PoLyScribers: Joint Training of Vocal Extractor and Lyrics Transcriber for Polyphonic Music

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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 transcription 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 novel end-to-end joint-training framework, that we call PoLyScribers, to jointly optimize the vocal extractor and lyrics transcription backend for lyrics transcription in polyphonic music. The experimental results show that our proposed joint-training model achieves substantial improvements over the existing approaches on publicly available test datasets.

Index Terms—Automatic lyrics transcription in polyphonic music, singing voice separation, music information retrieval

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 [1]. Music analysis have also attracted great attention recently including audio-visual music source separation, localization [2]–[4] and music generation [5], [6]. Being able to understand the sung text may well contribute to listeners’ enjoyment of music [7]. 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 [8] and query-by-singing [9] can benefit from automatic lyrics transcription.

In lyrics transcription, we encounter many technical challenges. A prior study [10] 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 [11], 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 [12], [13]. 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 (ALT) 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 [14], [15], 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 [16]–[19].

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. [14] 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. Gupta et al. [15] proposed music-informed acoustic modelling that incorporated music genre-specific information. This approach outperforms all other systems in MIREX 2020 lyrics transcription task [20]. The study in [15] 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 [10]. 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 [17], [21], [22] 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.
In the past two decades, the extraction-transcription approach makes use of a singing voice separation (SVS) frontend to separate singing vocal from polyphonic music. There are generally two approaches for SVS, namely waveform-based and spectrogram-based approaches. The waveform-based approach directly takes time-domain polyphonic music signal as input and separately outputs singing voice and music signals. 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 frontend. It predicts a power spectrum for each source and re-use the phase from the input mixture to synthesize two separated outputs.

The study in this paper proposes end-to-end neural solutions, i.e. PolyScribers, that perform vocal extraction and lyrics decoding in a single network. We hypothesize that the end-to-end solutions would produce an extracted singing voice signal that is suitable for better lyrics transcription, while alleviating the mismatch between frontend and backend in the two step approach.

To optimize the vocal extraction and lyrics decoding at the same time for lyrics transcription, we formulate a joint training process. To the best of our knowledge, this work presents the first study of such joint training process for lyrics transcription. Given this gap in the literature, it is possible that the insights of joint training of singing vocal extraction and singing acoustic modeling may shed light on factors hitherto unconsidered.

The contributions of this paper include: 1) we propose novel end-to-end neural solutions and firstly formulate joint-training processes for effective lyrics transcription of polyphonic music; 2) we propose a polyphonic data augmentation paradigm to simulate polyphonic music, thereby joint-training can be achieved without the need of parallel singing vocal and polyphonic music data; 3) we perform a systematic comparative study over several lyrics transcription joint-training solutions, and provide our findings with genre-specific analysis. We show that PolyScriber framework with a transcription-oriented joint-training strategy achieves the state-of-the-art (SOTA) lyrics transcription performance on polyphonic music.

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

II. RELATED WORK

We discuss the related work in singing voice separation, lyrics transcription, as well as speech separation and recognition to motivate this study.

A. Singing Voice Separation

The extraction-transcription approach makes use of a singing voice separation (SVS) frontend to separate singing vocal from polyphonic music. There are generally two approaches for SVS, namely waveform-based and spectrogram-based approaches. The waveform-based approach directly takes time-domain polyphonic music signal as input and separately outputs singing voice and music signals. 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 frontend. It predicts a power spectrum for each source and re-use the phase from the input mixture to synthesize two separated outputs.

Open Unmix and MMDenseLSTM are examples of spectrogram-based approaches, that show good results in the SiSec 2018 evaluation on the MusDB dataset. Spleeter 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 and ByteMSS, even though Spleeter is trained on much more data from Bean dataset with nearly 25,000 songs.

The spectrogram-based separation methods often suffer from incorrect phase reconstruction. Kong et al. 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.

1) Lyrics Transcription of Solo-singing: Lyrics transcription of solo-singing is typically performed by a speech recognition engine, such as Kaldi. 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. created a cleaner version of DAMP dataset and constructed a factorized Time-Delay Neural Network (TDNN-F) using Kaldi with WER of 19.60%. Demirel et al. further incorporated convolutional and self-attention layers to TDNN-F and achieved WER 14.96%. Our recent work 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 joint-training.

