The evolution of tango harmony, 1910-1960

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Abstract. In this article, we look at the diachronic changes in tango harmony with the methods of network science. We are able to detect some significant tendencies of harmonic discourse in the first half of the 20th century, among them an enrichment of harmonic transitions and power law frequency distribution of triadic chords with exponents compatible with a quite small rate of accretion of the vocabulary.
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1 Introduction

Tango is undoubtedly the most transcendent collective cultural creation of the Río de la Plata region. Several texts give account of its history, spanning from the last decades of the 19th century to the present day [1, 2]. In spite of this, to the extent of our knowledge, no computational musicological study has focused specifically on tango and its diachronic evolution.

The availability of big corpora of musical data has fostered quantitative evolutionary studies on American popular music [3], jazz harmony [4], electronic art music [5], musical influence of songs [6], to mention some examples. Recently, complex networks methods have been employed to analyse pitch and timbre transitions both in individual works [7], and large collections [8, 9].

We consider chord transition networks built from sampling whole decades of a corpus of tango recordings. To this end, we assembled a database of 510 recordings of tangos, composed between 1910 and 1960, by downloading all the tangos from the Web archive Todo Tango [10], and discarding those that contained extramusical elements such as speech or clapping. Some of the recordings were denoised using Adobe Audition. In case several recordings of the same tango were available, we preferred the one with the earliest recording date. The median number of years between composition and recording is 0.

We built different dictionaries of pitch class chroma chords, which became the networks' nodes, as follows: we extracted the chromagram with Mirtoolbox for Matlab [11], using a frame size of 0.2 seconds without overlapping, keeping only the chroma with energy level above the average over all files, and circularly shifted them according to an estimation of the tonality of each tango to transpose them to the tonality of C, in order to have a common tonal framework. Borrowing the terminology of [8], we call the resulting chroma vectors *codewords*.

The links of our pitch networks represent harmonic transitions between these codewords. Specifically, for the purpose of studying the evolution of harmonic discourse, we formed 5 collections of codewords, one for each decade in the year span 1910-1960. Two codewords are connected by a directed edge if they appear in consecutive analysis frames. In this way we are left with 5 networks corresponding to the periods 1910-1919 (16 tangos in the collection), 1920-1929 (176 tangos), 1930-1939 (135 tangos), 1940-1949 (139 tangos) and 1950-1959 (64 tangos).

Proceeding in this way, many of the generated codewords do not correspond to the standard harmonic vocabulary of Western tonal music: beyond usual triadic chords, all kinds of chromatic harmonies, including the 12-note chromatic cluster, are obtained. For this reason, we considered two kinds of networks:

a Unfiltered networks, containing all codewords.
b Triadic networks, that is, filtered networks generated by only the triadic codewords of at most 4 chroma classes, including single chromas and dyads. We call a codeword *triadic* if it can be obtained, modulo 12, from one (or more) of its pitches by stacking consecutive minor or major thirds over it (or them). In these reduced networks, two triadic codewords are connected if the second chord is the next triad appearing after the first, ignoring non-triadic codewords in between. In this way we aim to representing a core harmonic skeleton, ignoring noisy frames and non-triadic chords arising from passing notes.

2 Results

Based on the results of Serrà et al. [8] and the models of vocabulary frequency of [15], we essayed fitting the frequencies of codewords, sorted in decreasing order (that is, ordered by rank r, where $r = 1$ for the most frequent codeword 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 [13, 14]. In the case of unfiltered networks, we found, for all decades, nice fits with truncated power laws (see Figure 1a). The scaling exponents obtained vary very little over the years, ranging from $\alpha = 1.81$ to $\alpha = 1.94$. They are larger than those found in [8], pointing to a comparatively more compact and less innovative vocabulary [15], a fact which is to be expected since the corpus of Serrà et al. is much more varied and massive, consisting on a million themes of popular music of many different genres. These exponents are also somewhat smaller than those found in [15] for the distribution of notes in classical music.

For triadic networks, however, we did not find good fits with pure truncated power laws. One reason for this could lie in the limited vocabulary considered here. A more appropriate model in this case is a shifted power law $z = (a + br)^{-\alpha}$, with coefficients adjusted to the vocabulary size. This law is derived partly from the hypothesis that, as the musical corpus grows in time, the frequency of harmonic innovations goes as a power $1/\alpha$ of the pre-existing language size [15].

We found nice fits of this model with triadic codewords frequencies, with exponents now varying between 2.48 and 6.05. (Figure 1b). A tentative explanation of the unusually large exponents, in the context of the aforementioned

Zipfian shifted power law, is that there is a very slow innovation rate going on in the basic triadic vocabulary as we consider the whole collection of tangos from a given decade (hence very small innovation exponent $1/\alpha$), and that the changes occur, instead, mostly at the level of nontriadic chords. In order to see if the codeword ranking remains stable across the years, we compute the Spearman rank correlation coefficients of triadic codewords for all pairs of decades. They are all high, with a minimum of 0.81. So frequent codewords continue to be so along the history of tango. Tracking the relative frequencies of each triadic chord type between 1910 and 1960, we observe some steady changes: augmented triads, half diminished sevenths have a twofold increase, minor sevenths also grow, although in lesser proportion; there is a small transitory drop in minor triads in 1920-1930 while major triads show a long term falling tendency (Figure 2).

