ROC: A New Paradigm for Lyric-to-Melody Generation

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ABSTRACT

Lyric-to-melody generation is an important task in songwriting, and is also quite challenging due to its distinctive characteristics: the generated melodies should not only follow good musical patterns, but also align with features in lyrics such as rhythms and structures. These characteristics cannot be well handled by neural generation models that learn lyric-to-melody mapping in an end-to-end way, due to several issues: (1) lack of aligned lyric-melody training data to sufficiently learn lyric-melody feature alignment; (2) lack of controllability in generation to explicitly guarantee the lyric-melody feature alignment. In this paper, we propose ROC, a new paradigm for lyric-to-melody generation that addresses the above issues through a generation-retrieval pipeline. Specifically, our paradigm has two stages: (1) creation stage, where a huge amount of music pieces are generated by a neural-based melody language model and indexed in a database through several key features (e.g., chords, tonality, rhythm, and structural information including chorus or verse); (2) re-creation stage, where melodies are recreated by retrieving music pieces from the database according to the key features from lyrics and concatenating best music pieces based on composition guidelines and melody language model scores. Our ROC paradigm has several advantages: (1) It only needs unpaired melody data to train melody language model, instead of paired lyric-melody data in previous models. (2) It achieves good lyric-melody feature alignment in lyric-to-melody generation. Experiments on English and Chinese datasets demonstrate that ROC outperforms previous neural based lyric-to-melody generation models on both objective and subjective metrics. We provide our code in supplementary material and provide demos on github.1

1 INTRODUCTION

Automatic songwriting has always been the dream of human beings. In recent years, with the development of artificial intelligence, researchers have achieved great success in various aspects of automatic songwriting such as lyric generation [12, 20], melody generation [19, 23], lyric-to-melody generation [2, 5, 16, 21], and melody-to-lyric generation [8, 11, 20]. Among all directions, lyric-to-melody generation is one of the most fundamental tasks and is the focus of this paper. A high-quality lyric-to-melody generation should not only focus on beautiful melodies but also align rhythms and structures in lyrics with melodies.

Among all methods in lyric-to-melody generation, rule-based and neural-based are two main categories. Rule-based methods incorporate composition guidelines summarized by human composers so that the rhythm and structure alignment between lyrics and melodies can be ensured. However, they require too much labor and music expertise, and thus the research focus turns to neural-based methods. Currently, the end-to-end neural generation model is the mainstream method of lyric-to-melody generation but it suffers from many weaknesses. First, melody is weakly correlated with lyric, that is, a piece of melody can be accompanied by different lyrics as long as the lyric syllables align with notes. Therefore, the mapping from lyric to melody is hard to learn, which requires a large amount of aligned training data. But these data are rare actually. Second, an end-to-end model is a black box with weak guarantee of lyric-melody feature alignment, resulting in low quality of generation. SongMASS [16] proposes an unsupervised method to train lyric-to-lyric and melody-to-melody models respectively, and learns the alignment between two models. It sidesteps the insufficiency of paired data but still suffers from weak guarantee of feature alignment between lyrics and melodies. TeleMelody [5] proposes a two-stage generation: lyric-to-template and template-to-melody. With templates, it does not need paired data and some composition guidelines for tonality, rhythm and chord progression are better considered. However, feature alignment still can not be ensured explicitly because two stages are both neural-based.

Considering aforementioned weaknesses in existing methods, we combine merits of both rule-based and neural-based methods, and propose Re-creation of Creations (ROC), a new paradigm for lyric-to-melody generation with a generation-retrieval pipeline. There are two stages in ROC: creation and re-creation. In creation...
stage, we use melody data to train a melody language model, which is used to generate high-quality music pieces with a short-piece generation procedure. Generated melody pieces are stored in a database indexed by extracted key features including tonality, rhythm, chord, structural information (a piece belongs to a chorus or a verse). These features are used as the key for retrieval in the next stage. In re-creation stage, we compose melodies for lyrics (sentence by sentence) by retrieving melody pieces from the database. In detail, we first infer the features of a lyric sentence, where these features are used as the query for retrieval. We propose a lyric structure recognition algorithm to extract structure features by segmenting lyrics into choruses and verses. Then, we retrieve melody pieces by matching the features of a lyric sentence to those of melody pieces, and re-rank retrieved melody pieces by both composition guidelines and melody language model scores. For a better guarantee of rhythm and structure alignment, we propose a melody sharing scheme between lyrics with the same rhythm patterns (e.g., repetitive lyric segments). The best melody pieces for each lyric are concatenated as a complete song which is then polished because concatenation may cause some issues like overlapping bars. ROC has the following advantages. (1) Because we only train a melody language model, ROC does not need paired lyric-melody data. (2) The non-end-to-end pipeline, retrieval-based composition, and composition guidelines used in ROC can ensure the alignment of rhythm and structure between lyrics and melodies.

