

Automated Music Transcription

using Convolutional Neural Networks

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Contents

1	Theoretical Background	4
1.1	Introduction to Deep Learning	4
1.2	Neural Networks	4
1.2.1	Brief History	4
1.2.2	Components of an artificial neural network	5
1.2.3	Underfitting and Overfitting	7
1.3	Convolutional Neural Networks	8
1.3.1	Find subsections	8
1.4	Sound	9
1.4.1	Pitch	9
1.5	Digital Signal Processing	10
1.5.1	Discrete Fourier Transformation	10
1.5.2	Short-Term Fourier Transform	10
1.5.3	Constant-Q Transform	10
1.6	Music Transcription	12
1.6.1	Traditional Music Transcription	12
1.6.2	Automated Music Transcription	13
2	Related Work	14
2.1	State of the art in AMT	14
2.2	Products	16
2.2.1	Melodyne	16
2.2.2	AnthemScore	16
	References	17

List of Figures

1	Common activation functions	6
2	Example of overfitting and underfitting	7
3	Traveling Wave	9
4	Spectrogram using Short-Term Fourier Transform	11
5	Constant Q vs STFT spectrogram of C major scale	12

List of Tables

1 Theoretical Background

1.1 Introduction to Deep Learning

This section briefly introduces the concept of deep learning.

Machine learning (ML) is the scientific study of algorithms and statistical models that computer systems use to effectively perform a specific task without using explicit instructions, relying on patterns and inference instead. Machine learning algorithms build a mathematical model of sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task. Machine learning algorithms are used in a wide variety of applications, such as email filtering, and computer vision, where it is infeasible to develop an algorithm of specific instructions for performing the task. The representation of data fed into a ML algorithm plays a major role, as it affects the algorithm's ability to efficiently extract signals and make decisions. Thus, it is important to carefully select the information included in such a representation. Formally, the representation is composed of multiple features extracted from raw data. The process of creating new features requires good and intuitive understanding of the data at hand, becoming incrementally time-consuming with the sophistication of the new features. Thus, the biggest challenge of handcrafted features is deciding which features are important and relevant to the problem [1]

1.2 Neural Networks

This section introduces the main concepts related to neural networks. Neural networks have been around since the 1940s and could initially handle only one hidden layer. But with the development of technologies and hardware it became possible to build deeper, more effective architectures, which leads to deep learning as we know it today.

1.2.1 Brief History

At first, neural networks were inspired by how the biological brain works, which is why deep learning was also called artificial neural networks (ANNs)[1]. In biology, a neuron is the cell that receives, processes and transmits information to other neurons through connections called synapses [2]. On the other hand, artificial neurons are defined as computational units (usually mathematical functions) that take one or more inputs and generate an output.

McCulloch and Pits designed an initial version of the neuron as a linear model in 1943, aiming to replicate brain function [3]:

$$f(x, w) = x_1 * w_1 + x_2 * w_2 + \dots + x_n * w_n \quad (1)$$

where x_1, \dots, x_n are the input values and w_1, \dots, w_n is a set of hand-chosen weights.

1.2.2 Components of an artificial neural network

A simple artificial neural network (ANN) consists of input layer, hidden layer and output layer, where the values of the hidden layer are used as inputs for the output layer. A network with several layers is known as a deep neural network. Data flows through the neurons of the layer. Each neuron transforms the input it receives and sends it to the next layer. The neurons share the same characteristics regardless of the layer they are part of.

The Neuron, also called node, is the basic unit of a neural network. It's main components include inputs, weights, activation function and output(s). From a high level point of view the inputs are multiplied by weights, then an activation function is applied to the result and finally, another function computes the output[4][5].

- Weights are defined as adaptive coefficients, whose values are changed during the learning process. They represent the strength of the connection between units. A weight decides how much impact the input will have on the output.
- The summation function helps combine the input and weights, before passing the result to the activation function. Denote the input as $X = [x_1, x_2, \dots, x_n]$ and the weight vector as $W = [w_1, w_2, \dots, w_n]$.

