

On the Futility of Learning Complex Frame-Level Language Models for Chord Recognition

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Abstract

Chord recognition systems use temporal models to post-process frame-wise chord predictions from acoustic models. Traditionally, first-order models such as Hidden Markov Models were used for this task, with recent works suggesting to apply Recurrent Neural Networks instead. Due to their ability to learn longer-term dependencies, these models are supposed to learn and to apply musical knowledge, instead of just smoothing the output of the acoustic model. In this paper, we argue that learning complex temporal models at the level of audio frames is futile on principle, and that non-Markovian models do not perform better than their first-order counterparts. We support our argument through three experiments on the McGill Billboard dataset. The first two show 1) that when learning complex temporal models at the frame level, improvements in chord sequence modelling are marginal; and 2) that these improvements do not translate when applied within a full chord recognition system. The third, still rather preliminary experiment gives first indications that the use of complex sequential models for chord prediction at higher temporal levels might be more promising.

1 Introduction

Computational systems that extract high-level information from signals face two key problems: 1) how to extract meaningful information from noisy sources, and 2) how to process and combine this information

into sensible output. For example, in domains such as speech recognition, these translate to *acoustic modelling* (how to predict phonemes from audio) and *language modelling* (how to connect these phonemes into words and sentences).

A similar structure can be observed in many systems related to music processing, such as chord recognition. Chord recognition systems aim at recognising and transcribing musical chords from audio, highly descriptive harmonic features of music that form the basis of a myriad applications (e.g. key estimation, cover song detection, or directly to automatically provide lead sheets for musicians, to name a few). We refer the reader to [1, 2] for an overview.

Chord recognition systems comprise two main parts: an *acoustic model* that extracts frame-wise harmonic features and predicts chord label distributions for each time frame, and a *temporal model* that connects consecutive predictions and outputs a sequence of chord labels for a piece of audio.

The temporal model provides coherence to the possibly volatile predictions of the acoustic model. It also permits the introduction of higher-level musical knowledge—we know from music theory that certain chord progressions are more likely than others—to further improve the obtained chord labels.

A number of works (e.g. [3, 4, 5]) implemented hand-designed temporal models for chord recognition. These models are usually first-order Dynamic Bayesian Networks that operate at the beat or time-frame level. They are designed to incorporate musical knowledge, with parameters set by hand or trained

from data.

A different approach is to learn temporal models fully from data, without any imposed structure. Here, it is common to use simple Hidden Markov Models [6] or Conditional Random Fields [7] with states corresponding to chord labels.

However, recent research showed that first-order models have very limited capacity to encode musical knowledge and focus on ensuring stability between consecutive predictions (i.e. they only smooth the output sequence) [2, 8]. In [2], self-transitions dominate other transitions by several orders of magnitude, and chord recognition results improve as self-transitions are amplified manually. In [8], employing a first-order chord transition model hardly improves recognition accuracy, given a duration model is applied.

This result bears little surprise: firstly, many common chord patterns in pop, jazz, or classical music span more than two chords, and thus cannot be adequately modelled by first-order models; secondly, models that operate at the frame level by definition only predict the chord symbol of the next frame (typically 10ms away), which most of the time will be the same as the current chord symbol.

To overcome this, a number of recent papers suggested to use Recurrent Neural Networks (RNNs) as temporal models¹ for a number of music-related tasks, such as chord recognition [9, 10] or multi-f0 tracking [11]. RNNs are capable of modelling relations in temporal sequences that go beyond simple first-order connections. Their great modelling capacity is, however, limited by the difficulty to optimise their parameters: exploding gradients make training instable, while vanishing gradients hinder learning long-term dependencies from data.

In this paper, we argue that (neglecting the aforementioned problems) adopting and training complex temporal models *on a time-frame basis* is futile *on principle*. We support this claim by experimentally showing that they do not outperform first-order models (for which we know they are unable to capture musical knowledge) as part of a complete chord recog-

¹Note of our use of the term “temporal model” instead of “language model” as used in many publications—the reason for this distinction will hopefully become clear at the end of this paper.

nition system, and perform only negligibly better at modelling chord label sequences. We thus conclude that, despite their greater modelling capacity, the input representation (musical symbols on a time-frame basis) prohibits learning and applying knowledge about musical structure—the language models hence resort to what their simpler first-order siblings are also capable of: smoothing the predictions.

