CS230

# An Adaptive Model of Pulse in Jazz Percussion: Rhythmic Generation in Quasi-Periodic Musical Contexts using Sequence-to-Sequence Learning

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## Abstract

This project attempts to formulate a novel approach to musical rhythm generation by incorporating pulse estimation in a jazz performance context. In light of the success of sequence-to-sequence language models [17], this project oversees a "beat-to-beat" translation model to characterize the musical behavior of a particular jazz drummer. This "beat-to-beat" encoder-decoder recurrent neural network (RNN) is trained on data associated with local and global beat features extracted from audio in order to reproduce rhythmic sequences conditioned on prior pulse estimates. After training, I predict and generate sequences of musical rhythms that have been conditioned on the past rhythmic material of the performer. The model was shown to be able to infer future rhythmic sequences with a maximum accuracy of 30% on the test set. A small survey was conducted to gauge the qualitative performance of the generated rhythmic sequences in comparison to a ground-truth baseline.

## 1 Introduction

The establishment of the pulse percept, the basic unit of perceived rhythm that constitutes a musical beat, is critical to the way in which we listen, engage, and perform with music [12]. Fundamental to this notion of pulse is the way in which it orientates cognitive processes involved in anticipation, expectation, and arousal. Taking cues from connectionist theories related to musical structure, pulse can be construed to be an organizational unit from which we derive emergent orders of temporal structure [14]. Pulse extraction is the means through which we are able to manage time-dependent events, namely those that occur with some level of regularity. In fixed-tempo music, pulse often overlaps with the notion of the beat however in genres of music where time or tempo is more variable, pulse can vary with time.

Many neural network models for music generation focus on genres of music that are structured around fixed-beat time units (e.g. classical music, rock and pop) where musical material is constructed in reference to an isochronous pulse. However, a signature feature of jazz improvisation is the way in which time can expand and contract in the course of an improvisation. Jazz musicians will typically latch onto (or deviate from) a perceived pulse during a performance. Taken to the extreme, this adaptive sense of pulse entrainment is particularly present in the genre of free jazz. In this paper, I attempt to tackle the challenge of pulse fluctuations in the course of a performance by introducing a generative RNN model that attempts to improvise around a non-isochronous pulse.

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The input to the proposed neural network are beat descriptors (local pulse estimates and spectral onset envelopes) and drum set onsets (snare, hi-hat, and kick drum) which were extracted from uncompressed audio of solo drum improvisations; the network outputs the same feature set with variable sequence lengths. The network presented here is a sequence-to-sequence LSTM encoder-decoder network that is trained to produce sequences of rhythms that were conditioned on prior estimates of the pulse. After training, the network can generate rhythmic sequences that have been seeded by inputs from a test set.

## 2 Related work

A common challenge in working with sequence-based RNNs (e.g. word generation, time series prediction, etc.) is teaching the network to capture temporally distant inputs. Because of a vanishing (or exploding) gradient, when RNNs are trained with stochastic gradient descent they can have difficulties learning long term dependencies in the input. Recently, there have been many approaches to neural-network based music generation for jazz many of which use Long-short Term Memory (LSTM) [11] based RNNs [4][7][9][16].

Several of these approaches use variational autoencoders to generate semantically meaningful latent representations that can be traversed to generate related melodies, chords, and musical rhythms [8][16]. By interpolating between points in the latent space, these networks have the advantage of being able to generate novel music materials by sampling from a continuous distribution. The ıMetallicaLSTM network [4] explicitly encoded a reference to the beat as an input feature to the network where the word '<bar>' signals the end of each measure. This has the advantage of teaching the network the underlying metrical grid of the individual training samples even when a song is in a different time signature. Because many of these models focus on jazz harmony or melody generation, their inputs are MIDI representations that quantize time into subdivisions representing an eighth note or sixteenth note subdivision. While this approach simplifies the learning process and speeds up computation, it also forces the generated output to always land on an equal beat subdivision which is less suitable for the domain of free improvisation.

