brown fox jumps over a lazy dog.	Only the text sequence is provided.
Concatenated speech-text	[SPEECH] S12 S34 S33 S11 S59 [TEXT] A quick brown fox jumps over a lazy dog.	The speech sequence and text sequence are concatenated together.
Alternating speech-text	[SPEECH] S12 S34 S33 [TEXT] brown fox jumps over a lazy [SPEECH] S11 S59	The sequence is interleaved with speech and text tokens.

Table 3: Four different methods of jointly modeling speech and text tokens.

trained checkpoint and a larger training dataset.

The performance of SpeechLMs can be further enhanced by aligning the text and speech modality representations. SPIRIT-LM [Nguyen et al., 2024] found that continually pretraining on TextLM checkpoints using interleaving text and speech tokens can significantly boost the model's performance on speech understanding and generation. Additionally, their visualizations demonstrate that the similarity between text and speech features is notably higher in models trained with interleaved token sequences compared to those trained without this approach. AudioChatLlama [Fathullah et al., 2024] aims to ensure that the model produces consistent outputs regardless of whether the input is text or speech. They address this challenge by treating text data in ASR datasets as prompts, allowing LLaMA to generate the corresponding responses. Consequently, both text and speech versions of the prompt can be utilized to train the model to provide the appropriate response. Spectron [Nachmani et al., 2023] solves the text-speech representation alignment problem by jointly supervising multiple objectives. Specifically, the input speech prompt is first transcribed into its text tokens, and then the model predicts the text token response. Finally, the text response is synthesized to output speech.

#### **Language Model Instruction-Tuning**

Instruction-tuning refers to the process of fine-tuning SpeechLMs to follow specific instructions to perform a wide range of tasks. This phase is crucial for enhancing the pre-trained model's generalization capabilities and making it more adaptable to diverse applications. Therefore, the key focus is on creating effective instruction-following datasets.

Several approaches have been proposed to construct instruction-following datasets for SpeechLMs. SpeechGPT [Zhang et al., 2023a] and SpeechGPT-Gen [Zhang et al., 2024] propose a two-stage instruction-tuning, including cross-modal instruction fine-tuning and chain-of-modality instruction fine-tuning. In the first stage, instruction data are generated based on ASR datasets by appending the instruction to paired ASR data, asking the model to convert speech into text. Similarly, paired data is also used to create instruction data for performing TTS. In the second stage, they construct a speech-in-speech-out dataset by transforming a textbased instruction-following dataset using TTS. Llama-Omni [Fang et al., 2024] also creates instruction-following data by synthesizing text-based datasets, adhering to specific constraints. First, they transform the input text prompt into a format that mimics natural speech patterns. Next, they discard the original text response and employ a TextLM to generate answers to the converted prompts, ensuring these responses also follow natural speech patterns. Finally, they synthesize the prompt/response pairs using TTS. COSMIC [Pan *et al.*, 2023] constructed speech QA data by asking GPT-3.5 to generate question-answer pairs based on the transcriptions of English TED talk speeches. They showed the model trained on their proposed speech QA dataset can generalize to unseen tasks such as speech-to-text translation using in-context learning.

### 4.3 Speech Generation Paradigm

In the previous sections, we discuss the typical generation paradigm for SpeechLMs, which involves taking a predefined input sequence and generating a complete response. However, this approach does not reflect the natural flow of voice interactions. For instance, during a conversation, one person may interrupt another, switching from listening to speaking. Additionally, a person might choose not to respond if the other is engaged in a conversation with someone else. Based on these observations, we identify two key aspects of advanced voice interaction skills for SpeechLMs: real-time interaction and silence mode.

**Real-time Interaction** refers to the capability of SpeechLMs to engage with users instantaneously. This interaction consists of two key components:

- 1. User Interruption: SpeechLMs should be able to be interrupted by users and should respond appropriately to new instructions provided during the conversation.
- 2. Simultaneous Response: SpeechLMs should be capable of generating responses while the user is still speaking.