In the following, we describe three experiments: in the first, we judge two temporal models directly by their capacity to model frame-level chord sequences; in the second, we deploy the temporal models within a fully-fledged chord recognition pipeline; finally, in the third, we learn a *language model* at chord level to show that RNNs are able to learn musical structure if used at a higher hierarchical level. Based on the results, we then draw conclusions for future research on temporal and language modelling in the context of music processing.

2 Experiment 1: Chord Sequence Modelling

In this experiment, we want to quantify the modelling power of temporal models directly. A temporal model predicts the next chord symbol in a sequence given the ones already observed. Since we are dealing with frame-level data and adopt a frame rate of 10 fps, a chord sequence consists of 10 chord symbols per second. More formally, given a chord sequence $\mathbf{y} = (y_1, \dots, y_K)$, a model M outputs a probability distribution $P_M(y_k | y_1, \dots, y_{k-1})$ for each y_k . From this, we can compute the probability of the chord sequence

$$P_M(\mathbf{y}) = P_M(y_1) \cdot \prod_{k=2}^K P_M(y_k | y_1, \dots, y_{k-1}). \quad (1)$$

To measure how well a model M predicts the chord sequences in a dataset, we compute the average log-probability that it assigns to the sequences \mathbf{y} of a dataset \mathcal{Y} :

$$\mathcal{L}(M, \mathcal{Y}) = \frac{1}{N_{\mathcal{Y}}} \sum_{\mathbf{y} \in \mathcal{Y}} \log(P_M(\mathbf{y})), \quad (2)$$

where $N_{\mathcal{Y}}$ is the total number of chords symbols in the dataset.

2.1 Temporal Models

We compare two temporal models in this experiment: A first-order Markov Chain and a RNN with Long-Short Term Memory (LSTM) units.

For the **Markov Chain**, $P_M(y_k | y_1, \dots, y_{k-1})$ in Eq. 1 is simplified to $P_M(y_k | y_{k-1}) = A_{y_k, y_{k-1}}$ due to the Markov property, and $P_M(y_1) = \pi_{y_1}$. Both π and A can be estimated by counting the corresponding occurrences in the training set.

For the **LSTM-RNN**, we follow closely the design, parametrisation and training procedure proposed in [10], and we refer the reader to their paper for details. The input to the network at time step k is the chord symbol y_{k-1} in one-hot encoding, the output is the probability distribution $P_M(y_k | y_1, \dots, y_{k-1})$ used in Eq. 1. (For $k = 1$, we input a “no-chord” symbol and the network computes $P(y_1)$.) As loss we use the categorical cross-entropy between the output distribution and the one-hot encoding of the target chord symbol.

We use 2 layers of 100 LSTM units each, and add skip-connections such that the input is connected to both hidden layers and to the output. We train the network using stochastic gradient descent with momentum for a maximum of 200 epochs (the network usually converges earlier) with the learning rate decreasing linearly from 0.001 to 0. As in [10], we show the network sequences of 100 symbols (corresponding to 10 seconds) during training. We experimented with longer sequences (up to 50 seconds), but results did not improve (i.e. the network did not profit from longer contexts). Finally, to improve generalisation, we augment the training data by randomly shifting the key of the sequences each time they are shown during training.

2.2 Data

We evaluate the models on the McGill Billboard dataset [12]. We use songs with ids smaller than 1000 for training, and the remaining for testing, which corresponds to the test protocol suggested by the website accompanying the dataset². To prevent train/test overlap, we filter out duplicate songs. This reduces the number of pieces from 890 to 742, of which 571 are

²<http://ddmal.music.mcgill.ca/research/billboard>

	Markov Chain	Recurrent NN
$\mathcal{L}(M, \mathcal{Y})$	-0.273	-0.266
$\mathcal{L}_c(M, \mathcal{Y})$	-5.420	-5.219
$\mathcal{L}_s(M, \mathcal{Y})$	-0.044	-0.046

Table 1: Average log-probabilities of chords changes in the test set for the two temporal models. $\mathcal{L}(M, \mathcal{Y})$ is the number for all chord symbols, $\mathcal{L}_c(M, \mathcal{Y})$ for positions in the sequence where the chord symbol changes, and $\mathcal{L}_s(M, \mathcal{Y})$ where it stays the same

used for training and validation (59155 unique chord annotations), and 171 for testing (16809 annotations).

