Melody Harmonization with Controllable Harmonic Rhythm

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ABSTRACT
Melody harmonization, namely generating a chord progression for a user-given melody, remains a challenging task to this day. Although previous neural network-based systems can effectively generate an appropriate chord progression for a melody, few studies focus on controllable melody harmonization, and none of them can generate flexible harmonic rhythms. To achieve harmonic rhythm-controllable melody harmonization, we propose AutoHarmonizer, a neural network-based melody harmonization system that can generate denser or sparser chord progressions with the use of a new sampling method for controllable generation proposed in this paper. This system mainly consists of two parts: a harmonic rhythm model provides coarse-grained chord onset information, while a chord model generates specific pitches for chords based on the given melody and the corresponding harmonic rhythm sequence previously generated. To evaluate the performance of AutoHarmonizer, we use nine metrics to compare the chord progressions from humans, the system proposed in this paper and the baseline. Experimental results show that AutoHarmonizer not only generates harmonic rhythms comparable to the human level, but generates chords with overall better quality than baseline at different settings. In addition, we use AutoHarmonizer to harmonize the Session Lead Sheet Dataset (which were originally chordless), and ended with 40,925 traditional Irish folk songs with harmonies, named the Session Lead Sheet Dataset, which is the largest lead sheet dataset to date.

1 INTRODUCTION
Over the years, researchers have put a lot of efforts into making the applications of neural networks in music a reality. With neural networks, we can implement automatic transcription to convert audio into symbolic music [4, 23], recognize the genre of a piece of music [11, 13], or even ask machines to generate music [2, 5, 15]. In this paper, we address the melody harmonization task, to build a neural network-based system that can generate a chord progression to accompany a given melody with controllable harmonic rhythm.

Harmonization is the process of adding chords to a melody (i.e. chordal accompaniment). And harmonic rhythm, also known as harmonic tempo, refers to the rate of chord changes (or progressions) in a musical composition, in relation to the rate of the notes. The pace of harmonic rhythm is not absolute but relative, so that the overall pace of harmonic rhythm, or the amount of change in harmonic rhythm, varies from piece to piece. For example, a key difference in style between Baroque music and music of the Classical period is that the latter exhibits more harmonic rhythmic variation, although the harmony itself is less complex. This suggests that harmonic rhythm influences the style of the music to a certain extent.

Due to the complexity of melody harmonization, previous works on this task have several limitations. One of the most obvious limitations is that the chord progressions generated by current models have fixed harmonic rhythms [3, 8, 29, 34]. They always generate a chord for each or half-bar, which renders the listening experience monotonous. Moreover, those systems ignore the importance of the time signature in music, and typically only perform harmonization for melodies in 4/4. Although 4/4 is one of the most common time signatures, it is not the only one. Time signatures and rhythms are significant, because they create steady and consistent beats-pulses for music. It is the same for harmonic rhythm, since chords can only be placed on these pulses (almost always). Therefore, time signatures are essential in establishing a solid groove and harmonic rhythm.

In this paper, we proposed a harmonic rhythm-controllable melody harmonization system, AutoHarmonizer, that consists of a harmonic rhythm model and a chord model. Fig. 1 shows how AutoHarmonizer generates a chord sequence based on a given melody. It first extracts two types of meta-information from the lead sheet, namely the time signature and the key signature, and uses them to create the beat sequence $b_{1,T}$ and to transpose the melody to C-major/A-minor, respectively. The transposed melody is then quantized and encoded into a melody sequence $m_{1:T}$ of length $T$, which is fed into the harmonic rhythm model along with the beat sequence $b_{1:T}$. After that, we can get a harmonic rhythm sequence $r_{1:T}$ generated by this model. AutoHarmonizer then cuts the melody sequence $m_{1:T}$ according to harmonic rhythm sequence $r_{1:T}$ to obtain the melody segment sequence $M_{1:L}$ of length $L$, and feeds it to the chord model to get the chord sequence $c_{1:L}$. Finally, the system decodes the chord progression from the chord sequence $c_{1:L}$ and the harmonic rhythm sequence $r_{1:T}$, and transposes it back to the original key signature.
The main contributions of this paper are summarised as follows.

