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PhD Thesis
The Neural Substrates of Expertise and Flow Among Jazz Guitarists

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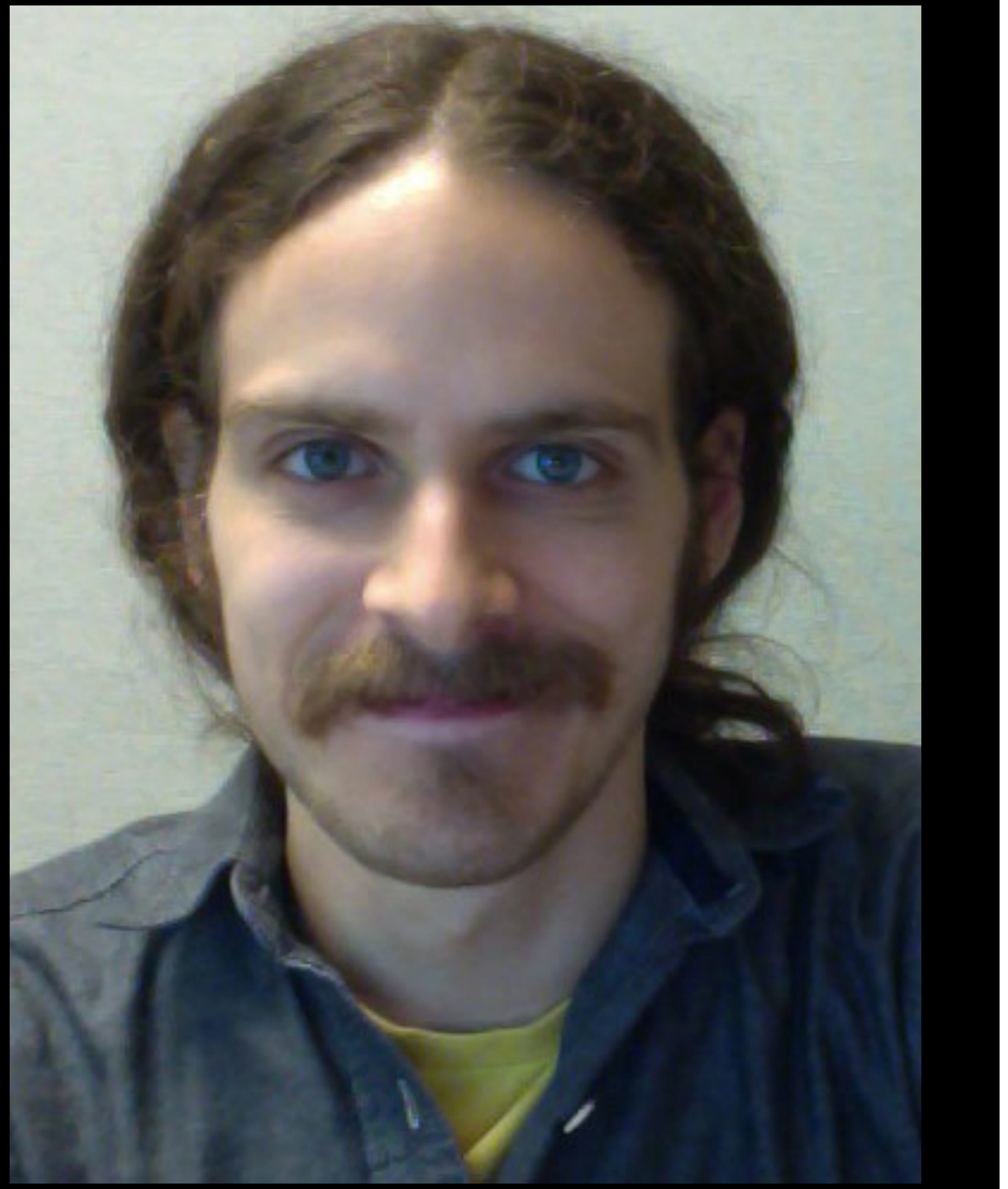

Jeff
Gregorio

Learned Timbral Controllers for Augmenting Parametric Synthesizer Interfaces

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Background

Feature-based synthesis applies machine learning and signal processing methods to the development of alternative interfaces for controlling parametric synthesis algorithms. One approach, geared toward real-time control, uses low dimensional gestural controllers and learned mappings from control spaces to parameter spaces, making use of an intermediate latent timbre distribution, such that the control space affords a spatially-intuitive arrangement of sonic possibilities. This work attempts to address questions regarding user experience in such systems, including the accuracy of user mental models, and how these techniques can be integrated in a way that simplifies interaction for novices while affording new abilities to experts without encumbering existing modes of interaction.