The summation function could be defined as the dot product between these two vectors:

$$X \cdot W = x_1 \cdot w_1 + x_2 \cdot w_2 + \dots + x_n \cdot w_n \quad (2)$$

The summation function could instead compute the minimum, maximum etc. depending on the designated network architecture. The simplest form of an artificial neuron is a linear function which computes the weighted sum of inputs, to which, optionally, bias can be added:

$$y = \sum_{i=1}^{i=n} (x_i \cdot w_i) + b, \text{ where } b \text{ is the bias, } x_i \in X, w_i \in W \quad (3)$$

- The activation function transforms the result of the summation function (usually) in a non-linear way. Typically, it has a squashing effect. It serves as a threshold. It divides the original space into two partitions. It's main

purpose is to make the neural network non-linear. We denote the activation function as g .

$$y = g\left(\sum_{i=1}^{i=n} (x_i \cdot w_i) + b\right), \text{ where } b \text{ is the bias, } x_i \in X, w_i \in W \quad (4)$$





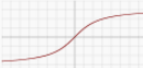


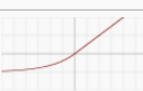

Name	Plot	Equation	Derivative
Identity		$f(x) = x$	$f'(x) = 1$
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$
Logistic (a.k.a Soft step)		$f(x) = \frac{1}{1 + e^{-x}}$	$f'(x) = f(x)(1 - f(x))$
TanH		$f(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$
ArcTan		$f(x) = \tan^{-1}(x)$	$f'(x) = \frac{1}{x^2 + 1}$
Rectified Linear Unit (ReLU)		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Parametric Rectified Linear Unit (PReLU) [2]		$f(x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Exponential Linear Unit (ELU) [3]		$f(x) = \begin{cases} \alpha(e^x - 1) & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} f(x) + \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
SoftPlus		$f(x) = \log_e(1 + e^x)$	$f'(x) = \frac{1}{1 + e^{-x}}$

Figure 1: Common activation functions.

Source: <http://prog3.com/sbdm/blog/cyh24/article/details/50593400>

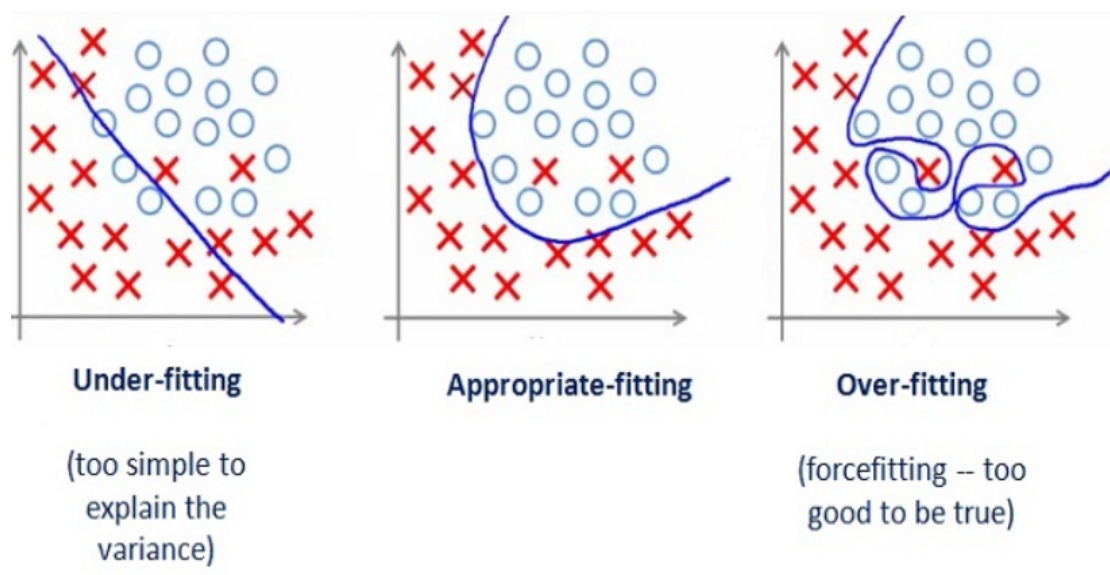
- The output is usually the result of an activation function.