- Instead of encoding time signatures directly, we create beat sequences based on time signatures. This choice has two advantages: 1) it can guide the model group notes explicitly, and 2) the model can also understand the beats of time signatures that do not exist in the dataset. Thus, the harmonic rhythm model can generate a harmonic rhythm that fits the current time signature.
- We use a tangent function to modify the log probability of a specified token for controllable generation. This method not only does not require annotated data during training, but enables traditional models to support controllable generation. In this paper, the specified token is the holding token, which has a strong correlation with the harmonic rhythm. Therefore, AutoHarmonizer achieves a harmonic rhythm-controllable melody harmonization task.
- We public two European folk song lead sheet datasets, namely the Nottingham Lead Sheet Dataset and the Session Lead Sheet Dataset. The former is a cleaned version of the 1,034 traditional British folk songs in the Nottingham Music Database. While the latter is using the system proposed in this paper to generate chord progressions for 40,925 traditional Irish folk songs in the Session Dataset, which were originally chordless.

The code and generated samples of AutoHarmonizer, and the two European folk song lead sheet datasets now are available at GitHub1.

2 RELATED WORK

2.1 Melody Harmonization

Melody harmonization is an application of the algorithmic composition [26], where the goal of some studies is to automatically generate a chord progression for a given melody [22, 29, 34], and others to compose a four-part chorale for a melody [14, 18, 21]. This paper focuses on the former.

Tsushima et al. represented chord hierarchies [30] based on a Probabilistic Context-Free Grammar (PCFG) of chords and developed a metrical Markov model describing harmonic rhythms for controllable chord generation through a hierarchical representation. However, this method is based on statistical learning, which prefers simpler and basic chord sequences, and the number of generated chords tends to be less than the number of bars. Lim et al. designed a model based on a Bi-directional Long and Short-Term Memory (Bi-LSTM) network in [22], which can generate a chord from 24 triads for each bar. However, the model has some limitations, such as ignoring note order, rhythm and octave information within bars, and generating results with overuse of common chords and inappropriate cadences. To address these problems, Yeh et al. extended Lim’s model in [34] (called MTHarmonizer) to predict a chord from the 48 triads for each half-bar, and include some extra information (e.g. tonic and dominant) to improve the performance of the model. In [29], Sun et al. applied orderless sampling and class weighting to the Bi-LSTM model and expanded the types of chords to 96, with subjective experiments showing that the generated results were comparable to those of human composers. Chen et al. proposed SurpriseNet in [8], a model based on Conditional Variational Auto-Encoder (CVAE) and Bi-LSTM, which enables user-controllable melody harmonization. Yang et al. use two LSTM models in [33], one focusing on the relationship between notes in the melody and their corresponding chords, and the other on the rules of chord transfer. Majidi et al. [25] combine genetic algorithms with LSTMs to generate and optimise melodies and chords. All of these models mentioned above except [30] can not generate flexible harmonic rhythms.

2.2 Controllable Music Generation

Controllable music generation systems are able to generate music that meets the requirements under the conditions given by the user, and mostly rely on the representation of different properties of the music, both subjectively (e.g. emotion, style) and objectively (e.g. tonality, beat).

Roberts et al. proposed a model based on recurrent variational autoencoders to achieve controllable generation through hierarchical decoders [28]. Huang et al. proposed a Transformer-based model [19] to learn the long-term structure of music, and can coherently generate well-structured melodies and accompaniments based on the given motif. Luo et al. proposed a model based on variational autoencoders with Gaussian mixture latent distributions [24] to learn decoupled representations of timbres and pitches. Zhang et al. proposed the representation learning model BUTTER [35] based on VAE to learn latent representation and cross-modal representation of music, to achieve searching or generating corresponding music by inputting text. Chen et al. proposed Music SketchNet [7], which decouples rhythmic and pitch contours based on VAE and can be guided by user-specified rhythms and pitches to generate music. Wang et al. proposed PianoTree VAE [31], which uses GRU to encode notes played at the same time and map them to a latent space to achieve controllable generation of polyphonic music based on a tree structure. Di et al. achieved rhythmic consistency between video and background music and proposed Controllable Music Transformer [12] to locally control the rhythm while globally controlling the music genre and instruments.

