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| Imperial College London  Department of Electrical and Electronic Engineering |
| Final Year Project Report |
| Machine learning applied to timbral acoustic analysis |
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Abstract

This project investigates the analysis of musical instrument timbre as a perceptual task by using Convolutional Neural Networks (CNNs). The timbre of a musical instrument is what allows it to be distinguished sonically from other instruments, independently of pitch and volume. We have chosen to approach timbral analysis by framing the task as an identification or classification problem, as opposed to targeting a glossary of timbral descriptions such as “bright”, “mellow”, which is a common alternative approach. Neural Networks are readily adapted to handling such classification problems; in particular, we will focus on the binary classification problem of distinguishing between recordings of different types of acoustic pianos using timbre. This is tackled with CNNs by transforming waveforms into spectrograms, so that two-dimensional maps can be input to the network. This approach allows us to draw inspiration from the convolutional architectures commonly used in image analysis, while applying signal processing and musical-domain considerations.

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# Introduction

Acoustical timbre is the quality of a sound that allows it to be “distinguished from other sounds at the same pitch and loudness” [1]. Thus, it is commonly defined by elimination, characterising all that does not correspond to pitch and volume in a sound. For the purposes of this project, we consider timbre as encapsulating the qualities characteristic to a musical sound, which allow it to be recognised as having been produced by a particular instrument.

Timbral analysis consists of automatically extracting information from a digital audio signal, in order to describe a sound source’s identifying timbral qualities. Timbre is a perceptual quality of sound, therefore it is subjective and can be complex to describe quantitatively. Therefore, accurately describing timbre in order to approximate the human ear’s fine differentiation abilities is a challenging problem not usually tackled by a single conventional signal processing method, such as spectral analysis, in isolation. The motivation for this project is to apply signal processing methods in combination with machine learning constructs to develop a system that can infer embeddings corresponding to timbral information, in order to distinguish between closely related musical sounds.

The timbre of a musical instrument can be affected by factors such as component materials, age, quality of construction, performance environment, and the articulation (or touch) of the player. For this reason, analysis of timbre may not only concern differentiating between instruments from different families, but also between different instances and types within a single family such as acoustic pianos, since these factors are rarely constant from one individual instrument to the next. While many research works have attempted to differentiate between different families of musical instruments by timbre (inter-instrument classification), few have focused on identifying the subtle variations that exist between different instances of the same type of instrument (intra-instrument classification). For this project, we focus our efforts on developing a system to detect the timbral differences between different types of acoustic piano, namely in order to classify upright and grand pianos. This type of fine differentiation task presents a relatively novel challenge, and can be tricky even for humans, as it requires a deep familiarity with the instruments.

The principal objective for the final system is to be able to distinguish between the two types of piano by using only an audio recording of the instrument as input. Another key aim for the classifier is to characterise timbre in a generalisable manner and in realistic scenarios, for example by identifying unseen examples recorded in different conditions than those seen in training.

In this report, we will first survey research that has been performed in the fields of timbral analysis and machine learning, especially research that applies machine learning to timbral classification of musical instruments. Then we will detail the background theory involved in timbral analysis, discussing both conventional signal processing features, and the machine learning methods studied and applied in the project. Next, we will describe the design considerations applied to the development the proposed system, including detail of the choices made at each stage: specification of the problem, data sourcing and processing, the decision to use Convolutional Neural Networks, their architecture, and the training process. In subsequent sections, we will describe the testing methods elaborated to evaluate the classifier, before reporting the results obtained for the final system in various scenarios. Finally, we will evaluate these results, present our conclusions, and ideas for potential further development.

# Literature review of timbral analysis methods

We subdivide the wide variety of timbral analysis research in the literature into approaches focusing mainly on timbral feature extraction via traditional signal processing methods, and methods which employ neural networks to learn the timbre of musical instruments for classification. Note that this is somewhat of a false dichotomy, since machine learning methods often inherently rely on signal processing theory and constructs, and usually depend on pre-processing of input features via signal processing. In this section, we will first give an overview of research on musical instrument timbral analysis performed with an emphasis on signal processing methods. We will then present a survey of more recent works which apply neural networks, specifically CNNs, to classifying the timbre of musical instruments, before detailing research that has been performed on related tasks in the field.

## Conventional signal processing methods

Many authors have tackled the problem of analysing timbre using signal processing descriptors, as well as the selection of an optimal set of these features for the purposes of identifying or differentiating instruments by their timbre. In order to gauge their timbral discrimination ability, authors usually use these features as input to simple machine learning systems such as K-Nearest Neighbour (KNN), Support Vector Machine (SVM) classifiers or Gaussian Mixture Models (GMM), but the emphasis of the works presented in this subsection remains on the feature selection and computation, as opposed to the optimisation of the downstream machine learning models.

### Inter-instrument and instrument type classification

First, we consider research aiming to discriminate between different instruments and broad families, as opposed to identifying the more subtle timbral variations between models, types or instances of the same instrument. One of the earlier such works on timbral instrument classification focuses on the steady-state part of individual isolated musical notes [2]. This approach narrows the analysis to the harmonic, or tonal, qualities of the sound as opposed to analysing the time evolution of the envelope and transient qualities over the course of a note. As a result, the author finds that discrimination between the considered orchestral instruments is achieved most effectively using spectral and harmonic features such as the spectral moments and the first two harmonic frequencies. The performance of the proposed system, which is a KNN-based classifier, also varies with the considered instrument, reporting much higher accuracy at identifying typically longer-sustained sounds, such as wind instruments, than shorter, more transient sounds such as plucked (*pizzicato*) violin. This shortcoming could be explained by the fact that the shorter sounds tend to be sonically recognisable primarily through their temporal envelope, specifically their harsh attack, as opposed to more sustained instrument timbres, which tend to contain richer tonal and harmonic information.

Another work which focuses on spectral and harmonic feature-based identification of instruments is [3], in which various classification methods (SVM, decision trees & Discriminant Analysis) are applied to identifying classical orchestra instruments from single-note recordings. Similarly to [2], the most representative features for classification are found to be the spectral centroid and the first partial’s energy; as well as inharmonicity, which as explained in section 3.1.5 quantifies the prominence of harmonics – thus expressing the extent to which the sound is tonal or noise-like. As a result of incorporating this additional information along with purely tonal descriptors, the authors report reasonable success in identifying both sustained and transient sounds such as *pizzicati*, although once again the highest scores are reported for identification of wind instruments. In the research presented in [4], many of the same spectral and harmonic features are also applied to classifying a broader range of instruments, including a large corpus of non-western sounds. Beyond the tonal features, the authors also find the attack slope, which characterises the speed of the transient, to be among the most indicative features; along with descriptors of the spectral envelope. These findings indicate that the accurate timbral classification of a wide range of sounds benefits from a combination of spectral/harmonic and time-envelope analyses.

Other research works integrate cepstral features as well as spectral and temporal descriptors in order to classify musical instruments by timbre. For instance in [5], cepstral and time-autocorrelation coefficients are found to be instrumental in accurately differentiating between the timbres of four woodwind instruments using a GMM. Notably, the input to this model consists of extracts from single-instrument performances as opposed to single-note samples. The input information is therefore more complex in nature, but may contain more timbral cues than a single isolated note. This indicates that cepstral features, paired with temporal descriptors, are well-adapted to capturing complex information efficiently; especially since only a small number (10) of cepstral coefficients is used. Similarly, the method presented in [6] applies MFCCs computed at different time scales as well as the time-derivatives of MFCCs to identify instruments using an SVM classifier from excerpts of single-instrument performances. This approach aims to capture timbral features at different time resolutions, both considering the finer details within a single note’s envelope as well as on a larger scale for short monophonic musical phrases. The temporal scale of analysis for MFCCs in the context of musical instrument identification was previously examined in [7], a work which also takes on the task of classifying clips of real single-instrument performances using a large number of temporal, spectral, wavelet, and cepstral features.

### Intra-instrument classification

A small number of research works focus on differentiating between the timbre of different instances of the same instrument type using signal processing features; either aiming to identify playing techniques or variation in the sonic qualities of the instruments themselves. For instance, in [8], the author examines the timbre of Irish traditional flute playing in order to detect the articulation, phrasing and the model of flute captured in a given recording. The analysis of playing style corresponds to higher-level longer timescale timbral characteristics such as trills, while the single-note study of timbral variation between flutes made from different materials is most relevant to our purposes. Many pre-processing steps are applied for feature extraction and note onset detection: fine variations in timbre between instruments are quantified using spectral and harmonic peak analysis on the harmonically-stable (steady-state) portions of single note recordings, which tends to be effective for timbral characterisation of wind instruments as we have seen in [2].

In the same vein, [9] attempts a similar task by examining the timbre of violins from two different eras. A set of spectral, temporal, harmonic and envelope features are selected to help make this differentiation on sets of single-note and musical scale recordings. Dimensionality reduction (via a clustering method called t-distributed Stochastic Neighbour Embedding (t-SNE)) of the feature space allows for a projected 3-dimensional visualisation to be used to compare the timbral similarity between the instruments. This paper finds that analysing the steady state and decay phases of the violin note sounds allows for differentiation between the two classes of contemporary and historical violins. This differentiation is made on the strength of certain timbral features, determined using feature selection and ranking tests; in particular are selected the spectral distribution features (the spectral moments, roll-off and flatness measures), as well as the Spectral Flux and MFCCs. The relevance of the selected candidate timbral features is verified by inputting them to a SVM for classification between the two types of violins considered: “contemporary” and “historical”. Low classification error rates are reported especially when identifying single-note recordings of open strings, which are considered to have more complex harmonic content in the sustain and decay phases of the note envelope, allowing for finer differentiation between violins of different quality.

## Timbral analysis using neural networks

We now turn our attention to research on the subject of identifying musical instrument timbre using neural networks. Despite their inherent advantages over other machine learning methods in terms of their ability for generalisation to unseen data and training set noise insensitivity [10], fully-connected neural network models provided limited early success when applied to musical instrument classification compared to other classifiers such as K-Nearest-Neighbours [11]. However, as initially demonstrated on visual character recognition with the LeNet-5 architecture [12], CNNs are more naturally suited to higher dimensional inputs such as images or spectrograms (both of which are 2-dimensional vectors), compared to fully-connected neural networks. CNNs are therefore popular in the timbral analysis and classification literature thanks to their ability to make perceptual inferences. In order to operate on audio signals, these timbral networks are commonly input pre-processed spectrograms, a feature which CNNs are able to handle and learn from efficiently by their propensity to process large amounts of data in 2-dimensional features such as time-frequency maps. This approach allows for popular image processing CNN architecture paradigms to be applied to acoustic signal analysis, and we will review approaches in the literature that leverage this interesting method in this subsection.

### Perceptual CNN standards

To solve complex perceptual inference tasks such as image recognition, CNNs have gained popularity in the last decade as the standard machine learning approach which does not require manually engineered features to be extracted from the input images, since these are learned by the CNN. A pivotal development in this field was AlexNet [13], which won the 2012 ImageNet image classification contest [14]. This was a large-scale network which has set the precedent for using a large number of filters within each convolutional layer (convolution channels). Compared to LeNet-5 [12], AlexNet increased the width of each convolution’s receptive field within images, increasing the number of optimisable filter weights. For instance, the first convolutional layer in the network uses 11x11 filter kernels, which, paired with pixel-region pooling and strided operations helps the network achieve dimensionality reduction on the larger and more complex 224x224 input images. The resulting leap in complexity from 600,000 to 46 million total optimisable parameters in AlexNet compared to LeNet was enabled by leveraging hardware developments in graphics processing units (GPUs), which are better suited to the matrix operations involved in CNN training and inference [15].