Proposed System

- Though others have explored learned many-to-many mappings from control spaces to parameter spaces based on timbre [1][2], such interfaces necessarily supplant traditional one-to-one interfaces due to the lack of integration between the two spaces.
- One system integrates the two, but uses no timbral arrangement of the control space. [3]
- The proposed system uses an invertible mapping layer allowing inference of parameter values from control space coordinates, but also ensures updates made in parameter space (using the one-to-one interface) can project into the control space, which provides strong visual intuition for the equivalence of the two spaces.

Deep Latent Gaussian Model

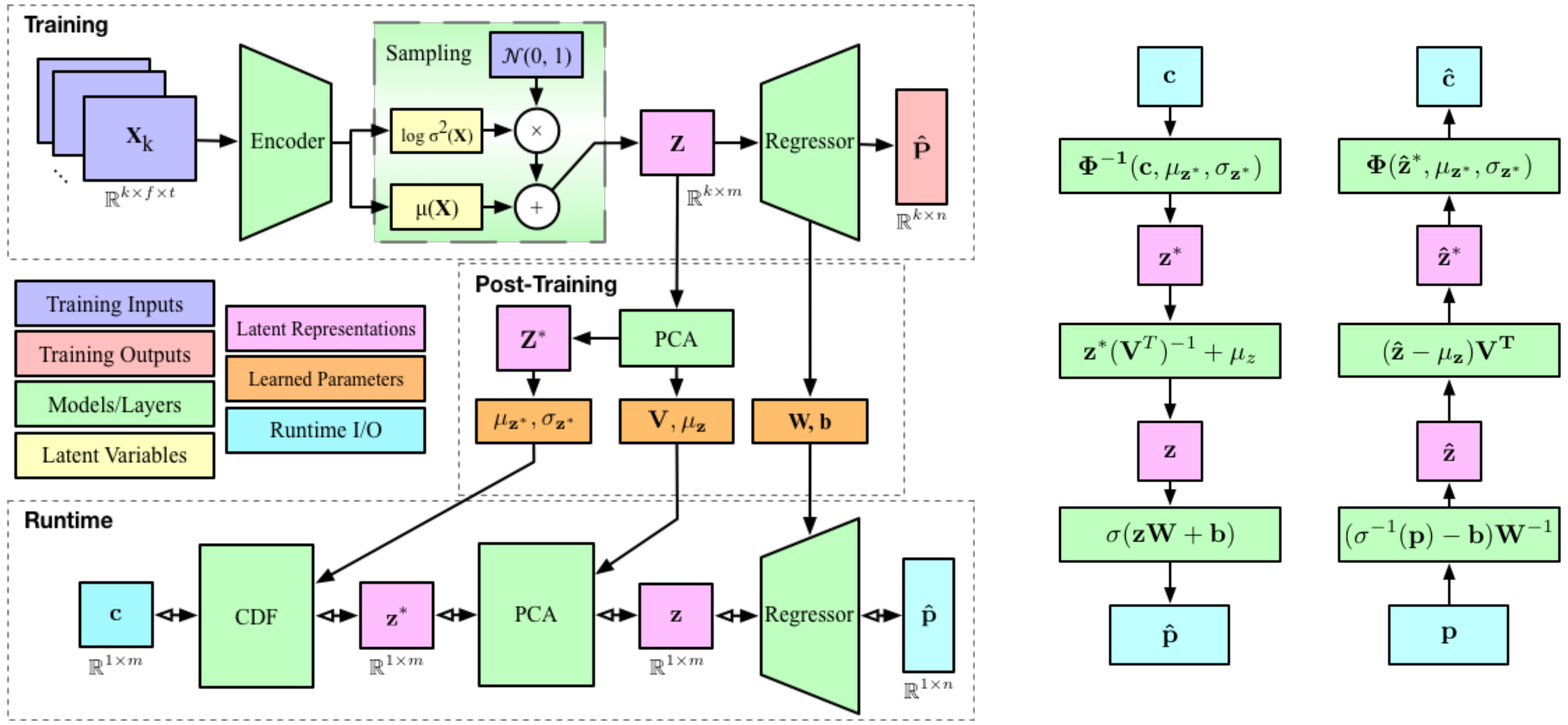

Figure 1: (Left) Overview of system during training and runtime. Encoded training examples are used to predict known parameter values. Training yields a normally-distributed latent encoding with predictive dimensions. Post-training, principal component analysis (PCA) re-orients the latent space and parameters are exported. (Right) Invertible runtime mapping model, consisting of (top to bottom) a uniform to normal scaling layer (using the normal CDF), PCA projection, and a dense layer.