The above works in controllable music generation have mainly been implemented in an unsupervised manner. However, how they achieve controllable generation are difficult to apply to other traditional models that do not support it originally.

3 METHODOLOGY

This section details how we realised the melody harmonization system AutoHarmonizer with controllable harmonic rhythm. Sec. 3.1 shows the data representation of this system. Sec. 3.2 and Sec. 3.3 describe the structure of the harmonic rhythm model and the chord model respectively. Finally, Sec. 3.4 illustrates the density sampling method we use for controllable generation.

3.1 Data Representation

3.1.1 Pre-processing. To facilitate the model’s learning, the following pre-processes are applied before the music is encoded.
- Duration Quantification: as most notes can be represented by sixteenth notes, it has often been chosen as the time resolution for previous symbolic music-related works [3, 17,
Before Quantification

After Quantification

Score Piano-roll

(a) (b)

Figure 2: Quantize notes with irregular rhythms to sixteenth notes. Fig. 2(a) shows some common irregular rhythms and their corresponding quantized rhythms, and Fig. 2(b) shows an example of an eighth triplet being quantized in the form of a piano-roll.

| Bar | First         | Second        |
|-----|---------------|---------------|
| Melody | 79 130 130 130 130 74 130 | 76 74 72 71 69 76 74 72 |
| Beat   | 3 0 1 0 2 0 1 0 | 3 0 1 0 2 0 1 0 |
| Rhythm (Chord) | 1 2 2 2 2 2 2 2 | 1 2 2 2 1 2 2 2 |
| Pitch (Chord) | 0 7 | 0 7 |
|       | 4    | 4 |
|       | 7    | 2 |

Figure 3: A two-bar sample of a melody, beat, rhythm (chord) and pitch (chord) representation. For simplicity, the time resolution in this example is set to eighth notes.

• **Transposition**: the distribution of key signatures is often uneven within a dataset, while the pitch distribution of notes can vary dramatically at different key signatures. Therefore, we transpose all music uniformly to C-major/A-minor, just like previous works [21, 37], making it effective for models to learn the patterns of music.

• **Beat Sequence**: according to the current time signature, we encode the beat information into 4-dimensional one-hot vectors, which correspond to four-beat classes: non-beat, weak, medium-weight and strong beat.

• **Harmonic Rhythm Sequence**: the sequence uses one-hot vectors with 3-dimension to represent three different chord’s rhythmic states: the rest state, the onset state and the holding state.

• **Chord Sequence**: each chord is represented by four 14-dimensional one-hot vectors: the first one-hot vector represents the name of the bass note, the second (third and fourth) represents the number of semitone intervals between the second (third and fourth) note and the bass note. The first 12 dimensions of each one-hot vector represent 12 different types of pitch within an octave, the 13th dimension represents a rest, and the 14th dimension is a special token separating two different chords. When the 13th or 14th dimension of the first vector is activated, the remaining three vectors will be identical to it. For chords containing more than 4 notes, we only encode the first 4 notes in ascending order of pitch.

We find that some melody generation models [9, 32] use similar representations. However, they differ from our representation in that: 1) they represent each chord as a single multi-hot vector, whereas we treat it as four one-hot vectors to predict pitch information more accurately, 2) the rhythm sequence in this paper encodes the rhythm of the chord (i.e. harmonic rhythm) rather than the melody one, and finally 3) their representations do not take into account the importance of time signatures, therefore only supports the most common one (i.e. 4/4).

3.2 Harmonic Rhythm Model

Previous models of melody harmonization [3, 8, 29, 34] always generate chords at a fixed time interval. The harmonic rhythm is not only related to the development of the melody, but depends on the current time signature. Therefore, we proposed a harmonic rhythm model that provides the harmonic rhythmic information of chords while considering time signatures.

As shown in Fig. 4, the harmonic rhythm model mainly consists of three components: a melody encoder, a beat encoder, and a harmonic rhythm decoder. The melody encoder and beat encoder...
are implemented using Bi-LSTM, and the harmonic rhythm decoder is implemented using LSTM.