Both of these abilities require the model to effectively perform speech understanding (processing input) and speech generation (producing output) simultaneously. The study by dGSLM [Nguyen et al., 2023b] introduces a dual-transformer architecture to model two-speaker dialogues, using one transformer to handle speech from each speaker. A cross-attention transformer layer is included to capture the interactions between the speakers' content. In contrast, LSLM [Ma et al., 2024] proposes a different approach, utilizing a single decoder-only Transformer to model one speaker's speech in the dialogue. This model incorporates a streaming SSL encoder that continuously processes input from the listening channel and fuses its embeddings with those from the speaking channel.

**Silence Mode** refers to the state in which the SpeechLMs remain inactive or silent during periods of non-interaction. This mode is essential for creating a natural conversational

flow, allowing the model to avoid unnecessary interruptions. It is crucial for situations where a small group of users is having a discussion, as the SpeechLM needs to discern when to join in and when to stay silent. Additionally, it is important for the model to learn when to disregard instructions when users are not speaking at it. VITA [Fu et al., 2024] is currently the only work that integrates silence mode. This method involves training the model on both query speech and non-query audio, which may include environmental sounds or non-query speech. As a result, the model learns to output the end-of-sequence token to terminate its response when non-query audio is detected.

## 5 Downstream Applications

Unlike traditional speech systems like ASR and TTS, which usually focus on specific tasks, SpeechLMs function as generative foundation models. They can handle a diverse array of speech-only, text-only, and multi-modal tasks by following various instructions. In this section, we explore the primary downstream applications of SpeechLMs. The tasks discussed here primarily consist of traditional speech-related tasks, along with some that are unique to SpeechLMs. In contrast to TextLMs, which generate text containing only semantic information, SpeechLMs can model both semantic and paralinguistic information—such as pitch and timbre—making them more powerful models. We thereby categorize the downstream applications of SpeechLMs into three main classes: semantic-related applications, speaker-related applications, and paralinguistic applications.

## 5.1 Semantic-Related Applications

Semantic-related applications encompass key tasks that facilitate meaningful interactions between humans and machines. These applications require SpeechLMs to understand the semantic meaning of the input and generate responses that are not only contextually relevant but also logically coherent. The primary Semantic-related applications of SpeechLMs are as follows.

**Spoken Dialogue.** Spoken dialogue is the most natural application of SpeechLMs. Spoken dialogue systems are designed to facilitate natural conversations between humans and machines in spoken format. They can engage users in interactive exchanges, understanding and generating responses based on the context of the conversation. Unlike TextLMs, SpeechLMs are able to perform conversations with humans directly in speech, which is a more natural way of communication. Note that SpeechLMs can not only perform speechonly dialogues but also perform cross-modal dialogues, such as taking texts as input and responding in speech format.

**Speech Translation.** Speech translation (ST) is the process of converting spoken language from one language to another. Similar to Spoken dialogue, SpeechLMs can perform ST in both single-modal and cross-modal settings. Specifically, the input and output of the ST task can be either in text or speech format.

**Automated Speech Recognition.** Automatic speech recognition (ASR) enables systems to convert spoken language into text. The input of ASR is a speech waveform,

and the system outputs the transcription in textual form. For SpeechLMs, the input would be a combination of the speech waveform and the instruction to tell the model to perform ASR on the given speech.

Keyword Spotting. Keyword spotting can be considered a special type of ASR, where its primary objective is to identify specific words or phrases within continuous speech. While traditional ASR systems aim to transcribe entire spoken utterances into text, keyword spotting focuses specifically on identifying and extracting predefined keywords or phrases within continuous speech. The primary application of keyword spotting is to build oice-activated assistants in smart home devices. Those devices are activated when the specific keywords are triggered. Therefore, although SpeechLMs are capable of spotting and understanding more than just a couple of words, keyword spotting can be used to efficiently trigger SpeechLMs to respond to user inputs.

