

Automatic Chord Recognition with Deep Learning

Pierre Lardet



4th Year Project Report
Computer Science and Mathematics
School of Informatics
University of Edinburgh
2025

Abstract

This skeleton demonstrates how to use the `infthesis` style for undergraduate dissertations in the School of Informatics. It also emphasises the page limit, and that you must not deviate from the required style. The file `skeleton.tex` generates this document and should be used as a starting point for your thesis. Replace this abstract text with a concise summary of your report.

Research Ethics Approval

This project was planned in accordance with the Informatics Research Ethics policy. It did not involve any aspects that required approval from the Informatics Research Ethics committee.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(Pierre Lardet)

Acknowledgements

Table of Contents

1	Introduction	1
1.1	Motivation	1
1.2	Aims	1
1.3	Outline	2
2	Background & Related Work	3
2.1	Background	3
2.2	Related Work	6
3	Experimental Setup	9
3.1	Data	9
3.2	Evaluation	14
3.3	Training	16
4	A Convolution Recurrent Neural Network	18
4.1	Baseline Models	18
4.2	CRNN	19
4.3	Model Analysis	24
5	Improving the Model	31
5.1	Weighted Loss	31
5.2	Decoding	32
5.3	Pitch Augmentation	34
5.4	Using Generative Features	35
5.5	Structured Training	35
5.6	Synthetic Data Generation	35
5.7	Results on the Test Set	35
5.8	Qualitative Analysis	35
6	Conclusions, Limitations and Further Work	36
6.1	Conclusions	36
6.2	Limitations	36
6.3	Further Work	36
	Bibliography	37

A	Appendix	41
A.1	Accuracy vs Context Length of Evaluation	41
A.2	Accuracy vs Hop Length	42
A.3	Incorrect Region Lengths With/Without Smoothing	42

Chapter 1

Introduction

1.1 Motivation

TODO: Rewrite introduction to focus on chord recognition.

- Useful for musicians - Useful for musicologists - Connection to lead sheets

Chords form an integral part of music. Used in music of all forms. Used for research

To this end, we investigate the use of deep learning for automatic chord recognition. Data-drive methods have dominated the field of automatic music transcription in recent years, and have shown great promise for chord recognition. However, progress has not been made since 2015. Why? What might be done to improve?

We conduct a thorough analysis of the state-of-the-art models for automatic chord recognition, and investigate methods of improving on these models. We look at the ways others have improved these models and compare and contrast them.

We also take inspiration from other fields of music transcription and leverage modern generative models to provide new representations training data and generate synthetic data itself.

1.2 Aims

The aims of this project are:

- Compare state-of-the-art models for automatic chord recognition.
- Conduct a thorough analysis of the models and their performance.
- Investigate methods of improving on these models.
- To perform experiments with new sources of data, data augmentation and synthetic data generation.

1.3 Outline

The report is structured as follows:

- **Chapter 2** provides background information on chord transcription and related work.
- **Chapter 3** describes the datasets, evaluation metrics and training procedure used in this project.
- **Chapter 4** compares various models from the literature and investigates improvements.
- **Chapter 5** extends this work with synthetic data generation and compares results on a new dataset.
- **Chapter 6** concludes the report and provides suggestions for future work.

Chapter 2

Background & Related Work

In this chapter, we first provide a brief introduction to harmony and chords in music and the importance of recognising them. We then discuss the different ways in which music can be represented as input to a machine learning model. We then provide an overview of the field of automatic chord recognition (ACR). We discuss the datasets, models, and evaluation metrics that are commonly used in ACR and the challenges that are faced in this field. Finally, we discuss related work in the generation of synthetic data for music transcription tasks.

2.1 Background

2.1.1 Harmony, Chords and Chord Recognition

Harmony is the combination of simultaneously sounded notes. A common interpretation of such sounds is as a chord, especially in Western music. Chords can be thought of as a collection of at least two notes, built from a root note often with the third and fifth degrees of the scale. They can be extended with any notes but the most common are the seventh, ninth, eleventh and thirteenth upper extensions. A chord's *quality* is determined by the intervals between notes in the chord irrespective of the root note. The most common chord qualities are major and minor, built from the major and minor scales. Many other qualities exist such as diminished, augmented, and suspended chords. Chords can be played in *inversion*, where the root note is not the lowest note, and can be played in different *voicings*, where the notes are played in different octaves. In this work, we represent chords using Harte notation (Harte et al., 2005) as described in Section 3.1.1.2.

Chords are an important part of music. They provide a harmonic context for a melody, and can be used to convey emotion, tension and release. They are also important for improvisation where musicians will often play notes that fit the chord progression such that they create a pleasing sound. Many forms of musical notation rely on chords. Contemporary guitar music and accompaniments are often represented by just a chord sequence. Lead sheets are a form of notation which strip down a piece of music to its chord sequence and the melody. Lead sheets are often used for improvisation,

especially in jazz music and chords are integral to this notation. A lead sheet for ‘Yesterday’ by The Beatles can be found in Figure 2.1. Chords are also important for songwriting, where a chord progression can be the basis of a song. They also play an important role in music analysis, where the harmonic structure of a piece can be analysed to better understand the composer’s intentions, and to understand why we enjoy certain kinds of music.

Chord recognition is the task of identifying the chords present in a piece of music. This can be useful for creating notated versions of songs, for music analysis, for music recommendation and for music generation. Those wishing to learn pieces of music may start by visiting websites such as Ultimate Guitar¹ where users submit chord annotations for songs. Music researchers may wish to analyse the harmonic structure of a piece of music, or analyse the changes in common chord sequences over time. Music recommendation systems may recommend songs based on their harmonic content as similar music will often have similar harmonic content. For example, modern pop music famously uses many similar chords² while jazz music is known for its complex and rich exploration of harmony. Music generation systems can generate audio based on a given harmonic structure (Jung et al., 2024).

All of the above motivate the need for accurate chord recognition systems. Annotations from online sources can be of varying quality and may not be available for all songs. The task of annotating chords is time-consuming and requires a trained musician. Automatic chord recognition systems have the potential to alleviate these problems by providing a fast, accurate and scalable solution.

Yesterday

Lennon and McCartney

The lead sheet for 'Yesterday' by The Beatles is presented in standard musical notation. The melody is written on a treble clef staff with a key signature of one flat (Bb) and a 4/4 time signature. The chords are written above the staff: F, Em, A, Dm, Bb, C, Bb, F, Dm, G, Bb, F. The lyrics are: 'Yes ter day, all my trou bles seemed so far a way. Now it looks as though they're here to stay, oh I be lieve in yes ter day.'

Figure 2.1: An example of a lead sheet for ‘Yesterday’ by the Beatles. We can see chords written above the stave and the melody written in standard musical notation. Such a chordal representation is useful for musicians who want to learn and perform songs quickly or improvise around them.

¹<https://www.ultimate-guitar.com/>

²<https://www.youtube.com/watch?v=o0lDewpCfZQ>

2.1.2 Music Features

Recorded music can be represented in a variety of ways as input to a machine learning model. The simplest is to leave the data as a raw time-series of amplitudes, often referred to as the waveform. Data in the raw audio domain has been successfully applied in generative models such as Jukebox (Dhariwal et al., 2020) and RAVE (Caillon and Esling, 2021).

Spectrogram: A common representation of audio data is the spectrogram. A spectrogram is a conversion of the time-series data into the time-frequency domain, calculated via a short-time Fourier transform (STFT). Spectrograms are commonly used in many audio processing tasks, such as speech recognition, music recognition (Wang, 2003) and music transcription, specifically polyphonic transcription (Toyama et al., 2023). However, as noted by Pauwels et al. (2019), only logarithmic spectrograms have been used in ACR tasks.

CQT: A common version of the spectrogram used in music transcription is the Constant-Q Transform (CQT), originally proposed by Brown (1991). The CQT is a version of a spectrogram with frequency bins that are logarithmically spaced and bin widths that are proportional to the frequency. This is motivated by the logarithmic nature of how humans perceive pitch: a sine wave has double the frequency is perceived as one octave higher. The CQT is used in many music transcription tasks, such as automatic chord recognition (Humphrey and Bello, 2012), and a popular alternative, Melspectrograms, have found use in melody transcription (Toyama et al., 2023). An example CQT from the dataset used in this work is shown in Figure 2.2.

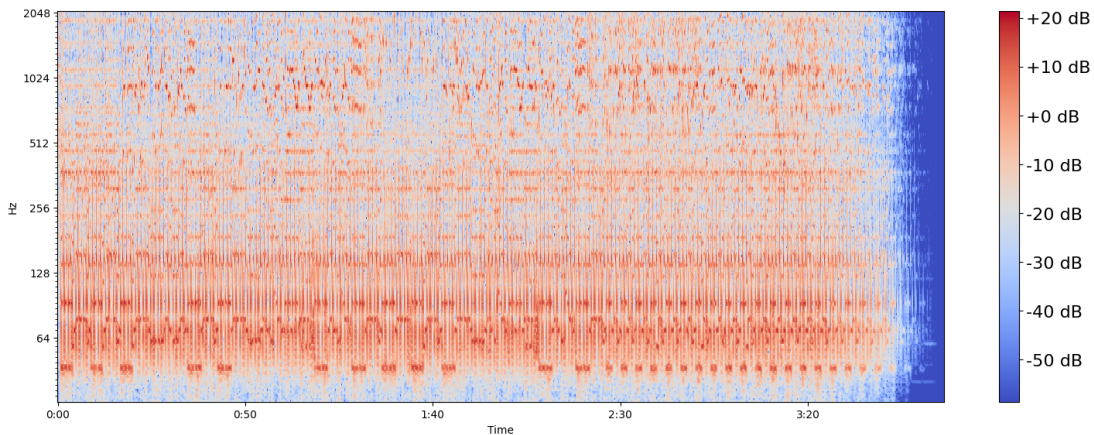


Figure 2.2: A sample CQT of ‘Girls Just Wanna Have Fun’ by Cyndi Lauper from the dataset used in this work. We can see the log-spaced frequency bins on the y-axis. There is clear structure and repetition in the song, particularly in the lower frequencies, which can be attributed to a regular drum groove and bass instruments. This is typical of songs in this dataset. Such structure and repetition gives an idea of the patterns a machine learning model may look for to identify chords.

Chroma Vectors: Chroma vectors are a 12-dimensional time-series representation, where each dimension corresponds to a pitch class. Each element represents the strength

of each pitch class in the Western chromatic scale in a given time frame. Such features have been generated by deep learning methods (Miller et al., 2022) or by hand-crafted methods (Mauch and Dixon, 2010) and have seen use in recent ACR models (Chen and Su, 2019).

Generative Features: More recently, features extracted from generative models have been used as input (Chris Donahue and Liang, 2022). The proposed benefit is that the vast quantities of data used to train these models allows for rich representations of the music. This work uses features from JukeBox (Dhariwal et al., 2020) to train a transformer (Vaswani et al., 2023) for both melody transcription and chord recognition. They then combine these into a lead sheet generation model. They found that these features outperformed hand-crafted features in melody transcription tasks but did not perform experiments in ACR.

2.2 Related Work

2.2.1 Automatic Chord Recognition

Chord recognition is a difficult task. Which chord is playing when is inherently ambiguous. Different chords can share the same notes and the same chord can be played in different ways. The same chord can also be played in different contexts, such as a different key, time signature or on a different instrument. Whether a melody note is part of a chord is ambiguous and whether a melody alone is enough to imply harmonic content is also ambiguous. In order to identify a chord, information across time must be considered as the chordal information may be spread over time. For example, a chord may vamped or arpeggiated. Audio contains many unhelpful elements for chord recognition such as reverb, distortion and percussion. Combined with the lack of labelled data, this makes chord recognition a challenging task.

Pauwels et al. (2019) provide an overview of ACR since the seminal work of Fujishima (1999) in 1999 up to 2019, and provide suggestions for future avenues of research.

Datasets: Sources of data that have seen common use in ACR relevant to this work include:

- *Mcgill Billboard*: over 1000 chord annotations of songs randomly selected from the Billboard ‘Hot 100’ Chart between 1958 and 1991. (Burgoyne et al., 2011)
- *Isophonics*: 300 annotations of songs from albums by The Beatles, Carole King and Zweieck. (Cannam et al., 2009)
- *RWC-Pop*: 100 pop songs with annotations available³ for chords. (Goto et al., 2002)
- *USPop*: 195 annotations of songs chosen for popularity. (Berenzweig et al., 2004)
- *JAAH*: 113 annotations of a collection of jazz recordings. (Durán and de la Cuadra, 2020)

³<https://github.com/tmc323/Chord-Annotations>

- *HookTheory*: 50 hours of labelled audio in the form of short musical segments, crowdsourced from an online forum called HookTheory⁴. (Chris Donahue and Liang, 2022)

Other small datasets also exist. Many of these have been compiled together into the *Chord Corpus* by de Berardinis et al. (2023), with standardised annotation formats.

