Towards CNN-based Acoustic Modeling of Seventh Chords for Automatic Chord Recognition

Christon-Ragavan Nadar, Jakob Abeßer, Sascha Grollmisch
Semantic Music Technologies Group, Fraunhofer IDMT, Ilmenau, Germany
jakob.abesser@idmt.fraunhofer.de

ABSTRACT

In this paper, we build upon a recently proposed deep convolutional neural network architecture for automatic chord recognition (ACR). We focus on extending the commonly used major / minor vocabulary (24 classes) to a large chord vocabulary of seven chord types with a total of 84 classes. In our experiments, we compare a joint and a separate classification of the chord type and chord root pitch class using one or two separate models, respectively. We perform a large-scale evaluation using various combinations of training and test sets of different timbre complexity. Our results show that ACR with a large chord vocabulary achieves high f-scores of 0.91 for isolated instrument recordings and 0.74 for mixed contemporary popular music recordings. While the joint ACR modeling leads to the best results for isolated instrument recordings, the separate modeling strategy performs best for complex music recordings. Alongside with this paper, we publish a novel dataset for large-vocabulary chord recognition, which consists of synthetically generated isolated recordings of various musical instruments.

1. INTRODUCTION

Automatic chord recognition (ACR) has been actively researched in the field of Music Information Retrieval (MIR) during the last 20 years. ACR algorithms are an essential part of many music applications such as music transcription systems for automatic lead-sheet generation, music education and learning applications, as well as music similarity and recommendation algorithms. In music practice, chord sequences can be played as different chord voicings (selection and order of chord tones) on a large variety of musical instruments, each with its own unique sound characteristic. Therefore, the biggest challenge of ACR is to extract the predominant harmonic changes in a music signal and to be robust against different instrument timbres at the same time. Furthermore, tuning deviations of music recordings as well as inherent ambiguities between different chords can complicate the task even more [1]. In general, ACR is approached as a two-step problem. First, the *acoustic modeling* step deals with the prediction of chord labels from short-term audio signal frames. Secondly, during the *temporal modeling* step, post-processing algorithms are applied to merge frame-level predictions to longer segment-level chord annotations.

As the first main contribution of this paper, we investigate the under-explored task of recognizing seventh chords as an extension to commonly used major and minor chords. Most previous publications focus on recognizing the 24 possible major and minor chords. In the large-vocabulary ACR scenario, we investigate 7 different chord types including four seventh chord types and the power-chord, which leads to a total of 84 classes. Throughout this paper, we solely focus on improving the acoustic modeling for ACR and do not apply any temporal modeling algorithms. As a second contribution, we compare joint and separate modeling of the chord root pitch class and the chord type as two possible strategies for ACR. Finally, we publish a novel dataset alongside with this paper that includes synthetically generated chord sequences of the investigated 7 different chord types played with different chord voicings on various keyboard and guitar instruments. [1]

2. RELATED WORK

Early algorithms for acoustic modeling in ACR used template matching in chromagram representations, which encode the local saliency of different pitch classes in audio signals [1, 2]. Here, musical knowledge about the interval structures in different chord types is used to design chord templates for template matching algorithms. In contrast, fully data-driven approaches based on deep neural network architectures have been lately shown to outperform hand-crafted feature representations. For instance, Convolution Neural Networks (CNN) [3], Recurrent Neural Networks (RNN) [4, 5], and feed-fowardDeep Neural Networks (DNN) [6] were used as acoustic modeling part. Most CNN architectures follow the VGG-style architectures [7] with a sequence of 2D convolutional layers and max pooling layers for a gradual down-sampling in the time-frequency space. Common time-frequency representations such Short-time Fourier Transform (STFT) [8], Constant-Q transform (CQT) [3] or its multi-channel extension Harmonic CQT [9] are used as two-dimensional input features for CNN models.

As we focus on the acoustic modeling in ACR algorithms, we only briefly review temporal modeling techniques here. The first approaches for temporal modeling in ACR sys-

[1] The URL will be published in the camera-ready version of the paper.

Abbreviation	Chord Type (# Chord Tones)
5	"Power-chord" (2)
maj	Major chord (3)
min	Minor chord (3)
maj7	Major-seventh chord (4)
min7	Minor-seventh chord (4)
dom7	Dominant-seventh chord (4)
m7b5	Half-diminished seventh chord (4)

Table 1. Investigated chord types with the corresponding number of chord tones.

tems have used techniques from automatic speech recognition such as Hidden Markov models (HMMs) [10, 11]. Recently, Korzeniowski & Widmer use RNN-based chord language and duration models as post-processing after a CNN-based acoustic model [12]. Wu & Li combine a bi-directional LSTM for sequence modeling and Conditional Random Field (CRF) to infer the final chord label sequence [9].

