Chord Progression Similarity of Recent Chinese Pop Music Based on the Markov Model

Jiaying Li
jli3269@gatech.edu

***Abstract*—In this paper, we present a new method to measure the similarity between chord *progressions*: the Chord Progression Similarity Index (CPSI). The CPSI is a sum of 1st-order transitions between pitch classes in successive chords. The algorithm can be modified by adding weights to prominent metric positions, chord degrees, etc. We evaluate the CPSI in two experiments: In a perceptual experiment, 34xxx rated the perceived similarity of 40 diatonic chord progressions. We compared various CPSI calculations to participants' responses, finding a weak correlation.xxx Generally, participants' responses were best predicted by root progression only. In a second, computational experiment, we use the CPSI to evaluate chord progression variety in a novel 200-song database, which consists of the twenty most popular Chinese songs from each year 2012–2021. We show evidence that Chinese pop music has become more and more similar in recent years, consistent with many reports.**

***Index Terms*—Music similarity, Markov Model, Chinese pop music**

I. Introduction

With the development of digital music technologies, the strengthening of copyright enforcement, and the popularization of short video platforms, the Chinese popular music industry has undergone huge and obvious changes in the past decade. Music has penetrated people's lives in more ways, and it is easier to gain exposure and attention than ten years ago. However, at the same time, it seems to be widely acknowledged that popular music in China is becoming more and more similar: In 2021, 64.2% of legal plagiarism cases involved music, sparking widespread discussion on social media [1]. At a time when the media is wailing that "creation is dead" [2], more and more professional musicians have also expressed concern and a negative attitude towards the future of China's music market. In this current environment, quantifying musical similarity has become increasingly important to Chinese music makers and consumers. Unfortunately, objectively quantifying musical similarity is not a simple task: in the USA, musical copyright precedent focuses almost entirely on melodic and lyrical plagiarism, with other musical features (e.g., rhythm, harmony, timbre) being effectively uncopyrightable. However, the recent controversies in China have largely involved plagiarism of chord progressions, not melody. For music lovers without professional musical training, the use of similar chord progressions is less likely to be noticeable [3], leading to more urgent market demand for the chord progression similarity. This paper aims at studying and exploring the similarity of chord progressions, and provides a new method to measure chord progression similarity based on a hidden Markov Model.

The measurement of music similarity has been a widely researched field [4], and has great significance for music searching and classification, copyright maintenance, and music criticism [5], as well as artistic/creative implications. The most common method of chord progression similarity measuring is the chord alignment method [5], but there are quite a few limitations to this method: Although convex optimization enables the calculation of similarity between chord progressions consisting of different numbers of chords, the chord alignment method cannot deal with inverted chords or mixed chord types [6]. Also, the chord alignment method cannot take into account the similarity between the chord progression as cyclic loop and the non-cyclic version. Conversely, our algorithm based on the Markov Model has wider compatibility. The directed Markov chain can provide both cyclic loop calculation and non-cyclic calculation.

Researchers in Natural Language Processing (NLP) have shown great success with similarity indices bases on Markov-chain transition matrices [7]. We apply a similar idea to the calculation of our *Chord Progression Similarity Index* (CPSI). By splitting chords into notes and calculating the Euclidean distance between the transition matrices constructed by the transition probabilities between notes—appropriately adjusting the weight of chords based on hyper-metric position—we can get a convincing chord progression similarity index.

Based on the Markov Model, our questions was addressed: is Chinese pop songs becoming more and more similar? To address this question, we applied the Markov based model to the top 20 Chinese pop songs from 2012 to 2021, and used statistical tests to measure the changes of CPSI.

This paper mainly has four sections: Section 1 introduces the sampling method of the Chinese Pop music database, Section 2 describes the chord progression similarity measuring algorithm based on the Markov Model, Section 3 shows the analysis and conclusions on the foundation of Chinese Pop music database, and finally, Section 4 is related to a summary and improvement directions.

II. Chord Progression Similarity Measuring Algorithm Based on a Markov Model

Our *Chord Progression Similarity Index* (CPSI) is actually a family of indices, with specific indices derived from the transition matrices between the constituent notes of successive chords. Specific versions of the CPSI depend on 1) which chord constituents (root, third, fifth, seventh, ninths, etc.) are included in the transition matrices; 2) whether chords are weighted by phrase position; 3) whether transitions from the final chord to the first chord are included.

Before starting to explain the algorithm, we map the notes with numbers to facilitate mathematical model calculation using the method of pitch classes: Although from the perspective of music theory Db and C# have different definitions, they display the same pitches and frequencies from the perspective of digital signal processing [8]. Therefore, we use the same number to represent the sharps and the flats.

