MUSIC TRANSCRIPTION WITH CONVOLUTIONAL SEQUENCE-TO-SEQUENCE MODELS

ABSTRACT

Translating an audio sequence to a symbolic representation of music a fundamental problem in Music Information Retrieval (MIR) refereed to Automatic Music Transcription (AMT). Recently, convolutional neural networks (CNNs) have been successfully applied to the task by translating frames of audioSigtia et al. (2016); Thickstun et al. (2017). However, those models can by their nature not model temporal relations and long time dependencies. Furthermore, it is extremely labor intense to get annotations for supervised learning in this setting. We propose a model that overcomes all these problems. The convolutional sequence to sequence (Cseq2seq) model applies a CNN to learn a low dimensional representation of audio frames and a sequential model to translate these learned features to a symbolic representation directly. Our approach has three advantages over other methods: (i) extracting audio frame representations and learning the sequential model is jointly trained end-to-end, (ii) the recurrent model can capture temporal features in musical pieces in order to improve transcription, and (iii) our model learns from entire sequences as opposed to temporally accurately annotated onsets and offsets for each note thus making it possible to train on large already existing corpora of music. For the purpose of testing our method we created our own dataset of 17K monophonic songs and respective MusicXML files. Initial experiments proof the validity of our approach.

1 INTRODUCTION

Automatic music transcription (AMT) is a challenging problem for humans and machines. The task at hand is to find a mapping $f : x \to y$ that translates an audio sequence x to a symbolic representation of that sequence y. The difficulty is no surprise because in the most general case, polyphonic AMT, separating the sources of sound alone, e.g. one key stroke on a piano from another, is already a highly under determined problem. Thus, any sufficient model needs to learn strong priors over the audio sequences it receives as input in order to perform well. Even if a model does learn these priors sufficiently it can not be guaranteed that the task at hand is well defined. For example, the harmonics of two distinct notes of possibly different instruments can have complex interactions. Furthermore, noise or recording technique may limit the prior assumptions that can be made. The space of expected events is huge as well: Musical pieces come in a great range of styles, forms, instrumentations and even playing techniques. However, the fact that machine performance lags behind human performance Klapuri & Davy (2007) is a strong indicator for the room of improvement for these models. Thus it is reasonable to believe that a good model needs to have the capacity to learn priors over musical sequences for example the (probabilistic) rules western music is following with respect to tempo, harmony or timbre. It has been the subject of several studies to work in this prior knowledge without restricting the flexibility of a model too much. One of the key limitations for state-of-the-art models is the lack of annotated data of sufficient size and diversity.

Notice that ATM falls in the regime of perceptional problems. Within this field, deep learning has been contributing remarkable improvements on several tasks, initially mainly in computer vision (CV) later also in several other domains such as natural language processing. There is reason to believe that Music Information Retrial (MIR) tasks are more challenging than CV tasks for example due to the ambiguity of annotation even to human perceivers. However, several pioneering studies in deep learning have shown significant improvement in various MIR challenges such as onset and structural boundary detection Schlüter & Böck (2014); Ullrich et al. (2014), piano transcription Sigtia et al. (2016), genre classification Dieleman et al. (2011); Van den Oord et al. (2013) or sound generation Bakshi & Stephanopoulos (1993) to just name a few. This gives reason to believe in the power of such techniques.

2 Related Work

AMT systems are usually complex pipelines that perform the following subtasks: pitch detection, onset/offset detection, instrument identification, rhythm parsing, identification of dynamics and expressions and typesetting. Depending on the context, an AMT system for western music does either percussive instrument transcription or multi-pitch analysis. The latter one knows two main approaches: analysis on the frame and on the note level. Note level analysis identifies notes by onset and offset detection. The identified notes are consequently classified Marolt (2004); Emiya et al. (2010); P. Grosche et al. (2012); O'Hanlon et al. (2012); Cogliati & Duan (2015a). However, a bottleneck of these methods is the accuracy of the onset detection method. Another unsupervised method is clustering harmonic temporal structures Kameoka et al. (2007). Alternatively, the audio signal can be modeled as a hidden Markov model that transitions between notes Ryynänen & Klapuri (2008). The same approach can also be used to model the signal as a mixture of note spectra Ewert et al. (2015); Cogliati & Duan (2015b).