A problem frequently encountered in ACR is the lack of labelled data. This is due to the difficulty and time associated with labelling data aligned in time and the legal sensitivity of the data involved. Data has been scaled up using augmentation and semi-supervised learning (Hung et al., 2023) with some success. Research has been done into the use of synthetic data (Kroher et al., 2023; Sato and Akama, 2024) and supervised learning (Li et al., 2024) for MIR tasks, but not for ACR.

Another problem is that the existing data is often imbalanced, with a large number of common chords like major and minor chords and fewer chords like diminished and augmented chords, or chords with upper extensions and inversions. This can lead to models that are biased towards predicting major and minor chords. Attempts to address such a long-tailed distribution have been made by re-weighting classes (Jiang et al., 2019), adding a term in the loss function rewarding the identification of individual notes (McFee and Bello, 2017; Jiang et al., 2019), re-sampling training examples to balance chord classes (Miller et al., 2022) and curriculum learning (Rowe and Tzanetakis, 2021).

Models: A variety of machine learning methods have been applied to such datasets. Older methods often use hidden Markov models (HMMs) (Lee and Slaney, 2006) but more recent methods use deep learning. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are used together in many works (Wu et al., 2019; Jiang et al., 2019; McFee and Bello, 2017) with a CNN performing feature extraction from a spectrogram feature and an RNN sharing information across frames. More recently, transformers have been applied to the entire process Chris Donahue and Liang (2022); Chen and Su (2019, 2021).

Decoding: HMMs still see use as a decoder operating on the frame-wise probability distributions over chords generated by the model (Miller et al., 2022). Other works have used conditional random fields (CRF) in their place to model the dependencies between chords (Jiang et al., 2019). Both methods have used simple transition matrices with uniform transition probabilities between different chords, or with transition probabilities learned from the data. Miller et al. (2022) note that performance is similar between the two methods. Decoding then follows the Viterbi algorithm to find the most likely sequence of chords.

Evaluation: Evaluation is typically done using weighted chord symbol recall (WCSR), that is, the recall of each chord class weighted by its duration. This definition is overly complicated as it can simply be thought of as the fraction of time that the prediction is correct. More music-aware measures of recall provide further insights such as the recall of the correct root note, third, seventh or mirex, a metric which checks whether a predicted chord has at least 3 notes in common with the label chord. These are all

⁴<https://www.hooktheory.com/>

implemented by Raffel et al. (2014) in the `mir_eval` library⁵. Qualitative evaluation is sometimes often carried out, with preferences between chord annotations being recorded

2.2.2 Synthetic Data Generation

⁵https://mir-evaluation.github.io/mir_eval/

Chapter 3

Experimental Setup

This chapter outlines the datasets used in this work, the preprocessing applied to the audio and chord annotations, the evaluation metrics used to compare the models and details of the training process.

3.1 Data

Two ACT datasets were used in this work. The first dataset is simply referred to as the *Pop* dataset, as much of the music in the dataset comes from the Billboard Hot 100 charts, or other explicitly chooses pop music from the last 70 years. The second dataset is the *JAAH* (Jazz Annotations and Analysis of Harmony) dataset mentioned in Section 2.2.1. While the chords annotations are publicly available on Github¹, the audio was kindly given to me by Andrea Poltronieri, a PhD student at the University of Bologna and the author of 'ChoCo' (the Chord Corpus) (de Berardinis et al., 2023). I spent the first weeks of the project contacting authors of several papers which have used these or other datasets and he was the only one helpful enough to provide me with the audio.

The rest of this chapter explains processing applied to the audio and chord annotations common to both datasets, before discussing details of the *Pop* and *JAAH* datasets relevant to each.

3.1.1 Preprocessing

3.1.1.1 Audio to CQT

The audio was first converted to a Constant-Q Transform (CQT) representation explained in Section 2.1.2. The CQT was computed using the `librosa` library (McFee et al., 2015), using the `.cqt` function. A sampling rate of 44100Hz was used, with a hop size of 4096, and 36 bins per octave, 6 octaves and a fundamental frequency corresponding to the note C1. These parameters were chosen to be consistent with

¹<https://github.com/smashub/choco>

previous works (McFee and Bello, 2017). This returns a complex-valued matrix containing phase, frequency and amplitude information. Phase information was discarded by taking the absolute value before being converted from amplitude to decibels (dB), equivalent to taking the logarithm. An alternative choice of frame length could be to use some fraction of a bar. For example, Chris Donahue and Liang (2022) use 1/16th of a bar. However, most work in the literature opts for a constant hop size. We followed this convention as a hop size which varies over songs introduces a new source of error in identifying the tempo and meter of a song, which the authors note as sometimes being problematic to their method.

This leads to a CQT matrix of size $216 \times F$ where 216 is the number of frequency bins and F is the number of frames in the song. The number of frames can be calculated as $F = \lceil \frac{44100}{4096} L \rceil$ where L is the length of the song in seconds, 44100 is the sampling rate in Hertz (Hz) and 4096 is hop size in samples. A 3 minute song has just under 2000 frames. To save on computational time, the CQT was pre-computed into a cached dataset rather than re-computing each CQT on every run.

3.1.1.2 Chord Annotations

The chord annotation of a song is represented as a sorted dictionary, where each entry contains the chord label, the start time and duration. The chord label is represented as a string in Harte notation (Harte et al., 2005). For example, C major 7 is C:maj7 and A half diminished 7th in its second inversion is A:hdim7/5. However, the majority chords in the dataset are not this complicated. The notation also includes N which signifies that no chord is playing.

This annotation is too flexible to be used as directly as a target for a machine learning model trained on limited data. This would lead to thousands of classes, many of which would appear only once. Instead, we define two chord vocabularies. The first is a simple chord vocabulary which contains only the major and minor quality for each root and a no chord symbol N. Chords outside the vocabulary are mapped to X, a dedicated unknown symbol. For example, C:maj7 is mapped to C:maj while A:hdim7/5 is mapped to X. Letting C be the size of the chord vocabulary, $C = 26$ for the small vocabulary. The second is a more complex vocabulary, which contains 14 qualities for each root: major, minor, diminished, augmented, minor 6, major 6, minor 7, minor-major 7, major 7, dominant 7, diminished 7, half diminished 7, suspended 2, suspended 4. Additionally, we retain the N and X symbols totalling $C = 12 \cdot 14 + 2 = 170$ chord labels. This vocabulary or similar vocabularies have been used by much of the literature (McFee and Bello, 2017; Humphrey and Bello, 2015; Jiang et al., 2019).

Chords in Harte notation were mapped to this vocabulary by first converting them to a tuple of integers using the Harte library. These integers represent pitch classes and are in the range 0 to 11 inclusive. They are transposed such that 0 is the root pitch. These pitch classes were then matched to the pitch classes of a quality in the vocabulary, similar to the work by McFee and Bello (2017). However, for some chords this was not sufficient. For example, a C:maj6(9) chord would not fit perfectly with any of these templates due to the added 9th. Therefore, the chord was also passed through Music21's (Cuthbert and Ariza, 2010) chord quality function which matches chords such as the one above

to major. This function would not work alone as its list of qualities is not as rich as the one defined above. If the chord was still not matched, it was mapped to X. This additional step is not done by McFee and Bello (2017) but gives more meaningful labels to roughly one third of the chords previously mapped to X.

3.1.2 Pop Dataset

The *Pop* dataset consists of songs from the *Mcgill Billboard*, *Isophonics*, *RWC-Pop* and *USPop* datasets mentioned in Section 2.2.1. This collection was originally proposed in work by Humphrey and Bello (2015) in order to bring together most of the known datasets for chord recognition. The dataset consists of a subset of the above datasets filtered for duplicates and selected for those with annotations available. In total, there are 1,217 songs. The dataset was provided with obfuscated filenames and audio as .mp3 files and annotations as .jams files (Humphrey et al., 2014).

3.1.2.1 Data Integrity

Several possible sources of error in the dataset are investigated below.

Duplicates: Files were renamed using provided metadata identifying them by artist and song title. This is done to identify duplicates in the dataset. The dataset was filtered for duplicates, of which there was one: Blondie’s ‘One Way or Another’ which had two different recordings. The duplicate was removed from the dataset to as validation and testing should ensure the model generalises across songs, not across different recordings of songs. Further duplicates may exist under different names but throughout the project no other duplicates were found. Automatic analysis of the audio could help, although cannot be guaranteed to find different versions of the same song. As such, we proceed with the assumption that there are no duplicates in the dataset.

Chord-Audio Alignment: 10 songs were manually investigated for alignment issues. This was done by listening to the audio and comparing it to the annotations directly at various points in the song, with a focus on the beginning. It became apparent that precise timings of chord changes are ambiguous. The annotations aired on the side of being slightly early but were all certainly good annotations, with detailed chord labellings including inversions and upper extensions.

Automatic analysis of the alignment of the audio and chord annotations was also done using cross-correlation of the derivative of the CQT features of the audio over time and the chord annotations, varying a time lag. A maximum correlation at a lag of zero would indicate good alignment as the audio changes at the same time as the annotation. The derivative of the CQT in the time dimension was estimated using librosa’s `librosa.feature.delta` function. The chord annotations were converted to a binary vector, where each element corresponds to a frame in the CQT, and is 1 if a chord change occurs at that frame, and 0 otherwise. Both the CQT derivatives and binary vectors were normalised by subtracting the mean and dividing by the standard deviation. Finally, cross-correlation was computed using numpy’s `numpy.correlate` function. A typical cross-correlation for a song is shown in Figure 3.1. We can see

that the cross-correlation repeats every 20 frames or so. Listening to the song, we can interpret this as one bar-length as drum transients will be highly correlated every bar.

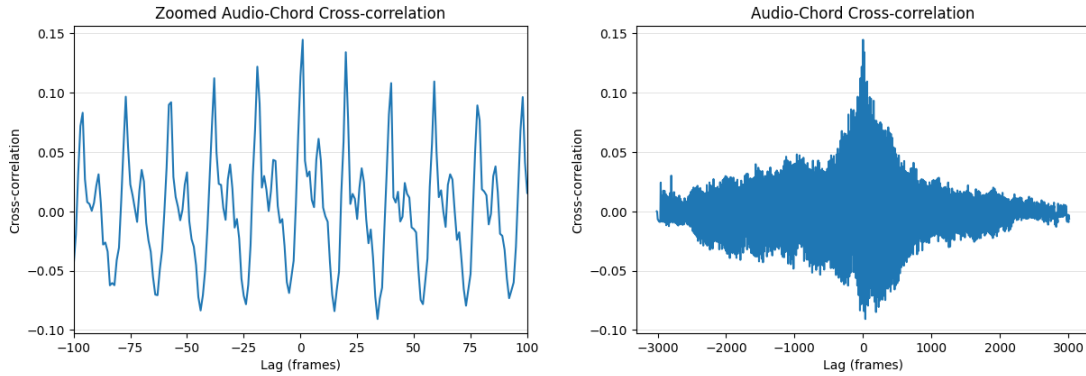


Figure 3.1: Cross-correlation of the derivative of the CQT of the audio and the chord annotations for a single song. We can see correlation peaking in regular intervals of around 20 frames, which corresponds to one bar length in this song. Zooming out, we observe peaks in correlation centred around 0.

To check alignment across the dataset, we can plot a histogram over songs of the lag of the maximum cross-correlations. If we further assume that the annotations are not incorrect by more than 10 seconds, we can restrict our maximum correlation search to a window of 100 frames either side of 0. A histogram of maximum-lags per song is shown in Figure 3.2 where the maximum is within a window of 100. This reduction does not change the shape of the picture. Rather, focusing on a reduced set of lags allows more detail to be visible. The majority of songs have a maximum lag in the region of 0, with a few outliers. This can be attributed to noise. A final check was done by looking at the difference in length of the audio files and chord annotations. A histogram of differences in length is also shown in the figure. Furthermore, the majority of songs have a difference in length of 0, with a few outliers, almost all less than a second. This evidence combined with the qualitative analysis was convincing enough to leave the annotations as they are for training.

