Pop Music Hook Generation Using Neural Networks

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In a Nutshell

I trained a neural network to **output eight-measure musical hooks in lead sheet form** using a dataset of U.S. contemporary pop music.

I took one output example from my model, made some tweaks, and **turned it into a full-length pop EDM track, “Will You Learn”.**

Motivation and Goals

Lyrics from “Will You Learn”

They tellin’ me you can learn anything

Drive a car, paint a picture, show the next thing I see

On my feed, babe if you can do all that

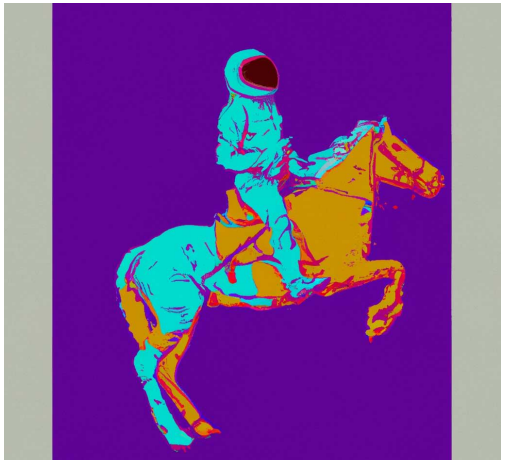
Maybe you can write for me a tune that slaps

Motivation: machine learning is becoming increasingly ubiquitous in our world.

“Drive a car”

Tesla Autopilot

“Paint a picture”



DALL-E 2: “an astronaut riding a horse in the style of Andy Warhol”

“Show the next thing I see on my feed”

Facebook News Feed

Project Goals

Design a deep learning-based program for generating eight-bar pop music hooks.

Investigate the capabilities of deep learning technology and use it to create a compositional tool for songwriters/producers.

Crash Course in Neural Networks

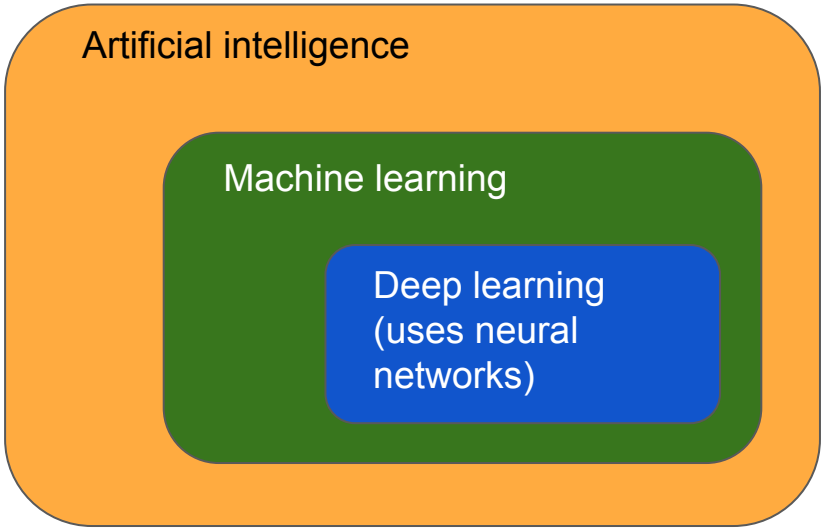
Clarifying Key Terms

Artificial intelligence (AI): any intelligent behavior exhibited by a machine

Machine learning (ML): using lots of data to train AI in machines

Neural network (NN): specific type of computational model used for ML

Deep learning (DL): ML using neural networks (often multiple network layers)



The mathematical foundation of NNs is *linear regression.*

Example: given the **square footage** of a house, determine its **price**


```
price = b + m * (sq. footage)

y     = b + m * x

h(x)  = b + Θx
```

Goal: "tune" the values of b and Θ to best fit the real-world data
(gradient descent etc.)

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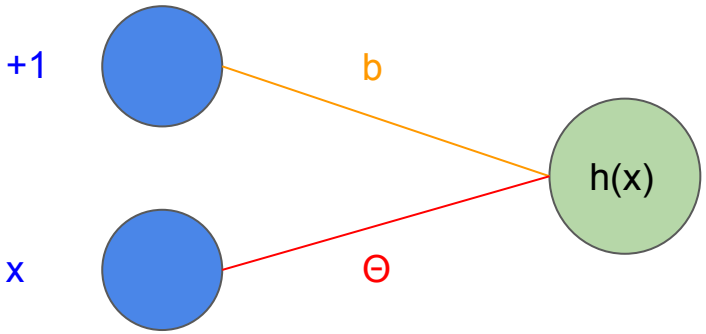
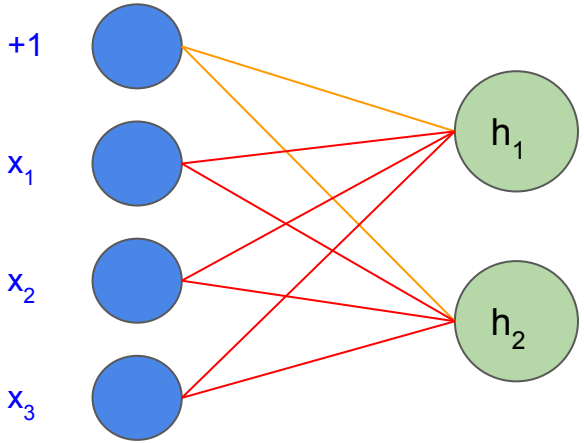


$$h(x) = b + \Theta x$$

The mathematical foundation of NNs is ***multivariate*** *linear regression.*

Example: given the **square footage**, **# bedrooms**, and **age** of a house, determine its **price** AND **average length of homeownership**