This increase in CNN complexity was continued by the introduction of the VGG network [16], which ranked top in the ImageNet Challenge 2014, achieving higher performance over AlexNet. The main contribution of VGG was increasing the number of convolutional layers in the network and reducing the kernel size of each to only 3x3 pixels. This was informed by the authors’ analysis which found that a larger number of smaller convolution filters are more expressive than a sequence of fewer large-kernel convolutional layers. This informed the trend in recent years in deep convolutional neural networks (DNNs) towards “deep and narrow” architectures using large number of filters, each using small filters [17].

Further developments have aimed to reduce network complexity by simplifying architectures and reducing parameter counts in order to create more compact models while maintaining performance. This has been achieved through structural innovations such as residual connections, which add parallel paths allowing layer inputs to bypass convolutional blocks to be added to a layer’s output. These were introduced in the ResNet architecture [18], the authors aiming to use the residual connections to increase expressiveness by making the network function behave by default as an identity mapping from input to output, essentially recentring the potential class of models which can be learnt by a given CNN towards more natural functions (by biasing the models towards the identity function as a “starting point”) [19]. As a result, ResNet is considered as a state-of-the-art standard architecture for general perceptual tasks such as visual feature extraction, dimensionality reduction, and image recognition.

### CNNs applied to timbre analysis

One CNN-based timbral classification system [20] is used to identify the predominant instruments in recordings of multi-instrument mixtures, using a deep CNN made up exclusively of small 3x3 filters in each convolutional layer, separated periodically by max-pooling layers for dimensionality reduction from the input spectrograms via abstracted feature maps to the low-dimensional fully-connected output layers. Broadly speaking, this type of deep and narrow CNN architecture has been commonly applied across the literature in recent years. For instance, [21] improves upon this system by adding source separation of the instrument mixture as a pre-processing step, achieving improved instrument classification results on identifying jazz instruments with closely related timbres. Contributing to this method’s success, the authors also cite transfer learning as a good way of getting around limited training data. This is achieved by using a model pre-trained on a different, larger dataset as a starting point for the CNN to then learn more application-specific timbral mappings from the small targeted dataset of jazz instruments.

Another piece of research considering classification the most prominent instrument from recordings of pieces played by multi-instrument mixtures is [22], which also uses log-Mel spectrograms as the input feature map. This work focuses on how to design CNN architectures to effectively capture timbral information, using musically-informed intuitions such as the fact that timbre should be inferred independently from pitch, duration and volume. Given that the network's layers operate on the spectro-temporal domain, the optimal choice of dimensions in time (number of frames) and frequency (number of bins) of the convolutional layers is discussed. The experiments on sung phoneme classification and instrument classification lead the authors to conclude that the first layer of the CNN benefits from using a diversity of filter dimensions to capture different scales of time-frequency feature mappings. Additionally, max-pooling layers over the frequency dimension are used in order to reduce the effects of pitch, as it can be shown that max-pooling (as opposed to average pooling) mitigates the effect of shifting the input of a CNN layer on its output feature maps.

Other CNN-based methods using Mel spectrograms are applied to less challenging data in the form of isolated recordings of individual instruments, often restricted to playing a single note at a time. In [23], the authors apply this class of method to recognising classical instrument families using a variety of recording types, comparing the performance of CNNs trained on Mel spectrograms drawn from isolated notes, monophonic melodies, and polyphonic pieces. It is found that CNNs trained on one sort of data do not generalise well to classifying the same instruments from another type of recording: for instance, high accuracy is reported for a model trained and tested on single-note recordings, but this performance does not carry over to testing the same model on recordings of pieces played on the same set of instruments. This implies that in the paradigm of CNNs using Mel Spectrograms as input, models are sensitive to polyphony, and that the embeddings that allow them to differentiate between single note samples of instruments differ from those characterising timbre in recordings of a piece of music being played on those same instruments.

## Research on related topics

Besides musical instrument classification, a great deal of recent research has concerned applications of and tasks related to timbral analysis. These include:

* *Music Information Retrieval* (MIR), including musical genre identification, for the automatic indexing of audio metadata. Genre or style identification is usually achieved by similar feature-based means to instrument classification, but applied to learning the texture or other style cues of a full mix of music as opposed to that of an instrument. A popular reference in the literature for this task is the approach presented in [24], where conventional signal processing timbral features are applied alongside features related to pitch and rhythm description for genre classification.
* *Source separation*, which aims to separate out audio corresponding to the different instruments in a mix. Notably, this task is tackled in [25] and [26], where the problem of overlapping harmonic partials (formants) between 2 instruments in a mix is mitigated using other timbral descriptors. In [25], the estimated spectral envelope of each instrument in the mixture is used to help separate the instruments from one another, while [26] aims to separate the sources by exploiting differences in their amplitude and frequency modulation characteristics (i.e. vibrato and tremolo playing effects respectively in musical terms).
* *Musical synthesis* and instrument *timbre transfer*: [27] uses a generative system (variational auto-encoder) to map musical instrument audio to a latent timbral space, a type of approach which the authors recently applied [28] to synthesising new sounds by selecting points in the space to transfer the timbre of one instrument to a different instrumental performance (e.g. between orchestral instruments and voice).
* *Speech recognition & diarization* (differentiation of who is speaking when): similarly to identifying variations between instruments, the timbral quality of the human voice is often used to help identify a speaker, which can be applied to diarization for dialogue transcription and voice authentication. Recent work [29] applies CNNs using Mel-spectrograms as input to the timbral classification of different voices on the basis of gender and age labels.

Another promising recent development relevant to timbral analysis is the integration of conventional signal processing elements, such as those presented in section 3.1 for extraction of timbral features, into an end-to-end neural network architecture [30]. This allows signal processing functions to be used within a deep-learning framework, as opposed to being limited to use as pre-processing steps. Notably, qualitatively promising results for this system are demonstrated on timbre transfer from voice to violin, as well as on the decomposition of musical instrument sounds into noise-like and tonal components.

*TODO: Add detail on who would be interested in the proposed timbral classifier that can identify fine differences between different acoustic pianos, e.g.:*

* *For automatic indexing of audio libraries, e.g. on streaming services, by the type of instrument present in the audio recording.*
* *For automatic indexing of sample libraries for musicians, so that musicians can search for a specific timbral class of instrument such as upright or grand pianos.*
* *To help instrument manufacturers, specialists, or virtual instrument creators better understand which technical features of acoustic pianos are responsible for their characteristic timbre which makes them sound like a particular type of piano. This information could be used to tune the sound of a piano in order to modify its character.*

# Background theory

## Signal processing features and theory for characterising timbre

### General background

*TODO: For sections other than the spectrogram and mel frequency scale, explain why I didn’t try to take them forward for the project.*

In this section, we present an overview of the most popular signal processing concepts, methods and features frequently applied in the literature to timbral analysis tasks. Understanding the role of these features, how to compute them and their interpretation will be instrumental in selecting a musically relevant and representative set of candidate features to use as pre-processed input to the timbral classifier. In the following discussion, sources [31] and [32] are referenced as comprehensive summaries containing more detailed definitions of each timbral feature and their computation, a subset of which are presented in the popular MPEG-7 standard for audio descriptors [33].

Digital audio signals being made up of samples recorded at a rate , features are often calculated over frames of length , where is the number of samples in a frame. Temporal features, which we will discuss in section 3.1.2, are computed from the waveform in the time domain, within a given frame or over several frames.

Conversely, spectral features are drawn from the magnitude spectrum, in the frequency domain, as discussed in section 3.1.3. Transformation into the frequency domain of an -sample signal is performed by applying the Discrete Fourier Transform (DFT), as follows (adapted from [34], slide 4):

This operation produces complex values in the frequency domain, each indexed by , which corresponds to a frequency Hz in normalised units (relative to the sampling frequency ). Frequency-domain analysis relies on the fact that musical sounds have periodic components, whose frequency distribution can be deduced from the spectrum . Some analysis methods aim to measure the extent to which the signal is periodic, as opposed to noise-like, in order to characterise whether the perceived timbre is more harmonic/pitched in the former case, or whether it is breathy in the latter case. We will discuss these approaches in sections 3.1.5 and 3.1.6.

In order to compute the DFT over a frame of analysis of finite length, the discrete Short-Term Fourier Transform (STFT) is applied, which produces the spectrum of the signal on a per-frame basis. This time-frequency representation allows for analysis of the magnitude of the frequency bins within a frame, as well as analysis of the evolution of the spectrum over consecutive frames. These methods yield the category of spectro-temporal features, which we will detail in section 3.1.4.

Computing the STFT yields a complex value for each frequency index and at each time frame ending at sample index , as follows (adapted from [35], Eq. 4.68):

In , the STFT is taken over a frame of samples in the input signal , producing frequency bins, and is a discrete window function of length . A commonly used function for is the Hamming window (adapted from [36], slide 5):

This window function serves a similar purpose as others with bell-shaped frequency responses, such as the Blackman-Harris and Hanning windows, by limiting spectral leakage artifacts caused by the boundary effects of windowing when the analysis frame is not the exact length of a period.

Phase information is not usually considered for timbral analysis, as it is broadly assumed that the character of a musical sound can be inferred from its waveform amplitude and magnitude spectrum primarily [37]. Therefore the phase characteristics of the signal are not considered in our discussion, and from the STFT we retain the magnitude spectrum .

### Temporal features

For extraction of temporal features, which concern the time evolution of the waveform over the course of the sound segment, we assume the signal analysis is applied to a single, isolated tone representative of the sound. For musical instruments, this would correspond to a single note played in isolation, and recorded from its onset to finish.

***Temporal envelope*** *(energy envelope)*

The envelope of a waveform is a smoothed version of the signal indicating the overall amplitude shape that the signal takes on over time. This can be achieved in its simplest form by taking the local average [32] or maximum of the waveform’s amplitude over a moving window, as demonstrated in [38].

***Envelope attack, sustain and decay***

* The ***attack time*** is defined as the period between the start of the sound until its maximum amplitude is reached [32]. Typically, the start of the attack is estimated by finding the time step at which a threshold (e.g. 10%) proportional to the amplitude’s maximum value over the considered sound is surpassed [31].
* The ***attack slope*** over the attack period further parametrises the speed of a sound’s rise, and is inferred from the average rate of increase of the waveform magnitude over the attack period [31].
* The ***steady-state***, or ***sustain*** period, corresponds to the phase after the attack during which the magnitude remains approximately constant near its maximum, and can be characterised by its length (sustain time).
* The ***decrease*** or ***decay***is characterised by the decrease slope, which can be calculated by estimating the rate at which the signal decays from the maximum-energy point [31].

The shape of the envelope characterises important timbral information relating to the articulation and form of a musical sound. For instance, a note played with *staccato* (“attacked”) articulation typically has a short envelope with a rapid rise (short attack time), as opposed to a note articulated as a swell, which will have a slower rise due to the note amplitude’s gradual increase initially. On a finer level, these envelope parameters depend not only on articulation (how the instrument is played), but also on the type of instrument and variations between different models of the same instrument, and have been shown experimentally to play an important role in humans’ perceptual ability to identify instruments [39].

***Temporal centroid***

The temporal centroid of a sound measures the time instant around which the energy of a sound is centred[32]. This is estimated using the time average over the signal's envelope, weighted by the signals energy.

***Zero-Crossings***

The zero-crossing count is the number of waveform sign changes in a given frame. This is computed after subtracting the DC offset (average amplitude) within each frame from the signal, and can be expressed as a zero-crossing rate per unit of time for each frame by normalising the count by the frame length [31].

