The Importance of Modeling in Computational Musicology

Fabian C. Moss

9 December 2020

Digital and Cognitive Musicology Lab
École Polytechnique Fédérale de Lausanne

Outline

I. Modeling in Computational Musicology

I. Modeling in Computational Musicology

A model specifies

- the objects to study and their formal representations
- the (probabilistic) relations between those objects

I. Modeling in Computational Musicology

A model specifies

- the objects to study and their formal representations
- the (probabilistic) relations between those objects

As such, it is an attempt to abstract from or approximate a phenomenon, e.g. harmonic progressions.

- $\mathrm{V} \longrightarrow \mathrm{I}$

(cf. Finkensiep, Neuwirth, and Rohrmeier, forthcoming)

I. Modeling in Computational Musicology

A model specifies

- the objects to study and their formal representations
- the (probabilistic) relations between those objects

As such, it is an attempt to abstract from or approximate a phenomenon, e.g. harmonic progressions.

- $\mathrm{V} \longrightarrow \mathrm{I}$
- $P(\mathrm{I} \mid \mathrm{V}) = p$

(cf. Finkensiep, Neuwirth, and Rohrmeier, forthcoming)

Potential of model-based computational musicology

Potential of model-based computational musicology

1. complementing music theory

I. Modeling in Computational Musicology

Potential of model-based computational musicology

1. complementing music theory
2. resolving ambiguities in terminology

I. Modeling in Computational Musicology

Potential of model-based computational musicology

1. complementing music theory
2. resolving ambiguities in terminology
3. empirically validating theoretical assumptions

I. Modeling in Computational Musicology

Potential of model-based computational musicology

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

II. Ex. 2: Chord distributions

II. Ex. 2: Chord distributions

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)
- ...

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

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

II. Ex. 2: Chord distributions

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

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

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

II. Ex. 2: Chord distributions

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

$$\hat{f}(r) = \frac{\alpha}{(\beta + r)^\gamma}$$

II. Ex. 2: Chord distributions

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

$$\hat{f}(r) = \frac{\alpha}{(\beta + r)^{\gamma}}$$

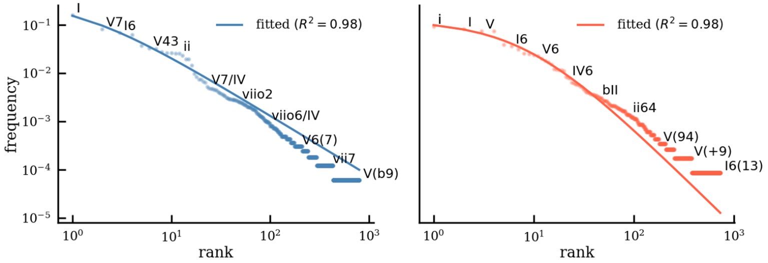


Figure 1: Frequency-rank distribution of chords in Beethoven's string quartets (major: blue, minor: red; Moss, Neuwirth, Harasim, and Rohrmeier, 2019).

Bigram model: probabilities of chord transitions; conditional entropies

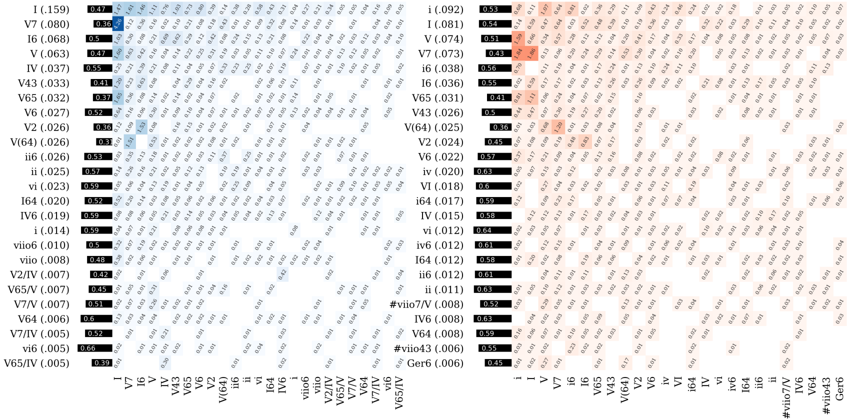


Figure 2: Transition probabilities in Beethoven's string quartets (major: blue; minor: red).