Beyond codeword frequencies, harmonic networks give us a panorama of how musical discourse transits between the elements of the vocabulary of codewords, creating stylistic patterns that can be learnt by repeated listening experiences and subsequently lead to the formation of expectancies and surprise [16, 17]. Usual network measures and metrics can be easily interpreted in our context in terms of their musical meaning. In the following, we consider several such typical network coefficients

Density is defined as the fraction of edges present, compared with all possible $n(n-1)/2$ edges (where n is the number of nodes of the network). All our harmonic networks are sparse in this sense. For triadic networks density is at most 0.21, while unfiltered networks are much sparser, with densities below 0.006. Phrased in terms of predictability, this sparseness makes accessible the statistical learning of transition rules, involving around 2000 different transitions between the 140 possible triads.

Degrees. Node out-degree k is the number of neighbors following a codeword. For unfiltered networks, degree distribution is nicely fit with a truncated power law $P(k) = k^{-\gamma}$ for $k > k_{min}$ for the period 1920-1929, with exponent 2.42, while in the other periods a better fit is a truncated power law with exponential cutoff, with exponents in the interval [1.93, 2.12]. These values are similar to those obtained by Serrà et al. [8]. For triadic networks, also good fits are obtained with truncated shifted power laws, with exponents ranging from 2.92 to 6.17. While in unfiltered networks the median degree varies little between 2 and 6 , for the triadic ones there is a big increase of degree connectivity from a median of 5 in 1910-1919 to values above 19 in the decades from 1920 to 1950, dropping somewhat in 1950-1959 to 13. This indicates a strong tendency towards greater freedom of harmonic discourse, and is also correlative with an increase of the size of the vocabulary, from 122 codewords in 1910-1919 to 139 codewords in 1920-1929, with a gradual and small decay to 133 nodes in the ‘50s. (Note that the total number of possible triadic codewords is 151).

From now on, we focus on networks of triads, where results are more easily interpreted in the framework of classical harmonic analysis. Codeword frequency and codeword degree are almost perfectly monotonically correlated, with Spearman rank coefficients above 0.99 for all decades. So the most frequent chords, among which there are the main triads defining tonality, are also the most connected. A notable symmetry emerges here, that also has been observed by Serrà et al. [8] Contrasting the out-degree of the major and minor triads over all chromatic scale degrees (in the musical sense of the word), with their similarly defined in-degree (the number of different chords that lead to a given one), their values are extremely similar, with their mean ratio over all triads between 0.99 and 1.02, and standard deviations between 0.01 and 0.1, for all decades.

Clustering measures the transitivity of the network. The local clustering coefficient $c_i = \frac{2T_i}{k_i(k_i-1)}$ gives the number of closed triangles among the nodes connected to node i. Harmonically, if we interpret the network as giving the stylistically permissible chord transitions, a high c_i implies that a transition between codeword i and another codeword that could be done directly, also could often be realized with an intermediate linking chord, adding to variety of harmonic conduction. Here we measure local connectivity by C, the average of c_i. A global measure of connectivity is the *average shortest path* length l. This gives the average of the minimum number of intermediate chords that are necessary to go between two given codewords. For instance, the appearance of bold and abrupt harmonic progressions that link tonally distant chords side by side would tend to reduce the value of l. High levels of clustering and small values of l define a small-world network [18]. Finally, *assortativity by degree* Γ is a coefficient measuring the tendency of nodes with similar degree to connect to each other. It is positive if this effectively occurs and negative if nodes of high degree tend to connect with nodes of low degree and vice versa. To interpret these coefficients, they are to be compared with the same coefficients computed from a random network with the same degree distribution, which we construct with the rewiring method described in [19]. For our networks, there is a marked increase of C (the average of c_i) from a value of 0.35 in 1910-1919 to values in the range [0.47, 0.58] for the following decades. Corresponding random networks have clustering coefficients in [0.1, 0.18]. At the same time, l decreases from 2.57 to 1.86 between the first two decades, and then slightly increases to 2.11 in the 50s; these values are smaller than the ones obtained by randomizing links. So globally, the small-worldness increases along time, implying a trend towards relatively more rich and daring harmonic progressions, with more different choices and also shorter ways to go from a chord to another (Figure 3). Assortativity remains negative, in the range [-0.09, -0.21], with a slight increase to -0.17 in the '50s. Keeping in mind the direct correspondence between frequent and connected chords, this means an increasing tendency to avoid direct connections between the most common triads. However, while assortativity values are more negative than random in 1920-1950, they are less negative than for the randomized networks in 1910-1919 and 1950-1959.

