

The Importance of Modeling in Computational Musicology

Fabian C. Moss

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Digital and Cognitive Musicology Lab
École Polytechnique Fédérale de Lausanne

- I. Modeling in Computational Musicology
- II. Example 1: Chord distributions
- III. Example 2: Pitch-class distributions
- IV. Perspectives

I. Modeling in Computational Musicology

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Potential of model-based computational musicology

1. complementing music theory
2. resolving ambiguities in terminology
3. empirically validating theoretical assumptions & asking entirely new questions

II. Ex. 2: Chord distributions

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Studying chord distributions to approximate **stylistic traits**, e.g. in

- **Western Classical music** (Jacoby, Tishby, and Tymoczko, 2015; Moss, Neuwirth, Harasim, and Rohrmeier, 2019)
- **Rock** (Temperley, 2018; Temperley and de Clercq, 2013)
- **Pop** (Burgoyne, Wild, and Fujinaga, 2011; Mauch et al., 2007)
- **Jazz** (Shanahan and Broze, 2012)
- **Choro** (Moss, Souza, and Rohrmeier, 2020)
- ...

II. Ex. 2: Chord distributions

Common (implicit) **assumptions**: n -gram or Markov models:

$$p(c_i \mid c_1, \dots, c_{i-1}) \approx p(c_i \mid c_{i-n+1}, \dots, c_{i-1})$$

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- unigram model: relative frequencies ($n = 1$)
- bigram model: transitions ($n = 2$)

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Unigram model: relation between chord **rank** and **frequency** often approximated with Zipf-Mandelbrot law:

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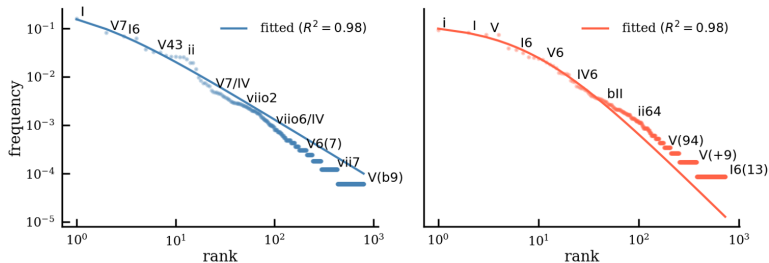


Figure 1: Frequency-rank distribution of chords in Beethoven's string quartets (major: blue, minor: red; Moss, Neuwirth, Harasim, and Rohrmeier, 2019).

II. Ex. 2: Chord distributions

Bigram model: probabilities of chord transitions; conditional entropies

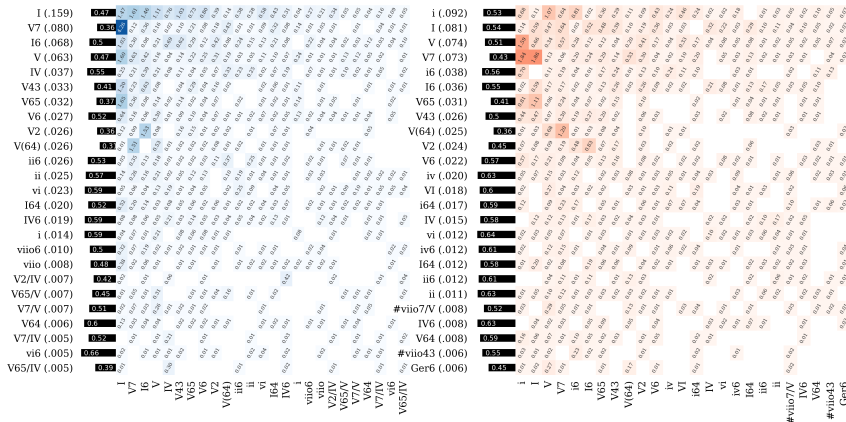


Figure 2: Transition probabilities in Beethoven's string quartets (major: blue; minor: red).

II. Ex. 2: Chord distributions

1. Chord progressions seem to be **asymmetrical**, e.g. $V2 \longrightarrow I6 \gg I6 \longrightarrow V2$
2. Chords with suspensions and applied chords (i.e., certain **chord features**) have lower entropies

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Comparing average entropies of randomly sampled chords to those with certain features

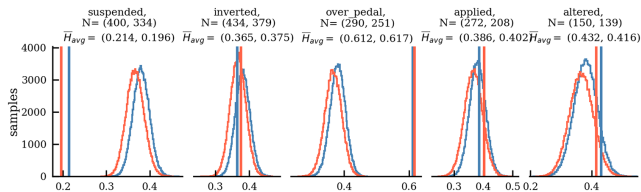


Figure 3: Conditional entropies of chords with certain features (major: blue; minor: red).