II. Ex. 2: Chord distributions

1. Chord progressions seem to be asymmetrical, e.g. V2 $\longrightarrow$ I6 $\gg$ I6 $\longrightarrow$ V2

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

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

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

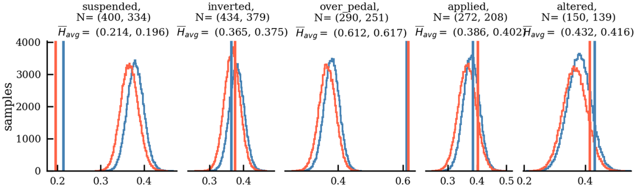


Figure 3: Conditional entropies of chords with certain features (major: blue; minor: red).

III. Ex. 2: Pitch-class distributions

III. Ex. 2: Pitch-class distributions

Theoretical (historical) models of tonal space

III. Ex. 2: Pitch-class distributions

Theoretical (historical) models of tonal space

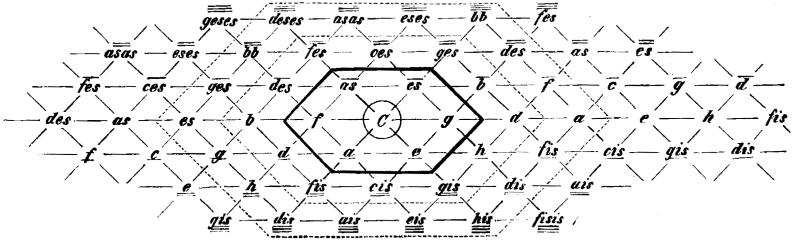


Figure 4: The *Tonnetz* (Hostinský, 1879).

III. Ex. 2: Pitch-class distributions

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

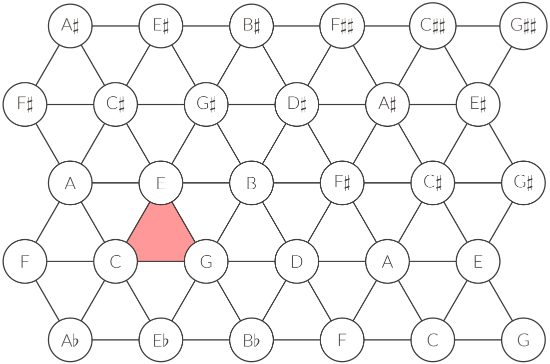
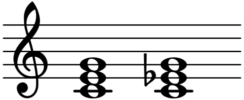


Figure 5: The *Tonnetz*.

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

- parallel (**P**)



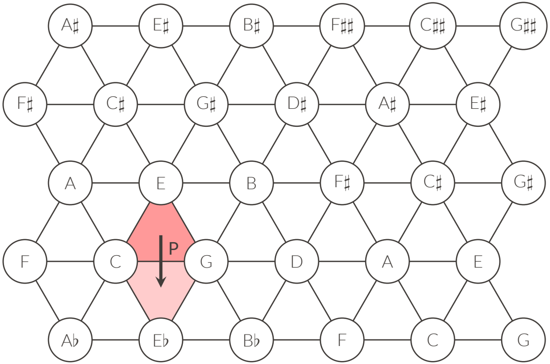
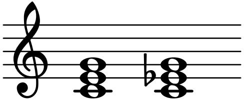


Figure 5: The *Tonnetz*.