1.2.3 Underfitting and Overfitting

Neural networks are able to learn complicated non-linear functions to fit any training set. On the downside, this may lead to overfitting where the neural network learns the training data so well that it is unable to generalize on new, unseen data. This problem can especially occur on datasets with a small amount of data to learn from.

Underfitting, the counterpart of overfitting, happens when a machine learning model isn't complex enough to accurately capture relationships between a dataset's features and a target variable. An underfitted model results in problematic outcomes on new data, or data that it wasn't trained on, and many times performs poorly even on training data.

Figure 2: Example of overfitting and underfitting
image source vitalflux.com



1.3 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a class of Deep Neural Networks, specialized in analyzing images. They were inspired by biological processes. The connectivity pattern between neurons resembles the animal visual cortex. [6]

1.3.1 Find subsections

1.4 Sound

Sound is produced when something vibrates. The vibration causes the medium around it to vibrate as well. Vibrations in the air are called traveling longitudinal waves [7], which we can hear. A sound wave is made out of two areas of high and low pressure called compressions and rarefactions (figure 3).

The pattern of the wave repeats after one wavelength. The height of the wave is called Amplitude. It is what determines how loud the sound will be, the greater the louder.

The wavelength and the speed of the wave determine the pitch (frequency of the sound).

$$Speed = Frequency \cdot Wavelength \quad (5)$$

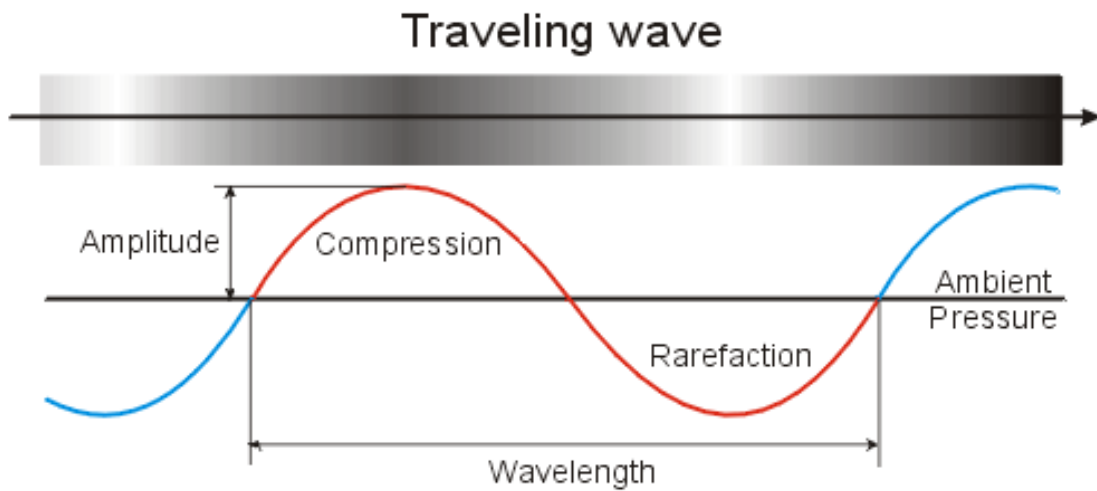


Figure 3: Source: <https://method-behind-the-music.com/mechanics/physics/>

1.4.1 Pitch

In music, the pitch tells how low or high a note is. In physics, it's measured in a unit called Hertz (Hz) and it's known as frequency. A note that vibrates at 256Hz will be caused by a sound wave vibrating at 256 times/second.