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Theoretical (historical) models of **tonal space**.

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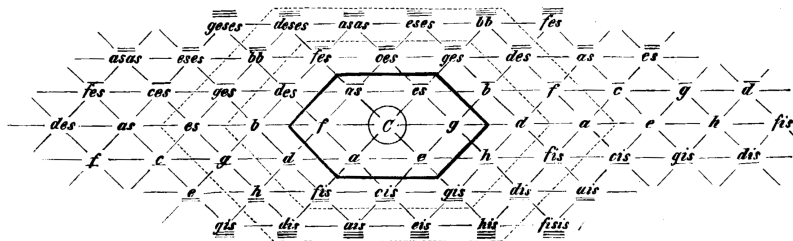


Figure 4: The *Tonnetz* (Hostinský, 1879).

III. Ex. 2: Pitch-class distributions

Neo-Riemannian **triadic transformations** on the *Tonnetz* (Cohn, 1998)

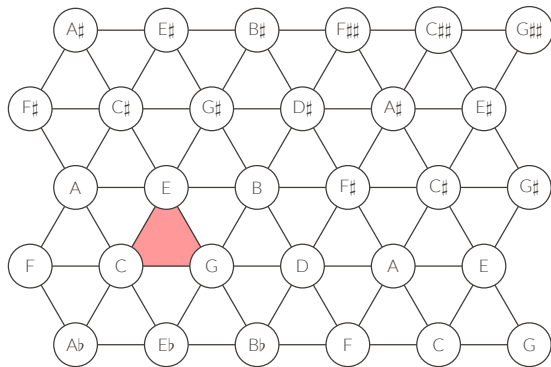


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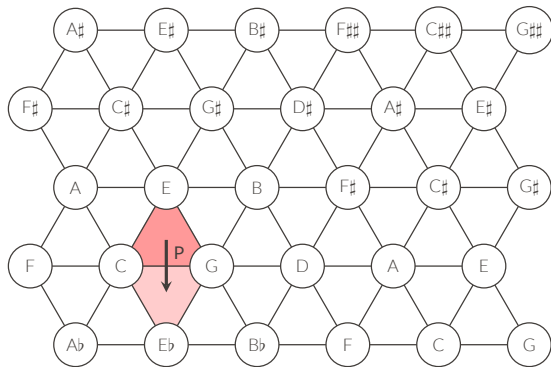


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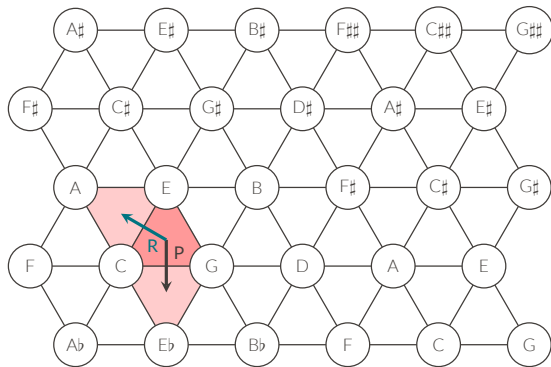


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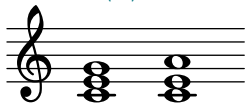
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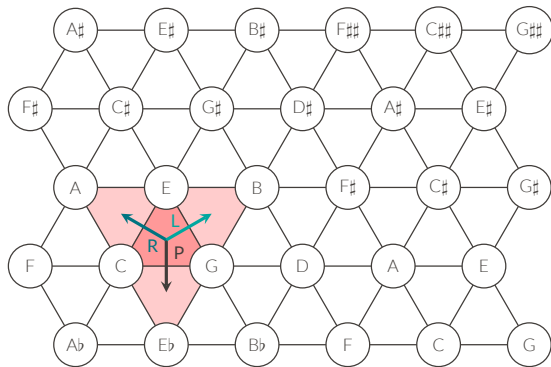
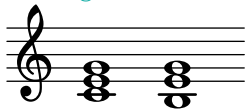