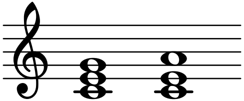
III. Ex. 2: Pitch-class distributions

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

- parallel (**P**)



- relative (**R**)



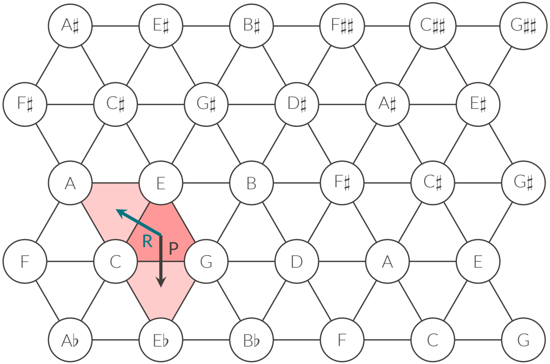
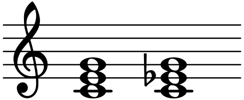


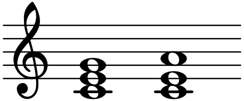
Figure 5: The *Tonnetz*.

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

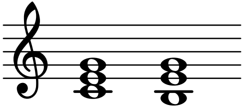
- parallel (**P**)



- relative (**R**)



- leading-tone exchange (**L**)



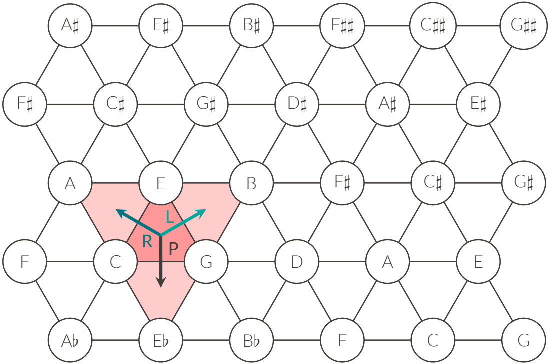
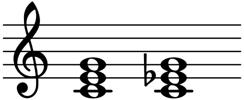


Figure 5: The *Tonnetz*.

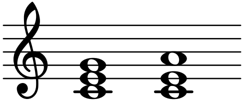
III. Ex. 2: Pitch-class distributions

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

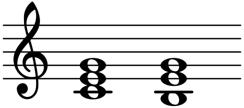
- parallel (**P**)



- relative (**R**)



- leading-tone exchange (**L**)



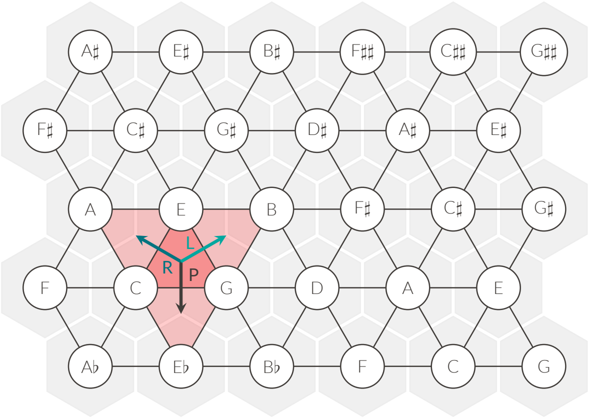


Figure 5: The *Tonnetz*.

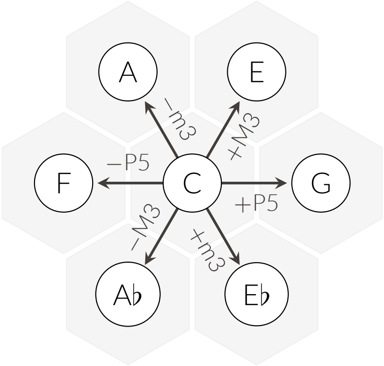
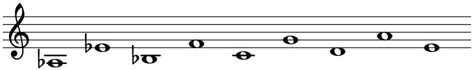


Figure 6: “Primary intervals” with respect to C.