### Spectral features

Spectral features characterise the distribution of frequencies across the magnitude spectrum for a given sound, within each STFT frame. The spectrum can be skewed towards higher frequencies, which is perceived as a brighter sound, or conversely towards lower frequencies, which corresponds to darker, muted sounds. Furthermore, the distribution of energy across the spectrum can either be concentrated in isolated peaks for tonal sounds, or have a broadband spread, which is perceived as a noisy, breath-like sound [31].

***Spectral envelope***

Analogous to the temporal envelope in the frequency domain, the spectral envelope corresponds to the overall shape of the spectrum, and can be computed by smoothing the energy spectrum of the signal. As stated in [40], the spectral envelope can characterise a sound independently of pitch, and therefore its shape is indicative of timbre. The following features seek to express this information more succinctly using a set of spectral metrics.

***Spectral moments***[31]

* The ***Spectral Centroid*** characterises the “central” frequency around which the signal’s energy is concentrated. It is calculated by the magnitude-weighted mean of the spectrum along the frequency axis. This can be interpreted as a broad measure of perceived “brightness” of the sound, in that it quantifies the proportion of high to low frequency energy [32]. But this does not account for the spread of frequencies; therefore this measure of brightness is especially indicative if the signal is distributed within a narrow-band of frequencies.
* ***Spectral Spread*** characterises how broadly or narrowly energy is distributed about the spectral centroid (the mean). It is measured as the standard deviation of the frequency distribution in the spectrum (weighted by the normalised magnitude of each bin). This measure is also equivalently described as the bandwidth relative to the centroid, for instance in [3].
* ***Spectral Skewness*** describes the skew, or asymmetry, of the spectrum about the spectral centroid. Negative values indicate energy concentrated below the centroid frequency, while positive values indicate the energy is concentrated in higher frequencies relative to the centroid.
* ***Spectral Kurtosis*** measures the spectrum’s flatness around the centroid. Particular ranges of the kurtosis value indicate different spectral shapes, as detailed in [31]: “[a kurtosis value of] 3 indicates a normal (Gaussian) distribution, < 3 a flatter distribution, and > 3 a peakier distribution". This allows us to describe with a single value the “peakiness” of the sound, which is an important part of characterising how tonal it is.

***Spectral slope*** *(spectral tilt)*

The spectral slope is the gradient of the spectrum, typically computed using a linear regression over the points in the spectrum to find the slope of the spectral magnitude [31] or the log-power spectrum, depending on the definition used. This is another descriptor which, similarly to the spectral centroid and skewness, characterises the overall relative prevalence of high and low frequencies in terms of spectral energy.

***Spectral Roll-off frequency***

The spectral roll-off attempts to measure the cut-off point of the spectrum, as another descriptor of the spectrum’s overall shape. This is computed as the frequency below which a majority of the energy in the spectrum is condensed [32], for instance in [31], "the frequency fc(tm) below which 95% of the signal energy is contained" is used. This is particularly relevant in characterising low-pass signals, as the roll-off frequency will yield an estimate of the cut-off or corner frequency of a filtered signal.

***Spectral Flatness Measure* *(SFM)***

The SFM aims to measure how close the spectrum approaches white noise, whose spectrum is ideally flat. This is estimated by taking the ratio of the geometric mean to the arithmetic mean of the spectral amplitudes in a given frame [31]. Beyond describing the shape of the spectrum, flatness measures such as SFM and Spectral Kurtosis allow us to place the periodicity of a sound along a scale between tonal and noisy sounds, where on one end we have an ideal single sine tone, and on the other extreme white noise, which can be approached using an infinite sum of sinewaves of different frequencies uniformly distributed across the spectrum. The space between these extremes is occupied by sounds of increasing complexity as more tones are combined; this will be further explored in our discussion of harmonic features, in section 3.1.5

### Spectro-temporal features

***Spectrogram***

The magnitude spectrogram of a signal is a spectral representation of the signal over time, made up of the magnitude spectrum computed over consecutive time frames. The resulting 2-dimensional matrix is typically plotted with frequency along the y-axis, and time on the x axis in visualisations using a colour intensity scale to show the magnitude of each time-frequency bin. This image is characteristic of the distribution over time of the input signal's energy across different frequencies. For instance, the fundamental and harmonic frequencies (see section 3.1.5) and their associated intensities can be observed in this representation, as well as the evolution of individual frequency components over the signal envelope. Therefore the spectrogram gives a fairly complete representation of a signal's timbral profile, although it is not inherently pitch-invariant since pitch is linked to the frequency-axis.

Computation the spectrogram involves applying the STFT (see ) over consecutive frames in order to obtain the spectrum over time. For this, we must consider the effect of the frame length, , on the precision in both time and frequency of the spectrogram. A longer analysis window allows us to perform the STFT over more samples, which results in a higher frequency resolution since the resulting spectrum will contain more points. However, if the window is larger, the time resolution of the analysis decreases, since we calculate the spectrum over longer durations. If the window is too large, we risk no longer capturing any rapid changes in the signal over short durations, while if it is too narrow, we lose precision in the spectrum and risk losing harmonic detail in the spectrogram. This time-frequency precision trade-off, determined by the selected duration of the analysis window, is illustrated in [35], Fig. 4.2.. This trade-off can be somewhat moderated by zero-padding the analysis frame such that the window over which the STFT is performed contains more samples, resulting in synthetically higher frequency resolution using the same number of points in the original waveform. Paired with overlapping consecutive windows, this frequency-domain interpolation allows us to increase both the frequency and time resolution of the spectrogram, which ensures that the spectrogram captures the continuously time-varying information in a signal [34].

*TODO: Give example plots using different frequency and time resolutions to show the impact of both on the aspect of the spectrogram, and what shows timbral qualities best.*

In an implementation, one must therefore select values for the following parameters: the STFT frame length, the length of the analysis window (i.e. how much padding to be applied to the STFT frame), the spacing of consecutive windows (determining the amount of overlap between them), the window function used, as well as the frequency range considered. In selecting these, we must ensure that the degree of overlap between frames is not such that adjacent frames contain redundant information, and that the zero-padding is limited so as to not dominate the analysis window (which would cause inaccurate interpolation and artifacts).

To summarise, the computation of the spectrogram involves the steps shown in ***Figure 3.1.4‑1*** First, we sample equally-spaced frames of length and add padding, commonly by appending and prepending a sequence of zeros either side of each frame. Then we apply the STFT over each padded frame as described in , and take the power spectrum in order to represent the power per frequency and per frame in the spectrogram, discarding the phase spectrum.

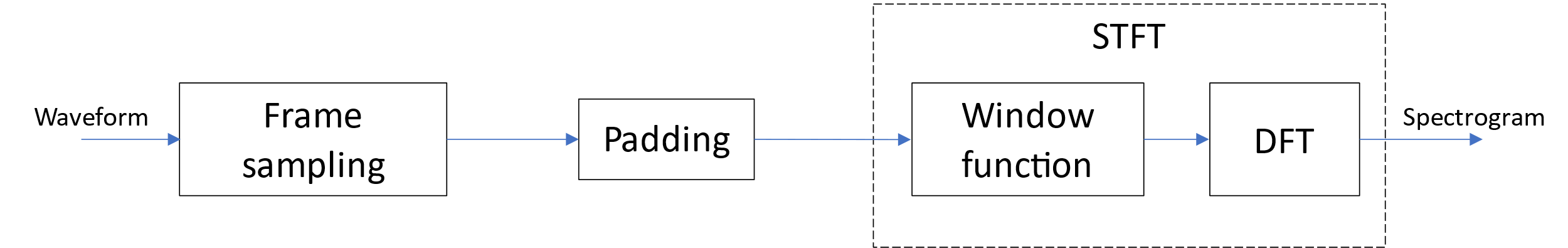


Figure 3.1.4‑1: Signal flow diagram summarising the steps involved in computing the spectrogram from a waveform. The output is typically converted to the power spectrum by taking the squared magnitude of the STFT result.

*Indicate which selections may be more appropriate to timbral analysis, as opposed to pitch or other analyses.*

***Spectro-temporal envelope***

The spectro-temporal envelope characterises the shape of the signal in both the frequency and the time domain, by encapsulating the evolution of the energy contained in each frequency bin over consecutive frames. The result is the shape of the signal over a given time period as a function of both time and frequency, and as stated previously, this can be seen in the spectrogram.

In [32], a feature characterising the spectro-temporal envelope is estimated for each frequency bin, calculated over a window of several frames by taking an average of the magnitude of each spectral component over consecutive frames (which the authors name “global spectral envelope”). The authors use this to derive “Harmonic Spectral Deviation”, which is a measure how much each spectral amplitude component differs from its neighbouring spectral envelope.

***Spectral flux*** *(spectral variation)*

The spectral flux or variation is a measure of the spectrum’s rate of change over time. Two different definitions exist in the literature, both consisting of comparing the spectral distribution at consecutive time frames. Both calculations produce a function of time from the spectra of two successive time frames.

In [31], spectral variation is computed as one minus the correlation between two consecutive spectral amplitudes (normalised by the spectral energy at both time steps). In [32], the sum (over the spectral components) of squared differences between spectral magnitudes at two consecutive time frames is used.

### Harmonic features

In the context of harmonic analysis, complex sounds such as those produced by musical instruments are modelled as a sum sinusoidal components of differing frequency and amplitude, which are called partials. Of these, harmonic components of the sound are those located at integer multiples of the fundamental frequency (the pitch of the musical sound).

The fundamental is not directly implicated in timbral analysis, since timbre is defined as being independent of pitch, but this feature can be used for estimation of the expected harmonic frequencies of a signal as described in detail in part II.B.4. of [31], and potentially to normalise pitch-dependent features such as the spectrogram (see section 3.1.4). Notably, the harmonic peaks present in a musical sound may deviate from the theoretical evenly-spaced harmonic distribution along the frequency axis, which the authors of [31] qualify as “inharmonic distortion”. The harmonic modelling context introduces a number of features which are commonly used to analyse the timbre of musical sources by characterising the distribution of harmonics (harmonic centroid, spread and variation) as well as the extent to which the signal conforms to harmonic assumptions (i.e. the tonality of the sound).

***Harmonic Centroid*** [32]

The harmonic centroid frequency, analogous to the first spectral moment, is the amplitude-weighted mean frequency of the harmonic peaks identified in the spectrum.

***Harmonic Spread*** [32]

The harmonic spread, similarly to the second spectral moment, is measured as the amplitude-weighted mean across the detected harmonics of the standard deviation of each of the harmonic peaks. This is expressed normalised by the harmonic centroid frequency.

***Inharmonicity*** and ***Harmonic energy skewness*** [3]

Inharmonicity is defined in[3]as the measure of how much the first 4 partials differ from the corresponding theoretical harmonic frequencies (integer multiples of the fundamental). This is computed as the sum of the distances on the frequency axis between each partial and the corresponding expected harmonic frequency (each distance is normalised by that harmonic frequency). The calculation of harmonic energy skewness is similar to that of inharmonicity, but each distance is scaled by the spectral energy in a neighbourhood of the considered partial, yielding a measure analogous to the third spectral moment (skewness).

***Harmonic Variation*** [32]

The harmonic variation is similar to the spectral flux between consecutive time frames. It is computed by the normalised correlation between the harmonic peak amplitudes between two consecutive frames.

***Harmonicity Rate*** and ***Harmonic Brightness***

These features, as defined in [32], both aim to characterise the prevalence of harmonic content in the sound, giving a measure of how tonal or noise-like (inharmonic) the sound is.

