

Towards Demystifying Transformations of Tchaikovsky's Children's Album with Support of Computational Models: Problem Conceptualization

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Abstract—Though the studies of rich metaphors hidden in the musical compositions lay mostly in scope of art and musicology, there is still large space for formal methods based on mathematical models and computer technology that can be helpful in discovering complementary insights to how the composition is structured, what are its relationships to the precursors' works, and how it affects the later works of the same or other authors. Our idea is to investigate how computational models can enhance musicology research on music style identification and comparative analysis using the case study of Tchaikovsky's Children's Album.

Keywords—*Musicology; music information retrieval; human-centric computing; similarity; music modeling.*

I. INTRODUCTION

In my recent talk on Jan 6th, 2021, in the University of Aizu “Tchaikovsky. Children's (?) Album: Time, Metaphors, Rediscoveries” [1], I discussed the phenomenon of Piotr Tchaikovsky's “Children's Album” for piano solo (Op. 39) [2]. This masterpiece was composed and published as far as in 1878, but today it still remains one of constant topics of interest for researchers [3][4]. Though the study of rich metaphors hidden in the pieces thought to be for children rather lies in the scope of art and musicology, there is still a large research space for formal methods based on mathematical and computational models, which may give additional insights into our understanding of the structure and organization of the whole work, its relationships to precursors (such as “43 Clavierstücke für die Jugend” by Robert Schumann [5]), as well as the reasons for significant differences between the original manuscript and the first published edition. Surprisingly, in musicology literature, one of the first careful studies of transformations between the manuscript and the published edition can be found in the early 1990s only; thus, more than 100 years after the whole work was completed [6][7]. These studies mostly remain in scope of music and art theory, with almost no involvement of machine learning approaches. Today, it is commonly not disputed that computer science and artificial intelligence may contribute to musicology research on music style identification and comparative analysis. In this study, we try to discover appropriate formal models that would enhance the analysis and understanding of Tchaikovsky's “Children's Album”, which can be considered as a very good example of applied human-centric computing research in the frame of art and humanities, where solutions cannot be designed within a certain context only, but require intensive cross-disciplinary efforts so as to bridge the communities working in different contexts and using different vocabularies [8].

The remaining text is organized as follows. Section II provides a brief review of state-of-the-art research on linking musicology and computerized analysis of music compositions with a particular attention to the case study of Tchaikovsky's “Children's Album”. Section III sketches a number of promising models that may contribute to music stylistic similarity recognition and evaluation aimed at bridging the gaps between musicology studies and computer models.

II. RELATED WORK

According to Nattiez, music is a symbolic fact characterized by the complex configuration of interpretants [9]. In music, we use various connected but independent models including letter-based notations, such as Helmholtz or scientific pitch notation (that can be considered as simple syntax based language constructions), complex symbolic notations in the form of graphic note scores ranging from hardly formalizable ancient models, such as Znamenny chant, at one pole, or relatively strict Mensural notation, at another pole, up to modern sheet music (based on many rules but giving some freedom to support the individual styles of composers), piano roll notation, tablature, MIDI representations, as well as audio signals and even spectral models, such as acoustic fingerprints. The great variety of models used for music representation is one of reasons why music provides an interesting and complex use case for experimenting with information retrieval, object recognition and classification algorithms. Music representation complexity can be explained by the presence of two arrays of elements and relationships, where the first one corresponds to the elements that can be treated mathematically (pitch, rhythm, or harmony), while the second one includes non-mathematical elements such as tension, expectancy, and emotion [10].

A. Bridging the gap between pure musicology and applied human-centric computer technology

Current approaches to music similarity evaluation (including our own work on melody extraction and similarity estimation using Earth Mover's Distance algorithms [11]) mostly target the searching and retrieval systems including well-known apps, such as Shazam [12], without a perfect fit to the problems of stylistic similarity evaluation. From this point of view, models of functional representation of music harmony and harmonic similarity estimation [13] seem to be more adequate to the problem of style identification. Indeed, usually, listeners can recognize similarity of compositions because of their harmonic similarity (see Figure 1). However, it does not immediately lead us to clearly conclude about the composition's stylistic resemblances or dependencies. Even

harmonic equivalence may not be enough to recognize the melody, as demonstrated in [14] and later analyzed in [15] in the experiments with melodies distorted by substituting the note octave by randomly selected ones within three octaves: every note in the sequence keeps its position on the scale, but the tune varies over a three-octave range (similarly to an example of such distortion shown in Figure 2).