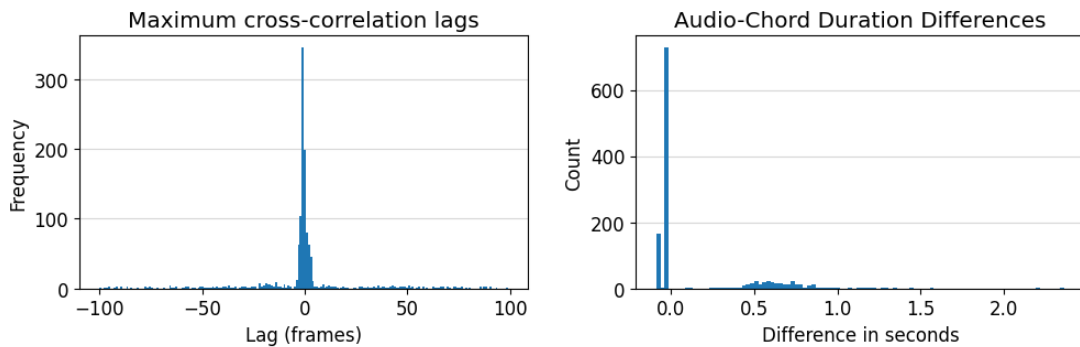


Figure 3.2: Cross-correlation of the derivative of the CQT of the audio and the chord annotations for a single song. The x-axis is the lag in frames and the y-axis is the correlation. The plot repeats every 100 frames, which corresponds to 4 bars.

Incorrect and Subjective Annotations: Throughout manual listening, no obviously wrong annotations were found. However, looking at songs which the first trained models perform the worst on using the `mirex` metric, three songs stick out. ‘Lovely Rita’ by the Beatles, ‘Let Me Get to Know You’ by Paul Anka and ‘Nowhere to Run’ by Martha Reeves and the Vandellas all had scores below 0.05. In these songs, the model consistently guessed chords one semitone off, as if it thought the song was in a different key. Upon listening, it became clear that the tuning was not in standard A440Hz for the first two songs and the key of the annotation was wrong for the other. These songs were kept in to maintain consistency with previous works and are unlikely to skew reported metrics much as explained in Section 3.2. No other songs were found to have such issues.

Chord annotations are inherently subjective to some extent. Detailed examples in *Pop* are given by Humphrey and Bello (2015). They also note that there are several songs in the dataset of questionable relevance to ACR, as the music itself is not well-explained by chord annotations. However, these are kept in for consistency with other works as this dataset is often used in the literature. Some works decide to use the median as opposed to the mean accuracy in their evaluations in order to counteract the effect of such songs on performance (McFee and Bello, 2017). We think that this is unnecessary as the effect of these songs is likely to be small and we do not wish to inflate our results. Further evidence is given in Section 3.2.

3.1.2.2 Chord Distribution

Much of the recent literature has focused on the long tail of the chord distribution, using a variety of methods to attempt to address the issue (Miller et al., 2022; Rowe and Tzanetakis, 2021). It is first helpful to understand the distribution of chords in the datasets, shown in Figure 3.3. The distribution is broken down both by root and by quality, only for the larger chord vocabulary. The smaller vocabulary does not have the same long-tailed distribution. The plots show that the distribution over qualities is highly skewed, with major and minor chords making up the majority of the dataset and qualities like majorminor and diminished 7th chords having two to three orders of magnitude fewer frames. Another display over chord qualities can be found in the work by Jiang et al. (2019). The distribution over roots is far less skewed, although there is a preference for chords for keys like C, D or E and fewer in C# or F#.

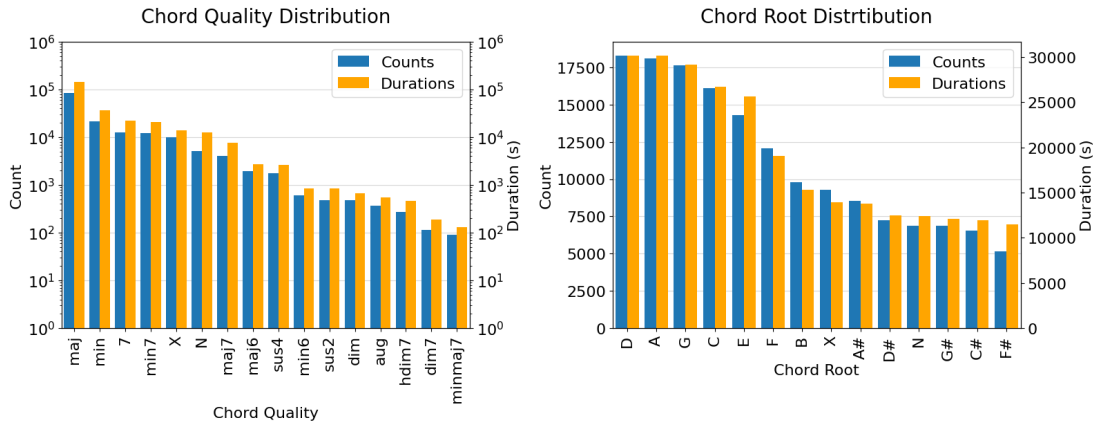


Figure 3.3: Chord distributions in the *Pop* dataset. The plots show both the raw counts in terms of frames and the duration in seconds for each chord root/quality. Note that the y-axis on qualities is in log-scale. We observe that the qualities are very imbalanced, with *maj* the most popular, but that roots are relatively balanced.

3.1.3 JAAH Dataset

TODO: I was warned by Andrea that the JAAH dataset has not been as commonly used as dataset the Billboard dataset. Therefore he could not guarantee that the audio was aligned for this dataset.

- As yet, JAAH is unused in this work - Data was received as .flac files which were first converted to .mp3 files to be in line with the Billboard dataset - Comparison of the two datasets - Description of the JAAH dataset and its use in this work - Intended to be used as a test set to test the synthetic data generation.

3.2 Evaluation

We evaluated models using the *mir_eval* library (Raffel et al., 2014). This library provides a variety of metrics for evaluating the performance of chord recognition models. The metrics used in this work follow standard practice in using *root*, *third*, *seventh* and *mirex* accuracies. For a given hypothesis and reference chord, these metrics all return 1 if the root/third/seventh/three notes of the chord match and 0 otherwise. They return -1 if the true label is X. X is a highly ambiguous class with a wide variety roots and qualities that are mapped to it. From a musician’s perspective, it would be better to have a reasonable guess at the chord rather than X which provides little information. Therefore, the model should not be penalised on frames with true label X and as such, these were ignored for all evaluation.

We also looked at the overall frame-wise accuracy, referred to as *frame* or simply accuracy. We chose not to use *majmin*, *triad* or *tetrad* as these are highly correlated with the previous metrics. This makes sense from a theoretical standpoint as the third and seventh are strong indicators of the triad and tetrad of the chord. This was also verified empirically on some initial results, where the *third* and *majmin* accuracies were always within ± 0.01 of one another.

For the above metrics, the mean is computed for each song, and both the mean and median of the mean across songs were returned. Values are in the range $[0, 1]$. The mean and median were found to within ± 0.01 on all values observed. The median was consistently slightly higher likely due to there being more negative outliers than positive outliers. Some of these outliers are those previously identified as having incorrect annotations in Section 3.1.2.1 or could be those identified as being unsuitable for chordal analysis (Humphrey and Bello, 2015). We report only the mean throughout this work. This was chosen in part for being more commonly used in recent literature and in part to measure how well the model performs well enough on all songs, which the mean is a better estimate of. In any case, the similarity between median and mean results in small differences between the two. These metrics can be formally defined as follows:

$$M(f) = \frac{1}{N} \sum_{i=1}^N \frac{1}{|\{t \in T : y_{i,t} \neq x\}|} \sum_{t \in T : y_{i,t} \neq x} f(y_{i,t}, \hat{y}_{i,t})$$

where M is the metric in question, f is a function which calculates the metric for a pair of reference and hypothesis chord labels, defined for each metric as above. N is the number of songs, T is the set of frames in a song, $y_{i,t}$ is the true chord at frame t of song i , and $\hat{y}_{i,t}$ is the predicted chord at frame t of song i .

For some experiments, we look at two more metrics. These are the mean and median class-wise accuracies, called `classmean` and `classmedian` respectively. These are the mean/median accuracy over each chord class. These metrics are formally defined as follows:

$$\text{class}_{\text{mean}} = \frac{1}{C} \sum_{c=1}^C \text{acc}(c), \quad \text{class}_{\text{median}} = \text{median}_{c=1}^C [\text{acc}(c)]$$

where $\text{acc}(c)$ is the accuracy of class c defined as:

$$\text{acc}(c) = \frac{\sum_{i=1}^N \sum_{t \in T : y_{i,t} \neq x} \mathbb{1}(y_{i,t}=c \wedge \hat{y}_{i,t}=c)}{\sum_{i=1}^N \sum_{t \in T : y_{i,t} \neq x} \mathbb{1}(y_{i,t}=c)}$$

where C is the number of chord classes, and N , T , $y_{i,t}$ and $\hat{y}_{i,t}$ are as defined before.

These metrics were intended to measure the model’s performance on the long tail of the chord distribution. It is important to measure both the mean and median as the distribution of accuracies over classes is highly skewed. These last two metrics are the only ones that take into account the entire evaluation dataset at once rather than on a per-song basis. Some songs may contain few or no chords of a particular class or quality, making the per-song metrics very noisy for class-wise metrics. We do not also compute *quality*-wise accuracies as seen in other work (Rowe and Tzanetakis, 2021). Compared to `classmean`, this metric only adds a weighted average over roots. As roots as fairly balanced, this would not add much information.

For the majority of experiments, the metrics on the validation set are used to compare performance. The test set is held out for use only to compare the final performances of selected models.

Finally, other evaluation tools were used, such as confusion matrices and accuracies over particular chord qualities and classes. Qualitative analysis was carried out to better understand the model's behaviour and to identify any systematic errors. We conclude our evaluation by looking at the predictions of the model in the context of its use for musicians or musical researchers.

3.3 Training

Three variants of the dataset were used for training, validation and testing. For training, an epoch consisted of randomly sampling a patch of audio from each song in the training set. The length of this sample was kept as a hyperparameter, set to 28 seconds for the majority of experiments. For testing, the entire song was used as performance was found to be marginally better if the model was allowed to see the entire song at once. This is later discussed in Section 4.3.4. Because songs are of variable length, songs were split into patches of the same length as the training patches when validating mid-way through training. This meant that computation could be parallelised without as many padded frames as validating on the entire song at once. For all variants, frames in the batch were padded to the maximum length of the batch and padded frames were ignored for loss or metric calculation.

The models were trained using the `PyTorch` library (Paszke et al., 2019). All final experiments were run on the ML Teaching Cluster with a variety of NVIDIA GPUs, mostly GTX 1080's (10GB VRAM) and RTX A6000's (48GB VRAM) depending on the size of experiments. Unless stated otherwise, models were trained with the Adam optimiser (Kingma and Ba, 2015) with a learning rate of 0.001 and `pytorch`'s `CosineAnnealingLR` scheduler, set to reduce the learning rate to 1/10th of its initial value over the run. Models were trained to minimise the cross entropy loss between the predicted chord and the true chord distributions. We used a batch size of 64 for a maximum of 150 epochs unless stated otherwise. This batch size was based on experiments testing the speed of computation of an epoch which are omitted for lack of relevance. Validation through training was only conducted every 5 epochs in order to save on computation time. Optionally, training was stopped early if the validation loss did not improve for 25 epochs. The model was saved whenever the validation loss improved. Each training run took approximately 30 minutes of GPU time.

For the majority of experiments, a random 60/20/20% training/validation/test split was used. This contrasts much of the literature which uses a 5-fold cross validation split introduced by Humphrey and Bello (2015). We did not maintain this split in order to obtain clean estimators of the generalisation error using the held-out test set. The split was kept constant across experiments. This unfortunately makes our results less comparable to those reported by the literature. However, we only Later, models were re-trained on the combined training and validation sets and tested on the test set. In Chapter 5.6, the models were trained on the entire *Pop* dataset and tested on the *JAAH*

dataset.

Chapter 4

A Convolution Recurrent Neural Network

In this section, we compare various model on the *Pop* dataset. We start by describing a baseline model. We then implement a model from the literature and investigate its behaviour. We look at weighting the loss function, training on a more structured loss function and a transformer model. Finally, we experiment with decoding method, investigate the use of generative features as input and compare the best models on the held-out test set.