The harmonicity rate aims to measure the proportion of the wider magnitude spectrum that corresponds to the harmonics of the sound. This is estimated by computing the maximum of the normalised autocorrelation of the signal. The harmonic brightness aims to quantify the prevalence of upper harmonics (higher frequency overtones) in the signal by taking the ratio of the sum of index-weighted partials’ magnitudes over the sum of the harmonics’ magnitudes.

***Tristimulus values***

Developed as an analogy to the three channels of visual colour, these coefficients aim to characterise the harmonic “colour” of a sound based on the distribution of energy over the harmonic series in the signal. Their computation, detailed in[31], relies on the sums of the amplitudes of the harmonic partials of the signal in a given frame.

***Odd-to-Even harmonic energy ratio***

Sounds containing mostly even harmonics are perceived as "smoother" than those in which the odd harmonics dominate the share of energy in the spectrum[31]. The odd-to-even ratio is computed by the sum of squares of the odd harmonic amplitudes divided by that of the even harmonics.

### Formant analysis and the source-filter model

Formant analysis is a popular approach in speech timbre analysis and synthesis [41], often applied to speaker differentiation and identification [42], and can be compared to harmonic analysis in the musical context (formants in speech processing corresponding to harmonics in musical contexts). The approaches and features involved in formant analysis and source-filter modelling could provide useful results in characterising the timbre of musical instruments via analogy to the human voice.

***Source-filter model*** and ***formants***

The source-filter model, typically applied to modelling the human vocal tract, interprets a sound as resulting from a linear system, by which a source (exciter) being passed through a filter (resonator), as shown in **Figure 3.1.6‑1**. The excitation at the model source accounts for the noise-like qualities, while the order and characteristics of the filter account for the resonant (tonal) qualities of the resulting sound.

Formant analysis concerns the study of the resonator, and consists of determining the resonant frequencies and bandwidths of the filter modelled for the signal, which are particular to the shape and nature of the body generating the sound. As discussed in [43], the relationship between these formant frequencies is relatively constant across different pitches played by musical instruments, indicating that the formant frequencies, magnitudes and bandwidths are a relevant set of features for characterising instrument timbre. Furthermore, many of the computations described in section 3.1.5 could be applied to characterising formants and their prominence in the spectrum analogously to harmonics.

***Linear Predictive Coding (LPC)***

The most common scheme for estimating the frequency and magnitude of formants from a waveform is Linear Predictive Coding, which predicts each value of the signal by linear combination of previous samples, as described in [41]. This corresponds to an auto-regressive filter model, which is computed by using the least squares solution to determine each filter coefficient (linear prediction coefficients) using a pre-determined order for the filter. The resulting LPC filter is an estimate of the filter part of the source-filter model, and the location of the filter’s poles in the z-plane yields the formant frequencies (the peaks in the filter’s frequency response), as shown in **Figure 3.1.6‑1**.

Machine generated alternative text:
s[n] E akS[n — k] + e[n] 
Pulse/noise 
excitation 
Vocal tract 
e[nl H(z) = 1/A(z) 
s[nl 
z-plane 

Figure 3.1.6‑1: Auto-regressive filter equation with coefficients ak, error e[n] and order p (top). Source-filter model showing z-domain filter transfer function H(z) and representing an illustrative frequency response and pole locations in the z-plane (bottom). Source: From [44], slide 7

*TODO: detail initial LPC formant analysis experiment, with plots*: Formant extraction and analysis using Linear Predictive Coding coefficients. Wrote a MATLAB script to extract formants from single-note recordings of a flute played at different pitches. LPC functions provided by the VOICEBOX toolkit were used to estimate LPC coefficients from the waveforms, which were then translated to estimated formant frequencies and bandwidths. The relative frequencies of the first few formants were plotted across the different pitches in the range of the instrument in order to confirm the pitch-invariance of the ratio between the formant frequencies of a given instrument, which is one of the reasons for which formants are considered as descriptors of timbre.

***Inverse filtering***

Inverse filtering complements formant analysis by attempting to model the excitation, or source, part of the source-filter model through applying an inverse filter to the signal in order to recover the output of the “source” element. The excitation can be estimated by applying Linear Predictive Coding and considering the linear prediction error term e[n] shown in **Figure 3.1.6‑1**, which is called the residual [45].

This atonal part of the sound corresponds to unvoiced sounds in speech, and analogously concerns the breathy, inharmonic aspects of the sound produced by musical instruments. Thus, isolating and characterising this excitation may provide interesting results in the way of encapsulating timbre beyond harmonic information.

### Cepstral features and the Mel scale

The Cepstrum of a signal is obtained by taking the discrete cosine transform (DCT) of the log-magnitude frequency spectrum. This Cepstral representation shows peaks corresponding to shifted echoes in the original waveform, and therefore reveals a representation of periodic events in a waveform, such as the periodicity corresponding to the fundamental pitch and formants in a complex signal such as speech [46].

***Mel-Frequency Cepstrum Coefficients (MFCCs)***

The Mel scale is a logarithmic frequency scale based on human perception of pitch relationships, relying on the fact that the ear can more finely differentiate between equally spaced low frequency sounds than their higher frequency counterparts. The Mel-frequency Cepstrum is obtained by mapping a signal’s spectrum to the Mel scale and computing the DCT of the logs of the spectral magnitudes across the Mel scale [46]. This Mel Cepstrum has discrete values which form the Mel-Frequency Spectrum Coefficients, a feature set which encapsulates pitch and harmonic information emulating human perception. These coefficients are therefore compact and powerful descriptors of the perceived harmonic content of a signal over time.

***The Mel scale, perceptual features and the log-Mel spectrogram***

The relationship between frequencies on the Hz scale (which we refer to as DFT or STFT frequency) and their mappings on the Mel scale is given by the following equation (adapted from [47], slide 91):

This mapping is plotted (in the discretised form produced by a Mel filter bank) in **Figure 3.1.7‑1**, where its approximately linear shape at low frequencies, and logarithmic shape elsewhere, can be observed.

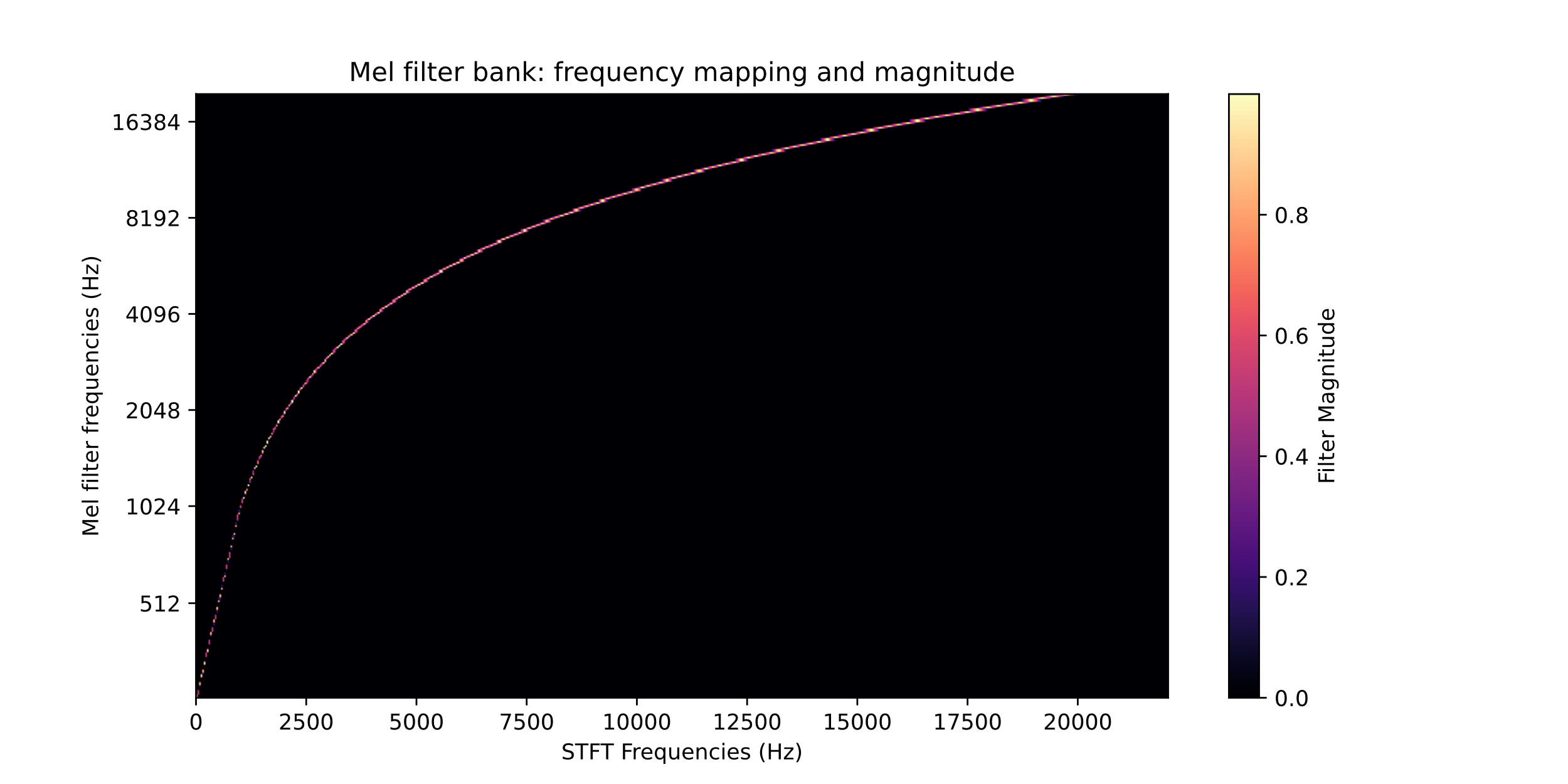


Figure 3.1.7‑1: Plot showing the mapping from STFT frequency to Mel-scale frequency, in the case of a 300-filter Mel bank (whose frequency response is shown in Figure 3.1.7‑2). This plot shows how the triangular filters in the Mel filter bank approximate the continuous logarithmic Mel scale, such that the mapping is applied with a uniform unit magnitude across all the considered frequencies.

In practice, in order to apply the Mel scale to a signal (for computing the MFCCs, for instance), a Mel filter bank is constructed and applied to the signal. The Mel filter bank, also called Mel basis, is a set of triangular overlapping filters whose bandwidths are spaced according to the Mel scale [47]. **Figure 3.1.7‑2** shows the aspect of a Mel filter bank’s magnitude response over different frequency regions. Therefore, filtering a signal with this bank approximates the transformation of the spectrum’s frequency axis to the Mel scale, and can be applied by convolution in the time domain or multiplication in the frequency domain.