In contrast to note level predictions, frame level approaches subdivide the audio stream into temporally equivalent frames. Multi-pitch prediction is performed on each frame independently. The predictions are usually made in the time or frequency domain. More specifically for time domain models, there are biologically inspired models Meddis & Hewitt (1991); Tolonen & Karjalainen (2000); Marolt (2004) and probabilistic models Walmsley et al. (1999); Davy & Godsill (2003); Cemgil et al. (2006) . Most recent algorithms perform in the frequency domain. Here for each frame a spectral representation such as the ERB filterbank, STFT or CQT spectrum, is computed.

The central idea of frequency domain approaches is that the given spectrum is a linear superposition of several pitches' spectra. Klapuri (2003) and Argenti et al. (2011) subtract detected pitches from the signal spectrum and iteratively proceed until the spectral frame is explained sufficiently. A range of methods focused on the most dominant peaks in the spectrum Pertusa & Iñesta (2008); Yeh et al. (2010); Duan et al. (2010); Emiya et al. (2008); Peeling & Godsill (2011). The most sophisticated methods in this area model the full spectrum either as a mixture model Goto (2004); Kameoka et al. (2007); Yoshii & Goto (2012); Smaragdis & Brown (2003), compute the eigen-spectra Dessein et al. (2010); Ari et al. (2012); Grindlay & Ellis (2011); Bay et al. (2012); Bertin et al. (2010); Benetos et al. (2014); Benetos & Dixon (2012); Fuentes et al. (2013); Abdallah & Plumbley (2006); O'Hanlon et al. (2012) or perform classification on the frames Marolt (2004); Poliner & Ellis (2007); Nam et al. (2011); Böck & Schedl (2012); Sigtia et al. (2016).

To our knowledge, our method is the first proposed that does not a "word-by-word"/ "frame-by-frame" translation but rather gathers the information of a sequence and translates it as a whole to a symbolic representation. The advantage of that model is that it can learn relevant priors on the signal since it does not consider frames independently. These priors could learn concepts from data that map our understanding of musicology and are thus expected to be superior to other methods. Furthermore, while still be considered supervised models seq2seq models have little labeling work.

3 Method

3.1 Preprocessing

We generate a spectral representation of the input sequence. For each audio sequence, we compute a magnitude spectrogram with a window size of 46.6 ms (2048 samples at 44.1 kHz) and 50% overlap. We apply an equivalent rectangular filterbank of 200 triangular filters from 27.5 Hz to 16 kHz. The entire preprocessing pipeline was realized with EssentiaBogdanov et al. (2013). Alternatively, we provide constant Q transformed sequences. With 16 bins per octave and 7 octaves resulting in 112 bins. This feature was computed with librosa McFee et al. (2015).

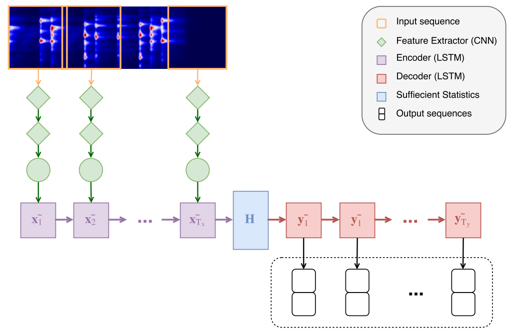

Figure 1: *Convolutional sequence to sequence model*: A spectral audio representation of N frames is fed into a CNN (green). The sequence of consequent representations is than submitted to an encoder LSTM (purple) that puts out a hidden state representing the input sequence. This hidden state is finally used to generate the output sequence via the decoder LSTM (red). Note that equal color represents units within the system, each unit shares parameter. However, the entire system is trained jointly.

