Generating new music with deep probabilistic models

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NATIONAL UNIVERSITY OF SINGAPORE

2020

Generating new music with deep probabilistic models

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(BSc, CentraleSupélec)

A THESIS SUBMITTED FOR THE DEGREE

OF MASTER OF COMPUTING

DEPARTEMENT OF COMPUTING
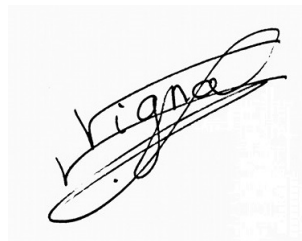
NATIONAL UNIVERSITY OF SINGAPORE

2020

Advisor:

Examiners:

DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

Valentin Vignal

25 March 2020

ACKNOWLEDGEMENTS

I would like to express my special thanks or gratitude to my advisor Harold Soh who gave me the opportunity to work on this project combining Artificial Intelligence and Music.

Secondly I would also like to thanks all the member of the research team, and especially the PhD. students Abdul Fatir and Yaqi Xie who, despite their busy schedules, taught me, and help me in many scenarios.

I also yould like to thanks the Doctor Dorien Herremans who gave me precious advises at the beginning of my project.

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Summary

This paper introduces the work I have done for my dissertation. As a musician, I like to play music, improvise and create or arrange songs. The main goal of this dissertation is to create a neural network architecture able to handle all the tasks a musician or a composer can do.

To do so, I created a new architecture that I call RMVAE (Recurrent Multimodal Variational AutoEncoder) (section 4.3) which combines the MVAE architecture [1] and LSTM cells (see section 2.4.5). Only one trained model can be used to create a melody, several musical parts at the same time, harmonize a melody or reconstruct missing parts in a song.

As a musician I also tried to integrate prior musical knowledge to the model by creating 3 cost functions (section 4.4).

For this project, I used the MIDI dataset which is Bach's Chorales dataset from the music21 corpus [2] and used their framework [3] to open and create MIDI files. The deep learning framework I used it Tensorflow/Keras [4, 5]. I made my python code for this dissertation available online: `https://github.com/ValentinVignal/midiGenerator`.

The results show that the extra losses are not helping the model which indicates that the neural network is able to understand those musical rules and tendencies by its own.

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LIST OF SYMBOLS

AE   Auto Encoder

AI   Artificial Intelligence

AMAE   ArgMax AutoEncoder

C-RBM   Convolutional Restricted Boltzmann Machine

CNN   Convolutional Neural Network

EQL   EQuation Learner

FC   Fully Connected

GAN   Generative Adversarial Network

GP   Gaussian Process

GRU   Gated Recurrent Unit

KLD   Kullback-Leibler Divergence

LSTM   Long Short-Term Memory

MCMC   Markov Chain Monte Carlo

MDMM   Multimodal Deep Markov Model

MIDI   Musical Instrument Digital Interface

ML   Machine Learning

MVAE   Multimodal Variational AutoEncoder

NADE   Neural Autoregressive Distribution Estimation

NN   Neural Network

PoE   Product of Experts

RBM   Restricted Bolzmann Machine

ReLU   Rectified Linear Unit

RL   Reinforcement Learning

RMVAE   Recurrent Multimodal Variational AutoEncoder

RNN	Recurrent Neural Network
RPoE	Recurrent Product of Experts
RTRBM	Recurrent Temporal Restricted Boltzmann Machine
SGD	Stochastic Gradient Descent
VAE	Variational AutoEncoder
VQ-VAE	Vectore Quantisation - Variational AutoEncoder
VRAE	Variational Recurrent AutoEncoder
VST	Virtual Studio Technology

CHAPTER 1

Introduction

As a musician, I like to play music alone or within a band. I spend some time to create songs and arrange them. And finally, I enjoy jamming with band and improvise.

On the deep learning part, music generation has recently considerably improved. Models like DeepBach [7], BachBot [8], BachDoodle [9] can generate, harmonize music in Bach's style. Other non-musical model came up recently. New architectures are being created and are able to generalize data in a more meaningful way, be more consistent through time [10], can handle more complex data with several modalities [11, 12].

Therefor, I try in this work to combine combine my understanding of music, the knowledge so far on music generation and the capability to handle complex data with several modalities. My goal is to create a unique model able to execute all the task I could perform as a musician, create a song, harmonize a melody, jam with someone... Instead of letting the model learn everything from scratch from the data, I also want to give it prior knowledge about music.

The choice I have made for this project was mostly relying on my musical instinct. I tried to stay as close as possible as my musical thoughts in the way I constructed a model, process the data et caetera.

CHAPTER 2

Background

In this chapter, I will introduce some background knowledge that might be useful to the reader. Since this project is about music generation, I will explain and illustrate some basic concepts about music.

I will consider the Western music using equal temperament and don't consider the inharmonicity of stringed instruments. These are common assumptions in all the existing works about music generation.

2.1 Music representation

In this section I will explain how musicians represent the music on paper, and from it, how it is possible to represent the music in a abstract way in a computer without encoding any waveforms or actual *sounds*.

2.1.1 Musical stave

It is very useful for anyone to be able to write down their work to save it or share it with someone else. Musicians faced this issue too. They came up with the musical stave :
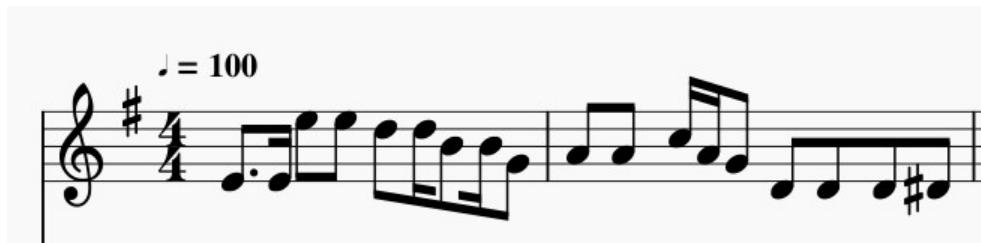
Figure 2.1: Musical Stave example

The vertical axis is the frequency axis an the horizontal axis corresponds to the time axis. In the figure 2.1, it is written that the tempo is $100BPM$, the scale is *G major* (one ♯) and the measure are divided with 4 beats (4/4 inscription). As said previously, the vertical position of a note indicates its frequency :

Figure 2.2: Notes on a musical stave

Figure 2.3: Notes on Piano

The figures 2.2 and 2.3 show the correspondence between the notes on a musical stave and on a piano keyboard. By default the notes correspond to the white keys of the piano (it is the C major scale).

One thing to know is that, between 2 followings notes (or piano keys, including white and black keys), the ratio between the fundamental frequencies of the 2 notes is always equal to $\sqrt{12}$. It means that if we consider the notes $A4$ and $A5$ (2 A notes in the octaves 4 and 5), the ratio between the fundamental frequencies is 2. This information will help to understand chords construction.

The length of a note is defined by its shape as shown in the Table 2.1. This table is describing the relation between the length of a note, and its shape on the musical stave.

In this work, we won't consider shorter notes than Sixteenth notes because most of the songs are not using them. This is a common assumption in the existing work.

Name	Duration	Symbol
Whole note	4 beats	𝅝
Half note	2 beats	𝅗𝅥
Quarter note	1 beat	♩
Eighth note	1/2 beat	♪
Sixteenth note	1/4 beat	♪

Table 2.1: Note names and duration

2.1.2 MIDI

MIDI format (*.mid*) is a technical standard that describes a protocol. It was first used to carry musical messages between electronic instruments, software and devices. These messages are events about note information (for example, pitch, velocity, panning...) an some other parameters (for example, vibrato, volume...). The to most important messages I will consider are:

- *Note on* is indicating that a note has to be played. It contains the channel information (which can be considered as an instrument), the pitch information (what note should be played) and the velocity. We could right an event as follow :

$$< NoteOn, 0, 50, 127 > \tag{2.1}$$

  To describe the event *Start to play the note D3 with the maximum velocity (127) for the channel (instrument) 0*

- *Note off* is indicating to stop playing a note (for instance, release the keyboard key). The given parameters are the same as the ones given to the *Note On* event.

$$< NoteOff, 0, 50, 127 > \tag{2.2}$$

will stop the note started with the previous *Note On* event.

Each note is associated with a time value which can be expressed in number of ticks (time division). The header of file specifies how may ticks there are per quarter note.

2.1.3 Pianoroll

The pianoroll is a common representation of a musical stale in the music production softwares.
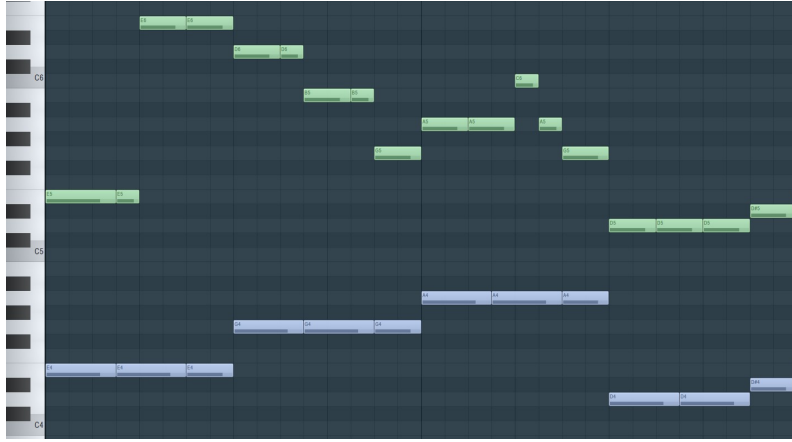
Figure 2.4: Pianoroll example from the software FL Studio [6]

The figure 2.4 shows a view of the pianoroll in the famous software *FL Studio* [6]. The composers of electronic music like EDM, Techno et caetera use this view to compose and arrange their songs.

2.2 Music theory

In this section, I will describe and explain some rules from the music theory which are related to this work. The rules I am going to explain about are the most common ones and most of the songs tend to follow them.

2.2.1 Scale and Rhythm

Scale

A *scale* is a set of notes. Because the human ear is now used to it, the notes of a scale will sound nice when they are played together. In traditional Western music, it generally consists of 7 notes. They are several types of scales. The most common is the *Major scale* or the *Natural Minor Scale*. For example, the C Major scale uses all the white keys of the piano (Figure 2.3: A, B, C, D, E, F and G), as well as the A Natural Minor scale.

Another type of scales often used by the musicians to creates their *solos* are the *Pentatonic* scales.
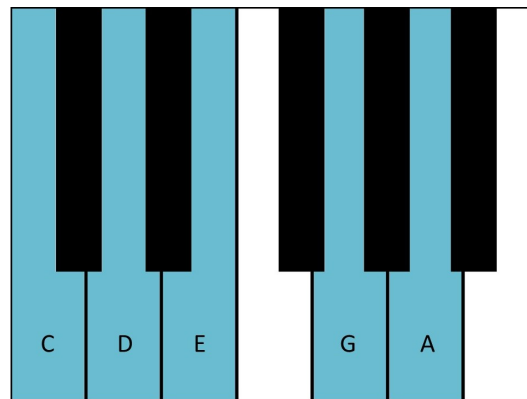
Figure 2.5: C Major Pentatonic scale (or A Minor Pentatonic scale)

As seen in the figure 2.5, the C Major pentatonic scale (which uses the same notes as the A Minor pentatonic scale) uses only five notes (A, C, D, E and G) which are contained in the C Major Scale. It is known that playing in this scale will easily produce enjoyable and in-tune melodies or any musical parts.

Rhythm

The rhythm is an important part of the current music like *Pop Music*. It has the tendency to remain consistent through the song and to repeat some

patterns. It helps the listener to easily follow the progression and allows him to listen what he's expecting to.

However, rhythm is more flexible than scale and harmonies, and there is no rhythm theory someone could follow. This is why classical music is not considered as a rhythmic music.

I this work, I considered and will consider only binary rhythm (each beat is divided into 2 smaller equal beats) and not ternary rhythm (each beat is divided into 3 smaller equal beats) because the binary rhythm is the most common one.

2.2.2 Harmonics

In this section, I will introduce some physical concept about musical sounds and timbre and then illustrate how it can explain some musical rules.