2) From Solo-Singing to Polyphonic Music: Studies show that acoustic models trained on solo-singing data performs poorly on polyphonic music test data. One way to adapt a solo-singing acoustic model towards polyphonic music is through domain adaptation. 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], [49] are based on hybrid modular architecture, that consists of acoustic, lexical and language models [35], each with a different objective, thereby suffering from disjoint training issue. Studies show that end-to-end (E2E) systems bring us many advantages [50]–[55] including its simplify 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 [37] 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 [37] as our network backbone.

C. Multi-Talker Speech Recognition

The studies of multi-talker speech recognition [50]–[58] adopts the joint training of speech separation and speech recognition [59], and provides useful insights for this work. A speech separation algorithm may introduce distortions or artifacts in the generated speech, that adversely affect ASR performance [60]. To alleviate this problem, a joint training of the speech separation front-end and ASR backend [60] was proposed. Wang et al. [61] also jointly trained speech separation and ASR towards an ASR objective. However, they observed that the inclusion of a separation loss to acoustic modeling loss did not bring clear improvements to ASR. A similar study was conducted for multi-channel multi-talker ASR [62]. It was found [63] that it is beneficial to only fine-tune the ASR back-end in some scenarios, especially when the separation task is more challenging. Knowing that the singing voice separation task is not trivial, we may also investigate the influences of using different training objectives, i.e. towards one transcription objective or towards both transcription and separation objective for the joint-training of our task. Nonetheless, the study of the joint-training of speech recognition and speech separation provide inspiration to our study of lyrics transcription in polyphonic music.

III. PoLYScriBERS OVERVIEW

Since singing vocals are highly correlated and overlapped with the background music in polyphonic music, it is difficult to achieve a perfect singing voice separation. In many studies, singing voice separation and singing acoustic modeling are two steps in a pipeline, where each of these modules is independently trained [17], [21], [22].

In this work, we propose end-to-end lyrics transcription frameworks for polyphonic music, called PoLyScribers, in which we investigate three approaches for jointly training singing voice extraction module and singing acoustic modeling, as illustrated in Fig. 1. We expect that PoLyScribers would be optimized jointly for singing vocal extraction and transcription. Next, we present the idea of PoLyScribers.

A. Joint-Training Approaches

We would like to study three joint-training strategies including transcription-oriented training, training with polyphonic data augmentation, and the inclusion of the extraction loss.

1) Transcription-oriented Training: The first joint-training method we explore is the end-to-end (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 with symbol (1).

2) Polyphonic Data Augmentation: The second joint-training method is augmentation-based E2E approach towards the lyrics transcription objective, that we call PoLyScriber. This model uses both realistic and simulated polyphonic music data, as explained in Fig. 1 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: In the third joint-training approach, we further incorporate an extraction loss named as PoLyScriber-L to supervise the extractor front-end training on the simulated as well as real data as illustrated in Fig. 1 with dotted lines and the symbol (3).

B. Network Architecture

We adopt the same network architecture for the three joint-training approaches. We simplify a residual-Unet vocal extraction front-end [33] and concatenate it with a transformer-based singing acoustic model together to build the PoLyScribers, and jointly adjust the weights in each of these modules via back-propagation.

To construct base models for joint-training initialization, we first pre-train the singing vocal extractor and the singing acoustic model (transcriber) separately by their own objectives. 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 [55] to transcribe lyrics from clean singing vocals. Second, we use the pre-trained extractor and transcriber as the base models and further jointly train the extractor and transcriber on a training dataset. The joint training allows the linguistic information captured by the acoustic model to flow back and inform the extraction front-end. By optimizing the joint 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. POLYScriBERS COMPONENTS

In this section, we formulate each of the components in detail for PoLyScribers.