The speed is influenced by the medium in which it travels. Under standard temperature and pressure sound's speed is 343 meters per second. [8]

The equation (5) can be rewritten as:

$$Frequency = \frac{Speed}{Wavelength} \quad (6)$$

1.5 Digital Signal Processing

Digital Signal processing (DSP) is an engineering field focused on analyzing and altering digital signals. It takes real-world signals like voice, audio, video and then mathematically manipulates them. [9]

Signals need to be processed so that the information they contain can be displayed, analyzed or converted to another type of signal. Analog-to-Digital converters take signals from the real-world and turns them into binary digital format. At this point the DSP takes over by capturing the digitized information and processes it, later to be fed back for use in the real-world.

1.5.1 Discrete Fourier Transformation

The Discrete Fourier Transformation (DFT) is one of the most important operation of DSP. It is any quantity or signal that varies over time, such as the pressure of a sound wave, sampled over a finite time interval (often defined by a window function). [10]

$$X[k] = \frac{1}{N} \sum_{j=0}^{N-1} (x[j] \cdot e^{-j \cdot (\frac{2\pi}{N}) \cdot n \cdot k}) \text{ for } k = 0 \dots N-1 \quad (7)$$

The DFT tells you what frequencies are present in your signal and in what proportions.

It has a complexity of $O(n^2)$ so in practice the Fast Fourier Transform (FFT) algorithm is used instead. FFT runs in $O(n \cdot \log(n))$

1.5.2 Short-Term Fourier Transform

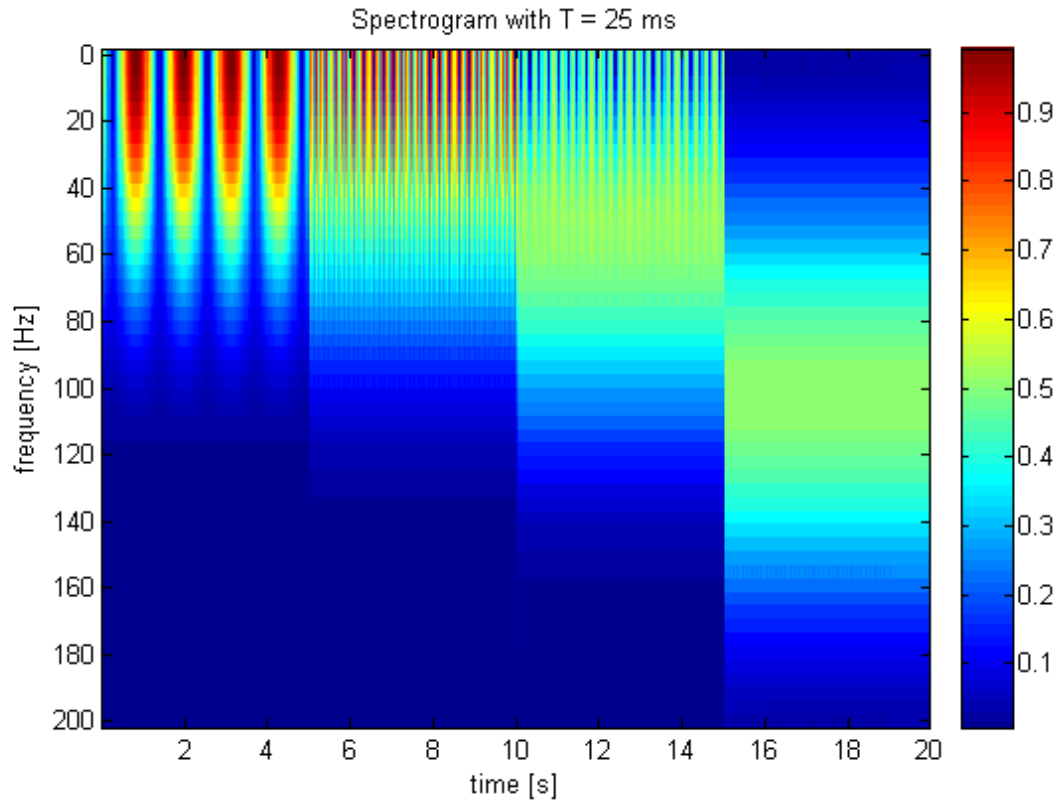
While DFT is really good by itself, if used on an entire song it would only tell what frequencies exist, but not when they occur. This is where Short-Term Fourier Transform (STFT) comes in handy. It computes DFT over a full signal, but in small segments. Because of this we can see how frequencies change over time, which makes it a good way to compute spectrograms. (see Figure 4)