In real music, the occurrence of different chord types is heavily imbalanced. While major and minor chords make up the bulk of annotated chords in available chord recognition datasets, other chord types such as seventh chords are heavily underrepresented. Hence, it becomes hard to train ACR systems to detect such chord types. If ACR algorithms should be used for analyzing jazz-related music styles, it becomes mandatory to extend the chord vocabulary to seventh chords. Only a few publications such [9, 13, 14] focus on large vocabulary chord recognition and go beyond the common 24 class major/minor chord vocabulary. In order to facilitate training models for large-vocabulary ACR, we created and published a novel dataset for large-scale chord recognition which will be detailed in Section 4.2.

3. SYSTEM OVERVIEW

3.1 Input Features

Audio signals with a sample rate of 44.1 kHz are converted into Short-time Fourier Transform (STFT) magnitude spectrograms using a blocksize of 8192 (186 ms), a hopsize of 4410 (100 ms), and a Hann window. The phase is discarded. Using a triangular filterbank, the spectrogram is mapped to a logarithmically-spaced frequency axis with 133 frequency bins and a resolution of 24 bins per octave [8]. Logarithmic magnitude compression is used to increase the invariance to dynamic fluctuations in the music signal. Spectral patches are extracted with a blocksize of 15 (1500 ms) and a hopsize of 4 (400 ms) and fed as two-dimensional input to the CNN model.

3.2 Modeling Strategies & Network Architecture

Figure 1 shows the CNN model architecture, which was adopted in this paper from [8]. As shown in Figure 2, we compare two modeling strategies for ACR: In the first strategy (**S1**), we aim to directly classify the chord label and use a single-output model. Depending on the chord vocabulary size, the final dense layer has either 24 units for classifying major & minor chords or 84 units for classifying all 7 chord types listed in Table 1. In the second strategy (**S2**), we predict the chord root pitch class (12 classes) and chord type (2 or 7 classes) using two separate models. In both scenarios, the final dense layers have a softmax activation function. During training, we use the categorical cross-entropy loss, 500 training epochs with early stopping, the Adam optimizer [15] with a learning rate of 0.003, and a batch size of 256. The input features were normalized to zero-mean and unit-variance for the whole training set. The normalization values were later applied to the test data. All experiments were conducted using the

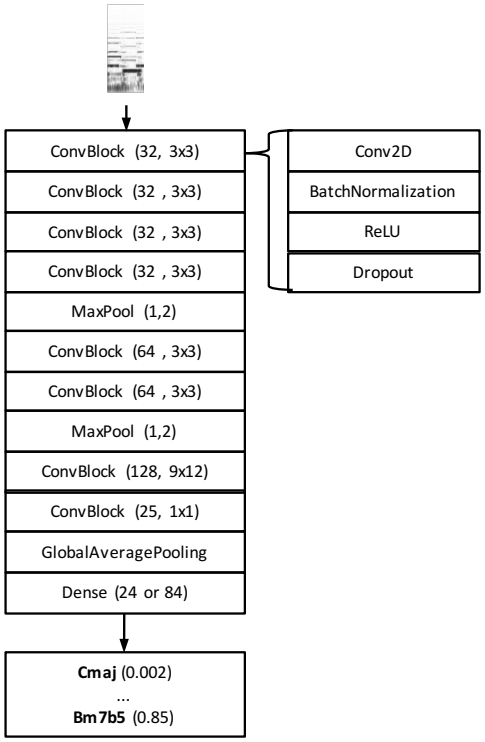

Figure 1. Architecture of the applied convolutional neural network. Number of filters and the kernel size are given in brackets for each ConvBlock. The softmax activation function is used in the final dense layer.

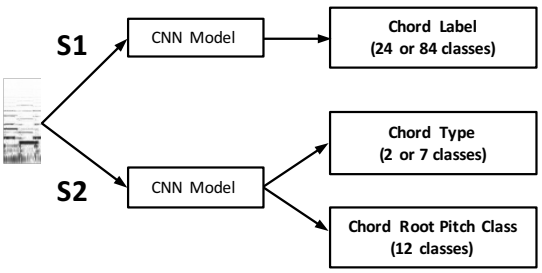

Figure 2. Illustration of two modeling strategies **S1** and **S2** for joint and separate chord type & root pitch class estimation.