3 Conclusions

Looking at tango from the network science perspective, we are able to single out some clear trends in tango evolution, and to compare them with the changes in other genres of music described in [8]. Tango appears to have a relatively limited harmonic vocabulary (even if we consider unfiltered networks), and data are compatible with an innovation model exhibiting a slow rate of appearance of novelties. But in the period considered here, inversely to the tendencies shown in [8], progressively richer and more complex chord transitions emerged within this universe, which increased its small world features.

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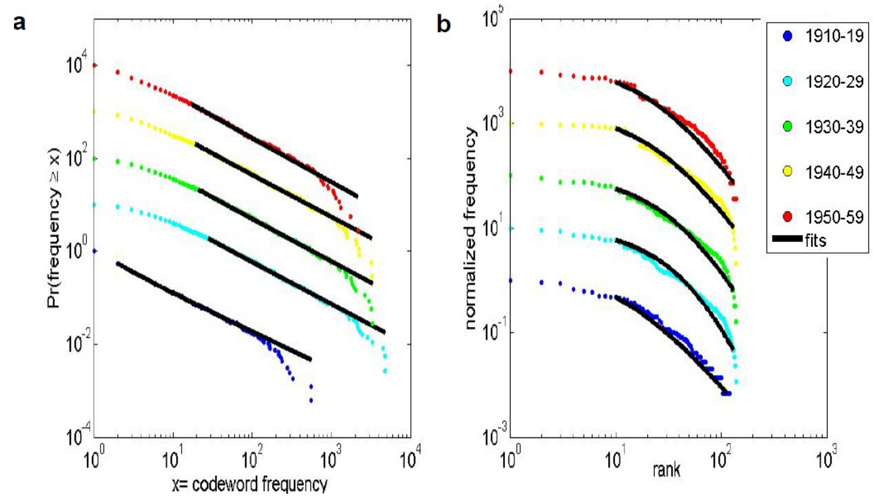

Fig. 1. a) Complementary cumulative distribution of codeword frequencies and their fits by power laws for unfiltered networks. Curves are chronologically shifted by a factor of 10 in the vertical axis for ease of visualization. b) Rank-frequency distribution of normalized codeword frequencies (respect to maximum frequency) and their fits by shifted power laws for triadic networks. Curves are chronologically shifted by 1 in the vertical axis.

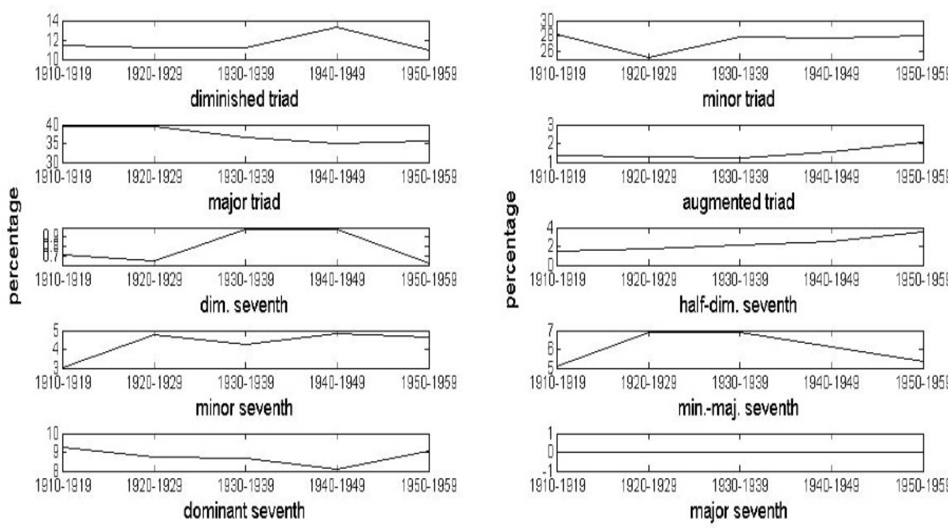

Fig. 2. Evolution of relative frequencies of triadic chord types.

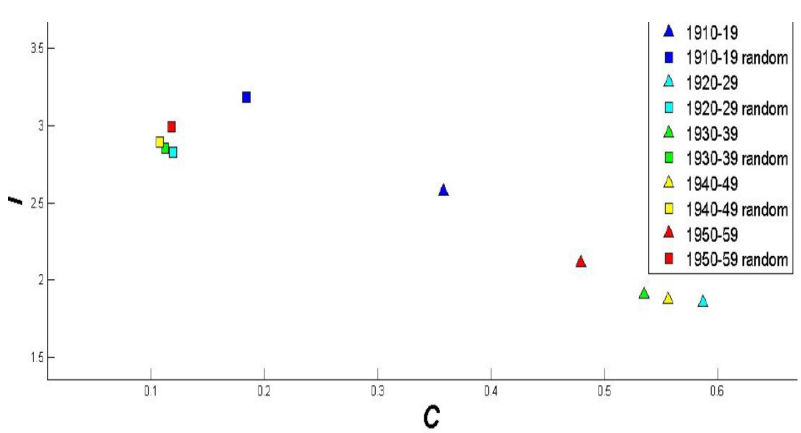

Fig. 3. Average shortest path length l versus clustering coefficients for actual (triangles) and randomized (squares) triadic networks.