By allowing one feature to mark/designate time within a beat, using some subdivision of the beat, the network will be better able to understand how musical events are orientated with respect to underlying metrical structures. However in the case of music that does not exist within an isochronous temporal frame, such as free jazz or forms of contemporary classical music, this problem becomes intractable in the absence of any strict tempo information. Using beat estimates of audio derived from a particular neural network based model, this project attempts to teach a recurrent network how to impose rhythmic events on top of shifting estimates of perceptual pulse information to better encode temporal structure in specific improvisation contexts. More specifically, I employ a recurrent sequence-to-sequence encoder-decoder network that is parameterized by the beat structure of the input data. By using the perceived beat (pulse) as a way to structure sequence learning, this network can better adapt to changes in tempo which allows it to generalizes to the flexible nature of time in free improvisation.

## 3 Dataset and Features

The input dataset consisted of approximately 1.2 hrs of uncompressed audio files (wav) sampled at 44.1kHz of solo jazz drum improvisations of the jazz drummer Paul Motion. 80% of the input was used as the training set, and the remainder 20% was split equally into the validation and test sets.

This audio went through a significant preprocessing stage to extract the relevant features for the network. This is shown in the top half of Figure 2. The audio is analyzed for global beat estimates and extracts a spectral onset envelope. The global tempo estimates used an offline dynamic programming model [6] to recursively calculate beat locations in the audio file; this function is capable of detecting tempo changes throughout the course of the audio being observed. The spectral onset envelope is another beat estimate feature but one that prioritizes local temporal events that incur a significant spectral flux (for more information, see appendix). These features operate at the frame level at the output of a short-time Fourier transform (hopsize=512) with each frame representing approximately 12 ms. The global beat estimate and spectral onset envelopes are combined to form a single vector which is segmented into 5 second (431 frames) clips.

To extract the other features, the audio is put through a pre-trained RNN (Automatic Drum Transcription (ADT) library[1]) to source separate the individual instruments in the drum set (high-hat, snare, and kick drum) and output a transcription of their rhythms. This notation was translated into a vectorized MIDI format and reformatted to be of the same length as the beat estimate vector with each time unit is 12ms. The beat features and MIDI onset features per time frame were combined to create a feature vector of length 5.

The number of time steps per sample passed to the encoder and decoder for training and teacher forcing is parameterized by differences between preceding and future global beat estimates which I refer to as the beat gradients, $\Delta L_e$ and $\Delta L_h$. The number of time steps was determined by difference between the current global beat estimate, $L[n]$, and the previous beat estimate $L[n-1]$ whereas the number of time steps for the target sequence is set by the different between $L[n]$ and $L[n+1]$. This is shown in Figure 1.

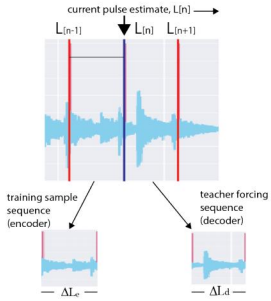



Figure 1: The beat gradients

## 4 Methods

The neural network proposed here is a sequence-to-sequence model with a single layer and 30 LSTM units in both the encoder RNN and decoder RNN. Unlike vanilla recurrent ANNs, the LSTM cells can allow the network to (ideally) handle long term dependencies in the input sequences by including input gates, forget gates, output gates and a new memory cell.

For sequence to sequence generation, the LSTM units can be thought of as trying to estimate the conditional probability of an output sequence, $y_{1...T^1}$ given an input sequence, $x_{1...T}$ where $T_1$ doesn't necessarily equal $T$. To determine this conditional probability, we can use an LSTM encoder network to obtain a fixed-dimensional representation, $v$, of the input $x_{0...T}$ given the last hidden state of the LSTM. Then we can compute the probability of $y_{1..T_1}$ using a LSTM decoder network whose hidden state is set to $v$. This is shown in equation .

$$p(y_1, ....y_{T^1}|x_1, ..., x_T) = \prod_{t=1}^{T^1} p(y_t|v, y_1, ..., y_{t-1})$$

An "end-of-sentence" (EOS) symbol is applied at the end of each generated sequence so that we can can define a distribution over sequences of all possible lengths.