To sum up, our main contributions are as follows:

1. We propose ROC, a new paradigm for lyric-to-melody generation with creation stage and re-creation stage, which does not need paired lyric-melody data for training, and can guarantee the rhythm and structure alignment between lyrics and melodies.

2. We make a series of designs to ensure ROC work effectively, including a lyric structure recognition algorithm, a melody piece generation procedure, a retrieval and re-ranking procedure, melody sharing scheme, melody polishing, etc.

3. Experimental results demonstrate that ROC outperforms end-to-end and non-end-to-end baselines on both objective and subjective metrics.

2 BACKGROUND

2.1 Characteristics of Melodic Songs

Empirically, beautiful and harmonious songs in pop music have common characteristics in lyric, melody, and lyric-melody feature alignment. We list a few characteristics in below. We omit lyric characteristics because we only consider how to generate melodies from given lyrics in lyric-to-melody generation task.

2.1.1 Melody. The following melody patterns are crucial to the quality of a song according to some composition guidelines.

- Chord progression. A good chord progression can guide the emotion development of a melody. Besides, the chord progression should return to the tonic chord to create a sense of stable and smooth ending.
- Tonality and tempo. They have an impact on emotional atmosphere. For example, fast tempo and major feel enthusiastic, gorgeous, bright and cheerful while slow tempo and minor feel cold, melancholy and magical.
- Varied pitch and note density. Average pitch and note density usually increase in choruses for more intensive emotion expression.
- Pitch range. Pitches in the beginning of a song should be mild to make room for lifting in the chorus. Also, pitches can not fluctuate too much in a chorus or a verse. These are for the ease of singing.
- Tendency. Some notes tend to be followed by some specific notes due to the tendency between notes.2

2.1.2 Lyric-Melody Feature Alignment. In lyric-to-melody generation, melody should not only follow good musical patterns, but also align with lyrics in some aspects:

- The structure of lyrics and melodies should match. In melody, choruses are usually more intensive and reach the climax of the whole song. In lyric, chorus lyrics are usually more lyrical than those in verses. The better match promotes emotion expression.
- Lyric segments with the same rhythm patterns (e.g., the same number of syllables) usually share melodies. Usually, lyrics in chorus are the longest repetitive segments.
- Composers should choose the proper tonality according to lyric sentiments to express emotion thoroughly.
- Lyric cadences and lyric endings should match for better rhythm and structure alignment.

2.2 Lyric-to-Melody Generation

In the early days, there are some statistical-based and rule-based methods for lyric-to-melody generation. Some researchers [10] focus on lyric-note correlation and propose a probability model but ignore music knowledge. Some researchers [1] study the Japanese prosody and its role in composition and propose a probability model to generate melody. They incorporate more musical patterns but still ignore structural features so that there are no repetitive segments in generated songs. Besides, these traditional methods require too much labor and expertise of music or linguistics, and thus the research focus turns to neural-based methods.

With the advent of the neural network era, major breakthroughs have been made in the field of lyric-to-melody generation [2, 5, 16, 21]. Songwriter [2] regards lyric-to-melody generation as a sequence-to-sequence task, which learns a mapping from lyric sentence to melody phrase. LSTM-GAN [21] have two LSTM networks as the generator and discriminator with lyrics as conditions. It encodes words of lyrics into embedding vectors and generates melodies. These models are end-to-end which require large amount of paired lyric and melody data. Such aligned data are insufficient, which greatly hinders research. SongMASS [16] trains lyric-to-lyric and melody-to-melody models separately then conducts interaction between models to sidestep the lack of paired data. However, it is an end-to-end method and suffers low controllability which results in no guarantee of aligned features between lyric and melody. To be more controllable, TeleMelody [5] divides the end-to-end generation pipeline into two stages: lyric-to-template and template-to-melody. As an intermediary, templates bridge the gap between lyric and melody. Besides, templates make the generation more

2http://www.musicnovatory.com/cqtendency.html
controllable, which increases the ease of aligning features between lyrics and melodies. However, two stages in TeleMelody are both neural-based so the guarantee of feature alignment is still insufficient.