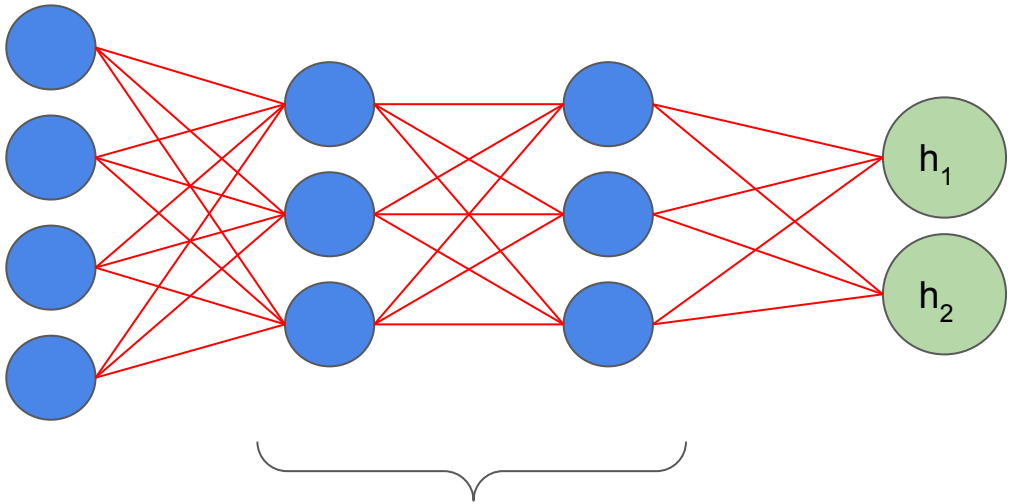


$$h(x) = b + \Theta x$$

h, b, and x are vectors. Θ is a 2 x 3 matrix

Goal: "tune" the values of b and Θ to best fit the real-world data

You can add multiple layers to the network! (This is deep learning.)



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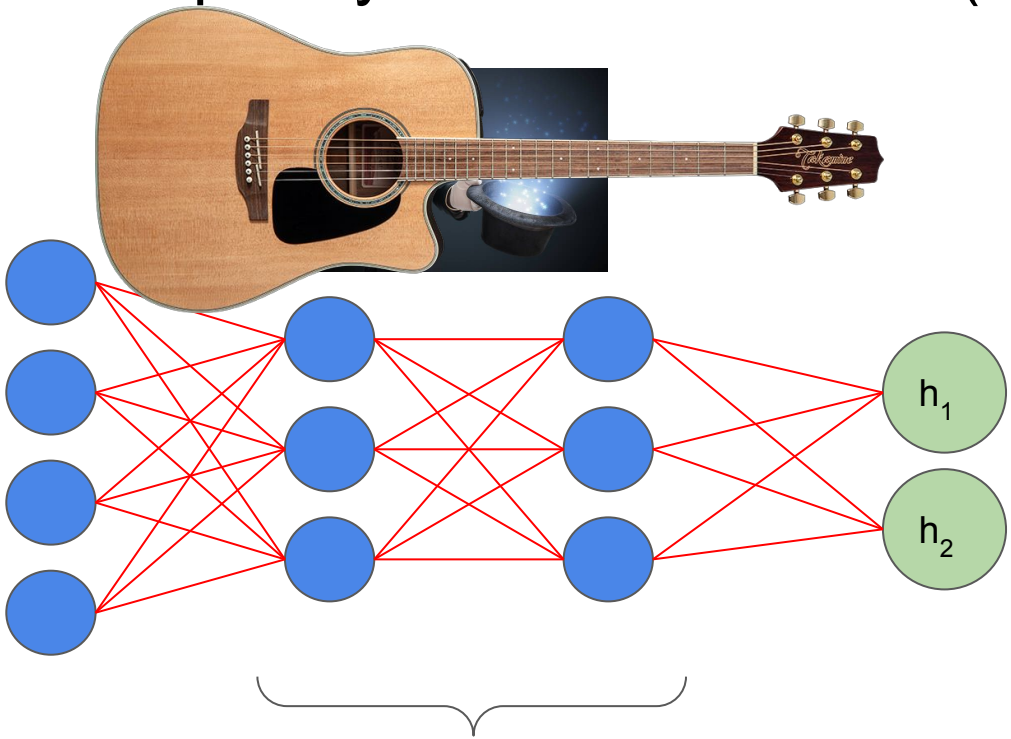
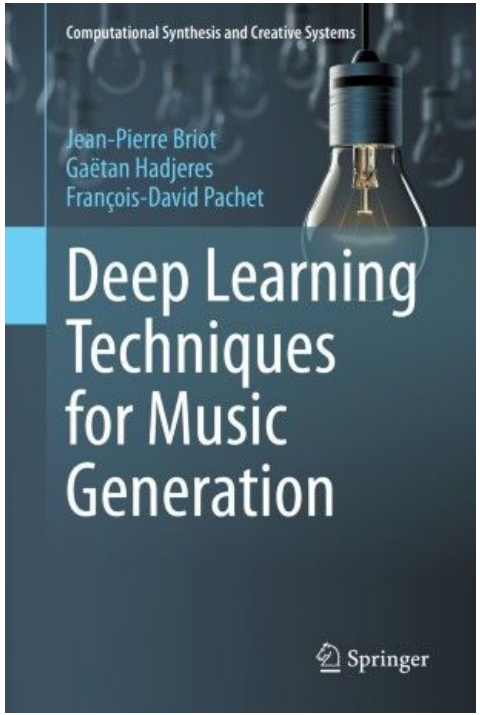


