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ONSETS AND FRAMES: DUAL-OBJECTIVE PIANO TRANSCRIPTION

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ABSTRACT

We consider the problem of transcribing polyphonic piano music with an emphasis on generalizing to unseen instruments. We use deep neural networks and propose a novel approach that predicts onsets and frames using both CNNs and LSTMs. This model predicts pitch onset events and then uses those predictions to condition framewise pitch predictions. During inference, we restrict the predictions from the framewise detector by not allowing a new note to start unless the onset detector also agrees that an onset for that pitch is present in the frame. We focus on improving onsets *and* offsets together instead of either in isolation as we believe it correlates better with human musical perception. This technique results in over a 100% relative improvement in note with offset score on the MAPS dataset.

Index Terms— Automatic Music Transcription, Piano, Neural Networks, Note Onset, Polyphony

1. INTRODUCTION

Automatic music transcription (AMT) aims to create a symbolic music representation (e.g., MIDI or sheet music) from raw audio. Converting audio recordings of music into a symbolic form makes many tasks in music information retrieval (MIR) easier to accomplish, such as searching for common chord progressions or categorizing musical motifs. A larger collection of symbolic music also broadens the scope of computational musicology studies [1].

Piano music transcription is a task considered difficult even for humans due to its inherent polyphonic nature. Accurate note identifications are further complicated by the way note energy decays after an onset, so a transcription model needs to adapt to a note with varying amplitude and harmonics. Nonnegative matrix factorization (NMF) is an early popular method used in the task of polyphonic music transcription [2]. With recent advancements in deep learning, neural networks have attracted more and more attention from the AMT community [3, 4]. In particular, the success of convolutional neural networks (CNN) for image classification tasks [5] has inspired the use of CNNs for AMT because two-dimensional time-frequency representations (e.g., constant-Q transform [6]) are common input representations for audio. In [4], the authors demonstrated the potential for a single CNN-based acoustic model to accomplish polyphonic piano music transcription. In [3], a similar approach to speech transcription is considered where an acoustic model and a language model are combined. In this paper, we investigate improving the acoustic model by focusing on note onsets.

Note onset detection looks for only the very beginning of a note. Intuitively, the beginning of a note is easier to identify because the amplitude of that note is at its peak. For piano notes, the onset is also percussive and has a distinctive broadband spectrum. Once the model has determined onset events, we can condition framewise note detection tasks on this knowledge. [7, 8] have shown the promise of modeling onset events explicitly in both NMF and CNN frameworks. In this work, we demonstrate that a model conditioned on onsets achieves state of the art performance for all common metrics measuring transcription quality: frame, note, and note with offset.

2. DATASET AND METRICS

We use the MAPS dataset [9] which contains audio and corresponding annotations of isolated notes, chords, and complete piano pieces. Full piano pieces in the dataset consist of both pieces rendered by software synthesizers and recordings of pieces played by a Yamaha Disklavier player piano. We use the set of synthesized pieces as the training split and the set of pieces played on the Disklavier as the test split, as proposed in [3]. When constructing these datasets, we also ensured that the same music piece was not present in more than one set. Not including the Disklavier recordings, individual notes, or chords in the training set is closer to a real-world testing environment because we often do not have access to recordings of a testing piano at training time. Testing on the Disklavier recordings is also more realistic because many of the recordings that are most interesting to transcribe are ones played on real pianos.

When processing the MAPS MIDI files for training and evaluation, we first translate "sustain pedal" control changes into longer note durations. If a note is active when sustain goes on, that note will be extended until either sustain goes off or the same note is played again. This gives the same note durations as the text files included with the dataset.

The metrics used to evaluate a model are frame-level and note-level metrics including precision, recall, and F1 score. We use the mir_eval library [10] to calculate note-based precision, recall, and F1 scores. We calculate two versions of note metrics: one requiring that onsets be within $\pm$50ms of ground truth but ignoring offsets and one that also requires offsets resulting in note durations within 20% of the ground truth. Frame-based scores are calculated using the standard metrics as defined in [11]. Both frame and note scores are calculated per piece and the mean of these per-piece scores is presented as the final metric for a given collection of pieces.

