PoLyScriber: Integrated Training of Extractor and Lyrics Transcriber for Polyphonic Music

Xiaoxue Gao, Student Member, IEEE, Chitralekha Gupta, Member, IEEE, Haizhou Li, Fellow, IEEE

Abstract—Lyrics transcription of polyphonic music is challenging as the background music affects lyrics intelligibility. Typically, lyrics transcription can be performed by a two step pipeline, i.e.

singing vocal extraction frontend, followed by a lyrics
transcriber backend, where the frontend and backend are trained separately. Such a two step pipeline suffers from both imperfect vocal extraction and mismatch between frontend and backend. In this work, we propose a novel end-to-end integrated training framework, that we call PoLyScriber, to globally optimize the vocal extractor front-end and lyrics transcriber backend for lyrics transcription in polyphonic music. The experimental results show that our proposed integrated training model achieves substantial improvements over the existing approaches on publicly available test datasets.

Index Terms—Lyrics transcription in polyphonic music, music information retrieval, integrated training, vocal extraction

I. INTRODUCTION

Lyrics constitutes the fundamental textual component of singing voice in music for the emotional perception of the song and also helps in foreign language learning. Music analysis have also attracted great attention recently including audio-visual music source separation, localization and music generation. Being able to understand the sung text may well contribute to listeners’ enjoyment of music. Lyrics transcription seeks to recognize the sung lyrics from singing vocals in the presence of instrumental music accompaniment. Various applications, such as automatic generation of karaoke lyrical content, music video subtitling and query-by-singing can benefit from automatic lyrics transcription.

In lyrics transcription, we encounter many technical challenges. A prior study shows that lyrics transcription in polyphonic music is challenging even for professional musicians, as the intelligibility is affected by many factors including complex structure of singing, the diverse polyphonic music and different environmental conditions. Specifically, singing shows a higher degree of pronunciation and prosody variation than speech, therefore lyrics transcription is more challenging than automatic speech recognition (ASR). Moreover, background music accompaniment interferes with the singing vocal. The accompaniment typically adds an intricate and structured source of musical information to the singing vocals, and often influences the lyrics intelligibility of the singing vocal. Thus, any detrimental effects of singing to lyrics intelligibility are likely to be exacerbated by background music distraction.

To address the problem of automatic lyrics transcription in polyphonic music, there are mainly two broad approaches, 1) direct modeling approach which models the polyphonic audio, i.e. singing vocals + background music directly, and 2) extraction-transcription approach which extracts singing vocals first through a trained source separation model, and then transcribes the lyrics of the extracted vocals.

In direct modeling approach, acoustic models are trained directly on the polyphonic music, a mixture of vocals and music accompaniments. For example, Stoller et al. developed a system based on a Wave-U-Net architecture to predict character probabilities directly from raw audio. This system performed well for the task of lyrics-to-audio alignment, however showed a high word error rate (WER) in lyrics transcription. Music-informed acoustic modelling that incorporates music genre-specific information are proposed. The study in suggested that lyrics acoustic models can benefit from music genre knowledge of the background music but it requires additional genre extraction step separately. Moreover, the background music is difficult to model explicitly due to complicated rhythmic and harmonic structure, diverse music genres and compositional styles. The effect of interference caused by the background music has not been well-studied under direct modeling approach.

Humans are able to recognize lyrical words of a song by paying more attention to the singing vocal than the background music. The extraction-transcription approach attempts to emulate such as human listening process through a two-step pipeline in which, first, the singing vocal is extracted from the polyphonic input signal, then the lyrics are transcribed from the extracted singing vocal. The two step pipeline suffers from both imperfect vocal extraction and mismatch between the vocal extraction frontend and the lyrics decoding backend. In the two step pipeline, the frontend is not optimized for lyrics transcription, and the mismatch is partly because frontend and backend are trained separately with different objective functions.

In this paper, we propose end-to-end (E2E) training solutions, i.e. PoLyScriber models, that integrate vocal extraction with lyrics transcription in a single network. This is a departure from the previous studies where extraction and transcription are trained separately with mismatch problem. To the best of our knowledge, this work presents the first study on an integrated extraction-transcription solution to automatic lyric transcription. The contributions of this paper include: 1) novel E2E neural solutions for automatic lyrics transcription that combines the two-step pipeline into one through an integrated training framework; 2) a systematic comparative study over several solutions and provide our insightful findings that the appropriate amount of removal of background accompaniments can be achieved by the integrated
trainign, where its intermediate vocal outputs lie in the middle of complete music removal and complete music presence.

The rest of this paper is organized as follows. Section II presents the related work to set the stage for this study. In Section III we present the overview of our proposed PoLyScriber. Section IV introduces the components of the proposed PoLyScriber in detail. Section V consists of the database and experimental setup. Section VI discusses the experiment results. Finally Section VII concludes the study.

II. RELATED WORK

We discuss the related work in singing voice separation as well as lyrics transcription of solo-singing and polyphonic music to motivate this study.

A. Singing Voice Separation

The extraction-transcription approach makes use of a singing voice separation (SVS) front end to separate singing vocal from polyphonic music. There are generally two approaches for SVS, namely waveform-based and spectrogram-based approaches [23]. The waveform-based approach directly takes time-domain polyphonic music signal as input and separately output singing voice and music signals [24]–[27]. As the waveform-based encoder learns directly from input data, it is sensitive to the change of music content. The spectrogram-based approach applies frequency analysis in the front end. It predicts a power spectrum for each source and re-use the phase from the input mixture to synthesize two separated outputs. Open Unmix [28] and MMDenseLSTM [29] are examples of spectrogram-based approaches, that show good results in the SiSec 2018 evaluation [30] on the MusDB dataset [31]. Spleeter [32] is another spectrogram-based system that has shown a strong performance and has been widely adopted by the digital music industry, but it is now outperformed by more advanced spectrogram domain architectures such as D3Net [33] and ByteMSS [34], even though Spleeter is trained on much more data from Bean dataset [35] with nearly 25,000 songs.

The spectrogram-based separation methods often suffer from incorrect phase reconstruction. Kong et al. [39] proposed ByteMSS to estimate the phase by estimating complex ideal ratio masks where they decouple the estimation of these masks into magnitude and phase estimations based on a deep residual U-Net model. This system achieves the state-of-the-art (SOTA) singing voice separation result of SDR with 8.98 dB on the MUSDB18 test dataset. This opens doors to many other closely related MIR tasks, such as music transcription, singing melody transcription and lyrics transcription.

In this paper, we explore end-to-end neural solutions to lyrics transcription that benefits from the best of both direct modeling and extraction-transcription studies. We explore the use of ByteMSS network for singing voice extraction.