Harmonics

A sound is a sum of harmonics:

$$s(t) = \sum_{n=1}^{\infty} \alpha_n \sin(nft + \phi_n) \tag{2.3}$$

where f is the fundamental frequency and ϕ the phase.

Let's take an example with the $A4$ note which has a its fundamental frequency equals to $440Hz$. Then the 2nd harmonic is $A5$ $880Hz$. The consequence is , when an instrument plays a $A4$, all the harmonics of a $A5$ are also present. Let us take one step further, the 3rd harmonic of $A4$ is $E5$ $1320Hz$. It means it is possible to hear a $E5$ from a played $A4$. The table 2.2 is referencing the firsts harmonics of the $A4$ note.

From the table 2.2, we can notice:

- The A and E notes are linked together (*Fifth* or reversed *Fourth* interval).

Harmonic number	Frequency (Hz)	Note Name	Musical Interval
1	440	$A4$	Unison
2	880	$A5$	Octave
3	1320	$E5$	Fifth
4	1760	$A6$	Octave
5	2200	$C\sharp6$	Major Third
6	2640	$E6$	Fifth

Table 2.2: Harmonics of $A4$

- The A and $C\sharp$ notes are linked together (*Major Third* interval).

Chords

The links between notes illustrated in the table 2.2 explains why a Major chord sound *nice* or *smooth*. A $A\ Major$ chord is composed with 3 notes : A, $C\sharp$ and E. All the notes are already contained in the harmonics of a A sound.

A Minor chords ($A\ Minor$ is A, C, E) will also sounds acceptable to the human ears because A and C share E in their harmonics (respectively the *Fifth* interval and *Third Major* interval)

Dissonance

When 2 frequencies are close to each other and added up, it is possible to observe a resonance phenomena:
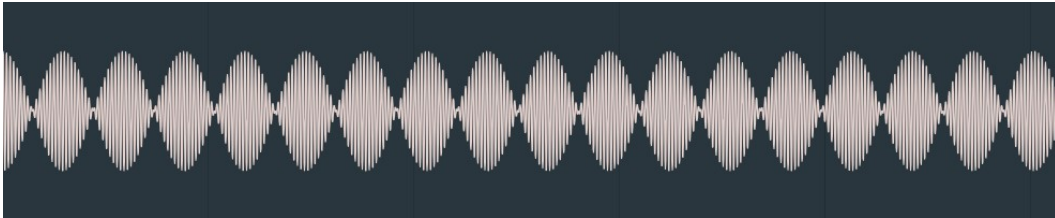
Figure 2.6: Resonance waveform

The figure 2.6 shows the waveform generated by a $B4$ ($494Hz$) and a $C5$ ($523Hz$) (*semitone* interval). This phenomena is explained by the trigonometric identity:

$$\cos(f) + \cos(f + \delta f) = 2\cos(\frac{2f + \delta f}{2})\cos(\frac{\delta f}{2}) \tag{2.4}$$

This phenomena is unpleasant to hear and this is why, musician usually try to avoid to play notes that generate a resonance between their harmonics:

- *Semitone* interval (ex: A and $A\sharp$)

- *Tone* interval (ex: A and B)

- *Tritone* interval (ex: A and $D\sharp$)

Harmony

Either for classical music (Bach Chorales) or pop music (back singers), a common method to *fill a song* is to add harmony parts to the lead melody. The harmony parts usually follow the lead melody but on other notes. An example is provided in the figure 2.7.

Figure 2.7: Lead voice and its harmony part

The harmony parts will usually avoid unpleasant interval and mostly try to create the following ones:

- *Octave* and *unison* interval

- *Fifth* interval

- *Fourth* interval

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- *Major Third* interval

- *Minor Third* interval

2.3   Music arrangement

Arranging a song is an entire musical field an a job. It is the art of giving an existing melody musical variety. To put it more simply, it is creating a accompaniment for an melody. I can includes chords, change the rhythm, add other musical parts.

To give an example, arranging a song could be create a piano/guitar/drums/bass parts from lyrics and a voice melody.

2.4   Neural Network architectures

In this section, I will briefly describe some neural network architectures.

2.4.1   Convolutional neural network

The convolutional networks are often used on images because they can preserve the spatial information. A CNN usually includes two types of layers :

- A convolutional layer

- A pooling layer

Convolutional Layer

For a 2D convolution, the convolutional layer which takes as input a tensor of shape (`height, width, channels`). The *filter* of the convolutional layer will have a shape (`h, w, channels`). Then the layer will do a $2D$ convolutional

operation between the filter and the input through the axes corresponding to the `height` and the `width`.

$$y_\tau = \sum_{t=0}^{l-1} w_t \times x_{\tau+t} \tag{2.5}$$

The equation 2.5 shows the mathematical transformation for a 1D convolution with x as the input, w as the filter/kernel and y as the output.

Pooling Layer

A pooling layer is used to reduce the size of a tensor. It extracts a value from a region of the tensor. Two common poolings are:

- The *Average pooling* which takes the average of the region

- The *Max pooling* which takes the maximum of the region

The figure 2.8 illustrates how the max pooling operation works.
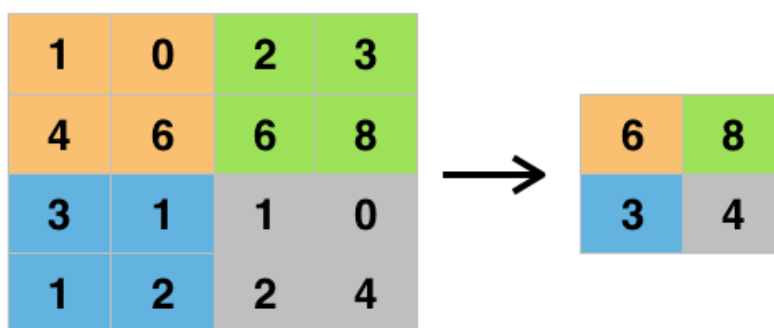

Figure 2.8: Max pooling operation
Source: Wikipedia

2.4.2   AutoEncoder

An AE [13, 14, 15] is composed of a *encoder* and a *decoder*. First, the input goes into the encoder. The output of the encoder is the latent space (the hidden layers), which is smaller than the input. The output of the encoder becomes the input of the decoder. The goal of the decoder is to reconstruct

the input from the latent space. The hidden layers of the AE are smaller than the input which forces the network to compress the input and reduce its dimensions. Therefor, the AE has to learn "high level features" about the inputs. The figure 2.9 summarizes this architecture.
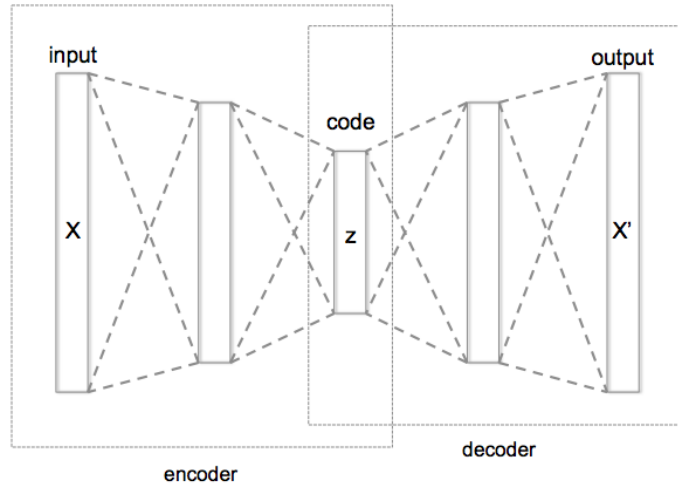
Figure 2.9: AutoEncoder
Source: Wikipedia

2.4.3 Variational AutoEncoder

A VAE [16, 17, 18, 19, 20] is an autoencoder. The steps are the following:

1. The input goes first in the encoder which encodes it as a gaussian distribution over the latent space.

2. A point is sample from this distribution.

3. This point is decoder by the decoder to reconstruct the input.

By encoding the normal distribution and not directly the latent space, it is possible to regularize the output of the encoder to avoid overfitting and ensure that the latent space as good properties that enable generative process.

To regularize the output of the decoder, an extra term is added to the loss function : Kulback-Leibler Divergence (KLD) between the encoded distribution and the centred and reduced normal distribution :

$$\mathbb{D}_{KL}(\mathcal{N}(\mu_{encoded}, \sigma_{encoded}), \mathcal{N}(0, 1)) \tag{2.6}$$

2.4.4 Generative Adversarial Network

GAN [21, 22, 23] are composed of two models that are trained simultaneously:

- The *Generator* will learn how to create data that look real

- The *Discriminator* will learn how to differentiate real and generated data.

The discriminator is trained with real data and data generated by the generator. The goal of the discriminator is to classify the real data as *"Real"* and the generated data as *"Fake"*. On the other side, the generator takes some noise as an input to generate a datum. Its goal is to make the discriminator classify its generated data as *"Real"*.

Through training, the generator will get better and create more consistent data so the discriminator classify them as Real. It will then for the the discriminator to get better and classify real and fake data more precisely. Thus, the generator is forced to create data which look more real. And so on...

2.4.5 Recurrent Neural Networks

A RNN is a neural network where connections between nodes form a direct graph along a temporal sequence. The general architecture is showed in the figure 2.10.

The most used cells used are the LSTM cell and the GRU cell. The architectures are showed in the figures 2.11 and 2.12.
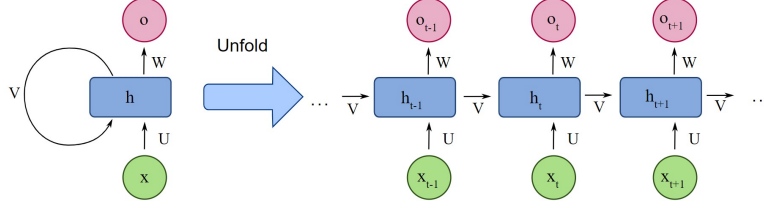
Figure 2.10: Recurrent Neural Network
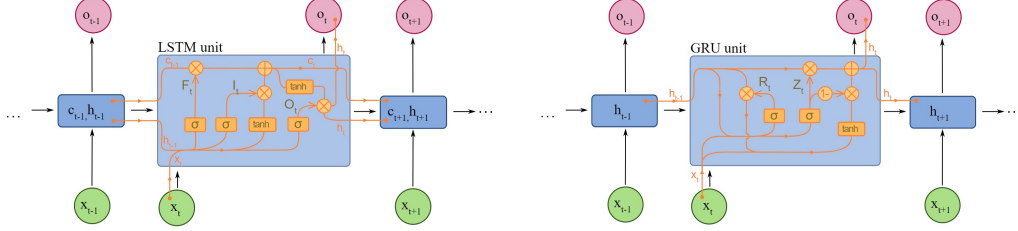Source: Wikipedia

Figure 2.11: LSTM cell
Source: Wikipedia

Figure 2.12: GRU cell
Source: Wikipedia

2.4.6 Transformers

The Transformers [10, 24, 25, 26, 27] have be introduced to the world by Ashish Vaswani et al. [28]. It is an attention mechanism illustrated in the figure 4. On this figure, the encoder is on the left and the decoder on the right.

The scaled dot-product attention and multi-head attention layers are drawn in the figures 2.13a and 2.13b.

The scaled dot-product attention operation is the follows the equation 2.7.
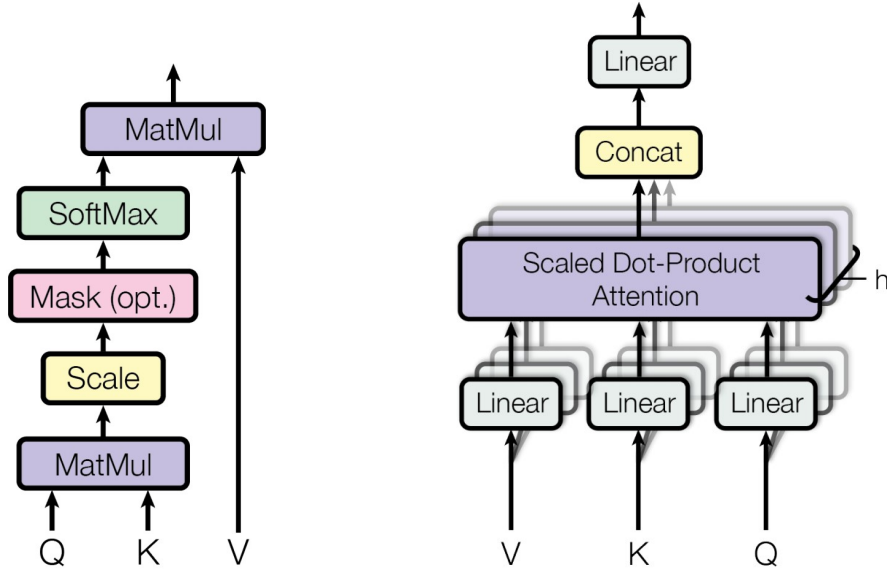
$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V \tag{2.7}$$

where d_k is the number of dimensions.

