Generative Bach Chorale Harmonizations

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Goals

- Generate accurate Bach Chorales using various AI techniques and sampling techniques
- Chordal approach rather than note based, and improved sampling to fix problem of "mode collapse" and dull character
- Compare to traditional Bach Chorales using metrics such as rhythm, flow, and technical accuracy.

Related Works

- Generation initially iterative and non-learned, using techniques such as *n*-grams [1].
- Soon enough, Markov Chains and other probabilistic models were used for various situations such as for different moods [2].
- Deep learning with RNNs/LSTMs become gold standard by featurizing the melody and scaling up to determine overarching chord progressions and harmonies [3].
- Novel experimental techniques utilizing GANs arise by dividing MIDI input into bars to retain timestamp information before generating melodies through conditional sampling [4].

Data and Preprocessing

- Raw data consisted of 371 complete Bach Chorales utilizing Music21, a Python music library to access notes and chords
- Separated each chorale into a major/minor bucket, as well as calculated scale degree difference for each note, which is "distance" from current chord
- Created CSP dictionaries for feature factors
- Created fill dictionary based off of transition frequency for chord progressions
- Input/Output: MIDI files separated into chords/Generated MIDI files
- Challenges: Chord representation and respective weighting

Methods

- **Baseline:** Random generation of chords
- ***N*-grams:** Using *n*-grams approach to keep track of previous chords and overarching phrasing using uniform cost search to find lowest cost
- **Fill Sampling:** Probabilistic sampling using log likelihood and also using lowest cost, assigned by $1/m$, where m is the amount of times the chord appears in that specific transition.
- **Features:** Issued a survey examining several musical features for objective weighting
- **Beam Search:** Reduce run time by choosing only top k fills that have the lowest cost
- **Constraint Satisfaction Factors:**
  - Harmonic and technical correctness
    - Follow typical Baroque rules to the same degree Bach did
  - Secondary dominance
    - Correct emphasis on secondary dominant chords, which are harmonic progressions used by composers to inject flair although technically "incorrect"
  - Voice leading
    - Stronger emphasis on having a fluid melody by preventing chords from moving outside of 3 scale degrees to reduce "nonmusical" changes
- **Gibbs Sampling:** Utilized MCMC sampling to mimic "guessing" the following chord
- **Final Model:** Combination of *n*-grams, beam search, CSPs to mimic best loss

$$\mathcal{L}_{\mathbf{x}\sim\theta} = \sum_{i=1}^{N} \alpha(r) + \beta(w) + \gamma(c) + \delta(h)$$