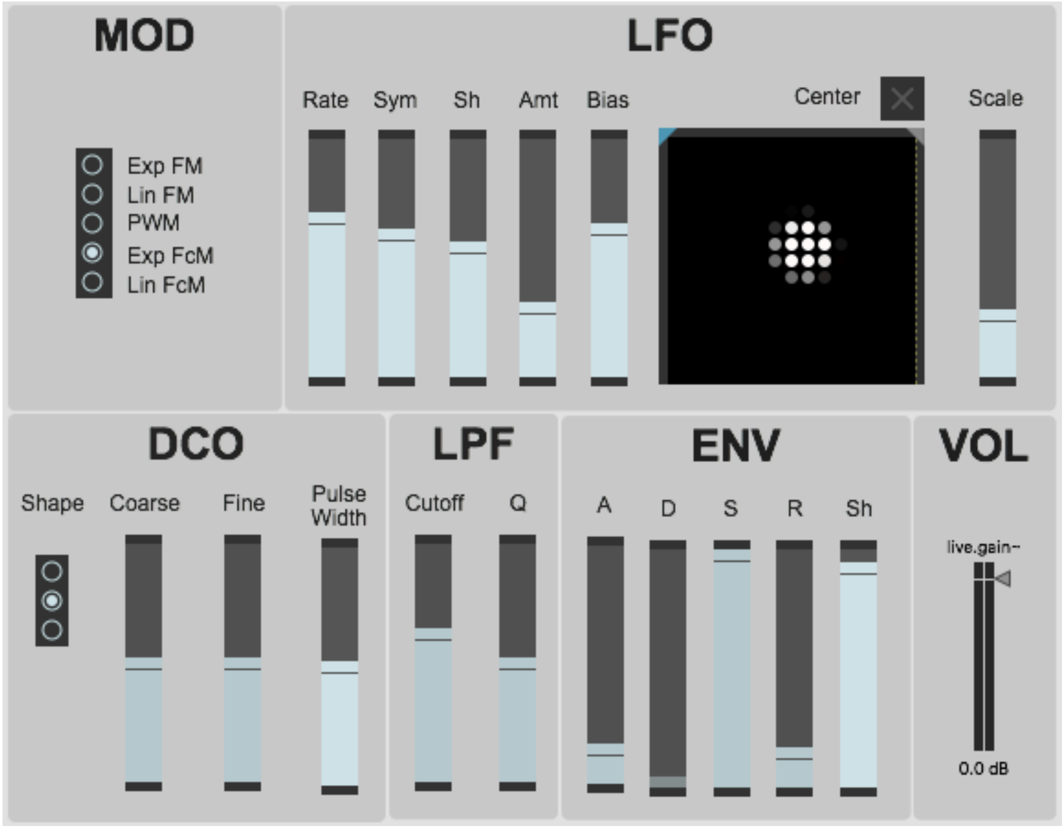

Figure 2: Example application using a 3D controller to control a 5D low-frequency oscillator (LFO).

Future Work

- While unimodal latent space constraints suffice for low-dimensional synths, multimodal latent spaces modeled by Deep Latent Gaussian Mixture Models (DLGMMs) may be more appropriate for high-dimensional synths, whose latent spaces are over-regularized by the current system.
- A systematic evaluation is needed to address whether the visual equivalence of parameter and control spaces is necessary to accurately understand the system, and whether control and parameter spaces support different modes of creation and ranges of synthesis expertise. We plan on conducting a user study consisting of open-ended exploration, musical tasks, and user interviews.

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[1] M. D. Hoffman and P. Cook. Feature-based synthesis: A tool for evaluating, designing, and interacting with music ir systems., 01 2006.