And the multi-head attention operation follows the the equation 2.8.

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_d)W^O \tag{2.8}$$

where $\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$.

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(a) Scaled Dot-Product Attention
Source: Ashish Vaswani et al.'s paper [28]

(b) Multi-Head Attention
Source: Ashish Vaswani et al.'s paper [28]

Figure 2.13: Scaled Dot-Product Attention and Multi-Head Attention
Source: Ashish Vaswani et al.'s paper [28]

To summarise the process, Q, K and V are respectively called the queries, the keys and the values. Their attention function can be described as mapping a query and a set of key-value pairs to an output, where the query, keys, values, and output are all vectors. The output is computed as a weighted sum of the values, where the weight assigned to each value is computed by a compatibility function of the query with the corresponding key.

The advantage of the transformer is that it is able to learn long-range dependencies. This is a challenge in many sequences tasks. However, a transformer doesn't take into account the position of the input from a sequence. Therefor, a positional encoding must be added.

2.4.7 Multimodel Variational AutoEncoder

The MVAE has been introduced by Mike Wu et al. [1]. The figure 2.14 represent the graphical model of the MVAE. The gray circles represent the observed

variables. The MVAE uses a *Product of Experts* (PoE) inference network and a sub-sampled training paradigm to solve the multi-modal inference problem.
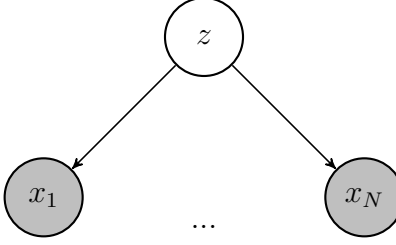

Figure 2.14: Graphical model of the MVAE

The conditional independence assumptions in the generative model (figure 2.14) imply a relation among joint- and single-modality posteriors :

$$
\begin{aligned}
p(z|x_1, ..., x_N) &= \frac{p(x_1, ..., x_N|z)p(z)}{p(x_1, ..., x_N)} \\
&= \frac{p(z)}{p(x_1, ..., x_N)} \prod_{i=1}^{N} p(x_i|z) \\
&= \frac{p(z)}{p(x_1, ...x_N)} \prod_{i=1}^{N} \frac{p(z|x_i)p(x_i)}{p(z)} \\
&= \frac{\prod_{i=1}^{N} p(z|x_i)}{\prod_{i=1}^{N-1} p(z)} \frac{\prod_{i=1}^{N} p(x_i)}{p(x_1, ..., x_N)} \\
&\propto \frac{\prod_{i=1}^{N} p(z|x_i)}{\prod_{i=1}^{N-1} p(z)} \approx \frac{\prod_{i=1}^{N}(\widetilde{q}(z|x_i)p(z))}{\prod_{i=1}^{N-1} p(z)} = p(z)\prod_{i=1}^{N} \widetilde{q}(z|x_i)
\end{aligned}
\tag{2.9}
$$

With $\widetilde{q}(z|x_i)$ the model approximation of $\frac{p(z|x_i)}{p(z)}$

The PoE can be used , including a *"prior expert"*, as the approximating distribution for the joint-posterior.

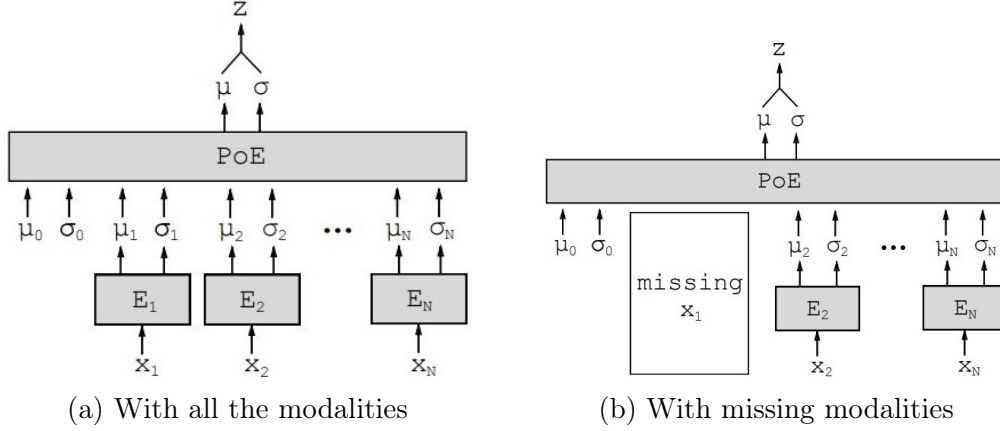The figure 2.15 shows how the PoE can handle missing modalities by simply ignoring them.

(a) With all the modalities   (b) With missing modalities

Figure 2.15: MVAE architecture
Source: Mike Wu's paper [1].

2.4.8 Muldimodal Deep Markov Model

2.4.9 Neural Autoregressive Distribution Estimation

A NADE [29, 30] is a neural network made to support a D-dimensional distribution $p(x)$ which verify:

$$p(x) = \prod_{d=1}^{D} p(x_{o_d}|x_{o_{<d}}) \tag{2.10}$$

It is a feed forward network parameterized as follow:

$$p(x_{o_d} = 1|x_{o_{<d}}) = \text{sigm}(V_{o_d,}.h_d + b_{o_d}) \tag{2.11}$$

$$h_d = \text{sigm}(W_{.,o_{<d}}x_{o_{<d}} + c) \tag{2.12}$$

where, with H as the number of hidden units, $V \in \mathbb{R}^{D \times R}$, $b \in \mathbb{R}^D$, $W \in \mathbb{R}^{H \times D}$, $c \in \mathbb{R}^H$.

The hidden matrix W and bias c are shared by each hidden layer h_d. The figure 2.16 illustrates the Nade model. There is no path of connections between an output and the value being predicted, or element x_O later in the
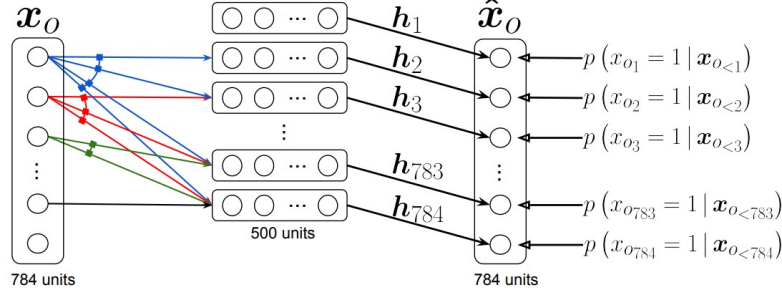
Figure 2.16: NADE architectue
Source: Benigno Uria et al.'s paper [29]

ordering. Arrows connected together correspond to connections with shared (tied) parameters.

2.4.10 Restricted Bolzmann Machine

A RBM is an undirected graphical model [31, 32, 33, 34] showed in the figure 2.17. As an AE, it encodes the input x in a latent space h where:

$$h_i = \text{sigmoid}(x^T W_i + a) \tag{2.13}$$

where x is the input, h is the vector corresponding to the hidden layer, W are the weights, a is the hidden layer bias vector. This is the endoding phase.

For the decoding, or reconstruction phase, the predicted output by the model is:

$$x_i^* = \text{sigmoid}(hW^T + b) \tag{2.14}$$

where x^* is the reconstructed input, W are the same weights as the forward pass, and b are the observed layer bias vector.

RBMs are Energy-based models and a join configuration (x, h) has an energy given by:

$$E(x, h) = -\sum_i a_i x_i - \sum_j b_j h_j - \sum_{(i,j)} x_i h_j w_{ij} \tag{2.15}$$

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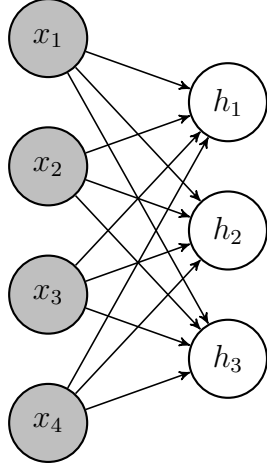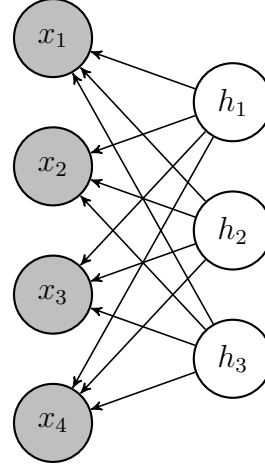
(a) RBM forward pass   (b) RBM backward pass

Figure 2.17: RBM architecture

The probability that the network outputs x^* is given by summing over all possible hidden vectors:

$$p(x^*) = \frac{1}{Z} \sum_h e^{-E(x^* h)} \tag{2.16}$$

where Z is the partition function:

$$Z = \sum_{(x,h)} e^{-E(x,h)} \tag{2.17}$$

Training a RBM consist of implementing a gradient descent of the log-likelihood to increase the value of $\log(p(x))$ for x in the dataset.

$$\frac{\partial \log(p(x))}{\partial w_{ij}}$$

CHAPTER 3

Related works

I will expose in this chapter the works that have already been done about music generation with deep neural networks. In a first time, I will expose the different objectives of some implementations. In a second time, I will introduce how the music is represented. I will then enumerate what architectures have already been used. Finally, I will illustrate what are the generation processes used.

3.1 Objectives

In this section, I will describe some examples of what it is possible to do with neural networks to generate music.

As explained in the section 4.1, my Dissertation's goal is to create a single model able to do everything.

3.1.1 Generator

First it is possible to create a music melody. It can be either monophonic (only one note played at one time) or polyphonic (several notes can be played at the same time).

Secondly, it is possible to create several musical parts at the same time. Each of them can be either monophonic or polyphonic. A musical part can be considered as an instrument or voice for a Chorale. The challenge is to create musical parts that work together.

Generation is the most common objective choice among the existing works [8, 35, 36, 37, 38].

3.1.2 Accompaniment

Given a melody, or some musical parts, the goal is to create new musical parts which can be combined with the input and be played together [7, 9].

This is for example the goal of DeepBach from Gaëtan Hadjeres et al.'s paper [7].

Bach Doodle [9] is an online tool developed by Google. Users can create their own melody and have it harmonized by a machine learning a model in the style of Bach. The figure 3.1 shows the view of this application. The black melody is the melody entered by the user (me) and Bach Doodle created the accompaniment (red, green and blue melodies).
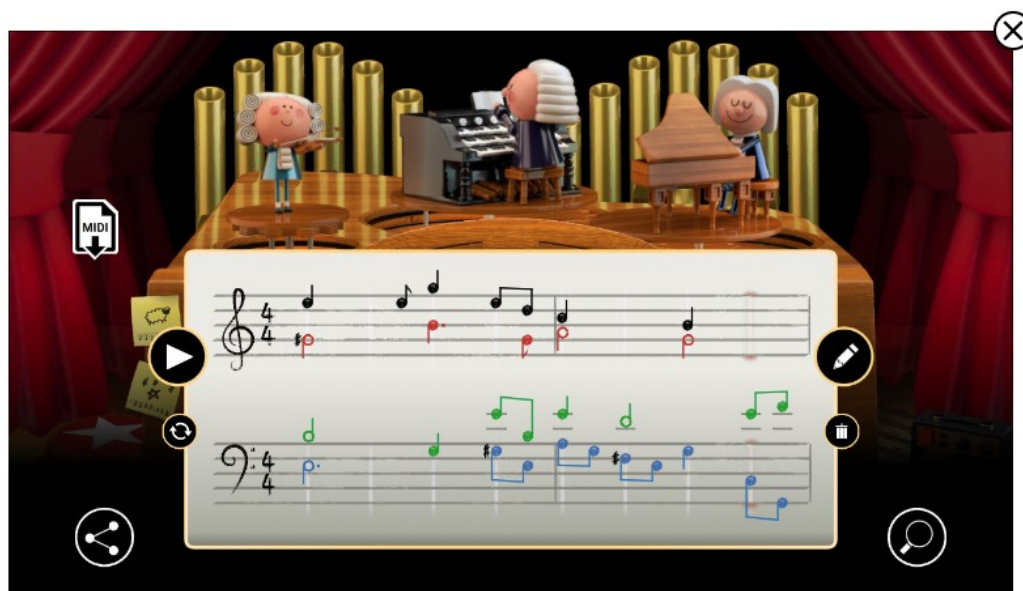

Figure 3.1: Bach Doodle application
Source: BachDoodle

3.2 Music Representation

In this section, I will present different types of inputs the related works use.