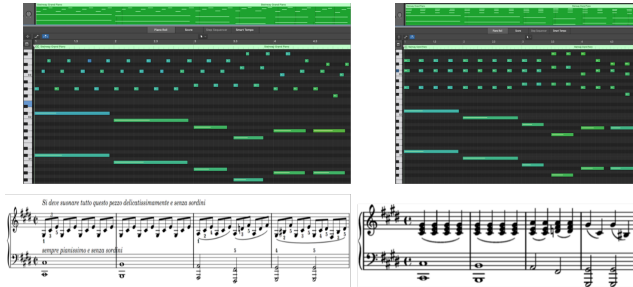


Figure 1. Harmony resemblance between Beethoven’s Moonlight Sonata and its variation

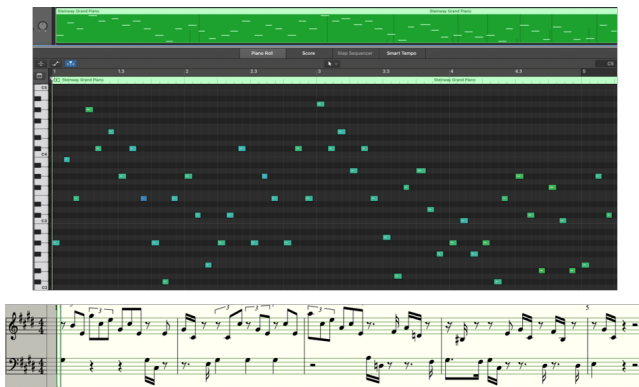


Figure 2. Distorted note sequence of Beethoven’s Moonlight Sonata with keeping harmonic equivalence

Harmonic functions were core elements of SPEAC music representation system developed by Cope [16][17], which is an implementation of augmented transition network, a finite-state automaton with recursive succession rules between music sub-phrases allowing for logical syntax substitutions [18]. Cope’s SPEAC system is based on a hierarchical representation of the structure of music composition in nested contexts beginning from notes and chords up to chapters and parts (see Figure 3 (a)). Five identifiers contributing to SPEAC acronym stand for statement *S*, preparation *P*, extension *E*, antecedent *A*, and consequent *C*, all of which are kinds of abstractions assigned to groups of notes “depending on levels of tension between intervals, metrical placement, and agogic emphasis, measured both in the preceding and following groups” [18]. Succession rules defined by Cope limit possible transitions between the SPEAC states (see Figure 3 (b)). Therefore, SPEAC progressions are like genome sequences using SPEAC identifiers as bases enforced by harmonic tension weights and hierarchical relationships between progressions at different levels. Modeling music structure using SPEAC-analysis can be a promising approach to recognize music style similarity through SPEAC progression similarity as well as with the help

of comparison between the corresponding graphs, specifically with respect to recent SPEAC-analysis implementations available as libraries in universal languages, such as Python [19].

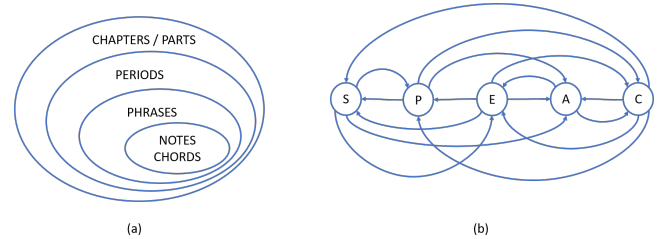


Figure 3. Progression bases in SPEAC system by David Cope.

Due to a large number of applications of using deep neural networks for object recognition and classification (especially for image recognition, including such subjective trait as image aesthetics), machine learning approaches and recurrent neural networks may be promising for music style identification, classification and analysis. Though, in contrast to a variety of works on computer music generation, we argue that the main challenge is not to teach AI to create art objects, but to be able to help us in perceiving objects created by humans [20].

B. Renditions and Implications of “Children’s Album”

Since both Tchaikovsky and Schumann belong to the romantic tradition rooted in part of leitmotif music by Beethoven and Wagner, on the one hand, and in the new music language of Glinka, Chopin and Liszt, on the other hand, certain harmony and music development similarity surely exists in their works. According to the network of influences on classical composers originally described by Smith and Georges et al. in the original Classical Music Navigator [21], Schumann is one of composers who greatly influenced Tchaikovsky (along with Balakirev, Beethoven, Chopin, Delibes and others) as shown in Figure 4.