The dataset contains 69 different chord types. These chord types are, to no surprise, distributed unevenly: the four most common types (major, minor, dominant 7, and minor 7) already comprise 85% of all annotations. Following [2], we simplify this vocabulary to major/minor chords only, where we map chords that have a minor 3rd as their first interval to minor, and all other chords to major. After mapping, we have 24 chord symbols (12 root notes \times {major, minor}) and a special “no-chord” symbol, thus 25 classes.

2.3 Results

Table 1 shows the resulting avg. log-probabilities of the models on the test set. Additionally to $\mathcal{L}(M, \mathcal{Y})$, we report $\mathcal{L}_s(M, \mathcal{Y})$ and $\mathcal{L}_c(M, \mathcal{Y})$. These numbers represent the average log-probability the model assigns to chord symbols in the dataset when the current symbol is the *same* as the previous one and, when it *changed*, respectively. They are computed similarly to $\mathcal{L}(M, \mathcal{Y})$, but the product in Eq. 1 only captures k where $y_k = y_{k-1}$ or $y_k \neq y_{k-1}$, respectively.

They permit us to reason about how well a model will smooth the predictions when the chord is stable, and how well it can predict chords when they change (this is where “musical knowledge” could come into play).

We can see that the RNN performs only slightly better than the Markov Chain (MC), despite its higher modelling capacity. This improvement is rooted in better predictions when the chord changes (-5.22 for the RNN vs. -5.42 for the MC). This might indicate

that the RNN is able to model musical knowledge better than the MC after all. However, this advantage is minuscule and comes seldom into play: the correct chord has an avg. probability of 0.0054 with the RNN vs. 0.0044 with the MC³, and the number of positions at which the chord symbol changes, compared to where it stays the same, is low.

In the next experiment, we evaluate if the marginal improvement provided by the RNN translates into better chord recognition accuracy when deployed in a fully-fledged system.

3 Experiment 2: Frame-Level Chord Recognition

In this experiment, we want to evaluate the temporal models in the context of a complete chord recognition framework. The task is to predict for each audio frame the correct chord symbol. We use the same data, the same train/test split, and the same chord vocabulary (major/minor and “no chord”) as in Experiment 1.

Our chord-recognition pipeline comprises spectrogram computation, an automatically learned feature extractor and chord predictor, and finally the temporal model. The first two stages are based on our previous work [7, 13]. We extract a log-filtered and log-scaled spectrogram between 65 and 2100 Hz at 10 frames per second, and feed spectral patches of 1.5s into one of three acoustic models: a *logistic regression classifier* (LogReg), a *deep neural network* (DNN) with 3 fully connected hidden layers of 256 rectifier units, and a *convolutional neural network* (ConvNet) with the exact architecture we presented in [7].

Each acoustic model yields frame-level chord predictions, which are then processed by one of three different temporal models.

3.1 Temporal Models

We test three temporal models of increasing complexity. The simplest one is Majority Voting (MV) within a context of 1.3s. The others are the very same we used in the previous experiment.

³Both are worse than the random chance of $1/25 = 0.04$, because both would still favour self-transitions

	None	MV	HMM	RNN
LogReg	72.3	72.8	73.4	73.1
DNN	74.2	75.3	76.0	75.7
ConvNet	77.6	78.1	78.9	78.7

Table 2: Weighted Chord Symbol Recall of the 24 major and minor chords and the “no-chord” class for the tested temporal models (columns) on different acoustic models (rows).