**Text-to-Speech Synthesis.** Text-to-speech synthesis (TTS) enables systems to synthesize written text into spoken language. In contrast to ASR, TTS takes text as input and outputs the converted speech waveform. Similarly, the input of the SpeechLMs would be a combination of the text to synthesize and the instruction, and the output is the synthesized speech.

Intent Classification. Intent classification is a critical task that identifies the underlying intention behind a user's input speech. The AI system can then perform certain actions based on the identified user intent (e.g., book a flight). Intent classification is particularly important in applications such as virtual assistants, customer service bots, and interactive voice response systems. To perform Intent Classification, it is more natural for SpeechLMs to take speech inputs and classify the results in text since it is easier to parse and classify the intent classification result in text than speech.

Slot Filling. Slot filling is an important task in spoken language understanding that involves identifying and extracting specific pieces of information from user inputs into predefined classes, such as intents, entities, and parameters that are essential for completing a task. For example, slot filling extracts the phrase "I want to fly from New York to San Francisco on June 5th." into distinct slots like "departure city" (New York), "destination city" (San Francisco), and "date" (June 5th). Similar to Intent Classification, it is more natural for SpeechLMs to take speech inputs and extract the pieces in texts.

**Query by Example Spoken Term Detection.** Another spoken term detection task is query by example spoken term detection (QbE-STD), which allows users to identify specific spoken terms or phrases within a larger audio stream by providing an example of the desired term. Unlike traditional keyword spotting methods that rely on predefined lists of keywords, QbE-STD leverages the flexibility of example-based querying, enabling users to specify their search terms through audio samples.

#### **5.2** Speaker-Related Applications

Speaker-related applications refer to the tasks that involve the processing of information related to speaker identity. It could involve classification tasks such as identifying, verifying, and

	Semantic-related Application	
Spoken Dialogue Speech Translation	Speech(I am so angry right now!) Speech(Good morning my friend!) Please translate the speech into French.	Speech(Sorry to hear that. What happened?) Speech(Bonjour mon ami!)
Automatic Speech Recognition	Speech(A river is on your left side.) Please perform automatic speech recognition to the speech	The transcribed speech is: A river is on your left side.
Keyword Spotting	Speech(How's your day? (Speaking to somebody else) Hey, Siri.) Please detect if the given speech contains any pre-defined keywords.	Keyword detected: "Hey, Siri."
Text-to-Speech Synthesis	Please synthesize the following text into speech: "A river is on your left side."	Sure. Here is the synthesized speech: Speech(A river is on your left side.)
Intent Classification	Speech(Can you help me book a flight?) Please detect the intent of the given speech.	Intent detected: "Book a flight".
Slot Filling	Speech(I want to fly from New York to San Francisco on June 5th.) Please fill the following slots based on the given speech: departure city, destination city, and date	Sure. Here are the filled slots. Departure city: New York. Destination city: San Francisco. Date: June 5th.
Query by Example Spoken Term Detection	Speech(Can you retrieve the audio documents that contain the word "happy"?) [A batch of audio documents]	Sure. I have found documents 2 and 4 contain the word happy.
	Speaker-related Application	
Speaker Identification	The following speech comes from Lucy: "[Lucy's speech]". The following speech comes from Bob: "Bob's speech". Question: Who is the speaker of the following speech [Unknown speech]	The speaker of the following speech: "[Unknown speech]" is Bob.
Speaker Verification	Here are two speeches. Speech 1: [Speech 1]. Speech 2: [Speech 2]. Do they come from the same speaker?	No, they do not come from the same speaker.
Speaker Diarization	[An audio file of the meeting] Please provide the speaker diarization output in the following format: [Start Time] - [End Time]: Speaker [Speaker].	Sure. Here is the speaker diarization result: 00:00 - 00:15: Alice, 00:16 - 00:40: Bob, 00:41 - 01:00: Carol, 01:01 - 01:20: Alice, 01:21 - 01:45: Bob and Carol (overlapping speech), 01:46 - 02:00: Carol.
Voice-Conditioned Speech Generation	Can you use a robotic voice to say "Hello world!" to me?	Sure. Speech([In robotic voice] Hello world!)
	Paralinguistic Application	S
Emotion Recognition	Speech(What are you doing) What emotion does the speech convey?	It seems that the speaker is pretty shocked and angry about something.
Speech Separation	Speech([Two overlapping speeches]) Can you separate the two speeches?	Sure. Here is the speech separation result. Speech 1: Speech(Should I go for this one?). Speech 2: Speech(That one seems good.)
Paralinguistics- Enhanced Generation	Speech(Please generate a speech that sounds happy.)	Speech([In happy mood] My friend just gave me a candy!!)