Problem Context and Related Work

DL-based music generation is still in its infancy.



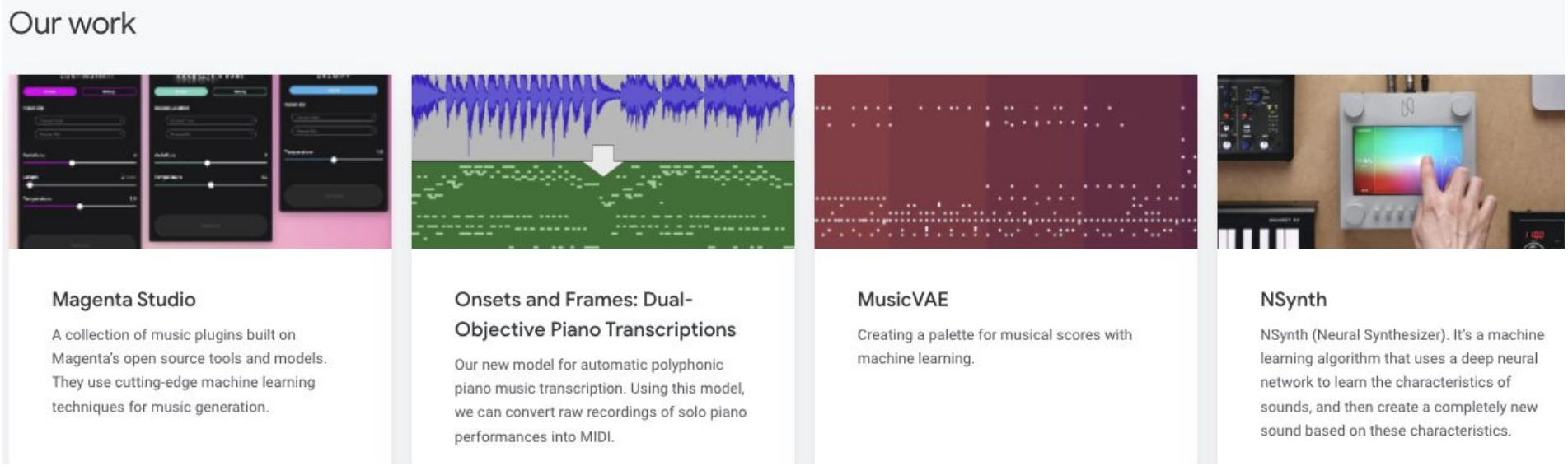
First comprehensive lit review of deep learning-base music generation.

Motivated out of “the lack … of a comprehensive survey and analysis of this active research domain” (p. 6)

Published in 2020! (Earlier draft in 2017)

DL-based music generation is gaining popularity.

Google Magenta: “an open source research project exploring the role of machine learning as a tool in the creative process.”



Current literature spans a wide range of generation objectives.

- Lead sheet generation
  - C. De Boom, S. Van Laere, T. Verbelen, and B. Dhoedt, “Rhythm, chord and melody generation for lead sheets using recurrent neural networks,” Machine Learning and Knowledge Discovery in Databases, pp. 454–461, 2020.
- Generating variations on a theme
  - P. Roy, A. Papadopoulos, and F. Pachet, “Sampling variations of lead sheets,” arXiv preprint arXiv:1703.00760, 2017.
- Generation of chords/harmony given an input melody
  - Y.-C. Yeh, W.-Y. Hsiao, S. Fukayama, T. Kitahara, B. Genchel, H.-M. Liu, H.- W. Dong, Y. Chen, T. Leong, and Y.-H. Yang, “Automatic melody harmonization with triad chords: A comparative study,” Journal of New Music Research, vol. 50, no. 1, pp. 37–51, 2021.
- MIDI performance generation (including note velocities and micro-timings)
  - S. Oore, I. Simon, S. Dieleman, D. Eck, and K. Simonyan, “This time with feeling: Learning expressive musical performance,” Neural Computing and Applications, vol. 32, no. 4, pp. 955–967, 2020.
- Raw audio waveform generation
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Narrowing the Problem Scope

I only consider U.S. contemporary pop music.