Connecting the Markov Chain temporal model to the predictions of the acoustic model results in a *Hidden Markov Model* (HMM). The output chord sequence is decoded using the Viterbi algorithm.

To connect the RNN temporal model to the predictions of the acoustic model, we apply the *hashed beam search* algorithm, as introduced in [10], with a beam width of 25, hash length of 3 symbols and a maximum of 4 solutions per hash bin. The algorithm only approximately decodes the chord sequence (no efficient and exact algorithms exist, because the output of the network depends on *all* previous inputs).

3.2 Results

Table 2 shows the Weighted Chord Symbol Recall (WCSR) of major and minor chords for all combinations of acoustic and temporal models. The WCSR is defined as $\mathcal{R} = t_c/t_a$, where t_c is the total time where the prediction corresponds to the annotation, and t_a is the total duration of annotations of the respective chord classes (major and minor chords and the “no-chord” class, in our case). We used the implementation provided in the “mir_eval” library [14].

The results show that the complex RNN temporal model does not outperform the simpler first-order HMM. They improve compared to not using a temporal model at all, and to a simple majority vote.

The results suggest that the RNN temporal model does not display its (marginal) advantage in chord sequence modelling when deployed within the complete chord recognition system. We assume the reasons to be 1) that the improvement was small in the first place, and 2) that exact inference is not computation-

ally feasible for this model, and we have to resort to approximate decoding using beam search.

4 Experiment 3: Modelling Chord-level Label Sequences

In the final experiment, we want to support our argument that the RNN does not learn musical structure because of the hierarchical level (time frames) it is applied on. To this end, we conduct an experiment similar to the first one—an RNN is trained to predict the next chord symbol in the sequence. However, this time the sequence is not sampled at frame level, but at chord level (i.e. no matter how long a certain chord is played, it is reduced to a single instance in the sequence). Otherwise, the data, train/test split, and chord vocabulary are the same as in Experiment 1.

The results confirm that in such a scenario, the RNN clearly outperforms the Markov Chain (Avg. Log-P. of -1.62 vs. -2.28). Additionally, we observe that the RNN does not only learn static dependencies between consecutive chords; it is also able to adapt to a song and recognise chord progressions seen previously in this song without any on-line training. This resembles the way humans would expect the chord progressions not to change much during a part (e.g. the chorus) of a song, and come back later when a part is repeated. Figure 1 shows exemplary results from the test data.

5 Conclusion

We argued that learning complex temporal models for chord recognition⁴ on a time-frame basis is futile. The experiments we carried out support our argument. The first experiment focused on how well a complex temporal model can learn to predict chord sequences compared to a simple first-order one. We saw that the complex model, despite its substantially greater modelling capacity, performed only marginally better. The second experiment showed that, when deployed within a chord recognition system, the RNN temporal model did not outperform the first-order HMM. Its

slightly better capability to model frame-level chord sequences was probably counteracted by the approximate nature of the inference algorithm. Finally, in the third experiment, we showed preliminary results that when deployed at a higher hierarchical level than time frames, RNNs are indeed capable of learning musical structure beyond first-order transitions.

Why are complex temporal models like RNNs unable to model frame-level chord sequences? We believe the following two circumstances to be the causes: 1) transitions are dominated by self-transitions, i.e. models need to predict self-transitions as well as possible to achieve good predictive results on the data, and 2) predicting chord changes “blindly” (i.e. without knowledge *when* the change might occur) competes with 1) via the normalisation constraint of probability distributions.

Inferring when a chord changes proves difficult if the model can only consider the *frame-level* chord sequence. There are simply too many uncertainties (e.g. the tempo and harmonic rhythm of a song, timing deviations, etc.) that are hard to estimate. However, the models also do not have access to features computed from the input signal, which might help in judging whether a chord change is imminent or not. Thus, the models are blind to the *time* of a chord change, which makes them focus on predicting self-transitions, as we outlined in the previous paragraph.