III. Ex. 2: Pitch-class distributions

- (extended) diatonic: $\pm$ P5



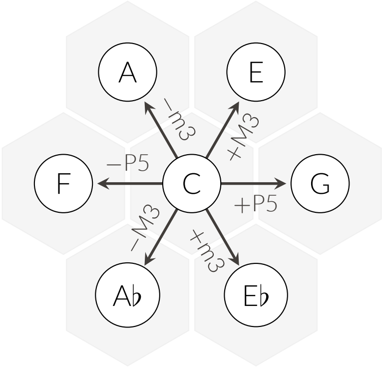
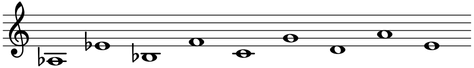


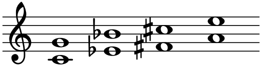
Figure 6: "Primary intervals" with respect to C.

III. Ex. 2: Pitch-class distributions

- (extended) diatonic: $\pm$ P5



- octatonic: $\pm$ m3, $\pm$ P5



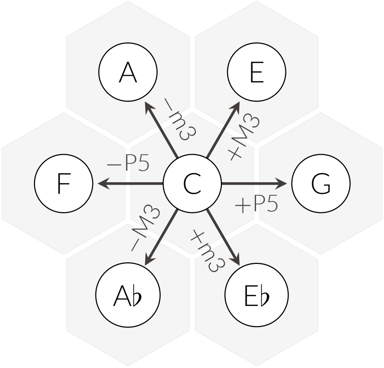
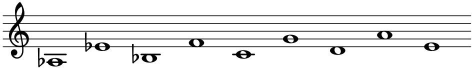


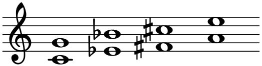
Figure 6: “Primary intervals” with respect to C.

III. Ex. 2: Pitch-class distributions

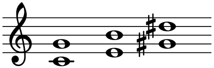
- (extended) diatonic: $\pm$ P5



- octatonic: $\pm$ m3, $\pm$ P5



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



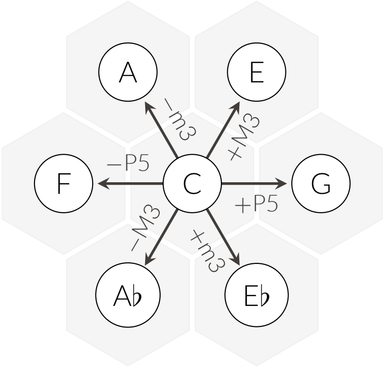
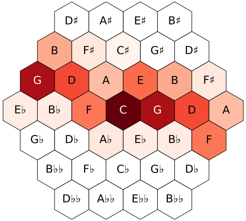


Figure 6: “Primary intervals” with respect to C.

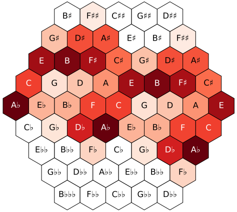
III. Ex. 2: Pitch-class distributions

diatonic



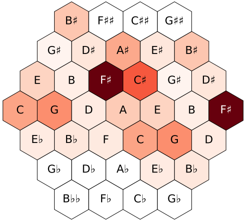
Bach, *Prelude in C major*, BWV 846 (1722).

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)

III. Ex. 2: Pitch-class distributions

Functional interpretation of interval relations on the Tonnetz:

Functional interpretation of interval relations on the Tonnetz:

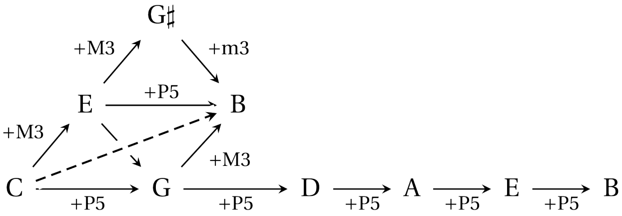


Figure 7: Different harmonic functions of B in relation to C.