B. Lyrics Transcription of Vocal and Polyphonic Music

The singing vocal carries the lyrics of a song, therefore lyrics transcription of polyphonic music can benefit a lot from the recent advances in the field of lyrics transcription of solo-singing [23].

1) Lyrics Transcription of Solo-singing: Lyrics transcription of solo-singing is typically performed by a speech recognition engine, such as Kaldi [36]. Gupta et al. developed a DNN-HMM using early version of DAMP dataset and reported 29.65% word error rate (WER) with duration-adjusted phonetic lexicon. More recently, Dabike et al. [37] created a cleaner version of DAMP dataset and constructed a factorized Time-Delay Neural Network (TDNN-F) using Kaldi [36] with WER of 19.60%. Demirel et al. [22] further incorporated convolutional and self-attention layers to TDNN-F and achieved WER 14.96%. Our recent work [38] introduced an end-to-end Transformer-based framework along with RNN-based language model and is shown to be competitive with current approaches. This provides possibility and flexibility for lyrics transcription in polyphonic music where we would need a pre-trained solo-singing model to initialize the acoustic model for integrated-training process.

2) From Solo-Singing to Polyphonic Music: Studies show that acoustic models trained on solo-singing data [37], [39]–[45] performs poorly on polyphonic music test data [21], [46]–[48]. One way to adapt a solo-singing acoustic model towards polyphonic music is through domain adaptation [49]. It is found that an acoustic model adapted on polyphonic music data outperforms that adapted on extracted vocals. This suggests that singing voice extraction or separation introduces unwanted artifacts, that adversely affect the lyrics transcription performance. Despite much progress, the lyrics transcription of polyphonic music remains to be improved. As singing vocals and background music are highly correlated in polyphonic music, resulting in overlapping frequency components, lyrics transcription of polyphonic music is more challenging than that of solo-singing.

3) Towards End-to-End Singing Decoder: Many lyrics transcription systems [14], [15], [17], [21], [22], [50], [51] are based on hybrid modular architecture, that consists of acoustic, lexical and language models [36], each with a different objective, thereby suffering from disjoint training issue. Studies show that end-to-end (E2E) systems bring us many advantages [52]–[57] including its simplicity without the need of elaborate controlling of GMM, HMM and neural network models, its independent capability of lexicon and its flexibility to incorporate other models. E2E model only needs one single neural network with one objective function to optimize for the lyrics transcription task. We reported an E2E transformer-based system for lyrics transcription of polyphonic music [38] that outperforms other approaches in the literature. It consists of a transformer based encoder-decoder framework with a multi-head attention that implicitly learns the global time contextual dependency of the singing vocal utterance, beyond just the current frame. We adopt this singing decoder [38] as our network backbone.

III. OVERVIEW OF POLYSCHIBER MODELS

A. Motivation

Since singing vocals are highly correlated and overlapped with the background music in polyphonic music, it is difficult to achieve a perfect singing voice extraction. In many studies, singing extractors and singing acoustic modeling are two steps
This raises the question - How to automatically cause the ideal amount of music suppression required for lyrics recognition? To answer this question, in this work, we propose an integrated optimization strategy for the extractor and the acoustic model for the task of lyrics transcription.

### B. Integrated-Training Strategies

In this work, we propose end-to-end lyrics transcription frameworks for polyphonic music in which we investigate three approaches for holistically training the singing voice extraction module and the singing acoustic model in a single integrated network, that includes transcription-oriented training, training with polyphonic data augmentation, and the inclusion of the extraction loss, as illustrated in Fig. [1].

1) **Transcription-oriented Training (PoLyScriber-NoAug):**
   As the first integrated training method, we explore an E2E approach where vocal extraction model is integrated with the lyrics transcription model and they are trained together solely towards the objective of lyrics transcription. The data used for this approach is only real-world polyphonic music data, as explained in Fig. 1(a) with symbol (1).

2) **Polyphonic Data Augmentation (PoLyScriber):**
   The second integrated training method is augmentation-based E2E approach towards the lyrics transcription objective. This model uses both realistic and simulated polyphonic music data for E2E training, as shown in Fig. 1(a) with dotted lines and the symbol (2). Having access to solo-singing data, simulated polyphonic music is created by data augmentation. We conduct polyphonic data augmentation by randomly selecting music and mixing it with solo-singing data with random signal-to-noise ratios (SNR) while training the PoLyScriber. By doing so, we expect to improve the diversity of polyphonic music data and further to be beneficial for model generalization.

3) **Inclusion of Extraction Loss (PoLyScriber-L):**
   In the third integrated training strategy, we further incorporate a vocal extraction loss along with the transcription loss to supervise the extractor front-end training on the simulated as well as real data as illustrated in Fig. 1(a) with dotted lines and the symbol (3).

### C. Network Architecture

We adopt the same network architecture for the three integrated training approaches. We simplify a residual-Unet vocal extraction front-end [34] and concatenate it with a
transformation-based singing acoustic model together to build the PoLyScribers, and globally adjust the weights in each of these modules via back-propagation.

To construct base models for integrated training initialization, we first obtain the pre-trained singing vocal extractor and the singing acoustic model (transcriber). Specifically, the extractor front-end is trained to reconstruct singing vocal using parallel polyphonic music and corresponding clean singing vocals data, and the transcriber is constructed with a joint encoder-decoder and connectionist temporal classification (CTC) architecture [57] to transcribe lyrics from clean singing vocals data, and the transcriber is constructed with a joint encoder-decoder and connectionist temporal classification (CTC) architecture [57] to transcribe lyrics from clean singing vocals data, and the transcriber is constructed with a joint encoder-decoder and connectionist temporal classification (CTC) architecture [57] to transcribe lyrics from clean singing vocals data, and the transcriber is constructed with a joint encoder-decoder and connectionist temporal classification (CTC) architecture [57] to transcribe lyrics from clean singing vocals data, and the transcriber is constructed with a joint encoder-decoder and connectionist temporal classification (CTC) architecture [57] to transcribe lyrics from clean singing vocals data, and the transcriber is constructed with a joint encoder-decoder and connectionist temporal classification (CTC) architecture [57] to transcribe lyrics from clean singing vocals data, and the transcriber is constructed with a joint encoder-decoder and connectionist temporal classification (CTC) architecture [57] to transcribe lyrics from clean singing vocals data, and the transcriber is constructed with a joint encoder-decoder and connectionist temporal classification (CTC) architecture [57] to transcribe lyrics from clean singing vocals data, and the transcriber is constructed with a joint encoder-decoder and connectionist temporal classification (CTC) architecture [57] to transcribe lyrics from clean singing vocals data, and the transcriber is constructed with a joint encoder-decoder and connectionist temporal classification (CTC) architecture [57] to transcribe lyrics from clean singing vocals data, and the transcriber is constructed with a joint encoder-decoder and connectionist temporal classification (CTC) architecture [57] to transcribe lyrics from clean singing vocals data.