TABLE I
THE RELATIONSHIP BETWEEN NOTES AND NUMBERS

	0	1	2	3	4	5	6	7	8	9	10	11
	C	C#	D	D#	E	F	F#	G	G#	A	A#	B
or	C	Db	D	Eb	E	F	Gb	G	Ab	A	Bb	B

A. Root-based Measuring Model

Before moving on to more complex situations, we start with the construction of the simplest root-based chord progression transition matrix [9].

Every chord has a fixed root, which largely determines the feature of the corresponding chord. For a chord progression K with chords $\{C_i\}$, where i represents its location index in K, we simplify it as a directed Markov chain based on its roots $\{R_i\}$. There are twelve notes in total, so each chord progression forms a 12×12 transition matrix. Assuming that each chord has the same weight in the chord progression. If chords are repeated in a chord progression, the original probability of 1 will be divided by the number of occurrences. Denote the transition probability from root R_i to R_j as P_{ij}.

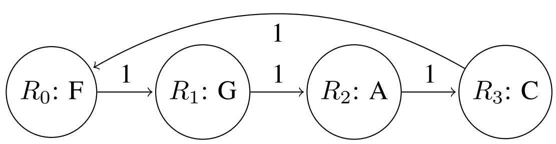

Fig. 1. Example of chord progression "F->G->Am->C"

Fig. 1 shows an example of a directed Markov chain of a chord progression. Generally, chord progressions are presented in loops in a song, so the last chord is connected to the first chord in our model.

B. Construction of Chord Progression Transition Matrix

We split every chord in a chord progression into notes. For notes N_{ij} in chord Ci, their transition probabilities to the notes N_{i+1j} in the next chord C_{i+1} are the same. Based on the previous root-based measuring model, the transition probability p_{ij} from note N_{ij} to N_{i+1k} can be defined as:

$$p_{ij} = \frac{P_{ij}}{\max j} \tag{1}$$

Fig. 2 shows the transition graph between notes in a chord progression. Consider that each chord in a chord progression has the same weight, then every arrow represents the same transition probability.

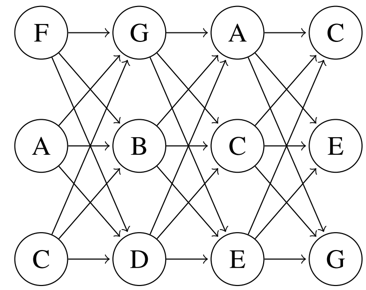

Fig. 2. Example of transition graph between notes in the chord progression "F->G->Am->C"

1) Extensions: In our basic CPSI, we consider only notes of each chords basic triad. However, our data set includes more complex chord types, such as C13 and Gsus4. The CPSI can easily incorporate these more complex chord types, without any additional complications: simply include them in the transition matrix calculations.

2) Non-cyclic Version: Although our basic CPSI algorithm considers a cyclic chord progression model, we can still calculate non-cyclic version. By removing the path pointed from the last chord to the first chord in a chord progression, we can reconstruct a transition matrix for non-cyclic version.

C. Chord progression similarity index

For chord progression K_1 and chord progression K_2, define their similarity index as the Euclidean distance of their note transition matrix Π_1 and Π_2:

$$\rho_{1,2} = \sqrt{\sum_{i,j} [\Pi_1(i,j) - \Pi_2(i,j)]^2} \tag{2}$$

D. Metric Weighting

Chord progressions in Chinese pop are set to a regular musical meter, with chord transitions occurring on or near strong metric beats. In addition, chord phrases (and their associated melodic phrases) generally align with regular hypermetric cycles of four or eight measures. Metric and hypermetric position are extremely important to musical organization and to music perception [10]. In particular, the first chord of each chord phrase (the downbeat of the hypermeter) is structurally important and perceptually salient, and is often accented by the musical accompaniment. Metric or phrase-position information can be incorporated into the CPSI by simply applying linear weights to note transitions, adding weight to strong metric transitions.

Play a chord progression with different chords as the starting position, record the difference between the practical human perception and the original chord progression, and calculate the chord weight of each position according to the data. Assume that the practical human perception weights w_i for chord C_i, modify the root-based chord progression transition matrix P:

$$P_{ijmodified} = \frac{w_i P_{ij}}{\sum_{i,j} w_i P_{ij}} \tag{3}$$

E. CPSI Examples

Here are some examples of chord progression pairs and their CPSI calculations. Notice that the smaller the CPSI values are, the more similar the two chord progressions are.