4.1 Baseline Models

As simple baselines, we consider a single layer neural network (NN) which treats each frame independently. The layer receives an input of size 216 and outputs a V -dimensional vector, where V is the cardinality of the chord vocabulary. For these experiments, $C = 170$. The outputs are then passed through a softmax layer such that values can be interpreted as the probability of each chord and the cross-entropy loss with the true distribution is calculated. We call this model *Logistic* as this can be seen as a logistic regression model trained using stochastic gradient descent (SGD). We could have used a logistic regression model implemented in `sklearn` which may have found better minima but implementation as a neural network was fast and easy and unlikely to yield significantly worse results.

A grid search on learning rates and learning rate schedulers was conducted on the sets `[0.1, 0.01, 0.001, 0.0001]` and `[Cosine, Plateau, None]` respectively. The `Plateau` scheduler halves the learning rate when the validation loss hasn't improved for 10 epochs and `Cosine` is as described in Section 3.3. The best model was found to be a learning rate of 0.01 with a `Cosine` scheduler. This best model was chosen for having the highest score on most of the metrics in validation set. All models with learning rates of 0.01 or 0.001 converged within 150 epochs. Although the best model had a learning rate 0.01, a learning rate of 0.001 over 150 epochs had a more stable validation accuracy. The model's results can be seen in Table 4.1. Full results are omitted as they are not relevant to the main discussion. The model serves simply as a baseline to

compare the more complex models to. These results give us the first empirical evidence that the task is non-trivial. The model is only able to predict the root of the chord with a mean frame-wise accuracy of 0.64 and a mirex of 0.65. The model identifies both the root and the third with an accuracy of 0.56 but struggles more with the seventh with an accuracy of 0.44. The lowest scores are the class-wise accuracies. The model is only able to predict the class of the chord with $\text{class}_{\text{mean}} = 0.13$ and $\text{class}_{\text{median}} = 0.03$. This gives us the first insight into each of the evaluation metrics and what we can hope from more complex models and other improvements.

Model	frame	root	third	seventh	mirex	$\text{class}_{\text{mean}}$	$\text{class}_{\text{median}}$
<i>Logistic</i>	0.42	0.64	0.56	0.44	0.65	0.13	0.03

Table 4.1: Baseline model results

4.2 CRNN

We implement a convolutional recurrent neural network (CRNN) as described in McFee and Bello (2017). The model takes as input a matrix of size $I \times F$ where I is the number of input features and F is the number of frames. The model passes the input through a layer of batch normalisation, before being fed through two convolutional layers with ReLU after each one. The first convolutional layer has a 5×5 kernel, and outputs only one channel the same size as the input. It is intended to smooth out noise and spread information about sustained notes across adjacent frames. The second layer has a kernel of size $1 \times I$, and outputs 36 values per frame intended to collapse the information over all frequencies with 36 bins per octave into a single 36-dimensional chroma vector. This also acts as a linear layer across frames with shared parameters. The output is passed through a bi-directional GRU (Cho et al., 2014), with hidden size initially set to 256 and a final dense layer with softmax activation. This produces a vector of length V for each frame, where V is the size of the chord vocabulary.

The authors of the model also propose using a second GRU as a decoder before the final dense layer, called ‘CR2’. However, we believe that a similar effect could be achieved with more layers in the initial GRU. Furthermore, both in the paper and in brief empirical tests of our own, the results with ‘CR2’ were indistinguishable from the model without it. We therefore do not include it in our final model. Results are omitted as they are neither relevant nor interesting.

4.2.1 Small to Large Vocabulary

Initial experiments were conducted on the simpler chord vocabulary with $C = 25$. Only if the model could somewhat accurately classify the smaller vocabulary and if performance did not decrease using a model trained on the larger vocabulary and tested on the smaller chord vocabulary, would we proceed to using the larger vocabulary. In keeping with the methodology in McFee and Bello (2017), we initially run experiments using a learning rate of 0.001. We reduce the learning rate to half its

previous value if the validation loss hasn't improved for 10 epochs and stop training if it has not improved for 25 epochs, with a maximum of 100 epochs. Training samples were set to 10 seconds long. Model convergence was manually checked using the validation and training losses over epochs.

Results are shown in Table 4.2. For comparison, the table also shows the performance of the same model trained with the large vocabulary, $C = 170$ and its predictions mapped back to the smaller vocabulary. A confusion matrix over chord roots of the model trained on $C = 26$ is shown in Figure 4.1. The model performs better than the baseline model which is tested on the larger vocabulary, which is to be expected given the nested nature of the models, and the harder task of classification with the larger vocabulary. From the confusion matrix, it becomes clear that many of the mistakes the model is making lie in the `x` symbol, which constitutes just over 7% of the smaller vocabulary dataset. Chords with qualities like `sus4` could be confused with `major` by a reasonable model but are represented with `x` in the smaller vocabulary. Interestingly, the model trained with $C = 170$ performs nearly as well on all metrics as the model trained with $C = 26$. This implies that training with $C = 170$ allows the model to learn almost all the relevant information about the smaller vocabulary, and gives it the chance to learn something about the larger vocabulary as well. Therefore, we proceed with the larger vocabulary for the rest of the experiments.

While some other works continue to measure performance on the smaller vocabulary (Park et al., 2019), we believe more metrics distract from the primary goal of increasing performance across a wider range of chords. Additionally, the `third` metric captures much of the information we would look for in evaluation with $C = 26$. We therefore only measure performance on the larger vocabulary from now on.

Model	V for training	root	third	class _{mean}	class _{median}
<i>CRNN</i>	26	0.79	0.77	0.74	0.74
<i>CRNN</i>	170	0.78	0.74	0.72	0.73

Table 4.2: CRNN model results on the small vocabulary with $C = 26$. The other metrics are omitted as they are identical to `third` for classification with $C = 26$.

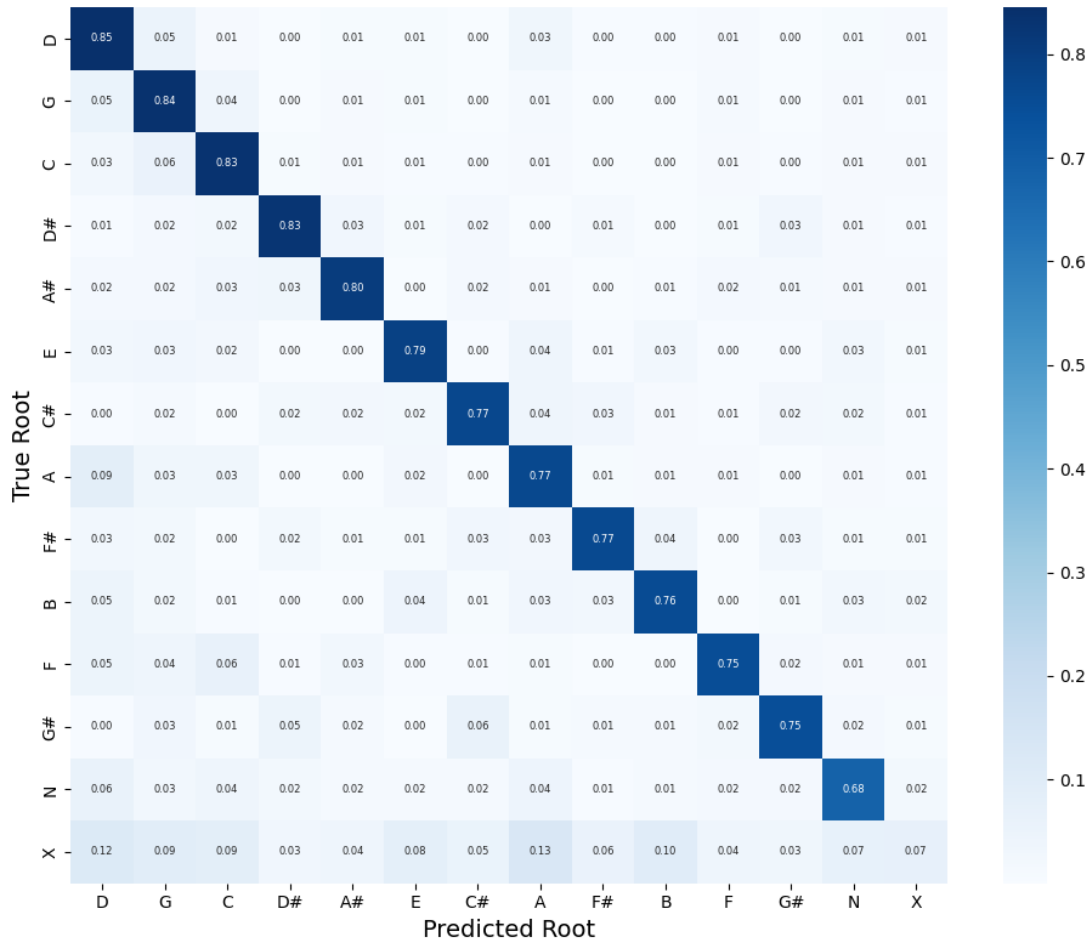


Figure 4.1: Confusion matrix over roots of the CRNN model trained on the small vocabulary. The values have been normalised over rows such that the values on the diagonals are recall metrics. There is a clear outlier in the model's recall with the label X, at just 0.07. It also performs poorly on N.

4.2.2 Hyperparameter Tuning

After progressing to the larger vocabulary, we thought it a good time to conduct some hyperparameter tuning.

4.2.2.1 Learning rates

We perform grid search on the same learning rates and learning rate schedulers as for the *Logistic* model. The learning rates were in the set of $[0.1, 0.01, 0.001, 0.0001]$ and the learning rate schedulers to $[\text{Cosine}, \text{Plateau}, \text{None}]$. We remove early stopping in order to check for convergence and overfitting without the possibility of a pre-emptive stop. Judging by training graphs seen in 4.2, the best learning rate is 0.001. Any lower and we do not converge fast enough; any higher and gradient updates cause the validation accuracy to be noisy. These figures also show that the validation loss does not get worse after convergence. We conclude that the model is not quick to overfit, perhaps due to the random sampling in the training process. Combined with the

fact that training is relatively quick and we only save on improved validation loss, we decided to remove early stopping. We therefore conduct future experiments without early stopping, for 150 epochs and with `lr=0.001` and `Cosine` scheduling.

SGD has been shown to be a good optimiser for a longer run over many epochs if the model is able to converge [XX]. We ran an experiment over 2000 epochs with the above hyperparameters and `momentum=0.9` and found that the model was able to converge, reaching its best validation loss at around 1000 epochs and remaining flat thereafter. The results with this model did not improve on the best model trained with Adam, with 3% lower root accuracy and 2% lower third accuracy, but with 2% better mirex. Due to the much longer training time and the lower root accuracy, we decided to stick with Adam for the rest of the experiments.

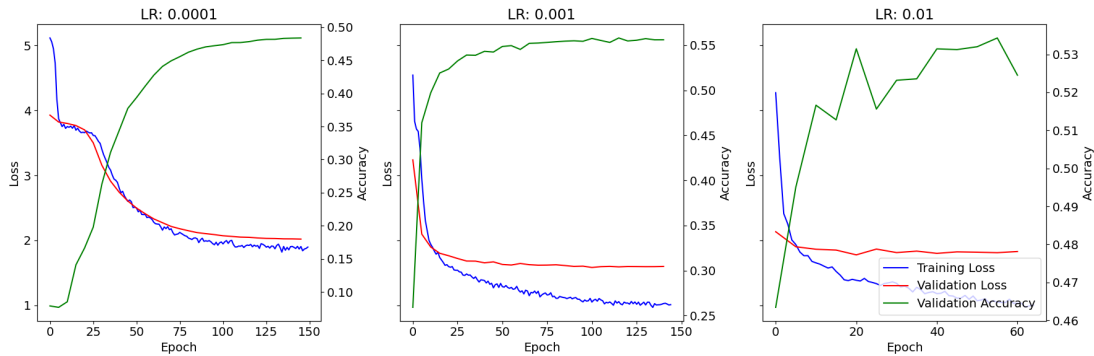


Figure 4.2: Training graphs for the CRNN model with different learning rates. The learning rate of 0.001 seems to be the best, as it converges in a reasonable time and the validation accuracy increases in a stable fashion.