The linguistic information captured by the acoustic model to flow back and inform the extraction front-end. By optimizing the integrated network in this way, the extractor would be able to extract features in a way that is suitable for the task of lyrics transcription.

IV. COMPONENTS OF PoLyScriber Models

In this section, we describe our design of each of the components in the PoLyScriber models in detail.

A. Singing Vocal Extractor Front-End

The goal of the singing vocal extractor in PoLyScribers is to remove, or at least suppress the background music to a certain level while sustaining lyrics transcription related vocal parts. The extractor is based on the Residual-Unet [34] model to estimate complex ideal ratio masks (cIRMs) and spectrogram, modified for the purpose of integrated training. Compared with conventional approaches that do not estimate phases of the extracted signals [29], [58]–[60], and suffers from poor audio quality due to incorrect reconstruction phase reconstruction, cIRMs based system contains phase prediction and therefore alleviates incorrect phase reconstruction problem. However, the direct predicting of real and imaginary parts of cIRMs suffers from being sensitive to time-domain signal shifts [34], [61]–[63]. Considering the superiority of cIRM for estimating phase [34], we use the extractor that is designed to decouple the estimation of cIRMs into magnitude and phase estimations. The extractor also combines the predictions of the cIRM mask and spectrogram where the spectrogram prediction is the direct magnitude prediction serving as a residual component to complement the bounded mask prediction [34]. This was one of the top performing systems in the recent Music Demixing Challenge 2021 [64] with a signal-to-distortion ratio (SDR) of 8.9 dB on a standard test dataset.

We employ a simplified version of the Residual-Unet network as our front-end vocal extractor that has an encoder, intermediate layers and a decoder as shown in Fig. 1 (b). We denote the cIRM as $M$. The input short-time Fourier transforms (STFTs) $X$ from the realistic polyphonic music or the simulated polyphonic music is compressed by the extractor encoder and intermediate layers into a lower dimensional descriptor and then the descriptor is re-expanded to the size of the target solo-singing STFTs $S$ by the extractor decoder. In the following subsections, we present the details of the vocal extractor.

1) Extractor Architecture: The extractor encoder consists of four residual encoder blocks (REBs) where each REB contains two residual convolutional blocks (RCBs) followed by an $2 \times 2$ average pooling layer to reduce the feature map size. The real/simulated polyphonic music STFT input $X$ is first encoded as polyphonic representations via the extractor encoder. Each RCB consists of two convolutional layers with kernel sizes $3 \times 3$. A residual connection is added between the input and the output of a RCB [34]. A batch normalization and a leaky ReLU non-linearity with a negative slope of 0.01 is applied before each convolutional layer inside each RCB following the pre-act residual network configuration [34].

The two intermediate convolutional blocks (ICBs) then transform the polyphonic representations into a hidden descriptor, where each ICB has the same architecture as the REB except the pooling layer. The hidden descriptor is further fed into the extractor decoder, which is symmetric to those in the extractor encoder and it contains four residual decoder blocks (RDBs). Each RDB consists of a transposed convolutional layer with a kernel size $3 \times 3$ and stride $2 \times 2$ to upsample feature maps, followed by two RCBs. After the extractor decoder, an additional ICB and a final convolutional layer are applied to generate four outputs (the magnitude of the cIRM $|M|$, direct magnitude prediction $|Q|$, real part of the cIRM $P_r$ and the imaginary part of the cIRM $P_i$). Therefore, the extracted singing vocal STFTs $\hat{S}$ is predicted following [34] as below:

$$\hat{S} = |\hat{S}|\cos\hat{\theta} \hat{S} + j|\hat{S}|\sin\hat{\theta} \hat{S},$$

$$|\hat{S}| = \text{relu}(|M||X| + |Q|),$$

$$\angle \hat{S} = \angle M + \angle X,$$

$$\cos\hat{\theta} \hat{S} = \cos\angle M \cos\angle X - \sin\angle M \sin\angle X,$$

$$\sin\hat{\theta} \hat{S} = \sin\angle M \cos\angle X + \cos\angle X \sin\angle M,$$

$$\cos\angle M = \hat{P}_r/\sqrt{\hat{P}_r^2 + \hat{P}_i^2},$$

$$\sin\angle M = \hat{P}_i/\sqrt{\hat{P}_r^2 + \hat{P}_i^2},$$

As illustrated in Fig. II (b) and Eq. (1) the angle of cIRM $\angle M$ and the angle of extracted vocal STFTs $\angle \hat{S}$ can be obtained from $\hat{P}_r$ and $\hat{P}_i$, while $|Q|$ is residual component to $|M|$ for getting extracted vocal magnitude $|\hat{S}|$. After obtaining the STFTs of the extracted vocal, an inverse STFT is applied to obtain the extracted vocal waveform.

2) Extractor Training Objective: The extractor is pre-trained on parallel polyphonic music and clean solo-singing data with a L1-loss that is computed on the waveform domain as shown below:

$$\mathcal{L}_{\text{Ext}} = \frac{1}{T} \sum_{t=1}^{T} ||\hat{s}(t) - s(t)||$$

where the $\hat{s}(t)$ and $s(t)$ are the extracted singing vocal waveform and the corresponding target solo-singing waveform with $t$ as the discrete time index, respectively.

B. Singing Lyrics Transcriber

The singing lyrics transcriber uses a transformer-based E2E lyrics transcription framework which is trained to decode input feature sequence of extracted singing vocal to output lyrical sequence, as shown in Fig. II (c). The transcriber encoder
converts the input acoustic features to intermediate representations, and the transcriber decoder predicts lyrical tokens (we use sub-words where 5,000 sub-words are generated using byte-pair encoding (BPE) in this work) one at a time given the intermediate representations and previously predicted lyrical tokens in an auto-regressive manner.