TABLE II
EXAMPLES OF CHORD PROGRESSION PAIRS AND CORRESPONDING CPSI

Chord Progression 1	Chord Progression 2	w1	w2	CPSI
C->Am->F->G	C->Am->F->G	10%	10%	0.0000
C->Am->F->G	Am->F->G->C	10%	10%	0.0552
C->Am->F->G	C->Am->F->C	10%	10%	1.6382
C->Am->F->G	C->G->Am->F	10%	10%	1.8555
C->Am->F->G	Cmaj7->Em->G->Dm	10%	10%	2.1538

III. EXPERIMENT: PERCEPTUAL EVALUATION

As we introduced in the previous part, the CPSI based on Markov Model allows parameter tuning to adjust the practical human perception. The adjustable parameter includes the position weight for each chord in a chord progression, and the note weight for component notes in a chord. Also, in our current analysis versions, we normalized the length of the chord progressions to simplify our calculations, so it will be interesting to explore the relationship between music perception and the length of the chord progression.

Therefore, there are three questions that we want to focus on:

- Perceptual difference between chord progressions with different length;
- Perceptual difference due to chord permutations;
- Perceptual difference between different type of chords.

We designed experiments to find out the results.

A. Method

Participants. Participants were 34 university students with normal hearing and variety music backgrounds in this experiment. Stimuli This experiment is divided into five parts:

- Calibration (exactly the same chord progressions and totally different chord progressions): Before starting the formal experiment, we asked participants to listen to 3 pairs of exactly same chord progressions and 3 pairs of totally different chord progression for calibration and rate on a scale. Each chord progression will repeat twice.
- Chord Progressions with different length: In find out the relationship between chord progression length and similarity, we asked participants to listen to 5 pairs of chord progressions with different length and rate on a scale. Each chord progression will repeat twice.
- Orders and Similarity (same chord progressions loops begin with different chords and same chords are shuffled to form different chord progressions): We provided a chord progression consists of 4 different chords and scrambled the chords into different orders to make new chord progressions. There are 24 ($4 \times 3 \times 2 \times 1 = 24$) different scrambling states in total, so we asked participants to listen to 12 pairs of chord progressions for comparison and rate on a scale. Each chord progression will repeat twice.
- Chord progressions with different last chord: In each pair of chord progressions, the chord located at the last will be replaced. This section includes six pair of chord progressions.
- Different chord types (triads, seventh chord, and ninth chord): In a pair of chord progressions, the first chord progression only contains triads, while the second chord progression contains more complex chords, such as seventh and ninth chords. We asked participants to listen to 10 pairs of chord progressions and rate on a scale. Each chord progression will repeat twice.

After collecting their data, we are able to do data analysis and parameter tuning.

There are a totally 40 pairs of chord progressions created using a MIDI sequencer (Logic Pro) and converted to . WAV format using ffmpeg commands using grand piano timbre. Each will last for about 30 seconds, and they are shuffled in the experimental interface.

1) Apparatus: Participants were tested on their own computers using our designed experimental interface. The experiment is controlled by jsPsych.

2) Procedure: The experiment began after participants signed a consent form. They also need to provide their genders, ages, and music backgrounds. During the experiment, they were able to use sliders to rate the similarity between two chord progression pairs. There are captions shown as “Totally similar”, “Very Similar”, “Somewhat Similar”, ”Somewhat Dissimilar”, ”Very Dissimilar”, and ”Extremely Dissimilar” on the slider, which allows the scores of the participants in the experiment are consistent.

3) Data Analysis: Pre-processing

Since similarity scores are subjective variables among people, the first thing we need to do is data standardization. By applying means and standard deviation to the response data as the formula shown below:

$$z = \frac{x - \mu}{\sigma}$$

As shown in Fig 3, different colors represent different part in

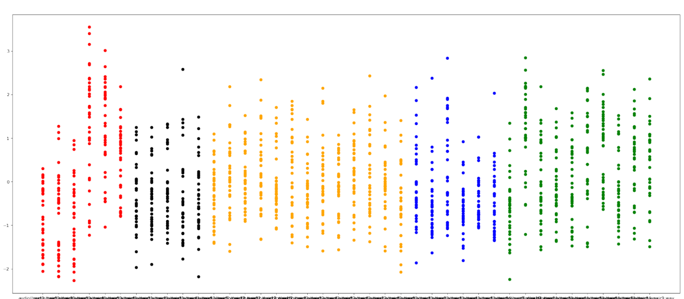

Fig. 3. Experiment Response Standarlization Overview

the experiment.

T-Test

We applied T-Test to the following cases with the calibration cases to find if there is a significant difference between them:

- CPSI between triads, seventh chords, and ninth chords;
- CPSI between the same loops and different loops;
- CPSI between chord progressions with different length;
- CPSI between different chord positions

Validation between different versions of CPSI

According to the previous part, we derived 12 different versions of CPSI calculating methods. By comparing to the response data from the experiment, we can find the most effective method by using Mean Squared Error (MSE). Also, we can set up models and find the best weight of the leading chord.