Our proposed ROC solves aforementioned weaknesses. ROC does not need paired data because only melodies involved in training. Incorporated composition guidelines enable ROC to consider more lyric and melody features comprehensively, resulting in better aligned rhythm and structure features between lyrics and melodies in generated songs.

3 METHODOLOGY
The whole pipeline of ROC is shown in Figure 1. In ROC, there are two stages: creation and re-creation. Two stages are conducted sequentially. We introduce details in each stage respectively.

3.1 Creation Stage
Creation stage creates melody pieces for re-creation stage. As shown in Figure 1(a), in creation stage, we use melody data to train a melody language model and let the model generate short melody pieces which are stored in the database indexed by key features. We introduce the melody language model, melody feature extraction and details about melody piece storage in below.

3.1.1 Melody Language Model. We train an auto-regressive melody language model based on transformer architecture with melody data to produce new melody pieces. However, the melody language model usually performs poor in generating long sequences. Therefore, we propose a short melody piece generation procedure: given two bars in melody data, the melody language model predicts next two bars. The predict interval of two-bar is an appropriate choice because if the interval is too long, the quality of generated melody pieces is low and re-creation will be inflexible; if the predict interval is shorter than one bar, the concatenation and polish in re-creation stage will be too complicated. Predicted pieces are removed if they are the same as their ground truth. In this way, we obtain original melody pieces of high quality. This trained melody language model is also reused for re-ranking pieces in re-creation stage.

3.1.2 Melody Feature Extraction. The importance of lyric-melody structure alignment, chord progression, tonality have been described in Section 2.1.1. Based on these characteristics, we summarize four key features in a melody piece that can be used as keys for storage and retrieval, which are: ‘Length’, ‘Structure’, ‘Chords’, ‘Tonality’.

- ‘Length’. It is the number of notes in a piece. We use this feature to guarantee the rhythm alignment between lyrics and melodies: In most cases, we decide the retrieval length according to the number of syllables in a lyric and align one syllable with one note. Occasionally, we allow one syllable to align with multiple notes and details are in Section 3.2.2.

- ‘Structure’. It indicates the piece belongs to whether a chorus or a verse. In re-creation stage, we also recognize this feature of a lyric for a better match between melody and lyric structure. ‘Structure’ is inferred by an algorithm based on self-similarity matrix\(^3\).

- ‘Chords’. It is the corresponding chord sequence of the melody piece. ‘Chords’ is inferred based on note pitch distribution based on a viterbi algorithm\(^4\).

- ‘Tonality’. It implies the tonality of the melody piece. It is important to choose the appropriate tonality to express the emotion of lyrics. In re-creation stage, a consistent tonality through the whole song is given based on lyric sentiment, and pieces with unmatched tonality are filtered during retrieval.

3.1.3 Melody Pieces Storage. A generated two-bar piece is stored as two one-bar pieces and one two-bar piece. The absolute bar indexes are replaced with the relative indexes (0 or 1) for the ease of retrieval and concatenation. Also, we deduplicate melody pieces and filter monotonous pieces. We call a melody piece as monotonous if there are too few unique pitches in a melody piece.

3.2 Re-creation Stage
As shown in Figure 1(b), ROC composes melodies for lyrics sentence by sentence in re-creation stage. First, we infer features from lyrics and use these features to retrieve melody pieces. Melody candidates are first filtered by composition guidelines and then re-ranked by the melody language model scores. When each lyric in a song has been assigned with a melody piece, we concatenate melody pieces together and polish the song. In this section, we first introduce how to extract features in lyrics for retrieval. Then, we discuss retrieval and re-ranking details. At last, we talk about polish, a post-process to further improve the quality of melodies.

3.2.1 Lyric Feature Extraction. As mentioned in Section 2.1.2, lyric-melody feature alignment matters. Given a lyric, we extract features and retrieve melody candidates based on these features. Among features mentioned in Section 3.1.2, the current ‘Chords’ is inferred based on a chord progression specified by users. ‘Length’ is the number of syllables in a lyric. ‘Tonality’ is automatically set as major or minor based on positive or negative sentiments of lyrics. We use third-party libraries for Chinese\(^5\) and English\(^6\) sentiment analysis. In terms of ‘Structure’, we design a heuristic algorithm to recognize choruses and verses in lyrics and introduce details in below.

According to Section 2.1.2, repetitive lyric segments with the same rhythm patterns share melodies. Among repetitive lyric segments, choruses are usually the longest ones. Therefore, we design an algorithm for searching repetitive segments in lyrics to recognize structure. The longest repetitive segments are regarded as choruses and the rest are regarded as verses.