However, admitting Schumann’s influence to Tchaikovsky does not lead us to automatically judge the “Children’s Album” as an imitation of Schumann’s pieces for the young (also with long history of editions but rather few scholarly studies [23]) even though Tchaikovsky claimed it explicitly in the subtitle for the published edition “24 simple pieces for children like Schumann” (but not in the manuscript! [24]). What if this subtle (?) subtitle is a kind of hint that Tchaikovsky gave us? Like saying: “Well, it is definitely not “like Schumann”! Should you then believe in the appropriateness of all made transformations?” These transformations (see Figure 5) destroy the structure of the album as an indissociable whole, and deform the micro-cycles existing in the manuscripts (where the Doll cycle is the clearest case), as well as evident harmonic links, for instance, between the first and the last pieces in the manuscript, “Morning prayer” and “The hurdy-gurdy man is singing”, respectively.

An idea that changes in the order of compositions between the manuscript and first published edition were mistakenly introduced by the publisher could not be accepted as convincing enough: indeed, Tchaikovsky approved this version. Nekhaeva suggested that these transformations can be considered as a “gesture of the composer, a natural desire to overcome the temporary barrier and directly appeal to future generations of musicians” [4]. This opinion supports an existing hypothesis

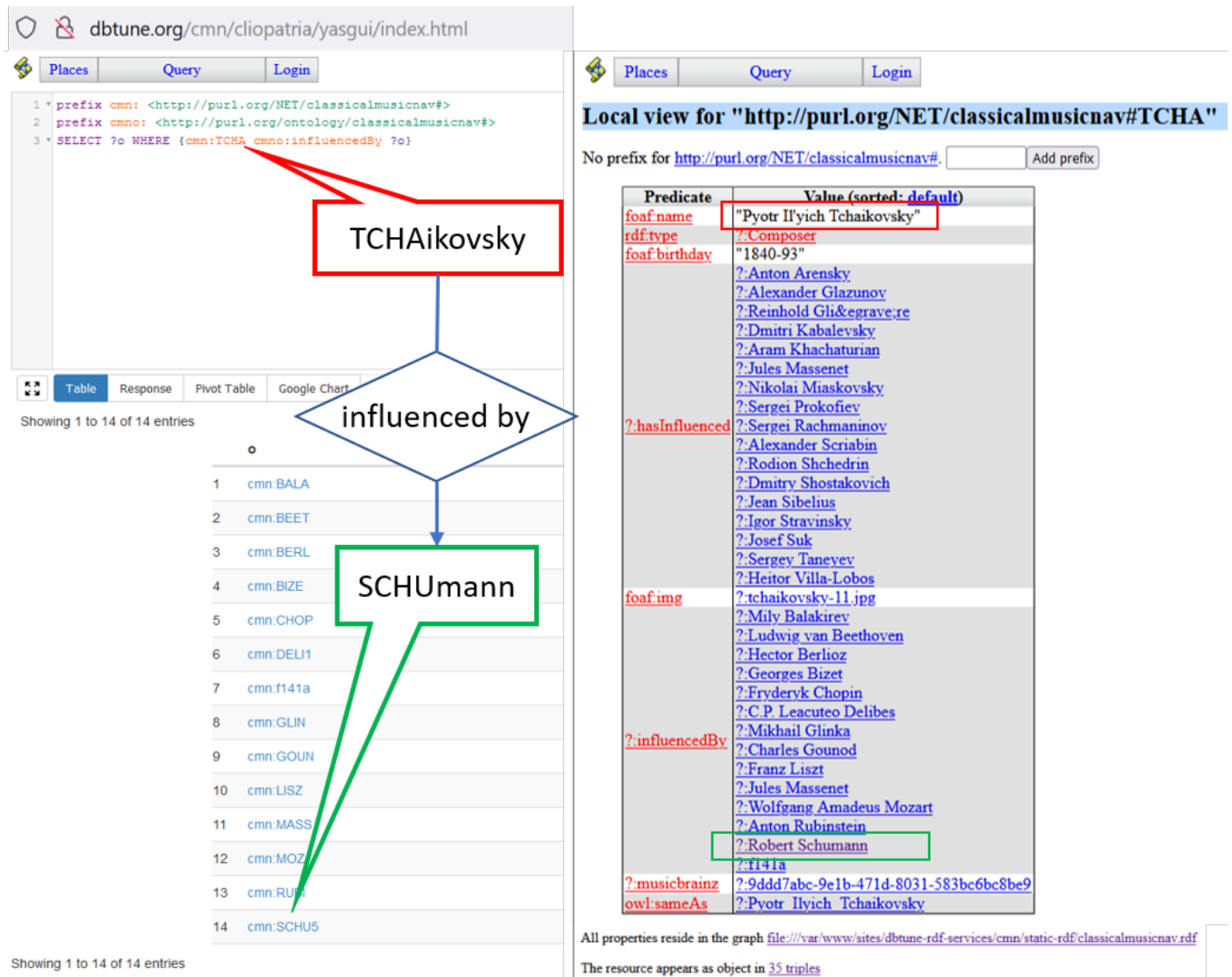


Figure 4. “Influenced-by” relationships for Tchaikovsky (as in Classical Music Navigator [22])