Keras framework with Tensorflow as backend [2].

4. DATASETS

4.1 Existing Datasets

The datasets used in this paper are summarized in Table 2. In addition to the total number of files, Table 2 provides the total dataset duration and total number of chord segments. In order to enlarge the dataset, we use pitch-shifting with total shifts of up to 4 semitones higher and lower as data augmentation technique. Hence, each original file results in 9 augmented files including the original recording. The datasets Beatles (`Bs`) [16], Queen (`Qn`) [16], Robbie Williams (`RW`) [17], `RWC` (100 songs from the RWC Popular Music Database [18]), and Osmalsky (`Os`) [19] have been used in the chord recognition literature previously. While the first four datasets include mixed music recordings with multiple instruments, the `Os` as well as the `ISGuitar` dataset (excerpts from the `IDMT_SMT_GUITAR` database published in [20]) consist of isolated recordings of different instruments playing chords. We created and published a novel dataset for chord recognition research (`IDMT_SMT_CHORDS`, abbreviated as `ISChords` in this paper), which will be detailed in the following section 4.2. The `ISInhouse` dataset is an in-house dataset covering various pop and rock music recordings, which cannot be published due to copyright constraints. In order to evaluate our model on music mixtures for the task of large-vocabulary ACR, we aggregated an additional dataset (`Combi7`) using files which include seventh chord annotations from the datasets `Bs`, `Qn`, `RWC`, `RW`, and `Os`.

Dataset		# Files	Duration (h)	# Chord Segments
`Bs`	Beatles	1152	53.1	86868
`Qn`	Queen	180	11.2	20610
`RW`	Robbie Williams	234	19.1	25569
`RWC`	RWC	900	61.0	110331
`Os`	Osmalsky	7200	3.8	7200
`Combi7`	Combined Dataset	1863	112.2	193194
`ISGuitar`	IDMT_SMT_GUITAR	48	32.1	684
`ISChords`	IDMT_SMT_CHORDS	16	4.1	7398
`ISInhouse`	IDMT Inhouse Dataset	111	4.9	9159

Table 2. Overview of all chord recognition datasets with the respective number of audio files, the total duration in hours, as well as the number of chord segments.

4.2 Synthetic Dataset for Large Vocabulary Chord Recognition

Currently used chord recognition datasets are only partially suitable for training and evaluation on seventh chord types. Therefore, we created and published a novel dataset (`IDMT_SMT_CHORDS`) [3]. We initially created two MIDI files which cover all seven chord types listed in Table 1.

[2] Keras: `keras.io`, Tensorflow: `www.tensorflow.org`

[3] The download link for the audio and MIDI files will be published in the camera-ready version of the paper.

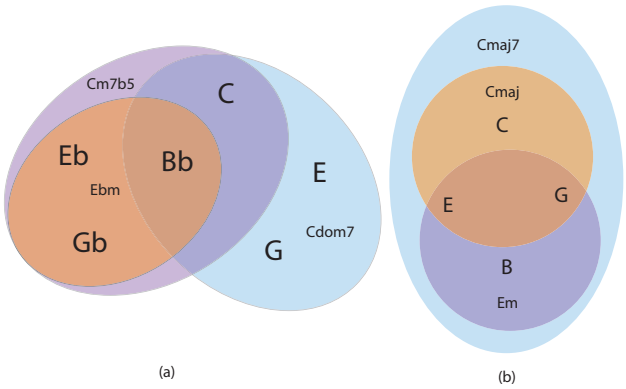

Figure 3. Illustration of ambiguities between chords due to shared chord tones between the chord types m7♭5, min, and dom7 (a), and maj7, maj, and min (b). Figure inspired by [1].

Here we focused on chord voicings, which are commonly used on keyboard instruments and guitars. The piano MIDI file includes all chord types in all possible root note positions and inversions. The guitar MIDI file is based on barré chord voicings with the root note located on the low E, A, and D strings. We used several software instruments from Ableton Live [4] and Garage Band [5] to synthesize these MIDI files with various instruments such as piano, synthesizer pad, as well as acoustic and electric guitar.

