THE CHAMBER ENSEMBLE GENERATOR: LIMITLESS HIGH-QUALITY MIR DATA VIA GENERATIVE MODELING

Yusong Wu\textsuperscript{1}  
Ian Simon\textsuperscript{3}  
Josh Gardner\textsuperscript{2,3}  
Curtis Hawthorne\textsuperscript{3}  
Ethan Manilow\textsuperscript{3}  
Jesse Engel\textsuperscript{3}

\textsuperscript{1}Université de Montréal, Mila  
\textsuperscript{2}University of Washington  
\textsuperscript{3}Google Research, Brain Team

ABSTRACT

Data is the lifeblood of modern machine learning systems, including for those in Music Information Retrieval (MIR). However, MIR has long been mired by small datasets and unreliable labels. In this work, we propose to break this bottleneck using generative modeling. By pipelineing a generative model of notes (Coconet trained on Bach Chorales) with a structured synthesis model of chamber ensembles (MIDI-DDSP trained on URMP), we demonstrate a system capable of producing unlimited amounts of realistic chorale music with rich annotations including mixes, stems, MIDI, note-level performance attributes (staccato, vibrato, etc.), and even fine-grained synthesis parameters (pitch, amplitude, etc.). We call this system the \textit{Chamber Ensemble Generator} (CEG), and use it to generate a large dataset of chorales from four different chamber ensembles (CocoChorales). We demonstrate that data generated using our approach improves state-of-the-art models for music transcription and source separation, and we release both the system and the dataset as an open-source foundation for future work in the MIR community.

1. INTRODUCTION

As deep learning systems become the go-to choice for solving more and more Music Information Retrieval (MIR) tasks, it behooves researchers to lean into the strengths of these systems. For example, it is now well-established that neural networks perform better when they are larger and have access to more data [1–3]. However, the bottleneck to scaling MIR systems is a lack of data with high-quality labels. If MIR researchers could access larger quantities of labeled data, we could scale our systems to further increase their ability to understand and generate musical audio.

In fact, MIR tasks that do have abundant data—such as music tagging [4–6] or piano transcription [7–9]—have already seen large performance gains with architectures (e.g., Transformers [10]) that can take advantage of large-scale data. For other tasks, researchers have found clever ways to scale MIR systems by using unsupervised generative modeling [11–13] thus loosening requirements for labeled data and enabling training on larger corpora. Researchers have also found ways to leverage these large unsupervised models for downstream MIR tasks [14, 15].

A common way to combat data scarcity is data augmentation. Data augmentation is a necessity for some MIR tasks like source separation [16–23], and is highly effective for others like self-supervised learning for classification [24–26] and pitch estimation [27]. However, augmentation relies on the labels provided with the original data; if those labels are small or unreliable, augmentation may not be helpful. Furthermore, even with perfect labels there is a limit to how much we can scale using augmentation alone. The amount and types of perturbations we can apply to musical data cannot be done indiscriminately because augmentations must preserve the semantic link between the audio content and labels.

One approach to realize the promise of large models is \textit{dataset amplification},\textsuperscript{1} whereby generative models are used to create larger datasets from existing data, thus “amplifying” small amounts of data [28–31]. Amplifying data is particularly auspicious in MIR tasks, where data is often costly to collect and label. Given a sufficiently good generative model trained on a small dataset, one could use the model to create a large amount of data with paired annotations. This data can then be used to train other large models, which would be impossible with the original dataset.

In this paper, we present the \textit{Chamber Ensemble Generator} (CEG), a pipeline of generative models which we use to create a large synthetic audio dataset. The CEG is a dataset amplification system built on generative models that are trained on small datasets (426 total examples). Specifically, we use a set of \textit{structured} generative models, i.e., models that have interpretable intermediate representations. Using structured models produces many types of high-quality labels and allows us to manipulate the generative processes in many different ways. Specifically, we use a music composition model, Coconet [32], to generate four-part note data in the style of Bach Chorales, and we use an audio generation model, MIDI-DDSP [33], to turn the note data into audio for each instrument in the ensemble. We used the CEG to generate 240,000 performances containing audio mixture data with high-quality annota-

\textsuperscript{1} By “amplification” we do not mean using an electronic amplifier (or amp simulation software), but rather the process of expanding a dataset using generative models.
Figure 1. The Chamber Ensemble Generator (CEG) generates a dataset of realistic-sounding performances of Bach Chorales by pipelining two generative models, CocoNet [32] and MIDI-DDSP [33]. Because these models form a structured hierarchy, we are able to produce data at many different stages in the generation process, including aligned note data with instrument labels, notewise expression data, synthesis parameter data, audio stem data, and audio mixture data. The structured hierarchy also enables us to manually add manipulation at certain stages to introduce variation. In the dataset accompanying this paper, CocoChorales, we vary the orchestration of the pieces and overall tempo, we alter the microtiming of notes, and we randomly apply pitch correction to the performances.