1) Transcriber Encoder: The transcriber encoder consists of an acoustic embedding module and twelve identical sub-encoders where each sub-encoder contains a MHA \[65\] and a position-wise feed-forward network (FFN). The extracted vocal acoustic features \( F \) for the transcriber are first obtained from the extracted singing vocal audio via the feature extraction block, which first performs downsampling on the audio to a sampling rate of 16kHz and then extracts 80-dim filterbank feature with a window of 25 ms, shifting 10 ms. \( F \) is then encoded into the acoustic embedding by the acoustic embedding module using subsampling and positional encoding (PE) \[65\]. The acoustic embedding block contains two CNN blocks with a kernel size of 3 and a stride size of 2. The sub-encoders then transform the acoustic embedding into a hidden representation \( H \). Residual connection \[66\] and layer normalization \[67\] are employed inside each of the sub-encoder.

\[
H = \text{TranscriberEncoder}(F) \quad (3)
\]

2) Transcriber Decoder: The transcriber decoder consists of a lyrical embedding module and six identical sub-decoders, where each sub-decoder has a masked MHA, a MHA and a FFN. During training, \( Y \) represents the lyrical token history that is offset right by one position, however, during run-time inference, it represents the previous predicted token history. \( Y \) is first converted to lyrics token embedding via lyrical embedding module, that consists of an embedding layer, and a positional encoding (PE) operation.

\[
O = \text{TranscriberDecoder}(H, Y) \quad (4)
\]

The lyrics embedding is fed into the masked MHA that ensures causality, i.e. the predictions for current position only depends on the past positions. The output of the masked MHA and the acoustic encoding \( H \) are then fed to the next MHA for capturing the relationship between acoustic information \( H \) and textual information from the masked MHA. The residual connection \[66\] and layer normalization \[67\] are also employed inside each of the sub-decoder.

3) Transcriber Learning Objective: A combined CTC and sequence-to-sequence (S2S) objective is conducted for the transcriber pre-training as shown below:

\[
\mathcal{L}_{\text{Transcriber}} = \alpha \mathcal{L}_{\text{CTC}} + (1 - \alpha) \mathcal{L}_{\text{S2S}},
\]

\[
\mathcal{L}_{\text{CTC}} = \text{Loss}_{\text{CTC}}(G_{ctc}, R),
\]

\[
\mathcal{L}_{\text{S2S}} = \text{Loss}_{\text{S2S}}(G_{s2s}, R)
\]

where \( \alpha \in [0, 1] \), \( R \) is the ground-truth lyrical token sequence. The transcriber decoder are followed by a linear projection and softmax layers, that converts the decoder output \( O \) into a posterior probability distribution of the predicted lyrical token sequence \( G_{s2s} \). The S2S loss is the cross-entropy of \( R \) and \( G_{s2s} \). Also, a linear transform is applied on \( H \) to obtain the token posterior distribution \( G_{ctc} \). CTC loss is computed between \( G_{ctc} \) and \( R \) \[57\].

C. Learning Objective of the PoLyScriber Models

To leverage on the acoustic and linguistic knowledge from the pre-trained extractor and transcriber models, the PoLyScriber models are initialized by the respective pre-trained models for training. The PoLyScribers are trained to minimize S2S, and CTC losses in the first and second integrated training approaches. S2S, CTC and extraction losses are holistically optimized in the PoLyScriber-L framework, with an objective function \( \mathcal{L}_{\text{PoLyScriber-L}}, \)

\[
\mathcal{L}_{\text{PoLyScriber-L}} = \alpha \mathcal{L}_{\text{CTC}} + (1 - \alpha) \mathcal{L}_{\text{S2S}} + \mathcal{L}_{\text{Ext}} \quad (6)
\]

During integrated-training, the parameters are differentiable and backpropagated all the way to the extractor towards the designed losses. At run-time inference, the PoLyScribers directly converts the input polyphonic music to the output lyrical token sequence by passing through the globally trained network of the extractor and the transcriber.

V. EXPERIMENTS

A. Dataset

Our experiments are conducted using four kinds of datasets - a polyphonic music dataset, a solo-singing dataset (clean vocals without background accompaniment), a music separation dataset, and a simulated polyphonic music dataset.

1) Polyphonic Music Dataset: We explore the task of lyrics transcription on polyphonic music. As shown in Table II the polyphonic music training dataset, Poly-train, consists of the DALI-train \[68\] dataset and a NUS proprietary collection. The DALI-train dataset consists of 3,913 English polyphonic audio tracks \[1\]. The dataset is processed into 180,034 lyrics-transcribed audio lines with a total duration of 208.6 hours. The NUS collection dataset consists of 517 popular English songs. We obtain its line-level lyrics boundaries using the state-of-the-art audio-to-lyrics alignment system \[15\], leading to 26,462 lyrics-transcribed audio lines with a total duration of 27.0 hours.

The Poly-dev dataset consists of the DALI-dev dataset of 100 songs from DALI dataset \[15\], and 70 songs from a NUS proprietary collection. We adopt three widely used test sets - Hansen \[69\], Jamendo \[14\], and Mauch \[70\] to form the Poly-test as shown in Table II. The test datasets are English polyphonic songs, that are manually segmented into line-level

| Name        | # songs | Lyrical lines | Duration |
|-------------|---------|---------------|----------|
| Poly-train  | DALI-train | 3,913 | 180,034 | 208.6 hours |
|             | NUS     | 517  | 264.62  | 27.0 hours  |
| Poly-dev    | DALI-dev | 100  | 5,356   | 3.9 hours   |
|             | NUS     | 70   | 2,220   | 3.5 hours   |
| Poly-test   | Hansen  | 10   | 212     | 0.5 hour    |
|             | Jamendo | 20   | 374     | 0.9 hour    |
|             | Mauch   | 20   | 442     | 1.0 hour    |

TABLE II
A DESCRIPTION OF POLYPHONIC MUSIC DATASET THAT CONSISTS OF DALI AND NUS COLLECTIONS.
audio snippets of an average length of 8.13 seconds, each of which we will refer to as an audio line. In our experiments, we transcribe the lyrics of a song line-by-line following [38].

2) Solo-singing Dataset: We study the use of pre-training on solo-singing for lyrics transcription. A curated version of the English solo-singing dataset Sing! 300 × 30 × 2 is adopted, and detailed in Table III. A recent study [22] reports the state-of-the-art performance on this dataset, that serves as a good performance reference. As indicated in [37], the training set Solo-train consists of 4,324 songs with 81,092 audio lines. The development set Solo-dev and the test set Solo-test contain 66 songs and 70 songs with 482 and 480 audio lines respectively. The lyrics of this database are also manually transcribed [37].

3) Music Separation Database: We use a standard music separation database, MusDB18 [31], for the singing vocal extractor pre-training and evaluation in our PoLyScriber models. MusDB18 is a widely used database for singing voice separation and music source separation tasks, and it contains 150 full-length tracks with separate vocals and accompaniment where 86, 14 and 50 songs are designed for training, validation and testing, respectively. All songs are stereo with a sampling rate of 44.1 kHz, as described in [34].

4) Simulated Polyphonic Music Dataset: For the purpose of data augmentation for training the transcription and PoLyScribers, we create a simulated polyphonic music dataset. The simulated training set (4,324 songs) is generated by adding music tracks, selected at random from MusDB18 [31], to every audio clip in Solo-train data at the time of training. Specifically, for each epoch of training, the solo-singing training set audio clips are mixed with random background accompaniment tracks at a wide range of signal-to-noise ratios (SNRs) sampled randomly between [-10dB, 20dB].

