Lead Sheet Generation and Arrangement by Conditional Generative Adversarial Network

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Abstract—Research on automatic music generation has seen great progress due to the development of deep neural networks. However, the generation of multi-instrument music of arbitrary genres still remains a challenge. Existing research either works on lead sheets or multi-track piano-rolls found in MIDIs, but both musical notations have their limits. In this work, we propose a new task called *lead sheet arrangement* to avoid such limits. A new recurrent convolutional generative model for the task is proposed, along with three new symbolic-domain harmonic features to facilitate learning from unpaired lead sheets and MIDIs. Our model can generate lead sheets and their arrangements of eight-bar long. Audio samples of the generated result can be found at https://drive.google.com/open? id=1c0FfODTpudmLvuKBbc23VBCgQizY6-Rk

Index Terms—Lead sheet arrangement, multi-track polyphonic music generation, conditional generative adversarial network

I. INTRODUCTION

Automatic music generation by machine (or A.I.) has regained great academic and public attention in recent years, due largely to the development of deep neural networks [1]. Although this is not always made explicitly, researchers often assume that machine can learn the rules people use to compose music, or even create new rules, given a sufficient amount of training data (i.e. existing music) and a proper neural network architecture. Thanks to cumulative efforts in the research community, deep neural networks have been shown successful in generating monophonic melodies [2], [3] or polyphonic music of certain musical genres such as the Bach Chorales [4], [5] and piano solo [6], [7].

One of the major remaining challenges is that of generating polyphonic music of arbitrary genres. Existing work can be divided into two groups, depending on the target form of musical notation. The first group of research aims at creating the *lead sheet* [8]–[11], which is composed of a melody line and a sequence of accompanying chord labels (marked above the staff, see Fig. 1(a) for an example). A lead sheet can be viewed as a middle product of the music. In this form, the melody is clearly specified, but the accompaniment part is made up of only the chord labels. It does not describe the chord voicings, voice leading, bass line or other aspects of the accompaniment [12]. The way to play the chords (e.g. to play all the notes of a chord at the same time, or one at a time)

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Fig. 1. (a) A lead sheet of Amazing Grace and (b) its arrangement version.

is left to the interpretation of the performer. Accordingly, the rhythmic aspect of chords is missing.

The second group of research aims at creating music of the *MIDI* format [13]–[15], which indicates all the voicing and accompaniment of different instruments. A MIDI can be represented by a number of piano-rolls (which can be seen as matrices) indicating the active notes per time step per instrument [13], [16]. For example, the MIDI for a song of a four-instrument rock band would have four piano-rolls, one for each instrument: lead guitar, rhythm guitar, bass, and drums. A MIDI contains detailed information regarding what to be played by each instrument. But, the major problem is that a MIDI typically does not specify which instrument plays the melody and which plays the chord.

An interesting and yet rarely-studied topic is the generation of something in the middle of the aforementioned two forms.



Fig. 2. Architecture of the proposed recurrent convolutional generative adversarial network model for lead sheet generation and arrangement.

We call it *lead sheet arrangement*. Arranging is the art of giving an existing melody musical variety [17]. It can be understood as the process to accompany a melody line or solo with other instruments based on the chord labels on the lead sheet [12]. For example, Fig. 1(b) shows an arrangement of the lead sheet of the popular gospel song, *Amazing Grace*. We see that it shows how the chords are to be played. Arrangement can be seen across different genres. In classical music, arrangement is used in basic type such as sonata, string quartet and also more complex type as symphony. In Jazz, arrangement is often used to accompany the solo instrument. Pop music nowadays also have lots of arrangement setting to increase the diversity and richness of the music.

Computationally, we define lead sheet arrangement as the process that takes as input a lead sheet and generates as output piano-rolls of a number of instruments to accompany the melody of the given lead sheet. In other words, the lead sheet is treated as a "condition" in generating the pianorolls. For example, we aim to generate the piano-rolls of the following instruments in our implementation: strings, piano, guitar, drum and bass. Compared to MIDIs, the result of lead sheet arrangement is musically more informative, for the melody line is made explicit.