Output

Table 4: Examples of the various capabilities of SpeechLMs.

distinguishing individual speakers based on their unique vocal characteristics, as well as generation tasks such as maintaining or modifying the timbre of a given speech. While we acknowledge that voice characteristics can be considered paralinguistic information, we believe that speaker-related applications are unique because they enable SpeechLMs to function in complex scenarios such as participating in multispeaker conversations. In this section, we survey common speaker-related applications of SpeechLMs.

Task

Input

**Speaker Identification.** Speaker identification is the process of recognizing a person's identity based on their voice characteristics. It is a multi-class classification of a given speech as input. SpeechLMs can perform this task by taking an input speech and outputting the classification result in

text or speech format. Moreover, SpeechLMs can also identify different speakers implicitly. Specifically, it can chat with multiple speakers at the same time, distinguishing the words from different speakers and responding to each speaker appropriately.

**Speaker Verification.** Speaker verification involves determining whether the speakers of a pair of speeches match with each other. Unlike speaker identification, which is a multiclass classification process, speaker verification is a binary classification process.

**Speaker Diarization.** Speaker diarization is the process of partitioning an audio stream into segments according to the identity of the speakers. It predicts "who is speaking when" for each timestamp [Yang *et al.*, 2021]. A natural way to

integrate speaker diarization into SpeechLMs is to have the model generate the transcript of each audio segment along with the identification of the speaker.

Voice-Conditioned Speech Generation. Voice-conditioned speech generation involves synthesizing speech based on the vocal characteristics of a specific speaker. This could involve voice cloning and voice conversion. Voice cloning utilizes a sample of the speaker's voice as a reference, enabling the model to reproduce the speaker's timbre when generating speech from input text. Voice conversion, on the other hand, modifies an existing speech signal to sound like it was produced by a different speaker while retaining the original content. Additionally, instead of giving the target vocal characteristics, SpeechLMs should also be able to adapt their output timbre based on various speech or text instructions.

## **5.3** Paralinguistic Applications

Paralinguistics refers to the non-verbal elements of communication that accompany spoken language. It encompasses various vocal attributes that convey meaning beyond the actual words spoken. These elements can significantly influence how messages are interpreted and understood. The key elements of paralinguistics include pitch, timbre, column, rate of speech, pauses, etc. Since combining elements in paralinguistics in different ways can result in a speech with different emotions, we include emotion-related tasks as paralinguistic applications as well.

**Emotion Recognition.** Emotion recognition task involves identifying and classifying the emotion carried by a given speech into predefined classes. Similar to speaker identification, SpeechLMs are capable of not only directly performing this task but also implicitly recognizing users' emotions through their speech queries and responding accordingly.

**Speech Separation.** Speech separation refers to the process of isolating individual speech signals from a mixture of sounds, such as when multiple speakers are talking simultaneously. When separating the input speech, SpeechLMs can not only output the contents of each person in speech but also in text format (i.e., transcriptions).