Dataset	maj	min	maj7	min7	5	dom7	m7b5
`Bs`	67.95	20.49	2.17	3.00	0.04	6.12	0.22
`Qn`	63.81	22.52	1.28	4.47	1.28	6.56	0.09
`RW`	69.64	28.30	0.36	0.50	0.89	0.32	-
`RWC`	48.09	26.57	5.94	13.25	-	5.87	0.28
`Os`	60.00	40.00	-	-	-	-	-
`Combi7`	53.24	25.20	4.65	9.75	0.19	6.71	0.27
`ISGuitar`	67.89	16.51	4.59	3.67	-	5.50	1.83
`ISChords`	17.11	17.11	14.31	14.31	8.55	14.31	14.31
`ISInhouse`	62.85	37.15	-	-	-	-	-

Table 3. Chord type distribution per dataset in percent (%).

5. EVALUATION

In the experiment described in this section, we focus on two types of ACR challenges: First, as discussed in [1], the assignment of a chord label is often ambiguous as different chord types partly share chord tones. Figure 3 illustrates this using two chord type triples, which share one or multiple chord tones. For instance, as shown on the left side, a half-diminished seventh chord (e. g., Cm7♭5) can potentially be confused with the minor chord built upon its minor third (E♭m) or with the dominant seventh chord built upon the same root note (Cdom7).

Secondly, the datasets introduced in Section 4 have different acoustic characteristics. While some of the songs in the `Bs` and `Qn` datasets were recorded in the 1970s already, other datasets such as `RW` and `ISInhouse` contain contemporary popular music recordings with a modern

[4] `https://www.ableton.com/en/live/`

[5] `https://www.apple.com/mac/garageband/`

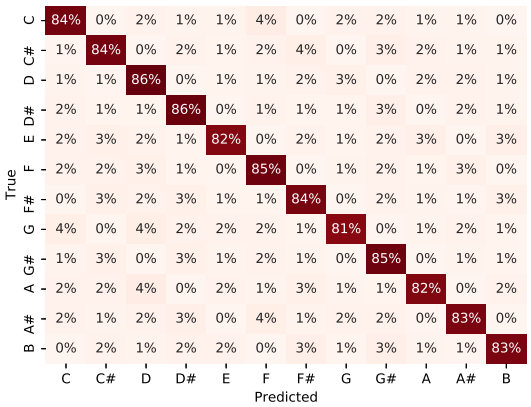

Figure 4. Confusion matrix for chord root pitch class classification on isolated chord recordings (experiment **E3**, strategy **S2**).

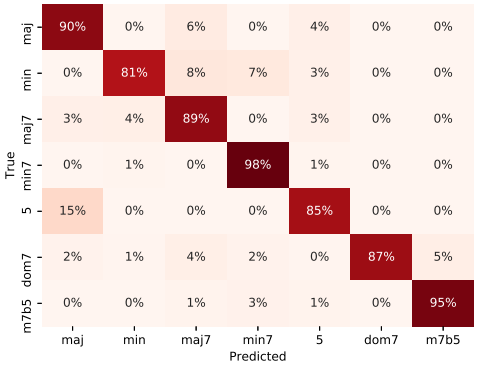

Figure 5. Confusion matrix for 7 chord types in large-vocabulary ACR on isolated chord recordings (`ISChords`, experiment **E3**, strategy **S2**).

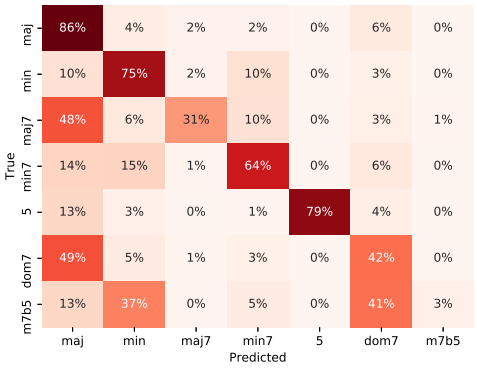

Figure 6. Confusion matrix for 7 chord types in large-vocabulary ACR on mixed chord recordings (`Combi7` + `ISChords`, experiment **E6**, strategy **S2**).

sound. Also, the datasets are of different timbre complexity ranging from simple isolated chords to complex audio mixtures. It was observed in related MIR tasks such as music transcription [21] that data-driven models trained for transcribing isolated notes do not generalize well to more complex acoustic mixtures. Here, we aim to investigate whether such findings can be replicated for ACR.