1.5.3 Constant-Q Transform

In general, the transform is well suited to musical data, and this can be seen in some of its advantages compared to the fast Fourier transform. As the output of the transform is effectively amplitude/phase against log frequency, fewer frequency bins are required to cover a given range effectively, and this proves useful where

Figure 4: Spectrogram using STFT

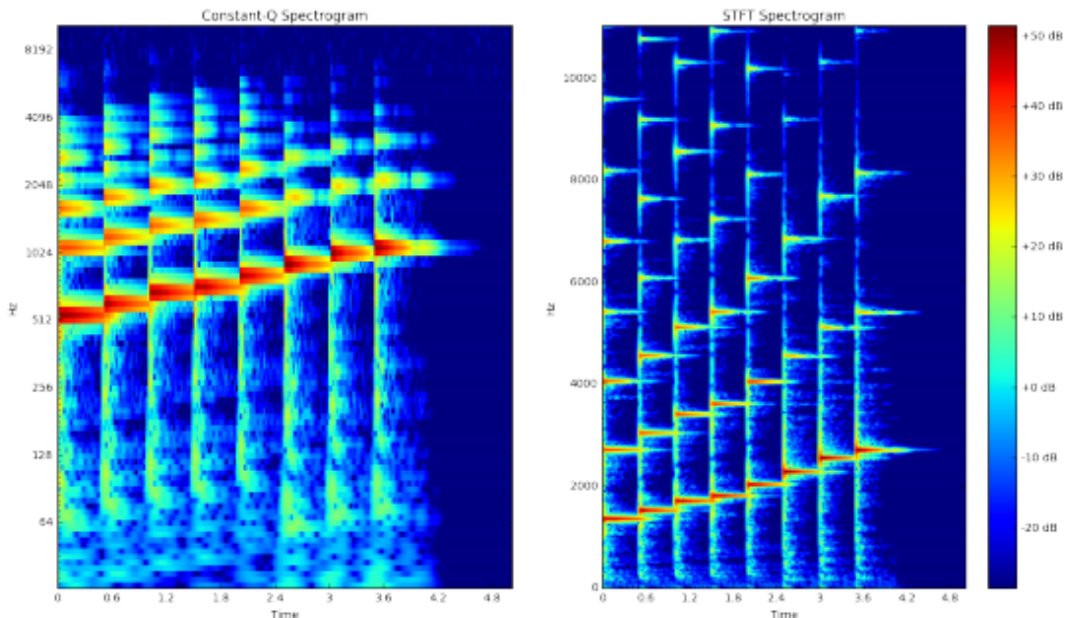
source: https://en.wikipedia.org/wiki/short-time_fourier_transform



frequencies span several octaves. As the range of human hearing covers approximately ten octaves from 20 Hz to around 20 kHz, this reduction in output data is significant. [11]

See Figure 5 for a comparison between Constant-Q transform and STFT.

Figure 5: Constant Q (left) vs STFT (right) spectrogram of C major scale



1.6 Music Transcription

In music, transcription is the process of creating a music sheet from a piece or sound. The sheet contains music notation, which consists of different symbols that can be interpreted by musicians, hence it is important for various reasons. Without it composers such as Mozart and Beethoven couldn't have passed their masterpieces across generations. In modern days it helps musicians play songs they never heard before. It's also universal so even if two musicians don't speak the same language, they can read the same notation.

1.6.1 Traditional Music Transcription

In the beginning transcription was done by humans. It's also called musical dictation in ear training pedagogy. [12] It is a skill by which musicians learn to identify pitches, intervals, melody, chords and other elements of music solely by hearing. It is a really hard skill, requires serious training and study and even the best don't have 100% accuracy.