3.2.1 Audio Signal

The first data used to create music is the audio signal. Some works [39, 40, 41, 42, 43, 44] have been done to generate music audio signal. This signal can be represented either by its waveform [39], its Fourier Transform, or its spectrogram (figures 3.2, 3.3).

Figure 3.2: Example of an audio wave-Figure 3.3: Example of audio spectro-
form   gram
           Source: Needpix.com   Source: Wikipedia
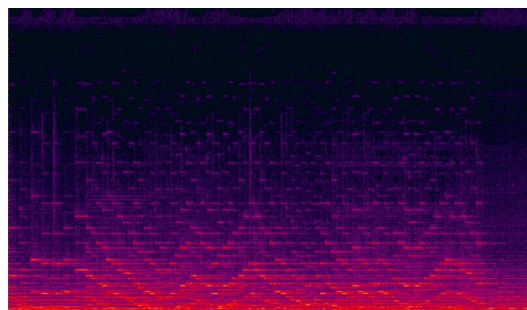
Using the audio signal allows the model to handle every aspects of the song at the same time (instrument, timber, emotion...), and every song in the same way. The biggest issue of this method is that the number of points need to create a waveform is incredibly huge. The usual sampling frequency is $48kHz$. Therefore, the main difficulty is to stay consistent through time.

3.2.2 MIDI Signal

Most of the works done on music generation use the *MIDI* representation (or any other translation of midi like pianoroll or text). [35, 7, 36, 8, 45, 46, 47, 37, 38, 48, 49, 50]

Pianoroll

The pianoroll representation can be considered as an image. Thus, usual deep learning methods on images can be applied [36, 35, 37, 38, 41]. The figure 3.4 shows a very naive example of how to convert a pianoroll view to an array.

Figure 3.4: Example of correspondence between a pianoroll representation and an array

Chin-Hua Chuan et al. [35] introduced another representation to help the model to understand relations between notes. They use *Tonnetz* matrix [51] to represent polyphonic music. As explained in their paper, *"Tonnetz is a graphical representation used by music theorists and musicologists in order to study tonality and tonal spaces"*.

Instead of encoding notes in a one-dimensional tensor (figure 3.5a), they encode them in a 2-dimensional tensor where the relative positions between two notes is meaningful.

The figure 3.5a illustrates a common form of tonnetz. Each node in the tonnetz network represents one of the 12 pitch classes. The nodes on the same horizontal line follow the circle-of-fifth ordering: the adjacent right neighbor is the perfect-fifth and the adjacent left is the perfect-fourth. Three nodes connected as a triangle in the network form a triad, and the two triangles connected in the vertical direction by sharing a baseline are the parallel major and minor triads. For example, the upside-down triangle filled with diagonal lines in the figure 3.5a is C major triad, and the solid triangle on the top is C

minor triad. Note that the size of the network can be expanded boundlessly; therefore, a pitch class can appear in multiple places throughout the network.

In Chuan's paper, they extended this matrix. The figure 3.5b shows an extended tonnetz matrix example. They include is this extended matrix the pitch (octave number) which was missing in the first one.
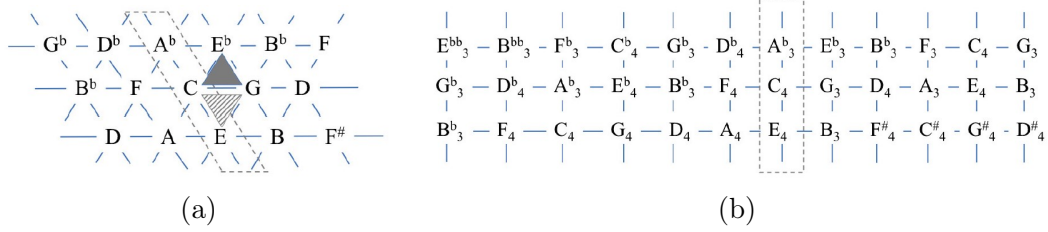

<div align="center">(a)</div>
<div align="center">(b)</div>

Figure 3.5: (a) tonnetz and (b) the extended tonnetz matrix with pitch register
Source: Ching-Hua Chuan's paper [35].

Text

Another approach is to convert the MIDI format into text. [7]

B5, _, B5, _, E6, _, E6, _, D6, _,
D6, B5, _, B5, D6, _
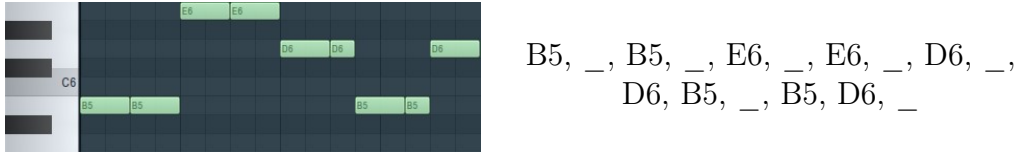
Figure 3.6: Example of correspondence between a pianoroll representation and a text

The figure 3.6 shows a simple example of how it is possible to convert an pianoroll view to a text. However, using text to represent image usually force the framework to work only in a monophonic way. A common choice of the existing works that working with text is to embed the text into a fix-sized vector using a `word2vec` [52, 53, 54, 55, 56] model [8, 47].

Despite the text constraint, Feynman Liang and al. [8] managed to encode polyphonic music in text and use it to correctly train their model: "BachBot".

They quantize time into sixteenth notes (♪). Consecutive frames are separated by a unique delimiter ("|||"). Within each frame, they represent individual notes rather than entire chords. Each frame consists of four (Soprano, Alto, Tenor, and Bass) `<Pitch; Tie>` tuples where `Pitch` $\in \{0; 1; \ldots; 127\}$ represents the MIDI pitch of a note and `Tie` $\in \{$`True`; `False`$\}$ distinguishes whether a note is tied with a note at the same pitch from the previous frame or is articulated at the current timestep. They *order notes within a frame in descending MIDI pitch*. The figure 3.7 shows the encoding process.


```
START           (59, True)      (55, False)
(65, False)     (55, True)      (48, False)
(59, False)     (43, True)      |||
(55, False)     |||             END
(43, False)     (.)
|||             (64, False)
(64, False)     (60, False)
```

(a) Three musical chords in traditional music notation. The red arrows indicate the order in which notes are sequentially encoded.

(b) A corresponding sequential encoding of the three chords in an eighth-note time quantization (for illustration, broken over three columns). Each line within a column corresponds to an individual token in the encoded sequence. ||| delimit frames and (.) indicate a fermata is present within the corresponding frame.

Figure 3.7: BachBot's example encoding of three musical chords ending with a fermata ("pause") chord
Source: Feynman Lian's paper [8].

Chords

This is the last approach I will describe in this paper. As the same way as Jazz music, it is possible to simplify the description of a musical piece by writing down the chords.
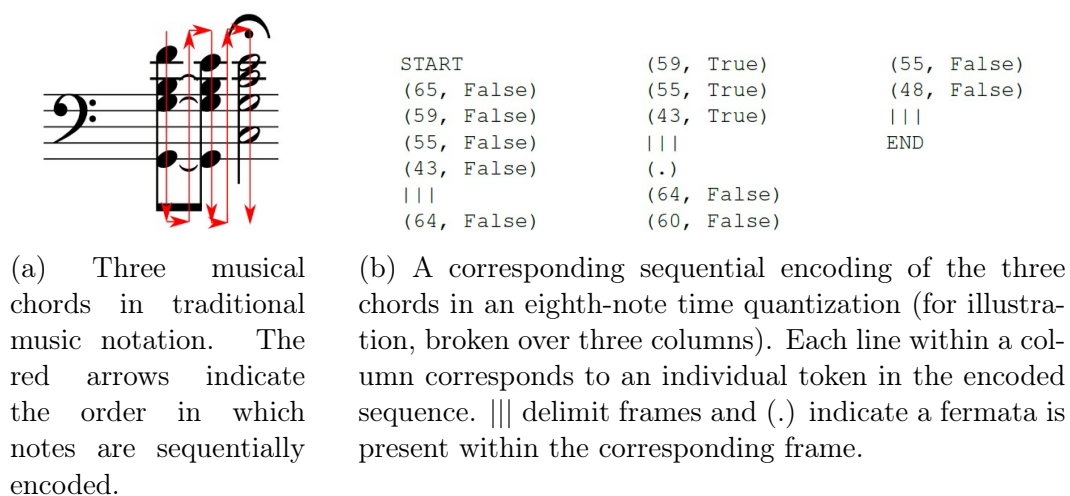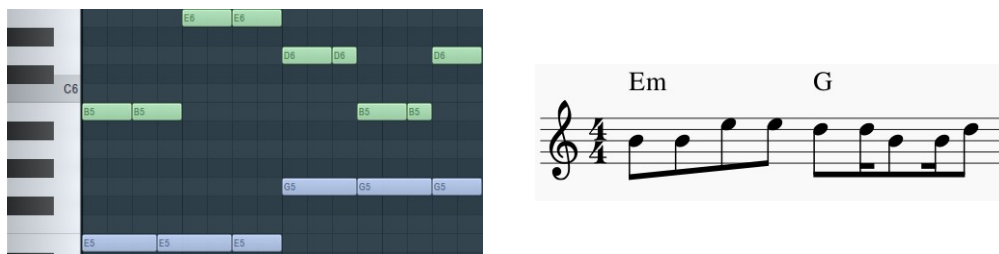
Figure 3.8: Example of correspondence between a pianoroll and its chords representation

For instance, in the figure 3.8, the bass line can be simplified by considering the chords. The chords are then writen and be considered as notes.

3.3 Encoding

3.3.1 Features

It is possible to extract features from the data to help the neural network to understand how music works, like the chords, the current key signature...

- The first option is to do it manually and give the features as an input of the model

- The second option is to let the model learn it by itself. This is the choice I have made for this project.

Metadata

The features that can be passed as an input to the model can also be metadata like the time signature or the key of the music...

Deep Bach from Gaëtan Hadjeres et al.'s paper [7] consider the fermata symbol (figure 3.9) and the beat subdivision number (an integer between 1 and 4).

Figure 3.9: Fermata symbol
Source: publicdomainvector

In this project I chose to not include any metadata in the model because of the difficulty to find or reconstruct them for the available dataset. However, I not intentionally gives to the model the information about the beats number and subdivisions by considering the entire measure as one input.

Another way to help the model by giving it information without actually passing metadata is to normalize the data. For example, BachBot [8] and other works [35, 37] transpose all their dataset in either C major or A major key.

For the same reason as not passing metadata, I don't normalize the data before training my models.

3.3.2 Tensor encoding

It is possible to extract two different methods on how to encode the tensor which will be given to the neural network

The first method is the *value encoding*. It means that the values in the input and/or output tensor are actually meaningful. For example, it can be an integer which is the pitch of a note.

The second method is called *item encoding*. Instead of having the number of the pitch in the tensor (let's say 60), it will be a very sparse tensor with a bunch on 0 and a 1 at the position 60 in the pitch dimension. This values stored in the tensors can be considered as *activation* values. This is the retained method in my Dissertation.