We report a subset of metrics in Table 4.3. The best performing model by validation metrics was found to be with `lr=0.001` and `Cosine` scheduling. However, there were no large differences in performance between the learning rate schedulers. We proceed with these hyperparameters as defaults for the rest of the experiments.

lr	scheduler	root	third	seventh	mirex	class _{mean}	class _{median}
0.01	Cosine	0.71	0.68	0.55	0.76	0.13	0.00
0.001	Cosine	0.77	0.73	0.60	0.80	0.17	0.01
0.0001	Cosine	0.70	0.65	0.54	0.70	0.10	0.00
0.001	Plateau	0.74	0.73	0.60	0.80	0.18	0.01
0.001	None	0.71	0.70	0.58	0.82	0.17	0.00

Table 4.3: CRNN model results on the large vocabulary with different learning rates and schedulers. Overall, a learning rate of 0.001 and a scheduler of `Cosine` performs the best in many metrics, though a scheduler of `Plateau` performs just as well or better on many metrics. We prioritise the performance of the model on the root as this is more important than the `mirex` metric.

4.2.2.2 Model Hyperparameters

With this learning rate and learning rate scheduler fixed, we perform a random search on the number of layers in the GRU, the hidden size of the layers in the GRU and the training patch segment length. The search is performed by independently and uniformly randomly sampling 32 points in the sets $\text{hidden_size} \in \{64, 65, \dots, 512\}$, $\text{num_layers} \in \{1, 2, 3\}$ and $\text{segment_length} \in \{10, 11, \dots, 60\}$. A sample of the results are shown in Table 4.4. The models were then ranked according to each metric and their ranks for each metric added up. The models were ordered by this total rank. The best model was found to have a hidden size $h = 201$, a single layer GRU and a segment length of $L = 28$, although the differences between models were very small. Such small differences might indicate that the model is learning something relatively simple and that increased model complexity does not help. We proceed with this model as the default for the rest of the experiments, referred to simply as the *CRNN*.

L	layers	h	frame	root	third	seventh	mirex	class _{mean}	class _{median}
28	1	201	0.58	0.78	0.75	0.62	0.79	0.18	0.01
23	2	295	0.58	0.78	0.75	0.62	0.78	0.19	0.02
14	2	374	0.57	0.77	0.74	0.61	0.79	0.19	0.02
56	1	463	0.58	0.77	0.74	0.61	0.78	0.19	0.02
42	3	222	0.57	0.77	0.74	0.60	0.79	0.16	0.00
...

Table 4.4: CRNN model results on the large vocabulary with different hyperparameters. Best unrounded metrics are bolded. Results across all hyperparameters were very similar. We proceed with the best model found with hidden size of 201, a single layer GRU and a segment length of 28, although any configuration would work similarly. This may implies that model is learning something simple because the increased complexity of larger models did not help with performance. The variance within the data may be entirely due to the stochastic nature of SGD. Regardless of what makes the results different, the effect size is small enough to conclude that it does not make a meaningful difference.

Hyperparameters for CQT computation were chosen to be the same as in McFee and Bello (2017). However, the hop length was chosen to be 4096 samples. Other works have used 512 samples Jiang et al. (2019) or 2048 samples Rowe and Tzanetakis (2021). It should be noted that performance is not directly comparable across hop sizes as we are changing the number of frames and so the likelihoods are different. Nonetheless, if drastically different results are obtained, it may be worth using a different hop size. A plot of accuracy against the hop size is shown in Appendix A.2. The plot shows that performance is not affected by hop size much at all. This may be because the hop sizes used are all granular enough such that every chord has at least one frame associated with it, but not so granular that the features in a frame become too noisy. We proceed with the hop size of 4096 samples to keep computational cost low while keeping consistent with some of the literature.

4.3 Model Analysis

4.3.1 Qualities and Roots

How does the model deal with the long tail of the chord distribution? The class-wise metrics give strong indication that the performance is poor. We used a confusion matrix over qualities of chords to provide more granular detail. The confusion matrix is shown in Figure 4.3.

We also looked at confusion matrices over roots. We do not illustrate these matrices as the model performs similarly over all roots with a recall between 0.74 and 0.82, approximately increasing with commonality of the chord. This aligns with the fact that the roots do not represent a long-tailed distribution as with the qualities, as previously seen in Figure 3.3. However, the two special symbols, \mathbb{N} and \mathbb{X} , have poorer performance with recalls of 0.63 and 0.24 respectively. Many of the \mathbb{N} chords are at the beginning and end of the piece. Clearly, the model struggles with understanding when the music begins and ends. An example where the model mistakenly thinks chords are playing part-way through a piece is discussed in Section 4.3.5. The low performance on \mathbb{X} is to be expected. It is a highly ambiguous class with many possible inputs that are mapped to it, all of which will be fairly close to some symbol in the true vocabulary. It is unreasonable to expect the model to be able to predict this class well which further supports the argument for ignoring this class during evaluation.

4.3.2 Transition Frames

We hypothesise that the model is worse at detecting chords on frames where the chord changes. Such transition frames are present because frames are calculated based on hop length irrespective of the tempo and time signature of the song. To test this, we isolate the transition frames and compare the accuracies for transition and non-transition frames separately. We found that with a hop length of 4096, 4.4% of frames are transition frames. On the *CRNN* model with a `frame` of 0.59, the model achieves a `frame` of 0.36 on the transition frames and 0.60 on non-transition frames. Therefore, the model is certainly worse at predicting chords on transition frames. However, improving performance on these frames to the level of non-transition frames would increase the overall frame-wise accuracy by less than 0.01.

Through manual investigation explained in Section 4.3.4 we found that on some songs the model did struggle to correctly identify the boundary of a chord change. This was not captured by the above metrics as if the boundary is ambiguous enough to span multiple frames, there may be a larger impact in accuracy than a single frame. Furthermore, some songs will have more obvious boundaries than others. Though the average may be low, for some songs this may be the main limiting factor in performance. However on such songs, the boundaries are likely to be highly subjective and the model would have to learn to detect the beat to consistently predict the boundaries. As previously discussed, we did not wish to introduce another failure mode by using a separate model for beat detection. Some work has attempted to simultaneously predict chord changes and chord classes (Chen and Su, 2019). This is a related task which we do not address here.

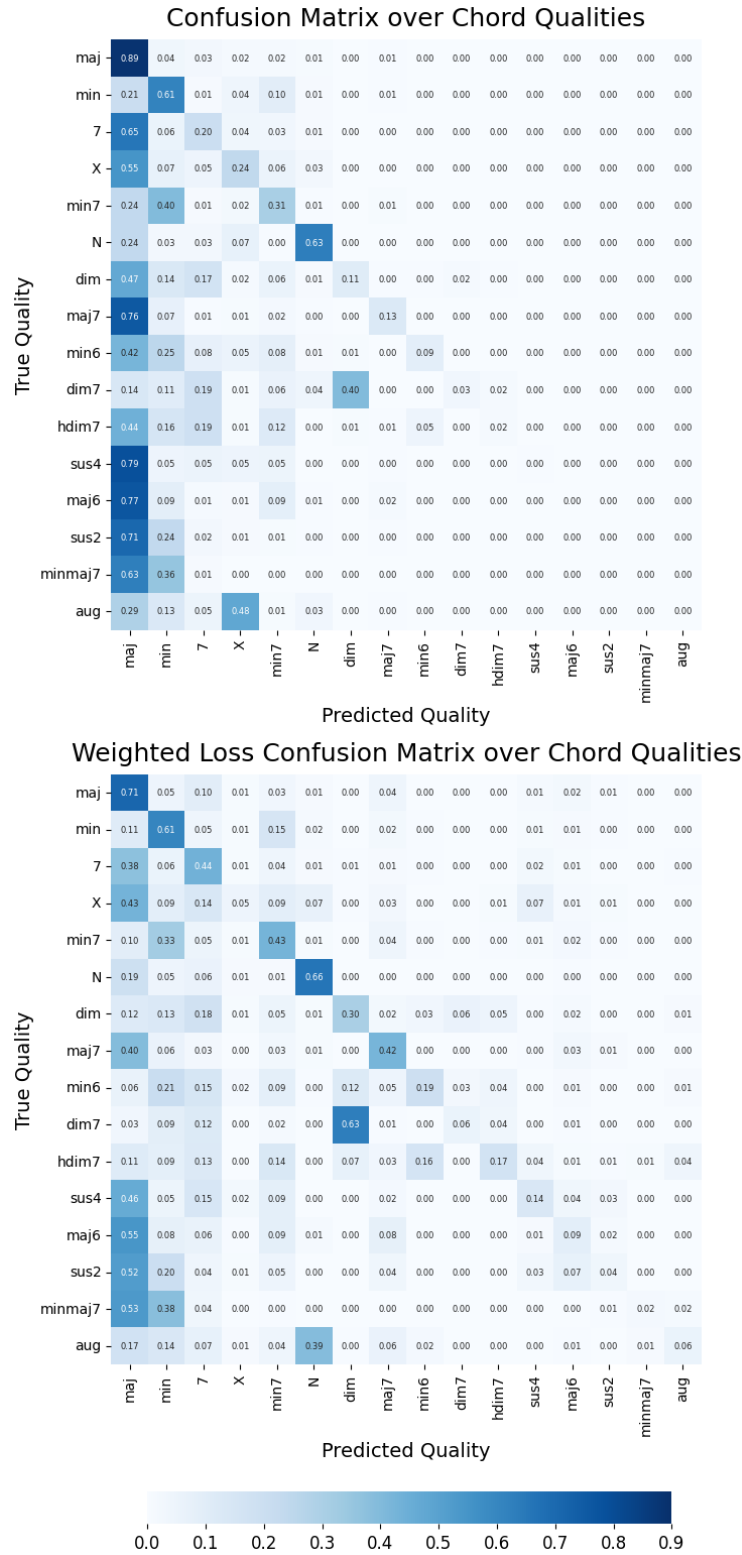


Figure 4.3: Row-normalised confusion matrices over qualities of the *CRNN* model without (above) and with (below) weighted loss. The weighting is with $\alpha = 0.55$ as in Equation 5.2. Rows are ordered by frequency of chord quality. We can see that both models struggle with the long tail. However, weighting the loss does improve the model, notably on 7 and maj7 qualities and predicts maj less often. Recall on the maj worsens by 0.18 and recall on X decreases from 0.24 to 0.05. The weighted model predicts X approximately four times less often. This may be how the weighted model improves class-wise metrics without sacrificing too much overall accuracy, since X frames are ignored. We can also see that both models frequently confuse dim7 and dim qualities, consistently predict maj for sus2, sus4, maj6, maj7 and minmaj7 and struggles with aug.

Given the above evidence that few frames are affected, and the difficulty of directly addressing the beat detection problem, we leave further investigation of transition frames to further work.

4.3.3 Smoothness

Are the model's outputs *smooth*? Most chords in the dataset last longer than a second but there are more than 10 frames per second. If many of the model's errors are due to rapid fluctuations in chord probability, some post-processing could be applied to help smooth out predicted chords. We use two crude measures of smoothness.

Firstly, we look at the number and length of incorrect regions. Such a region is defined as a sequence of incorrectly predicted frames with the same prediction. We find that 26.9% of all incorrect regions are one frame wide and 3.8% of incorrect frames have different predictions on either side. This can be interpreted as 3.8% of errors being due to rapidly changing chord predictions. A histogram over region lengths can be found in Appendix A.3.

Secondly, we can simply count the mean number of chord transitions per song and compare with the labels. We find that the model predicts 170 transitions per song in the validation set versus the a true count of 104 transitions per song. This raises significant concerns as the smoothness of its outputs.

With these two observations combined, we conclude that further work on the model to improve the smoothness would might performance a little, but not significantly. Although we might hope to improve on roughly 3.8% of errors, this would not improve overall accuracy very much. While rapid changes may be smoothed out, there is no guarantee that smoothing will result in correct predictions. Indeed, it may even render some previously correct predictions erroneous. Nonetheless, the model is clearly over-predicting transitions in general and when being used by a musician or researcher, smoothed predictions are valuable to make the chords more interpretable. This motivates the exploration of a decoding step in Section 5.2.

4.3.4 Performance Across the Context

How does the model perform across its context? We hypothesise that the model is worse at predicting chords at the beginning and end of a patch of audio as it has less context on either side. Analysing this will also help to understand to what extent the bi-directional context is important for performance.