There are some tools to help with the process:

- Musical instruments, help musicians test for certain sounds, trying to mimic what they hear

- Tape recorders
- Nowadays software

1.6.2 Automated Music Transcription

The term "Automated Music Transcription" was used for the first time in 1977, by audio researchers James A. Moorer, Martin Piszczalski, and Bernard Galler [13]. With their knowledge about digital engineering they believed that computers could be programmed to analyze digital recordings of songs such that they could identify things like rhythm, melodies, pitch, bass lines. It's not an easy task. For more than three decades researchers have been trying to crack it open.

Fundamentally, AMT is about identifying the pitch and duration of played notes, so they can be converted in traditional music notation on a sheet.

It has many advantages over traditional transcription:

- Aids experienced musicians in the process of transcribing pieces, increasing their accuracy.
- Makes music transcription available to more people, especially beginners, giving them a chance to share their ideas with others.
- Helps people learn new songs. There are a lot of music sheets online that are not free.
- It speeds up the process. Manual transcription takes a lot of time.

2 Related Work

Automatic music transcription (AMT) has been attempted since the 1970s and polyphonic music transcription dates to the 1990s [14]

2.1 State of the art in AMT

A model used in [15] uses 87 Support Vector Machine (SVM) classifiers to perform frame-level classification with the advantage of simplicity, and then a Hidden Markov Model (HMM) post-processing was adopted to smooth the results. On top of it, Deep Belief Network (DBN) was added to learn higher layer representation of features in [16]. Since none of the approaches has reached the same level of accuracy as human experts, most music transcription work is completed by musicians. With the development of deep learning in recent years, many researchers were inspired to apply networks to accomplish AMT. A model based on Convolutional Neural Networks (CNN) was proposed in [17]. More models adopted Recurrent Neural Networks (RNN) or Long Short-Term Memory (LSTM) due to its capability of dealing with sequential data [14] [18] [19]. In [20], 5 models were compared and the ConvNet model was reported as resulting in the best performance.

The first major AMT work is Smaragdis et al. [21]. This approach uses Non-Negative Matrix Factorization (NMF). This is the main methodology employed in software for automatic transcription, but it has its limitations. For example, it needs to know how many individual notes are desired for the transcription (information that is not always available).

The next work worth mentioning is Emiya et al. [22], not because of their transcription system (as it was out-performed in the same year), but because of the dataset they created that has become the standard in evaluating any multi-pitch estimation system. They created the MIDI-Aligned Piano Sounds (MAPS) data set composed of around 10,000 piano sounds either recorded by using an upright Disklavier piano or generated by several virtual piano software products based on sampled sounds. The dataset consists of audio and corresponding annotations for isolated sounds, chords, and complete pieces of piano music. For our purpose we use only the isolated sounds (daca nu gasesc ceva mai bun).

Sigita et al. [23] built the first AMT system using CNN, outperforming the state of the art approaches using NMF. Convolutional Neural Networks are a discriminative approach to AMT, which has been found to be a viable alternative to

spectrogram factorization techniques. Discriminative approaches aim to directly classify features extracted from frames of audio to the output pitches. This approach uses complex classifiers that are trained using large amounts of training data to capture the variability in the inputs, instead of constructing an instrument specific model.

2.2 Products

In this section, we present products that use deep learning for AMT.

2.2.1 Melodyne

Melodyne is a popular plugin used for Music Transcription and Pitch Correction. It costs up to \$700.

The Melodic and Polyphonic algorithms offer you, in the case of vocals as well as both mono- and polyphonic instruments, full access to the notes of which the sound is composed as well as to their musical parameters.

2.2.2 AnthemScore

AnthemScore is a product used for Music Transcription that uses CNN.

They approach note detection as an image recognition problem by creating spectrograms of the audio. They show how the spectrum or frequency content changes over time. The method used for creating the spectrograms is the constant Q transform instead of the more common Short Time Fourier Transform (STFT) method.

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