Given a melody sequence \( m_{1:T} = \{m_1, m_2, ..., m_T\} \) of length \( T \) and a corresponding beat sequence \( b_{1:T} = \{b_1, b_2, ..., b_T\} \), this model can generate a harmonic rhythm sequence \( r_{1:T} = \{r_1, r_2, ..., r_T\} \). When at time step \( t \in \{1, 2, ..., T\} \), it generates the current harmonic rhythm token \( r_t \), from \( m_{1:T}, b_{1:T} \), and the previously generated \( r_{1:t-1} \):

\[
r_t = M_R(m_{1:T}, b_{1:T}, r_{1:t-1}, \theta_R),
\]

where \( M_R \) denotes the harmonic rhythm model and \( \theta_R \) is its parameter. Since the harmonic rhythm model can refer to melody information \( m_{t+1:T} \) and beat information \( b_{t+1:T} \) after time step \( t \), a longer-term choice is made when generating \( r_t \). This approach is also consistent with the compositional approach of most composers, just as they usually rely on subsequent melodies as well as time signatures to decide how to arrange the current chord.

### 3.3 Chord Model

How to represent chords is one of the challenges in melody harmonization. A common approach is to predefine the types of chords \([3, 29, 34]\). However, it has three disadvantages: 1) it is difficult to cover all possible chords, 2) it cannot generate chords that are not predefined, and 3) it is prone to imbalanced classification.

To solve these problems, we encode each chord \( c_i \) as four one-hot vectors \( c_i^{1st}, c_i^{2nd}, c_i^{3rd} \) and \( c_i^{4th} \) (see Sec. 3.1.2) and ask the chord model to predict the four vectors of the chord \( c_i \): the first vector is used to determine the bass of the chord, while the last three vectors are used to determine the structure of the chord. Thus, the model does not need to predefine the types of chords. Moreover, it can generate chords that do not present in the training set.

The structure of the chord model is given in Fig. 5. This model mainly consists of two components, namely the melody segment encoder and the chord decoder. The purpose of this model is to generate a chord sequence \( c_{1:L} = \{c_1, c_2, ..., c_L\} \) of length \( L \) based on a given melody segment sequence \( M_{1:L} = \{M_1, M_2, ..., M_L\} \).

As shown in Fig. 6, we cut the melody into small segments according to the duration of each chord. Furthermore, we need to make sure that these segments are of equal length to be used as input. Usually, a chord has a duration of up to a whole note, so melodies that are longer than a whole note are truncated, and those that are shorter than a whole note are filled in with padding tokens. Finally, we concatenate these segments by inserting separators (the 131st dimension of the melody vector) between them.

When at time step \( l \in \{1, 2, ..., L\} \), the chord model generates four chord vectors \( c_l^{1st}, c_l^{2nd}, c_l^{3rd} \) and \( c_l^{4th} \) of the current chord based on \( M_{1:L} \) and the previously generated chords \( c_{1:l-1} \):

\[
c_l^n = M_P(M_{1:L}, c_{1:l-1}, \theta_P),
\]

where \( M_P \) denotes the chord model, \( \theta_P \) is its parameter and \( n \in \{1, 2, 3, 4\} \) is the index of the chord vector. By combining these four outputs for time step \( l \), we can get the chord \( c_l \) at time step \( l \).

In addition, unlike the harmonic rhythm model, the chord model has four outputs, thus it also has four corresponding loss values. Since modifying any note in the chord will change the nature of it, we do not set weights for the four loss values.
3.4 Density Sampling

In general, modern language models require not only a lot of efforts from researchers to design a structure for controllable generation, but a large amount of annotated data for training. However, in certain generation tasks, some of the properties of the generated sequences are strongly correlated with specific tokens. For example, the holding token is highly correlated with the rhythmic property of music. Therefore, we can achieve controllable generation by adjusting how often they appear in a sequence. Not only is it easy to introduce prior knowledge into the sampling process, but there is no need to redesign the structure or retrain the model with annotated data.