Specifically, I only consider a subset of U.S. pop with certain attributes:

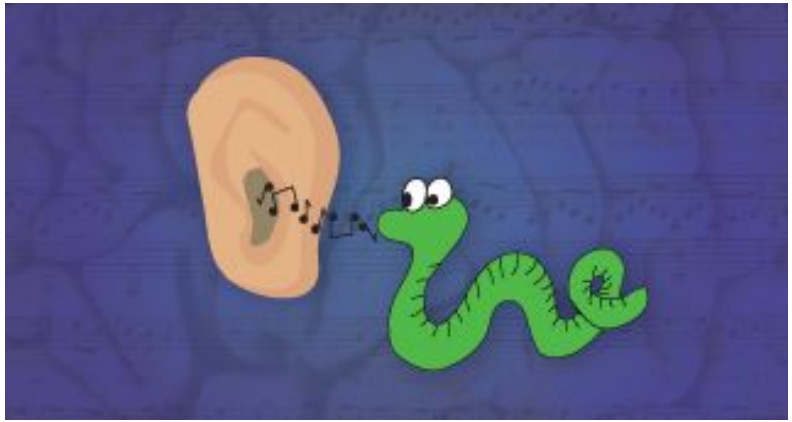
- 4/4 time
- No changes in meter or key signature
- Features prominent melodic component
- Melody range < 2 octaves
- Other attributes (stay tuned!)

I only consider *hooks*, not entire songs.

Working definition: eight-bar self-contained unit of pop music with a memorable tune, usually synonymous with chorus***

Long-term structure is difficult to learn.

Hooks are meant to be catchy, so they are a high-impact area to focus on.

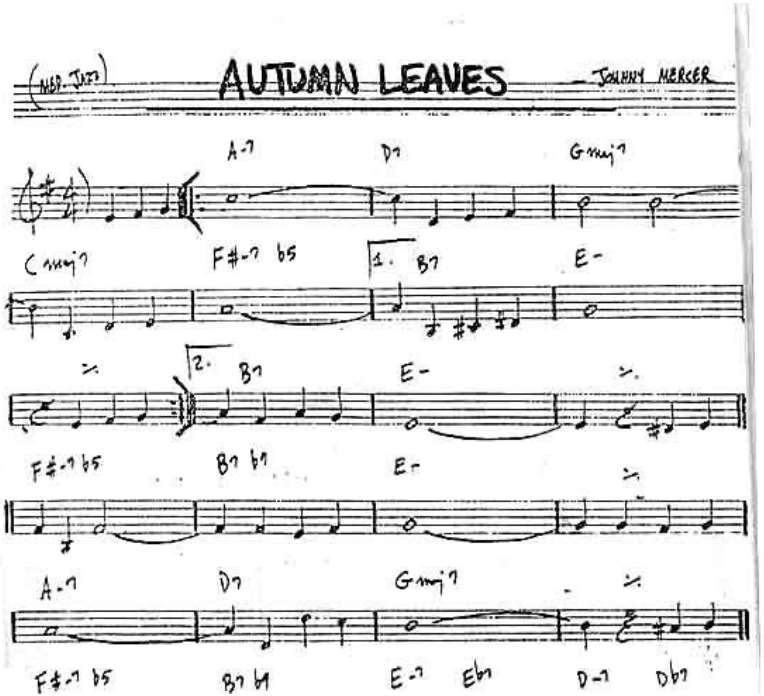


I represent hooks in a symbolic lead-sheet-like form.