The **Tonal Diffusion Model** – modeling assumptions:

The **Tonal Diffusion Model** – 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

III. Ex. 2: Pitch-class distributions

The **Tonal Diffusion Model** – modeling assumptions:

1. all notes are related to a tonal center
2. relations are given by (combinations of) intervals on the *Tonnetz*

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

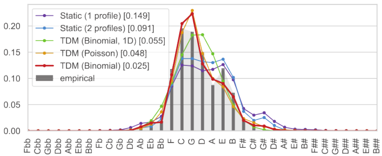
III. Ex. 2: Pitch-class distributions

The **Tonal Diffusion Model** – modeling assumptions:

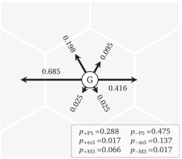
1. all notes are related to a tonal center
2. relations are given by (combinations of) intervals on the *Tonnetz*
3. the probability of a pitch class to occur in a piece is a result of all path probabilities to reach it from the tonal center (prefer shorter paths)

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

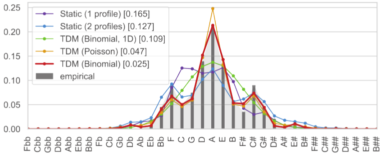
III. Ex. 2: Pitch-class distributions



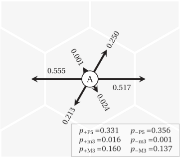
(a) Bach, C major Prelude.



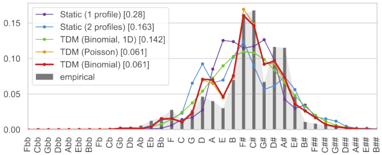
(a) Bach, C major Prelude ($\mu = 1.44, \sigma = 0.69$).



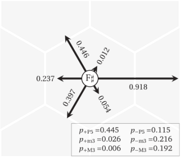
(b) Beethoven, 'Tempest' Sonata.



(b) Beethoven, 'Tempest' Sonata ($\mu = 1.56, \sigma = 0.76$).

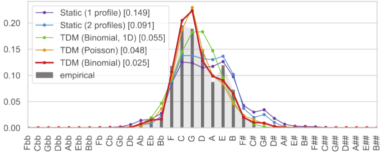


(c) Liszt, *Bénédiction de Dieu dans la Solitude*.

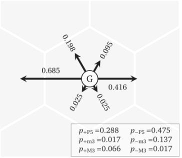


(c) Liszt, *Bénédiction de Dieu dans la Solitude* ($\mu = 2.06, \sigma = 1.25$).

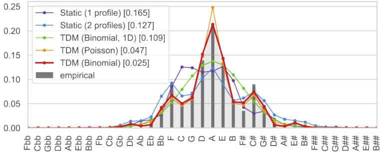
III. Ex. 2: Pitch-class distributions



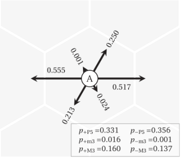
(a) Bach, C major Prelude.



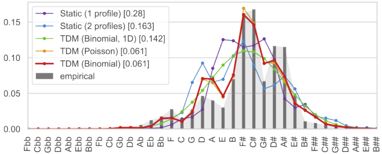
(a) Bach, C major Prelude ($\mu = 1.44, \sigma = 0.69$).



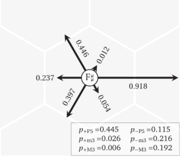
(b) Beethoven, 'Tempest' Sonata.



(b) Beethoven, 'Tempest' Sonata ($\mu = 1.56, \sigma = 0.76$).

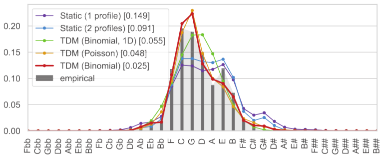


(c) Liszt, *Bénédiction de Dieu dans la Solitude*.

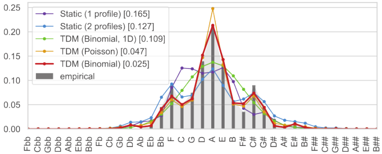


(c) Liszt, *Bénédiction de Dieu dans la Solitude* ($\mu = 2.06, \sigma = 1.25$).