3.4 Architectures

In this section, I will present different architectures that have already been used for music generation. It will expose the architecture of my project in the section 4.3.

3.4.1 RBM

The RBM architecture is explained in the section 2.4.10.

Nicolas Boulanger-Lewandowski et al. [37] use an RBM based model RTRBM [57, 58] and created their own architecture called RNN-RBM. They applied their model on different MIDI dataset to create polyphonic music.

Stefan Lattner et al. [38] use another RBM based model called C-RBM [59, 60]. They apply this model on pianoroll images. They also implement a different constraints like their self-similarity constraint to specify a repetition structure (e.g. AABA) in the general music piece.

3.4.2 NADE

The NADE architecture is explained in the section 2.4.9.

And as an example, Cheng-Zhi Anna Huang et al. [36] use an orderless NADE [30] to generate music. They introduce COCONET, a deep convolutional model to reconstruct partial scores. It consists of a corruption process that masks out a subset $x_{\neg C}$ of variables, followed by a process that independently resamples variables x_i (with $i \notin C$) according to the distribution $p_\theta(x_i|x_C)$ emitted by the model with parameters θ.

The figure 3 illustrates how the process works. At each step, a random subset of notes is removed, and the model is asked to infer their values. New values are sampled from the probability distribution put out by the model,

and the process is repeated.

Google also Bach Doodle [9], an online tool re-implementing COCONET in Tensorflow.js [61] which harmonizes a melody given by the user.

3.4.3   AE

The AutoEncoder architecture is explained in the section 2.4.2.

This is the most common architecture used for music generation at the time I am writing this report. The AutoEncoder can be recurrent [8, 35, 7, 42, 43] as Feynman Liang et al.'s BachBot [8] or not [40].

For instance, BachBot [8] and DeepBach [7] use an encoder/decoder architecture with LSMT layers on the latent space. [35]

Soroush Mehri et al. [43] or Nal Kalchbrenner et al. [42] have created different AE architecture to synthesize audio waveform and can be applied to music sounds.

3.4.4   VAE

The Variational AutoEncoder architecture is explained in the section 2.4.3.

Sander Dieleman et al. [40] use a VAE (or more precisly a VQ-VAE [62] or a AMAE [40]) to encode audio waveform and reconstruct it with a stylistic consistency accross tens of seconds.

3.4.5   RMVAE

Since I created this new architecture, there is no existing work using this architecture. My project is, for now, the only work done using a Recurrent Multimodal Variational AutoEncoder to generate music.

The RMVAE's architecture is explained in the section 4.3

3.4.6 GAN

The Generative Adversarial Network Architecture is explained in the section 2.4.4

For instance, the model WaveGan from Chris Donahue et al. [41] use a GAN architecture to synthesize audio waveform in several domains including drums and piano.

Gino Brunner et al. [49] use CycleGAN [63] to create a model able to apply a style transfer on musical pieces (between jazz, pop and classical style).

3.4.7 Transformers

The Transformer's architecture is explained in the section 2.4.6. Some works have already been on music with Transformers as, for instance, Cheng-Zhi Anna Huang et al. [64] and Kristy Choi et al. [65].

Huang et al. introduce the Music Transformer, a model able to generate consistent samples longer than samples generated by a RNN architecture. They achieve this perfomance by using a Transformer with self attention (equation 3.1).

$$\text{RelativeAttention} = \text{Softmax}(\frac{QK^T + S^{rel}}{\sqrt{D_h}})V \tag{3.1}$$

3.5 Generation Process

In this section, I will enumerate different techniques to generate music from different model architectures.

3.5.1 Sampling

The sampling process can either be done with a VAE, or an GAN architecture [41].

A VAE keeps its latent space distribution as the standard normal distribution $\mathcal{N}(0,1)$. Thus, by giving a random vector sampled from a standard normal distribution $\mathcal{N}(0,1)$, the decoder will construct an output similar to the dataset the model trained on.

The generator of a GAN has been trained to generated consistent data from noise. Then, the process generation for a GAN is to give a random input from a standard normal distribution to generator.

3.5.2 Input Manipulation

Generating music by manipulating the input is typically how style transfer algorithms work [66, 67, 68]. The input is considered as a variable which is updated to minimize a loss function constructed from a content target and a style target. The content similarities between the input and the content target is reduced through the iterations. In the same way, the style similarities between the style target and the input will minimized.

This process works well for images to create a new image combining content and style from 2 different images. People tried to apply the same methods on music [69, 70, 49, 44], but as Shuqi et al. [71] say, music is more complex and has several level of style (timber, performance and composition). Therefor, creating a music style transfer algorithm is more complicated than for images and the results are currently not as good.

3.5.3   Feed forward and RNN architecture

This is the easiest and most common generation process through all the works [8, 35, 36, 50], and this is the one I chose for this project. And input is given to the model. The model returns an output. The figure 3.10 illustrates this process. This output can be the next frame/beat/measure (in my case, a measure) of the music.

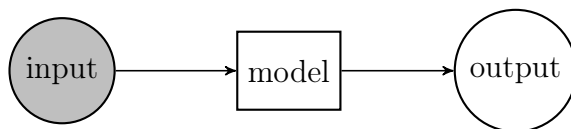I also chose this generation process for my project. In my case, the model returns the next measure of the music.

Figure 3.10: Feed forward generation process

DeepBach

To give an illustration, DeepBach [7] uses a Markov Chain Monte Carlo algorithm to re-harmonize a song and transform it. From the existing song, it re-predicting every notes one by one. The algorithm is describe in the figure
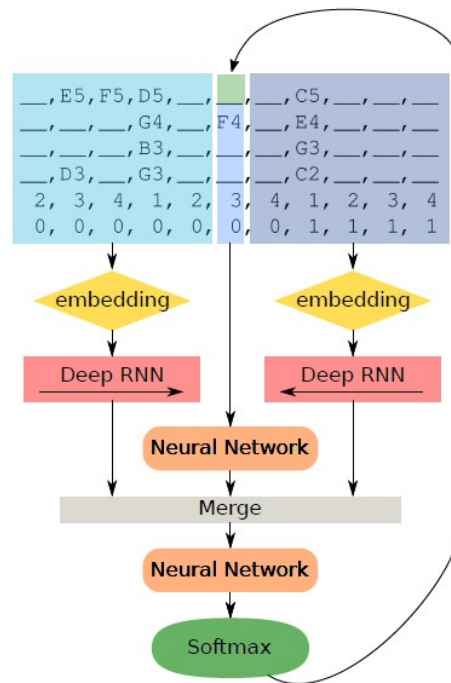
Figure 3.11: Graphical representation of DeepBach's neural network architecture for the soprano prediction
Source: DeepBach paper [7]

CHAPTER 4

Contribution

4.1 Objectives

As a musician, I wanted to create an model architecture who could copy the way I think about music. The challenge is to use only one trained model to be able to

- Generate music with several musical parts (meaning several instruments)

- Create a accompaniment from a melody

- Create a melody from a accompaniment

- Create a musical part from other musical parts

The created model can also handle missing data (for example a missing measure from a instrument).

To summarize, the objective is to create a unique trained model which can generate or arrange a musical piece whatever is already present or missing.

4.2 Data representation

This project works with MIDI data. These music representation is explained in the section 2.1.2.

The shortest beat division is a quarter of a beat (sixteenth note: ♪)

The considered music are binary and with 4 beats per measure.

Because I think that a measure can be consider as an entire object (with its

rhythm, its chords ...), I chose to divide music by measure. Thus, a time step for the neural network is the representation of an entire measure. The shape of shape of a tensor representing a measure will be (16, 128, channels):

- 16 is the number of sixteenth notes (♪) is a measure.

- 128 is the number of different MIDI notes possible (from 0 to 127).

- channels $\in \{1, 2\}$ is explained in the sections 4.2.1 and 4.2.2.

The number of instruments is fixed and are different inputs of the neural network. Hence, for one instrument, its associated tensor has a shape of (nb_measures, 16, 128, channels). nb_measures is the number of measures considered.

4.2.1   Polyphonic music

For polyphonic music, the number of channels it 2.

The first channel is called the *activation* channel. The value is either 1 for a played note or 0 for a non-played note.

The second channel is called the *duration* channel. The value is an integer corresponding of *"how many sixteenth notes (♪) it lasts"*. The table 4.1 shows the correspondence between the value of the duration channel and the musical length representation.

If a note is note activated (activation channel = 0), then the duration channel is set to 0 too.

$$\text{channel}_{\text{activation}} = 0 \iff \text{channel}_{\text{duration}} = 0 \qquad (4.1)$$

35

Duration value	Musical length
1	♪
2	♪
3	♪.
4	♩
5	♩ ♪
6	♩.
7	♩ ♪.
8	♩
9	♩ ♪
10	♩ ♪
11	♩ ♪.
12	♩.
13	♩. ♪
14	♩. ♪
15	♩. ♪.
16	o

Table 4.1: Correspondence between duration value and musical length

4.2.2 Monophonic Music

The goal was too reduce the memory space a simplify the model for monophonic music. Since monophonic music can means there is a maximum of one note played simultaneously at a time t, I chose to not consider the rests and consider that every notes last until an another note is played.

Thus, I get read of duration channel and the number of `channels` $= 1$.

An *additional note* is inserted which is the $note_{continue}$. The tensor shape of a step is now `(16, 128 + 1, 1)`. When $note_{continue}$ is set to 1, it means there is no new note to be played. And when $note_{continue}$ is set to 0, it means a new notes has to be played.

$$note_{continue} = 1 \implies \forall \ note \in notes_{[0:128]}, note = 0 \qquad (4.2)$$

$$note_{continue} = 0 \implies \exists! \ note \in notes_{[0:128]}, note = 1 \qquad (4.3)$$

And since I consider in this part only monophonic music, there is only on note (included $note_{continue}$ per each time division)

$$\exists! note \in notes_{[0:129]}, note = 1 \tag{4.4}$$

4.3 RMVAE Architecture

I have created a new architecture which is able to handle all the objectives defined in the section 4.1.

To do so, I continued the work of Mike We et al. [1] and their Multimodal Varational AutoEncoder (MVAE) (see section 2.4.7) and I simplified the work of Tan Zhi-Xuan et al. [12] and their Multimodal Deep Markov Models (MDMM) (see section 2.4.8).

4.3.1 Global Architecture

I use the capability of the MVAE to reconstruct data and handle several modalities at the same time with the help of the product of expert operation. But because the MVAE doesn't handle time across the data, it had to be transformed. And that is basically what does the MDMM. However, the training process of a MDMM is quite complicated and slow. Because of this reason, I came up with a novel architecture that I call RMVAE (Recurrent Multimodal Varational AutoEncoder). This architecture is describe in the figure 4.1.