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[3] R. Tubb and S. Dixon. A zoomable mapping of a musical parameter space using hilbert curves. Computer Music Journal, 38:23–33, 2014.

Shaun

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InfoWaveGAN: Informative Latent Spaces for Waveform Generation

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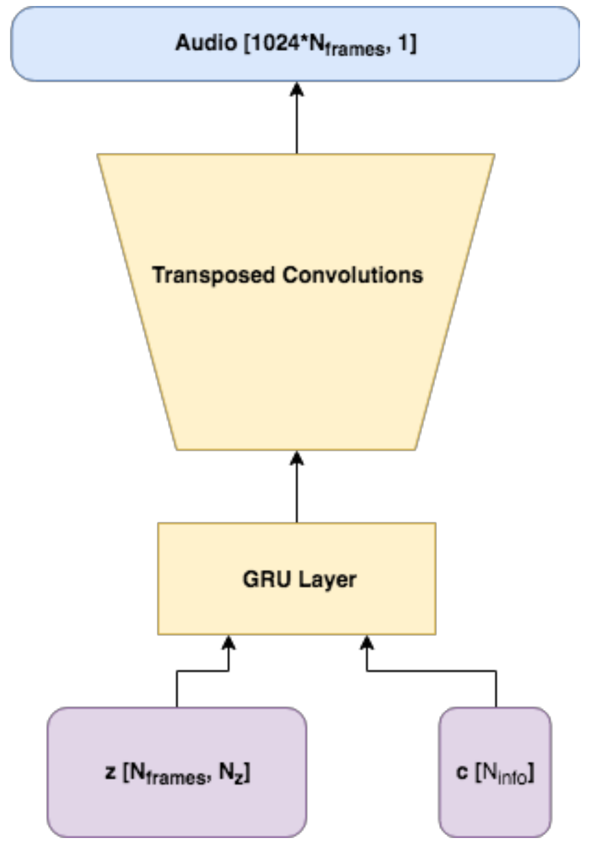
Introduction

While autoregressive generative models for waveform audio trained on musical datasets achieve high fidelity results, there is still a question of how to design these model to make them more expressive from the user end? One approach to achieving this is the use of conditioning on both local (time-varying) variables like MIDI and global variables such as instrument or genre. However, this requires well-annotated musical datasets. We approach this problem by using using information theory to learn informative latent variables. We look at extending the capabilities of WaveGAN [1] to be able to generate any length of time, achieve high-fidelity results, and have powerful conditional variables learned without any labels.

Methods

Generating any length of audio

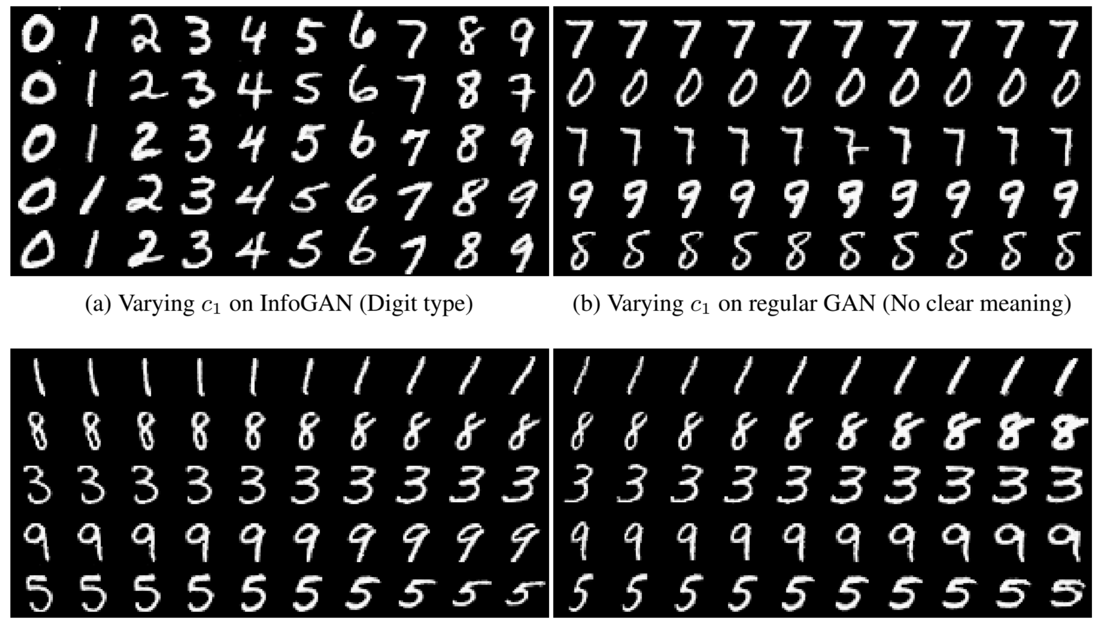
We propose using a recurrent layer as the first layer of the network to replace the dense layer in WaveGAN. This allows us to model the input to the network, **z**, as a (N_{frames} x N_z) matrix rather than an 1x N_z vector. In training, we use N_{frames} = 16 to generate 16384 samples, corresponding to 1.024 seconds at a sampling rate of 16 kHz. At test, however, we use any integer N_{frames} to generate a 1024* N_{frames} long sample of audio. This extends the capabilities of the network after training by exploiting the statefulness of the recurrent layer.