We know from other domains such as natural language modelling that RNNs are capable of learning state-of-the-art language models [15]. We thus argue that the reason they underperform in our setting is the frame-wise nature of the input data. For future research, we propose to focus on *language models* instead of frame-level temporal models for chord recognition. By “language model” we mean a model at a higher hierarchical level than the temporal models explored in this paper (hence the distinction in name)—like the model used in the final experiment described in this paper. Such language models can then be used in sequence classification framework such as sequence transduction [16] or segmental recurrent neural networks [17].

Our results indicate the necessity of hierarchical models, as postulated in [18]: powerful feature extractors may operate at the frame-level, but more abstract

⁴We expect similar results for other music-related tasks.

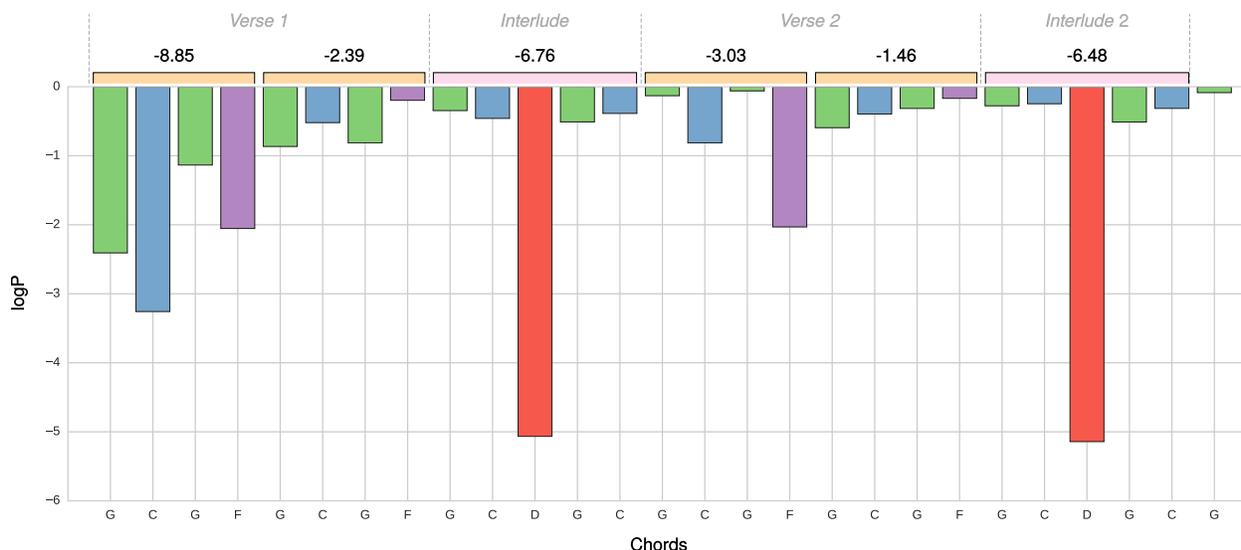


Figure 1: Log-probabilities of chords at the beginning of The Beatles’ “A Hard Day’s Night”, as computed by a RNN language model at the chord level. Bar colors indicate chord type: green corresponds to G major, blue to C major, purple to F major, and red to D major. We observe that the two repeated chord sequences (“G-C-G-F” and “G-C-D-G-C”, marked with light orange and light pink on the top) achieve higher probabilities as they are repeated, with the exception of one repetition of the first sequence at the beginning of Verse 2 (in this case, the network did not expect to see the “F” after several repetitions of a G-C transition). This indicates that the network was able to remember to some degree the chord progressions seen earlier in the song.

concepts have to be estimated at higher temporal (and, conceptual) levels. Similar results have been found for other music-related tasks: e.g., in [19], dividing longer metrical cycles into their sub-components led to improved beat tracking results; in the field of musical structure analysis (an obviously hierarchical concept), [20] extracted representations on different levels of granularity (although their system scored lower in traditional evaluation measures for segmentation, it facilitates a hierarchical breakdown of a piece).

Music theory teaches that cadences play an important role in the harmonic structure of music, but many current state-of-the-art chord recognition systems (including our own) ignore this. Learning powerful language models at sensible hierarchical levels bears the potential to further improve the accuracy of chord recognition systems, which has remained stagnant in recent years.

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