A. Singing Vocal Extractor Front-End

The goal of the singing vocal extractor is to remove, or at least suppress the background music. The extractor we use in this work is based on the Residual-Unet [33] model to estimate complex ideal ratio masks (cIRMs) and spectrogram, modified for the purpose of joint training. Compared with conventional approaches that do not estimate phases of the extracted signals [28], [64]–[66], 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 [33], [67]–[69]. Considering the superiority of cIRM for estimating phase [33], 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 [33]. This was one of the top performing systems in the recent Music Demixing Challenge 2021 [70] 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. 4 (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 [33]. 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 [33].

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 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 [33] as below:

$$
\hat{S} = |\hat{S}| \cos \angle \hat{S} + j |\hat{S}| \sin \angle \hat{S},
\hat{|S}| = \text{relu}(|M||X| + |Q|),
\angle \hat{S} = \angle M + \angle X,
\cos \angle \hat{S} = \cos \angle M \cos \angle X - \sin \angle M \sin \angle X,
\sin \angle \hat{M} = \sin \angle X \cos \angle M + \cos \angle X \sin \angle M,
\sin \angle \hat{M} = \hat{P}_r/\sqrt{\hat{P}_r^2 + \hat{P}_i^2},
\cos \angle \hat{M} = \hat{P}_i/\sqrt{\hat{P}_r^2 + \hat{P}_i^2}
$$

As illustrated in Fig. 1 (b) and Eq. 1 the angle of cIRM $\angle \hat{M}$ 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:

\[
\mathcal{L}_{\text{Ext}} = \frac{1}{T} \left( \sum_{t=1}^{T} |\hat{s}(t) - s(t)| \right) \tag{2}
\]

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, end-to-end lyrics transcription framework which is trained to decode input feature sequence of extracted singing vocal to output lyrical sequence, as shown in Fig.1(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 paper) one at a time given the intermediate representations and previously predicted lyrical tokens in an auto-regressive manner. The core module of the transformer-based encoder and decoder is a multi-head attention (MHA) \([71]\), that employs a self-attention mechanism to make use of the temporal context of the extracted singing vocal input sequence.

1) **Transcriber Encoder**: The transcriber encoder consists of an acoustic embedding module and twelve identical sub-encoders where each sub-encoder contains a MHA 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) \([71]\). 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 \([72]\) and layer normalization \([73]\) are employed inside each of the sub-encoder.

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

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.

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

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 \([72]\) and layer normalization \([73]\) 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:

\[
\begin{align*}
\mathcal{L}_{\text{Transcriber}} &= \alpha \mathcal{L}_{\text{CTC}} + (1 - \alpha) \mathcal{L}_{\text{S2S}}, \\
\mathcal{L}_{\text{CTC}} &= \text{Loss}_{\text{CTC}}(G_{\text{ctc}}, R), \\
\mathcal{L}_{\text{S2S}} &= \text{Loss}_{\text{S2S}}(G_{\text{s2s}}, R)
\end{align*}
\]  \tag{5}

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 \(G_{\text{ctc}}\). CTC loss is computed between \(G_{\text{ctc}}\) and \(R\) \([55]\).

### C. PoLyScribers Learning Objective

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 joint training approaches. S2S, CTC and extraction losses are jointly optimized in the PoLyScriber-L framework, with an objective function \(\mathcal{L}_{\text{PoLyScriber-L}}\).

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

During joint-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 jointly 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.

### TABLE I

| Name          | # songs | Lyrical lines | Duration |
|---------------|---------|---------------|----------|
| Poly-train DALI-train | 3,913   | 180,034       | 208.6 hours |
| Poly-train NUS                  | 517     | 264,62        | 27.0 hours  |
| Poly-dev DALI-dev               | 100     | 5,356         | 3.9 hours   |
| Poly-dev NUS                    | 70      | 2,220         | 3.5 hours   |
| Poly-test Hansen                | 10      | 212           | 0.5 hour    |
| Poly-test Jamendo               | 20      | 374           | 0.9 hour    |
| Poly-test Mauch                 | 20      | 442           | 1.0 hour    |
TABLE II
A DESCRIPTION OF SOLO-SINGING DATASET.

| Name       | # songs | Lyrical lines | Duration  |
|------------|---------|---------------|-----------|
| Solo-train | 4,324   | 81,092        | 149.1 hours |
| Solo-dev   | 66      | 482           | 0.7 hours  |
| Solo-test  | 70      | 480           | 0.8 hours  |