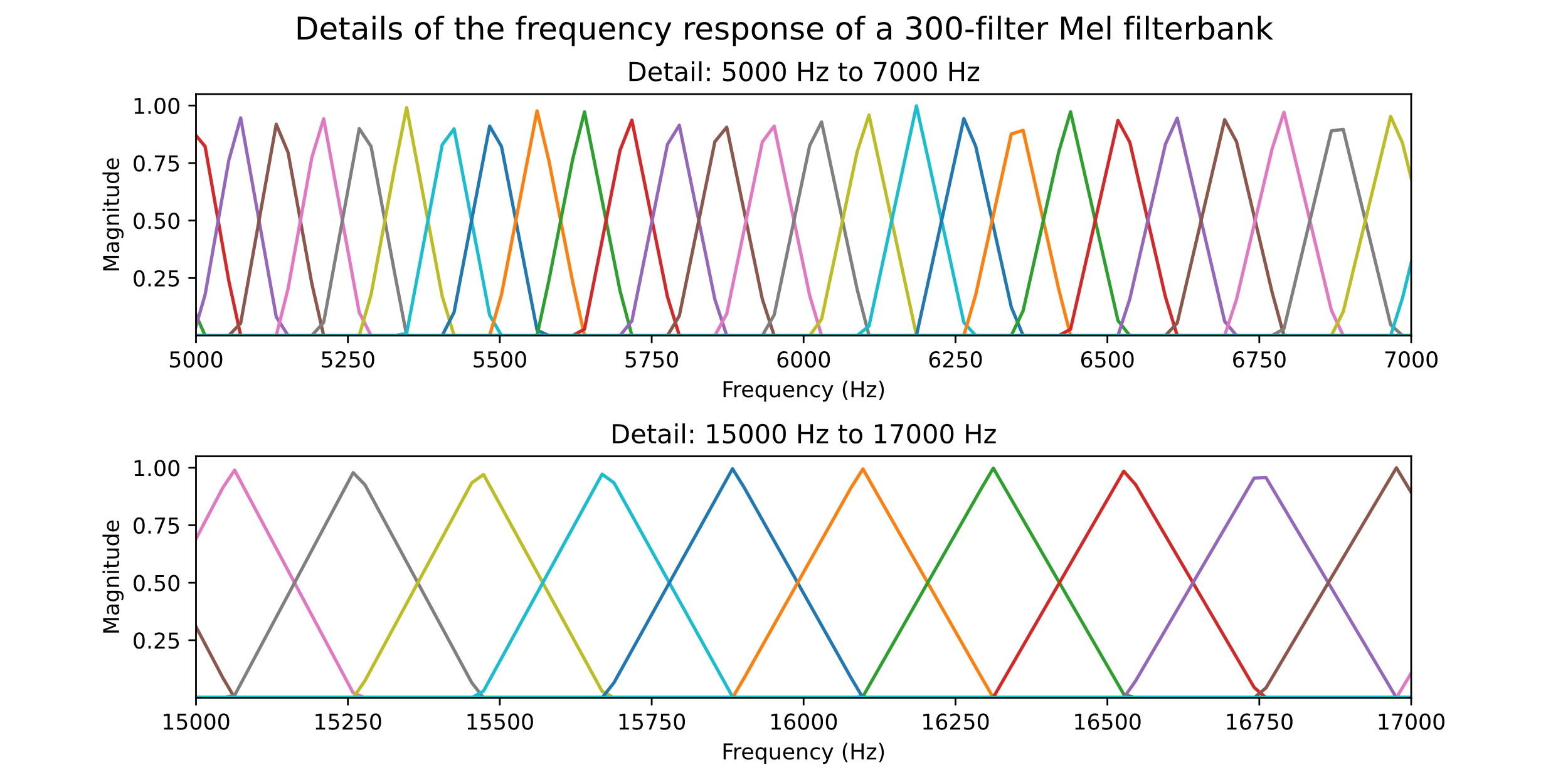


Figure 3.1.7‑2: Mel filter bank magnitude response plots corresponding to a 300-filter Mel bank. Each coloured line is a separate filter’s frequency response, each having a triangular shape and roughly unit gain. The top figure shows a lower-frequency detail of 2 kHz bandwidth within the full magnitude response of the filter bank, while the bottom figure shows a detail of the same bandwidth in a higher-frequency portion of the spectrum. Note the higher density of filters in the top plot in order to achieve higher Mel-scale resolution in the lower frequencies.

An important parameter involved in the application of the Mel scale is the number of filters to be used in the construction of the Mel bank. This essentially controls the frequency resolution of the Mel scale discretisation, but the resolution of the resulting Mel spectrum also depends on the number of points used in the DFT computation (which determines the spectrum’s native frequency resolution). Therefore the number of Mel filters can be selected so as to maximise the resolution of the Mel spectrum, while keeping in mind that too large a number relative to the DFT’s resolution will result in empty frequency bins being produced, and will increase the computational complexity of applying the scale.

The Mel scale biases the resolution of the frequency axis to scale with the ear’s ability to differentiate between pitches, making it appropriate for application to musical acoustic analysis. For example, this can be observed empirically by the roughly logarithmic distribution of note pitches on the piano keyboard with respect to their fundamental frequency, as illustrated in **Figure 3.1.7‑3**, a standard which, like the Mel scale, reflects human perception of acoustic frequency.

Figure 3.1.7‑3: Plot presenting the relationship between the 88 notes on the piano keyboard and their fundamental frequencies. We note here how this relationship closely resembles that between DFT frequency and Mel frequency plotted in Figure 3.1.7‑1, supporting the idea that the Mel scale is adapted to musical-domain analysis. Piano key fundamental frequencies obtained from [48].

Taking the log of the magnitudes, or similarly applying the decibel scale to the power spectrogram similarly mimics human perception, as this emulates the human ear’s logarithmic response to acoustic amplitude. Thus, both the frequency axis and magnitude range in the spectrogram can be warped to approximate human perception of pitch and volume respectively. A representation which applies both of these perceptual characteristics is the log-Mel spectrogram, which uses the Mel frequency scale for the y-axis and a logarithmic magnitude scale for the intensities in each bin. The log-Mel spectrogram is therefore a powerful standalone feature encapsulating spectro-temporal information by leveraging perceptual features, an approach which is applied for instance in [49] as detailed in section 2.2.2. To summarise the computation of the log-Mel spectrogram, we illustrate the steps involved in **Figure 3.1.7‑4**.

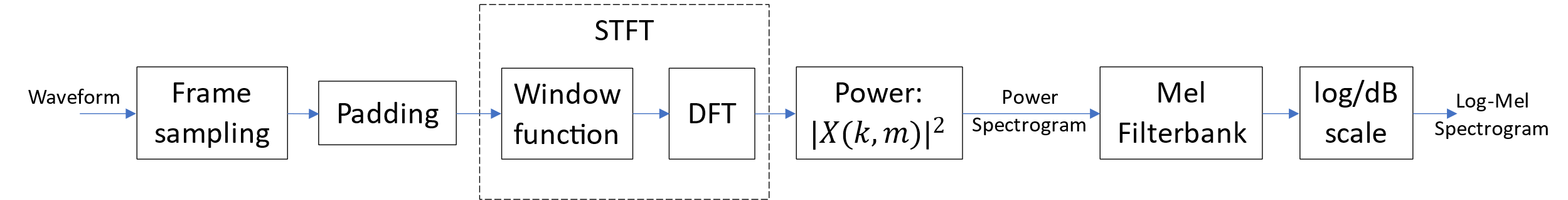


Figure 3.1.7‑4: Signal flow diagram summarising the steps involved in computing the Log-Mel spectrogram, including computation of the power spectrogram (see Figure 3.1.4‑1) and application of the Mel and log or decibel scales. Adapted from [47], slide 92.

## Machine learning applied to timbral identification

A popular application of timbral analysis of musical audio signals is the automatic classification or grouping of musical instruments from audio recordings; we will guide our attention to the various ways in which musical instruments can be identified from their timbre. In order to draw a classification label from timbral input features, or to cluster samples corresponding to instruments with similar timbres based on an input feature set, many inference algorithms have been applied in the literature. This section gives an overview of the machine learning classification and clustering methods most commonly applied to timbral analysis tasks, especially in the context of musical instrument identification by timbre. We will discuss the most popular methods for timbral classification, while also mentioning clustering methods which are also used in the context of timbral analysis; and then explain the motivation behind our focus on neural network classification.

### Non-neural network methods

Traditional machine learning algorithms generally require careful pre-processing of input waveforms into low-dimensional input features to infer the timbre qualities of a signal. These inference models therefore inherently require more structured data as input in order to make informed decisions for classification and clustering, but some are advantaged by their simplicity and their ability to make decision using a smaller amount of data, for instance for methods that do not require training, as opposed to neural network models.

***Timbral classifiers (supervised inference)***

A supervised classification system seeks to assign one or multiple labels from a pre-defined set to an unseen sample (from the test set), based on the seen samples’ known labels (sometimes called the training set if the learning process involves training). This inference results from relating the set of input feature values taken by the unseen example to the set of input features associated with the known labels.

K-nearest-neighbours (KNN) is a simple yet popular scheme for classification of unseen samples given a set of known examples, as described in [11]. The method consists of plotting all samples on the input feature space, such that each known sample forms a point of known label and coordinates in the space resulting from the values taken on by the features for that sample. When presented with an unlabelled sample, the KNN algorithm simply classifies it using the most prevalent label out of the K nearest samples (usually measured by Euclidean distance in the space), where K is a parameter of the method. Variations on this method include distance-weighted voting from the K neighbours. This algorithm performs poorly, however, when using a greater number of input features, as the feature space becomes increasingly sparse according to the “curse of dimensionality” (a concept coined by Richard Bellman and detailed in [50]). Additionally, its ability to generalise inference to unseen data is limited due to the local nature of the connections established between data points, as noted in [3].

Decision trees (or binary trees) is another straightforward classification scheme described in [11] which builds a tree structure based on the distribution of each feature’s values across a training set. This structure divides the known samples such that each branch groups all the samples taking a particular common range or class for a given feature, by splitting the tree on the point subdividing the feature space with maximum information gain (i.e. entropy reduction). When an unseen sample is input, the tree is traversed from the top down, at each node taking the branch corresponding to the test sample’s input feature value, until a leaf node (where all seen samples grouped by a branch share the same label) is reached and its label is assigned.

Other classification algorithms often cited in timbral analysis work include Support Vector Machines (SVM) and Discriminant Analysis (e.g. Linear, Quadratic, Canonical) as detailed in [3], though these schemes have in recent years fallen out of favour in machine learning research due to their implementation complexity, instead replaced largely by neural network classification.

Despite their limitations, simply-implementable classification schemes such as KNN and decision trees remain useful tools to pre-validate the quality of a choice of input features or data when exploring a classification problem, before moving on to developing a more generalisable classifier such as a neural network model. In particular, the maximum information gain strategy in the construction of a decision tree could help elucidate the most telling features in discriminating between instrument timbres, as noted in [11].

***Timbral clustering (unsupervised inference)***

Clustering methods differ from classification schemes in that known examples with output labels are usually not supplied; the models are left to relate (or group) samples in a set with one another without supervision, only using their input feature values. This provides a viable alternative to classification for inference when manual ground truth annotations are not available or inconsistent. For timbral analysis, clustering methods such as Gaussian Mixture Models (GMMs) (described in [11]) and Self-Organising Maps (SOMs) are applied in the literature to plotting a low-dimensional timbral space for visualisation and quantification of the relationship between musical instrument sounds [9]; or to provide a system for indexing audio databases by timbral similarity [51].

*TODO: Keep the sections which don’t concern Neural Networks as studied background material, but mention why I didn’t decide to try to take these forward.*

### Neural Network based classification

***Neural Networks***

In the context of more complex pattern recognition and feature extraction from data, many of the machine learning algorithms previously discussed have been superseded in recent years by gradient-based backpropagation learning of multilayer neural networks. As explained in detail in [10], this supervised learning method relies on samples being input to a network of nodes called a multi-layer perceptron, which models a learnt non-linear function. Each layer (set of nodes) of the network is connected to the next using a linear combination between the input values and the layer parameters, followed by a differentiable non-linear activation function. Each layer’s parameters is made up of a weight which multiplies the input for each pair of input-output nodes, and an added bias for each output node. The output value of node at a layer , denoted , given a set of inputs is defined in , adapted from [52].

where:

* is the output value at node in layer .
* is the vector of inputs to the considered layer.
* is the vector of learnable weights of the linear combination between the layer inputs and the considered layer output node , unique to node in layer .
* is a learnable scalar bias unique to node in layer .
* is a non-linear activation function applied to the result of the linear combination.

can therefore be used to compute the output value at each of the hidden or output layer nodes in ***Figure 3.2.2‑1*** in the forward computation, and the same applies to networks with more hidden layers, feeding values from the input of the network to its output.