2. RELATED WORK

Training on synthetic data to help real-world downstream applications has long been used in Machine Learning, and Reinforcement Learning [31, 34–37]. Recently, the use of generative models for dataset amplification, i.e., enlarging a dataset by generating large synthetic datasets, has become more common in vision and other domains [28–30,38]. In the image domain, Zhang et al. [29] trained an additional semantic map decoder on the latent space of a pre-trained StyleGAN [39]. By training the decoder on a few annotated examples, the model becomes an “infinite dataset generator” with paired semantic maps, achieving the similar performance as a model trained on 100x more human-annotated data. Here, we implement a similar approach in the music domain, with the hope of enlarging the effective size of our training data. Specifically, we train a set of generative models from scratch instead of using a pre-trained model.

Synthetic datasets have been proposed a handful of times in the music domain. The JS Fake Chorales dataset [40] consists of 500 synthetic Bach Chorales generated by an RNN-based generative model. However, the JS Fake Chorales dataset is small compared to this work and consists of symbolic note data, lacking any audio performance data. Similarly, Liu et. al. [41] propose a system to grade model’s generated data and feed high-quality data from the model back into its training set. This work, also, only used symbolic data and no audio performance data. The Synthesized Lakh (Slakh) Dataset [18] is constructed by synthesizing 2100 MIDI files using professional-grade sample-based synthesizers, resulting in 145 hours of mixture audio with paired stem audio and MIDI files. Other work has also proposed using sample-based synthesizers for source separation specifically [42–44] or drum transcription [45]. However, the output of these synthesizers can lack finer-grained annotations like $f_0$’s for each note, and—most importantly—due to the limitations of automating these synthesizers for large scale data creation, the resulting audio does not sound like it was performed by live musicians. In other words, there is a risk of a mismatch between the distributions of the synthesized data and real world data. Here, we use generative models to produce highly realistic audio as a step towards mitigating this potential distribution mismatch.

There are a large number of terrific options for generative music models that could be used to amplify or generate a dataset. For instance, the output quality of general purpose audio generation models has steadily increased in recent years [13,55–59], however, controlling fine-grained aspects of the performance (e.g., whether vibrato is applied to an individual note) is difficult with these models. Therefore, we must look elsewhere if we desire to use such models to make datasets with detailed annotations. This leads us toward using a set of models for structured generation, each with a designated job. For instance, one could use a composition model (e.g., a piano [11], singing [60, 61],...
| Name                      | Instrumentation | # Examples | Duration (hrs) | Content  |
|---------------------------|-----------------|------------|----------------|----------|
| **MIDI-only Datasets**    |                 |            |                |          |
| Bach Chorales [46]        | 4-part chorale   | 382        | 26             | MIDI     |
| JS Fake Chorales [40]     | 4-part chorale   | 500        | 1              | MIDI     |
| Lakh MIDI [47]            | 128 MIDI instru | 176,581    | 10,521         | MIDI     |
| Meta MIDI [48]            | 128 MIDI instru | 436,631    | 19,224         | MIDI     |
| **Audio & MIDI Datasets – Single Instrument** | |            |                |          |
| MAPS [49]                 | Piano           | 270        | 18             | Audio, MIDI |
| MAESTRO [7]               | Piano           | 1,276      | 199            | Audio, MIDI |
| GuitarSet [50]            | Guitar          | 360        | 3              | Audio, MIDI, f0’s, Tempo, Chords |
| FiloSax [51]              | Saxophone       | 240        | 24             | Audio, MIDI |
| **Audio & MIDI Datasets – Ensembles** | |            |                |          |
| MUSDB18 [52]              | 4 instruments   | 150        | 10             | Mix and stem audio only |
| MusicNet [53]             | 11 instruments  | 330        | 34             | Mix audio, MIDI |
| URMP [54]                 | 14 instruments  | 44         | 1              | Mix and stem audio, video, MIDI |
| Slakh [18]                | 34 instruments  | 2,100      | 145            | Mix and stem audio, MIDI |
| **CocoChorales (this work)** | |            |                |          |
| String                    | String ensemble | 60,000     | 350            | Mix and stem audio, MIDI |
| Brass                     | Brass ensemble  | 60,000     | 350            |          |
| Woodwind                  | Woodwind ensemble | 60,000 | 350         | + Note: volume, vibrato, attack, ... |
| Random                    | Random instru   | 60,000     | 350            | + Synthesis: f0’s, loudness, noise, ... |
| Total                     | 13 instruments  | 240,000    | 1,400          |          |