To our knowledge, there is no prior work on lead sheet arrangement, possibly because of the lack of a dataset that contains both the lead sheet and MIDI versions of the same songs. Our work presents three technical contributions to circumvent this issue:

• First, we develop a new conditional generative model (based on generative adversarial network, or GAN [18]) to learn from unpaired lead sheet and MIDI datasets for lead sheet arrangement. As Fig. 2 shows, the proposed model contains three stages: *lead sheet generation, feature extraction*, and *arrangement generation* (see Section III for details). The middle one plays a pivotal role by extracting symbolic-domain harmonic features from the given lead sheet to condition the generation of the arrangement. For the conditional generation to be possible, we use features that can be computed from both the lead sheets and the MIDIs.

- Second, we propose and empirically compare the performance of three such harmonic features to connect lead sheets and MIDIs for lead sheet arrangement. They are *chroma piano-roll* features, *chroma beats* features, and *chord piano-roll* features (see Section III-D).
- We employ the convolutional GAN model proposed by Dong *et al.* for multi-track piano-roll generation [13] for both lead sheet generation and arrangement generation, since the former can be viewed as two-track piano-roll generation and the later can be viewed as conditional fivetrack piano-roll generation. As a minor contribution, we replace the convolutional layers in the temporal generators (marked as G_{temp} and $G_{\text{temp,i}}$ in Fig. 2) by recurrent layers, to better capture the repetitive patterns seen in lead sheets. As a result, we can generate realistic lead sheets (and their arrangement) of eight bars long.

In our experiment, we evaluate the effectiveness of the lead sheet generation component and the overall lead sheet arrangement model through objective metrics and subjective evaluation, respectively. Upon publication, we will set up a github repo to demonstrate the generated music and to share the code for reproducibility.

II. RELATED WORK

Many deep learning models have been proposed for lead sheet generation, possibly because lead sheets are commonly used in pop music. Lead sheet generation can be done in three ways: given chords, generate melody (e.g., [8]); given melody, generate chords (a.k.a. melody harmonization, e.g., [9], [10]); or generating both melody and chords from scratch (e.g., [11]). Some recent models generate not only the melody and chords but also the drums [19]. But, as the target form of musical notation is still the lead sheet, only a sequence of chord labels (usually one chord label per bar or per half-bar) is generated, not the chord voicing and comping [20].

To generate music that uses more instruments/tracks, Dong *et al.* proposed MuseGAN, a convolutional GAN model that learns from MIDIs for multi-track piano-roll generation [13]. MuseGAN creates music of five tracks (strings, piano, guitar, drum and bass), whereas a later variant of it that uses binary

neurons considers eight tracks (replacing strings by ensemble, reed, synth lead and synth pad) [14]. Recently, Simon *et al.* [15] used a variational auto-encoder (VAE) model to obtain a bar embedding space with instrumentation disentanglement and a chord conditioned structure. Their model demonstrates the ability of generating polyphonic measures conditioned on predefined chord progression. The instrumentation in this model can be viewed as part of arrangement. Another work that is concerned with the instrumentation of music is the MIDI-VAE model proposed by Brunner *et al.* [21]. Learning from MIDIs, the model creates a bar embedding space with instrument, pitch, velocity disentanglement and style label condition. Although all these models can arrange the instruments in multi-track music, they cannot specify which track plays the melody.

There are some other models for multi-track music generation. DeepBach [5] aims at generating four-track chorales in the style of Bach. Jambot [22] generates a chord sequence first and then uses that as a condition to generate polyphonic music of a single track (e.g., piano solo). MusicVAE [23], an improved version of Google Magenta's MelodyRNN model [2], uses a hierarchical autoencoder to create melody, bass and drums (i.e. three tracks) of 32 bars long. However, all these models are based on recurrent neural networks (RNNs), which may work well in learning the long-term temporal structure in music but less so for local musical textures (e.g. arpeggios and broken chords), as compared with convolutional neural networks (CNNs) [13].