DBSCAN Model

Density-based spatial clustering of applications with noise (DBSCAN) model is often used to determine noises and density of the datapoints. We use it here to remove the outliers and find the most density scores people prefer to rate. Also, DBSCAN model allows us to check how people agree with scores.

We used responses as x-axis and time elapsed for each question as y-axis. By observing whether the clusters have large sizes or small sizes, we are able to find out how dense or sparse people's responses are. The disadvantage for DBSCAN model is that it's very sensitive with epsilon value. Therefore, different epsilon value will lead to very different results.

B. Results

1) T-Test: As shown in Table III, we can find that there are significant differences between groups besides comparing to chord progressions between the same loops and different loops.

TABLE III
T-TEST RESULTS

Comparing Pairs	p-value
Ninth and Triads	5.23e-21
Seventh and Triads	2.7e-09
Ninth and Seventh	4.37e-07
Between Different Loops	0.1276
Between Same Loops	0.1238
Different Chord Progression Length	1.8167-06
Changing the Last chord	1.4236e-08

2) The Best Fit Version: By using mean squared error (MSE) between people's responses and the CPSI calculated by our models, we can compare and find the best fit version.

TABLE IV
MSE CORRESPONDS TO DIFFERENT WEIGHTS AND VERSIONS

Version	MSE
Version1.1	1863.3888407894074
Version1.2	1722.6772342802751
Version1.3	1451.215659945812
Version2.1	1670.0114265159
Version2.2	1745.977080184865
Version2.3	1451.215659945812

3) Find the Best Weight: Now we are able to find the best weight adding to the leading chord. An iteration is shown as follow:

TABLE V
MSE CORRESPONDS TO DIFFERENT WEIGHTS AND VERSIONS

weight	Version 2.1	Version 2.2	Version 2.3
0.0	1863.388841	1722.677234	1451.21566
0.05	1863.388841	1722.677234	1451.21566
0.10	1829.670193	1722.677234	1451.21566
0.15	1713.587635	1745.977080	1451.21566
0.20	1670.011427	1745.977080	1451.21566

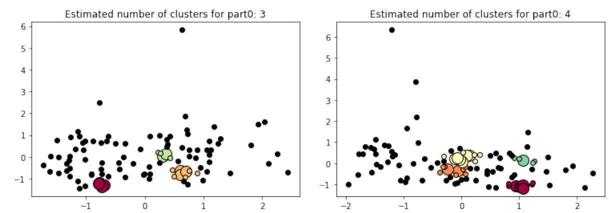

Fig. 4. Part 0 DBSCAN

4) DBSCAN: Fig 4 shows that the clusters are of small size, which means that people's responses are sparse.

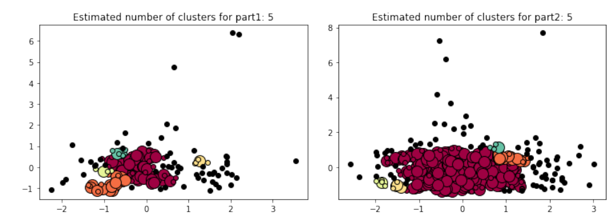

Fig. 5. Part 1 and Part 2 DBSCAN

Fig 5 shows the plot of part 1 and part 2 of the experiment, which are experiments about the same loops and different loops. From the figure, we can find that clusters are of large size, which means that people's responses are concentrated.

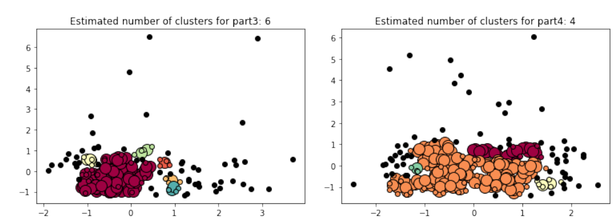

Fig. 6. Part 3 and Part 4 DBSCAN

Fig 6 shows the results for part 3 and part 4 in the experiment. We can find that the data points are concentrated in both sections.

C. Discussions

In the analysis of experimental data, we first used T-test. Through the t-test test, we were able to find that there are statistical significant differences between groups:

- Ninth chords, Seventh chords and triads
- Adding weights to different chord positions in a chord progression
- Chord progressions of different length.

Next, we checked the versions we proposed when building the model, and found that the root version was the best fit so far. From the experiment results, when people listen to the similarity of chord progressions, they are more inclined to judge by the upward or downward trend of the root notes.

Also, we solved for the convex optimization of the weights applied to the first chord in the chord progression via the gradient descent lookup method. In this process, we found that all three versions had cases where weights were applied to a certain percentage without affecting the MSE.