Table 1. This table compares our work, CocoChorales (last 5 rows), to a selection of existing datasets. Durations are counted in hours of mixture data (where applicable) and are rounded to the nearest hour.

or symphonic [62] composition model) to generate notes, and sonify its output with a score-to-audio synthesis model [63–66]. Still, few score-to-audio models enable low-level performance details, like the vibrato of a single note. In this work we chose Coconet [32] and MIDI-DDSP [33] because of the high amount of structure these models contain (i.e., Coconet only generates four-part Bach chorales, and MIDI-DDSP has a 3-level interpretable hierarchy). These models enable more control and variation of the generation process (e.g., ensemble types, notewise performance characteristics, etc) and, thus we are able to create a dataset with more types of labels to support more tasks.

3. THE CHAMBER ENSEMBLE GENERATOR

In this section, we will first describe the two generative models used in our Chamber Ensemble Generator (CEG), which is used to create the CocoChorales dataset. An overview of the CEG is illustrated in Figure 1.

3.1 Coconet

Coconet [32] is a music composition model that generates four-part harmonic note data in the style of a Bach chorale. Coconet is trained on the J.S. Bach Chorales dataset [46, 67], which consists of 382 pieces. Coconet trains a convolutional neural network to complete partial musical scores by infilling a randomly masked input score. During inference, Coconet iteratively applies blocked Gibbs sampling to rewrite its generation for a fixed number of steps before producing its final output score. For more details, we refer interested readers to the original Coconet paper [32].

For the current work, we used an open-source implementation of Coconet [68]. However, our model slightly differs from the original Coconet in the following ways: (1) We apply pitch augmentation during training by randomly transposing the input by \{−3, −2, −1, 0, 1, 2, 3\} semitones. (2) The loss used during training is simply unweighted cross-entropy, compared to the reweighted loss in the original paper [32]. (3) Our model does not generate rests.

3.2 MIDI-DDSP

MIDI-DDSP [33] is a score-to-audio generation model which uses a three-level structured hierarchy (notes, performance, synthesis) when generating single-note audio. Given input MIDI, the audio synthesis via MIDI-DDSP proceeds as follows. First, MIDI-DDSP generates a set of “note expression” characteristics for each note, each controlling one aspect of a note’s performance: volume, volume fluctuation, volume peak position, vibrato, brightness, and attack noise. Second, MIDI-DDSP uses the note expressions and the accompanying MIDI to generate frame-wise synthesis parameters. The synthesis parameters of an audio clip consist of a fundamental frequency $f_0$, an amplitude curve, a distribution of amplitudes for each harmonic frequency above the $f_0$, and a set of filtered noise magnitudes. Finally, the Differentiable Digital Signal Pro-
cessing (DDSP) [69] modules synthesize a waveform using the generated synthesis parameters. Figure 1 provides an overview of this process, but we refer readers to the original MIDI-DDSP paper for further details [33].

The intermediate representations (i.e., note expressions and synthesis parameters) generated by MIDI-DDSP can provide rich annotations for many MIR tasks. For example, the $f_0$ curves can be used for $f_0$ estimation, and the note expression can be used for performance analysis.

MIDI-DDSP is trained on the URMP dataset [54], which consists of 3.75 hours of solo recordings (1 hour of mixture data, as shown Table 1). MIDI-DDSP is thus capable of generating the 13 common orchestral instruments present in URMP: violin, viola, cello, double bass, flute, oboe, clarinet, saxophone, bassoon, trumpet, horn, trombone, and tuba.