1) Polyphonic Music Dataset: We explore the task of lyrics transcription on polyphonic music. As shown in Table I the polyphonic music training dataset, Poly-train, consists of the DALI-train [74] dataset and a NUS proprietary collection. The DALI-train dataset consists of 3,913 English polyphonic audio tracks. 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 [75], Jamendo [14], and Mauch [76] to form the Poly-test as shown in Table I. The test datasets are English polyphonic songs, that are manually segmented into line-level 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 by-line to avoid the possibility of accumulated errors in Viterbi decoding that is known to occur in long audio clips, for example, when a whole song of 3.4 minutes is transcribed in one decoding step [21], [44], [77]. We have manually verified and ensured correctness of these line-level segments and their corresponding transcription.

2) Solo-singing Dataset: We study the use of pre-training on solo-singing for lyrics transcription. A curated version [56] of the English solo-singing dataset Sing! 300 × 30 × 2 [1] is adopted, and detailed in Table I. A recent study [22] reports the state-of-the-art performance on this dataset, that serves as a good performance reference. As indicated in [55], 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 [56].

3) Music Separation Database: We use a standard music separation database, MusDB18 [30], 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 [33].

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 [30], 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 III 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 and another extractor for comparison is the Open Unmix [27] that was the best performing open-source music source separation system in the source separation challenge SiSEC 2018 [29]. We further detail the network architecture of the simplified Residual-Unet and Open-Unmix below.

For Simplified Residual-Unet Vocal Extractor, model compression is applied to reduce the model size and speed up the joint-training process. The original Residual-Unet model [33] employs model architecture with a large parameter size of 102M trainable parameters, which brings difficulties in model deployment due to the expensive and time-consuming computation. To reduce the model size, we apply model compression with several redundant layers removed while ensuring that the performance of vocal extraction does not get affected significantly. Compared to the original Residual Unet [33], in this work, we have removed two REBs, two ICBs and two RDBs where two RCBs are further removed in each REB and each RDB to establish the simplified Residual-Unet. The simplified Residual-Unet thus contains four REBs, two ICBs, and four RDBs with only 4.4 M trainable parameters.

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 [30] 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 [30] 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 cIRMs, while the Umx extractor does not predict the phases for extracted singing vocal that makes it suffer from incorrect phase reconstruction problem [33].

2) Baseline Frameworks: Reference baselines are presented in Table III and they include direct modeling method as well as two-step pipeline approaches. Specifically for direct modeling method, direct modeling (DM) and DM-Aug are well as two-step pipeline approaches. Specifically for direct modeling method, direct modeling (DM) and DM-Aug are separately trained. So during inference, the first strategy, plug-and-play [36], the extractor and the transcriber are separately trained. The second strategy involves re-training [48] of the solo-singing based singing acoustic model using the vocals extracted from the front-end extractor. We employ re-training strategy by using the singing vocal extraction front-end to extract singing vocals from polyphonic music of both training and test set, and re-train the solo-singing based singing acoustic model on the extracted vocal training set.

To be more specific, we use off-the-shelf state-of-the-art 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-Umix model “Umx” [66] 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 realisimulated polyphonic music for DM or DM-aug models, and extracted singing vocal for play-and-plug and re-training models.

3) Joint Training Frameworks: In order to jointly train the extractor and the transcriber, we conduct pre-training of the simplified Residual-Unet extractor first, and then jointly train the pre-trained extractor and transcriber in a single network. The pre-training uses MusDB18 dataset [30] following the default parameter settings in [33], and the joint-training of Polyscribers (PolyScriber-NoAug, PolyScriber and PolyScriber-L) uses the polyphonic music data as detailed in Table III. Specifically, data augmentation is performed for PolyScriber and PolyScriber-L models but not for PolyScriber-NoAug model. The feature extraction block inputs for the joint-training PolyScribers are intermediate extracted singing vocal audio from the extractors.