III. PROPOSED MODEL

The proposed model is composed of three stages: lead sheet generation, feature extraction, and arrangement generation, as illustrated in Figure 2. We introduce them below.

A. Data Representation

In order to model multi-track music, we adopt the piano-roll representation as our data format. A piano-roll is represented as a binary-valued score-like matrix [13]. Its x-axis and y-axis denote the time steps and note pitches, respectively. An *N*-track piano-roll of one bar long is represented as a tensor $X \in \{0,1\}^{T \times P \times N}$, where *T* denotes the number of time steps in a bar and *P* stands for number of note pitches. Both lead sheets and MIDIs can be converted to piano-rolls. For example, a lead sheet can be seen as two-track (melody, chord) piano-rolls, as illustrated in the upper part of Fig. 3.

B. Lead Sheet Generation

The goal of our lead sheet generation model is to **generate** lead sheets of eight bars long from scratch. As the left hand side of Figure 2 shows, it contains two sets of generative models: the *temporal* generators G_{temp} and the *bar* generators G_{bar} . The temporal generators are in charge of the temporal dependency across bars and their output becomes part of the input of the bar generator. The bar generators generate music one bar at a time. Since the piano-rolls for each bar of a lead



Fig. 3. Lead sheet arrangement system flow.

sheet are two image-like matrices (one for melody, one for chords), we can use CNN-based models for G_{bar} .

In order to generate realistic music, we train the generators in an "adversarial" way, following the principal of GAN [18]. Specifically, in the training time, we train a CNN-based discriminator D (not shown in Figure 2) to distinguish between real lead sheets (from existing songs) and the output of G_{bar} . While training D, both G_{temp} and G_{bar} are held fixed, and the learning target is to *minimize* the classification loss of D. In contrast, while training G_{temp} and G_{bar} , we fix D and the learning target is to *maximize* the classification loss of D. As a result of this iterative mini-max training process, G_{temp} and G_{bar} may learn to generate realistic lead sheets.

Following the design of MuseGAN [13], we use four types of input random noises z for our generators, to capture time dependent/independent and track dependent/independent characteristics. However, unlike MuseGAN, we use a twolayer RNN model instead of CNN for G_{temp} . Empirically we find that RNNs can better capture the repetitive patterns seen in lead sheets. Although such a hybrid recurrent-convolutional design is not new (e.g. used in [24]), to our knowledge it is the first recurrent CNN model (RCNN) for lead sheet generation.

C. Arrangement Generation

The goal of our arrangement generation model, denoted as the *conditional bar* generators $G_{\text{bar}}^{(c)}$ on the right hand side of Figure 2, is to **generate five-track piano-rolls of one bar long conditioning on the features extracted from the lead sheets**. This process is also illustrated in Fig. 3. We generate the arrangement one bar at a time, until all the eight bars have been generated (and then concatenated). We also use the principal of GAN to train $G_{\text{bar}}^{(c)}$ along with a discriminator $D^{(c)}$. Both $G_{\text{bar}}^{(c)}$ and $D^{(c)}$ are implemented as CNNs.

As the bottom-right corner of Fig. 2 shows, we train a CNN-based encoder E along with $G_{\text{bar}}^{(c)}$ to embed the harmonic features extracted by the middle feature extractor to the same

space as the output of the intermediate hidden layers of $G_{\rm bar}^{\rm (c)}$ and $D^{\rm (c)}$. Conditioning both $G_{\rm bar}^{\rm (c)}$ and $D^{\rm (c)}$ empirically performs better than conditioning $G_{\rm bar}^{\rm (c)}$ only.