To achieve the harmonic rhythm-controllable melody harmonization task, we use a tangent function according to the parameter density \( d \in (0, 1) \), to modify the log probability of the holding token: the lower the value of \( d \), the fewer chords will be generated, and vice versa. The basic idea of this method is to increase or decrease the probability of a given token by the given \( d \), which can be formulated as follows:

\[
\begin{align*}
\hat{p}_h^* &= p_h^{\tan(\frac{\pi d}{2})}, \\
\hat{p}_i^* &= (p_h - \hat{p}_h^*) \cdot \frac{p_i}{\sum p_h} + p_i,
\end{align*}
\]

where \( p_h \) and \( p_h^* \) are the original and the new probability of the holding token, while \( p_i \) and \( p_i^* \) are the original and the new probabilities of non-holding tokens (\( i \in \backslash \{h\} \)). The first step in Eq. 3 is to change the probability of the holding token, and the second step is to ensure that the sum of the probabilities of all tokens is equal to 1. As shown in Fig. 7, when \( d < 0.5 \), the probability of the holding token is increased, and when \( d > 0.5 \), the probability of the holding token is decreased. Particularly, when \( d = 0.5 \), the probabilities of all tokens do not change.

As this specified token is the holding token in this implementation, \( d \) can be used to control the sparsity of the chord progression. Furthermore, this method is not limited to controlling rhythm density. For example, in a music generation task, if we know which token represents the tonic, we can use density sampling to control the probability of the tonic token and achieve a controllable generation of tonality. More generally, density sampling can be applied to any language model for controllable generation based on modifying the probability of a specified token.

4 EXPERIMENTS

This section describes the experiments we have conducted. Sec. 4.1 provides the implementation details. Sec. 4.2 presents the metrics we used and analyses the results. Sec. 4.3 shows several melody harmonization examples of AutoHarmonizer. Finally, Sec. 4.3 introduces the Session Lead Sheet Dataset harmonized by our system.

4.1 Implementation Details

AutoHarmonizer trained/validated on a lead sheet version of Nottingham Music Database\(^2\) (NMD), a collection of 1,034 British folk songs. NMD has been appearing more and more in machine learning researches [6, 20, 36] for music over the past few years. However,\(^3\) these tunes are not originally checked by hand, so there are some mistakes in this dataset. The music generation start-up company Jukedeck put some efforts into cleaning the database and released it at GitHub\(^4\) in MIDI format, but we still found some mistakes in this version about 5% of tunes (e.g. mismatches, or no harmonies at all). Therefore, we manually corrected the MIDI version cleaned by Jukedeck, and all the tunes now are titled while present in the form of the lead sheet. This version is named as the Nottingham Lead Sheet Dataset (NLSD).

We implemented AutoHarmonizer using Keras with the Tensorflow backend. A grid search is performed through the parameter grid in Table 1. For the harmonic rhythm model, \( num\_layers = 2, \) \( rnn\_size = 128, \) \( batch\_size = 64 \) achieves the lowest cross-entropy loss of 0.038 bits on a 10% validation corpus. For the chord model, \( num\_layers = 3, \) \( rnn\_size = 128, \) \( batch\_size = 64 \) achieves the lowest one of 1.198 bits.

Table 1: The grid of hyperparameters searched over while optimizing our system.

| Parameter   | Values Searched       |
|-------------|-----------------------|
| num_layers  | \{1, 2, 3, 4\}        |
| rnn_size    | \{64, 128, 256, 512\} |
| batch_size  | \{32, 64, 128\}       |

4.2 Evaluations

4.2.1 Baseline. We found that the most recent neural network-based works [8, 29, 34] related to melody harmonization use the TheoryTab Database (TTD), which is not in the symbolic music common XML format (i.e. MusicXML). Thus it cannot be opened with the score editors (e.g. MuseScore, Sibelius) or read by music21 toolkit [10]. The codes for these related works are highly related to

\(^2\)http://abc.sourceforge.net/NMD/

\(^3\)https://github.com/jukedeck/nottingham-dataset
Table 2: The results comparison of among the validation set of NLSD, AutoHarmonizer in three different settings, and the baseline.