4. COCOCHORALES

Using our Chamber Ensemble Generator pipeline, we generated a dataset which we call CocoChorales. CocoChorales consists of 240,000 pieces, totaling 1411 hours of mixture data. The CocoChorales is orders of magnitude larger than existing MIR datasets [18, 46, 51–54, 67] (see Table 1). Every example in the dataset contains MIDI data, note expression data, synthesis parameter data, and audio for each instrument stem, audio of the mixture, and additional metadata about tempi, ensemble type, etc. We make train/valid/test splits of CocoChorales using 80%/10%/10% portion of the overall data, respectively. Further information about CocoChorales—including download links—can be found in the online supplement. The rest of this section is dedicated to describing the creation process for CocoChorales.

4.1 MIDI Generation and Augmentation

Coconet [11] is a generative model of Bach Chorales. We use Coconet to compose 8 measures of a standard four-part chorale (Soprano, Alto, Tenor, and Bass) in 4\text{"} time. We generate samples from Coconet by running 1024 sampling steps. In order to ensure that each part generated by Coconet falls into the range of expected pitches for the given SATB part (e.g., a soprano note should not be too low), we reject a generated sample piece if any of the pitches fall 3 semitones outside of the min/max pitch used in the J.S. Bach Chorales dataset [67] for that part.

Once we have a set of valid chorales as MIDI, we augment this data to add more variety to the dataset. Because we are operating on MIDI data rather than audio data, we can apply tempo and timing variations without worrying about a time-stretching or pitch-shifting algorithm introducing artifacts. To that end, we randomly set the tempo (in BPM) to an integer drawn from Uniform([50, 150]). Furthermore, the raw output of Coconet is quantized at the granularity of 16th notes, so to add an extra level of expressiveness to the MIDI, we add microtiming offsets to the notes. Following the observation that human timing approximates a normal distribution [70, 71], we add a random timing offset to each note sampled from a truncated normal distribution between [−50, 50] ms with $\mu = 0$ ms, $\sigma = 15$ ms.

The final way that we add variation to the MIDI data is by changing the orchestration of the ensembles. We define four ensembles—String, Brass, Woodwind, and Random—with 60,000 examples in each. The first three ensembles have a fixed orchestration throughout, and the random ensemble has a varied orchestration, with instruments randomly selected from a pool of instruments according to the pitch range of the SATB part. These ensembles and their instrumentation for Soprano, Alto, Tenor, and Bass, respectively, are defined as:

- **String**: Violin 1, Violin 2, Viola, Cello.
- **Brass**: Trumpet, French Horn, Trombone, Tuba.
- **Woodwind**: Flute, Oboe, Clarinet, Bassoon.
- **Random**: Each SATB part is randomly assigned an instrument according to the following:
  - Soprano: Violin, Flute, Trumpet, Clarinet, Oboe.
  - Alto: Violin, Viola, Flute, Clarinet, Oboe, Saxophone, Trumpet, French Horn.
  - Tenor: Viola, Cello, Clarinet, Saxophone, Trombone, French Horn.
  - Bass: Cello, Double Bass, Bassoon, Tuba.

Once a composition is generated by Coconet, a tempo is chosen, microtiming is added to the notes, and the orchestration is determined. The MIDI dataset is then given to MIDI-DDSP to synthesize into audio performances.

4.2 Audio Synthesis and Mixing

After the MIDI data is generated, MIDI-DDSP [33] is used to synthesize the MIDI into a realistic-sounding audio performance. Because MIDI-DDSP can only synthesize monophonic audio, each Soprano, Alto, Tenor, and Bass (SATB) part is rendered separately.

As described in Section 3.2, MIDI-DDSP offers multiple ways to manipulate the sonic characteristics of its output.

The first way MIDI-DDSP output can be manipulated is by making edits to the note expression parameters (e.g., note-wise volume, vibrato, etc), and even though it is possible to manually edit these, here we opt to use the expressions that are automatically generated by MIDI-DDSP without manipulation or augmentation.

