Complex networks of chord transitions in Alexander Scriabin's piano pieces

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Abstract

We consider chord transition networks built from piano pieces by Aleksandr Skriabin. We design a random walk algorithm for composing music based in the networks, and present two pieces generated in this fashion.

1. Introduction

Recently, complex networks methods have been employed to analyze pitch and timbre transitions, both in individual works [1] and large collections of pieces [2]

We employed this method for analyzing selected piano pieces by A. Skriabin (see Table 1)

From the MIDI files of the pieces, transposed to C (major or minor), we built networks of pitch class (chroma) chords, see Figure 1 for a schematic description.

a)

b)

Figure 1. Network creation. a) Original score (Mazurka opus 25 n 3, bar 11), b) network nodes and links after transposition to C minor.

Note that we are only considering chord types and not harmonic functions, so we don't take into account enharmonic spelling.

2. Network structure

We fitted the frequencies of chords, sorted in decreasing order (that is, ordered by rank r, where r = 1 for the most frequent chord and so forth), with a Zipf law of the form z $=Cr^{-\alpha}$. For our fitting procedure, we used the approach of Clauset et al [3]. We found nice fits with truncated power laws (see Figure 2). The scaling exponents range from 2.07 to 3.43, comparable to those found in [4] for the distribution of notes in classical music. Usual network measures and metrics are given in Table 1. They stand in strong contrast to other harmonic networks such as those of [2], being far for the small-worldness that characterizes mainstream popular music. Clustering and average shortest path length are similar to those of random networks with the same number of nodes and links.

3. Artificial music generation

A simple random walk algorithm in the networks generates a sequence of chords with transition probabilities proportional to the weights (defined as the number of transitions between two given chords in a piece). We generated two piano pieces using this method.

Opus	P-law freq	P-law degree	Sp	r	C	L
Sonate 7	2.78	3.5	0.005	-0.03	0.06 (0.007)	33.17 (13.8)
Op. 25 n 3	3.43	3.16	0.005	0.1	0.03 (0.02)	9.90 (8.45)
Op. 42 n 5	2.62	2.8	0.004	0.1	0.1 (0.03)	5.70 (5.48)
Op. 69 n 2	3.46	3.5	0.01	-0.04	0.03 (0.03)	8.06 (6.46)
Op. 72	2.16	3.5	0.001	-0.008	0.0210 (0.005)	54.45 (14.81)
Op. 45 n 1	2.17	2.68	0.006	0.0008	0 (0.002)	33.06 (20.22)
Op 74 n 3	2.15	3.5	0.01	-0.21	0.02 (0.01)	19.49 (13.16)
Op 25 n 9	2.07	2.51	0.006	0.04	0.04 (0.04)	5.89 (6.16)

Table 1. Network measures. P-law frequency and P-law degree are the fitted exponents, Sp denotes sparseness, r the assortativity, C the average local clustering coefficient, L the average shortest path length. Coefficients for random networks are in brackets.

3.1 First piece[1]

The following composition was created from the above mentioned MIDI scores of the Russian composer Aleksandr Skriabin (1872 – 1915). Rhythm was generated by a random walk in a Barabasi-Albert network of ten rhythmic cells distributed independently in both hands.

3.2 Another piece[2]

This composition is based in Op. 69 n 2. Chords are diluted in resonance and fuzzily presented with extremely soft dynamics and complex rhythms.

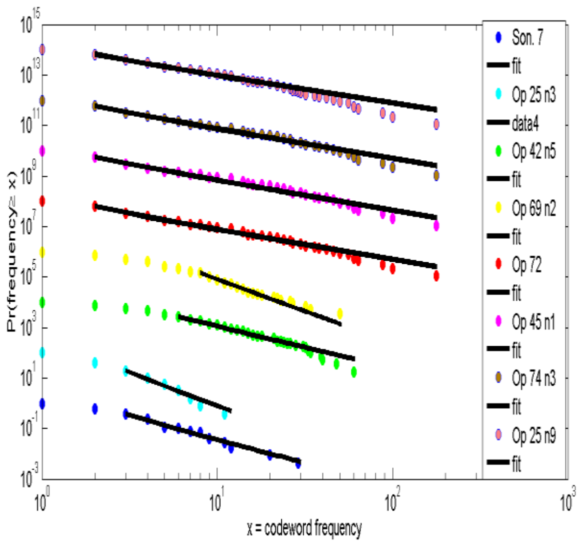

Figure 2: Complementary cumulative distribution of codeword frequencies and their fits by power laws. Curves are shifted by a factor of 100 in the vertical axis for ease of visualization.

4. Conclusion

Complex networks give a global picture of first order harmonic transitions, providing information relative to **chord frequency power laws** (the greater the α, the more limited the vocabulary, with few frequent chords and many rare ones), **sparseness** (going from 0 to 1; small values mean fewer possible chord transitions, potentially favoring the learning of harmonic expectancies), **chord degrees** (variety of chords following a given one), **clustering** (more clustering means more different ways of reaching neighboring chords from a given one), **shortest average path length** (when this is small, arbitrary pairs of chords are connected by few transitions, in average). These network coefficients appear useful for stylistic comparison between composers and genres [5], and can be applied also to other musical parameters such as timbre. We also began to explore the use of network structures for music generation.

References

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