3.2 Convolutional Sequence-to-Sequence model

The spectral representation of a musical piece with index i is split into a series of spectrogram excerpts $\mathbf{X}^{(i)} = \{\mathbf{x}_t^{(i)}\}_{t=1}^{T}$ of T frames with 25% overlap. We propose to couple a CNN with a seq2seq model and train the combination jointly. The CNN represents the automated feature extractor aka for each except $\mathbf{x}_t^{(i)}$ it extracts meaningful information from the spectral representation and compresses it. This low dimensional representation $\tilde{\mathbf{x}}_t^{(i)}$ is than the input to the recurrent model that decodes the sequence $\tilde{\mathbf{X}}^{(i)} = \{\tilde{\mathbf{x}}_t^{(i)}\}_{t=1}^{T}$ to a hidden state $\mathbf{H}$ that ideally contains all information of the sequence much like a sufficient statistics. Consequently the information is being ”translated” to the symbolic space with another RNN, the decoder, to the output sequence $\mathbf{Y}^{(i)} = \{\mathbf{y}_t^{(i)}\}_{t=1}^{T}$. More specifically, we choose LSTM models as our RNNs due to their ability to learn long term dependencies better . The whole model is illustrated in Figure 1.

3.3 Objective

The model may be trained with categorical data, i.e., pitch classes and duration in quarter notes or with continuous labels with frequencies and durations in seconds . The former method would naturally be trained with the categorical cross entropy loss, whereas the latter would be trained with mean squared error.

3.4 Training

The input to the Cseq2seq model are batches of series of spectrogram excerpts of T frames. Note that the spectrograms are padded with zeros so that all sequences in a batch are equally long. Each frame is passed through the CNN. The representation is than passed on to the LSTM-encoder, which computes a hidden state. Based on this hidden state, an LSTM-decoder generates an output sequence to match the labels given as (pitch, duration) which is padded as well with stop tokens. We train the system with sequence mini batches of size 64. The objective is the categorical cross entropy or mean squared error depending on the labeling we choose (see section **??**). We use the Adam optimizer with a notability small learning rate of 8×10^{-4}. We apply 15% dropout to the inputs and 25% in the convolutional network. We train for 50 epochs. Training a single Cseq2seq on an Nvidia GTX Titan X graphics card took 30h to 60h. Note that the method is almost trainable end-to-end, however, the spectral representation can be seen as hand engineered feature.

4 Experiments

We present initial experiments with the Cseq2seq model on the Musescore dataset. We determine the best modeling choices and examine how sensitive the model is to augmentation. We report a

	A	B	C
layer 1	1024	16 $\times$ [5,3], [1,2]	16$\times$ [5,3], [2,2]
layer 2	512	32$\times$ [5,3], [1,2]	32 $\times$ [5,3], [2,2]
layer 3	256	32$\times$ [5,3], [1,2]	32 $\times$ [5,3], [2,2]
layer 4		256	256

Table 1: Network architectures for feature extractor models. Fully connected layers are simply identified by number of units, convolutional layers are specified # of filters $\times$ kernel size, striding

pitch and a duration accuracy for categorical data. If the system puts out a correct pitch and duration this will be a successful note detection, which will also be reported. In the case of continuous output, following the authors of Dixon (2000) and Kameoka et al. (2007), duration is counted as correct if it is within $\pm 50ms$ of the ground truth. The pitch will be rounded to its next class. Note that our system can by definition not produce any false positives or negatives, all output is regarded as a prediction.

4.1 INITIAL EXPERIMENT

We perform initial experiments to determine successful models. First, we test one of the most important modeling choices: weather to predict categorical or continuous outputs. Categorical durations will be presented in quarter notes, continuous ones in seconds.Obviously, durations and pitches are (almost) linearly related in the proposed representations thus we expect continuous output to perform well. On the other hand, neural networks are known to perform best on categorical data. To our surprise, categorical prediction networks outperformed continuous ones strongly even though they had to guess the note duration with different BPM rates. Thus all future experiments will be carried out on categorical output networks.

We furthermore tested the effect of log-scaling and normalizing the spectral representations. For the CQT representations, we find those measures to not perform better than the raw input. ERB bands on the other hand benefit from normalization.

4.2 FEATURE EXTRACTOR

Computing an optimal representation for the sequential model is an important part in the translation process. Our method consists of ”hand engineered” features, the spectral representations, and learned features, the CNN part of the model. We experiment with different choices for either of the two components. We vary the spectral representation between ERB bands and CQT features and experiment with 3 different network architectures. We call them A, B and C. The motivation for these choices is the following conflict. Introducing convolutional layers and sub-sampling operations introduces translation equivariance and invariance, respectively, a feature that we might not desire in the frequency domain. Thus we test a fully connected architecture in model A, an architecture with strided convolutions only in the time domain and finally a model with both. The precise specification can be found in table 1. For all experiments we set the following hyperparameters, for the activation functions we choose relu units and the LSTM has 256 units. Furthermore, we use dropout with a probability of 25% and a window size of 3.8s with 50% overlap. The results of this experiment are visualized in figure 2. We see that there is barely a difference between the two spectral representations. However, the choice of model does seem to matter. Somewhat counterintuitive model C works best. We suspect that to be related to the importance of dimensionality reduction.