Paralinguistics-Enhanced Generation. Paralinguistics-enhanced generation refers to the process of instructing SpeechLMs to produce speech that exhibits specific paralinguistic characteristics. Users can define these characteristics in their prompts, allowing the model to generate speech that aligns with their specifications. Examples of paralinguistics-enhanced generation include synthesizing speech with a specific style, speaking at a fast pace, and even singing. This capability distinguishes SpeechLMs from TextLMs and facilitates a more engaging and interactive form of communication with the AI models.

## 6 Evaluations

Similar to TextLMs, SpeechLMs have a wide range of capabilities, making it challenging to compare different SpeechLMs. Consequently, it's essential to evaluate SpeechLMs from various perspectives to determine their effectiveness. In this section, we review the commonly used

methods and benchmarks for evaluating SpeechLMs. We categorize these evaluation methods into automatic and human assessments, each containing distinct evaluation aspects.

## 6.1 Automatic (Objective) Evaluation

Automatic evaluation methods are essential for providing quick and consistent assessments of SpeechLMs. These methods typically rely on quantitative metrics that can be computed without human intervention. Below, we outline some of the most commonly used automatic evaluation techniques.

**Representation Evaluation.** Representation (embedding) is a crucial component in SpeechLMs (and TextLMs). It refers to how input data, such as speech or text, is transformed into a format that the model can understand and process. Effective representation lays a solid foundation for models to understand lexical, syntax, and contextual information, which are vital for generating coherent and contextually relevant outputs.

In the context of SpeechLMs, representation evaluation focuses on how well the model encodes speech features into meaningful vectors. GSLM [Lakhotia et al., 2021] uses between-speaker ABX score to measure the embedding similarity. It quantifies how well-separated the phonetic categories are. Specifically, It works by comparing three sound samples: two from the same category (A) and one from a different category (B). The test measures how often the system correctly identifies that two sounds from category A are more similar to each other than one sound from A is to a sound from B. Another way of evaluating representations is through speech resynthesis [Lakhotia et al., 2021]. Specifically, an input speech is encoded into tokens and then synthesized back to speech. Then, word error rate (WER) or character error rate (CER) can be computed on the ASR results of the input and resynthesized speech. This measures the information loss caused by discretizing the input speech into speech tokens, thereby evaluating the robustness of the latent representations.

Linguistic Evaluation. Linguistics, including lexical, syntactic, and semantic evaluation methods, assess the model's ability to generate and understand the rules for constructing words, sentences, and meaningful contents. These evaluations focus on the correctness and appropriateness of word choices, the grammatical structure of the outputs, and the coherence and relevance of the generated content. In terms of benchmark datasets, sWUGGY [Nguyen et al., 2020] assesses at the lexical level by determining if the model can distinguish a real word from a (real, non-real) word pair. sBLIMP [Nguyen et al., 2020] evaluates at the syntactic level by determining if the model can identify the grammatically correct sentence from a (grammatical, ungrammatical) sentence pair. Spoken StoryCloze [Hassid et al., 2024] evaluates semantic comprehension by assessing the model's capability to select the genuine ending of a story from a pair of ending choices. All the evaluation is conducted by comparing the model's negative log-likelihood of the data pair.

**Paralinguistic Evaluation.** In contrast to linguistic evaluation, paralinguistic evaluation focuses on the non-verbal aspects of communication that accompany speech. Some works