D. Feature Extraction

Given a lead sheet, one may think that we can directly use the melody line or the chord sequence in the lead sheet to condition the arrangement generation. This is, however, not feasible in practice, because few MIDIs in the training data have the melody or chord tracks specified. What we have from MIDIs are usually the multi-track piano-rolls. We need to project the lead sheets and MIDIs to the same feature space to make the conditioning possible.

We propose to achieve this by extracting harmonic features from lead sheets and MIDIs. In this way, arrangement generation is conditioned on the harmonic part of the lead sheet. We propose the following three symbolic-domain harmonic features. See the middle of Fig. 3 for an illustration.

- Chroma piano-roll representation (chroma-roll): The idea is to neglect pitch octaves and compress the pitch range of a piano-roll into chroma (twelve pitch classes) [25], leading to a 12 × 48 matrix per bar. Such a chroma representation has been widely used in audio-domain music information retrieval (MIR) tasks such as audio-domain chord recognition and cover song identification [26]. For a lead sheet, we compute the chroma from both the melody and chord piano-rolls and then take the union. For a MIDI, we do the same across the N piano-rolls.
- Chroma beats representation (chroma-beats): From chroma-roll, we further reduce the temporal resolution by taking the average per beat (i.e. per 12 time steps), leading to a 12 × 4 matrix per bar. The lead sheets and MIDIs may overlap more in this feature space, but the downside is the loss of detailed temporal information.
- Chord piano-roll representation (chord-roll): Instead of using chroma features, we estimate chord labels from both lead sheets and MIDIs to increase the information of harmony. This is done by first synthesizing the audio file of a lead sheet (or a MIDI), and then applying an audiodomain chord recognition model for chord estimation. We use the DeepChroma model implemented in the Madmom library [27] for recognizing 12 major chords and 12 minor chords for each beat and use piano-roll without compressing to chroma, yielding a 84×48 matrix per bar. We do not use the (ground truth) chord labels provided in the lead sheets, as we want the lead sheets and MIDIs to undergo the same feature extraction process.

IV. IMPLEMENTATION

This section presents the datasets used in our implementation and some technical details.

A. Dataset

We use the TheoryTab dataset [28] for the lead sheets and the Lakh piano-roll dataset [13] for the multi-track piano-rolls.

TABLE I

Comparison of the two datasets employed in our work. They are respectively from https://www.hooktheory.com/theorytab, and https://salu133445.github.io/lakh-pianoroll-dataset/.

	TheoryTab [28]	Lakh Pianoroll [13]
Song length	Segment	Full song
Symbolic data	Lead sheet	Multi-track piano-rolls
Musical key	C key only	Various keys
Genre tag	Yes	Yes
Number of songs	16K	21K

We summarize the two datasets in Table I and present below how we preprocess them for the sake of model training.

1) **TheoryTab Dataset (TTD)** contains 16K segments of lead sheets stored with XML format. Since it uses scale degree to represent the chord labels, we could think of all the songs as C key songs without further key transposition. We parse each XML file and turn the melody and chords into two piano-rolls. For each bar, we set the height to 84 (note pitch range from C1 to B7) and the width (time resolution) to 48 for modeling temporal patterns such as triplets and 16th notes. As we want to generate eight-bar lead sheets, the size of the target output tensor for lead sheet generation is 8 (bars) \times 48 (time steps) \times 84 (notes) \times 2 (tracks). We use all the songs in TTD, without filtering the songs by genre. For segments that are longer than eight bars, we take the maximum multiples of eight bars.

2) Lakh Piano-roll Dataset (LPD) is derived from the Lakh MIDI dataset [29]. We use the lpd-5-cleansed subset [13], which contains 21,425 five-track piano-rolls that are tagged as Rock songs and are in 4/4 time signature. These five tracks are, again, strings, piano, guitar, drum and bass. Since the songs are in various keys, we transpose all the songs into C key by using the pretty_midi library [30]. Since arrangement generation aims at creating arrangement of one bar at a time, the size of the target output tensor for arrangement generation is 1 (bar) \times 48 (time steps) \times 84 (notes) \times 5 (tracks).