Our goal is to generate piano transcriptions that contain all perceptually relevant performance information in an audio recording without prior information about the recording environment such as characterization of the instrument. We need a numerical measure that correlates with this perceptual goal. Poor quality transcriptions can still result in high frame scores due to short spurious notes and

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repeated notes that should be held. Note onsets are important, but a piece played with only onset information would either have to be entirely staccato or use some kind of heuristic to determine when to release notes. A high note with offset score will correspond to a transcription that sounds good because it captures the perceptual information from both onsets and durations. More perceptually accurate metrics may be possible and warrant further research. In this work we focus on improving the note with offset score, but also achieve state of the art results for the more common frame and note scores.

3. MODEL CONFIGURATION

Framewise piano transcription tasks typically process frames of raw audio and produce frames of note activations. Previous framewise prediction models [3, 4] have treated frames as both independent and of equal importance, at least prior to being processed by a separate language model. We propose that some frames are more important than others, specifically the onset frame for any given note. Piano note energy decays starting immediately after the onset, so the onset is both the easiest frame to identify and the most perceptually significant.

We take advantage of the significance of onset frames by training a dedicated note onset detector and using the raw output of that detector as additional input for the framewise note activation detector. We also use the thresholded output of the onset detector during the inference process. An activation from the frame detector is only allowed to start a note if the onset detector agrees that an onset is present in that frame.

Our onset and frame detectors are built upon the convolution layer acoustic model architecture presented in [4], with some modifications. We use librosa [12] to compute the same input data representation of mel-scaled spectrograms with log amplitude of the input raw audio with 229 logarithmically-spaced frequency bins, a hop length of 512, an FFT window of 2048, and a sample rate of 16khz. However, instead of presenting the network with one target frame at a time we instead present the entire sequence at once. The advantage of this approach is that we can then use the output of the convolution layers as input to an RNN layer.

The onset detector is composed of the acoustic model, followed by a bidirectional LSTM [13] with 128 units in both the forward and backward directions, followed by a fully connected sigmoid layer with 88 outputs for representing the probability of an onset for each of the 88 piano keys.

The frame activation detector is composed of a separate acoustic model, followed by a fully connected sigmoid layer with 88 outputs. Its output is concatenated together with the output of the onset detector and followed by a bidirectional LSTM with 128 units in both the forward and backward directions. Finally, the output of that LSTM is followed by a fully connected sigmoid layer with 88 outputs. During inference, we use a threshold of 0.5 to determine whether the onset detector or frame detector is active.

Training RNNs over long sequences can require large amounts of memory and is generally faster with larger batch sizes. To expedite training, we split the training audio into smaller files. However, when we do this splitting we do not want to cut the audio during notes because the onset detector would miss an onset while the frame detector would still need to predict the note's presence. We found that 20 second splits allowed us to achieve a reasonable batch size during training of at least 8, while also forcing splits in only a small number of places where notes are active. When notes are active and we must split, we choose a zero-crossing of the audio signal. Inference is performed on the original and un-split audio file.