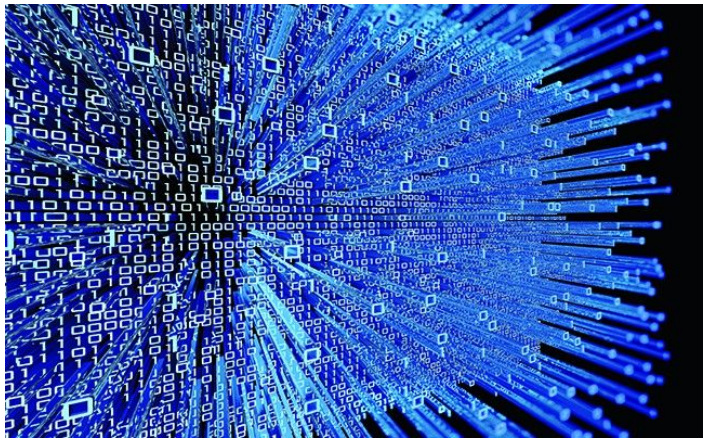
Two streams: melody and chords

Less parameters for DL model to learn

Encodes essential musical information while leaving room for personal creativity

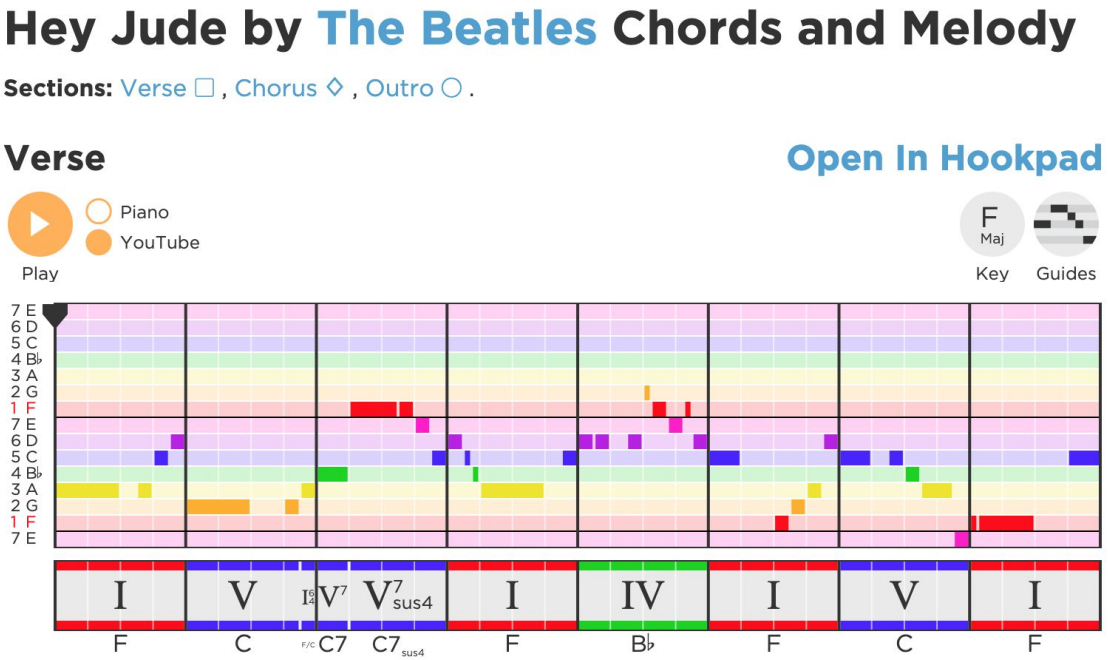


Dataset



HookTheory TheoryTab Database

More than 30,000 user-submitted snippets of music from a wide range of genres.



HookTheory TheoryTab Database

Advantages:

- Music is already pre-partitioned into sections like intro/verse/chorus/bridge.
- Music is already in lead-sheet-like form (i.e. melody and chords).
- Database is up-to-date with respect to U.S. pop.





HookTheory TheoryTab Database

Only hooks tagged under the “pop” genre were considered.

4,338 pop hooks in JSON format were obtained after web-scraping.

Imported into Google Colaboratory dev environment.

Description of Final Model

Preprocessing Steps

- Only keep hooks that stay in a single key, and standardize all keys to C.
- Only keep hooks in 4/4 time.
- Only keep hooks containing both melodies and chords.
- Only keep hooks with melody range < 2 octaves.
- **Ignore all rests (except for pickup rests)**
- **Simplify all chords to their root triadic forms.**
- **Modulo all note values to fit into a one-octave range (ouch!)**

Raw web-scraped dataset size: **4338**

Sanitized dataset size: **2917**

Dataset Encoding

A hook is a sequence of musical **events**.

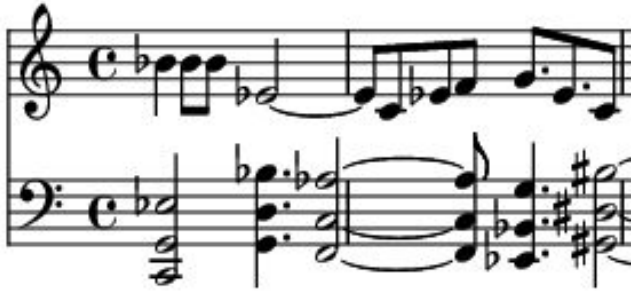
An **event** is the beginning of a note, the beginning of a chord, or time step 0.

Each event encodes four pieces of information: **note**, **chord**, **duration**, and **“position”**.

Special case:

1. If the next event is a new chord and the previous note is held, the note is *marked as “hold”.* (Unlike De Boom et al.)