4.3.2 Encoder

Each instruments (each modalities) has its own encoder. As explained in the section 4.2, the input tensor for one instrument has the following shape: (nb_steps, 16, 128, channels). For a given instrument i, and a given step

37
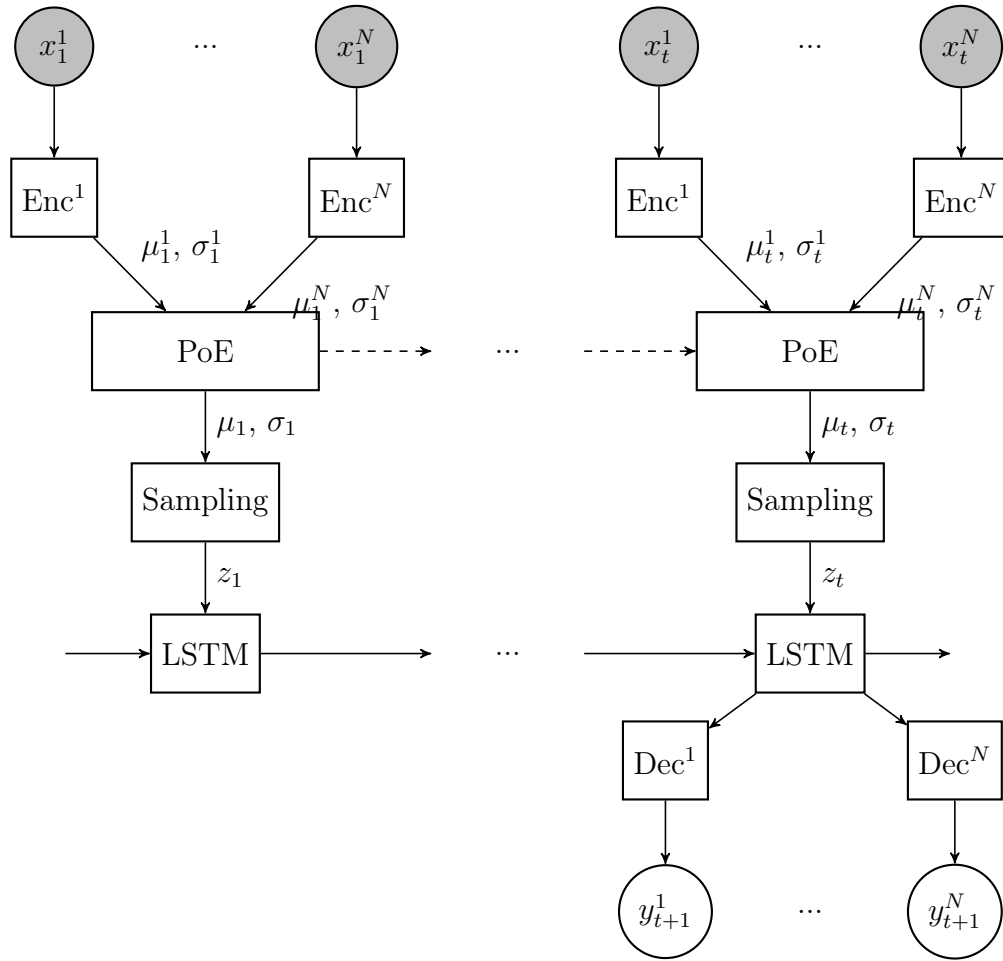
Figure 4.1: Architecture of the RMVAE

t, the tensor (with a shape of `(16, 128, channels)`) can be considered as a pianoroll image, hence usual imaging operations can be applied.

The encoder Enc^i process each steps of a the instrument i. And encoder is composed of:

1. Convolutional layers and pooling layers

2. Fully Connected layers

The general architecture of the encoder is showed in the figure 4.2.
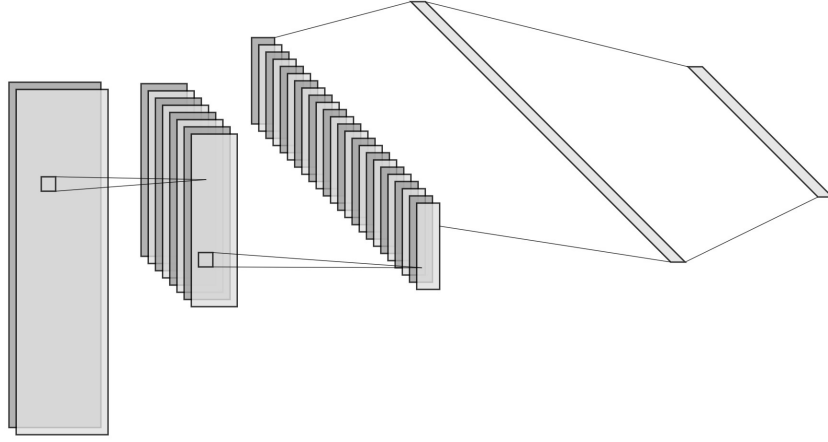
Figure 4.2: RMVAE encoder architecture

The filter sizes of the convolutional layers are `(5, 5)`. I chose this dimension so the receptive field of the first layer is a third major interval and an entire beat.

4.3.3 PoE

For a given instrument i and a given step t, the output of the encoder Enc^i will then go through 2 different FC layers fc^i_μ and fc^i_σ which will return the mean and variance of the encoded normal distribution (figure 4.3).

Then, for a given step t, all the distribution representation go through the PoE layer to be combined and sampled as shown in the figure 2.15.
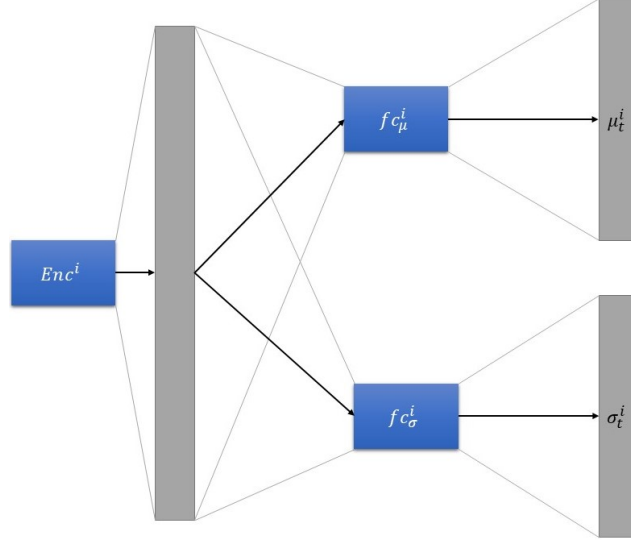
Figure 4.3: RMVAE PoE Fully Connected layers
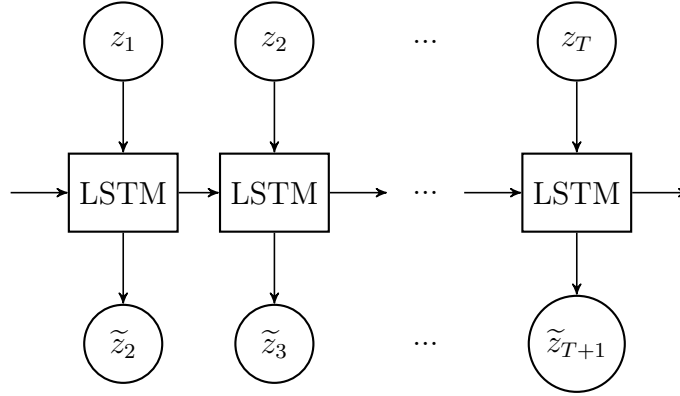
Figure 4.4: RMVAE LSTM layer

4.3.4 Recurrent layers

I have now all the latent represenations for every steps : $\{z_1, ..., z_T\}$.

LSTM cells

To learn, how this latent space evolves through time, RMVAE uses recurrent layers with LSTM cells (figures 2.10 , 2.11). This is shown in the figure 4.4.

RPoE

To try to catch the time dependency as good as possible, I implemented a new layer architecture. I call it Recurrent Product of Experts (RPoE).

The result of the Product of Experts at the step t is given as a modality for the Product of Experts at the step $t+1$.

The architecture is displayed in the figure 4.5.
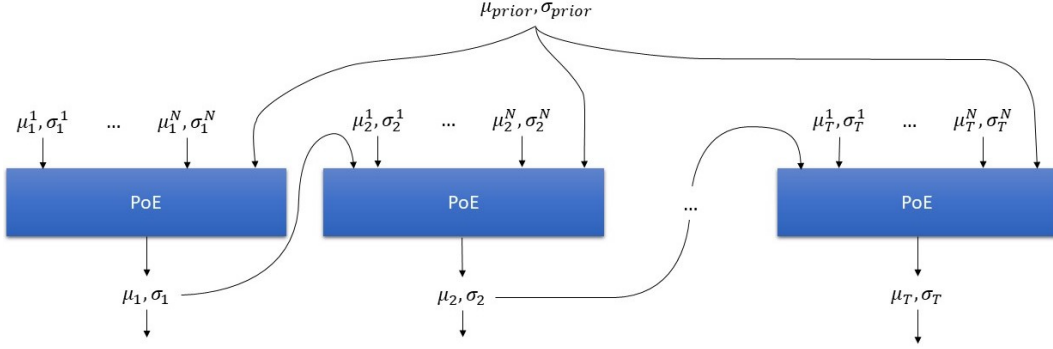
Figure 4.5: RPoE architecture

4.3.5 Decoder

Each instruments (each modalities) has its own decoder. The decoder Dec^i associated to the instrument i will, for a given step t, reconstruct back the output with the same shape as the input (`(16, 128, channels)`).

A decoder is composed of:

1. Fully Connected layers

2. Transposed Convolutional layers

The dimensions of the layers of the encoder Enc^i are the same as the dimensions of the decoder Dec^i.

The decoder global architecture is showed in the figure 4.6.

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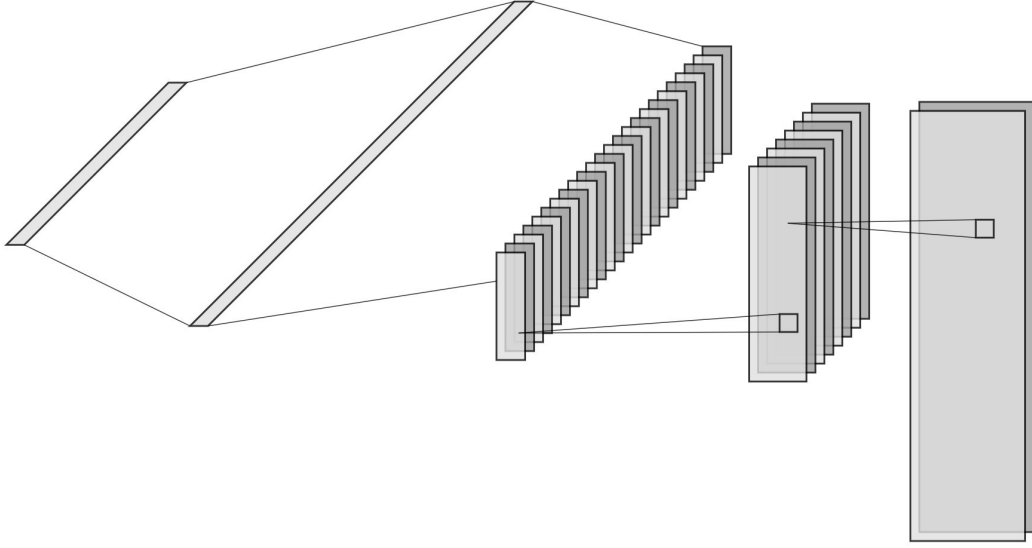
Figure 4.6: RMVAE decoder architecture

4.3.6 Last layer

The last layer of the NN is a Fully Connected layer with a well chosen activation function.

Polyphonic Music

For polyphonic music (section 4.2.1), the activation function is a *sigmoid* function for the `channel 1` which represents the activation of the notes. The activation function for the `channel 2` is a *ReLU* function.

Monophonic Music

For monophonic music (section 4.2.2), the activation function is s *sigmoid* function for the *additional note* (index 128: $note_{continue}$) because it is an activation note indicating if it wants to continue the previous note or play a new one. And for the other 128 notes, the activation function is a *softmax* function since only one note can be played at the same time.

At the beginning of my project, I was considering the $note_{continue}$ as a

normal note and simply apply a softmax across all the notes. But the result was disappointing: the frequency of $note_{continue}$ in the dataset was to high. The network wasn't generating anything because the $note_{continue}$ had the highest probability.

4.4 Loss Function

For this project, I created new loss functions to help the network to understand how music works. As a musician, I asked myself how I would proceed if I was given the same task as the NN (generation of music, accompaniment...). This is how I got the idea to create those new loss functions.

In a song, when a musician is playing, it is not possible for him play every one of the 12 notes whenever he wants. A music usually follows a pattern, a chord progression, and he has to follows it. From the chords played, the scale, some notes will sounds better to the human ears than other. But there is no *"ground truth"* for a solo part for example. Every solo can be considered as a *"ground truth"* if it sounds nice. And I wanted my model to be able to *improvise*, generate new music.

I got the idea of helping the model to do *acceptable mistakes* and restraint it do *unacceptable mistakes*. In other word, during the training part, it the model doesn't hit the note it should have hit, I don't want to *punish* it to much with a high loss value if the note sounds actually nice with the music. On the other side, I want to *punish* it if the note it hits is completely wrong with a higher loss value.

To summarize what I previously just said, during the training part, if the model hits a note which sounds nice, a reward is given by adding a negative number to the loss. If the hit note doesn't sound nice, then a penalty is given by adding a positive number to the loss. The algorithm 1 describe the process.