| Metrics               | Nottingham (validation) | AutoHarmonizer (d=0.1) | AutoHarmonizer (d=0.5) | AutoHarmonizer (d=0.9) | Baseline |
|-----------------------|-------------------------|------------------------|------------------------|------------------------|----------|
| CHE↑                  | 1.3424                  | 1.1155                 | 1.2668                 | 1.3067                 | 1.1381   |
| CC↑                   | 5.2574                  | 4.7204                 | 5.4623                 | 5.8690                 | 4.6893   |
| CTD↓                  | 0.9266                  | 0.7566                 | 0.8310                 | 0.8357                 | 0.7808   |
| CTnCTR↑               | 0.9176                  | 0.8881                 | 0.8950                 | 0.8951                 | 0.8983   |
| PCS↑                  | 0.5660                  | 0.5512                 | 0.5802                 | 0.6171                 | 0.5985   |
| MCTD↓                 | 1.0968                  | 1.1315                 | 1.1188                 | 1.1016                 | 1.0113   |
| HRHE↑                 | 0.5332                  | 0                   | 0.3568                 | 0.1721                 | 0        |
| HRC↑                  | 2.0792                  | 1                     | 1.6666                 | 1.6309                 | 1        |
| CQL↓                  | 2.7099                  | 3.5107                 | 2.9834                 | 1.9706                 | 3.4611   |

this dataset, which makes it difficult for us to modify their codes to support common symbolic music formats. In the meantime, we note a melody harmonization model proposed by Lim et al. [22]. Although they did not release the code of this model, the mechanics and specific settings of this model are described in great detail, which provides a good guide for our reproduction.

For these reasons, we reproduced the work in [22] as the baseline (public available at GitHub^4). This work employs the idea of bag-of-words models to encode each bar, while the chords are encoded as one-hot vectors. It assumes that each bar corresponds to a chord and that four chords are predicted simultaneously. This reproduced model is the same as the original setup, except that we replaced the dataset with the NLSD (the original one trained/validated on the Wikifonia Dataset).

4.2.2 Metrics. For melody harmonization evaluations, we use nine different metrics.

The first six metrics are proposed in [34], which measure the quality of the chord progression, and the harmonicity between the melody and the chords.

- **Chord Coverage (CC)**: the number of chord types in a piece of music, the higher the value of CC, the more chord types are present.
- **Chord Histogram Entropy (CHE)**: creates a histogram of chord occurrences based on a chord sequence. The counts are then normalised so that they sum to 1 and their entropy is calculated according to the following formula:

\[
CHE = - \sum_{k=1}^{CC} p_k \cdot \log p_k. \tag{4}
\]

where \(p_k\) is the frequency of the \(k\)-th chord occurrence. The higher the value of CHE, the greater the uncertainty and the variety of chords.

- **Chord Tonal Distance (CTD)**: the average value of the tonal distance computed between every pair of adjacent chords in a given chord sequence. The lower the value of CTD, the smoother the chord progression.

\[
\frac{1}{u-1} \sum_{u=1}^{u} p_u \cdot \log p_u, \tag{6}
\]

where \(p_u\) is the frequency of the \(u\)-th harmonic rhythm occurrence.

- **Chord Quarter Length (CQL)**: the ratio of the total duration of the chords to the number of chords. The smaller the value of CQL, the more frequently the chords are changed.

4.2.3 Analyses. Table 2 gives the evaluation results in nine metrics introduced in Sec. 4.2.2 to various models.

Among the chord progression metrics (CHE, CC, and CTD), the ground truth, AutoHarmonizer \((d = 0.9)\), and AutoHarmonizer \((d = 0.1)\) perform the best, respectively. In terms of the CHE, although the ground truth is the most information-rich, when \(d = 0.9\), the AutoHarmonizer’s performance only differed from that of ground truth by about 0.03 bits, while surpassing the ground truth in CC. Conversely, when \(d = 0.1\), the smoothness of the chord progression also exceeds that of ground truth. This means that by adjusting \(d\), a
balance can be achieved between the smoothness and the richness, to achieve a desirable result. When \( d = 0.9 \), the values for CHE, CC and CTD are smaller compared to other settings. In other words, the higher the value of \( d \), the greater the diversity of chord types while the smoothness of chord progressions is reduced.