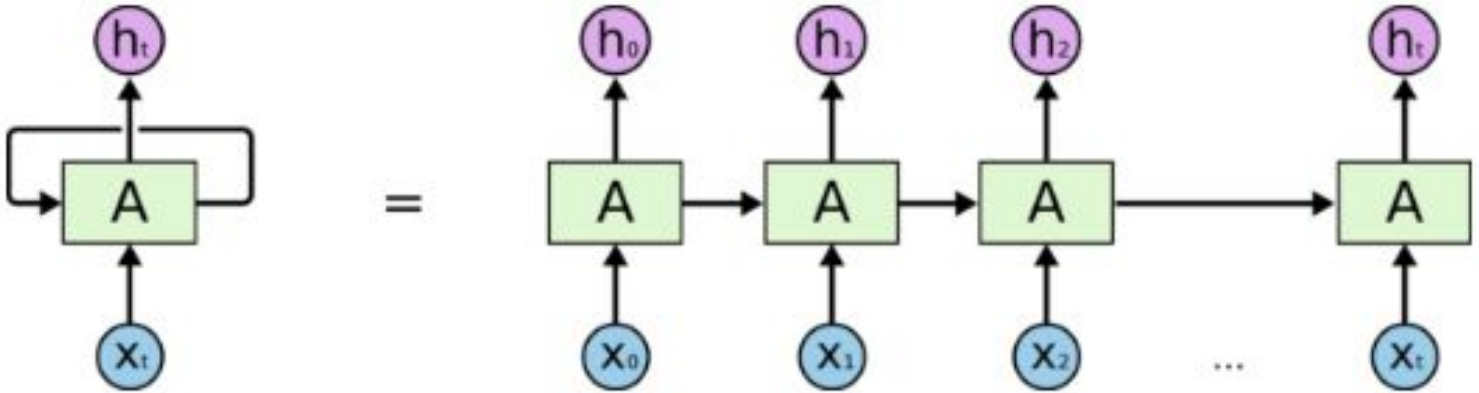
“I’m Coming Out” by Diana Ross



i	n_i	c_i	d_i	p_i
1	B♭4	C-min	4	0 (0000)
2	B♭4	C-min	2	4 (0100)
3	B♭4	C-min	2	6 (0110)
4	E♭4	G-min	6	8 (1000)
5	hold	F-min	4	14 (1110)
6	C4	F-min	2	2 (0010)
7	E♭4	F-min	2	4 (0100)
8	F4	F-min	2	6 (0110)
9	G4	E♭-maj	3	8 (1000)
10	E♭4	E♭-maj	3	11 (1011)
11	C4	A♭-maj	2	14 (1110)

Model Definition and Training

Recurrent Neural Networks (RNNs): NNs with **memory**



An unrolled recurrent neural network.

Model Definition and Training

Basic idea: given a input sequence of length *n*, predict the next item in the sequence.

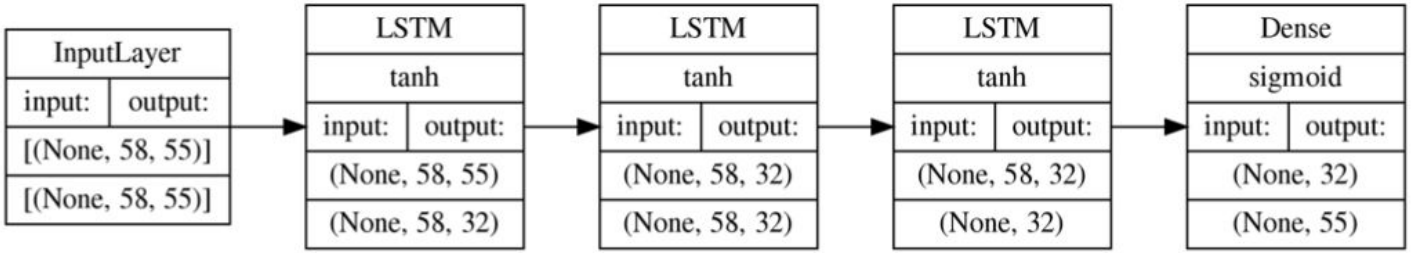
Sequences of events were split into **input** and **output** pairs.

Example: consider a hook with events *a, b, c, d, e, f, g.* Assuming ***n* = 3**:

- Inputs: (*a*, *b*, *c*) (*b*, *c*, *d*) (*c*, *d*, *e*) (*d*, *e*, *f*)
- Outputs: *d* *e* *f* *g*

For this project: ***n* = 58** (somewhat arbitrary)