B. Model Parameter Settings

The G_{temp} in the lead sheet generation model is implemented by two-layer RNN with 4 outputs and 32 hidden units. G_{bar} , $G_{\text{bar}}^{(c)}$, D and $D^{(c)}$ are all implemented as CNNs. The total size of the input random vectors z for G_{bar} and $G_{\text{bar}}^{(c)}$ are both set to 128. For the encoder E in arrangement generation, we adopt skip connections (as done in [13]) and use slightly different topology for encoding the three features described in Section III-D. More details of the network topology will be presented in an online appendix. We use WGAN-gp [31] for model training. Each model is trained with a Tesla K80m GPU in less than 24 hours with batch size being 64.

V. EXPERIMENT

A. Lead Sheet Generation Evaluation

We adopt the objective metrics proposed in [13] to evaluate lead sheet generation, using the code they shared. *Empty bars* (EB) reflects the ratio of empty bars; *used pitch classes* (UPC)

 TABLE II

 Result of objective evaluation for lead sheet generation, in four metrics. The values are better when they are closer to that computed from the training data (i.e., the TheoryTab dataset), shown in the first row.

	empty ba	urs (EB)	used pitch classes (UPC)		qualified notes (QN)		tonal distance (TD)
	Melody	Chord	Melody	Chord	Melody	Chord	Melody-Chord
Training data	0.02	0.01	4.18	6.12	1.00	1.00	1.50
1st iteration	0.00	0.00	16.5	83.7	0.16	0.42	0.45
1,000th iteration	0.00	0.00	6.99	7.59	0.55	0.71	1.34
2,000th iteration	0.00	0.00	6.47	7.85	0.71	0.80	1.42
3,000th iteration	0.00	0.00	4.96	6.75	0.69	0.84	1.46
4,000th iteration	0.00	0.00	4.48	6.66	0.82	0.87	1.49
5,000th iteration	0.00	0.00	4.10	6.69	0.83	0.84	1.53

represents the average number of pitch classes used per bar, *qualified note* (QN) denotes the ratio of notes that are longer than or equal to the 16th note (i.e. low QN suggests overly fragmented music); *tonal distance* (TD) [32] represents the harmonicity between two given tracks. Table II shows that the UPC, QN and TD of the generated lead sheets get closer to those of the training data (i.e., the TheoryTab dataset) as the learning unfolds, suggesting that the model is learning the data distribution of real lead sheets. The values gradually saturate after around 5,000 training iterations (one batch per iteration). We find no empty bars in our generation result.

B. Lead Sheet Arrangement User Study

We conduct an online user study to evaluate the result of arrangement generation. In the study, we ask respondents to listen to four groups of eight-bar music phrases arranged by our models. Each group contains one lead sheet and its three kinds of arrangements based on chroma-roll, chroma-beats and chord-roll features, respectively. The lead sheet is put at the top of each group and can be viewed as the reference. We use "bell sound" to play the melody. We play the melody and chord along with the five tracks generated by the arrangement model to show the compatibility of these two models. After listening to the music, respondents are asked to compare the three arranged versions. They are asked to vote for the best model among the three, in terms of harmonicity, rhythmicity and *overall feeling*, respectively. Moreover, they are asked to rate each sample according to the same three aspects. To focus on the result of arrangement generation, we use existing lead sheets from TheoryTab for this evaluation.

Figure 4 shows the average result of 25 respondents, 88% of which play some instruments and 16% are studying in music-related departments or working in music-related industries. The following observations can be made:

- In terms of harmonicity, chord-roll outperforms chromaroll and chroma-beats by a great margin, suggesting that chords carry more harmonic information than chroma.
- In rhythmicity, we see from the votes that chroma-beats are clearly inferior to chord-roll and chroma-roll. We attribute this to the loss of temporal resolution in the chroma-beats representation.
- In overall feeling, chord-roll performs significantly better than the other two (which can be seen from the standard deviation shown in Fig. 4(b)) and attains a mean opinion



Fig. 4. Result of subjective evaluation for three arrangement generation models using different features, in terms of three metrics—(a) The vote result and (b) the MOS rating scores in a Likert scale from 1 to 5.

score (MOS) of 3.5675 in a five-point Likert scale. The result seems to suggest that harmonicity has stronger impact on the overall feeling, compared to rhythmicity.