B. Experimental Setup

We detail the network architectures of the extractors and the transcribers as well as the training and decoding parameter settings for the proposed PoLyScriber frameworks and reference baselines in the following. Reference baselines in Table IV consist of the two-step pipelines (play-and-plug and re-training models) and direct modeling (DM) using transformer-based model as described in Section IV-B.

1) Extractor: To understand the effects of different extractor architectures on lyrics transcription, we implement two systems - the main extractor is the simplified Residual-Unet described in Fig. 1 and Section IV-A, which is one of the top performing systems for singing vocal extraction in Music Demixing Challenge 2021 [64], and another extractor for comparison is the Open Unmix [28] that was the best performing open-source music source separation system in the source separation challenge SiSEC 2018 [50]. We further detail the network architecture of the simplified Residual-Unet and Open-Umx below.

For Simplified Residual-Unet Vocal Extractor, we utilize “Umx” model from Open-Umx serving as Umx vocal extractor [60] as a comparison system for the front-end as it is a widely used open-source singing vocal extraction system. Umx is trained by parallel polyphonic mixture and clean singing vocal audio in MusDB18 dataset [31] using bidirectional LSTM, and it learns to predict the magnitude spectrogram of singing vocal from the magnitude spectrogram of the corresponding mixture inputs (singing vocal+background music). The network consists of a 3-layer BLSTM where each layer has 512 nodes. Umx is optimized in the magnitude spectrogram level using mean square error, and the singing vocal prediction is obtained by applying a mask on the input polyphonic music.

Regarding to Umx Vocal Extractor, we utilize “Umx” model from Open-Umx serving as Umx vocal extractor [60] as a comparison system for the front-end as it is a widely used open-source singing vocal extraction system. Umx is trained by parallel polyphonic mixture and clean singing vocal audio in MusDB18 dataset [31] using bidirectional LSTM, and it learns to predict the magnitude spectrogram of singing vocal from the magnitude spectrogram of the corresponding mixture inputs (singing vocal+background music). The network consists of a 3-layer BLSTM where each layer has 512 nodes. Umx is optimized in the magnitude spectrogram level using mean square error, and the singing vocal prediction is obtained by applying a mask on the input polyphonic music.

We compare the two extractors briefly. The simplified Residual-Unet and Umx extractors are both spectrogram-based approach built on top of the MusDB18 dataset [31] and produces the extracted vocal spectrogram, but the objective function of Umx is computed on spectrogram-level while that...
of Residual-Unet is on time-domain. The idea of obtaining extracted vocal spectrogram are also different. Simplified Residual-Unet extractor estimates both phase and magnitude of the cIRM as well as incorporates the additional direct magnitude prediction to compensate the magnitude of cIRM, while the Umx extractor does not predict the phases for extracted singing vocal that makes it suffer from incorrect phase reconstruction problem [34].

2) Baseline Frameworks: Reference baselines are presented in Table [V] and they include direct modeling (DM) as well as two-step pipeline approaches. Specifically for direct modeling method, DM and DM-Aug are directly trained and validated on polyphonic music data.

There are two kinds of two-step pipeline strategies. First, plug-and-play [37], [45], the extractor and the transcriber are separately trained. During inference, the trained extractor front-end is used to get the extracted singing vocal that is then passed to the transcriber, that is trained on clean solo-singing vocals, for the decoding of the polyphonic music development and test sets. The second strategy involves re-training [49] of the solo-singing based singing acoustic model using the vocals extracted from the front-end extractor. We employ re-training strategy by firstly pre-training the transcriber by solo-singing, and then re-training the transcriber using extracted singing vocal by extractor front-end from polyphonic music. Polyphonic music data also goes through the extractor for testing the re-training model.

To be more specific, we use off-the-shelf SOTA systems for both the modules in our two-step baseline, where Plug-and-play and re-training approaches are experimented on two pre-trained extractors including simplified Residual-Unet and Open-Umx. The pre-trained Open-Unmix model “Umx” [60] is utilized to extract singing vocals for the two-step pipelines Play-and-Plug Umx and Re-Training Umx, and the pre-trained simplified Residual-Unet is employed to extract vocals for Play-and-Plug Res and Re-Training Res models. We note that the audio inputs for the feature extraction block are real/simulated polyphonic music for DM or DM-aug models, and extracted singing vocal for play-and-plug and re-training models.

3) Integrated Training Frameworks: In order to integrate the extractor and the transcriber for training, we conduct pre-training of the simplified Residual-Unet extractor first, and then globally train the pre-trained extractor and transcriber in a single network. The pre-training uses MusDB18 dataset [31] following the default parameter settings in [34], and the integrated training of PolyScribers (PolyScriber-NoAug, PolyScriber and PolyScriber-L) uses the polyphonic music data as detailed in Table [V]. Specifically, data augmentation is performed for PolyScriber and PolyScriber-L models but not for PolyScriber-NoAug model. The feature extraction block inputs for the integrated training PolyScribers are intermediate extracted singing vocal audio from the extractors.

4) Training and Inference Configurations: We use ESPNet [71] with pytorch backend to build all transcribers, and the interpolation factor α between CTC loss and S2S loss is set to 0.3 for training. Other parameters of the transcriber follow the default setting in published LibriSpeech model (LS online [4] where attention dim is 512, the number of heads is 8 in MHA and FFN layer dim is 2048. During integrated training, the extractor input are upsampled to 44.1k sampling rate using the training data as indicated in Table [IV]. All baselines and PoLyScriber models are trained using the Adam optimizer with a Noam learning rate decay, 25,000 warmup steps, 2,000,000 batch-bin, and 20 epochs [65]. We follow the default setting in ESPNet [71] to average the best 5 validated model checkpoints on the development set (Solo-dev for plug-and-play models, librispeech dev set for LS model and Poly-dev for the rest models) to obtain the final model as in Table [IV]. We follow the common joint decoding approach [57], [72], which takes CTC prediction score into account during decoding by setting different CTC weight. During decoding for different models, we use the same default parameter setting (penalty, beam width and CTC decoding weight are set to 0.0, 10 and 0.3, respectively).

VI. RESULTS AND DISCUSSION

We study the effects of pre-training, different extractor models, two-step strategies, integrated learning, data augmentation and the incorporation of the extraction loss on lyrics transcription of polyphonic music. In-depth spectrogram analysis, error analysis and music genre analysis are also performed to understand the behavior of lyrics transcription systems for different music genres. We further conduct ablation study on the proposed model to explore the contributions of each sub-component. Also, a comparative study of the proposed models with the existing approaches is presented.

