From Note2Vec to Chord2Vec

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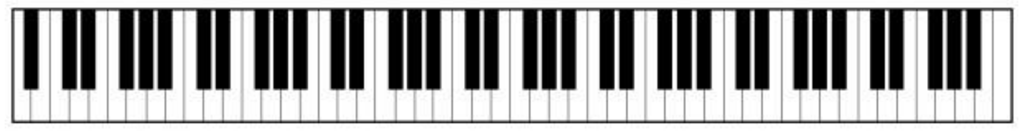
Overview

- Through the mapping of characters to notes and words to chords, we can draw a comparison between natural language and music and achieve challenging tasks, such as music generation.
- Similar to Word2Vec, we created a Note2Vec that contains vector embeddings for each musical note based on chord representation.
- Our results indicate that the chord embeddings are able to bring out basic music theory concepts and accurate classify musical chords.

Problem

- Unlike sentences that have many words, chords are comprised of a small amount of notes, which inspired us to model Word2Vec and create vectors for notes.
- Our goal is to generate embeddings to create a better representation system for musical notes, and to apply these embeddings to generate music.
- Current work in music generation includes the Music Transformer, which has very significant results in generating similar music. We use the same JSB Chorales dataset that they utilize to generate our embeddings.



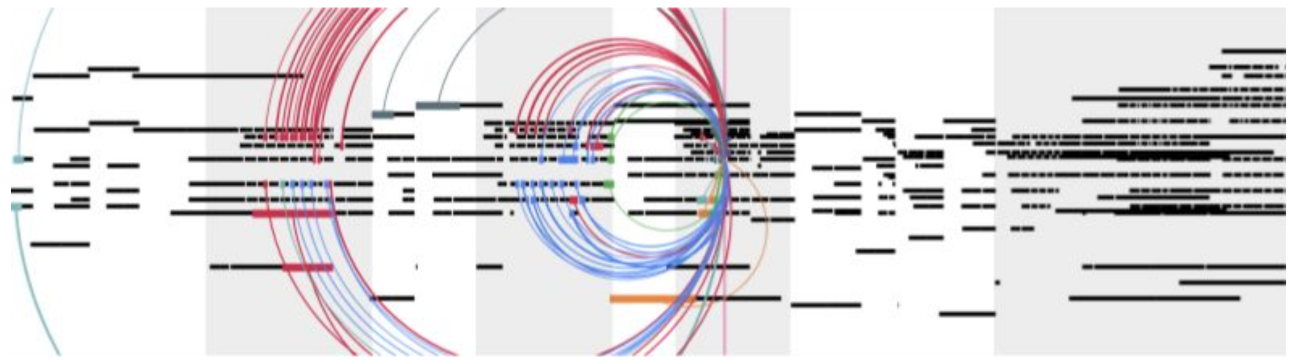
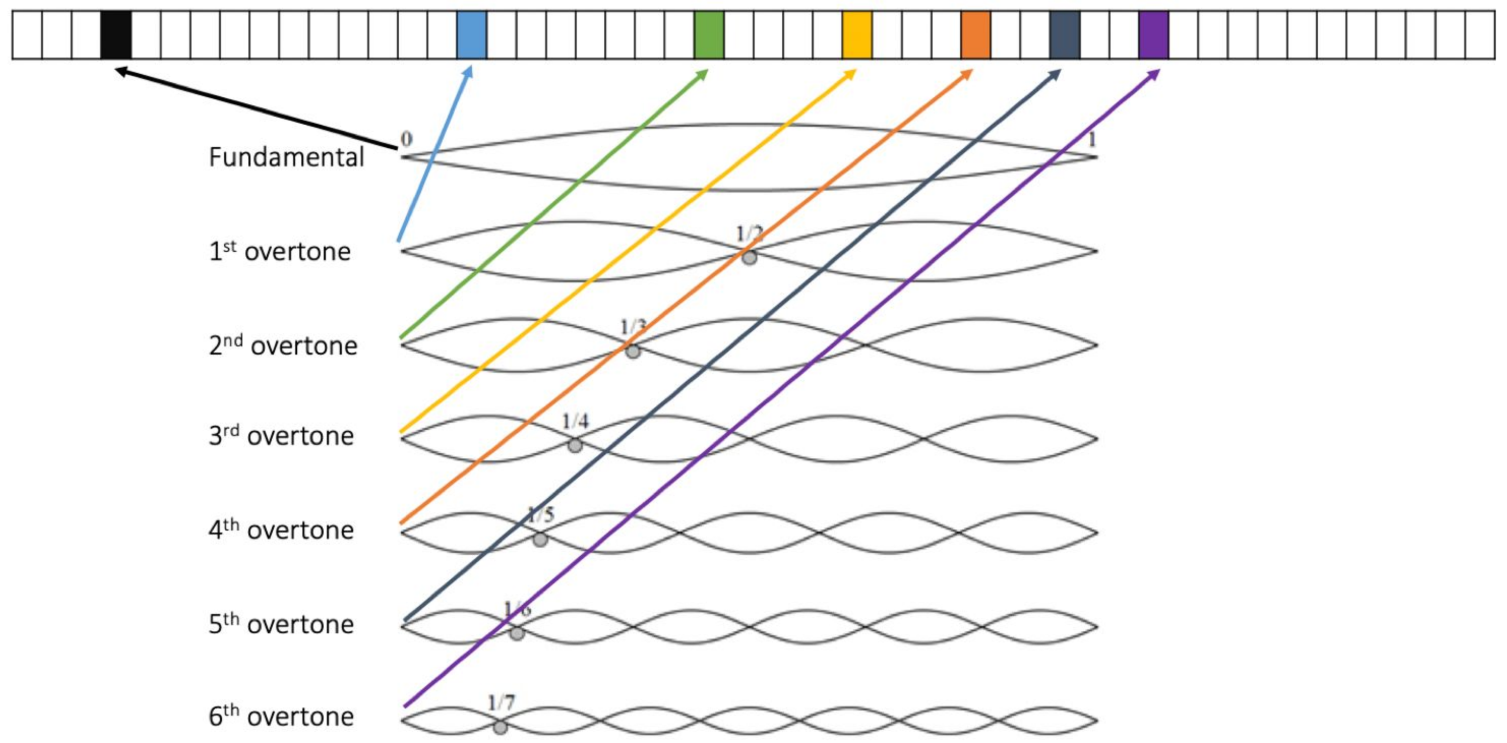