4) Training and Inference Configurations: We use ESPnet [78] with pytorch backend to build the transcriber for all the models in this paper, 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) where attention dim is 512, the number of heads is 8 in MHA and FFN layer dim is 2048. During joint-training, the extractor input of PolyScribers are upsampled to 44.1k sampling rate using the training data as indicated in Table III. 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 [71]. We follow the default setting in ESPnet [78] to average the best 5 validated model checkpoints on the development set (Solo-dev for PolyScriber-NoAug, PolyScriber and PolyScriber-L) uses the polyphonic music data as detailed in Table III. 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 [71]. We follow the default setting in ESPnet [78] to average the best 5 validated model checkpoints on the development set (Solo-dev for plug-and-play models, librispeech dev dataset for LS model and Poly-dev for the rest models) to obtain the final model as in Table III. We follow the common joint decoding approach [55], which takes CTC prediction score into

| Baseline Models        | Train data | Extractor | Transcriber | Poly-dev | Hansen | Poly-test | Mauch |
|------------------------|------------|-----------|-------------|----------|--------|-----------|-------|
| Plug-and-Play Umx      | Solo-train | fix Umx   | fix SoloM   | 97.21    | 97.87  | 98.00     | 97.59 |
| Plug-and-Play Res      | Solo-train | fix Res   | fix SoloM   | 67.77    | 66.76  | 62.48     | 58.28 |
| Re-Training Umx        | Poly-train | fix Umx   | finetune SoloM | 63.06    | 64.35  | 58.24     | 78.31 |
| Re-Training Res        | Poly-train | fix Res   | finetune SoloM | 44.33    | 42.03  | 48.00     | 34.89 |
| Direct Modeling (DM)   | Poly-train | –         | finetune SoloM | 44.95    | 40.15  | 44.77     | 38.13 |
| DM-Aug                 | Poly-train+ DataAug | –         | finetune SoloM | 46.70    | 35.61  | 44.75     | 36.43 |

| Joint-training Models  | Train data | Extractor | Transcriber | Poly-dev | Hansen | Jamendo | Mauch |
|------------------------|------------|-----------|-------------|----------|--------|---------|-------|
| PolyScriber-NoAug      | Poly-train | finetune Res | finetune SoloM | 39.47    | 34.91  | 41.38   | 31.34 |
| PolyScriber            | Poly-train + DataAug | finetune Res | finetune SoloM | 39.10    | 32.02  | 40.41   | 30.78 |
| PolyScriber-L          | Poly-train + DataAug | finetune Res | finetune SoloM | 40.25    | 32.58  | 40.13   | 32.77 |

DataAug denotes the simulated polyphonic music. Res and Umx denote simplified Residual-Unet extractor and the Umx extractor, respectively.

TABLE III
A SUMMARY OF THE BASELINES AND THE PROPOSED JOINT-TRAINING MODELS AND THEIR LYRICS TRANSCRIPTION RESULTS (WER%) ON BOTH POLY-TEST AND POLY-DEV DATASETS.

4See 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 [80] 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 II. 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 IV, 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.

VI. RESULTS AND DISCUSSION

We study the effects of pre-training, different extractor models, two-step strategies, joint learning, data augmentation and the incorporation of the extraction loss on lyrics transcription of polyphonic music. A music genre analysis together with error and spectrogram analysis is 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 joint training approaches in Table III. We also present different joint-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 [33], [66], [70], which is defined as:

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

(7)

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 $\epsilon = 10^{-7}$ in Eq. 7, to avoid divisions by zero. The higher the SDR score, 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 PoLyScribers.

A comparison of speech recognition and lyrics recognition (WER%) performances between published online models and our models is presented in Table IV. The pre-trained solo-singing model SoloM achieves competitive performance compared with the current published SOTA [22] reference model that is based on Kaldi speech recognition engine.
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 Joint Training Approaches

1) Comparison of Joint-Training and Two-Step Pipelines: We investigate the effect of the joint-training by comparing the proposed PoLyScribers with the two-step approaches. In Table III 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 end-to-end 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 joint-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 Joint-training and Direct Modeling: To study the importance of tackling music interference problem for lyrics transcription, we compare direct modeling (DM) approach with joint-training approach. DM method directly trains the transcriber on polyphonic music data without considering the background music as an interference. In Table III we observed that the proposed PoLyScriber-NoAug outperforms the DM method across all the datasets, which suggests that lyrics transcription can benefit from the joint-training process with the extractor to handle the music interference problem.