We present a summary of the performance of the baseline approaches - the two-step extraction-transcription models, and direct modeling approaches, as well as the proposed approaches in Table [V]. We also present different integrated training mechanisms that include transcription-oriented training, data augmentation and inclusion of the extraction loss.

A. Evaluation Methods

We report the lyrics transcription performance in terms of word error rate (WER), which is the ratio of the total number of insertions, substitutions, and deletions with respect to the total number of words. Signal-to-Distortion ratio (SDR) is used for evaluating the singing voice extraction following [34], [60], [64], which is defined as:

\[
SDR = 10 \log_{10} \frac{\sum_n ||s(n)||^2 + \epsilon}{\sum_n ||s(n) - \hat{s}(n)||^2 + \epsilon},
\]

where \(s(n) \in \mathbb{R}^2\) denotes the waveform of the ground truth solo-singing and \(\hat{s}(n)\) is the waveform of the estimate for the extracted singing vocal with n being the (discrete) time index. We use a small constant \(\epsilon = 10^{-5}\) in Eq. [7] to avoid divisions by zero. The higher the SDR score is, the better the output of the system is.

B. Performance of the Pre-trained Models

We first present the pre-trained model performances of the extractor and the transcriber to prepare for constructing the proposed PoLyScriber models.

3See the pretrained librispeech model “pytorch large Transformer with specaug (4 GPUs) + Large LSTM LM” from the ESPNET github [https://github.com/espnet/espnet/blob/master/egs/librispeech/asr1/RESULTS.md].
Since singing vocals extracted from polyphonic music are noisy version of clean solo-singing vocals, it is reasonable to initialize the polyphonic lyrics transcriber with a pre-trained solo-singing lyrics transcription model. We developed the pre-trained solo-singing transcription model (SoloM) by first training a speech recognition model (LS) on LibriSpeech dataset [73] following LS online model setting with 80-dim fbank features. As shown in Table IV, the LS model is comparable in performance with the online published LS-online model. The pre-trained solo-singing model SoloM is then initialized with the LS model, and then trained on solo-singing database as detailed in Table III. We note that the pre-trained LS and SoloM models have the same transformer-based E2E architecture design as in Section IV-B. In Table V, we can see that the transformer-based SoloM model achieves competitive performance compared with the current published SOTA [22] reference model that is based on Kaldi speech recognition engine.

While developing the pre-trained model for the main extractor (we call it Res in Table IV), we employ model compression on the original residual Unet [34] with 102 M trainable parameters and obtain a simplified Residual-Unet with 4.4 M trainable parameters as described in Section IV-B. We observe that the simplified Residual-Unet (Res) achieves comparable performance of SDR 8.41 dB on widely used MusDB18 testset [31] in comparison with the original model [34] of SDR 8.90 dB.

### C. Performance of the Baseline Approaches

To explore the different strategies of incorporating singing vocal extractor for lyrics transcription, we report the lyrics transcription performances of two-step pipelines, i.e. the plug-and-play and the re-training approaches.

In Table IV, we can see that the re-training approaches significantly outperform the corresponding play-and-plug approaches on both the extractors (eg. Re-training Res with WER of 34.89% achieves relative 40.10% improvement from Play-and-Plug Res with WER of 58.25% on Mauch dataset). This consistent improvement from plug-and-play approach to re-training approach indicates that re-training approach is more capable of addressing the mismatch problem that exists in the plug-and-play approach between the training and testing for the transcriber.

In Table IV, we also compare the two-step approaches on two different extractors, a popular open-source Umx and and recent high performing vocal extractor Residual-Unet, eg. Re-Training Res vs. Re-Training Umx. Note that the simplified Residual-Unet outperforms Umx for the task of singing vocal extraction on MusDB18 testset with SDR of 8.41dB and 6.32dB, respectively. We observe a superior performance of the simplified Residual Unet extractor over the umx extractor for both plug-and-play and re-training approaches for lyrics transcription as well. This corroborates the intuition that an improved vocal extraction front-end helps the downstream tasks, e.g. the lyrics transcription. To this regards, we perform the rest of the experiments using the simplified Residual-Unet extractor.

We note that the DM approach outperforms Plug-and-Play Umx, Plug-and-Play Res and Re-Training Umx systems across all datasets significantly, and performs better than Re-Training Res for Hansen and Jamendo datasets. This suggests that the DM approach is as competitive as the two-steps pipelines, and the presence of music in DM actually contributes to compensate the distorted parts that is lack in two-step pipelines.

### D. Performance of the Integrated Training Approaches

1) **Comparison of Integrated Training and Two-Step Pipelines:** We investigate the effect of the Integrated training by comparing the proposed PoLyScribers with the two-step approaches. In Table IV, we observe that the proposed PoLyScriber-NoAug framework consistently outperforms Re-Training-Res and Play-and-Plug Res models. This suggests that our proposed strategy of combining the training process of the extractor indeed yields better results in predicting lyrics compared to the two-step approaches, because both of these modules are optimized towards the common objective of lyrics transcription. Since the extractor in the two-step methods is not optimized towards the goal of lyrics transcription, the output from the extractor may not be a suitable input for the lyrics transcriber, leading to a sub-optimal solution. This is due to the fact that singing vocal extraction front-ends are optimized to estimate the target singing vocal, which is different from optimizing for lyrics transcription. Therefore, the E2E PoLyScriber-NoAug, that optimizes the whole network towards lyrics transcription objective, performs better, and is able to address the mismatch problem between the frontend and backend in the two-step approaches.

Furthermore, the superiority and effectiveness of the PoLyScriber-NoAug model over Re-Training Res model suggests that the integrated training approach is capable of performing effective transcription using only real-world polyphonic music data independently, without needing any parallel singing vocal and polyphonic music data generated from data augmentation.

2) **Comparison of Integrated Training and Direct Modeling:** To study the importance of tackling music interference problem for lyrics transcription, we compare direct modeling (DM) approach with integrated training approach. DM method directly trains the transcriber on polyphonic music data without considering the background music as an interference. In Table V, we observed that the proposed PoLyScriber-NoAug outperforms the DM method across all the datasets, which suggests that lyrics transcription can benefit from the integrated training process with the extractor to handle the music interference problem.

| TABLE V | COMPARISON OF SPEECH RECOGNITION AND LYRICS RECOGNITION (WER%) PERFORMANCES BETWEEN PUBLISHED ONLINE MODELS AND OUR MODELS. |
|-----------------|-------------------------------|--|---|
| **Pre-trained Speech Model** | LS-online | LS |
| dev-clean | 3.29 | 3.72 |
| dev-other | 8.49 | 9.91 |
| test-clean | 3.63 | 4.05 |
| test-other | 8.35 | 9.66 |
| **Pre-trained Solo-sing Model** | SOTA [22] | SoloM |
| Solo-dev | 18.74 | 16.33 |
| Solo-test | 14.79 | 16.30 |
It is interesting to note that the DM method has a comparable, sometimes even better, performance than the two-step methods. This has also been observed previously in [15], [46]. This may be an indication that background music may not be as harmful as the vocal artifacts introduced by the vocal extractor in lyrics transcription [15], [38]. This observation also indicates that the integrated training would finally optimize the extractor into a state where its output will be somewhere in-between absolute background music suppression and complete background music presence, so as to gain from the benefits of both.