First, we define some preliminaries. Assume a song contains \(n\) sentences. We represent a sentence with the number of syllables in it. Therefore, lyrics of a song can be abstracted into a number string \(S\). We call a substring in \(S\) as \((L, K)\) Repeat if it is of length \(L\) and repeats \(K\) times non-overlappingly in \(S\). The collection of these repetitive substrings is denoted as \(R(L, K)\). \(R(L, K)\) denotes the \(i\)-th repeat in \(R(L, K)\), where \(i \in [1, K]\). Each segment in \(R(L, K)\) should have the same melody.

\(3\)https://github.com/vivjay30/pychorus
\(4\)https://github.com/magenta/note-seq
\(5\)https://pypi.org/project/cessent/\n\(6\)https://pypi.org/project/textblob/
For the sake of diversity, we randomly select a top-k melody piece from the database. Considering some characteristics in Section 2.1.1, we use features extracted from lyrics to retrieve melody candidates which are stored in the database along with key features. In re-creation stage, we infer the features of each lyric in a song, which are used as the query to match melody pieces. Melody pieces are retrieved by features and re-ranked by both composition guidelines and the melody language model scores. The final melodies are generated after concatenating and polishing these melody pieces.

Algorithm 1 Lyric Structure Recognition with (K, L) Repeat Algorithm.

1: Input:
   The string S abstracted from lyrics;
   The segmentation granularity g.
2: Initialize:
   Set all elements in struct array as 0.
3: while True do
4:   Search R(L, K) with the largest L from S.
5:   if L > g and K > 1 then
6:     Assign the struct value of each element in R(L, K) as the index in S of each element in R(L, K)_i, where i ∈ [2,K].
7:     Remove elements with non-zero struct value from S.
8:   else
9:     break
10: end if
11: end while

Now, the problem turns to find R(L, K) in S. In each iteration, we only search R(L, K) with the longest L greedily. Because in the first iteration, the algorithm finds the R(L, K) with the global longest L, we regard this R(L, K) as chorus. To record structure, we introduce an auxiliary array of length n called struct. If the X-th lyric should share with melody from the Y-th lyric, then the X-th element in struct is assigned as Y. Initially, all elements in struct are ‘0’ which means no sharing relationship. We introduce a searching granularity g to control the minimum length of repetitive segments. When searched R(L, K) with L shorter than g or K less than 1, the algorithm stops. In ROC, we set g as 2 by default. The algorithm details are shown in Algorithm 1. Figure 3 is an intuitive illustration of the algorithm. We choose "We Are the Champions" by Queen. In the first iteration, the algorithm recognizes that the chorus is from ‘We are the champions my friends’ to ‘Cause we are the champions of the world’. The second chorus shares melody with the first chorus. In the second iteration, the second chorus recognized in last iteration is skipped when the struct value is non-zero. The loop stops because there are no more repetitive segments longer than g, which is 2 here. Lyrics corresponding to zero struct values will retrieve melodies independently in retrieval and re-ranking stage.

3.2.2 Retrieval and Re-ranking. With extracted features, ROC does the following operations to assign the best matching melody to each lyric:

(1) Retrieve Melodies: When the struct value of a lyric is ‘0’, we use features extracted from lyrics to retrieve melody candidates from the database. Considering some characteristics in Section 2.1.1, retrieved candidates are filtered with the following guidelines:

- If we are at the beginning of the song, the pitch of the first note should be in range of G3 to F4. This is to prevent an overly pitched verse followed with a further higher pitched chorus, making it difficult to sing. The pitch range we set is suitable for most people to sing.
- The first pitch in a melody piece must be less than 8 semitones apart from the last pitch of the melody context (concatenated melody pieces of previous lyrics). The reason is for the ease of singing, too.
- The tendency of last pitch in the context should be satisfied as much as possible. This is to make the two melodies connect more naturally.

After filter, we concatenate each candidate with the melody context, and let the melody language model score these candidates. For the sake of diversity, we randomly select a top-k melody piece as the final result.