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], [45]. This is a clear indication that background music provides some aid to the lyrics transcriber [15], [37], which is suppressed or removed by the vocal extractor in the two-step methods. This observation also indicates that the joint 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 joint-training approaches. In Table III, 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 joint-training framework. We investigate if the additional extraction loss is helpful to the joint-training. In Table III, 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 [60]–[62].

To further investigate if the additional extraction loss is beneficial to the extractor performance, we present the extraction performances of PoLyScriber and PoLyScriber-L models in SDR (dB) on MusDB18 test dataset over training epochs in Fig. 2. We observe that the joint-training model with the extraction loss (PoLyScriber-L) generally performs better than the model without the extraction loss (PoLyScriber) on the singing vocal extraction task throughout the training period.
This indicates that the inclusion of the extraction loss to joint-training is beneficial to singing vocal extraction task.

To analyse the relationship between the transcriber performance and the extractor performance in the joint-training approach, we present WER for polyphonic music development set and SDR for the MusDB18 testset for the PoLyScriber model in Fig 3. We observe that SDR decreases at the beginning and then remains almost stable for the rest time while WER keeps decreasing in general. This shows that during training, the joint network adds in some background music/noise and settles somewhere between completely suppressed background music (as in two-step approaches) and completely present background music (as in DM approaches), yielding better results than both. Indeed, qualitatively, when we listened to the outputs of the extractor after joint training, we found that some background music got added back into the audio and distorted vocal parts in two-step approaches were recovered in joint-training approach. Some interesting observations were that the lyrics transcription improved, compared to two-step methods, especially in the chorus sections of the song where multiple voices were present simultaneously. The joint training seemed to have drowned out the other vocals present in the background by adding back some music. Similar observation are also presented through spectrogram visualization in the following Section VI-F. The extracted singing vocals from our different systems and the corresponding original polyphonic music, along with their predicted transcriptions are available at this link [5].

E. 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 V 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 V.

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 joint-training technique over the conventional approaches. PoLyScriber-NoAug model without data

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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 VII 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], [81], 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 [81]. 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], [81]. 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 VII.

To better understand model generalization ability across genres for both extractor and transcriber, genre-specific joint-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 from Poly-test. We present extractor performance on MusDB18 test set together with its music genre distribution in Table VI and transcriber performance in Table VII. Table VI shows that PoLyScriber-NoAug-Hiphop generalizes well on metal and pop songs, and other genre-specific models also show good generalization ability on other genres that are not covered in the training set. 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 VI. This indicates that there is a trade-off between the extractor and the transcriber performances while models converge, wherein transcription performance improves when the extractor performs worse.

F: Error Analysis and Spectrogram Visualization

To provide in-depth analysis for different models, we conduct error analysis for an example in Table VII and provide a 2-seconds snippet magnitude spectrogram visualization in Fig. 4. We present decoded examples with error analysis on an example in Table VII and provide a 2-seconds snippet magnitude spectrogram visualization in Fig. 4. We present decoded examples with error analysis on an example in Table VII and provide a 2-seconds snippet magnitude spectrogram visualization in Fig. 4. We present decoded examples with error analysis on an example in Table VII and provide a 2-seconds snippet magnitude spectrogram visualization in Fig. 4. We present decoded examples with error analysis on an example in Table VII and provide a 2-seconds snippet magnitude spectrogram visualization in Fig. 4.

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F: Error Analysis and Spectrogram Visualization

To provide in-depth analysis for different models, we conduct error analysis for an example in Table VII and provide a 2-seconds snippet magnitude spectrogram visualization in Fig. 4. We present decoded examples with error analysis on different models in Table VII which shows the number of deletions in proposed PoLyScribers are substantially reduced from Re-Training and DM approaches and PoLyScriber performs better than PoLyScriber-NoAug, which suggests the joint training helps to capture words that tends to get deleted in traditional methods. This again indicates the effectiveness of the joint-training and data augmentation. We can observe from Fig. 4 that Re-Training Res model suffers from the vocal distortion issue especially for the duration of 0s-0.75s and 1.5s-2s, which has been alleviated by the proposed joint-training models. While comparing with original polyphonic music from DM, PoLyScribers contributed to the music removal with some noises added. The audio samples are available for listening as
the example 2 at this link [6]