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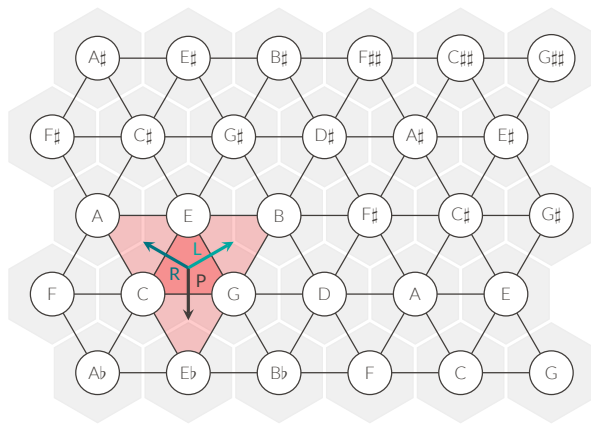
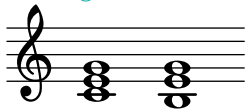
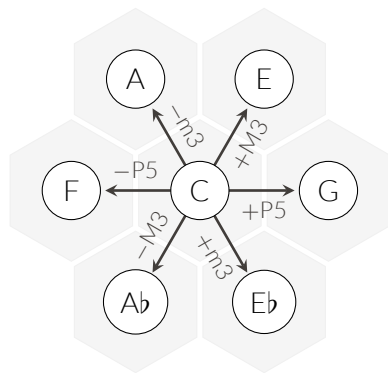


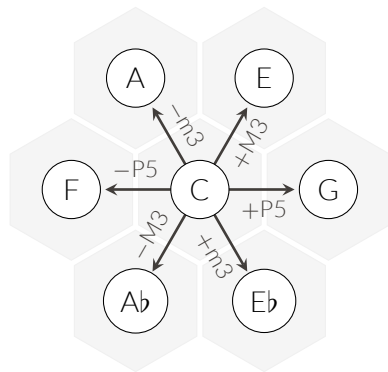
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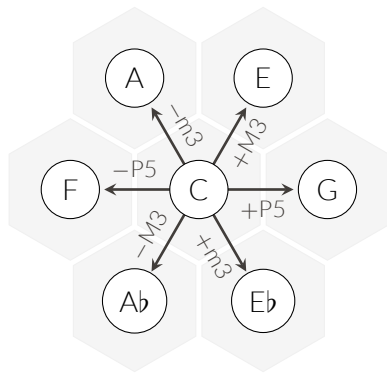
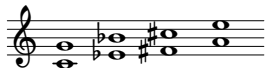


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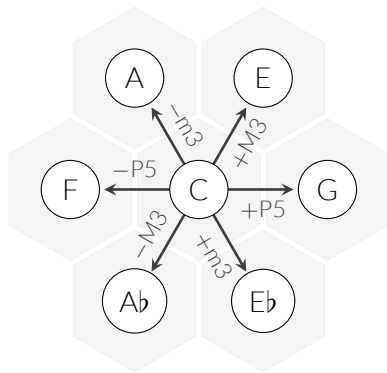
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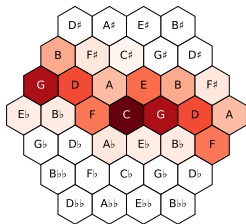


- hexatonic**: $\pm M3, \pm P5$



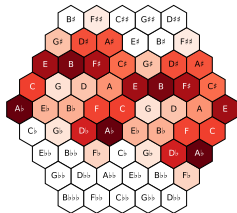
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diatonic



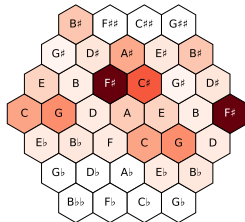
Bach, *Prelude in C major*,
BWV 846 (1722).

hexatonic



Liszt, *Lugubre gondola I*,
S. 200/1 (1882).

octatonic



Scriabin, *Prelude*,
op. 74/2 (1914).

Plots generated with the *pitchplots* Python library (Moss, Loayza, and Rohrmeier, 2019)

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Music-theoretical **interpretation** of interval relations on the Tonnetz:

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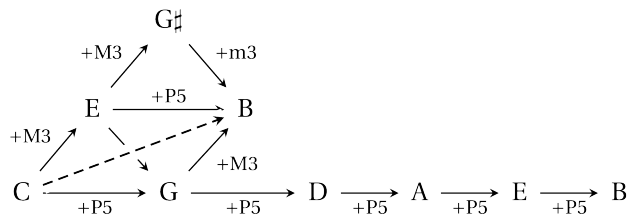


Figure 6: Different harmonic functions of B in relation to C.