claiming that Tchaikovsky probably preferred to hide some metaphors so that they are not so explicitly exposed as in the manuscript. From the perspective of musicology, we could not expect to find a final answer (and perhaps it is not needed). Instead, a possibility to incorporate formal computational approaches into informal art discourse can, produce a number of important additional insights for better understanding of genesis of one of Tchaikovsky’s masterpieces in piano music.

C. Dataset Issues

In the process of study, we need to investigate, what are the suitable computational approaches that may contribute to style identification. Because of the subjectivity of style attribution and style dependency analysis, a possibility to construct and assess different computational models should be considered. It may be that particular models can contribute to particular characteristics of music style recognition.

We also need to define a dataset with the selection of compositions including the following components:

- 24 piano compositions from the “Children’s Album”;
- Selection of characteristic piano compositions by Schumann, including those from Op. 68;
- Selection of compositions with expected high degree of style similarity, which were attributed by their authors as imitations, such as piano works of Liszt, Chopin, Schumann (referential dataset);
- Selection of other characteristic compositions (e.g., by Tchaikovsky), where style similarity was reported by musicology experts (referential dataset). The studies [25][26] can provide information for selection of relevant referential datasets.

III. PROMISING APPROACHES FOR FURTHER STUDIES

There is a number of works contributing to music analysis based on audio signal processing. Detection music file similarity based on tonality, tempo and chord progression similarity (that can be extracted from sound files using signal processing algorithms as demonstrated in [27]) is very helpful to improve