For the chord/melody harmonicity metrics (CTnCTR, PCS, and MCTD), the best performance is achieved by the ground truth, AutoHarmonizer \( (d = 0.9) \) and the baseline, separately. It is reasonable that the ground truth scored highest on CTnCTR, as the chords composed by the human are more likely to avoid the use of non-chord tones. Since the harmonic density is greater at \( d=0.9 \), AutoHarmonizer generates denser chord progressions, making it easier to achieve the best results in terms of PCS. For MCTD, the baseline is the best performer. Probably it is because the baseline overuses common triads, which makes it more likely to perform better in this metric.

Among the harmonic rhythm metrics (HRHE, HRC and CQL), the first two perform the best for the ground truth, while baseline and AutoHarmonizer \( (d = 0.1) \) perform the worst (generate a chord once a bar). And for CQL, AutoHarmonizer \( (d = 0.9) \) perform the best. In both HRHE and HRC, AutoHarmonizer scored somewhat less well than ground truth, suggesting that it is challenging to generate flexible harmonic rhythms as humans. However, the CQL value of AutoHarmonizer \( (d = 0.9) \) is significantly exceeded the one of ground truth, indicating that a higher value of \( d \) makes chord switching of the chord progressions generated by AutoHarmonizer more frequent than that of ground truth.

Fig. 8 gives the distribution of onset of chords on various beat types. It is easy to see that humans place chords on the strong beat in most cases, but arrange chords on other types of beat. The generated chords of both AutoHarmonizer \( (d = 0.1) \) and baseline are all located on the strong beat, i.e. they generate chords once a bar. This means that their harmonic rhythms are quite different from those of humans. And when \( d = 0.5 \), the distribution of onset is much more similar to the ground truth, indicating that the system effectively learns the distribution of harmonic rhythms arranged by humans. When \( d = 0.9 \), onsets are more predominant on the medium-weight and weak beats compared to ground truth. The above results suggest that adjusting the value of \( d \) can significantly influence the distribution of onset of chords on different beats.

### 4.3 Melody Harmonization Examples

We present several representative examples harmonized by AutoHarmonizer, to illustrate the capabilities of this system. For more examples, we developed a publicly accessible musical discrimination test at GitHub\(^\text{5}\).

#### 4.3.1 Density Sampling Examples

Four examples are given in Fig. 9 to demonstrate intuitively the effect of \( d \) on the AutoHarmonizer. As can be seen from these examples, the effect of \( d \) on the harmonic rhythm is very significant. In addition, the system does not generate chords in pickup bars, regardless of the setting.

Fig. 9a is the result of melody harmonization at \( d = 0.1 \). The most obvious feature of this example is that each chord corresponds to a bar. Furthermore, only two types of chords (D major and G major) are included in this example. Although this result is acceptable, it lacks dynamics and variety compared to the other results.

The example in Fig. 9b is generated with the setting \( d = 0.5 \), which contains chords on the medium-weight beat of the last three bars and introduces a new chord A major.

Fig. 9c is the result generated when \( d = 0.9 \). It places chords on every strong and medium-weak beat. Compared to Fig. 9b, the fourth chord here has changed from G major to A major, although both of them are reasonable.

Fig. 9d is the ground truth. This result is almost the same as Fig. 9c, except that A major is replaced with A7, which is a better choice. Although this difference is trivial for most people, it still means that the system has a gap compared to the human level.

#### 4.3.2 Complex Time Signatures

To verify the effectiveness of the beat sequence, we tested the melody in Fig. 10, which contains time signatures 5/8 and 3/8 that are not present in the dataset. It is easy to observe that the harmonic rhythms generated by the AutoHarmonizer still conform to the pattern of these time signatures.

![Figure 10: An example harmonized by AutoHarmonizer (d = 0.9) with complex time signatures.](https://sander-wood.github.io/autoharmonizer)

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5. [GitHub](https://sander-wood.github.io/autoharmonizer)
4.4 Dataset Harmonized by AutoHarmonizer
Symbolic music datasets are important for both music information retrieval and music generation. However, there is a lack of large-scale lead sheet symbolic music datasets. Therefore, we create a lead sheet dataset based on Session Dataset, named as the Session Lead Sheet Dataset (SLSD), containing 40,925 tunes with chords.