To test this, we evaluate the model using the same fixed-length validation conducted during training as described in Section 3.3. We then calculate average frame-wise accuracies over the context and plot them in Figure 4.4. We use a segment length of 10 seconds corresponding to $L = 108$ frames. We can see performance is worst at the beginning and end of the patch, as expected, but not by much. Performance only dips 0.05, perhaps because the model still does have significant context on one side. We can also see that performance starts decreasing 5 or 6 frames from either end.

We conducted a further experiment, measuring overall accuracy with increasing segment

lengths used during evaluation. Indeed accuracy increases, but only by a tiny 0.005 from 5 seconds to 20 seconds and is flat thereafter. Results can found in Appendix A.1. We conclude that the context length does not make a big difference and continue to evaluate the model over the entire song at once.

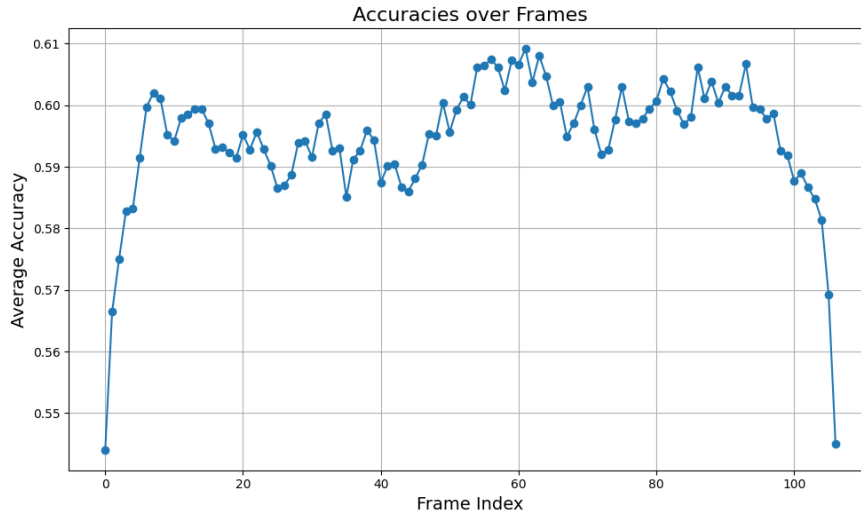


Figure 4.4: Average frame-wise accuracy of the *CRNN* model over the patch of audio. The model performs worse at the beginning and end of the patch of audio, as expected. However, the differences are only 0.05. We propose that the context on one side is enough for the model to attain the vast majority of the performance attained with bi-directional context. This plot supports our procedure of evaluating over the entire song at once.

4.3.4.1 Generalising Across Songs

Does the model do well consistently over different songs? We plot a histogram of accuracies and mirex scores over songs in the validation set in Figure 4.5. We find that the model has very mixed performance with accuracy, with 17% of songs scoring below 0.4. However, when we use the more generous mirex metric, almost all of the scores below 0.4 improve, and only 6% are below 0.6. Many of the mistakes that the song makes are a good guess in the sense that it may have omitted a seventh or mistaken a major 7 for its relative minor. Examples of such mistakes are discussed in Section 4.3.5. We conclude that, in general, the model’s outputs are reasonable predictions, but lacks the detail contained in good annotations like correct upper extensions of the chords.

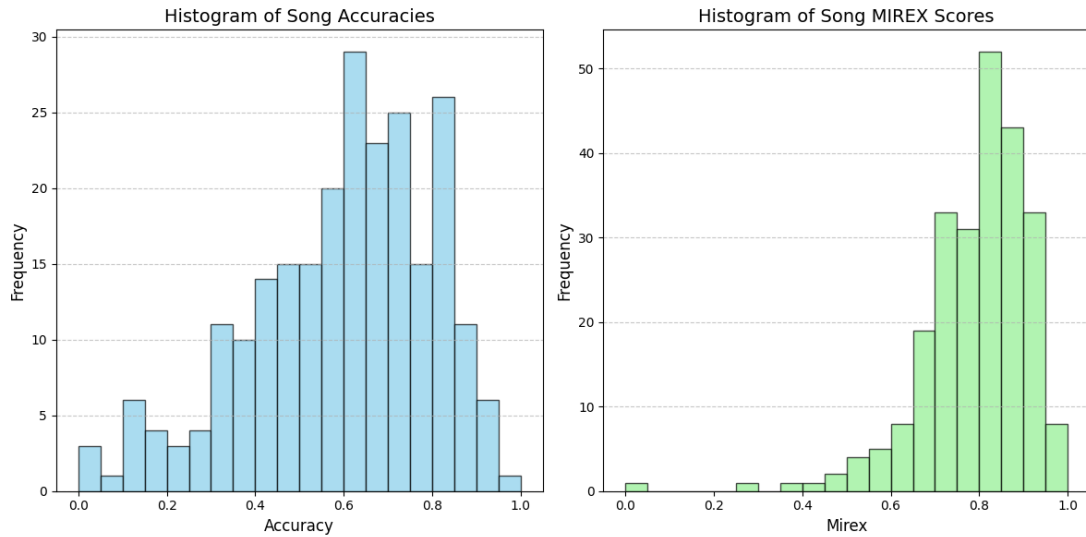


Figure 4.5: Histogram of accuracies and mirex scores over songs in the validation set. Accuracies are mixed, with 17% of songs below 0.4, and 64% between 0.4 and 0.8. However, with the more generous `mirex` metric, we find that there are almost no songs below 0.4 and only 6% below 0.6. Many of the mistakes the model makes are small, like predicting `C:maj` instead of `C:maj7`. Such examples are discussed in more detail in Section 4.3.5. The very low outliers in the `mirex` score were found to be songs with incorrect annotations found in Section 3.1.2.1.

4.3.5 Four Illustrative Examples

Let us now inspect a few songs to see how the model performs. We choose four examples showing different behaviours and failure modes of the model. We show illustrations of frame-by-frame correctness as measured by both accuracy and `mirex` in Figure 4.6.

In ‘Mr. Moonlight’, there are few differences between the accuracy and `mirex`. There are regular repeated errors, many of which are mistaking `F:sus2` for `F:maj`. This is an understandable mistake to make, especially after hearing the song and looking at the annotation where the main guitar riff alternates between `F:maj` and `F:sus2`. As evidenced by the confusion matrices in Figure 4.3, this mistake is very fairly common on qualities like `sus2` which are similar to .

In ‘Ain’t not Sunshine’, the `mirex` is significantly higher than the accuracy. This is because the majority of the mistakes the model makes are missing out a seventh. For example, the model predicts `A:min7` for the true label of `A:min7` or `G:maj` for `G:7`. Other mistakes that `mirex` allows for include confusing the relative minor or major, such as `E:min7` for its relative major `G:maj`. All of these mistakes occur frequently in this song. The mean difference between the accuracy and `mirex` is 0.2, with one song reaching a difference of 0.9. Hence, we can attribute many of the model’s mistakes to such behaviour. ‘Ain’t no Sunshine’ also contains a long incorrect section in the middle. This is a section with only voice and drums which the annotation interprets as `N` symbols but the model continues to predict harmonic content. The model guesses

A:min, which is a sensible label as when this melody is sung in other parts of the song, A:min7 is playing. Examples like this combined with incorrect predictions of when a song starts and ends explain why the model's recall on the N class is only 0.63.

In the next two songs, 'Brandy' and 'Earth, Wind and Fire', the model's mistakes are less interpretable. While performance is okay on 'Brandy' with a mirex of 0.74, the model struggles with the boundaries of chord changes resulting in sporadic short incorrect regions in the figure. In 'Earth, Wind and Fire', the model struggles with the boundaries of chord changes and also sometimes predicts completely wrong chords which are harder to explain. Listening to the song and inspecting the annotation makes it apparent that this is a difficult song for even a human to annotate well and similarly the model does not fare well.

Despite these mistakes, the average mirex over the validation set is 0.79 while the accuracy is 0.58. The examples above highlight the models' errors but the model fares well with many songs. We conclude that the majority of the model's outputs are reasonable predictions but that many lack the detail contained in good annotations like correct upper extensions of the chords. The model consistently confuses qualities that can be easily mistaken for major or minor chords. Sometimes the model makes mistakes on the boundaries of chord changes, and sometimes it predicts completely wrong chords, although these are on songs which are more difficult to annotate for a human too.

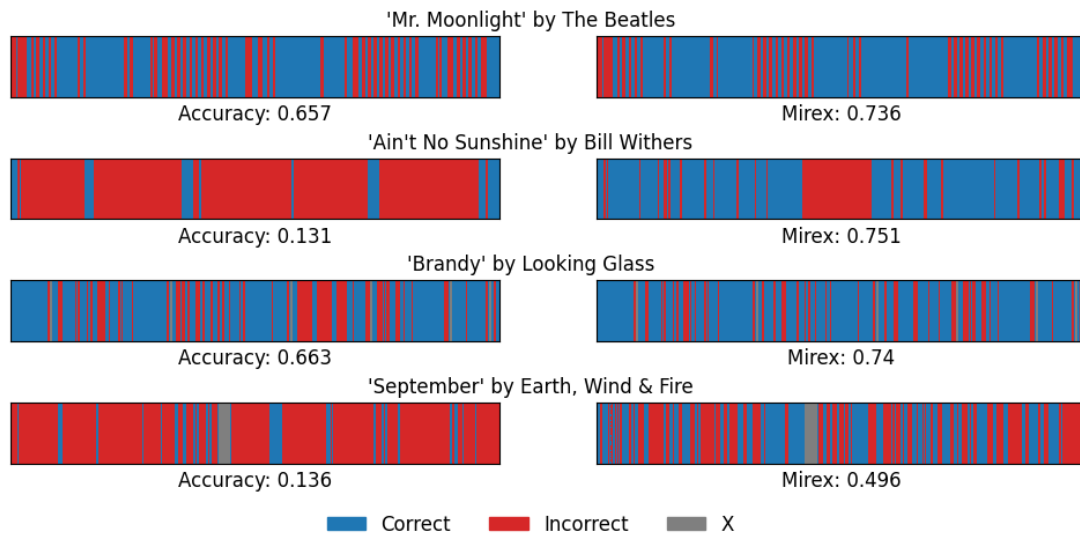


Figure 4.6: Chord predictions of the *CRNN* model on four songs from the validation set (blue: correct, red: incorrect, gray: X). This allows us to understand some of the behaviour of the model. We can see regular repeated errors in 'Mr. Moonlight', which are mostly mistaking two similar qualities. The discrepancy between accuracy and `mirex` on 'Ain't No Sunshine' can be explained by missing sevenths in many predictions. The large incorrect region is a voice and drum only section where the model continues to predict chords due to implied harmony by the melody. Predictions in 'Brandy' are quite good in general, though many errors arise from predicting the boundaries of chord changes incorrectly. The model struggles with 'Earth, Wind and Fire', missing chord boundaries, and sometimes predicting completely wrong chords. There are clearly songs where the model's outputs are less sensible. However, in general most of the model's mistakes can be explained and are reasonable.

Chapter 5

Improving the Model

5.1 Weighted Loss

One of the biggest problems highlighted above is low recall on less common qualities. Two common methods for dealing with long-tailed distributions are re-sampling and weighting the loss function. Rowe and Tzanetakis (2021) also explore the use of curriculum learning as form of re-sampling which we do not explore here. Sampling is explored by Miller et al. (2022) but they use a different model based on pre-computing chroma vectors and re-sampling these chroma vectors for use in training a random forest for frame-wise decoding. In our setting, re-sampling training patches of audio may be interesting but is left as future work as it would require significant effort to manage sampling many chords at once. Weighting has been explored by Jiang et al. (2019) however their weighting is over chord classes and chord ‘components’ which they define in their work. We employ a similar but simpler implementation here.

A standard method of weighting is to multiply the loss function by the inverse of the given class’ frequency, with a parameter controlling the strength of the weighting. This is defined as below.

$$w_c = \frac{1}{(\text{count}(c) + 1)^\alpha} \quad (5.1)$$

Where w_c is the weight for chord c , $\text{count}(i)$ is the number of frames with chord c in the dataset and α is a hyperparameter controlling the strength of weighting. $\alpha = 0$ results in no weighting and increasing *alpha* increases the severity of weighting. We add 1 in the denominator to avoid dividing by 0 and to diminish the effect of chords with very few occurrences. We then define normalised weights w_c^* below.

$$w_c^* = \frac{w_c}{s} \text{ where } s = \frac{\sum_{c \in \mathcal{C}} \text{count}(c) \cdot w_c}{\sum_{c \in \mathcal{C}} \text{count}(c)} \quad (5.2)$$

Where \mathcal{C} is the set of all chords in the vocabulary. This keeps the expected weight at 1 such that the effective learning rate remains the same. We calculate these values over

the training set. We test values of α in the set $\{0, 0.05, 0.1, \dots, 0.95, 1\}$. The plot in Figure 5.1 shows the effect of the weighting on the model’s performance.