Model Definition and Training



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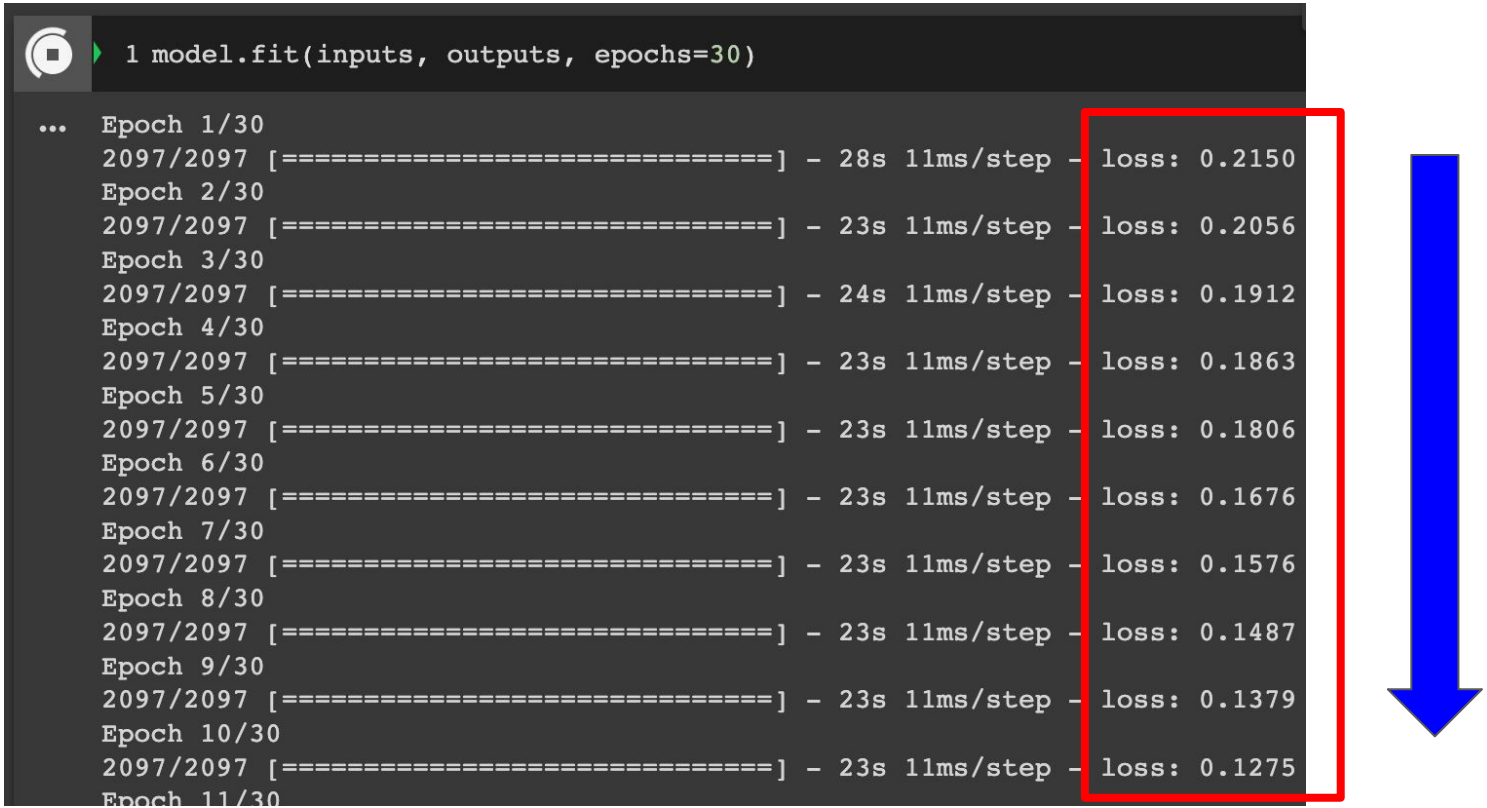


Music Generation Strategy

Simplified schematic, assuming *n* = 3:

```
Seed input: a, b, c
Prediction: δ
Input:      b, c, δ
Prediction: ε
Input:      c, δ, ε
Prediction: ζ
```

Generated hook:

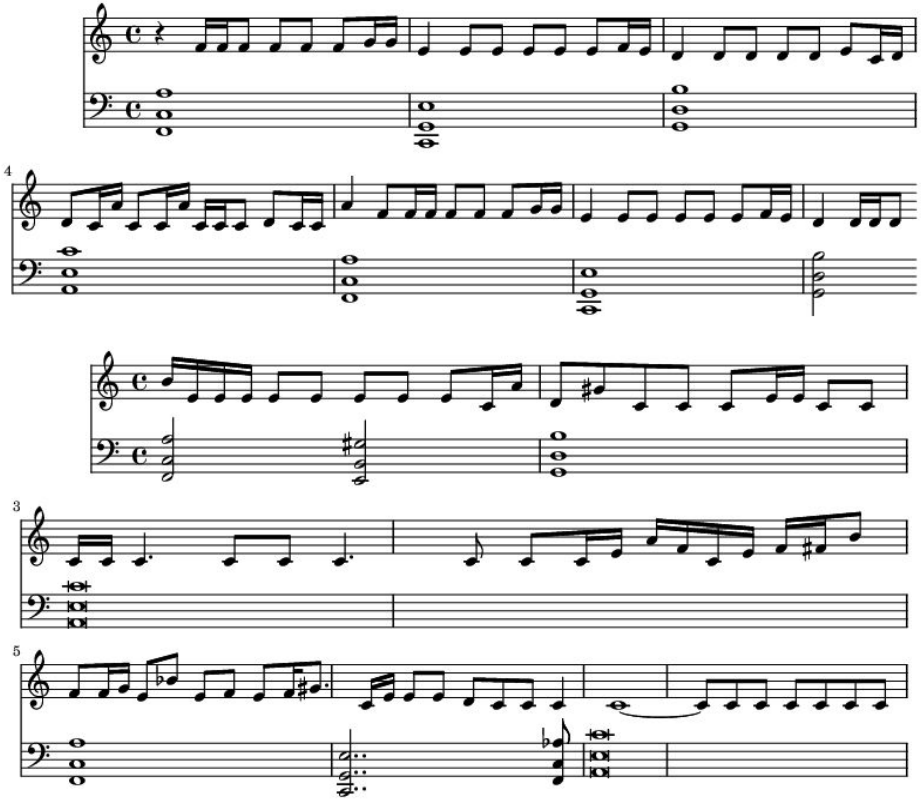
δ

ε

ζ

Etc. etc.