4.3 RNN CAPACITY

After having established good choices to extract features from incoming frames, we turn to an optimal recurrent model. There are two quantities that need to be chosen carefully. One is the information that needs to be encoded by the feature extractor and one is the amount of information to be encoded by the recurrent model. These properties correspond to the window size and the amount of hidden units in encoder and decoder, respectively. Ideally, there is a balance between the work the feature extractor and the recurrent model need to accomplish. Too small sizes window sizes might be a problem for the RNN because it can not resolve long time dependencies. Too large sizes

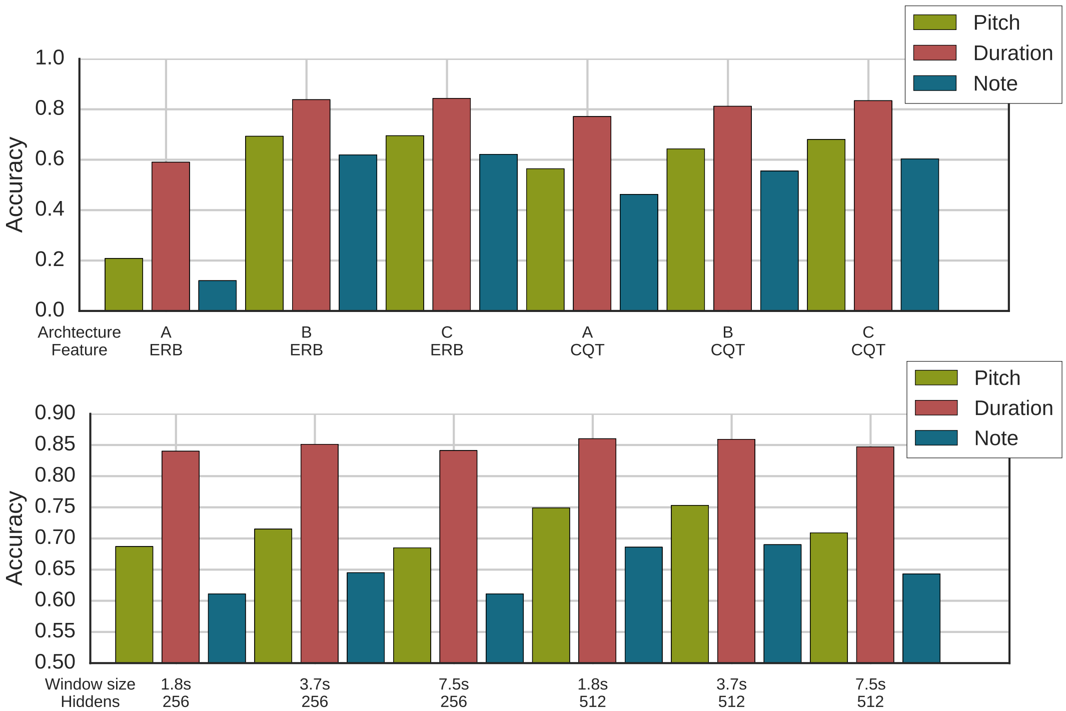

Figure 2: **Top:** We test our model on various feature extractors. We report pitch, duration and note accuracy. **Bottom:** We optimize the proposed model's recurrent part on the validation set. We experiment with different variations of window size and recurrent model capacity. We report the pitch, duration and note accuracy.

might be a problem because the CNN needs to store too much information in the features. In this experiment, we vary window sizes from 1.8s and 3.7s to 5.5s. Furthermore, we vary the number of hidden units in both LSTMs between 256 and 512. We fix the feature extractor to ERB bands and a CNN model with architecture C. We continue training with the same dropout rates as in the previous experiment. Again we train the model for 50 epochs with Adam. We present results on our validation set in figure 2.