Table 4 summarizes 11 experiments, which are designed to analyze the chord type ambiguity on isolated chord recordings (**E1** - **E3**, see Section 5.1), the generalization of ACR models to mixture recordings (**E4** - **E6**, see Section 5.2), as well as two real-life ACR application scenarios (**E7** - **E11**, see Section 5.3). In addition, we tested the state-of-the-art ACR algorithm proposed in [8] (**REF**) for the major / minor chord vocabulary, which is available in the madmom [6] python library. Its performance in four of our experiments is documented in the last column of Table 4.

In all experiments, audio recordings are split into training set and test set on a dataset-level or on a file-level. When a dataset is used for training and test we perform a two-fold random cross-validation with a split of 60 %, 20 %, and 20 % into training, development, and test set, respectively. We use the weighted average class f-score throughout this paper as evaluation measure. The f-scores F_{24} and F_{84} are used to indicate if the evaluation was performed on 24 chord classes (major/minor vocabulary) or 84 classes (large vocabulary ACR). The "no chord" class is neglected in all experiments. In the following subsections, three groups of experiments will be detailed whose results are summarized in Table 4.

5.1 Chord Type Ambiguity on Isolated Chord Recordings

In experiments **E1**, **E2**, and **E3** (first section of Table 4), we train and evaluate ACR models on isolated chord recordings (`ISChords`) to study the effect of chord tone ambiguity in large-vocabulary ACR. As explained in Section 4.2, the contained chords are based on two systematically generated MIDI files with chord voicings from keyboard and non-keyboard instruments. In our experiments, we evaluate the influence of the chord voicing types as well as of the modeling approach (compare Section 3.2).

For the major/minor chord vocabulary (24 classes), we obtain high accuracy scores F_{24} between 0.81 and 0.99 using the strategy **S1**. In the two experiments **E1** & **E2**, we perform a chord voicing "cross-test" by exclusively assigning piano chord voicings to the training set and test on non-piano chord voicings and vice versa. Intuitively, we observe lower accuracy scores (compared to **E3**) since the models are confronted with a different timbre (instrument) and previously unseen chord voicings at test time. Contrary to the 24 classes major/minor scenario, we observe that for the 84 classes scenario (large-vocabulary ACR), strategy **S2** clearly outperforms **S1**. We assume that the network capacity is large enough to learn distinct spectral patterns for classifying among 24 chord labels. For the large-vocabulary scenario however, the amount of 84 classes is presumably too high to be learnt by one model using strategy **S1**. Instead, splitting the classification task into two easier sub-tasks (with not more than 12 classes

[6] `https://github.com/CPJKU/madmom`

#	Training Set	Test Set	Strategy S1		Strategy S2		Reference System (K)
			F_{24}	F_{84}	F_{24}	F_{84}	F_{24}
Chord Type Ambiguity on Isolated Chord Recordings (Section 5.1)							
E1	ISChords (non-guitar)	ISChords (guitar)	**0.92**	0.58	0.90	**0.76**	-
E2	ISChords (guitar)	ISChords (non-guitar)	**0.81**	0.49	0.54	**0.56**	-
E3	ISChords	ISChords	**0.99**	**0.97**	0.90	0.82	0.74
Generalization of ACR Models towards Complex Recordings (Section 5.2)							
E4	ISChords	Combi7	**0.40**	**0.36**	0.18	0.28	-
E5	Combi7	Combi7	0.83	0.63	**0.84**	**0.64**	0.83
E6	ISChords + Combi7	ISChords + Combi7	0.84	0.65	**0.84**	**0.66**	-
Real-Life ACR Application Scenarios (Section 5.3)							
E7	ISChords	ISInhouse	**0.56**	-	0.27	-	-
E8	ISChords	ISGuitar	**0.90**	-	0.70	-	-
E9	Bs + Qn + RW + RWC + Os +ISChords	ISInhouse	0.71	-	**0.74**	-	**0.76**
E10	Bs + Qn + RW + RWC + Os + +ISChords	ISGuitar	0.90	-	**0.91**	-	**0.91**
E11	Bs + Qn + RW + RWC + Os +ISChords	Bs + Qn + RW + RWC + Os +ISChords	0.81	-	**0.84**	-	-

Table 4. This table lists all ACR experiments grouped into three sections described in Section 5.1, Section 5.2, and Section 5.3. Table lists datasets contained in the training and test set, respectively. For both modeling strategies **S1** and **S2** introduced in Section 3.2, f-scores F_{24} and F_{84} are provided for the 24 classes major / minor chord vocabulary and the 84 classes large-vocabulary with the 7 chord types listed in Table 1. The last column gives the f-score using the reference system (**REF**) for the most important test scenarios.

each) using strategy **S2** seems slightly beneficial here. Interestingly, in experiment **E3**, where all chord voicings are mixed, strategy **S1** outperforms strategy **S2** in both the 24 and 84 classes scenarios. When testing with state of the art model (**REF**) in **E3** we see that it does not perform as well since it is likely trained on complex audio mixtures.