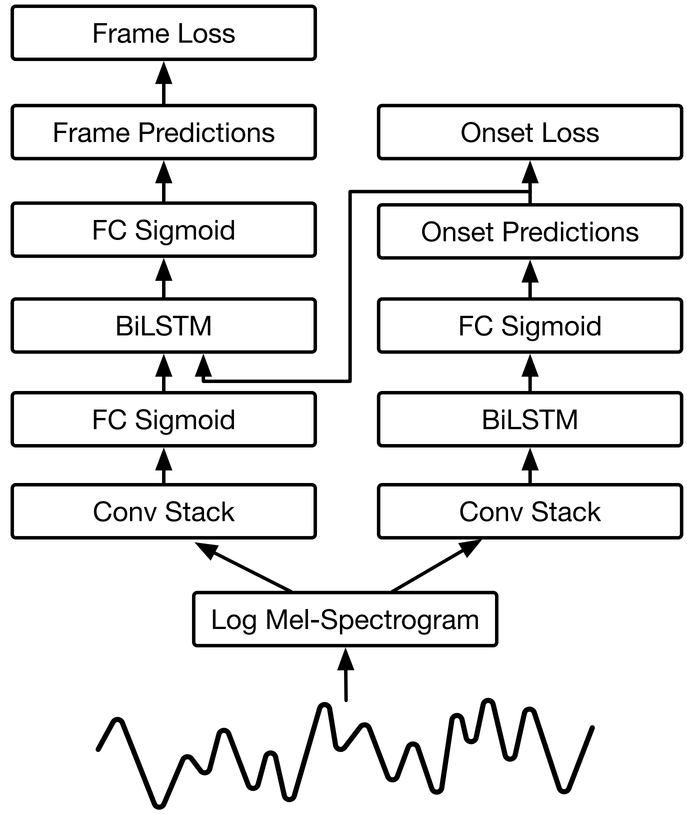

Fig. 1. Diagram of Network Architecture

Our ground truth note labels are in continuous time, but the results from audio processing are in spectrogram frames. So, we quantize our labels to calculate our training loss. When quantizing, we use the same frame size as the output of the spectrogram. However, when calculating metrics, we compare our inference results against the original, continuous time labels.

Our loss function is the sum of two cross-entropy losses: one from the onset side and one from the note side.

$$L_{total} = L_{onset} + L_{frame} \quad (1)$$

$$L_{onset}(l, p) = \sum_i -l(i) \log p(i) - (1 - l(i)) \log(1 - p(i)) \quad (2)$$

where $l = labels_{onsets}$ and $p = predictions_{onsets}$. The labels for the onset loss are created by truncating note lengths to $min(note\_length, onset\_length)$ prior to quantization. We performed a coarse hyperparameter search over $onset\_length$ and found that 32ms worked best. In hindsight this is not surprising as it is also the length of our frames and so almost all onsets will end up spanning exactly two frames. Labeling only the frame that contains the exact beginning of the onset doesn't work as well because of possible mis-alignments of the audio and labels. We experimented with requiring a minimum amount of time a note had be to present in a frame before it was labeled, but found that the optimum value was to include any presence.

Even within the frame-based loss term, we apply a weighting to encourage accuracy at the start of the note. A note starts at frame t_1, completes its onset at t_2 and ends at frame t_3. Because the weight vector assigns higher weights to the early frames of notes, the model is incentivized to predict the beginnings of notes accurately, thus preserving the most important musical events of the piece. First, we define a raw frame accuracy as:

$$L'_{frame}(l,p) = \sum_i -l(i)\log p(i) - (1-l(i))\log(1-p(i)) \quad (3)$$

where $l = labels_{frames}$ and $p = predictions_{frames}$. Then, we define the weighted frame loss as:

$$L_{frame}(l,p) = \begin{cases} cL'_{frame}(l,p) & t_1 \le t \le t_2 \\ \frac{c}{t-t_2}L'_{frame} & t_2 < t \le t_3 \\ L'_{frame}(l,p) & elsewhere \end{cases} \quad (4)$$

where $c = 5.0$ as determined with coarse hyperparameter search. We use the Adam optimizer [14] and train for 50,000 steps. Training takes 5 hours on 3 P100 GPUs. The source code for our model is available at `https://goo.gl/7zTMPf`.

4. EXPERIMENTS

We trained our onsets and frames model using TensorFlow [15] on the training dataset described in 2 using a batch size of 8, a learning rate of .0006, and a gradient clipping L2-norm of 3. A hyperparameter search was conducted to find the optimal learning rate. The same hyperparameters were used to train all models, including those from the ablation study, except when reproducing the results of [3] and [4], where hyperparameters from the respective papers were used.

To compare our results with other models, we reimplemented the models described in [3, 4] to ensure evaluation consistency. We also compared against the commercial software Melodyne version 4.1.1.011[1]. We would have liked to compare against AnthemScore[2] as well, but because it produces a MusicXML score with quantized note durations instead of a MIDI file with millisecond-scale timings, an accurate comparison was not possible.

Results from these evaluations are summarized in Table 1. Our onsets and frames model not only produces better note-based scores (which only take into account onsets), it also produces the best frame-level scores and note-based scores that include offsets.

The importance of restricting frame activations based on onset predictions during inference can be seen clearly in Figure 2. The first image shows the results from the frame and onset predictors. There are several examples of notes that either last for only a few frames or that reactivate briefly after being active for a while. The second image shows the frame results after being restricted by the onset detector. Most of the notes that were active for only a few frames did not have a corresponding onset detection and were removed. Cases where a note briefly reactivated after being active for a while were also removed because a second onset for that note was not detected.

Despite not optimizing for inference performance, our network currently performs at 70× faster than real time on a Tesla K40c. The MIDI files resulting from our inference experiments are available at `https://goo.gl/U3YoJz`.