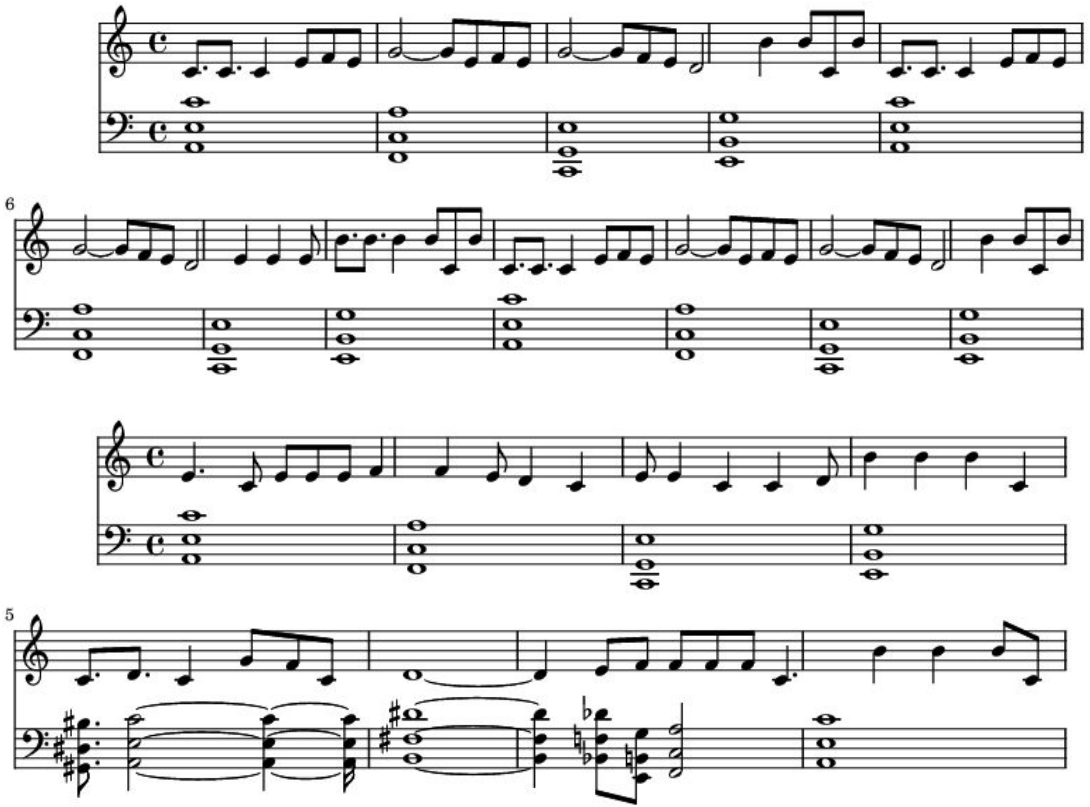
Generation Demo



Seed: “Umbrella” by Rihanna

Generated hook

Generation Demo



Seed: “A Sky Full Of Stars” by Coldplay

Generated hook

Analysis

Positive attributes

- The rhythms are realistic.
- Chord changes are particularly convincing (at least compared to previous models).
- The generated hooks appear to capture the harmonic and rhythmic essence of the seed without plagiarizing.

Negative attributes

- The output tends to get “lost” as the hook progresses
- The model still chooses funky/atonal notes and chords somewhat regularly.

Plagiarism Checker

Plagiarism Checker Algorithm

Remove durations and repeated notes in all melodies and encode as a sequence of integers.

- Example: Chorus of “Hey Soul Sister” by Train
- [7, 4, 2, 0, 7, 4, 2, 0, 2, 4, 0, 4, 0, 4, 2, 9, 0]

Use Python `SequenceMatcher` algorithm to compare melody in question against all melodies in the database.

Sort and print results.

What is plagiarism? Also why only melodies?

Song Example: “Will You Learn”

Using generated hook from “Sky Full Of Stars” seed (with some tweaks).

Produced and mixed with Logic.

Special thanks to **Claudia Humphrey ‘22** for her outstanding vocal talent (which vastly outshines my painfully mediocre songwriting abilities).

Discussion

Takeaways

When working with complex data like music, **encoding is the hardest part.**

Having **musical intuition** makes encoding easier.

Finding a **suitable dataset** can be challenging.

For music, the process of evaluating a model's output will necessarily be **more qualitative**.

Because neural networks are intrinsically **difficult to understand**, they are more **difficult to tweak**.

Future Work

Increase **dataset size**.

Try **different architectures/approaches**.

- Markov model, transformer architecture, etc.

Package into user-friendly **app interface**.

Add **user-selectable options**.

- Genre selection
- Type of hook (intro/verse/chorus/etc.)

Acknowledgements

Image Sources

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Thank you!