The model proposed here differs from this one in several ways. Most notably, the location of the 'end-of-sentence' symbol in each sequence is predetermined during training using the beat gradient, $\Delta L_{e,d}$ where $x_T = \Delta L_e$ and $y_{T^1} = \Delta L_d$. Figure illustrates the sequence to sequence network under consideration. Since the input is a multi-variate time series (multiple features), the loss function was categorical crossentropy.

## 5 Experiments/Results/Discussion

All the code for these experiments was written in Keras 2.0 using tensorflow as a backend. This model was trained using stochastic gradient descent (batch size=1), adam optimization and a learning rate of 1.0 that was decayed by a factor of 0.8 after epoch 20. The initial weights were randomly initialized within a range between -0.05 and 0.05. During training, I applied dropout to the units with a probability of 20% The input and target data sequences were processed 'statefully' (meaning that the prior states are used as the initial state for the next batch). Because the input sequences were arranged in order (according to the beat gradients), this was performed so that the network might learn the to model dependencies across training examples[2]. I also trained the network on mini-batches of size 64, 128 which sped up computation but did not result in improved performance.

Observing Figure 3, in terms of loss and accuracy the model is clearly overfitting the training data as it cannot generalize as well to the validation set. Normally this might call for performing batch

[1] https://github.com/CarlSouthall/ADTLib

[2] This might have the added benefit of informing certain compositional decisions in the drummer's performance