In summary, as there are no existing work on lead sheet arrangement, we have to compare three variants of our own model. The result shows that using chord-roll to connect the lead sheets and MIDIs performs the best. The MOS in overall feeling suggests that the model is promising, but there is still room for improvement.

As illustrations, we show in Fig. 5 the scoresheet of the arranged result (based on chord-roll) of a four-bar lead sheet from TTD and another one generated by our model. Audio examples can be found in the link described in the abstract.

VI. CONCLUSION

In this paper, we have presented a conditional GAN model for generating eight-bar phrases of lead sheets and their arrangement. To our knowledge, this represents the first model



Fig. 5. Result of lead sheet arrangement (based on chord-roll) for (a) an existing lead sheet from TTD and (b) a lead sheet generated by our model.

for lead sheet arrangement. We experimented with three new harmonic features to condition the arrangement generation and found through a listening test that the chord pianoroll representation performs the best. The best model attains 3.4350, 3.4325, and 3.5675 MOS in harmonicity, rhythmicity, and overall feeling, respectively, in a Likert scale from 1 to 5.

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Theorytab Lead Sheet Arrangement

TABLE III CONDITIONED GENERATORS

Input: $z \in \Re^1$	128					
Reshaped to (transconv	$(1,1) \times 1024$	128 cha 1×1	(1,1)	BN	ReLU	(1, 1, 128) (1, 1, 1024)
Reshaped to ($(2,1) \times$	512 cha	innels			(2, 1, 512) (2, 1, 528)
transconv	512	2×1	(2,1)	BN	ReLU	(4, 1, 512)
transconv	256	2×1	(2,1)	BN	ReLU	(4, 1, 328) (8, 1, 256)
transconv	256	2×1	(2,1)	BN	ReLU	(8, 1, 2/2) (16, 1, 256)
chord-roll[2] transconv	128	3×1	(3.1)	BN	ReLU	(16, 1, 272) (48, 1, 128)
chord-roll[1]	64	1~7	(1,1)	BN	Del II	(48, 1, 144) (48, 7, 64)
chord-roll[0]	04	1	(1,1)	DIN	Relu	(48, 7, 80) (48, 7, 80)
transconv	1	1×12	(1,12)	BN	tanh	(48, 84, 1)
Output: $G_{chord-roll}(z) \in \Re^{48 \times 84}$						

(a) Chord-roll conditioned generator

Input: $z \in \Re^{128}$					
Reshaped to $(1,1) \times$	128 cha	innels			(1, 1, 128)
transconv 1024	1×1	(1,1)	BN	ReLU	(1, 1, 1024)
transconv 512	1×12	(1, 12)	BN	ReLU	(1, 12, 512)
chroma-roll[5]					(1, 12, 528)
transconv 256	2×1	(2,1)	BN	ReLU	(2, 12, 256)
chroma-roll[4]					(2, 12, 272)
transconv 256	2×1	(2,1)	BN	ReLU	(4, 12, 256)
chroma-roll[3]					(4, 12, 272)
transconv 128	2×1	(2,1)	BN	ReLU	(8, 12, 128)
chroma-roll[2]					(8, 12, 144)
transconv 128	2×1	(2,1)	BN	ReLU	(16, 12, 128)
chroma-roll[1]					(16, 12, 144)
transconv 64	3×1	(3,1)	BN	ReLU	(48, 12, 64)
chroma-roll[0]		(4 =)			(48, 12, 80)
transconv 1	1×7	(1,7)	BN	tanh	(48, 84, 1)
Output: G _{chroma-s}	$r_{oll}(z) \in$	$\Re^{48 \times 84}$	1		