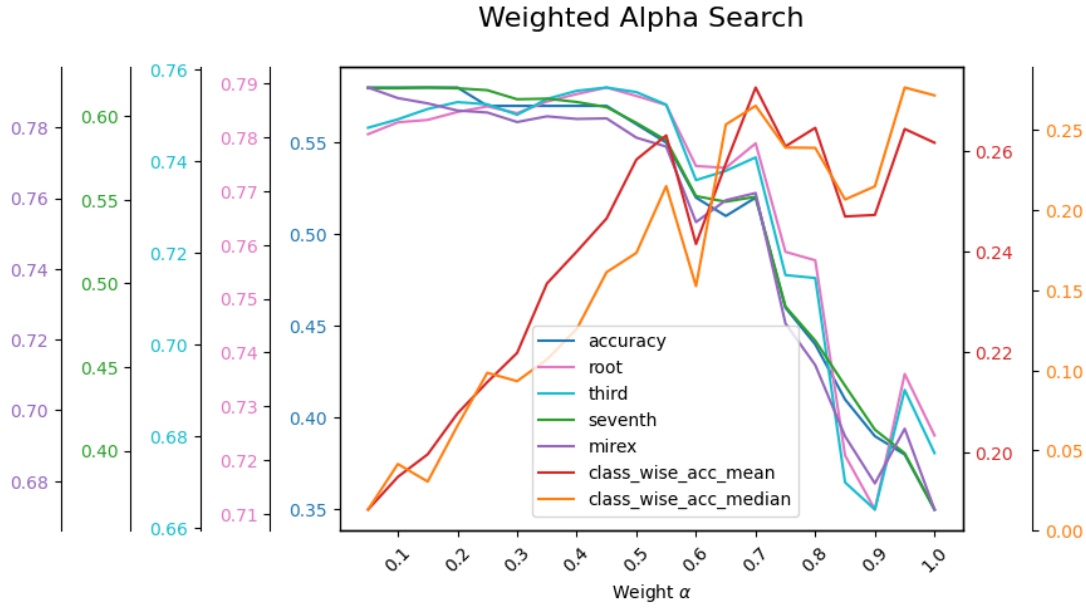


Figure 5.1: Effect of weighted loss on the *CRNN* model with varying α . As we increase α , class-wise metrics improve but accuracy-based metrics worsen. We claim a sweet-spot in the middle where we trade only a little overall performance for better class-wise recall. We choose this to be $\alpha = 0.55$. The `root` and `third` metrics improve and less than 3% is lost on other metrics while mean class-wise accuracy improves by 6% and the median improved by 0.2. This plot also reveals strong correlation between metrics.

5.2 Decoding

As observed in 4.3.3, taking the maximum probability over each frame results in 170 transitions per song as opposed to the 104 seen in the ground truth data. We implemented a decoding step over the frame-wise probability vectors to smooth predicted labels. Common choices for decoding models include a conditional random field (CRF) (Jiang et al., 2019; Park et al., 2019) and a hidden Markov model (HMM) (Miller et al., 2022).

For the sake of simplicity, we first implemented an HMM and found it to be able to smooth chords predictions well. The HMM treats the frame-wise probabilities as emission probabilities and the chord labels as hidden states. O’Hanlon and Sandler (2019) note that using a transition matrix with all non-recurrent transitions equally likely performs similarly to using a learned transition matrix. We adopt such a transition matrix for our HMM, with a parameter β denoting the self-transition probabilities, and all other transition probabilities equal to $\frac{1-\beta}{C-1}$. We then compute a forward and backward pass of the Viterbi algorithm to output the most likely sequence of chords.

A plot of the effect of β on the model’s performance and the number of transitions per song is shown in Figure 5.2. From this plot we conclude that smoothing has little affect on `root` while successfully reducing the number of transitions per song to that

of the true labels. We choose $\beta = 0.2$ as it results in 102 transitions per song while maintaining high performance.

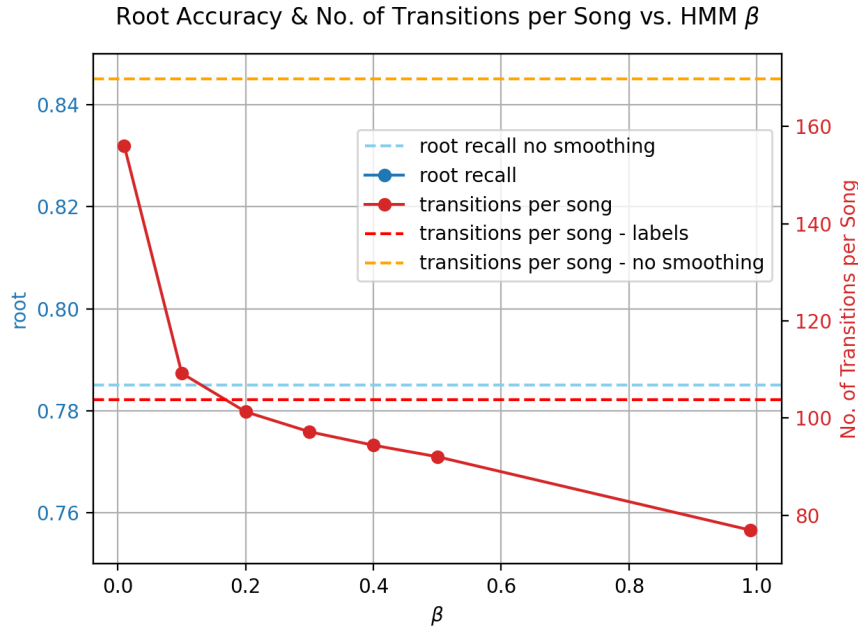


Figure 5.2: Effect of the HMM smoothing parameter β on the *CRNN* model. As we increase β , the number of transitions per song decreases. We choose $\beta = 0.2$ as it results 102 transitions per song, very close to the 104 of the ground truth. Performance is stable across β with a slight degradation for $\beta > 0.3$. Other performance metrics showed similarly stable results.

The effect of the HMM on the incorrect regions previously discussed in Section 4.3.3 can be found in Appendix A.3. The HMM reduced the percentage of incorrect regions which are a single frame long from 26.7% to 16.7%. A more intuitive way to see the effect of the HMM is to look at a section of a song which was the model previously predicted many chord transitions for. We show this in Figure 5.3.

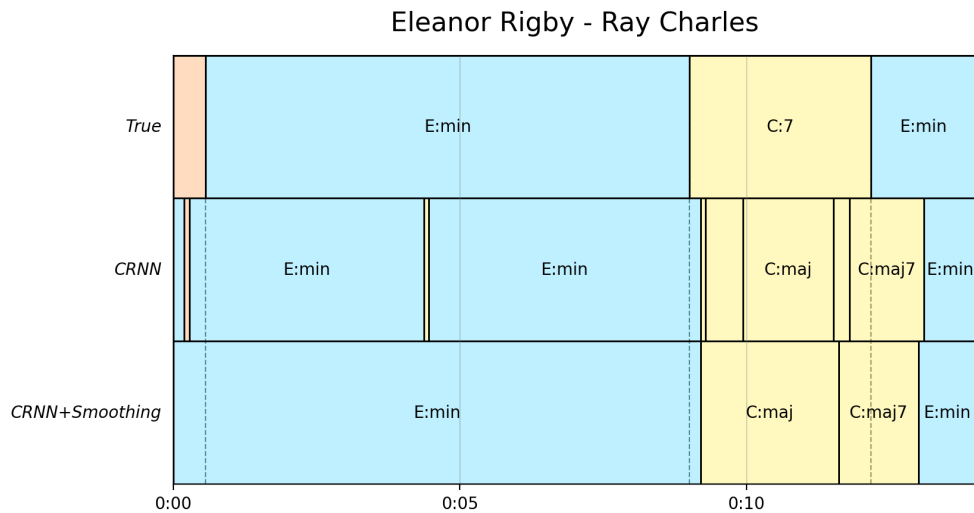


Figure 5.3: An example of the effect of the HMM on the *CRNN* model. The top plot shows the ground truth. The middle plot shows frame-wise predictions of the *CRNN* without smoothing. The bottom plot shows the predictions after smoothing. Chords are coloured by their equivalent chord in the small vocabulary as it makes the plot easier to interpret. The original predictions contain many unnecessary and nonsensical chord transitions. These have been smoothed out by the HMM. The resulting chords appear more similar to the ground truth even if frame-wise accuracy has not changed much.

We did not implement a CRF. All related works to use a CRF use a linear chain CRF with either hand-crafted transition penalties or learned transition penalties. We believe that such simple CRF's are unlikely to outperform the HMM given the effective smoothing of the HMM and do not explore further. We also do not wish to bias the model towards the transitions contained in the dataset. Given the long-tailed distribution, a learned transition matrix will further encourage the model to predict more common transitions. Thus, we believe that the HMM with a simple transition matrix which effectively smooths the predictions is a satisfactory solution.

5.3 Pitch Augmentation

- Two methods: - On CQT Jiang et al. (2019), not good. - Using `pyrubberband`¹ on the audio [everyone else], works?

Pitch augmentation has been done in other works on chord recognition. This has been done on the CQT (Jiang et al., 2019) by shifting the CQT bins and directly on the audio (Park et al., 2019; McFee and Bello, 2017). These are not the same process. Shifting the CQT is a simple matrix operation, whereas pitch shifting introduces other artefacts due to

¹<https://github.com/bmcfee/pyrubberband>

5.4 Using Generative Features

- As in [MelodyTranscriptionViaGenerativePreTraining], use Jukebox (?) to generate features at frames (? is it possible to do it on the same frames?). Train on these features and evaluate.

5.5 Structured Training

- Add structured loss and retrain. From literature. Should (?) further improve accuracies on sevenths etc.

5.6 Synthetic Data Generation

Motivation

5.6.1 Generation method

- Generation method.

5.6.2 Experiments

- Brief description of the experiments and metrics I'm looking at

5.6.3 Results

- Results of the experiments on the validation set

5.7 Results on the Test Set

- Directly compare CRNN, weighted loss, pitch augmentation, structured, transformer, generative features, generated data and any meaningful combination on the test set. - Also compare to BTC as a transformer model.

5.7.1 Performance on JAAH

- The performance of existing models on JAAH

5.8 Qualitative Analysis

- Qualitative analysis of the results

Chapter 6

Conclusions, Limitations and Further Work

6.1 Conclusions

- What do the results say?

6.2 Limitations

Limitations: - Genre - Standard tuning, Western - No lyrics - No beat/segmentation detection - No chord inversion - Size of vocabulary lacking leading to tricky X chord

6.3 Further Work

- Further work: - More data e.g. HookTheory - Larger vocabulary? Inversion as in? Why didn't I do this? - Make into a useful tool by outputting chords in a more useful format
- Investigate other methods of synthetic data generation? - Stuff I didn't have time to incorporate e.g. beat/segmentation detection, structured loss, curriculum learning
 - Focus on incorporating more musical knowledge into the problem. Criticism of the field for simply trying to push up these metric, when its not really a useful problem to be solving. - Especially since making the model more complex doesn't help, it's difficult to get more data, and things like weighting the loss does help, but not nearly enough.