Finally, through the DBSCAN model, we found that when the chord progressions are exactly the same or completely different, it is not easy for people to reach a consensus conclusion. This is most likely because the order was disrupted during the experiment, and people tended to be more conservative in their judgment after hearing too many similar chords. Even so, we can still observe that people's judgments of numerical measures of chord similarity agree well with our model.

D. *Conclusions*

According the results in the previous section, we can get the conclusions now:

- The best fit model is the root-based model;
- The best weight for the leading chord is 20%.

IV. Musicological Evalulation: Chinese Pop Music

A. *Construction of the Chinese Pop music database*

To evaluate our algorithm and test our hypothesis, we constructed a new data set of chord progressions from 200 Chinese pop songs. Since the popular controversy, and our hypothesis, focuses on the most popular Chinese music of the last decade, we decided to target the twenty most popular songs in each year from 2012 to 2021.

1) Sampling Method: China has no single dominant music-popularity ranking enterprise comparable to the US-based Billboard charts. The last decade has seen the development and proliferation of numerous Chinese media platforms, and although the sources for obtaining music vary a lot, Mobile music software is still the most mainstream music platform. According to the market survey, users of music APPs under Tencent Music and Entertainment (TME) account for 94% of music streaming in China [11]. TME's annual financial report shows that QQ Music, Kugou Music, and Kuwo Music include 72.8% of users, and the user groups among these music APPs overlap considerably [12]. Based on the tracking data of these music APPs, the top 100 music list calculated by the clickthrough rate and the searching rate is provided by TME every year. To identify the most popular songs in China for each year, our approach is to average the rankings provided by these three most significant music streaming services. Suppose that for year $i \in \{2012, 2013, ..., 2021\}$, song j on music APP k and $k \in \{1, 2, 3\}$, where $k = 1$ represents QQ Music, $k = 2$ represents Kugou Music, $k = 3$ represents Kuwo Music. We recalculate its average ranking as:

$$r_{ij} = \frac{1}{3}\sum_{k=1}^{3} r_{ij}(k) \tag{4}$$

Among the three music APPs, since Kugou Music was renamed in 2017, its list from 2012 to 2016 is not included in the ranking of songs.

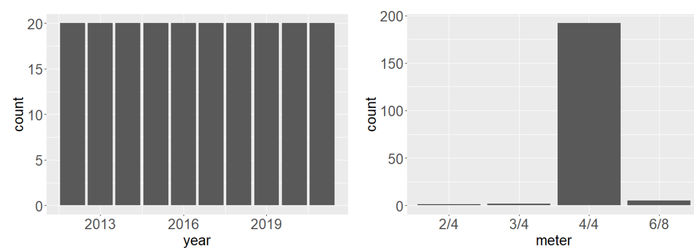

Fig. 7. Songs in China Pop Music Database

In the recalculated list, the top 20 songs of each year were targeted for inclusion in our Chinese Pop Music database, as shown in Fig. 7.

2) Chord Progression Notations: For each of the 200 sampled songs, we accessed existing chord-transcriptions from the Echangwang website [13]. To avoid complexity, we only encoded chord progressions from the verses and choruses of each track, with some bridge sections labeled as choruses To main a simple and consistent structure in each encoding, we divide each annotation into verse and chorus chord progressions—other formal sections were excluded, except bridge sections which were sometimes grouped into the chorus part of transcriptions.

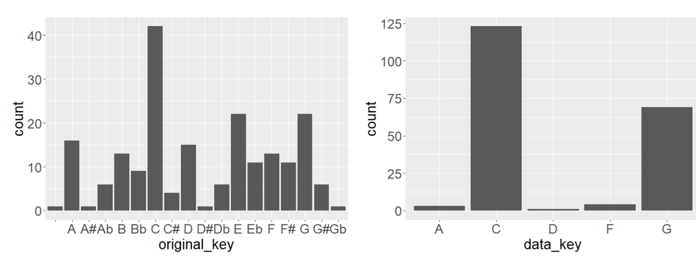

Fig. 8. Original key and data key in Chinese Pop Music Database

Additional data cleaning steps included key normalization and missing-data imputation. The chord-transcriptions marked the "original key", which is the key the song, and "data key", which is the key the chord-transcriptions used as notation. We transferred them into major keys during data sampling.

Every chord type mentioned in the chord-transcriptions is recorded in our database, including 11th chords, 13th chords and so on. A list of chord types and notations is shown as Fig. 8. The figure shows a count-plot of basic information about the original key and the data key in the Chinese Pop Music Database.

All the sampled songs divide their verse and chorus sections into one, two, three, or four phrases of equal length—delineated clearly in all cases by the accompanying lyrical/melodic phrase. The data record for each consists of up to four verse phrases, and up to four chorus phrases.