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The Tonal Diffusion Model

Computational modeling assumptions:

1. all notes are related to a tonal center

Details: Lieck, R., Moss, F. C., & Rohrmeier, M. (2020). The Tonal Diffusion Model. *Transactions of the International Society for Music Information Retrieval*, 3(1), 153–164. <https://doi.org/10.5334/tismir.46>

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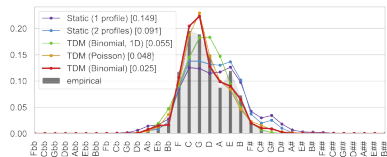
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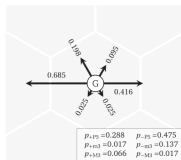
1. all notes are related to a **tonal center**
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3. the probability of a pitch class to occur in a piece is a result of all **path probabilities** to reach it from the tonal center (shorter paths preferred)

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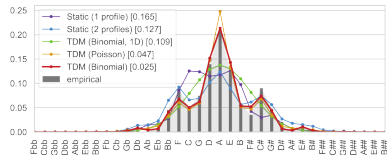
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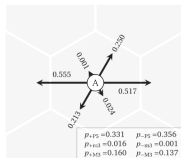
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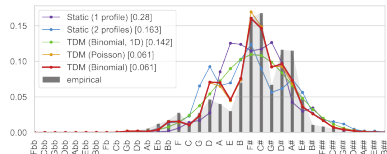
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($\mu = 1.44, \sigma = 0.69$).



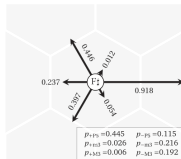
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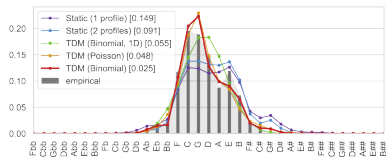


(c) Liszt, *Bénédiction de Dieu dans la Solitude*.

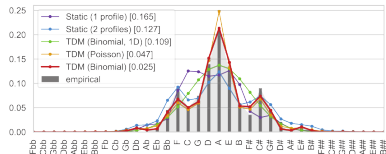


(c) Liszt, *Bénédiction de Dieu dans la Solitude* ($\mu = 2.06, \sigma = 1.25$).

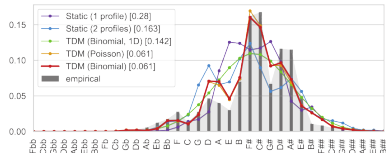
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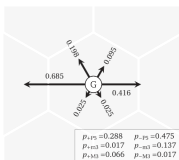
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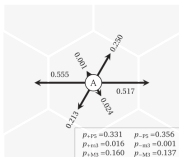
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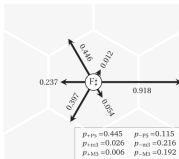
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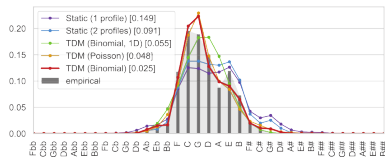
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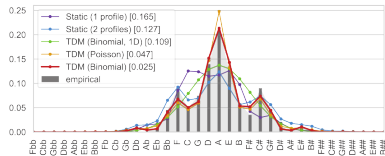
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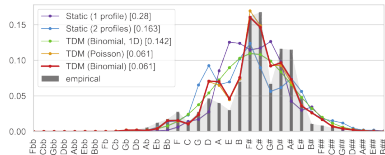
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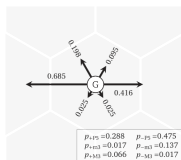
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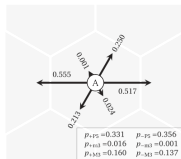
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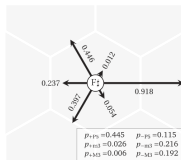
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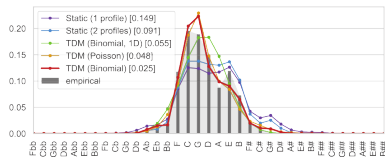
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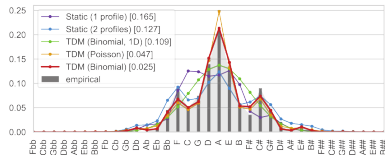
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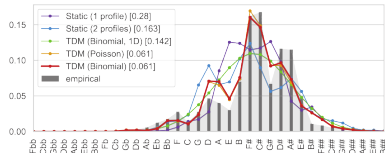
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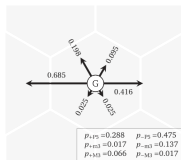
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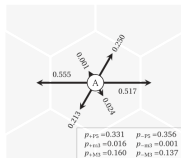
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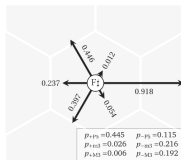
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3. **corpus-level comparison** shows that a 'line-of-fifths model' is sufficient for Bach but TDM is better for Beethoven and Liszt (see paper)

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4. potential for purely historical and theoretical approaches: understanding analysis as inference, evaluating plausibility of models (“theories”)
5. requires and facilitates reflection, critique, and interpretation

Thank you very much!

Slides: <http://www.fabian-moss.de>

References

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