(b) Chroma-roll conditioned generator

Input: $z \in \mathfrak{H}$	2128					
Reshaped to	$(1,1) \times$	128 cha	innels			(1, 1, 128)
transconv	1024	1×1	(1,1)	BN	ReLU	(1, 1, 1024)
transconv	512	1×12	(1, 12)	BN	ReLU	(1, 12, 512)
transconv	256	2×1	(2,1)	BN	ReLU	(2, 12, 256)
transconv	256	2×1	(2,1)	BN	ReLU	(4, 12, 256)
chroma-beats	s[0]					(4, 12, 272)
transconv	128	2×1	(2,1)	BN	ReLU	(8, 12, 128)
transconv	128	2×1	(2,1)	BN	ReLU	(16, 12, 128)
transconv	64	3×1	(3,1)	BN	ReLU	(48, 12, 64)
transconv	1	1×7	(1,7)	BN	tanh	(48, 84, 1)
Output: $G_{chroma-beats}(z) \in \Re^{48 \times 84}$						

(c) Chroma-beats conditioned generator

Table III shows three conditioned generator networks on (a) chord-roll, (b) chroma-roll and (c) chroma-beats features, respectively. Table IV presents the discriminators (a)-(c) and encoders (d)-(f) designed for the same three features, respectively. The values showned in rows of transconv and conv (from left to right) represent: number of channels, filter size, strides, batch normalization (BN) and activation function. For fully-connected layers, the values represent (from left to right): number of hidden nodes and activation functions. LReLU stands for leaky ReLU. The column after activation function denotes the dimension of each hidden layer. The names (chordroll, chroma-roll, chroma-beats) in generator and discriminator networks shows the skip connection on the information with respect to those feature names in the corresponding encoders.

TABLE IV CONDITIONED DISCRIMINATORS AND ENCODERS.

Input: $\tilde{x} \in \Re^{1 \times 1}$	18×84	×5				
Reshaped to $(48, 84) \times 5$ channels (48, 84, 5)						
chord-roll[6]					(48, 84, 6)	
conv	128	1×12	(1, 12)	LReLU	(48, 7, 128	
conv	128	1×7	(1,7)	LReLU	(48, 1, 128)	
conv	128	2×1	(2,1)	LReLU	(24, 1, 128)	
conv	128	2×1	(2,1)	LReLU	(12, 1, 128)	
conv	256	4×1	(2,1)	LReLU	(5, 1, 256)	
conv	512	3×1	(2,1)	LReLU	(2, 1, 512)	
fully-connected	1024			LReLU	1024	
fully-connected	1				1	
Output: D _{chord}	-roll	$(\tilde{x}) \in \Re$				
(a) C	hord-r	oll cond	itioned	discrimina	tor	
(u) C.	liona i	on cond	nuoneu	aiseinnia	101	
	10.70	C F				
Input: $\tilde{x} \in \Re^{1\times}$	40 X 04	1X0				
Reshaped to (48	3,84) >	× 5 cha	nnels		(48, 84, 5)	
conv	128	1×7	(1,7)	LReLU	(48, 12, 128)	
chroma-roll[0]					(48, 12, 144)	
conv	128	3×1	(3,1)	LReLU	(16, 12, 128	
chroma-roll[1]					(16, 12, 144)	
conv	128	2×1	(2,1)	LReLU	(8, 12, 128)	
chroma-roll[2]	100	a 1	(0.1)		(8, 12, 144)	
conv	128	2×1	(2,1)	LReLU	(4, 12, 128)	
cnroma-roll[3]	250	2.1	(2,1)	ID-III	(4, 12, 144)	
conv	236	2×1	(2,1)	LKeLU	(2, 12, 230)	
conv	512	2×1	(21)	IDALI	(2, 12, 2/2) (1, 12, 512)	
chroma roll[5]	512	2 × 1	(2,1)	LKELU	(1, 12, 512) (1, 12, 528)	
fully connected	1034			TRATT	(1, 12, 320)	
fully connected	1024			LKELU	1024	
Tuny-connected	1	(~)	~~		1	
Output: <i>D_{chror}</i>	na-ra	$S_{ll}(\tilde{x}) \in$	R			
(b) Chroma-roll conditioned discriminator						
(c) entonia fon conditioned discriminator						
	48×84	1×5				
Input: $x \in \Re^{1}$	10 \ 04	1/0				
Reshaped to $(48.84) \times 5$ channels $(48.84.5)$						