choose to utilize paralinguistic tokens alongside semantic tokens to enhance the paralinguistic abilities of SpeechLMs [Kharitonov et al., 2021; Nguyen et al., 2024], so one way is to evaluate the paralinguistic tokens. pGSLM [Kharitonov et al., 2021] measures the correctness, consistency, and expressiveness of the prosodic tokens. Correctness evaluates the model's ability to generate accurate prosodic profiles by calculating the minimal mean absolute error (min-MAE) of the prosodic tokens from 20 generated samples against the prosodic tokens from the reference, consistency is assessed through the Pearson correlation between the mean values of the prompt prosodic and its generated continuation prosodic tokens, and expressiveness is measured by the standard deviation of the generated prosody token values, with the expectation that it matches the variability of the ground truth. We note that the same metrics can also be applied to other paralinguistic tokens. Instead of evaluating from the token level, [Nguyen et al., 2024] propose to measure on the perceptual level. They introduced a speech-text sentiment preservation benchmark (STSP), which requires the model to generate a text or speech sequence of tokens that preserves the sentiment of the prompt. A sentiment classifier is used to assess the sentiment in the generated speech. It should be noted that although they only apply the preservation approach on sentiment, this idea can be generalized to other paralinguistic features, such as timbre or prosody.

Generation Quality and Diversity. Quality and diversity are two crucial aspects of model generation. Typically, there is a trade-off between these dimensions when sampling model responses at different temperatures, so GSLM [Lakhotia *et al.*, 2021] suggests using the Area Under the Curve (AUC) with various temperature values. Specifically, AUC on perplexity and VERT are employed to assess these factors, where VERT represents the geometric mean of the ratio of k-grams in the generated speech that appears at least once. Additionally, the ChatGPT score can be utilized to evaluate the quality of the generated speech. In this process, the generated speech is transcribed using state-of-the-art ASR models and then sent to ChatGPT for quality (and diversity) assessment.

**Downstream Evaluation.** Downstream evaluation refers to evaluating the ability of SpeechLMs to perform specific tasks, such as ASR, TTS, Speaker Identification, etc. The evaluation can be performed on pre-trained models by adding few-shot example(s) at the start of the prompt or on the instruction-tuned models by directly instructing them to do so. SUPERB [Yang *et al.*, 2021] is a benchmark containing a wide range of downstream tasks that can be performed by SpeechLMs.

## 6.2 Human (Subjective) Evaluation.

Human evaluation plays a crucial role in assessing the performance of SpeechLMs, as ultimately, speech is designed to be heard and perceived by humans. This type of evaluation relies on human judgment to assess the quality of the outputs generated by SpeechLMs. Below, we outline several commonly used human evaluation methods.

**Mean Opinion Score.** Mean opinion score (MOS) is a widely used metric in the field of speech evaluation that quantifies the perceived quality of speech output as judged by hu-

man listeners. Typically, a group of evaluators listens to a series of audio samples generated by the SpeechLM and rates each sample on a predefined scale, often from 1 (poor quality) to 5 (excellent quality).

MOS is calculated by averaging the scores given by all evaluators for each audio sample, providing a single score that reflects the overall quality as perceived by humans. Variations of MOS focus on different aspects of speech quality, including MMOS, PMOS, and SMOS [Kharitonov *et al.*, 2021; Zhang *et al.*, 2024]. They evaluate the aspects of naturalness, prosody, and timbre similarity of the given speech, respectively.

Typically, evaluating naturalness or timbre similarity involves collecting human opinions. However, this process can be complicated due to the challenges of recruiting participants and gathering their evaluations. As a result, researchers often turn to machine-based evaluations. They commonly employ neural network models specifically trained for these tasks. For instance, a naturalness prediction model [Mittag et al., 2021] can assess the naturalness of generated outputs, while a speaker identification model can evaluate timbre similarity.

# 7 Challenges and Future Directions

While SpeechLMs have demonstrated impressive abilities, the research in this area is still in its infancy. In this section, we survey challenges, unsolved questions, and possible directions for future research in the study of SpeechLMs.

## 7.1 Understanding Different Component Choices

Current research on SpeechLMs encompasses key components such as speech tokenizers, language models, and vocoders, each offering a diverse range of options. While some studies have compared various component choices—primarily focusing on speech tokenizers—the comparisons tend to be limited in scope and depth [Lakhotia et al., 2021; Rubenstein et al., 2023]. Consequently, there remains a significant gap in understanding the advantages and disadvantages of different component selections. Therefore, studies aimed at comprehensively comparing these choices are essential. Such an investigation would yield valuable insights and serve as a guide for selecting more efficient components when developing SpeechLMs.