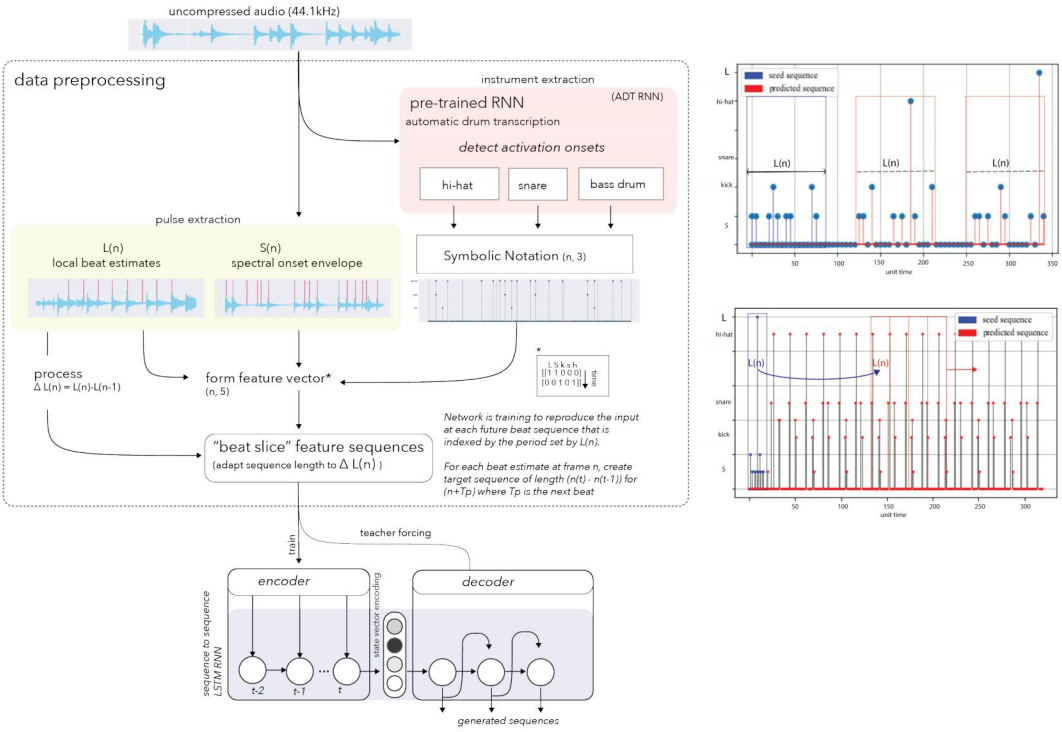


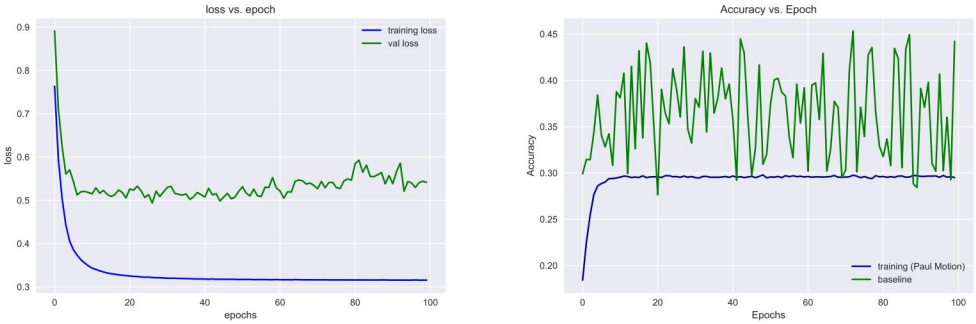

Figure 2: (left) Data Pre-processing pipeline and Beat-to-Beat encoder-decoder RNN (right) Two generated sequences using two different sequence lengths. The generated sequences retain periodicity of the seeded sequence

normalization on the data, increasing dropout or reducing the number of hidden units. However, given that one of the goals of this project is to generate rhythmic sequences that are representative of the drummer, this is not necessarily an undesirable consequence. In fact, the overfitting has the general outcome of being a forcing function. In this case, it results in forcing the output to conform to the sequence width set by the beat gradient. Observing the two example generated sequences shown in Figure 2 where I allowed the network to generate continuously (without an 'end of sentence' token), the pulse width of the seeded input sequence is clearly echoed (and repeated) in the output sequence. The generated sequences also tended to conform to the general instrumental density of the seed.

Other than the loss and accuracy metrics, evaluating this model is difficult because there aren't very many well-established quantitative measures to serve as baselines. Nevertheless, I reproduced several of the 'ground truth' sequences (outputs of the ADT transcriptions) alongside their generated sequences using MIDI drum set instruments to conduct a small qualitative survey. I had a sample size of 12 participants listen to 10 examples[3] of the ground truth sequence and the generated sequences and determine which one was 'computer-generated'. They were able to on average detect the fake sequence 60 % of the time.

The fundamental limitation of this model is its reliance on how accurate the beat estimates and the percussion transcriptions are in the data preprocessing. The ADT transcription algorithm is not well-suited for high fidelity transcriptions of this type of audio (this can be heard by listening to the 'ground truth' outputs of the ADT model that I synthesized with MIDI instruments). Similarly, the beat estimates are in no way an indicating of how the drummer himself is constructing time. One way to get more reliable beat estimates would be to use manually beat tagged estimates from actual drummers (who ideally know the performances well).

[3]please see: www.nolanlem.com/pulse-b2b




(a) training and validation loss over epoch

(b) accuracy over epoch

Figure 3: Model Statistics

## 6 Conclusion/Future Work

The beat-to-beat RNN was shown to be capable of learning pulse sequences of the drummer's performances in the training set but could not generalize as well to other performances. The teacher forcing, when training the decoder, was shown to be an effective way to teach the network how to reproduce the sequence length and instrumental density of the training set. This model might also be improved by adding attention mechanisms and trying out different architectures. For reasons of time (and since I was the sole author), I would've liked to have been able to invest more time in fine tuning the hyperparameters and formed better quantitative evaluation metrics. In the future, I think this network might be best used in real-time musical applications where after training, it could be seeded to produce rhythmic data that reflects the the performing group's rhythmic dynamics.

## 7 Contributions

I was the sole author of this paper.

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