3) Data Augmentation: Data augmentation is employed by randomly adding music to solo-singing to create simulated polyphonic music data while training the transcriber. We use this data augmentation method in direct modeling and integrated-training approaches. In Table [V], we can see that DM-Aug outperforms DM for all the three testsets, and PoLyScriber outperforms PoLyScriber-NoAug. This indicates that the proposed singing data augmentation is a simple yet beneficial solution to the problem of lack of diversity in training data, thereby improving model generalization.

4) The Inclusion of the Extraction Loss: Having access to the parallel solo-singing and simulated polyphonic music, we are able to incorporate the extraction loss for the integrated training framework. We investigate if the additional extraction loss is helpful to the integrated training. In Table [V], we can see that the incorporation of the extraction loss in the PoLyScriber-L model shows a slight performance degradation on hansen and mauch datasets. Similar observations have been made in ASR studies where ASR-oriented optimization is effective for multi-talker speech recognition but an additional separation loss would not bring improvement to the recognition performance [74]–[76].

To analyse the relationship between the transcriber and the extractor in the integrated-training approaches, we present the extracted singing vocals from different systems and the corresponding original polyphonic music. The same 2-second audio clip is used for plotting spectrograms as the example in Table [VI] with the transcription “Just a taste of my bad side”.

### TABLE VI

| reference (ref): get a taste of my bad side just a taste of my bad side | # C I D S | WER (%) |
|-----------------------------|-----------------------------|-----------------------------|
| Re-Training Res hypothesis (hyp): get your text up and touch the taste of | 3 0 1 2 6 | 85.71 |
| DM hypothesis: get a taste of my bad side Im just a taste of my bad side | 11 0 6 4 | 47.62 |
| PoLyScriber-NoAug hypothesis: get a taste of my bad time just a taste of my bad side | 12 0 7 2 | 42.86 |
| PoLyScriber hypothesis: get a taste of my bad times into the taste of my body just a taste of my | 14 0 3 4 | 33.33 |
| PoLyScriber-L hypothesis: get a taste of my outside and just a taste of my bad time just a taste of my | 16 0 2 3 | 23.81 |

E. Error Analysis and Spectrogram Visualization

We show an example in Table [VI] and conduct an error analysis on the Poly-test in Table [VII]. We also visualize the magnitude spectrogram of a 2-second snippet for the example in Fig. 2. It is noted that the number of deletions in the proposed PoLyScriber models is substantially reduced from that of the Re-Training and DM approaches. Furthermore, PoLyScriber outperforms PoLyScriber-NoAug, which suggests the integrated training helps to recover words that are deleted by the traditional methods. This again confirms the effectiveness of the integrated-training and data augmentation.
We can observe from Fig. 2 that the DM input spectrogram Fig. 2(d) contains loud music accompaniments and Re-Training Res input spectrogram Fig. 2(c) suffers from the vocal distortion especially for the duration of 0s-0.75s and 1.5s-2s, which has been alleviated by the proposed integrated-training models as in Fig. 2 (a) (b). By comparing Fig. 2 (d) with Fig. 2(a) and Fig. 2(b), we observe that the background accompaniments are removed from the spectrograms by the PoLyScriber models, leading to improved lyrics transcription. The audio samples are available online [1].

F. Music Genre Analysis

We analyse the performance of different music genres per song on the polyphonic test sets – Hansen, Jamendo and Mauch. The music genre distribution and average lyrical word duration per utterance in poly-train, poly-dev and poly-test is summarized in Table VIII and the test datasets consist of three broad genre categories – pop, hiphop and metal, as given in [15]. We report the lyrics transcription performance by music genre for our best performing models in Table VIII.

We observe that the proposed PoLyScriber frameworks consistently outperform the DM-based approaches and two-step approaches across all the genres, which further verifies the effectiveness of the integrated-training technique over the conventional approaches. PoLyScriber-NoAug model without data augmentation performs the best for the metal songs, which suggests that the SNR-based diversity generated in the training data through our augmentation method does not appropriately generalize the model for metal songs. Metal songs often contain loud distorted guitar sounds which is not that common in pop and hip hop songs. The kinds of instruments used in metal songs differ from pop or hiphop songs, and the music tracks used for augmentation were mostly from pop genre, which may have been the reason of this drop in performance for metal songs. For hiphop songs, data augmentation involved models including PoLyScriber and PoLyScriber-L perform better than other models without data augmentation. This suggests that data augmentation provides more diversity and robustness that helps in lyrics transcription of hiphop songs.

Furthermore, we observe from Table VIII that metal songs have the longest lyrical word duration, and lyrical word duration for hiphop songs is significantly lower than that of metal and pop songs across all datasets. This indicates that the hiphop songs show higher syllable rates, and genre affects lyrical words in terms of speaking rate. As described in [15], [77], metal and hiphop songs show lower lyrics intelligence compared with pop songs. Specifically, metal songs possess louder background music than pop songs and “Death Metal” songs shows zero lyrics intelligibility score [77]. Hiphop songs that always consist of rap with many words have a higher syllable rate and rapid vocalization than pop songs, thereby receiving lower lyrics intelligibility scores [15], [77]. Moreover, the percentage of available training data for pop songs is much more than metal and hip hop songs. This explains why hiphop and metal songs have a higher word error rate than pop songs across all models in Table VIII.

To better understand model generalization ability across genres for both extractor and transcriber, genre-specific integrated-training (NoAug) models are trained using genre-specific data from Poly-train while tested on all the genres. For example, the PoLyScriber-NoAug-Pop model is trained on pop songs from Poly-train and tested on all the genres. PoLyScriber-NoAug-Pop and PoLyScriber-NoAug-Hiphop achieve the lowest WER across all the models for metal and hiphop songs respectively. For example, the PoLyScriber-NoAug-Pop model trained on pop songs from Poly-train and tested on all the genres. We present extractor performance on MusDB18 test set and vocal extractor performance on MusDB18 test set.