We find the best model performance with large recurrent model capacity and a small window size. This finding is not surprising. It is expected that if we segment a sequence in many small pieces the RNNs need to have to resolve longer time dependencies. We clearly see that the performance drops significantly when we restrict the RNN capacity to 256 hidden units. In contrast to those results, the results for the larger context vary only little since RNN and CNN "share the work" of encoding more evenly.

4.4 Data augmentation

In a final experiment, we determine if data augmentation does benefit the training. Data augmentation is a popular way to enrich artificial data such that it extrapolates to real wold data, for example, in scenarios where there is only artificial training data available. We apply pink noise on the audio sequences and report the accuracy of the validation data with and without this noise. We present results with small, moderate and large induced noise levels in table 2

We find low levels of pink noise to neither benefit nor detriment the performance of the network. Moderate noise does benefit the overall accuracy, whereas too much noise obfuscates the information in the data.

In our final experiment, we train the network with varying levels of pink noise by uniform randomly sampling its dB rate per training example in $[0, 1]$. We evaluate the performance of this experiment on the test set. For the non-augmented test set we achieve scores of 0.723, 0.847 and 0.654 for pitch,

Noise level	0.1 dB	1 dB
Test set without augmentation		
Pitch accuracy	0.732	0.418
Duration accuracy	0.853	0.600
Note accuracy	0.666	0.284
Test set with augmentation		
Pitch accuracy	0.732	0.725
Duration accuracy	0.852	0.844
Note accuracy	0.666	0.663

Table 2: Final results: We trained the best model architecture as determined earlier on a training set with augmentations with varying levels of noise. We tested the resulting model on the validation set and the tested with additional augmentations relating to the training augmentation.

duration and total accuracy, respectively and 0.721, 0.845 and 0.650 for the augmented test dataset. Hence, we can train a single model that is robust to a wide range of noise present in the signal.

5 Discussion and future Work

In this study we present a novel approach to ATM. Our solution is an important step towards an end-to-end trainable system. We combine the benefits of differentiable feature extractors such as CNNs with recurrent models that can pick up long time dependencies in data. We need both of these properties to tackle ATM successfully. More precisely, we propose the convolutional sequence-to-sequence model. We pass spectrogram excerpts through a CNN, the consequent representation is fed into a sequence-to-sequence model. Ideally, the model distributes the difficulty of this task to its components. The problem of relevant feature extraction is carried out by the CNN while the seq2seq model learns long time dependencies and data priors such as derived by musicology automatically from the data. Our model is preferable not just because the model can capture the complexity of the data well, but it is to our knowledge, the first method that does not rely on note level annotations but rather on sequence annotation, i.e., audio recordings and respective scores. Thus, we do not only propose a very flexible model but also one that can be trained with data that exists en mass already. There is no need of on- and offset annotations which is often considered as a bottleneck of ATM methods. In experiments we determine the best modeling choices and we can show that the model is robust to synthetic recording noise. We achieve convincing results on monophonic scores. We are sure we could improve these results by additional information such as the BPM rate. In future efforts, we will extend this method to polyphonic scores. This however does require us to change the labeling scheme to a version that is closely related to the MIDI or piano roll format.

However, the format is not the only challenge in order to extrapolate to multi-pitch prediction. Given the proposed multi-pitch labeling scheme, target sequences will be substantially longer thus our recurrent models will need more capacity, and further enroll longer sequences over time through which we need to back-propagate. This poses substantial computational challenges. To address the latter we propose to use models with flexible hidden space such as Shi et al. (2017). Another approach to address is problem is to introduce attentionBahdanau et al. (2014); Sabour et al. (2017). Our main focus and challenge for future work, however, will be to replace the spectral representation and CNN by a fully differentiable feature extractor. Recently, there were promising results such as Dieleman & Schrauwen (2014); van den Oord et al. (2016); Thickstun et al. (2017) but also biologically inspired models McDermott & Simoncelli (2011) that show that this goal is in reach. The former authors achieve astonishing results by interpret the CNN as a feature extractor and a recurrent model. Finally, we want to test our approach on multi-pitch prediction and real world recordings in a competitive setting. For that we need to make approximations between the accuracy measures in use today and the method that we proposed.

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