Within each phrase, the chords are separated by "->", for example, "F->G->Am->C."

TABLE VI
CHORD NOTATIONS IN CHINESE POP MUSIC DATABASE

Chord Type	Chord Notation	Example
Major	-	C
Minor	m	Cm
Dim	dim	Cdim
Aug	aug	Caug
Dominant 7	7	C7
Major 7	maj7	Cmaj7
Minor 7	m7	Cm7
Add 9	add9	Cadd9
Major 9	maj9	Cmaj9
Minor 9	m9	Cm9
Dominant 9	9	C9
Major 6	maj6	Cmaj6
Sus 4	sus4	Csus4
Sus 2	sus2	Csus2
Dominant 11	11	C11
Dominant 13	13	C13
Minor 7 flat 5	m7b5	Cm7b5
Dim 7	dim7	Cdim7
Aug 7	aug7	Caug7
7 sharp 9	7b9	C7b9
7 sharp 5	7b5	C7b5
...	...	...

Besides the chord progression information, the database also contains metadata for each song, including the song name, ranking year, artist, meter, original key, and the data key of a song. To keep the consistency of the data information, we use major keys uniformly.

B. Similarity Analysis of the Chinese Pop Music Database

To test our hypothesis, we compare the chord progressions between the 200 songs in our data set. We next use the CPSI to compute more fine-grained measures of similarity in the dataset. Since approach to chord-similarity measurement is unknown, we compare the following twelve versions:

- Version 1.x.x: No weight for chords;
- Version 2.x.x: Add weight to leading chord;
- Version x.1.x: Non-simplified chords;
- Version x.2.x: Simplified chords into triads;
- Version x.3.x: Root-based model;
- Version x.x.1: Progression group as basic analysis unit;
- Version x.x.2: Combining all chord progressions together as basic analysis unit.

In each version, we calculated its verse similarity, chorus similarity, and total similarity which is measured by adding up verse similarity and chorus similarity.

1) Chord Progression Exact Reuse: We first simply ask how often sampled songs in a given year reuse the exact same chord progression.

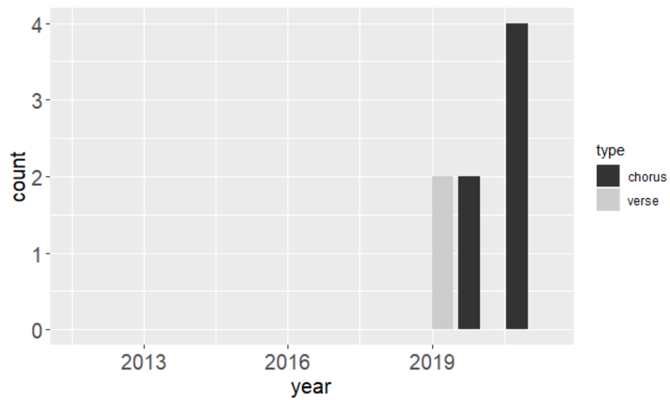

Fig. 9. Exactly same chord progression numbers in non-simplified version

If we only consider "non-simplified" chords, including chord extensions and alterations (7ths, 11ths, etc.) we find that the last few years do indeed show the first examples of top-20 songs reusing the exact same chord progressions: including four of the twenty songs in 2021 (Fig. 9).

If we generalize to "simplified" versions of chords (triad notes only) we again see a marked increase in exact duplication in the last five years:

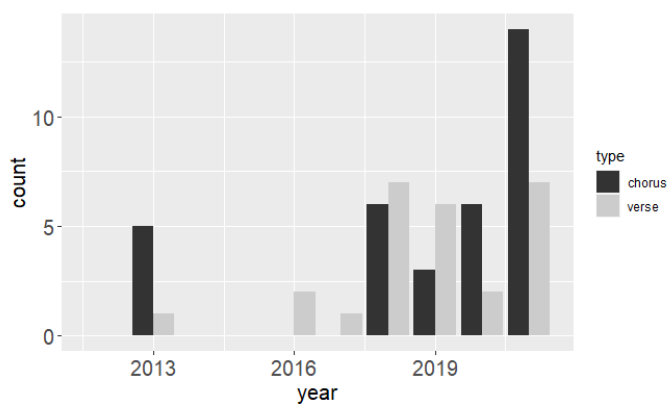

Fig. 10. Exactly same chord progression numbers in simplified version

In more general cases, we only consider the root of the chords, we can find a similar tendency as the 'simplified" versions.

2) CPSI Analyses: As we mentioned in the previous parts, we used 12 different versions for CPSI calculation. However, not all versions are effective. In order to select the appropriate versions, we applied one-way ANOVA test to each version.