Input. $x \in \mathfrak{N}$					
Reshaped to (48	3,84) >	< 5 cha	nnels		(48, 84, 5)
conv	128	1×7	(1,7)	LReLU	(48, 12, 128)
conv	128	3×1	(3,1)	LReLU	(16, 12, 128
conv	128	2×1	(2,1)	LReLU	(8, 12, 128)
conv	128	2×1	(2,1)	LReLU	(4, 12, 128)
chroma-beats[0]					(4, 12, 144)
conv	256	2×1	(2,1)	LReLU	(2, 12, 256)
conv	512	2×1	(2,1)	LReLU	(1, 12, 512)
fully-connected	1024			LReLU	1024
fully-connected	1				1
Output: D _{chron}	na-be	$ats(\tilde{x})$	$\in \Re$		

(c) Chroma-beats conditioned discriminator

Input: $y \in \Re^{48 \times 4}$	34			feature name
Reshaped to (48, 100) conv 16 1 × 120 conv 16 1 × 120 conv 16 1 × 120 conv 16 2 × 120	$\begin{array}{c} 34) \times 1 \ {\rm channel} \\ 2 \ (1,12) \ {\rm BN} \\ (1,7) \ {\rm BN} \\ (3,1) \ {\rm BN} \\ (2,1) \ {\rm BN} \\ (2,1) \ {\rm BN} \\ (2,1) \ {\rm BN} \end{array}$	LReLU LReLU LReLU LReLU LReLU LReLU	$\begin{array}{c} (48, 84, 1) \\ (48, 7, 16) \\ (48, 1, 16) \\ (16, 1, 16) \\ (8, 1, 16) \\ (4, 1, 16) \\ (2, 1, 16) \end{array}$	chord-roll[0] chord-roll[1] chord-roll[2] chord-roll[3] chord-roll[4] chord-roll[5]
Output: chord-rol	1[.]			

(d) Chord-roll encoder

Input:	$y \in$	$\Re^{48 \times 1}$	2				feature name	
Reshap conv conv conv conv conv	ed to 16 16 16 16 16	$ \begin{array}{c} 0 (48,1) \\ 3 \times 1 \\ 2 \times 1 \end{array} $	$\begin{array}{c} \hline 2) \times 1 \\ (3,1) \\ (2,1) \\ (2,1) \\ (2,1) \\ (2,1) \\ (2,1) \end{array}$	chann BN BN BN BN BN	el LReLU LReLU LReLU LReLU LReLU	$\begin{array}{c} (48, 12, 1) \\ (16, 12, 16) \\ (8, 12, 16) \\ (4, 12, 16) \\ (2, 12, 16) \\ (1, 12, 16) \end{array}$	chroma-roll[0] chroma-roll[1] chroma-roll[2] chroma-roll[3] chroma-roll[4] chroma-roll[5]	
Output	$\frac{\text{Conv} \text{10} 2 \times 1 (2,1) \text{Biv} \text{Excelor} (1, 12, 10) \text{emona-ron[5]}}{\text{Output: chroma-ron[5]}}$							

(e) Chroma-roll encoder

Input: $y \in \Re^{4 \times 12}$	feature name
Replicated to $(4,12) \times 16$ channels (4, 12, 16)	chroma-beats[0]
Output: chroma-beats[:]	

(f) Chroma-beats encoder