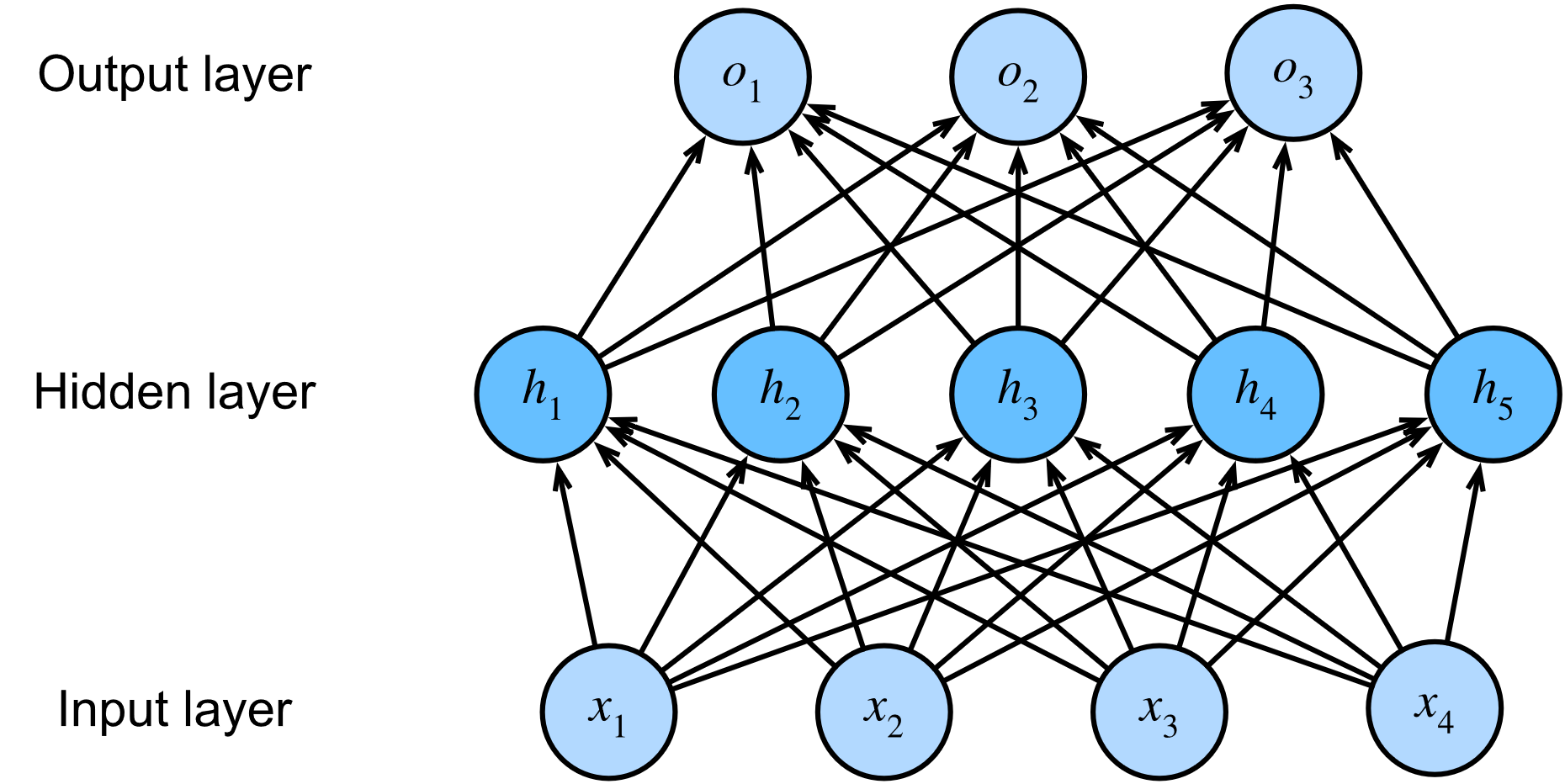


Figure 3.2.2‑1: Diagram of a 3-layer fully connected neural network, containing 4 input nodes, 1 hidden layer with 5 nodes, and 3 output nodes showing arrows between the nodes of consecutive layers where linear combination weights are applied to connect nodes from one layer to the next. The non-linear activations are not shown, but are implied as being applied after the linear combination at each “hidden” or “output” node. Figure adapted from [52].

When training samples are input to the network, the weights are randomly initialised, and the value for each input feature is fed through the nodes via the weights and activations in each layer in a forward pass to produce the activation outputs of the final layer of nodes, which is compared with the ground truth label corresponding to the given known example. The resulting error, which is computed using a specified loss function, is then used to update each connection weight using a chosen optimisation algorithm. In Stochastic Gradient Descent (SGD) optimisation, the goal of the optimisation given a batch of inputs is to take a step towards minimising the error between the batch network outputs and batch labels, informed by the error gradient (from which the direction of descent towards a local minimum can be derived). The error gradient is backpropagated through the network using the chain derivative rule, so that the error gradient with respect to the parameters of each layer can be computed to inform the updated value for each weight in the network.

Classification problems are typically handled by setting the number of output layer nodes to match the number of possible classes, with an output activation function bounded between 0 and 1, and encoding a ground truth label during training with “1” for the output node corresponding to that class and “0” for all the others. For example, in the case of binary classification (discrimination between two classes), only a single output node is required in the final layer. Then, at test time, the input values of a given test sample are passed forward through the network, and the class corresponding to the output node with the highest activation is selected as the model’s prediction.

***Convolutional Neural Networks (CNNs)***

Relative to fully connected neural networks and other machine learning methods, Convolutional Neural Networks have been shown to bring notable performance improvements to perceptual inference tasks such as image classification, computer vision and, given the suitable pre-processing is applied (e.g. generation of spectrograms), audio processing. The same training process, nonlinearities, and hyperparameters detailed previously apply to CNNs; however the structure of CNNs differs greatly from that of NNs. From a high-level perspective, the key difference between traditional NNs and their convolutional counterparts is their handling of high-dimensional inputs, since NNs operate natively on 1-dimensional vectors while CNNs operate directly on maps of dimension 2 or above, without needing to flatten to an array. While standard NNs have all nodes in a given layer’s input individually connected to each node in the output of the layer with a unique weight, convolutional networks use a weight-sharing structure in which the layer connections are shared between multiple input nodes, or pixels in the image domain.

In 2 dimensions, convolution is achieved by applying the spatial filter kernel of size using a sliding window across all locations in the input map of size to produce an output map . The output of a convolutional layer at pixel location is given by the sum of products of the input values by the kernel weights within the considered window of size , centred around location , as defined in (adapted from [53], slide 7).

Where are commonly chosen to be odd numbers in order to centre the kernel’s sliding window on the output pixel’s location . Note that in the context of CNNs, as opposed to the signal processing definition of convolution, this operation does not require the filter kernel to be flipped before taking the entry-wise sum of products, since the filter weights are learnt by the CNN in either case, as explained in [54]. Border pixels in the input map may be ignored, or padded by the appropriate amount in order to produce an output map of the same shape (i.e. and) [55]. From we can see that the output pixel at location only depends on the learned filter weights and the input pixels in a small region around . In a convolutional network layer, to this value is added a learned bias, which is a single scalar applied across the whole map.

CNNs are made up of a series of these convolutional connections between layers as illustrated in, with each convolution followed by a nonlinear activation function as with standard NNs. In each convolutional layer, independent 2 dimensional learnable filters can be stacked along the 3rd dimension, producing corresponding channels in the output map, in order to extract multiple features in parallel paths and operate on -channel data such as a 3-channel RGB image. Thus each convolutional layer has learnable parameters, independently of the input/output map dimensions. This is generally much fewer than the equivalent fully connected NN layer, which would depend on the map dimensions, requiring parameters; therefore CNNs have fewer optimisable parameters between layers, reducing the cost of each optimisation step and the size of a model. In some variations, a combination of different sizes of filters can be used even within a single CNN layer, allowing analysis and transformations can be applied at multiple scales and levels of abstraction in a single model, for example as seen in [17].

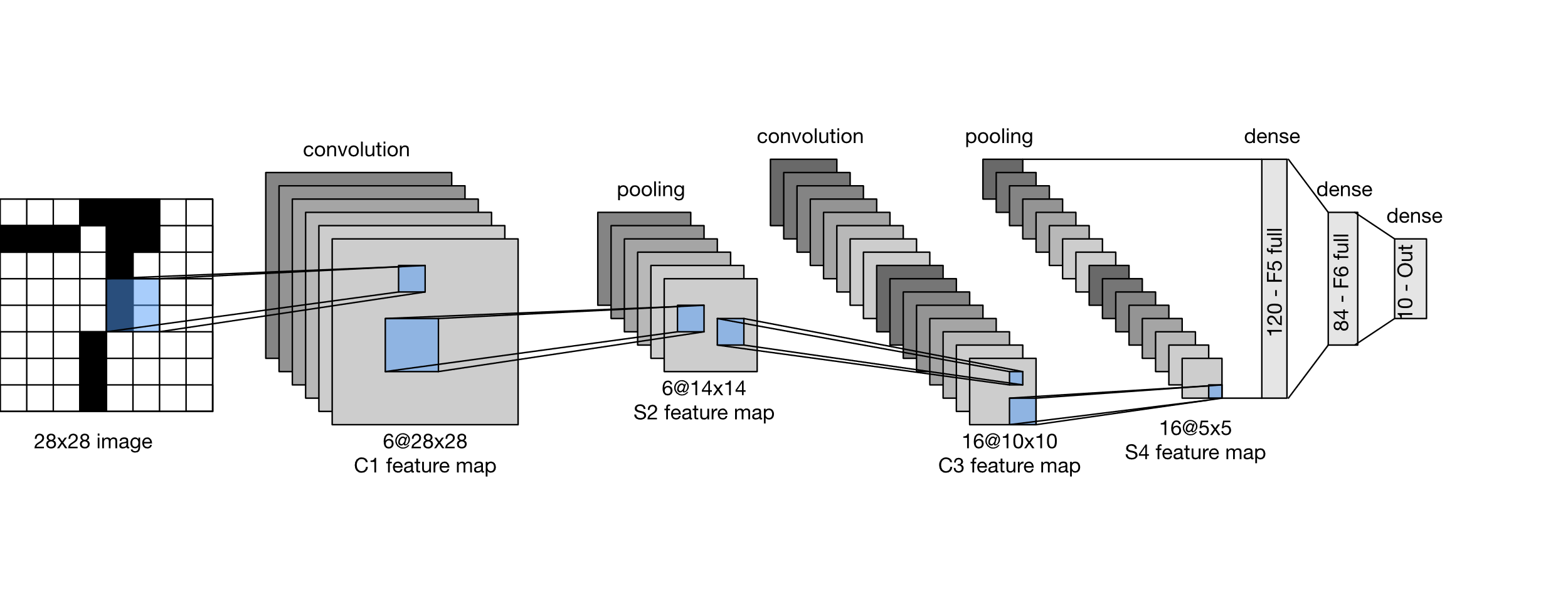


Figure 3.2.2‑2: Diagram of a simple convolutional neural network architecture, namely LeNet [12] which classifies 28x28 input images as belonging to one of 10 classes. The network contains 2 convolutional layers interspersed with 2 pooling layers. For instance, the first convolutional layer, C1, uses a 6-channels of 2x2 filters, producing 6 feature maps (labelled “C1 feature map”) which are the same shape as the input images since the input images are padded by 1. The output of the last pooling layer is flattened into an array to be processed by a small fully-connected neural network whose layers are labelled “dense”, in order to produce a 10-element array. Figure adapted from [56].