Algorithm 1 Add a Reward or a penalty to the generated note

Input: $noteTruth, notePredict$
Output: $loss$

 1: $reward > 0, penalty > 0$
 2: **function** Loss($noteTruth, notePredict$)
 3:     $loss \leftarrow$ commonLoss($noteTruth, notePredict$)
 4:     **if** soundsGood($notePredict$) **then**
 5:         $loss \leftarrow loss - reward$
 6:     **else**
 7:         $loss \leftarrow loss + penalty$
 8:     **end if**
 9:     **return** $loss$
10: **end function**

The difficulty is to create the function `soundsGood` from the algorithm 1. The following sections describe the idea I have had to know whether a note sounds nice or not.

4.4.1   Scale

I call this loss function *Scale* because the idea is to reconstruct the *local scale*. This loss function takes as inputs all the instruments output:

$$\texttt{Scale}(truth, predict)$$

where the shape of the input tensors is (`nb_instruments, 16, 128`) for both which the represent the activated notes (where there is a 1) of every instruments for the next measure. The figure 4.7 shows the operations of this function.

The idea is to take all the played notes for all the instruments in the truth tensor. Because the same note from different octaves should be considered as the same note, I apply a segment sum to get in the end a tensor of shape (`12,`) which corresponds to the 12 notes. The details of the segment sum operation are explained in the appendix .2.
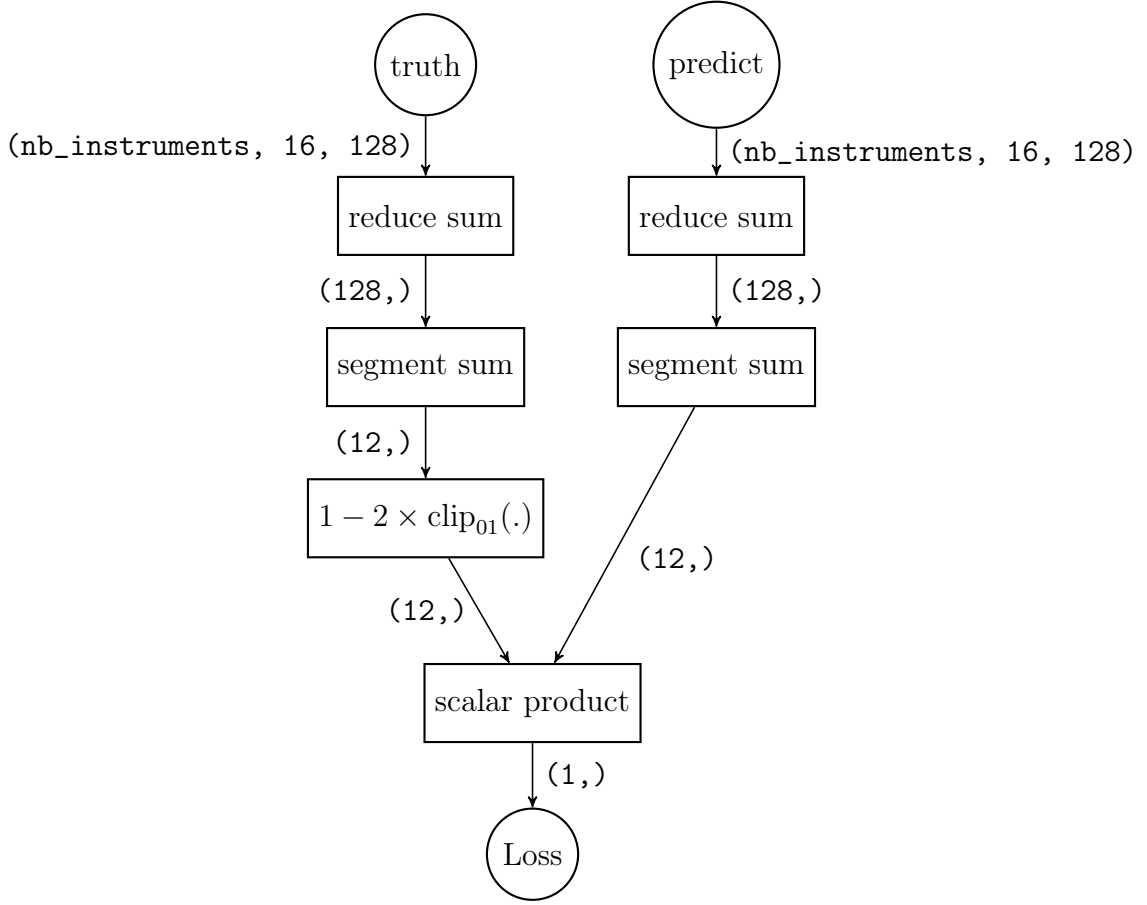
Figure 4.7: Scale Loss

4.4.2 Rhythm

The idea behind the Rhythm loss is that we want to preserve the rhythm of the music. Indeed, the rhythm is sometimes important and consistence is need through the musical piece. Thus, to preserve it, every time the model plays a note that is not played at the same time as an instrument in the ground truth, it gets a penalty. Conversely, every time the model plays a note at the same time as another one in the ground truth, it gets a reward.

The implementation showed in the figure 4.8 is very similar as the Scale implementation.
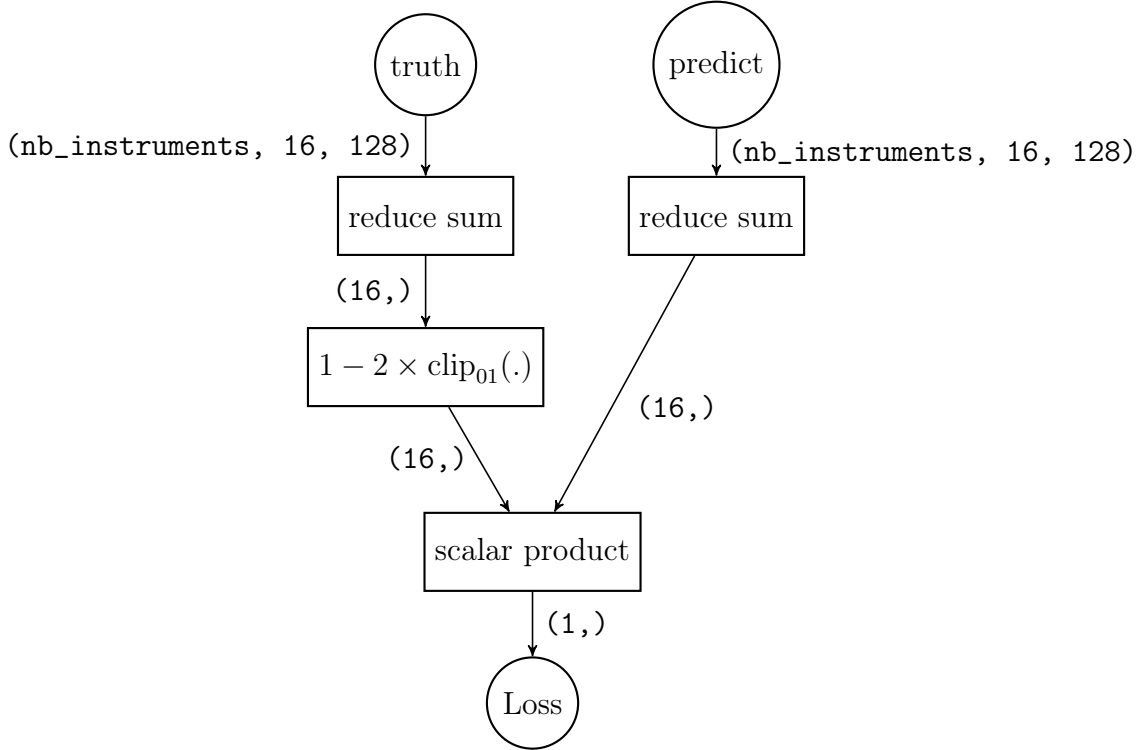
Figure 4.8: Rhythm Loss

4.4.3 Harmony

I explained in the section 2.2.2 that some notes will sound smooth together because of their common harmonics. On the other side, some notes won't be elegant when played together because of the resonance problem between some of their harmonics.

This is something every composer has in mind when he creates a second musical part which will harmonize the first one. He will keep the second voice in the scale and he will keep an acceptable musical interval between the notes of the 2 melodic parts.

The figure 4.9 shows the acceptable and non-acceptable musical intervals for the note A.

From this figure, I realized there are actually 3 musical intervals to avoid:
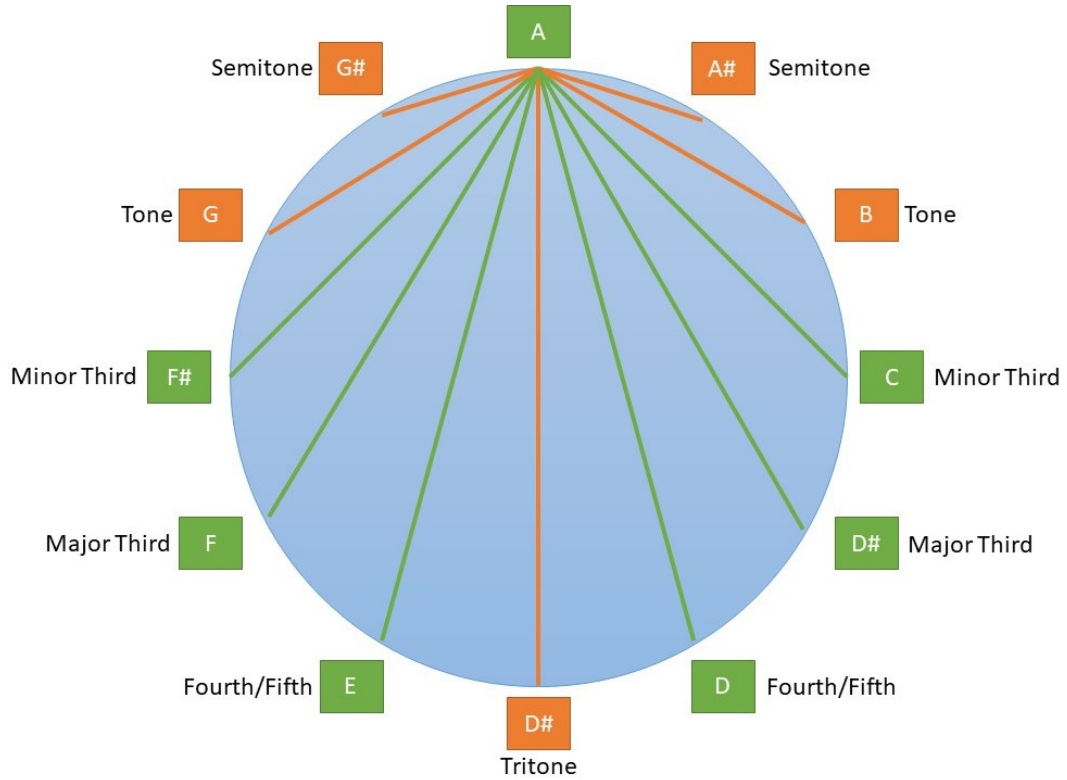
Figure 4.9: Harmony Circle for A

- The *semitone* interval

- The *tone* interval

- The *tritone* interval. Actually, this interval was named *"Diabolus in musica"* ("Devil in the music") and was forbidden by the church.

To prevent the model to generate such intervals, I created a loss function which gives a penalty every time there is one of this intervals. To do so, I created a sub-function harmony$_n$ which penalizes the presence of the nth interval (counted in semitone).