The second way MIDI-DDSP output can be manipulated is by altering the synthesis parameters, which directly influences the audio output. As mentioned, MIDI-DDSP is trained on the URMP dataset [54]. The performances in URMP contain notes that are noticeably sharp, according to twelve-tone equal temperament tuning (12-TET), as

3 https://g.co/magenta/ceg-and-cocochorales/
shown in the white histogram in Figure 2. This systematic bias is reflected in the raw $f_0$ curves output by MIDI-DDSP (orange histogram, Figure 2). To mitigate this, we randomly adjust these intonation deviations for each note by scaling MIDI-DDSP’s generated fundamental frequency, $f_0$. We apply a random amount of pitch correction, which helps ensure that the synthesized audio corresponds to the MIDI notes, while allowing a realistic amount of deviation from “perfect” 12-TET in the output audio. We hope this could avoid introducing the bias of perfect intonation and makes model trained on CocoChorales robust to intonation errors that are likely to occur in real-life music performances.

MIDI-DDSP predicts an $f_0$ curve in semitone space as a decimal offset from the in-tune integer pitch value. We randomly transpose the pitch value of each note like so

$$f_0 = f_{0}^{\text{Note}} + \hat{f}_{0}^\Delta - \alpha \hat{f}_{0}^\Delta$$

where $\alpha \sim U[0, 1]$, \(1\)

and $\hat{f}_0$ is the new fundamental frequency in semitones, $f_{0}^{\text{Note}}$ is the prescribed 12-TET frequency of the note in semitones, $\hat{f}_{0}^\Delta$ is the model’s predicted $f_0$ offset in semitones, $\hat{f}_{0}^\Delta$ is the model’s predicted $f_0$ offset in semitones averaged across the note, and $\alpha$ is a random scaling factor. $\alpha = 1$, the note is transposed to have a average pitch of the in-tune integer pitch value while $\alpha = 0$, the $f_0$ curve is left unchanged from the model prediction.

We synthesize each of the four instrument parts independently and save the audio at 16kHz and 16-bit PCM. We mix each of the four instrument stems following the mixing strategy used by Slakh [18]: first, each stem is normalized to have integrated loudness of -13dB, calculated according to the ITU-R BS.1770-4 specification [72]. Then, all the stems are summed create an instantaneous mixture. Finally, to prevent clipping, if the summed mixture has a peak loudness larger than -1dB, a uniform gain is applied to the mix (and stems) to ensure that the mix has a peak loudness of exactly -1dB.

5. EXPERIMENTS

We conduct experiments in multitrack music transcription and source separation to demonstrate the benefits of additional data. Our goal in these experiments is not to propose novel models or architectures for these tasks; instead, it is to demonstrate how the additional data in CocoChorales can be leveraged to improve existing models for the respective tasks.

5.1 Music Transcription

We conducted two sets of music transcription experiments as a demonstration of the effectiveness of our Chamber Ensemble Generator (CEG) and the resulting CocoChorales dataset.

Music transcription, the task of producing a symbolic representation from a raw waveform, is often challenging due to the “low-resource” nature of many transcription datasets—that is, high-quality paired data (audio and aligned note annotations) is scarce and expensive to collect. Dataset amplification can provide unlimited data, potentially alleviating this resource limitation. However, whether data from generative models can improve music transcription models is yet unproven.

To explore this, we performed a set of experiments designed to investigate how dataset amplification can improve existing state-of-the-art transcription systems, both in a very low-resource setting (on URMP [54], the dataset that was “amplified”) and in a combined setting where we train on many existing transcription datasets of various sizes. For all experiments, we used the MT3 transcription model [73], with no modifications. For consistency, we used MIDI-DDSP’s train/test split of URMP in order to ensure that no inputs used to train the MIDI-DDSP generative model occur in the test set for the transcription model.

Our first study compares the transcription performance of an MT3 model trained only on URMP to an identical model trained on a combined CocoChorales and URMP dataset. This allows us to observe the effectiveness of dataset amplification on the original dataset, URMP. The results of this experiment are shown in Ta-

| Training Dataset(s) | On/Off F1 | Multi-Inst. F1 |
|---------------------|-----------|---------------|
| URMP                | 0.28      | 0.22          |
| URMP + CocoChorales | 0.55      | 0.44          |

Table 2. Transcription results when training an MT3 [73] model on URMP [54] alone versus training one on URMP and CocoChorales, higher is better. URMP is a small dataset (1 hour), so using dataset amplification, as done in here to create CocoChorales, has a large effect on transcription performance.
Table 4. Mean separation results (dB) for the Woodwind ensemble over the CocoChorales test set using SISDR [76], higher is better.