***Figure 3.2.2‑2*** shows the typical structure of a simple CNN, whose final layers are fully-connected “dense” layers. These dense layers can be replaced, as it is possible to continue reducing the dimensionality of the 2-dimensional feature maps using convolution operations so as to produce the correct number of output activations. Such architectures are called Fully Convolutional Neural Networks (FCNNs) and have the advantage of retaining spatial information at different levels of abstraction until the final output layer.

Dimensionality reduction between consecutive layers can be achieved by strided convolution, or by pooling (down-sampling by grouping regions) patches of the feature map by average or maximum value, as detailed in [57]. For these reasons, CNNs are readily adapted to dimensionality reduction and to fusion of high dimensional features, for instance in the context of fusing timbral features as in [58]. This dimensionality reduction achieved by series of convolutions and pooling operations allows the network to output a low-dimensional vector given a large-scale input image, in order to perform classification for instance. Another key advantage of CNNs demonstrated in [57] is that the combination of convolution and pooling operations yields approximate translation invariance, making the network less sensitive to input locality. This means that a series of CNN layers, each made up of convolution followed by pooling, produces a similar response to a given input pattern regardless of where the pattern appears in the input map. This is a desirable quality for image recognition applications in which a visual shape needs to be recognised regardless of its location, but also when applied to timbral analysis using spectrogram inputs, since it allows the network to make inferences independently of the timing (location on the x-axis of the spectrogram) and pitch (y-axis of the spectrogram) of the signal.

*TODO: Add a section on how to typically interpret CNNs: visualising filters/activations at different layers to observe different level of abstraction, inversion/inception*

***Common training and data considerations for neural networks***

In general, on top of choosing which type of neural network architecture to use for a classifier problem based on the nature of the given problem and input features, designing a neural network involves the choice of a large number of architectural parameters, including the number of nodes and activation functions in each layer, and the total number of layers in the network. In the case of CNNs, we choose the number of convolutional filters to apply between layers, as well as their dimensions.

A pitfall commonly encountered when using a Deep Neural Network (DNN) structure, i.e. a NN containing many sequential layers, is the issue of vanishing gradients. This refers to the problem of the gradients being applied during backpropagation being small in magnitude such that the applied optimisation updates are too slight, causing the learning process to stall before convergence. This occurs since backpropagation involves calculating the gradient of each functional component (linear layers and non-linear activations) in the network with respect to the optimisable parameters, and combining them by applying the chain rule. If activation functions in the chain are too flat in the region of differentiation, their gradient will be small. Because the chain rule is multiplicative, when combining the gradients from the output layer backwards through each layer in the network to reach a given layer, each small gradient in this path will shrink the magnitude of the parameter update applied. Deeper networks are thus more affected, as the update applied to the earlier layers can shrink exponentially as we add more layers to the end of the network. This effect can be mitigated by selecting appropriate activation functions for the network: sigmoid and other smooth functions such as Tanh are subject to vanishing gradients, while ReLU and its variants are rectilinear so as to prevent small gradients, as illustrated in ***Figure 3.2.2‑3***. Therefore, we will generally prefer using ReLU-like activations in deeper neural networks.

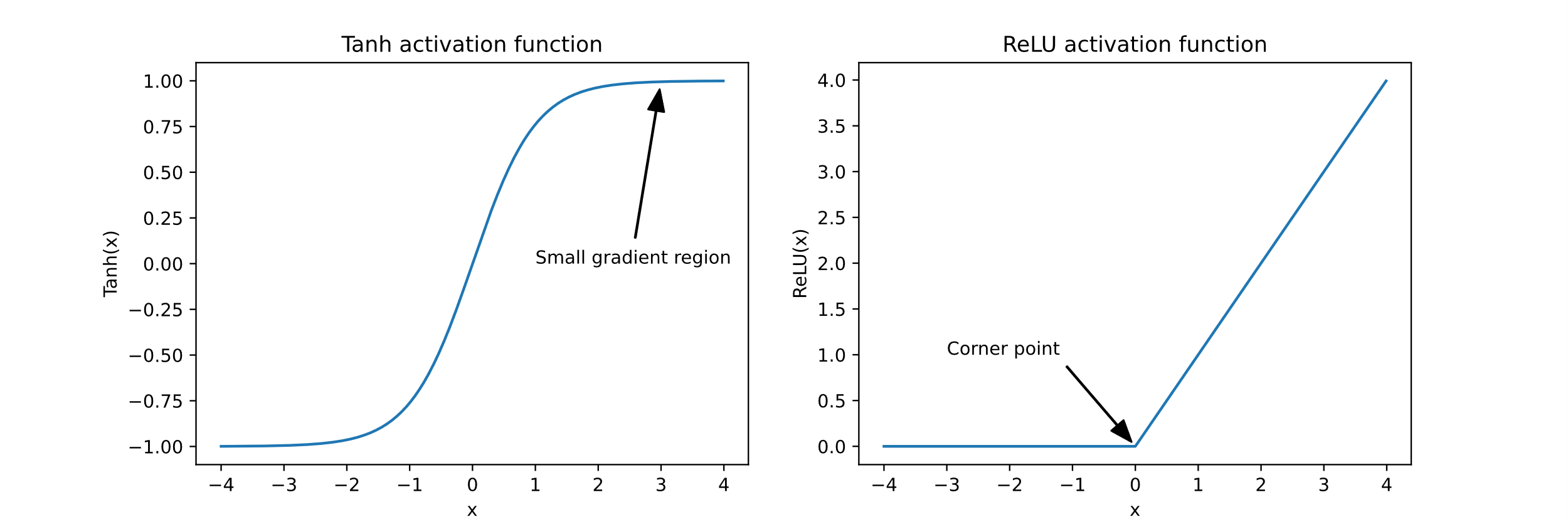


Figure 3.2.2‑3: Comparison of a smooth activation function (Tanh, left plot) subject to vanishing gradients to a linear-by-parts ReLU activation function (right plot), whose gradient is either 0 or 1 depending on the sign of the input, and is therefore not subject to vanishing gradients.

Added to these architectural choices are training hyperparameters, such as the number of times random batches of training samples are passed through the network (the number of training epochs), the size of each batch of training samples (the batch size), as well as the optimisation algorithm and its parameters including the optimisation step size (the learning rate). Finally, a loss function appropriate to the tackled problem must be selected so as to model the type of error we seek to minimise by training the NN. While the sum of squares error is usually adapted to regression problems, classification error is usually measured using loss functions measuring the mutual information between the ground truth and the network outputs, such as cross-entropy. The formula to measure the cross-entropy loss, or log-likelihood, between a network output prediction and the ground truth label of a -class classification problem is given by (adapted from [59]).

In the case of a binary classification problem in which , then this function is called binary cross-entropy loss. Note that in the minibatch Stochastic Gradient Descent optimisation scheme typically applied to neural network training, optimisation is performed over a batch of data drawn from the training set, as detailed in [60]. Therefore, the sample mean of the loss function is taken over a batch of labels and predictions, in order to compute the estimated error of the current model, and this is then applied in one step of backpropagation.

Deeper neural networks require a large amount of training data in order to learn complex patterns [17]. Therefore, a number of considerations are required to properly handle data so as to allow a generalisable model to be learnt, especially to prevent overfitting a model to a particular dataset and to avoid bias. Strategies to mitigate these pitfalls include ensuring the employed dataset is class-balanced or representative of a wider population, data normalisation to ensure each input feature is considered equivalent by the network at the start of training, data augmentation, transfer learning [61], and regularisation measures [62]. Regularisation, in general, aims to penalise or prevent over-specified high-variance models during the training process, since these are likely to overfit the training data. This can be achieved by simply injecting random noise into the training data, or by adding a penalisation term to the loss function in order to constrain the magnitude of the model parameters (e.g. L1 and L2 regularisation). Another form of regularisation is batch normalisation, which, as further detailed in [63] adds learnable layers which track the batch means and variances during training, and uses them to standardise the previous layer’s output before feeding it to the next layer. Similarly to dataset normalisation, this methods has been found to improve training performance considerably, a benefit which is believed to result from the injection of further noise given the use of batch sample statistics.

***Other applicable Neural Network variants***

RNNs, LSTMs allow for a more dynamic response to time-sequential inputs to be learnt, taking as input consecutive frames of features instead of a single time-sample at a time. These networks are very popular in speech recognition and Natural Language Processing (NLP) tasks since they are designed to model the temporal relationship between consecutive inputs [17]. Therefore, these models would also be appropriate for analysing musical audio, and could provide improvements over systems that do not take into account the temporal dependencies of timbre.

As network architectures have increased in complexity as enabled by larger datasets and more capable hardware, a recent development is end-to-end learning. This powerful approach lets a deep neural network learn both feature extraction and the solution to the tackled problem jointly, by using raw unprocessed data as input. This type of approach will not be considered for this project, since we aim to leverage the mature conventional signal processing timbral feature extraction methods described in section 3.1, which will help us better control the complexity of the system and gain insight into how the task is performed by the network by using handcrafted features.

# System Design and analysis

## Specification: feature selection and classification using single note samples

*TODO: give rationale for using the Mel spectrogram as input feature.*

*TODO: give rationale for applying CNNs to the problem*

*TODO*: *Give rationale for specifying the project to classification of single-note piano sounds, on the basis of research on existing methods in the literature and the available databases.*

*TODO: Give rationale for selecting grand vs. upright binary classification as the task:* selecting the technical characteristic (e.g. type, model, dynamics or articulation) of pianos to target as timbre label for the classifier. Results from the data sources used, since our selection of a characteristic to predict using the classifier is limited by which ground truth annotations are available in the chosen databases.

## Feature extraction: generation of Mel spectrograms

*TODO: describe selection of Mel spectrogram analysis parameters, based on values typically applied for speech processing/MIR in the literature, notably those selected by* [22]*:*

* *Number of Mel filters in the filter bank (frequency resolution)*
* *Analysis window length and type*
* *STFT window length and padding*
* *Analysis window overlap/frequency*
* *Minimum and maximum frequencies*

*Add plots of the filter bank frequency response and the mapping from STFT frequency to Mel frequency.*

*Add example spectrogram plots generated from the single-note samples.*

*Librosa implementation uses Fast Fourier Transform STFT.*

## Pre-processing methods applied

### Single-note data: spectrograms pre-processing

*TODO: Describe spectrogram normalisation* modes using equations, and detail the choice made in the end:

* Normalisation by statistics
* Normalisation by the magnitude of the fundamental, determined using the available pitch annotations in the dataset.

### Generation of melodies as alternative classifier input

*TODO: Describe the motivation for and the data manipulations specific to the generation of melodies using the sample instruments:*

* *Necessity for waveform normalisation of single note samples*
* *Applying a slight envelope to each note to prevent clicks and pops*
* *Detail selection of the number of melodies used to construct the dataset*
* *Selection of spectrogram time-frame length based on the average number of notes which appear per window in the dataset of melodies.*

*Add example spectrogram plots for the generated melodies.*

## Data considerations, CNN architecture & training

### Partitioning the dataset into Training, Validation and Testing subsets

*Choice made: restricting the dataset to two central octaves.*

*TODO: Describe the MIDI monophonic dataset used as input to the sequency for the generation of the melody dataset.*

Ensuring the dataset and each of its subsets is balanced as possible to ensure each class is sufficiently represented to train an unbiased classifier, and that a variety of examples of each class from different environments are represented in each subset.