Figure 1: The pipeline of ROC. There are two stages in ROC. In creation stage, melody language model generates melody pieces which are stored in the database along with key features. In re-creation stage, we infer the features of each lyric in a song, which are used as the query to match melody pieces. Melody pieces are retrieved by features and re-ranked by both composition guidelines and the melody language model scores. The final melodies are generated after concatenating and polishing these melody pieces.
**Syllables**

4. I’ve paid my dues
4. Time at the time
7. We are the champions my friends
9. And we’ll keep on fighting till the end
5. We are the champions
5. No time for losers
9. ’Cause we are the champions of the world
4. I’ve taken my bows
5. And my cur vend calls
7. We are the champions my friends
9. And we’ll keep on fighting till the end
5. We are the champions
5. No time for losers
9. ’Cause we are the champions of the world

**Initialization:**

S: [4, 4, 7, 9, 5, 5, 9, 4, 5, 7, 9, 5, 5, 9, 5, 5, 9]

struct: [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]

**Iteration 1:** L = 5, K = 2

S: [4, 4, 7, 9, 5, 5, 9, 4, 5, 7, 9, 5, 5, 9, 5, 5, 9]

struct: [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]

**Iteration 2:** L = 3, K = 2

S: [4, 4, 7, 9, 5, 5, 9, 4, 5, 7, 9, 5, 5, 9, 5, 5, 9]

struct: [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]

Figure 2: A case of Algorithm 1. Due to page limit and demonstration of algorithm properties, we simplify and modify the original lyrics. We use red to highlight the operation in each step and grey to indicate these elements are skipped in string S.

(2) Share Melodies: When the struct value of a lyric is positive, we use the struct value as the index to find which melody of lyric should the current lyric share with. For example, in Figure 1, when composing the second chorus, we directly reuse melodies of the first chorus.

(3) Align One Syllable with Multiple Notes: One syllable aligning with multiple notes appears with a certain probability. When it happens, ROC retrieves pieces having more notes than the number of syllables in the lyric and randomly decide which notes connect.

3.2.3 Concatenation and Polish. We concatenate retrieved melody pieces together as the final composition result. Limited by the concatenation, there are some inevitable flaws have to be polished, so we conduct following operations:

(1) If adjacent lyrics have the same amount of syllables, we make their melodies sound similar.

(2) We make sure that the pause between phrases is appropriate.

(3) Concatenated bars may overlap in melodies or chords, which should be avoided.

4 EXPERIMENTAL SETTINGS

In this section, we introduce the experimental settings, including datasets, system configurations, baselines and evaluation metrics.

4.1 Dataset

We use LMD-matched MIDI dataset [15], which contains 45,129 MIDI data. First, we separate tracks [4] and extract melodies. Tonality is normalized to “C major” or “A minor”. Ten percent of the data constitutes the validation set for training the melody language model. Because of short melody piece generation procedure mentioned in Section 3.1.1, all data are used for generating database pieces. There are 139,678 records in the database. We select 20 famous English and Chinese songs as test set.

4.2 Baselines

We compare ROC with previous neural-based generation models. We choose SongMASS [16] and TeleMelody [5] as representative of end-to-end models and non end-to-end models, respectively. Song-MASS trains lyric-to-lyric and melody-to-melody models and makes two models interact to solve the insufficient data issue. TeleMelody designs templates to bridge the gap between lyrics and melodies. Such templates introduce controllability to realize a better lyric-melody feature alignment. To evaluate the effectiveness of our lyric structure recognition algorithm, we also compare our algorithm with self-similarity matrix based methods [3, 18].

4.3 System Configuration

We choose the decoder-only transformer [17] as our melody language model and our training code is based on [13]. The language model consists of 4 decoder layers. The hidden size, input dimension and output dimension are 256. There are 4 attention heads in a layer. In training, warmup steps are 4000 and learning rate is 0.0001. We use Adam optimizer [6] with Adam β = (0.9, 0.98). To avoid overfit, we adopt the dropout mechanism at the rate of 0.1. The best checkpoint is selected on perplexity on the valid set. We apply early stop scheme with 20 epochs patience. When generating melody pieces, decoding scheme is top-k and k is 5. When scoring melody pieces, the k in top-k mentioned in 3.2.2 is 30. Because the original SongMASS is trained with English lyric data, we follow [5] to obtain a SongMASS model of Chinese version. To compute the self-similarity matrix of lyrics, we use pretrained embedding vectors GloVe [14] for English and CA8 [9] for Chinese.