5. ABLATION STUDY

To understand the individual importance of each piece in our model, we conducted an ablation study. We consider removing the onset detector entirely (a), i.e., using only the frame detector, not using the onset information during inference (b), making the bi-directional RNNs uni-directional (c,d), as well as removing the RNN from the onset detector entirely (e), pre-training the onset detector rather than jointly training it with the frame detector (f), weighting all frames equally (g), sharing the convolutional features between both detectors (h), removing the connection between the onset and frame detectors during training (i), using a Constant Q-Transform (CQT) input representation instead of mel-scaled spectrograms (j), and finally removing all the LSTMs and sharing the convolutional features (k).

These results show the importance of the onset information – not using the onset information during inference results in a significant 18% relative decrease in the note onset score and a 31% relative decrease in the note with offset score while increasing the frame score slightly. Despite the increased frame score, the output sounds significantly worse than our best model. To our ears, the perceptual decrease in audio quality is best tracked by the note with offset scores.

The model which doesn't have the onset detector at all – consisting of convolutions followed by a bi-directional RNN followed by a frame-wise loss – does the worst on all metrics, although it still outperforms the baseline Kelz model. The other ablations indicate

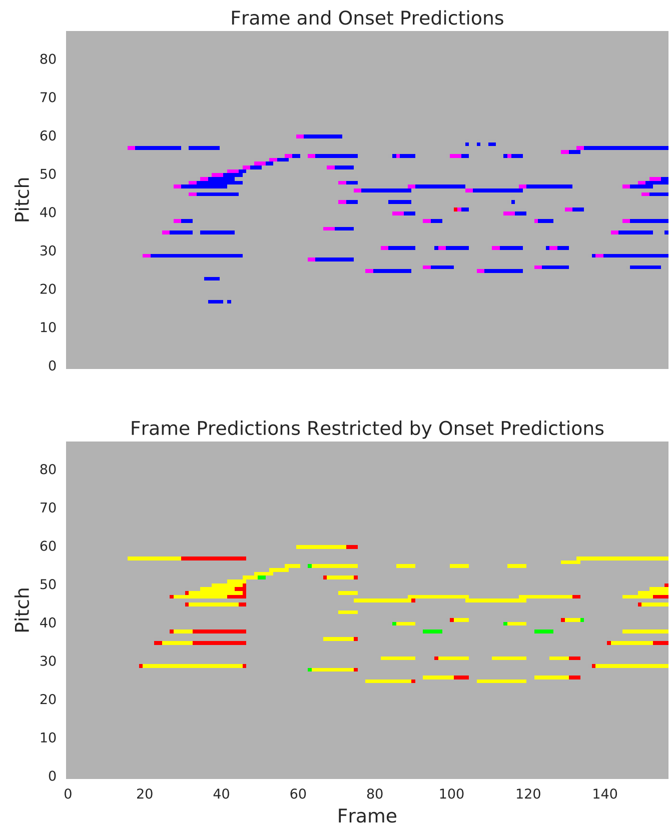

Fig. 2. Inference on the first 10 seconds of MAPS_MUS-grieg_butterfly_ENSTDkCl.wav. In the first image, blue indicates frame prediction, red indicates onset prediction, and magenta indicates frame and onset prediction overlap. In the second image, green indicates frame prediction restricted by onset predictions, red indicates ground truth, and yellow indicates frame prediction and ground truth overlap.

[1] `http://www.celemony.com/en/melodyne`

[2] `https://www.lunaverus.com/`

	Frame			Note			Note with offset		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Sigtia [3] (our reimpl.)	71.99	**73.32**	72.22	44.97	49.55	46.58	17.64	19.71	18.38
Kelz [4] (our reimpl.)	81.18	65.07	71.60	44.27	61.29	50.94	20.13	27.80	23.14
Melodyne (decay mode)	71.85	50.39	58.57	62.08	48.53	54.02	21.09	16.56	18.40
Onsets and Frames	**88.53**	70.89	**78.30**	**84.24**	**80.67**	**82.29**	**51.32**	**49.31**	**50.22**

Table 1. Results on MAPS configuration 2 test dataset (ENSTDkCl and ENSTDkAm full-length .wav files). Note-based scores calculated by the mir_eval library, frame-based scores as defined in [11]. Final metric is the mean of scores calculated per piece. MIDI files used to calculate these scores are available at `https://goo.gl/U3YoJz`.

a small impact for each component ($< 6\%$). It is encouraging that forward-only RNNs have only a small accuracy impact as they can be used for online piano transcription.