## 7.2 End-to-End Training

Although SpeechLMs can generate speech directly without relying on text signals, they still need to train the three components separately. This separate optimization may hinder the model's overall potential. Consequently, it would be worthwhile to investigate whether training can be conducted in an end-to-end manner, allowing gradients to be back-propagated from the vocoder's output to the tokenizer's input. By exploring this fully end-to-end approach, we could potentially enable SpeechLMs to produce more coherent, contextually relevant, and high-fidelity speech outputs.

#### 7.3 Real-Time Speech Generation

Enabling real-time speech generation is crucial in SpeechLM as it fosters a more interactive way of engaging with hu-

mans. However, the most adopted approaches described in section 3 still result in noticeable delays between input and output speech generation. This delay occurs because a typical vocoder must wait for the entire sequence of output tokens to be generated by the language model before functioning, making it the most time-consuming process in the inference pipeline. One potential solution to improve latency is to develop a streamable vocoder, allowing it to begin synthesizing output speech while the language model generates output speech tokens. Another option could involve the SpeechLM autonomously generating audio samples in waveform. Overall, this area of real-time speech generation remains underexplored and requires further investigation.

## 7.4 Safety Risks in SpeechLMs

Safety is a highly significant subject in the field of Machine Learning, particularly when it comes to large-scale generative AI models. While there has been extensive research on safety concerns in TextLMs, the safety issues in SpeechLMs have not been thoroughly investigated. The safety challenges in SpeechLMs present both similarities and unique aspects compared to TextLMs, as highlighted in OpenAI's recent report on the safety issues of GPT-4o's voice model [OpenAI, 2024]. Therefore, it is crucial for future research to explore safety vulnerabilities in SpeechLMs and develop safer SpeechLMs.

Primary concerns for the safety issues in SpeechLMs include but are not limited to toxicity and privacy. Toxicity refers to the harmful nature of the content generated by SpeechLMs. For instance, these models might produce semantically dangerous content, such as instructions for making explosives. Additionally, they could generate acoustically inappropriate content, like erotic speech [OpenAI, 2024], which presents a unique challenge. *Privacy* involves the risk of revealing personal information from the speech input after it has been processed by a SpeechLM. For example, the model might infer the speaker's identity based on the semantic content or acoustic features of the input. Even more concerning is the potential for the model to make biased inferences about the speaker, such as their ethnicity or religious beliefs, based on insufficient (e.g., acoustic) information [OpenAI, 2024].

#### 7.5 Performance on Rare Languages

SpeechLMs directly model speech data, which allows them to more effectively handle "low-resource" languages compared to TextLMs. "Low-resource" languages are those that lack extensive textual data, making it challenging for TextLMs to model them efficiently. In contrast, SpeechLM provides a better solution by modeling the speech data of these "low-resource" languages, which often have more available audio data than text [Lakhotia *et al.*, 2021]. Therefore, future research could focus on training SpeechLMs in "low-resource" languages or dialects to expand their capabilities.

## 8 Conclusions

This survey provides a comprehensive overview of recent advancements in Speech Language Models (SpeechLMs). We begin by addressing the limitations of the naive framework

that combines Automatic Speech Recognition (ASR), Large Language Models (LLMs), and Text-to-Speech (TTS) systems for voice interactions. Next, we highlight the key advantages offered by SpeechLMs. Following this, we explore the architectures of SpeechLMs, detailing the components involved and their training recipes. We also discuss their capabilities in various downstream applications as well as their various evaluation methods. Finally, we identify the major challenges in developing SpeechLMs and outline potential directions for future research. We hope this survey will illuminate the field and assist the research community in creating more powerful Speech Language Models.

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