*TODO: Describe the scheme for splitting the dataset into training, validation and testing subsets, without introducing artificial bias to any of the subsets. Detail partition modes and give the rationale for the final selection for both the single note data and the melody dataset:*

* *Mixed*
* *By instrument*
* *By velocity layer*

### Design of CNN architecture

Reviewed the code for one of the research works on CNN-based timbral classification [22] discussed in section 2.2.2, from the code repository published online by the author [64]. demo experiments described in the code repository [64] (sung phoneme classification and identification of the predominant instrument in a mixture). Used as point of inspiration for the CNN architecture and approach for processing spectrograms.

*TODO: Give rationale for the selection of the Neural Network type (Fully-connected, CNN, RNN, or LSTM). Deep CNN architecture, given this sort of design’s prevalence and success in the literature on timbral classification of musical instruments.*

*TODO: Describe the CNN architecture and give the rationale for the selection and ordering of (reference* [*https://d2l.ai/*](https://d2l.ai/) *as the textbook for this):*

* *Activation function*
* *BatchNorm layers, how this interacts/compares with other forms of normalisation*
* *Max pooling layers*

### Training and cross-validation methods

*TODO: Describe training process applied*

*TODO: Describe the hyperparameter tuning process (e.g. grid search or trial and error). Give a rationale the final training parameter selection*:

* *Epochs*
* *Learning rate*
* *Batch size*
* *Loss function*

*TODO: Describe how and why I used cross-validation to evaluate my selection of parameters:* Cross-validation is used to select optimal hyperparameters on a small dataset without overfitting to any one subset of the data.

*TODO: Describe how I used loss curves to evaluate performance:* Training uses training set loss for backpropagation, but we also track validation set loss to evaluate generalisation capability as training progresses.

# Implementation

## Software standards and toolkits

We plan to develop the classifier primarily in Python, mainly as a result of prior experience with Python, as well as its popularity in the machine learning community and the availability of various open-source neural network development libraries. MATLAB and libraries for MATLAB are also included in the list of software tools used, since they are useful both for initial experimentation and for feature extraction, potentially for integration into the Python environment [65]. A key aspect of the software libraries used is the fact that they are open-source, allowing for examination of the underlying source codebases for understanding, debugging and modification.

Signal processing feature extraction toolkits

* VOICEBOX for MATLAB [66]: includes a wide range of standard audio Digital Signal Processing functions, including timbral analysis, for voice processing, many of which are appropriate also for processing musical audio. Used for initial experiments.
* The Librosa [67] library for Python: implementation of MIR signal processing algorithms, including spectral, harmonic, statistical, and temporal analysis, and extraction of timbral features. Used for spectrogram generation, audio file loading and resampling.

Machine learning development libraries for Python

* NumPy for MATLAB-like mathematical operations, array/matrix functions and data manipulation.
* Pandas dataframes to handle the datset storage and operations.
* Pickle to save variables from memory to cold storage so that we can save generated & pre-processed data and models to speed up execution and back up progress.
* PyTorch for designing, training and testing neural network architectures. Preference is for PyTorch due to personal familiarity from prior experience.
* Scikit-learn for additional machine learning and data science functions, including evaluation tools.

## Dataset assembled for the system

**Table 1** presents the main attributes of musical instrument sample databases available online, many of which are used in works reviewed in the literature. These datasets were initially destined for various applications including signal processing research, music information research, and digital music creation. We place a special emphasis on databases containing samples of a range of acoustic pianos, since this will be our target instrument; and using a larger amount and variety of training data for our classifier will improve its ability to generalise timbral inference.

We have also sought out datasets in which timbral information on the articulation (the playing technique used, e.g. vibrato), type, or model of instrument is annotated, since these are the sort of timbral labels we plan to predict with our classifier. For piano sounds, these labels could include different body shapes and sizes, such as upright and grand, different mechanisms (e.g. use of the felt pedal on an upright piano) affecting the timbre, or dynamics (e.g. pianissimo, forte, etc.). Many databases destined for music creation, called sample libraries or virtual instruments, capture a given instrument in high-quality note-by-note audio recordings, sometimes with several passes over the range of notes available on the instrument, at multiple dynamic levels (called velocity layers). These detailed recordings could be particularly useful for our purposes, since they include a large number of carefully parametrised and labelled samples for training and testing a neural network.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Dataset name** | **Affiliation / Reference** | **Intended purpose** | **No. / type of instruments** | **Timbral Annotations** | **No. / type of pianos** | **No. of samples** |
| *SOL* | IRCAM [68] | Research | 16  wind + string | Articulation | None | 25000 |
| *MUMS Revised* | Eerola et al. [69] | Research | 100+  varied | Model Articulation | 3 Upright, Grand | N/A (large) |
| *SHARC* | G. Sandell [70]  Derived version of MUMS containing only steady-state portions | Research | 39 orchestra | Articulation | None | 1338 |
| *conTimbre* | T. Hummel [71] | Various | 150  orchestra | Articulation | 1  N/A | 4073 |
| *MIS* | University of Iowa [72] | Research | 30+  orchestra | Model  Dynamics | 1  Grand | N/A (large) |
| *MAPS* | Telecom ParisTech [73] | Research | 9  pianos | Articulation  Type & Model  Dynamics  Conditions | 9  Grand, Upright, Hybrid | N/A |
| *RWC* | Real World Computing Partnership [74] | Research | 50  varied | Articulation  Dynamics | 5  Acoustic, Electric | 2000+ |
| *Concert Piano* | N. Plath [75] | Research | 1  piano | Model  Dynamics  Conditions | 1  Grand, before and after concert use | 600+ |
| *BiVib* | Papetti et al. [76] | Research | 2  pianos | Type & Model  Dynamics | 2  Grand, Upright | 1000+ |
| *Piano Pedalling* | L. Beici [77] | Research | 1  piano | Articulation (pedal)  Type & Model  Dynamics | 1  Grand | 500+ |
| *Pianobook* | C. Henson [78] | Music Creation | 450+  varied | Articulation (pedals)  Type/Model  Dynamics | 100+ Grand, Upright, Electric | N/A (large) |

Table 1: Comparison of single-note musical instrument sample databases

*TODO: Describe how the dataset of piano sounds was assembled for the task, pulling from multiple database sources. Loading only the timecodes in the files between the onset and release of the note (as indicated in the accompanying annotations).*

*TODO: Detail which datasets are actually used in the project: MAPS, BiVib, Nord Piano Library.*

*Justify this choice as these being the most straightforward to adapt to research purposes, the most comprehensive in terms of having multiple velocity layers for all notes on the keyboard which makes us more flexible as to how the dataset is split up for ML tasks, and the advantage of having multiple pianos sampled in the same format, reducing the effort required to manually merge them into my own dataset.*

A combination of datasets provides a greater diversity of examples, types, recording conditions and sources of instruments, as well as a larger number of samples to support training and testing of a classifier.

## System structure

*TODO: Detail code structure and object-oriented approach, how each component (class or function) is implemented and fits together in the overall system:*

* *Instrument loader class:*
  + *BiVib and MAPS loading and formatting functions. Describe the format that the .wav files were converted into, and how we optimized precision and efficiency of the subsequent data processing. Processing applied includes channel summing to mono, normalization of waveforms, resampling to the common sample rate.*
  + *Spectrogram generation preprocessing function: includes casting to float for compatibility with librosa, padding waveforms to the same length, spectrogram magnitude normalisation.*
* *Melody loader class: inherits from the instrument loader, since this requires calling the single-note loading functions as well as functions for spectrogram generation.*
  + *Monophonic MIDI sequencing function implemented from scratch specifically for this purposes. Add a lot of detail to this as this was a key engineering step.*
  + *Spectrogram generation preprocessing function applied to the generated melodies*
* *CNN classes: one for each CNN design (the single note classifier and the melody classifier):*
  + *SingleNoteTimbreCNN: inherits from PyTorch’s standard NN class so that all the convenient functions and classes supplied by PyTorch for constructing and training a CNN can be used.*
  + *MelodyTimbreCNN: inherits from SingleNoteTimbreCNN so that inference (forward()) function and helper functions can be shared. Specifies only a different architecture by setting different cnn layers from its parent class in the constructor.*
* *Run-time functions:*
  + *Dataset partitioning function, with the desired mode, number/size of each partition, and random seed passed in as parameters.*
  + *Model training function, which takes in as parameters the desired type of model (SingleNoteTimbreCNN or MelodyTimbreCNN) with the targeted training set. This creates a model and trains it using the hyperparameters set as global variables.*
  + *Model evaluation function, which takes in as parameters the already trained model under evaluation and the targeted test set. This function passes the data through the model in inference mode and computes scores by comparing network predictions to ground truth labels.*
  + *Cross-validation function, which takes in as parameters the type of model we want to validate, the training/validation set we want to split for 2 fold cross-validation, and the desired partition mode to apply. This calls the partitioning, training and evaluation functions for each fold, then calculates the mean test scores over the folds. Training is performed using the hyperparameters specified in the global variables.*

*Add a diagram showing an overview of the system, each component, and the flows of data between them.*

Reference my GitHub code repository for the source code of the project.

# Testing and evaluation methods

## Evaluating the amount of training data used

*TODO: describe how the size of the dataset was evaluated*, using learning curves: Dataset size evaluation by plotting the prediction accuracy of models trained on subsets of various sizes of the actual training data, in order to determine whether the amount of data used is a limiting factor in the performance of the classifier. For instance, if we find that the performance gains brought by increasing the portion of training data used taper off as we approach full training set utilisation, we can rule out the hypothesis of the dataset being too small for a given architecture.

## Scoring the timbral classifier

*TODO: describe approach to scoring* *predictions on the test set*:

* For the single note system, evaluation can be performed on a sample-by-sample basis, or by making the classifier to vote for the most likely match by inputting multiple samples at a time from the same instrument.
* *Describe the* *set of classification scoring metrics used:*
  + *Accuracy/error rate*
  + *Confusion matrix – True/False positives/negatives*
  + *Precision, recall, F1*
  + *AUC (area under the curve) scores to assess the proposed model’s classification performance.*
* For comparison between the two proposed systems (single note and melody-based), analyse the statistical significance of the performance difference between their scores.

## Evaluating the classifier’s generalisation and interpretability

*TODO: Describe how we evaluate the CNN’s capacity for generalisation and interpretability*:

* Sampling/recording a piano from a new source (either from an unused dataset or in the field) in order to evaluate the final system’s ability to generalise to unseen data recorded in different conditions from any of the used train/validation/test sets.
* Evaluating how & why the timbral classification works: plot filters/activations of different layers in the CNN in order to interpret the results in terms of the type of timbral information extracted by the network at different levels of abstraction.

# Results and Evaluation

*TODO: Report the following results for the best model obtained for both the single note and melody-based tasks/networks:*

* *Training set and validation set loss curves over training process (loss against epochs plots).*
* *Cross validation metrics.*
* *Test set results for the re-trained model.*
* *Performance on unseen data (generalisation).*
* *Learning curves.*
* *Statistical significance of performance differences between the two systems*
* *Interpretability of the networks*

# Conclusions and Further Work

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|  |  |
| --- | --- |
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