4.4 Evaluation Metrics

We conduct objective and subjective experiments. Evaluation metrics are listed as below:

4.4.1 Objective Metrics. (1) Diversity (Dist-n) [7]: this metric is widely used in NLP fields to measure the diversity of generation, i.e., how many unique n-grams in generated songs. This metric can measure the quality of music to a certain extent because a song having few unique n-grams is very monotonous. We only consider the diversity of pitch, which is the most important feature in a piece. (2) Entropy (Ent-n) [22]: Dist-n neglects the frequency difference of n-grams. As a complement, we also compute Entropy which reflects how evenly the n-gram distribution is for a given melody: Ent =
Table 1: Objective and subjective evaluation results on Chinese and English lyric-to-melody test set.

| Models               | Objective | Subjective |
|----------------------|-----------|------------|
|                      | Dist-1    | Dist-2     | Ent-1   | Ent-2   | Struc | Rhy | LMC | CLC | Melo |
| SongMASS (EN) [16]   | 0.62      | 4.32       | 2.18    | 3.83    | 2.80  | 2.80 | 2.60 | 3.00 | 3.30 |
| TeleMelody (EN) [5]  | 0.81      | 4.61       | 2.30    | 3.88    | 3.20  | 3.30 | 2.90 | 3.80 | 3.80 |
| ROC (EN)             | 0.97      | 6.81       | 2.58    | 4.40    | 4.50  | 4.00 | 4.20 | 4.00 | 4.00 |
| SongMASS (ZH) [16]   | 0.45      | 3.97       | 2.05    | 3.75    | 2.30  | 2.60 | 2.50 | 3.00 | 2.90 |
| TeleMelody (ZH) [5]  | 0.75      | 4.54       | 2.32    | 3.85    | 3.20  | 3.50 | 2.90 | 3.80 | 3.70 |
| ROC (ZH)             | 0.91      | 6.60       | 2.57    | 4.41    | 4.50  | 4.10 | 4.20 | 4.00 | 4.10 |

\[ \sum_{w} F(w) \sum_{w \in V} F(w) \log \frac{F(w)}{\sum_{w} F(w)} \], where \( V \) is the set of all n-grams, \( F(w) \) represents the frequency of n-gram \( w \).

4.4.2 Subjective Metrics. We recruit 10 evaluators having basic music knowledge to evaluate the performance of lyric-to-melody system from the following five aspects:

1. Structure (Struc): how well the melody structure matches lyric structure? Specifically, whether lyrics with similar rhythm patterns have similar melodies? (2) Rhythmic (Rhy): is the rhythm of a song flexible? (3) Lyrics and melodies compatibility (LMC): is lyric-melody feature alignment significant, e.g., when the lyrics enter the chorus, does the melody have a pitch lift or emotional intensity? Do similar lyrics share similar melodies? (4) Cadence and lyric ending compatibility (CLC): whether cadences in the song sounds harmonic and whether there is an appropriate pause at the end of a lyric? (5) Melodic (Melo): is the melody beautiful and attractive?

In each aspect, evaluators can score from '1' for bad to '5' for good.

5 EXPERIMENTAL RESULTS

5.1 Main Results

Table 1 shows results of objective and subjective judgement. In objective experiments, ROC outperforms baselines in each language. The comprehensive gains on all metrics demonstrate the effectiveness of our new paradigm for lyric-to-melody generation:

1. Higher diversity scores of ROC imply that there are more ups and downs in melodies generated by ROC, which prevents the melody being flat and unattractive. More diverse melodies are more likely to promote the emotion expression.

2. Higher entropy scores indicate that diverse notes are distributed more evenly than those of baselines, that is, the attractiveness and the ability of better emotion expression are more likely to maintain from the start to the end.

These conclusions are confirmed in the subjective experiments, where ROC also outperforms baselines by a large margin in two languages:

ROC achieves significant gains in Struc thanks to lyric structure recognition and melody sharing scheme. In baselines, perhaps an implicit structural feature is captured during training, there are some weak structural patterns, but they are not as evident and neat as those in ROC. Also thanks to explicit structure features, we can distinguish chorus and verse which is an explicit activation for pitch range change or emotion expression promotion.

2. ROC has an improvement in Rhy because our generation has more flexible notes, e.g., durations vary much more often than those in baselines. This is because in ROC, pieces are short whereas baselines suffer from modeling longer-term dependency.

3. Due to the feature match between melody pieces and lyrics, we also beat baselines on LMC by a large margin.

4. Because the pipeline of ROC includes pause and cadence polish, CLC is ensured.

5. Last but maybe the most important, ROC generates more melodic songs (highest Melo). Better Struc, Rhy, LMC and CLC are also factors making songs more beautiful, improving Melo.

Overall, the objective and subjective evaluation results demonstrate that the new paradigm we propose outperforms conventional generation paradigm. The effectiveness of each component in ROC will be discussed in detail in Section 5.3.