Bibliography

- Adam Berenzweig, Beth Logan, Daniel P. Ellis, and Brian Whitman. A large-scale evaluation of acoustic and subjective music-similarity measures. *Computer Music Journal*, 28(2):63–76, 2004.
- Judith Brown. Calculation of a constant q spectral transform. *Journal of the Acoustical Society of America*, 89:425–, 01 1991. doi: 10.1121/1.400476.
- John Burgoyne, Jonathan Wild, and Ichiro Fujinaga. An expert ground truth set for audio chord recognition and music analysis. pages 633–638, 01 2011.
- Antoine Caillon and Philippe Esling. Rave: A variational autoencoder for fast and high-quality neural audio synthesis, 2021. URL <https://arxiv.org/abs/2111.05011>.
- Chris Cannam, Craig Landone, and Mark Sandler. Omras2 metadata project. In *Proceedings of the 10th International Society for Music Information Retrieval Conference (ISMIR)*, pages 309–310, 2009.
- Tsung-Ping Chen and Li Su. Harmony transformer: Incorporating chord segmentation into harmony recognition. In *International Society for Music Information Retrieval Conference*, 2019. URL <https://api.semanticscholar.org/CorpusID:208334896>.
- Tsung-Ping Chen and Li Su. Attend to chords: Improving harmonic analysis of symbolic music using transformer-based models. *Trans. Int. Soc. Music. Inf. Retr.*, 4:1–13, 2021. URL <https://api.semanticscholar.org/CorpusID:232051159>.
- Kyunghyun Cho, Bart van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using RNN encoder–decoder for statistical machine translation. In Alessandro Moschitti, Bo Pang, and Walter Daelemans, editors, *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1724–1734, Doha, Qatar, October 2014. Association for Computational Linguistics. doi: 10.3115/v1/D14-1179. URL <https://aclanthology.org/D14-1179/>.
- John Thickstun Chris Donahue and Percy Liang. Melody transcription via generative pre-training, 2022. URL <https://arxiv.org/abs/2212.01884>.
- Michael Scott Cuthbert and Christopher Ariza. Music21: A toolkit for computer-aided musicology and symbolic music data. In J. Stephen Downie and Remco C. Veltkamp, editors, *ISMIR*, pages 637–642. International Society for Music Information Retrieval,

2010. ISBN 978-90-393-53813. URL <http://dblp.uni-trier.de/db/conf/ismir/ismir2010.html#CuthbertA10>.
- Jacopo de Berardinis, Albert Meroño-Peñuela, Andrea Poltronieri, and Valentina Presutti. Choco: a chord corpus and a data transformation workflow for musical harmony knowledge graphs. *Scientific Data*, 10, 09 2023. doi: 10.1038/s41597-023-02410-w.
- Prafulla Dhariwal, Heewoo Jun, Christine Payne, Jong Wook Kim, Alec Radford, and Ilya Sutskever. Jukebox: A generative model for music, 2020. URL <https://arxiv.org/abs/2005.00341>.
- Gabriel Durán and Patricio de la Cuadra. Transcribing Lead Sheet-Like Chord Progressions of Jazz Recordings. *Computer Music Journal*, 44(4):26–42, 12 2020. ISSN 0148-9267. doi: 10.1162/comj_a_00579. URL https://doi.org/10.1162/comj_a_00579.
- Takuya Fujishima. Realtime chord recognition of musical sound: a system using common lisp music. In *International Conference on Mathematics and Computing*, 1999. URL <https://api.semanticscholar.org/CorpusID:38716842>.
- Masataka Goto, Hiroki Hashiguchi, Takuichi Nishimura, and Ryuichi Oka. Rwc music database: Popular, classical, and jazz music databases. 01 2002.
- Christopher Harte, Mark Sandler, Samer Abdallah, and Emilia Gómez. Symbolic representation of musical chords: A proposed syntax for text annotations. pages 66–71, 01 2005.
- Eric J. Humphrey and Juan P. Bello. Rethinking automatic chord recognition with convolutional neural networks. In *2012 11th International Conference on Machine Learning and Applications*, volume 2, pages 357–362, 2012. doi: 10.1109/ICMLA.2012.220.
- Eric J. Humphrey and Juan Pablo Bello. Four timely insights on automatic chord estimation. In *International Society for Music Information Retrieval Conference*, 2015. URL <https://api.semanticscholar.org/CorpusID:18774190>.
- Eric J. Humphrey, Justin Salamon, Oriol Nieto, Jon Forsyth, Rachel M. Bittner, and Juan P. Bello. Jams: A json annotated music specification for reproducible mir research. pages 591–596, 2014. 15th International Society for Music Information Retrieval Conference, ISMIR 2014 ; Conference date: 27-10-2014 Through 31-10-2014.
- Yun-Ning Hung, Ju-Chiang Wang, Minz Won, and Duc Le. Scaling up music information retrieval training with semi-supervised learning, 2023. URL <https://arxiv.org/abs/2310.01353>.
- Junyan Jiang, K. Chen, Wei Li, and Gus G. Xia. Large-vocabulary chord transcription via chord structure decomposition. In *International Society for Music Information Retrieval Conference*, 2019. URL <https://api.semanticscholar.org/CorpusID:208334209>.
- Jongmin Jung, Andreas Jansson, and Dasaem Jeong. Musicgen-chord: Advancing

- music generation through chord progressions and interactive web-ui, 2024. URL <https://arxiv.org/abs/2412.00325>.
- Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015. URL <http://arxiv.org/abs/1412.6980>.
- Nadine Kroher, Helena Cuesta, and Aggelos Pikrakis. Can musicgen create training data for mir tasks?, 2023. URL <https://arxiv.org/abs/2311.09094>.
- Kyogu Lee and Malcolm Slaney. Automatic chord recognition from audio using a hmm with supervised learning. pages 133–137, 01 2006.
- Yizhi Li, Ruibin Yuan, Ge Zhang, Yinghao Ma, Xingran Chen, Hanzhi Yin, Chenghao Xiao, Chenghua Lin, Anton Ragni, Emmanouil Benetos, Norbert Gyenge, Roger Dannenberg, Ruibo Liu, Wenhui Chen, Gus Xia, Yemin Shi, Wenhao Huang, Zili Wang, Yike Guo, and Jie Fu. Mert: Acoustic music understanding model with large-scale self-supervised training, 2024. URL <https://arxiv.org/abs/2306.00107>.
- Matthias Mauch and Simon Dixon. Approximate note transcription for the improved identification of difficult chords. pages 135–140, 01 2010.
- Brian McFee and Juan Pablo Bello. Structured training for large-vocabulary chord recognition. In *International Society for Music Information Retrieval Conference*, 2017. URL <https://api.semanticscholar.org/CorpusID:3072806>.
- Brian McFee, Colin Raffel, Dawen Liang, Daniel Ellis, Matt McVicar, Eric Battenberg, and Oriol Nieto. librosa: Audio and music signal analysis in python. pages 18–24, 01 2015. doi: 10.25080/Majora-7b98e3ed-003.
- Jeff Miller, Ken O’Hanlon, and Mark B. Sandler. Improving balance in automatic chord recognition with random forests. In *2022 30th European Signal Processing Conference (EUSIPCO)*, pages 244–248, 2022. doi: 10.23919/EUSIPCO55093.2022.9909558.
- Ken O’Hanlon and Mark B. Sandler. Comparing cqt and reassignment based chroma features for template-based automatic chord recognition. In *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 860–864, 2019. doi: 10.1109/ICASSP.2019.8682774.
- Jonggwon Park, Kyoyun Choi, Sungwook Jeon, Dokyun Kim, and Jonghun Park. A bi-directional transformer for musical chord recognition. In *Proceedings of the 20th International Society for Music Information Retrieval Conference (ISMIR)*, pages 620–627, 2019. URL <https://archives.ismir.net/ismir2019/paper/000075.pdf>.
- Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Köpf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning

- library. In *Advances in Neural Information Processing Systems 32*, pages 8024–8035. Curran Associates, Inc., 2019. URL <https://papers.nips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf>.
- Johan Pauwels, Ken O’Hanlon, Emilia Gómez, and Mark B. Sandler. 20 years of automatic chord recognition from audio. In *International Society for Music Information Retrieval Conference*, 2019. URL <https://api.semanticscholar.org/CorpusID:208334309>.
- Colin Raffel, Brian McFee, Eric J. Humphrey, Justin Salamon, Oriol Nieto, Dawen Liang, and Daniel P. W. Ellis. Mir_eval: A transparent implementation of common mir metrics. In *International Society for Music Information Retrieval Conference*, 2014. URL <https://api.semanticscholar.org/CorpusID:17163281>.
- Luke O. Rowe and George Tzanetakis. Curriculum learning for imbalanced classification in large vocabulary automatic chord recognition. In *Proceedings of the 22nd International Society for Music Information Retrieval Conference (ISMIR)*, pages 586–593, 2021. URL <https://archives.ismir.net/ismir2021/paper/000073.pdf>.
- Gakusei Sato and Taketo Akama. Annotation-free automatic music transcription with scalable synthetic data and adversarial domain confusion, 2024. URL <https://arxiv.org/abs/2312.10402>.
- Keisuke Toyama, Taketo Akama, Yukara Ikemiya, Yuhta Takida, Wei-Hsiang Liao, and Yuki Mitsufuji. Automatic piano transcription with hierarchical frequency-time transformer, 2023. URL <https://arxiv.org/abs/2307.04305>.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need, 2023. URL <https://arxiv.org/abs/1706.03762>.
- Avery Wang. An industrial strength audio search algorithm. 01 2003.
- Yiming Wu, Tristan Carsault, and Kazuyoshi Yoshii. Automatic chord estimation based on a frame-wise convolutional recurrent neural network with non-aligned annotations. In *2019 27th European Signal Processing Conference (EUSIPCO)*, pages 1–5, 2019. doi: 10.23919/EUSIPCO.2019.8902741.

Appendix A

Appendix

A.1 Accuracy vs Context Length of Evaluation

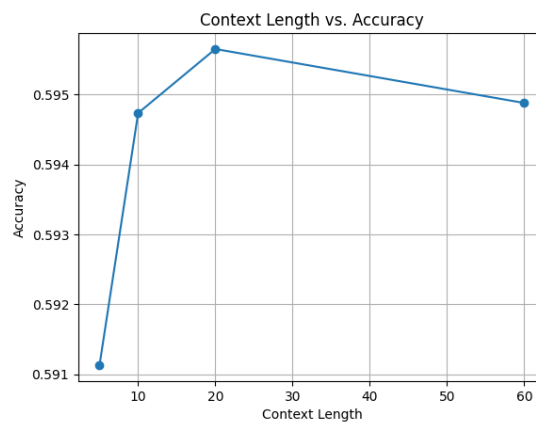


Figure A.1: Accuracy vs context length of evaluation. The accuracy increases very slightly. The effect size is so small that we conclude it does not make a difference, and choose to evaluate over the entire song at once.

A.2 Accuracy vs Hop Length

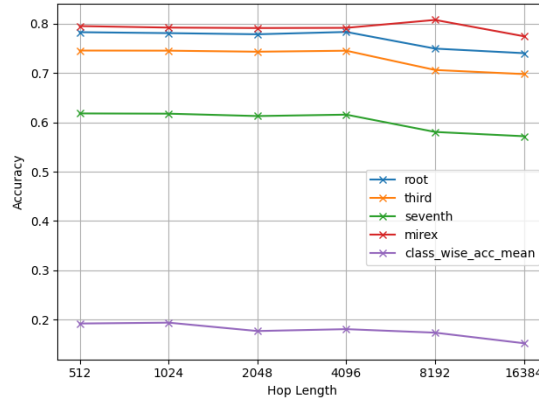


Figure A.2: Accuracy vs hop length. Metrics are not directly comparable over hop lengths due to different likelihoods. However, the metrics are fairly consistent over different hop lengths, certainly over the region explored by the literature [512, 2048, 4096]. Every hop length tested is short enough to be more granular than chords, but not so short that the computed CQT is too noisy. We continue with the default hop length of 4096, to be consistent with some of the literature while keeping computational cost low.

A.3 Incorrect Region Lengths With/Without Smoothing

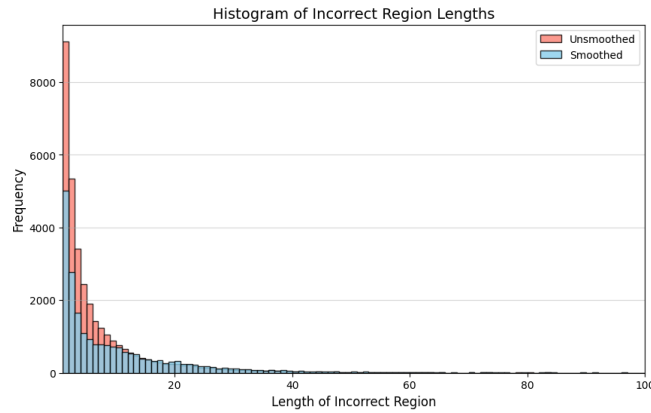


Figure A.3: Histogram over incorrect region lengths for a *CRNN* with and without smoothing. An incorrect region is defined as a sequence if incorrect frames with correct adjacent of either end. Both distributions have a long-tail, with 26.7% regions being of length 1 without smoothing. This raises concerns over the smoothness of outputs and requires some form of post-processing explored in Section 5.2. The distribution is more uniform with smoothing, with approximately half the very short incorrect regions.