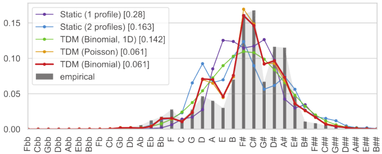
1. inferred parameters reflect characteristic intervals



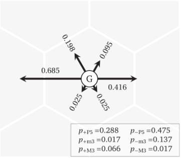
(a) Bach, C major Prelude.



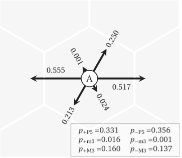
(b) Beethoven, 'Tempest' Sonata.



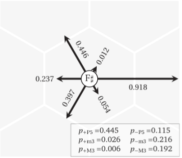
(c) Liszt, *Bénédiction de Dieu dans la Solitude*.



(a) Bach, C major Prelude ($\mu=1.44, \sigma=0.69$).



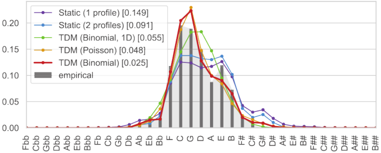
(b) Beethoven, 'Tempest' Sonata ($\mu=1.56, \sigma=0.76$).



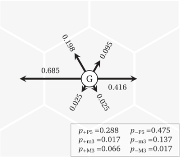
(c) Liszt, *Bénédiction de Dieu dans la Solitude* ($\mu=2.06, \sigma=1.25$).

1. inferred parameters reflect characteristic intervals
2. tonal center is not identical to the tonic

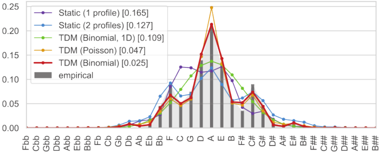
III. Ex. 2: Pitch-class distributions



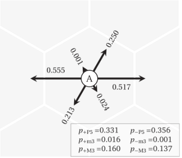
(a) Bach, C major Prelude.



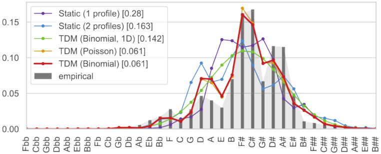
(a) Bach, C major Prelude ($\mu = 1.44, \sigma = 0.69$).



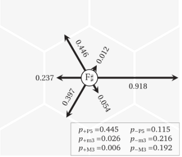
(b) Beethoven, 'Tempest' Sonata.



(b) Beethoven, 'Tempest' Sonata ($\mu = 1.56, \sigma = 0.76$).



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



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

1. inferred parameters reflect characteristic intervals
2. tonal center is not identical to the tonic
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)

IV. Perspectives

Modeling in Computational Musicology

1. not new: established in Music Information Retrieval and Mathematical Music Theory

Modeling in Computational Musicology

1. not new: established in Music Information Retrieval and Mathematical Music Theory
2. modeling also beneficial for music theory and musicology:
    - clearly defining objects and their interrelations
    - specifying assumptions that impact on analysis

Modeling in Computational Musicology

1. not new: established in Music Information Retrieval and Mathematical Music Theory
2. modeling also beneficial for music theory and musicology:
   - clearly defining objects and their interrelations
   - specifying assumptions that impact on analysis
3. potential for purely historical and theoretical approaches: understanding analysis as inference, evaluating plausibility of models ("theories")

Modeling in Computational Musicology

1. not new: established in Music Information Retrieval and Mathematical Music Theory
2. modeling also beneficial for music theory and musicology:
    - clearly defining objects and their interrelations
    - specifying assumptions that impact on analysis
3. potential for purely historical and theoretical approaches: understanding analysis as inference, evaluating plausibility of models (“theories”)
4. probabilistic modeling & corpus-based approach can bridge between mathematical abstractions (e.g. pc sets) and musical data (e.g. pc distributions)

Modeling in Computational Musicology

1. not new: established in Music Information Retrieval and Mathematical Music Theory
2. modeling also beneficial for music theory and musicology:
   - clearly defining objects and their interrelations
   - specifying assumptions that impact on analysis
3. potential for purely historical and theoretical approaches: understanding analysis as inference, evaluating plausibility of models ("theories")
4. probabilistic modeling & corpus-based approach can bridge between mathematical abstractions (e.g. pc sets) and musical data (e.g. pc distributions)
5. requires and facilitates reflection, critique, and interpretation

Thank you very much!