We test the accuracy of structure recognition algorithm. The average IoU of our algorithm reaches 0.77 with variance 0.09. By contrast, the average IoU of self-similarity matrix is 0.47, with variance 0.08, which is much worse than our proposed algorithm. In fact, we find most of the errors in our algorithm come from pre-choruses that are classified as choruses, which is completely acceptable in terms of the sense of hearing. A case of structure recognition is showed in the next section.

5.2 Case Study

In this section, we present some cases to illustrate the effectiveness of ROC. More detailed demos can be found in the github link. First, we visualize the recognized structure of the full version of We Are The Champions in Figure 3.

To highlight that ROC is not limited by any specific language, we choose a Chinese case in Figure 4 to demonstrate the generation quality. Lyrics are from the beginning of a famous Chinese pop song All the Way North by Jay Chou. In this case, we compare ROC with the origin song and the better baseline, TeleMelody. TeleMelody generates flat melodies while the output from ROC
We Are The Champions by Queen

| Syllables | Lyrics                                      | Syllables | Lyrics                                      |
|-----------|---------------------------------------------|-----------|---------------------------------------------|
| 4         | I've paid my dues                           | 4         | I've taken my bows                          |
| 4         | Time after time                             | 5         | And my curtain calls                        |
| 5         | I've done my sentence                       | 15        | You brought me fame and for tune and ev’ry thing that goes with it |
| 6         | But com mit ted no crime                    | 4         | I thank you all                            |
| 4         | And bad mis takes                           | 8         | But it’s been no bed of roses               |
| 4         | I've made a few                             | 4         | No plea sure cruise                         |
| 10        | I've had my share of sand kicked in my face | 15        | I con sider it a challenge before the whole human race |
| 4         | But I've come through                       | 5         | And I ain’t gon na lose                     |
| 12        | And I need to go on and on and on and on    | 7         | We are the champions my friends             |
| 7         | We are the cham pions my friends            | 9         | And we’ll keep on fight ing till the end    |
| 5         | We are the cham pions                       | 5         | We are the cham pions                       |
| 5         | We are the cham pions                       | 5         | No time for lo sers                        |
| 9         | ’Cause we are the cham pions of the World   | 9         | ’Cause we are the champ ions of the World   |

Figure 3: Extracted lyric structure of We Are The Champions. Choruses identified by our algorithm are in orange squares and ground truths are in the red squares. Because two verses have different rhythms, only choruses share melody in this case. The IoU of this case is 0.85 (12/14). Our algorithm regards the pre-chorus as chorus which is acceptable from an appreciative standpoint.

5.3 Method Analyses

To better study the effect of each component in ROC and explore properties of ROC more thoroughly, we analyze the impact of the structure recognition algorithm, model scores and composition guidelines in retrieval and re-ranking, and the size of database. Because of the slight performance difference in different languages, we report the average scores of two languages in below.

5.3.1 Study on Structure Recognition. We disable the lyric structure recognition to study its effectiveness. The results are in Table 2. Note that because lyric structure recognition is the foundation of melody sharing scheme in ROC, a fair objective comparison here should be between the results from standard ROC but only considering shared parts once (-repeat.) and results from ROC without lyric structure recognition scheme (-recog.). Because CLC is guaranteed by polish operations in ROC, it maintains stable in this study and thus is omitted.

Objective experimental results demonstrate that without the lyric structure recognition, the diversity drops by a large amount. The reason is that if we do not distinguish chorus and verse, the model will continue the song without an emotion activation or an explicit change of style so that melodies will be flat and less emotional, resulting in lower diversity scores. Because the melody language model and composition guidelines ensure the basic quality and stability, the entropy scores maintain.

As for subjective judgement, the structure score becomes very low because without repetitive structure and rhythm patterns, songs are not impressive any more. The sense of hearing is influenced so some other metric scores drop too.

is more varied and cadenced, which sounds more melodic. The diversity in ROC is similar to that in the origin song. Note that these are the first two lyrics in the song, so melodies of TeleMelody are overly pitched, where some notes reach D5 which is difficult even for some professional singers. By contrast, pitches in ROC are appropriate.
When the melody language model scores are removed, the quality of different parts of a song varies because of randomness. The melodies are so diverse that dull and the melody progression is not harmonic as before whereas Rhythm subjective metrics that the melody is flat and monotonous, which can be confirmed by subjective metrics.