The null hypothesis (H_0) of the ANOVA is no difference in means for CPSI values grouped by years. A list of p value for Verse CPSI, Chorus CPSI and Total CPSI (the sum of Verse CPSI and Chorus CPSI) is shown in Table. VII. The significance codes '**' represents $p < 0.001$, '*' represents $p < 0.01$, and '.' represents $p < 0.05$.

According to the table, we reject the null hypothesis, which means that there are significance difference between CPSI

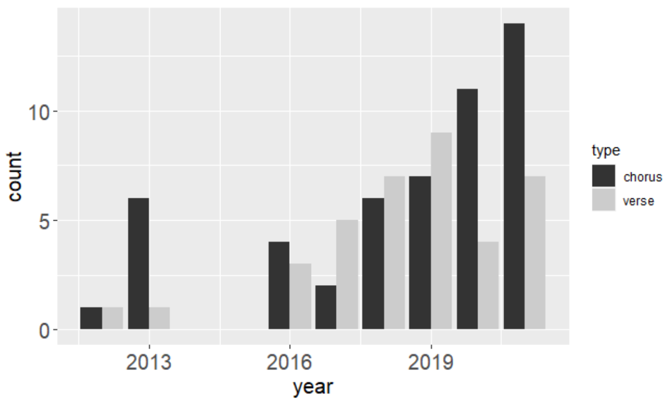

Fig. 11. Exactly same chord progression numbers in root version

TABLE VII
ANOVA TEST FOR EACH VERSION

Version	p for Verse CPSI	p for Chorus CPSI	p for Total CPSI
1.1.1	0.00282 **	0.0141 *	0.00205 **
1.1.2	0.0557 .	0.0128 *	0.014 *
1.2.1	0.00298 **	0.0575 .	0.00702 **
1.2.2	0.0145 *	0.204	0.0384 *
1.3.1	0.00186 **	0.873	0.0662 .
1.3.2	0.467	0.519	0.441
2.1.1	0.00327 **	0.0122 *	0.00191 **
2.1.2	0.0562 .	0.0113 *	0.0131 *
2.2.1	0.00271 **	0.24	0.0338 *
2.2.2	0.0147 *	0.19	0.0365 *
2.3.1	0.00219 **	0.922	0.0775 .
2.3.2	0.565	0.47	0.463

values from years to years. We take 95% as the confidence interval in this statistical test. Therefore, we only consider version 1.1.1 (No weight for chords, non-simplified chords, progression group as basic), version 1.1.2 (No weight for chords, non-simplified chords, combining all chord progressions together as basic analysis unit), 2.1.1 (Add weight for leading chords, non-simplified chords, progression group as basic) and 2.1.2 (Add weight for leading chords, non-simplified chords, combining all chord progressions together as basic analysis unit) as qualified versions.

3) CPSI Data Analysis by Mean: From the selected four versions, we calculate the CPSI mean value of the 20 songs in groups of versions and years. A box-plot for the top 20 songs in the past ten years is shown in Fig. 12.

We applied Mann-Kendall test for monotonic trend analysis, and find that the songs in 2017-2021 has lower CPSI value than songs in 2012-2016, and CPSI values are decreases in the recent three years with 95% confidence.

4) CPSI Data Analysis by Mean: From the selected four versions, we calculate the CPSI median value of the 20 songs in groups of versions and years. A box-plot for the top 20 songs in the past ten years is shown in Fig. 13.

We applied Mann-Kendall test for monotonic trend analysis, and find that the songs in 2017-2021 has lower CPSI value than songs in 2012-2016, and CPSI values are decreases in

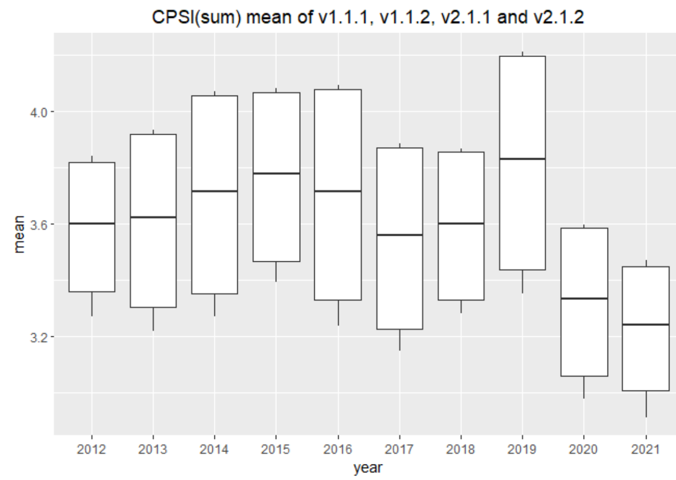

Fig. 12. CPSI mean

the recent three years with 95% confidence.