| Network      | Flute | Oboe | Clarinet | Bassoon |
|--------------|-------|------|----------|---------|
| Demucs v2 [19] | 18.7  | 17.3 | 21.0     | 20.7    |
| MI+TR [75]    | 12.5  | 6.9  | 10.7     | 6.9     |

Table 3. Transcription results on the combination of all datasets used by MT3 [73], higher is better. (Note that we use the MIDI-DDSP [33] train-test split for URMP, not the MT3 train-test split for URMP.)

| Model                  | MAESTRO | Cerberus4 | GuitarSet | MusicNet | Slakh2100 | URMP |
|------------------------|---------|-----------|-----------|----------|-----------|------|
| MT3 Datasets           | 0.83    | 0.80      | 0.78      | 0.33     | 0.57      | 0.61 |
| + CocoChorales         | 0.83    | 0.80      | 0.79      | 0.34     | 0.57      | **0.66** |

**Onset-Offset F1**

| Model                  | MAESTRO | Cerberus4 | GuitarSet | MusicNet | Slakh2100 | URMP |
|------------------------|---------|-----------|-----------|----------|-----------|------|
| MT3 Datasets           | 0.83    | 0.79      | 0.78      | 0.30     | 0.58      | 0.50 |
| + CocoChorales         | 0.83    | 0.75      | 0.79      | 0.30     | 0.57      | **0.56** |

**Multi-Instrument F1**

The majority of music separation systems have focused on separating sources where data is ample, which has historically excluded many instruments (e.g., flutes, oboes, clarinets, or bassoons). Because the CEG enables us to generate a limitless quantity of high-quality ensemble data, we are able to train separation systems on instruments that have been neglected by existing separation systems.

To that end, we train two separation networks to separate instruments from the Woodwind ensemble in CocoChorales. Specifically, we train a Demucs v2 [19], which is a state-of-the-art waveform-to-waveform U-Net, and a Cerberus-style [75] separation network, which is a set of 4 LSTM layers that create a mask which is applied to the mixture spectrogram. The Cerberus-style network is the same as Cerberus, except we omit the clustering head and only use the Mask Inference and TRanscription heads. We refer to this as MI+TR in Table 4, and only report its separation performance. For more network details, refer the reader to [19, 75]. We train these models for 55k steps and report results over all 5 second segments of the CocoChorales test set in Table 4, where we report mean SISDR [76].

Furthermore, we also showcase a separation example from URMP [54] in Figure 3. As noted, URMP alone is an extremely small dataset to train a separator on. To train a woodwind ensemble separator, URMP only has two recordings that are woodwind ensembles, totalling less than 4 minutes. Even if one wanted to just make an oboe separator, URMP has less than 12 minutes of oboe data, which would quickly lead to overfitting using modern networks! For this reason, we do not have a URMP-trained baseline for Table 4. With CocoChorales, the woodwind ensemble has 360 hours of oboe data, which enables us to train separation models that work well on URMP.

6. CONCLUSION AND FUTURE APPLICATIONS

In this paper we introduce the Chamber Ensemble Generator (CEG), which we use to produce the CocoChorales dataset. The CEG is a combination of a generative model for notes (Coconet) and a generative model for audio (MIDI-DDSP) that we set up as a structured hierarchy. In doing this, we can produce an unlimited amount of chamber ensemble mixture data with a rich set of aligned annotation data, with note data, notewise expression data, synthesis parameter data and stem audio data. Using Coco-
Chorales we trained a state-of-the-art transcription system and showed how the data can boost performance on low-resource transcription datasets. We also showed separation results for sources that have been historically underserved by prior separation work.

The experiments we show in Section 5 are only two of many possible applications enabled by the Chamber Ensemble Generator and CocoChorales. Because of the rich annotations in the dataset, we are excited by the many other potential applications that this work will enable. Such applications could include, but are not limited to, performance analysis [77, 78] (e.g., using the note expressions in the dataset, or deriving new ones from the synthesis parameters), multi-\(f_0\) estimation [79, 80] (e.g., using the \(f_0\)’s in this dataset used to synthesize each instrument), or new advances in source separation (e.g., separating multiple instances of similar sounding sources like the string ensemble [81–83], or separating random ensembles [84–86]). We look forward to the new directions the MIR community will explore using this data and what new variations on dataset amplification will be explored.

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