Table 3: Study on re-ranking schemes.

| Models          | Objective | Subjective |
|-----------------|-----------|------------|
|                 | Dist-1    | Dist-2     | Ent-1 | Ent-2 | Rhy | Melo |
| ROC             | 0.94      | 6.71       | 2.58  | 4.41  | 4.50 | 4.10 |
| ROC - recog.    | 0.84      | 7.80       | 2.58  | 4.41  | 2.20 | 3.90 |
| ROC - repeat.   | 1.55      | 11.94      | 2.58  | 4.40  | 4.50 | 4.10 |

Table 4: Study on database size.

| Database Size | Objective | Subjective |
|---------------|-----------|------------|
|               | Dist-1    | Dist-2     | Ent-1 | Ent-2 | Rhy | Melo |
| 20%           | 0.93      | 6.54       | 2.49  | 4.28  | 3.80 | 3.90 |
| 50%           | 0.94      | 6.67       | 2.57  | 4.34  | 3.80 | 4.00 |
| 80%           | 0.96      | 6.60       | 2.56  | 4.35  | 4.00 | 4.10 |
| 100%          | 0.94      | 6.71       | 2.58  | 4.41  | 4.10 | 4.10 |

This study reveals that aligning the structure of melodies to that of the lyrics is indispensable to high-quality lyric-to-melody generation.

5.3.2 Study on Model Scores and Composition Guidelines. We study the impact of model scores and composition guidelines in retrieval and re-ranking on the performance of ROC. We remove the melody language model and composition guidelines respectively. Evaluation results are shown in Table 3. Because Struc, CLC and LMC are unrelated to this study, their scores do not change and are omitted in the table.

With only composition guidelines, there are too many retrieved candidates, therefore there is a lot of randomness in the determination of the final result piece. Because without neural network computing, the running speed is 4 times faster than the standard ROC. As shown in objective results, the diversity increases a lot. The melodies are so diverse that Rhythm increases a little. But too much diversity also decreases Melody.

When composition guidelines are removed, there are also too many candidates remains for the melody language model to score, the running speed is 70 times slower than that of ROC with only composition guidelines. Lower diversity and entropy scores indicate that the melody is flat and monotonous, which can be confirmed by subjective metrics Rhythm and Melody.

Overall, when composition guidelines are removed, songs sound dull and the melody progression is not harmonic as before whereas when the melody language model scores are removed, the quality of different parts of a song varies because of randomness. This study reveals that the melody language model scores and composition guidelines complement each other in retrieval and re-ranking, which are both crucial to the quality and efficiency of ROC.

5.3.3 Study on the Size of Database. Performance of ROC depends on the size of database. For example, if there is no melody that satisfies both the length requirements and chord progressions, ROC has to compromise, e.g., using the tonic chord as an alternative. Therefore, we study the effect of the size of database. We prune the database to 20%, 50%, and 80% of the full size, respectively. Results are listed in Table 4. We have conclusions as below.

First, as we expect, the running time and the database size are positively correlated. The running time increases from 3.99 seconds per song to 10.17 seconds per song when the size increases from 20% to 100%.

Second, because we remove data from the database randomly, the average quality and distribution of music pieces do not change, so Dist and Ent basically maintain. Because Struc, LMC, CLC is not determined by the database size and there is indeed no change in scores on these metrics, they are omitted in the table. To our surprise, we find that as long as the average quality of melody pieces can be guaranteed, the generation quality remains relatively stable even though only 20% data remain. However, in practice, when we use 20%-size database, sometimes there are no candidates with matching features.

Besides, we study the method of generating melody pieces in the database. If we generate a long melody and separate it into pieces instead of conducting short melody piece generation procedure mentioned in Section 3.1.1, all metrics drop by a lot because of low-qualify melody pieces in the database.

6 CONCLUSION

In this paper, we propose ROC, a new paradigm for lyric-to-melody generation, which divides the end-to-end generation into two stages: creation and re-creation. In creation stage, ROC generates a large amount of short music pieces and store them in a database indexed by key features including chords, tonality, structural information (a melody piece belongs to a chorus or a verse). In re-creation stage, ROC recreates melody by retrieving pieces according to key features extracted from each lyric and concatenate them based on melody language model scores and composition guidelines. ROC does not need paired lyric-melody data for training and has a strong guarantee of feature alignment between lyrics and melodies. Both objective and subjective experimental results demonstrate the effectiveness of ROC. In the future, there is some research to be explored such as how to model one syllable aligning with multiple notes by neural networks, how to take accompany into consideration, or...
how can neural models help the lyric structure recognition. Moreover, we hope to apply the motivation of ROC to other NLP tasks like knowledge-grounded dialogue and story telling.

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