### Table VIII

| Model               | Metal | Pop  | Hiphop |
|---------------------|-------|------|--------|
| PoLyScriber-NoAug-Pop | 1.383 | 1.565| 1.419  |
| PoLyScriber-NoAug-Hiphop | 1.502 | 1.613| 1.073  |
| PoLyScriber-NoAug-Metal | 3.783 | 3.145| 3.448  |
| PoLyScriber         | -0.983| -0.876| -1.783 |
| PoLyScriber-L       | 36    | 104  | 247    |

| Statistics          | Metal | Pop  | Hiphop |
|---------------------|-------|------|--------|
| # songs Hansen      | 3     | 6    | 1      |
| # songs Jamendo     | 7     | 9    | 4      |
| # songs Mauch       | 8     | 12   | 0      |
| Percentage in Poly-train | 35%  | 59%  | 6%     |
| Percentage in Poly-dev | 48%  | 49%  | 3%     |
| Percentage in Poly-test | 34%  | 56%  | 10%    |
| Word duration in Poly-train (seconds) | 0.96  | 0.90 | 0.65   |
| Word duration in Poly-dev (seconds)   | 0.76  | 0.69 | 0.58   |
| Word duration in Poly-test (seconds)  | 0.78  | 0.74 | 0.44   |

### Table IX

| Model               | Metal | Pop  | Hiphop |
|---------------------|-------|------|--------|
| PoLyScriber-NoAug-Pop | 1.383 | 1.565| 1.419  |
| PoLyScriber-NoAug-Hiphop | 1.502 | 1.613| 1.073  |
| PoLyScriber-NoAug-Metal | 3.783 | 3.145| 3.448  |
| PoLyScriber         | -0.983| -0.876| -1.783 |
| PoLyScriber-L       | 36    | 104  | 247    |

| Statistics          | Metal | Pop  | Hiphop |
|---------------------|-------|------|--------|
| # songs in MusDB18 testset | 33    | 15   | 2      |

We observe that the model with the extraction loss (PoLyScriber-L) generally performs better than the model without the extraction loss.
Moreover, we wonder if we can train a singing vocal extractor of transcription-oriented optimization for integrated training. You can observe from Table X that integration brings slight improvement for lyrics transcription performance, which further verifies the advantage of extraction loss (PoLyScriber-L) in Table X. The removal of extraction loss (PoLyScriber-NoAug) produces ablation study on the proposed integrated training model (model A) with extraction loss (PoLyScriber-NoAug) in Table IX. This indicates that there is a trade-off between the extractor and the transcriber for PoPolyScriber-NoAug-Hiphop, and it is not well-trained towards lyrics transcription purpose with less training data while it remains the pre-trained vocal extractor performance. We can observe from Table VII that genre-specific models show worse generalization ability on other genres that are not covered in the training set. This indicates that there is a tradeoff between extractor and transcriber for PoPolyScriber-NoAug-Hiphop, and it is not well-trained towards lyrics transcription purpose with less training data while it remains the pre-trained vocal extractor performance. We can observe from Table VII that genre-specific models show worse generalization ability than the proposed models in terms of lyrics transcription performance, while genre-specific models perform better than the proposed models for vocal extraction in Table IX. This indicates that there is a tradeoff between the extractor and the transcriber performances while models converge, wherein transcription performance improves when the extractor performs worse.

G. Ablation Study

To study where the contributions come from and verify the effectiveness of the integrated-training, we conduct an ablation study on the proposed integrated training model with extraction loss (PoPolyScriber-L) in Table X. The removal of extraction loss brings slight improvement for lyrics transcription performance, which further verifies the advantage of transcription-oriented optimization for integrated training. Moreover, we wonder if we can train a singing vocal extractor (PoPolyScriber-NoAug) on the singing vocal extraction task. This indicates that the inclusion of the extraction loss to integrated-training is beneficial to singing vocal extraction task. Table VI shows that PoPolyScriber-NoAug-Hiphop for extraction purpose generalizes well on metal and pop songs but it performs not well on transcription performance in Table VIII and other genre-specific models also show good generalization ability on other genres that are not covered in the training set. This indicates that there is a tradeoff between extractor and transcriber for PoPolyScriber-NoAug-Hiphop, and it is not well-trained towards lyrics transcription purpose with less training data while it remains the pre-trained vocal extractor performance. We can observe from Table VII that genre-specific models show worse generalization ability than the proposed models in terms of lyrics transcription performance, while genre-specific models perform better than the proposed models for vocal extraction in Table IX. This indicates that there is a tradeoff between the extractor and the transcriber performances while models converge, wherein transcription performance improves when the extractor performs worse.

H. Comparison with the State-of-the-Art

We compare the proposed PoPolyScribers with the existing approaches for lyrics transcription on the polyphonic music testsets in Table XI. Specifically, we would like to compare the PoPolyScribers with the SOTA reference models [14], [15], [47], [50], [78], [79]. Stoller et al.’s [14] system is based on E2E Wave-U-Net framework and [38] is built on an E2E transformer with multi-transcriber solutions. The rest of the systems [15], [47], [50], [78], [79] are all based on the traditional Kaldi-based ASR approach.

In Table XI, we report the lyrics transcription performance of the existing systems on the same test sets for whole songs evaluation. We decode short nonoverlapping segments of songs in Hansen, Jamendo and Mauch using our proposed models and combine the transcriptions of these segments to report WER results for the complete songs as in [38]. We also test on a larger database DALI-test [50] with 240 whole-song polyphonic recordings processed as in [38]. We observe that the proposed PoPolyScriber outperforms
all previous E2E and Kaldi-based approaches for Hansen, Mauch and the large set DALI-test, which shows the general superiority of the integrated training model over the conventional pipelines. To avoid segmentation problems, we further consider the performance of E2E models on line-level test sets for comparison as in [38] in Table XII which shows that the proposed PolyScriber models outperform the E2E models [38], thereby achieving better performance among all the existing models. We also note that the PolyScriber-NoAug without data augmentation performs better than E2E models, which shows the proposed integrated training is capable of achieving good lyrics transcription performance without the need of data augmentation where the parallel solo-singing and polyphonic music is created.

VII. CONCLUSION

PolyScriber models serve as an important step into the exploration of lyrics transcription for polyphonic music via an E2E integrated training setting. We propose and idea to globally train singing voice extraction with lyrics transcriber towards the lyrics transcription objective for polyphonic music for the first time. We advocate novel PolyScriber frameworks with data augmentation for lyrics transcription of polyphonic music, that is proven to be effective. Our integrated-training approach is able to perform well with only real-world polyphonic music, which alleviates the need of parallel solo-singing and polyphonic music for extractor training. The proposed data augmentation paradigm enables PolyScriber to leverage diverse polyphonic pattern and music knowledge from simulated polyphonic music for hiphop songs. We have shown that the proposed PolyScribers outperform baseline frameworks for lyrics transcription through a comprehensive set of experiments on publicly available datasets.

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