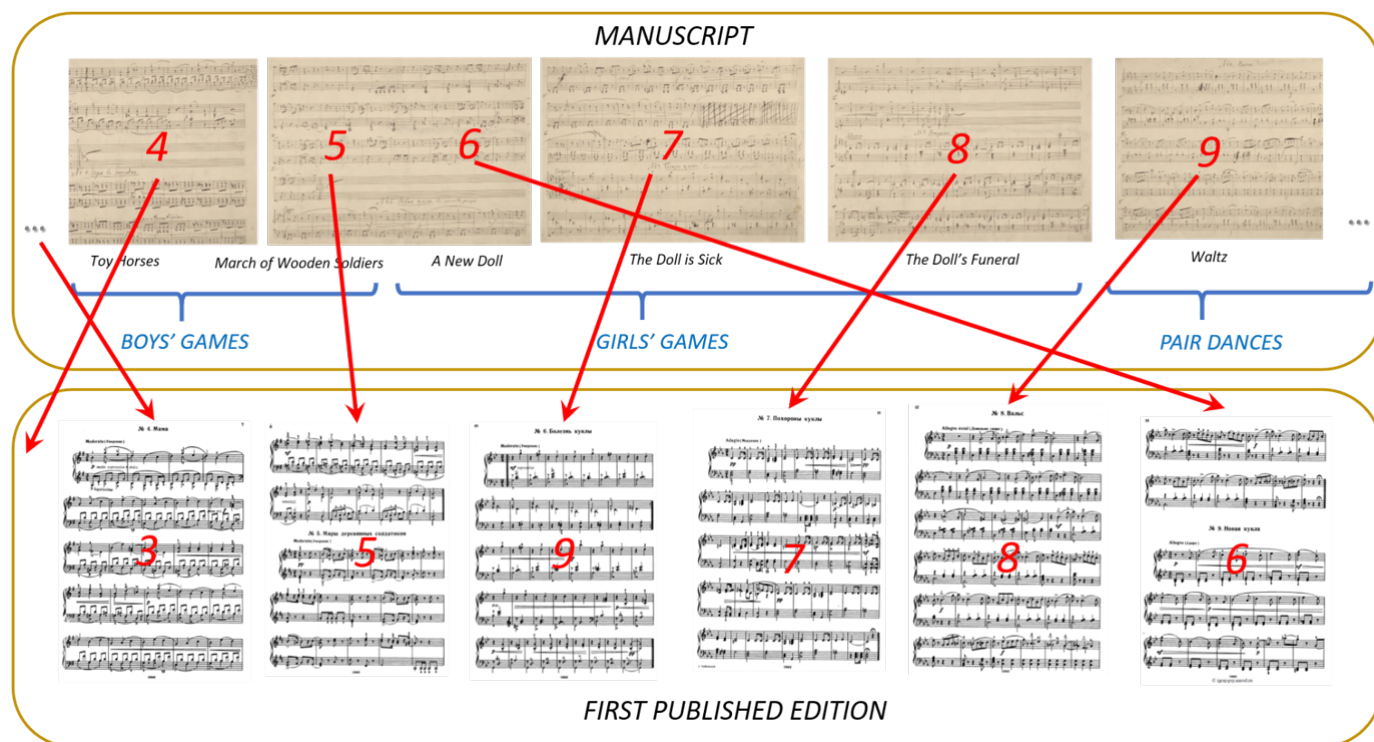


Figure 5. “Children’s Album”: Original structure is destroyed in the published version.

algorithms of music retrieval, but may not be enough to judge about stylistic and harmonic similarity or about the presence of transformed citations where the key, tempo and melody can be significantly modified compared to the original but keeping almost intangible traits of similarity, still perceptible by an experienced ear. Great opportunities provided by signal processing algorithms enforced by hierarchical semi-Markov models of music enable automatic music transcription for given audio signals [28]. Though these works are naturally closely related to music similarity analysis, the findings could not be directly applicable to the problem of developing computational models of style similarity, which remains challenging even if the note score is available.

Similarity detection based on note sequences (e.g., in [29]) can give interesting insights into the genesis of music styles, but does not help much in solving specific problems of influence assessment, where study of exact or slightly transformed note sequences may be insufficient. However, the idea of grouping compositions based on weaker traits of similarity in their themes and sub-themes [30] can be promising.

With respect to studies on analysis of acoustic spectral fingerprints for unique identification of the music fragments (e.g., according to the algorithms described in [31][32]), comparison between such fingerprints can give one component for similarity analysis. Figure 6 displays an example of piano composition spectral representation constructed using the online tool [33].

Among other interesting works relevant to this study, there are studies on approaches using deep neural networks for object recognition applied to the case of music for a variety of adjacent problems, including music genre classification [34], content-based music recommendation [35], music style modeling [36], deep learning-based music generation [37], and style-

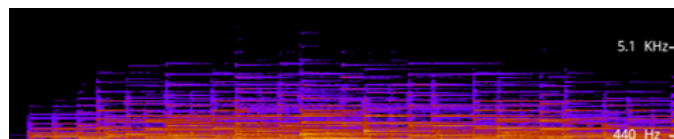


Figure 6. Sample spectrogram of “A New Doll” (Op. 39, orig. No. 6): first 30 measures recorded by Evgeny Pyshkin at Yamaha YDP-144

specific based music composition [38]. In addition, considering music as a semi-chaotic natural process with recurrences and irregular cyclicities analyzed and visualized with the help of recurrence plots [39] (similar to spoken pitch as we did in our prosody visualization research [40]).

IV. CONCLUSION

In this study, the problem of music style identification is sketched via a brief analysis of computational models and technical solutions that may be helpful to musicologists in their research on genesis and implications of musical compositions with an example of exploring the links between Tchaikovsky’s “Children Album” and Schumann’s “Album für die Jugend”. With the help of computer technology we can discover more findings to support meaningful hypotheses about the possible reasons explaining significant discrepancies between Tchaikovsky’s manuscript and the following editions of “Children’s Album”.

Naturally, the outcomes from such compact joint musicology and computer science studies can naturally address the broader scope of research on music style understanding, modeling, and recognition for the benefit of both computer technology and humanities so as to provide interesting use

cases for AI applications as well as “a further strand of evidence for systematic musicology to exploit” as nicely formulated by Collins in [41].

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