We tried many other architectures and data augmentation strategies not listed in the table, none of which resulted in any improvement. Significantly, augmenting the training audio by adding normalization, reverb, compression, noise, and synthesizing the training MIDI files with other synthesizers made no difference. We believe this indicates a need for a much larger training dataset of real piano recordings that have fully accurate label alignments. These requirements are not satisfied by the current MAPS dataset because only 60 of its 270 recordings are from real pianos, and they are also not satisfied by MusicNet [16] because its alignments are not fully accurate. Other approaches, such as seq2seq [17] may not require fully accurate alignments.

	F1		
	Frame	Note	Note with offset
Onset and Frames	**78.30**	**82.29**	**50.22**
(a) Frame-only LSTM	76.12	62.71	27.89
(b) No Onset Inference	**78.37**	67.44	34.15
(c) Onset forward LSTM	75.98	80.77	46.36
(d) Frame forward LSTM	76.30	82.27	49.50
(e) No Onset LSTM	75.90	80.99	46.14
(f) Pretrain Onsets	75.56	81.95	48.02
(g) No Weighted Loss	75.54	80.07	48.55
(h) Shared conv	76.85	81.64	43.61
(i) Disconnected Detectors	73.91	**82.67**	44.83
(j) CQT Input	73.07	76.38	41.14
(k) No LSTM, shared conv	67.60	75.34	37.03

Table 2. Ablation Study Results.

6. NEED FOR MORE DATA, MORE RIGOROUS EVALUATION

The most common dataset for evaluation of piano transcription tasks is the MAPS dataset, in particular the ENSTDkCl and ENSTDkAm renderings of the MUS collection of pieces. This set has several desirable properties: the pieces are real music as opposed to randomly-generated sequences, the pieces are played on a real physical piano as opposed to a synthesizer, and multiple recording environments are available ("close" and "ambient" configurations). The main drawback of this dataset is that it is only 60 .wav files.

Many papers, for example [8, 3, 18, 19], further restrict the data used in evaluation by using only the "close" collection and/or only the first 30 seconds or less of each file. We believe this results in an evaluation that is not representative of real-world transcription tasks. Table 3 shows how the score of our model increases dramatically as we increasingly restrict the dataset.

	Note		
	Precision	Recall	F1
Cl and Am, Full length	84.00	80.25	81.96
Cl only, Full length	85.95	83.05	84.34
Cl only, First 30s	**87.13**	85.96	**86.38**
Wang [8] Cl only, First 30s	85.93	75.24	80.23
Gao [18] Cl only, First 30s*	83.38	**87.34**	85.06

Table 3. Model results on various dataset configurations.
* Results from Gao cannot be directly compared to the other results in this table because their model was trained on data from the test piano.

In addition to the small number of the MAPS Disklavier recordings, we have also noticed several cases where the Disklavier appears to skip some notes played at low velocity. For example, at the beginning of the Beethoven Sonata No. 9, 2nd movement, several A♭ notes played with MIDI velocities in the mid-20s are clearly missing from the audio (`https://goo.gl/U3YoJz`). More analysis is needed to determine how frequently missed notes occur, but we have noticed that our model performs particularly poorly on notes with velocities below 30.

To best measure transcription quality, we believe a new and much larger dataset is needed. However, until that exists, evaluations should make full use of the data that is currently available.

7. CONCLUSION AND FUTURE WORK

We demonstrate a jointly trained onsets and frames model for transcribing polyphonic piano music and also show that using onset information during inference yields significant improvements. This model transfers well between the disparate train and test distributions.

The current quality of the model's output is on the cusp of enabling downstream applications such as MIR and automatic music generation. To further improve the results we need to create a new dataset that is much larger and more representative of various piano recording environments and music genres for both training and evaluation. Combining an improved acoustic model with a language model is a natural next step. Another direction is to go beyond traditional spectrogram representations of audio signals. Dilated convolutions [20] could enable sub-frame timing predictions.

It is very much worth listening to the examples of transcription. Consider Mozart Sonata K331, 3rd movement. Our system does a good job in terms of capturing harmony, melody and even rhythm. If we compare this to the other systems, the difference is quite audible. Audio examples are available at `https://goo.gl/U3YoJz`.

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