Image from the Music Transformer with Long-Term Structure

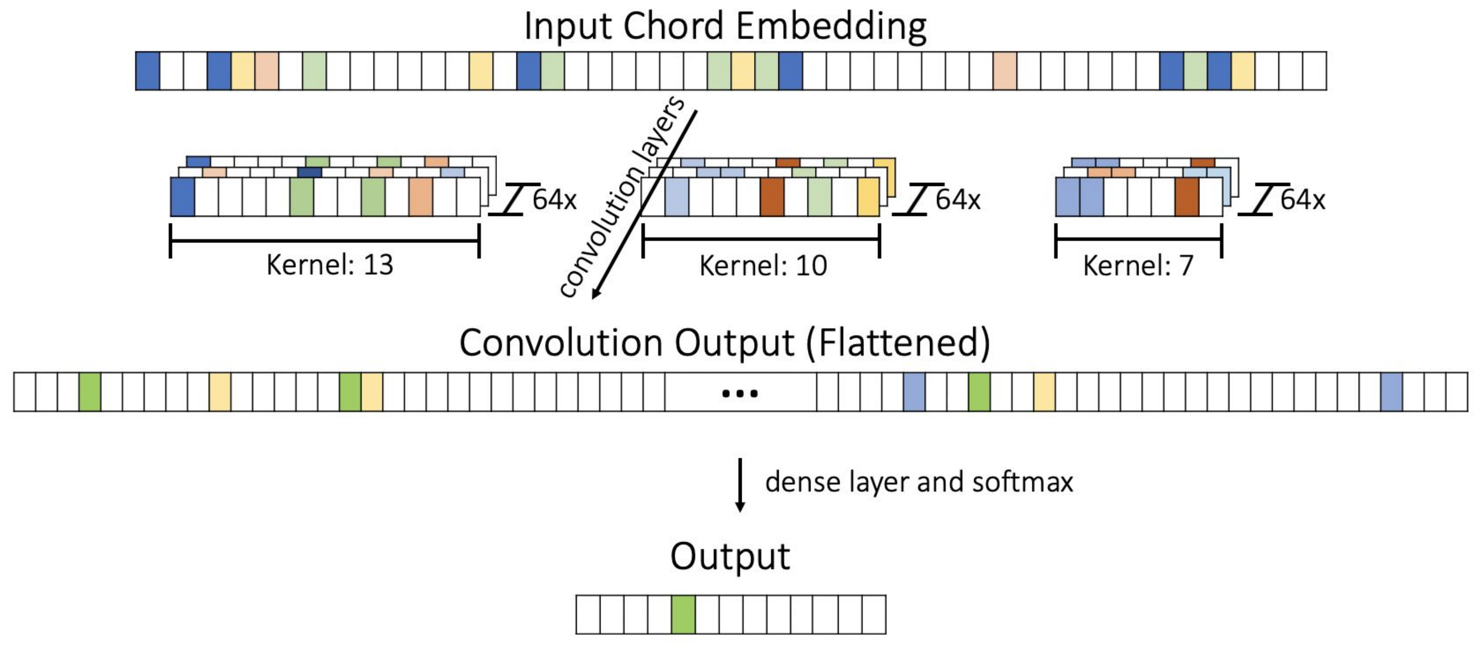
Models

Simultaneous Note2Vec and Chord2Vec



- Combine music theory and physics of sound to embed each “note” as a combination of its fundamental frequency and its overtones
- Chords are superpositions of notes and therefore their embeddings are the arithmetic mean of their constituent notes’ embeddings

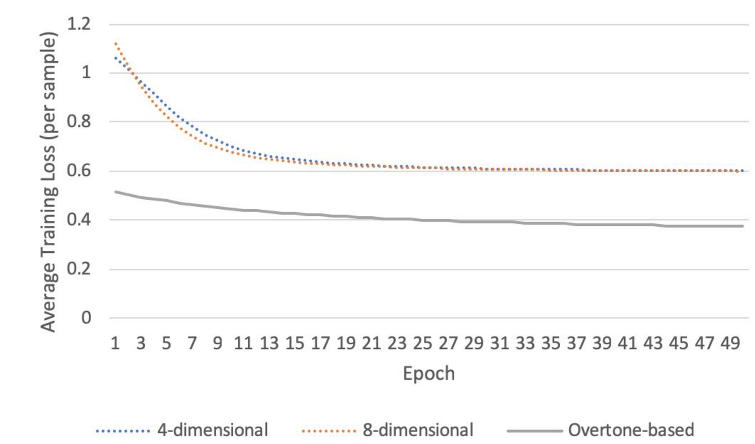
Chord Classification

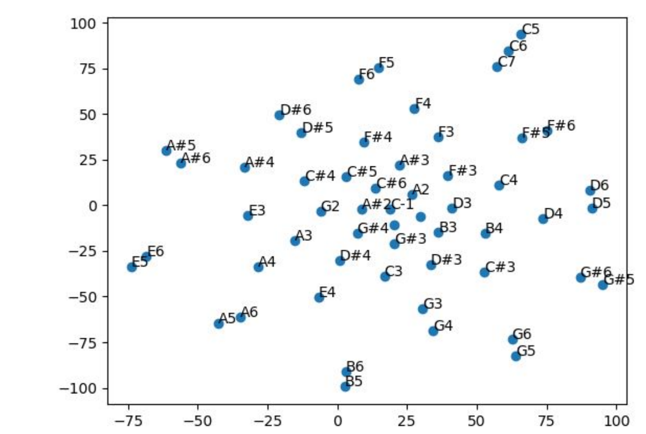


2-layer classification of chords to demonstrate the power of the embeddings:

- Convolutional layer: 3 kernels of size 13, 10, and 7, each with 64 channels to identify spatial patterns in the embeddings
- Dense layer: generates probabilities for each class

Results





- The figure above records the average training loss of 4-dimensional, 8-dimensional, and overtones (91-dimensional) embeddings.
- The Note2Vec with overtones embeddings have the lowest training loss.
- The TSNE plot of chord embeddings above clusters notes with similar names and octaves together.
- Notes octaves and fifths away have very similar cosine distance.

	Major/Minor	Root Note Name
Baseline Embeddings (Train Accuracy)	100%	100%
Baseline Embeddings (Test Accuracy)	81.1%	84%
Chord2Vec Embeddings (Train Accuracy)	100%	100%
Chord2Vec Embeddings (Test Accuracy)	100%	97.7%

- The table above shows the training and testing accuracies of our chord classification.
- Chord2Vec Embeddings have a significantly higher test accuracy in both classifications.

3 Closest Notes to Focus Notes

	C5	G4	D#3	F#5
Baseline Counts	G5, C4, G4	G5, D5, C5	A#4, D#5, G4	D5, A5, D4
Note2Vec	C#5, D#3, G#5	G6, G2, D#4	C7, C#3, C#6	D#6, A3, A#3
Note2Vec with Overtones	C4, C6, G6	G5, G3, E4	D#4, F#3, C3	F#4, F#6, C#6

- The table above records the three closest notes to each focus note (C5, G4, D#3, F#5).
- Note2Vec with Overtones is able to categorize notes octaves and fifths away as close, so it has learned basic music theory concepts.

Summary and Future Work

- Simultaneous embeddings for notes and chords in music
- Use embeddings in music transformer system to generate even better music