G. Ablation Study

To study where the contributions come from and verify the effectiveness of the joint-training, we conduct an ablation study on the proposed joint-training model with extraction loss (PoLyScriber-L) in Table VIII. The removal of extraction loss brings slight improvement for lyrics transcription performance, which further verifies the advantage of transcription-oriented optimization for joint-training. Moreover, we aim to answer the following questions: can we train a singing vocal extractor without parallel vocal and mixture data via joint-training system? And can we even train the joint system from scratch?

A clear benefit of finetuning the extractor can be noticed while removing the extractor finetuning of PoLyScriber-NoAug. Concerning the lack of the extractor pre-training, model A still outperforms Re-training Res and DM for two testsets. To this regards, the performance of model A is acceptable and it is possible to train a singing vocal extractor without parallel vocal and mixture data inside the joint-training framework. We can further observe that the model B suffers from a big performance drop from model A, which shows it is essential to pre-train the transcriber.

To compare the two-step pipelines with joint-training, we can find that the lyrics transcription performance drops significantly from joint-training approach (PoLyScriber-NoAug) to Re-Training Res and DM. This indicates that joint-training is critical to improve lyrics transcription performance. We also notice that the pre-training for the transcriber is also important while comparing DM with DM-Scratch.

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

We compare the proposed PoLyScribers with the existing approaches for lyrics transcription on the polyphonic music testsets in Table IX. Specifically, we would like to compare the PoLyScribers with the SOTA reference models [14], [15], [20], [46], [49], [82]. Stoller et al.'s [14] system is based on E2E Wave-U-Net framework and our recent work [37] is built on an E2E transformer network and provides multi-transcriber solutions (Multi-transcriber-FO and Multi-transcriber-PI) with chord transcription as an additional task. The rest of the systems [15], [20], [46], [49], [82] are all based on the traditional Kaldi-based ASR approach. A subset of these existing systems [20], [46], [49] were submitted to the lyrics transcription task in the 16th Music Information Retrieval Evaluation eXchange International Benchmarking Competition (MIREX 2020), and the system by Gao et al. [20] outperforms other submissions. The results of this challenge are publicly available [4].

In Table IX, we first report the lyrics transcription performance of all 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 [37]. We also test on a larger database DALI-test [49] with automatic segmentation applied as in [37], where DALI-test contains 240 whole-song polyphonic recordings. We observe that the proposed PoLyScriber outperforms all previous E2E and Kaldi-based approaches for Hansen, Mauch and the large set DALI-test, which shows the general superiority of the joint training model over the conventional pipelines.

To avoid segmentation problems, we further report the results for line-level transcription with post-processing in Table X which is performed by manually correcting the lexical inconsistency between the ground truth and the predicted lyrics, for example, by removing punctuation marks from lyrics and standardizing non-lexical items such as ‘la’ and ‘lah’. The details of line-level test data are described in Section V-A1. We further consider the performance of E2E models [37] on line-level test sets for comparison. We can consistently see that the proposed PoLyScribers outperform the E2E models [37] as shown in Table X thereby achieving better performance among all the existing models. We also note that the PoLyScriber-NoAug without data augmentation performs better than E2E Transformer and Multi-transcriber models, which shows the proposed joint-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.

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VII. CONCLUSION

PoLyScibers serve as an important step into the exploration of lyrics transcription for polyphonic music via an E2E joint-training objective. We propose and idea to jointly train singing voice extraction with lyrics transcriber towards the lyrics transcription objective for polyphonic music for the first time. We advocate novel PoLySciber frameworks with data augmentation for lyrics transcription of polyphonic music, that is proven to be effective. Our joint-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 PoLySciber to leverage diverse polyphonic pattern and music knowledge from simulated polyphonic music for hiphop songs. We have shown that the proposed PoLyScibers outperform baseline frameworks for lyrics transcription through a comprehensive set of experiments on publicly available datasets.

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