This dataset is collected as follows. We first download all the tunes in ABC format from the Session⁶, a community website dedicated to Irish traditional music. We then convert those ABC files to MusicXML with the music21 toolkit [10]. However, the conversion is not entirely accurate (e.g., extra rests are added at the end of pickup bars). Therefore, we clean the converted files and remove the repeat notation by flattening each score to make them more machine-readable. Finally, we use AutoHarmonizer (d = 0.5) to generate the corresponding harmonies for these Irish traditional tunes. Each harmonized piece contains melody and corresponding chord progression, and metadata information such as key signature, time signature, title and genre.

To the best of our knowledge, SLSD is the largest lead sheet MusicXML dataset so far. Table 3 shows the number of notes, chords, bars and pieces of different datasets. In addition, as we cannot read the original TTD directly, we use its MIDI version for statistical information other than chords (the MIDI version does not contain chords), which is instead obtained by counting the number of occurrences of the keyword “<chord>” in those XML files. Therefore, the statistical results in this dataset are for information purposes only and are not guaranteed to be accurate.

The SLSD can be used but not limited to the following research topics including: 1) harmonic study [1], 2) ethnomusicological study [16], 3) melody harmonization [22] and 4) melody generation based on chords [9]. Although the chords are machine-generated, the AutoHarmonizer is closer to human-composed chord progressions than other melody harmonization systems, as it takes into account harmonic rhythms. In addition, given that Ireland and Britain share a very similar cultural background, using the AutoHarmonizer trained on NLSD to produce the chord progressions for the Session Dataset would be more in keeping with its melodic style. For intuitive comparison, Table 4 gives the results of NLSD and SLSD in each metric. We suggest using this dataset for pre-training and later fine-tuning on a dataset like NLSD to further improve the performance of deep learning models.

Table 3: Comparison of some existing public lead sheet datasets and the proposed dataset.

| Dataset     | Notes  | Chords | Bars  | Pieces |
|-------------|--------|--------|-------|--------|
| Fiddle Tunes| 48,321 | 4,978  | 8,128 | 226    |
| Nottingham  | 189,215| 51,342 | 38,821| 1,034  |
| RJ Tunebook | 193,916| 24,930 | 38,218| 1,078  |
| Wikifonia   | 932,813| 330,241| 496,437| 6,244  |
| TheoryTab   | 869,052| 284,936| 180,488| 18,167 |
| Session     | 7,783,509| 1,638,386| 1,353,370| 40,925 |

Table 4: The results comparison of NLSD and SLSD in various metrics.

| Metrics  | Nottingham | Session |
|----------|------------|---------|
| CHE↑     | 1.3590     | 1.2812  |
| CC↑      | 5.3805     | 5.4528  |
| CTD↓     | 0.9387     | 0.8861  |
| CTnCTR↑  | 0.9228     | 0.8836  |
| PCS↑     | 0.5770     | 0.5427  |
| MCTD↓    | 1.0809     | 1.1265  |
| HRHE↑    | 0.5653     | 0.4139  |
| HRC↑     | 2.1000     | 1.7757  |
| CQL↓     | 2.6711     | 2.9232  |

5 CONCLUSIONS
In this paper, we proposed AutoHarmonizer, a harmonic rhythm-controllable melody harmonization system which trained/validated on the Nottingham Lead Sheet Dataset. Since we consider time signatures and represent them as beat sequences, the encoding method we use enables AutoHarmonizer to capture complex harmonic rhythms within chord progressions, and even can generate suitable harmonic rhythms based on time signatures that do not exist in the dataset. Furthermore, we experimentally verified that AutoHarmonizer not only generates chord progressions of better quality than baseline, but can significantly alter the generated harmonic rhythms according to the user-given rhythmic density parameter d. In addition, we created the largest lead sheet MusicXML dataset, namely the Session Lead Sheet Dataset, with the use of AutoHarmonizer.

According to our experimental results, although overall AutoHarmonizer is closer to the ground truth than the baseline method, there is still a gap with humans, which means we still have room for improvement. In addition, the density sampling proposed in Sec. 3.4 is not only for harmonic rhythms, but for more diverse and controllable generation, which needs to be further verified in later works. In the future, we plan to port this system to the browser to provide novices and artists with an approachable and interactive way of composing music.

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⁶https://thesession.org/tunes/download