Model Diagram for improved WaveGAN with learned global conditioning

InfoGAN

InfoGAN [2] extends the standard GAN model by proposing a method for learning latent codes, **c**, that follow any distribution (Gaussian, Uniform, Categorical, etc.) that are appended to the standard, non-informative latent variable, **z**. They argue that these latent codes should have an impact on the generated images by maximizing mutual information between the learned codes and generated images, **I(c, G(z,c))**. Since this is intractable, however, they use variational inference to estimate the lower bound of mutual information.



(a) Varying c_1 on InfoGAN (Digit type)

(b) Varying c_1 on regular GAN (No clear meaning)

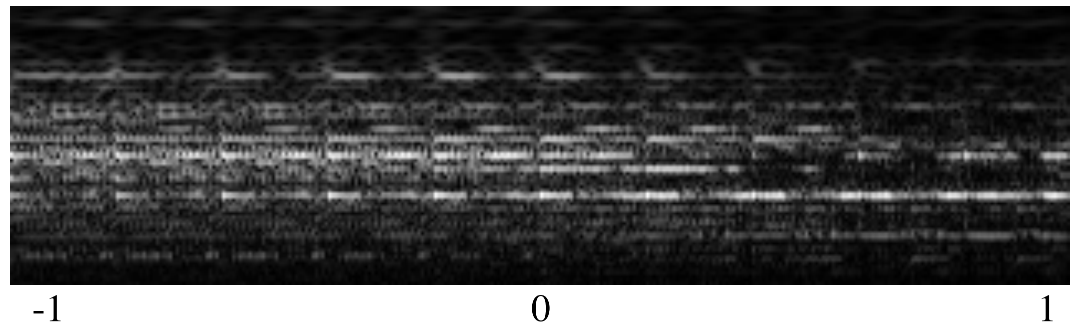
(c) Varying c_2 from -2 to 2 on InfoGAN (Rotation)

(d) Varying c_3 from -2 to 2 on InfoGAN (Width)

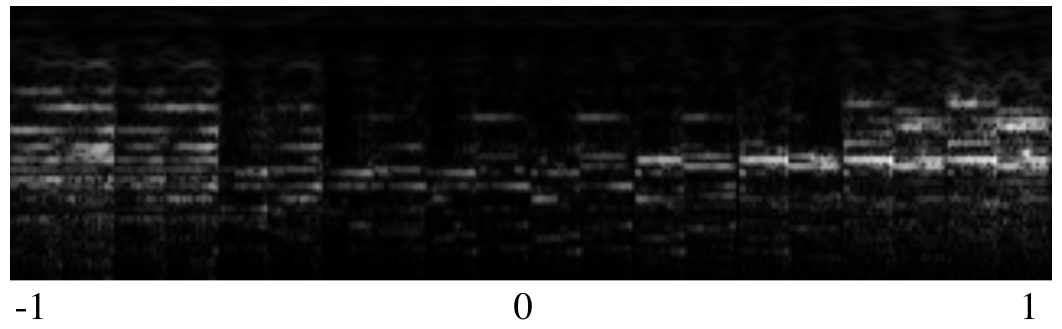
InfoGAN with categorical and continuous latent variables trained on MNIST

Results

We trained a network that had multiple continuous variables together and one categorical variable on the MAESTRO dataset. This dataset features over 80 hours of professional piano playing. From early results, the model is able to separate piano playing on the lower register from the higher register and levels of reverb, sustain pedal usage, and volume as features. Further experiments are required to confirm this algorithm generalizes well to other types of datasets.