Figure 4 shows the confusion matrix for the classification of the chord root pitch class for the 84 class scenario for experiment **E3**. It can be observed that the model shows a good performance for all classes between 82 % and 86 %. Similarly, as can be seen in Figure 5, the model easily learns to distinguish between different chord shapes for isolated chord recordings (ISChords dataset). However, Figure 6 shows the more complicated test case of mixed audio recordings (Combi7 + ISChords datasets). The most prominent misclassifications between the maj7 towards the maj, the dom7 towards the maj, as well as the m7♭5 towards the min and the dom7 all confirm the chord tone ambiguities discussed in Section 5.

5.2 Generalization of ACR Models towards Complex Recordings

In experiments **E4** to **E6** (second section of Table 4), we investigate (similar to [21]) whether and to what extent ACR models trained on isolated instrument recordings generalize towards complex music recordings in the Bs, Qn, and RWC datasets. Also, we test whether adding the proposed ISChords dataset can help to improve the performance on large vocabulary ACR. As expected, a poor accuracy value of $F_{24} = 0.4$ in **E4** shows that the investigated CNN-based ACR model does not generalize well from a simple training scenarios (ISChords) towards a complex test scenario (Combi7). The clearly higher accuracy values of $F_{24} = 0.84$ and $F_{84} = 0.66$ show that this kind of data-driven classification models need to be trained on data of similar timbre complexity as in the test scenario. We only observe a small improvement of 0.02 for the 84 classes scenario in accuracy when training with both datasets (**E6**). The reference algorithm **REF** shows a similar performance as **S2** in **E9**.

5.3 Real-Life ACR Application Scenarios

In the experiments **E7** to **E11** (third section of Table 4), we address realistic requirements for ACR systems to be deployed in real-life. In a music education scenario, musical instruments usually can be directly recorded and analyzed without background sounds. Therefore, we test the chord recognition performance on isolated polyphonic electric guitar recordings (ISGuitar), which include both chords and arpeggios. In a music annotation scenario, we evaluate ACR models on a set of 111 contemporary pop and rock music recordings of various instrumentations (ISInhouse). Similarly to **E4**, we can observe in experiment **E7** that ACR models trained only on isolated chord recordings do not perform well on complex mixtures (ISInhouse). However, such models show a good performance ($F_{24} = 0.9$, $F_{84} = 0.7$) when being applied to isolated guitar recordings (**E8**). In both test cases, the performance can be clearly improved by adding more datasets to the training set, which reflect a larger variety of music recordings (compare experiments **E9** and **E10**). In both experiments **E9** and **E10**, the reference algorithm **REF** performs almost similar.

In summary, for the two real-application scenarios sketch-

ed above, we obtain a best performance of $F_{24} = 0.91$ for isolated guitar recordings and $F_{24} = 0.74$ for contemporary popular music recordings. This shows that the recently proposed CNN architecture can be readily deployed into real-life MIR applications.

6. CONCLUSIONS

In this paper, we used a state-of-the-art deep convolutional neural network architecture for ACR. In addition to publishing a novel dataset of isolated chord recordings, we propose an alternative modeling strategy using two models for the separate classification of the chord type and the chord root pitch class. In our experiments, we first evaluate this strategy for the controlled test case of isolated instrument recordings. Most of the chord type misclassifications are due to shared chord tones. The results indicate that ACR even with large-vocabulary is feasible (f-scores above 0.9), but the performance depends on whether the chord voicings and instrument timbre used in the test set have been learnt by the model before.

In a second set of experiments, we were able to replicate the finding from automatic music transcription that data-driven ACR models need to be trained on data of the same complexity as the expected test data. Models trained on isolated instrument recordings performed poorly on mixed audio data. Finally, we evaluated the CNN model on two separate datasets, which acted as a proxy for deploying an ACR model into real-life production systems for the two use cases music education and music annotation. Here, we achieved high f-scores of 0.91 for isolated instrument recordings and 0.74 for mixed contemporary popular music recordings showing the usefulness for real-life MIR applications.

Acknowledgments

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