Equation 1: Loss function over top 4 features

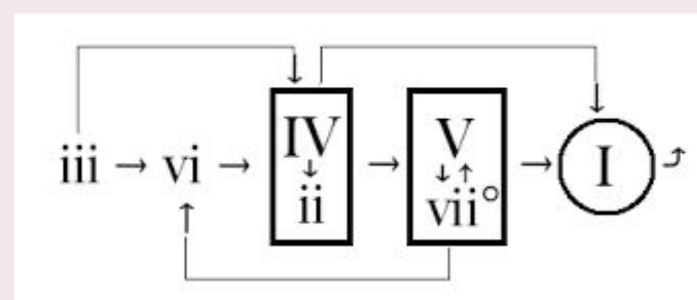


Figure 1: Finite State Diagram for technical correctness

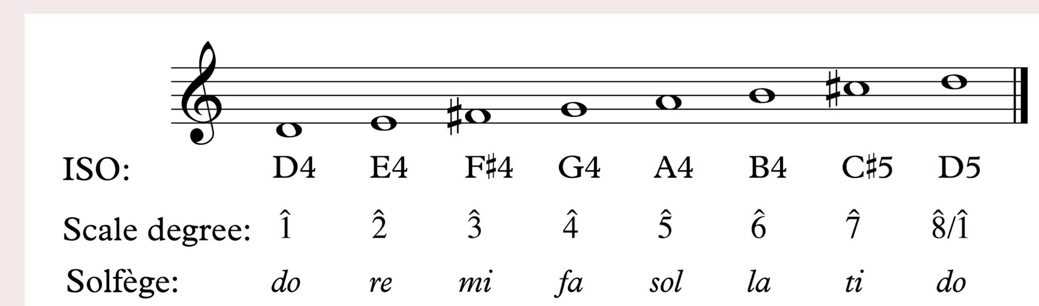
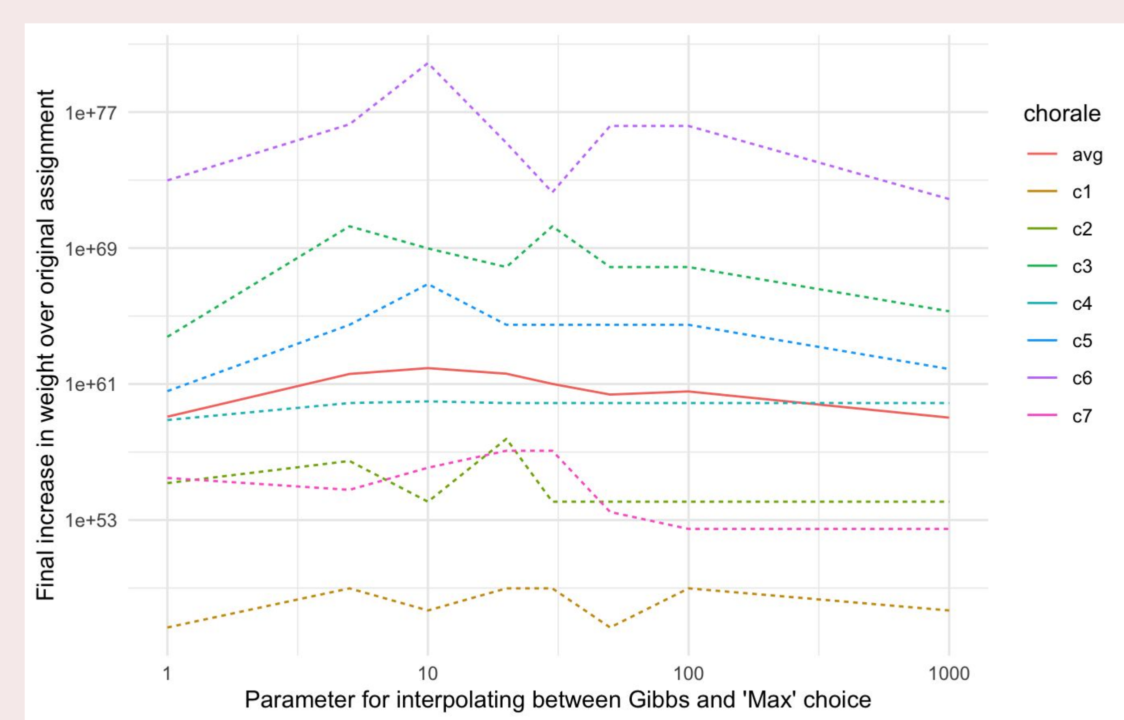


Figure 2: Scale Degree Separation governs frequency for selecting fills

Results

Figure 3: Baseline Chorale (Randomly Generated)

Figure 4: Trigram Chorale (Lowest Cost)



Weighted CSP results for different methods of sampling. For most chorales, it is best to augment the weight of the "best" solution by a factor of ~10, so as not to lead the harmonization in a sideways direction. However, overweighting the best assignment can get the CSP stuck in a local optimum.

Model Results

Model Name	Repetition	Weak Beats	Incorrectness	Rhythm	Loss
Baseline (Random)	0.35	0	0.57	0.87	0.460
Unary (Probabilistic)	0.85	0.12	0.51	0.75	0.561
Unary (Lowest Cost)	0.40	0.04	0.51	0.92	0.453
Bigram	0.83	0.11	0	0.81	0.305
Trigram	**0.73**	**0.09**	**0**	**0.75**	**0.271**
Tetragram	0.74	0.09	0	0.74	0.273
Bach	0.40	0.01	0	0.7	0.169

Discussion

- Initial CSP assignment generation using trigrams; has the lowest loss since it is able to capture the 3-beat harmonic phrasing (predominant, dominant, tonic) typically found in Baroque/Bach music
- Pure Gibbs Sampling injects too much noise, especially since a single poorly sampled variable then affects all of the following generations
- Interpolating between Gibbs and 'Max' sampling maximizes weights

Future Work

- Tune Gibbs Sampling by reweighting probabilities
- Utilize auxiliary variables in CSP to allow for n-ary factors involving more diverse harmonic rhythm

References

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3. Lim, Hyungui, Seungyeon Rhyu, and Kyogu Lee. "Chord generation from symbolic melody using BLSTM networks." arXiv preprint arXiv:1712.01011 (2017).
4. Yang, Li-Chia, Szu-Yu Chou, and Yi-Hsuan Yang. "MidiNet: A convolutional generative adversarial network for symbolic-domain music generation." arXiv preprint arXiv:1703.10847 (2017).