Varying a Uniform continuous latent variable from -1 to 1 increased sustain and removes higher frequencies.



Varying a Gaussian continuous latent variable from -1 to 1. Magnitude is amplitude, and phase is related to harmony

Future Work

Better Quality Generation

We hope to attempt other GAN training algorithms like Progressive growing GANs to see if it is possible to get competitive results with autoregressive models. Alternatively, it may be possible to use an auto-regressive model that learns latent codes using mutual information.

Local Conditioning

We would like to explore using both ground truth labels and learned variables together. Ideally, figuring out a way to extend this method while conditioning on MIDI data, letting the learned codes focus on non-labels features such as reverb and sustain.

References

[1] Donahue, Chris, Julian McAuley, and Miller Puckette. "Synthesizing Audio with Generative Adversarial Networks." arXiv preprint arXiv:1802.04208 (2018).

[2] Chen, Xi, et al. "Infogan: Interpretable representation learning by information maximizing generative adversarial nets." Advances in neural information processing systems. 2016.

APA

Andy Wiggins

Automatic Guitar Tablature Transcription with Convolutional Neural Networks

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Motivation

Guitarists commonly use tablature notation to learn and share music. As it stands, most tablature is created by an experienced guitarist taking the time and effort to annotate a song. As the process is time consuming and requires expertise, we are interested in automating this task. Previous approaches to automatic tablature transcription [1, 3] break the problem into two discrete steps: 1) polyphonic pitch detection followed by 2) tablature fingering estimation. Using a convolutional neural network (CNN) model, we can learn a mapping directly from audio data to tablature. The model can simultaneously leverage physical playability constraints and differences in string timbres to determine the actual fingerings being used by the guitarist. We propose TabCNN, a convolutional neural network for transcribing guitar tablature from audio of a solo acoustic guitar performance.

TabCNN

Model: TabCNN is a convolutional neural network that takes as input an image representing a short window of isolated guitar audio and outputs a probability mass function for each string's fret classification. (See model architecture in *Figure 1* below.)

Dataset: We use the GuitarSet dataset [2], which contains acoustic guitar performances in a variety of musical keys and playing styles. The dataset's string-wise pitch annotations are sampled to produce ground truth tablature labels.

Preprocessing: The audio is segmented into 200ms clips. Each clip is downsampled to 22050Hz, and then the magnitude Constant-Q Transform (CQT) is computed, with 24 frequency bins per octave, spanning 8 octaves. Using a CQT reduces dimensionality and offers linearity in time and pitch, which can be can be exploited by the model's convolutional layers.

Training*:* We train the model for 30 epochs using a 6-dimensional categorical cross-entropy loss function. Dropout regularization is used to reduce overfitting.