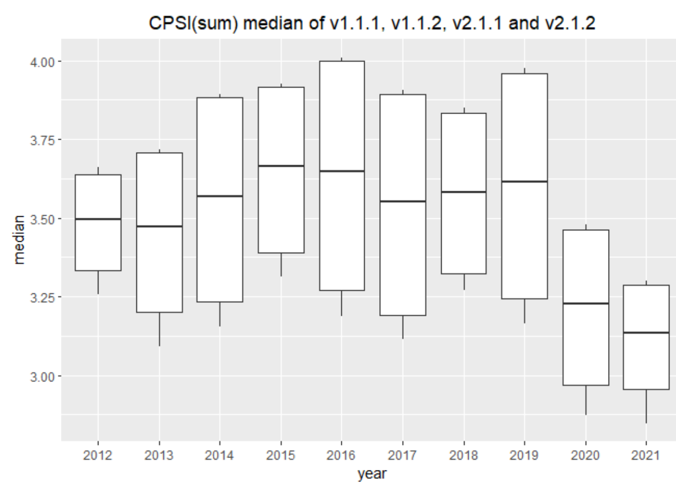

Fig. 13. CPSI median

The summarized results are listed as follows:

- The tendency of the top 20 songs is not as clear as the top 10 songs because there are repeated songs in the top 20 rankings, especially in the neighbor years.
- After chord simplification (to triads or to roots), the similarity index becomes obviously smaller, and trend of similarity is harder to identify;
- There is not convincing statistical evidence showing that Chinese pop music use more and more similar chord progressions from 2012 to 2016, but the decreasing CPSI is significant in the past five years.
- Comparing to the verse, chorus part more likely appears the same chord progressions.

V. CONCLUSIONS

This paper presents a new chord progression similarity measuring method, analyzes the similarity of the Chinese pop music database with the proposed method, and obtains the conclusion that Chinese pop music is using more and more similar chord progressions. The chord progression similarity index based on the Markov model shows encouraging results in its accuracy and adaptability, and also brings more possibilities for future related work.

There is still a lot to explore about chord progression similarity. Due to the limited time and space, we did not finish collect the survey data for parameter tuning, and we didn't discuss the relationship between chord progression similarity and chord rhythms in detail, nor did we complete the verification of more musical styles and other cross-cultural music. More relative exploration will be considered in the future.

REFERENCES

[1] China News, "Blockchain technology empowers copyright protection: breaking through the "hardest link" and improving the efficiency of rights protection," https://www.chinanews.com.cn/cj/2021/09-30/9577904.shtml, 2021.

[2] P. Xu, "Why is the "divine comedy" on top: Algorithmic logic, chord routines and template lyrics," http://www.inewsweek.cn/survey/2022-02-14/15052.shtml, 2022.

[3] C. Wongsaroj, N. Prompoon, and A. Surarerks, "A music similarity measure based on chord progression and song segmentation analysis," in *2014 Fourth International Conference on Digital Information and Communication Technology and its Applications (DICTAP)*. IEEE, 2014, pp. 158–163.

[4] J.-J. Aucouturier, F. Pachet *et al.*, "Music similarity measures: What's the use?" in *Ismir*, 2002, pp. 13–17.

[5] E. Pampalk, "Computational models of music similarity and their application in music information retrieval," Ph.D. dissertation, 2006.

[6] M. Slaney, K. Weinberger, and W. White, "Learning a metric for music similarity," in *International Symposium on Music Information Retrieval (ISMIR)*, vol. 148, 2008.

[7] B. H. Juang and L. R. Rabiner, "Hidden markov models for speech recognition," *Technometrics*, vol. 33, no. 3, pp. 251–272, 1991.

[8] B. Logan and A. Salomon, "A music similarity function based on signal analysis." in *ICME*, 2001, pp. 22–25.

[9] A. Van Der Merwe and W. Schulze, "Music generation with markov models," *IEEE MultiMedia*, vol. 18, no. 3, pp. 78–85, 2010.

[10] R. Cohn, "Metric and hypermetric dissonance in the menuetto of mozart's symphony in g minor, k. 550," *Intégral*, vol. 6, pp. 1–33, 1992.

[11] P. Redelinghuys, "Tencent music entertainment rules the music coop," *finweek*, vol. 2021, no. 12, pp. 24–25, 2021.

[12] Sina Finance, "Tencent music 2021q4 and full-year financial report: total annual revenue increased to 31.24 billion yuan, a year-on-year increase of 7.2%," https://finance.sina.com.cn/stock/usstock/c/2022-03-22/doc-imcwiwss7360236.shtml, 2022.

[13] "Echangwang," [EB/OL], http://www.echangwang.com/.