Slides: **http://www.fabian-moss.de**

References

Burgoyne, J. A., Wild, J., & Fujinaga, I. (2011). Compositional Data Analysis of Harmonic Structures in Popular Music (J. Yust, J. Wild, & J. A. Burgoyne, Eds.). In J. Yust, J. Wild, & J. A. Burgoyne (Eds.), *Mathematics and Computation in Music: 4th International Conference, MCM 2013*. https://doi.org/10.1007/978-3-642-21590-2

Cohn, R. (1998). Introduction to Neo-Riemannian Theory: A Survey and a Historical Perspective. *Journal of Music Theory*, *42*(2), 167–180.

Finkensiep, C., Neuwirth, M., & Rohrmeier, M. (forthcoming). Music Theory and Model-Driven Corpus Research. In D. Shanahan, J. A. Burgoyne, & I. Quinn (Eds.), *Oxford Handbook of Music and Corpus Studies*. Oxford University Press.

Hostinský, O. (1879). *Die Lehre von den musikalischen Klängen: Ein Beitrag zur aesthetischen Begründung der Harmonielehre*. H. Dominicus.

Jacoby, N., Tishby, N., & Tymoczko, D. (2015). An Information Theoretic Approach to Chord Categorization and Functional Harmony. *Journal of New Music Research*, *44*(3), 219–244. https://doi.org/10.1080/09298215.2015.1036888

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

Mauch, M., Dixon, S., Harte, C. A., Casey, M., & Fields, B. (2007). Discovering chord idioms through Beatles and Real Book songs. *ISMIR 2007, Proceedings of the 8th International Conference on Music Information Retrieval, Vienna, Austria, September 23-27*, 255–258.

Moss, F. C. (2019). *Transitions of Tonality: A Model-Based Corpus Study* (Doctoral Dissertation). École Polytechnique Fédérale de Lausanne. Lausanne, Switzerland. https://doi.org/10.5075/epfl-thesis-9808

Moss, F. C., Loayza, T., & Rohrmeier, M. (2019). Pitchplots. https://doi.org/10.5281/ZENODO.3265393

Moss, F. C., Neuwirth, M., Harasim, D., & Rohrmeier, M. (2019). Statistical characteristics of tonal harmony: A corpus study of Beethoven's string quartets. *PLoS ONE*, *14*(6), e0217242. https://doi.org/10.1371/journal.pone.0217242

Moss, F. C., Souza, W. F., & Rohrmeier, M. (2020). Harmony and form in Brazilian Choro: A corpus-driven approach to musical style analysis. *Journal of New Music Research*, *49*(5), 416–437. https://doi.org/10.1080/09298215.2020.1797109 _eprint: https://www.tandfonline.com/doi/pdf/10.1080/09298215.2020.1797109

Shanahan, D., & Broze, Y. (2012). A Diachronic Analysis of Harmonic Schemata in Jazz. In *Proceedings of the 12th International Conference on Music Perception and Cognition and the 8th Triennial Conference of the European Society for the Cognitive Sciences of Music*.

Temperley, D. (2018). *The Musical Language of Rock*. Oxford University Press. https://doi.org/10.1093/oso/9780190653774.001.0001

Temperley, D., & de Clercq, T. (2013). Statistical Analysis of Harmony and Melody in Rock Music. *Journal of New Music Research*, *43*(2), 187–204. https://doi.org/10.1080/09298215.2013.839525