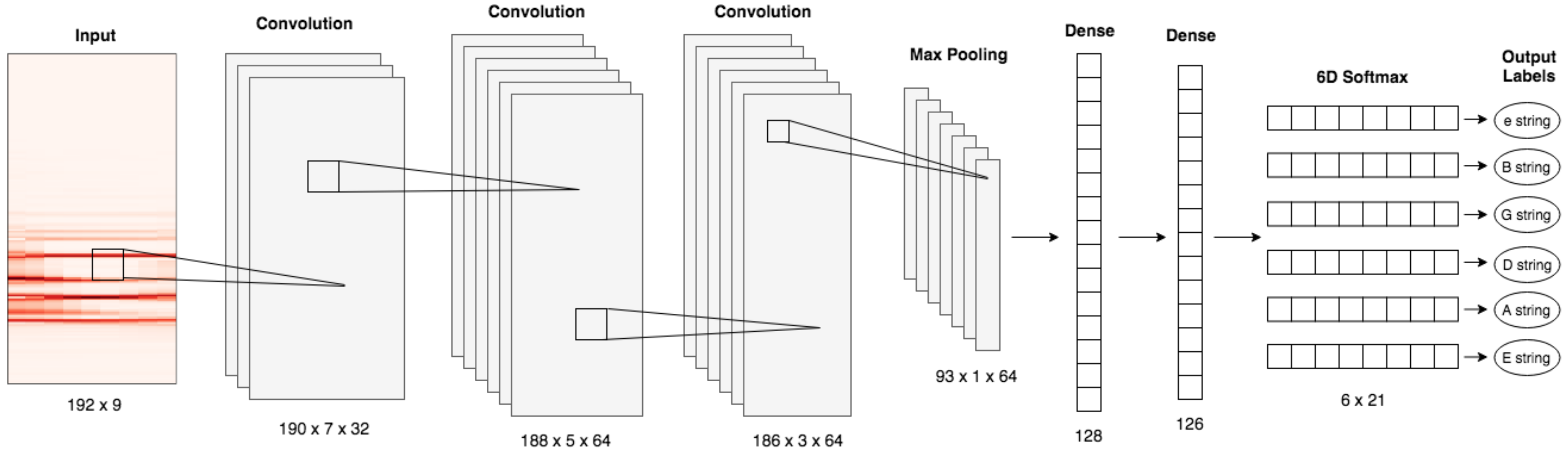


Figure 1: The TabCNN model architecture.

Input: The inputs are 192 (frequency bins) x 9 (time frames) CQT images, representing 200ms of isolated acoustic guitar audio.

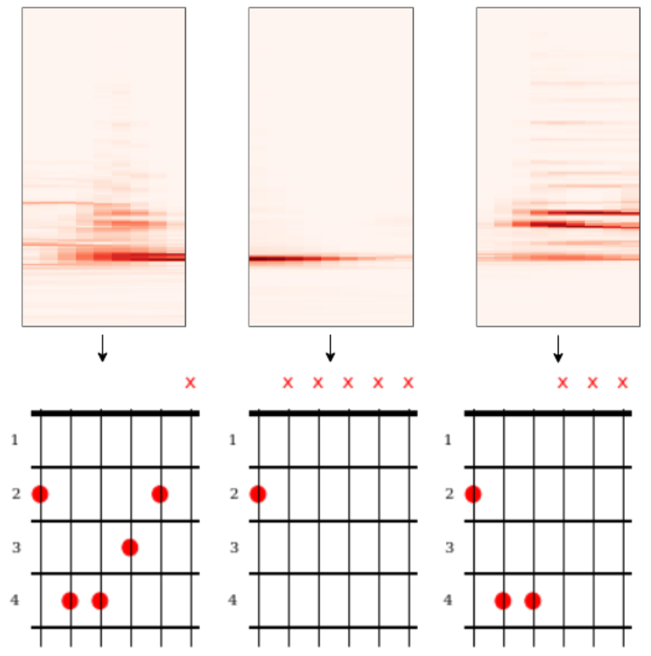
Convolutional Layers: First, there is a series of three convolutional layers, each with a filter size of 3 x 3. The first convolutional layer has 32 filters, and the latter two each have 64. Each convolution is immediately followed by a Rectified Linear Unit (ReLU) activation.

Max Pooling: Next, the feature maps are subsampled by a max pooling layer. Both the filter size and the stride for this operation are 2 x 2.

Dense Layers: The structure is then flattened and followed by a dense layer of dimension 128, which includes a ReLU activation. This is connected to a second dense layer of dimension 126 with no activation.

Softmax: In the final layer, the vector is reshaped to 6 x 21, and a 6-dimensional softmax activation is applied. The output shape represents the 6 guitar strings and the 21 different fret classes a string can be assigned: open, closed, and the 19 numbered frets. As a result, the model learns to output a set of six probability mass functions, which represent the probability of each fret class for each string.

Results



Guitar String	Fret Classification Accuracy
1st *(e)*	0.898
2nd *(B)*	0.760
3rd *(G)*	0.801
4th *(D)*	0.808
5th *(A)*	0.884
6th *(E)*	0.921
Average	**0.845**

Figure 2: (Left) Example input-audio/output-tablature pairs predicted by TabCNN during testing. (Right) Table of string-wise and average accuracy metrics calculated during testing

Future Work

- The current system determines tablature window by window, and does not take into account the sequence over the course of the performance. The addition of a recurrent layer to model the progression of labels over time will help smooth the output labels and create a more realistic tablature sequence.
- Data augmentation may help reduce any overfitting in the model. Additional training data can be constructed by pitch shifting the training audio and adjusting the tablature labels accordingly.

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[1] Kehling, Christian, et al. "Automatic Tablature Transcription of Electric Guitar Recordings by Estimation of Score-and Instrument-Related Parameters." DAFx. 2014.

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