The operations of the cost function harmony and harmony$_n$ are showed in the figures 4.10 and 4.11. The roll$_n$ operation is explained in the appendix .3.
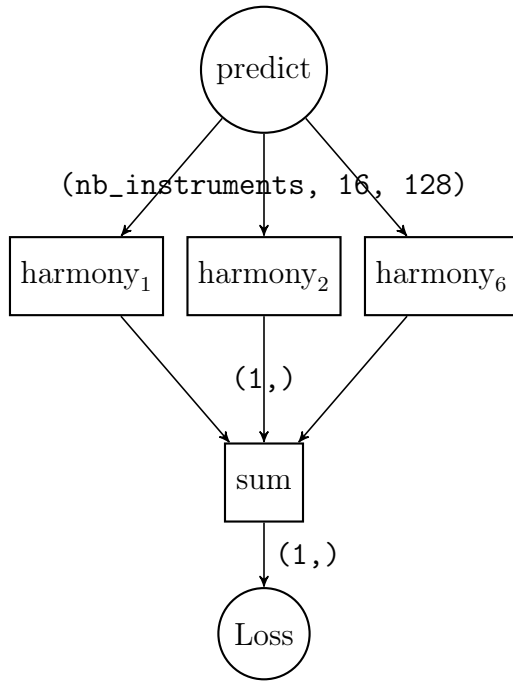
Figure 4.10: Harmony Loss
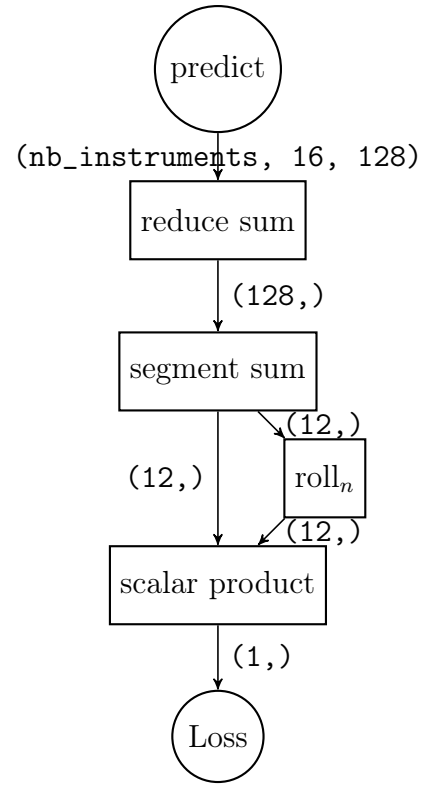
Figure 4.11: Harmony$_n$ Loss

CHAPTER 5

Experiments

5.1 Transpose the data

5.2 Custom losses

5.3 Activation

CHAPTER 6

Conclusion

This dissertation project provides a new neural network architecture (RM-VAE) and a new layer to handle time dependencies between data (RPOE).

I have showed that the RMVAE architecture is able to learn musical rules from a pianoroll view and adding extra losses (Scale, Rhythm and Harmony losses) doesn't help the training.

Future work

Find the scale with some already known scale template ?

Try with different encoding : Text BachBot or DeepBach says the way you write music with text is important Maybe convolution and image is not good enough

I constructed my own pianoroll view. Maybe try to use Pypianoroll will give a better representation.

I didn't want to change the dataset to C major so it can handle change of key. But seems too hard for the neural network

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Appendices

.1 Interpolation project

At the start of my dissertation, I tried another project which haw to create music with a waveform representation. Subham S. Sahoo et al. [72] present their improved network for equation learning $EQL^{\div}$, that overcomes the limitation of the earlier works. In particular, their main contribution are:

- They propose a network architecture that can handle divisions as well as techniques to keep training stable

- They improve model/instance selection to be more effective in identifying the right network/equation

- They demonstrate how to reliably control a dynamical robotic system by learning its forward dynamics equations from very few random try-outs/tails.

More precisely, their model is a shallow network able to learn complex function containing multiplication, sinus and cosine functions, and it is able to extrapolate them. Those very usual operations processed by most of the VST to create musical sounds.

Thereby, I tried to interpolate musical waveform with their architecture. My idea was to construct a transition between 2 parts (for example a verse and a chorus) or reconstruct some missing data from a song.

Unfortunately, the results were poor... Most of the time, the model was converging to the mean of the functions (which is 0 for musical waveform).

I think their model is working well for their applications because they use it to extrapolate robotic dynamic equations which usually don't include many sine and cosine components. Contrariwise, a musical waveform contains enormous number of sine and cosine components.

.2 Segment Sum

The segment sum operation allows me to sum the values of a vector of shape `(128,)` (corresponding of all the different notes in the different octaves) in a vector of shape `(12,)` (corresponding to the different 12 notes).

The figure 1 describes what the segment sum operation would perform if there were only 4 different notes (*A, B, C, D*) and 3 different octaves (*1, 2, 3*) for a total of 12 notes.
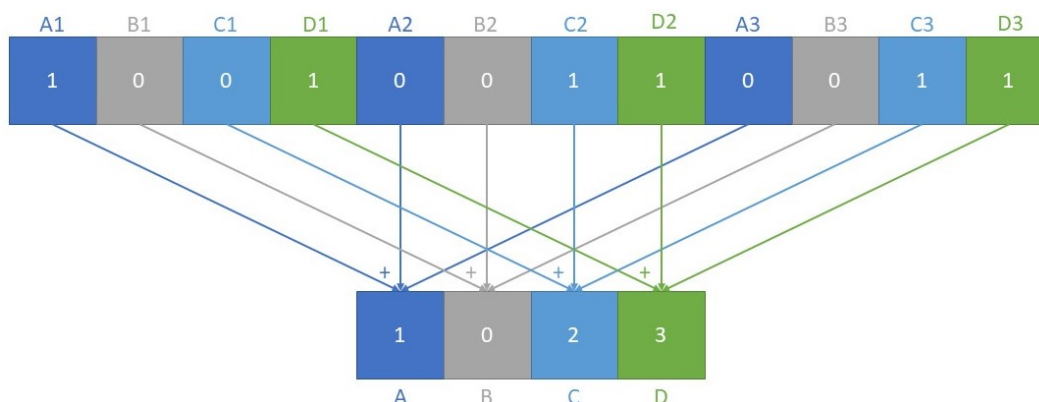

Figure 1: Segment sum operation

.3 Roll$_n$

The Roll$_n$ operation takes a one dimensional tensor, takes the first n values and put append them at the end. The algorithm 2 explains how it works and the figure 2 shows an example with $n = 2$.

Algorithm 2 Roll$_n$ function

Input: tensor, n
Output: $tensor$ (Rolled tensor)

1: **function** ROLL($tensor, n$)
2:     **for** $k \leftarrow 1$ to n **do**
3:         $firstElement \leftarrow tensor.pop(0)$
4:         $tensor.append(firstElement)$
5:     **end for**
6:     **return** $tensor$
7: **end function**
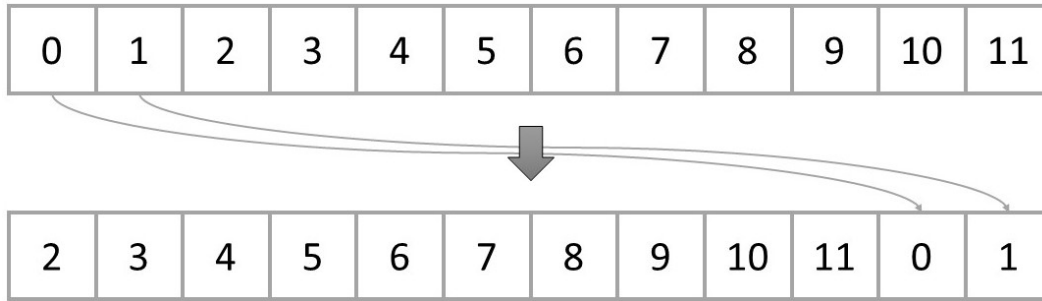
Figure 2: Roll$_2$ example

.4 BandPlayer

Train a model and generate music is nice. But as musician I wasn't fully satisfied with this application. To fulfil my need, I created a python script to be able to play with the trained model in real time. I call this application `BandPlayer` because the user can play with and jam with a virtual band.

The application I have created

- Allows the user to plays music with the instrument of his choice

- Can load a trained model

- Allows the user to choose what part he wants to play in the *"band"*

- Allows the user to choose what parts from the *"band"* he wants to keep

- Feeds the model with the notes played

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- Play the generated notes by the model with the user

- Display the notes played by the model and the user in a pianoroll view

Calling the model to make the notes prediction while the user is playing is computationally feasible because my model is working on an entire measure at one time. Therefor the model is called only one time per measure which is not to frequente to allow the application to be real time.

.5 Coconet Process

The figure 3 illustrates the coconet process. This process is explained in the section 3.4.2.

.6 Transformer architecture

The figure 4 illustrates the transformer's architecture. This architecture is explained in the section 2.4.6.

.7 Hyper-Parameters tuning

Tuning hyper-parameters to train the best possible model is a difficult task in deep learning. The reason is because every number or setting can be considered as a hyper-parameter and, most of time, there is no proof and rule to guide use to choose the best value they should have. The only help the researcher can have is his intuition and his understanding on how an specific parameter will influence a specific process.

A common doing is to implement a grid-search algorithm. For each hyper-parameters, a set of possible value is specified and the algorithm is simply to
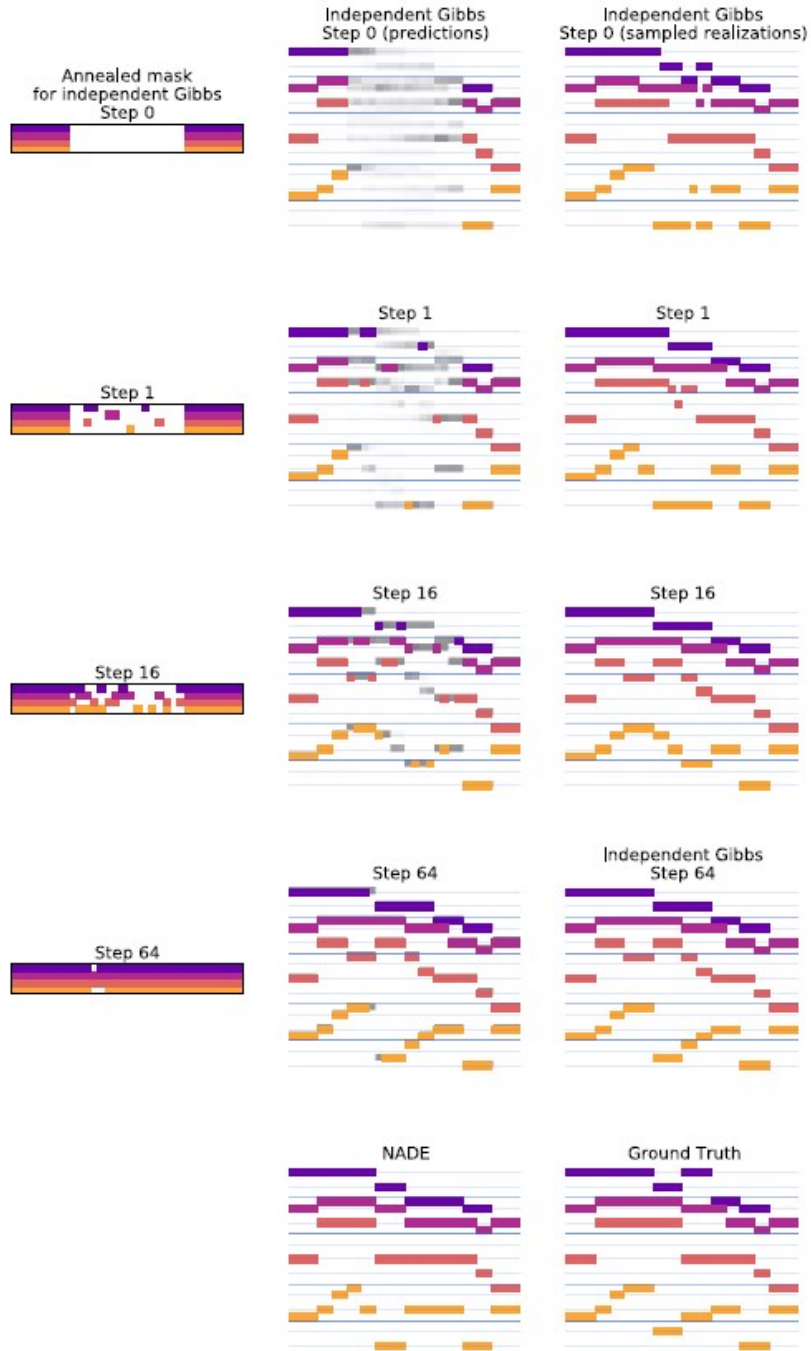
Figure 3: COCONET process
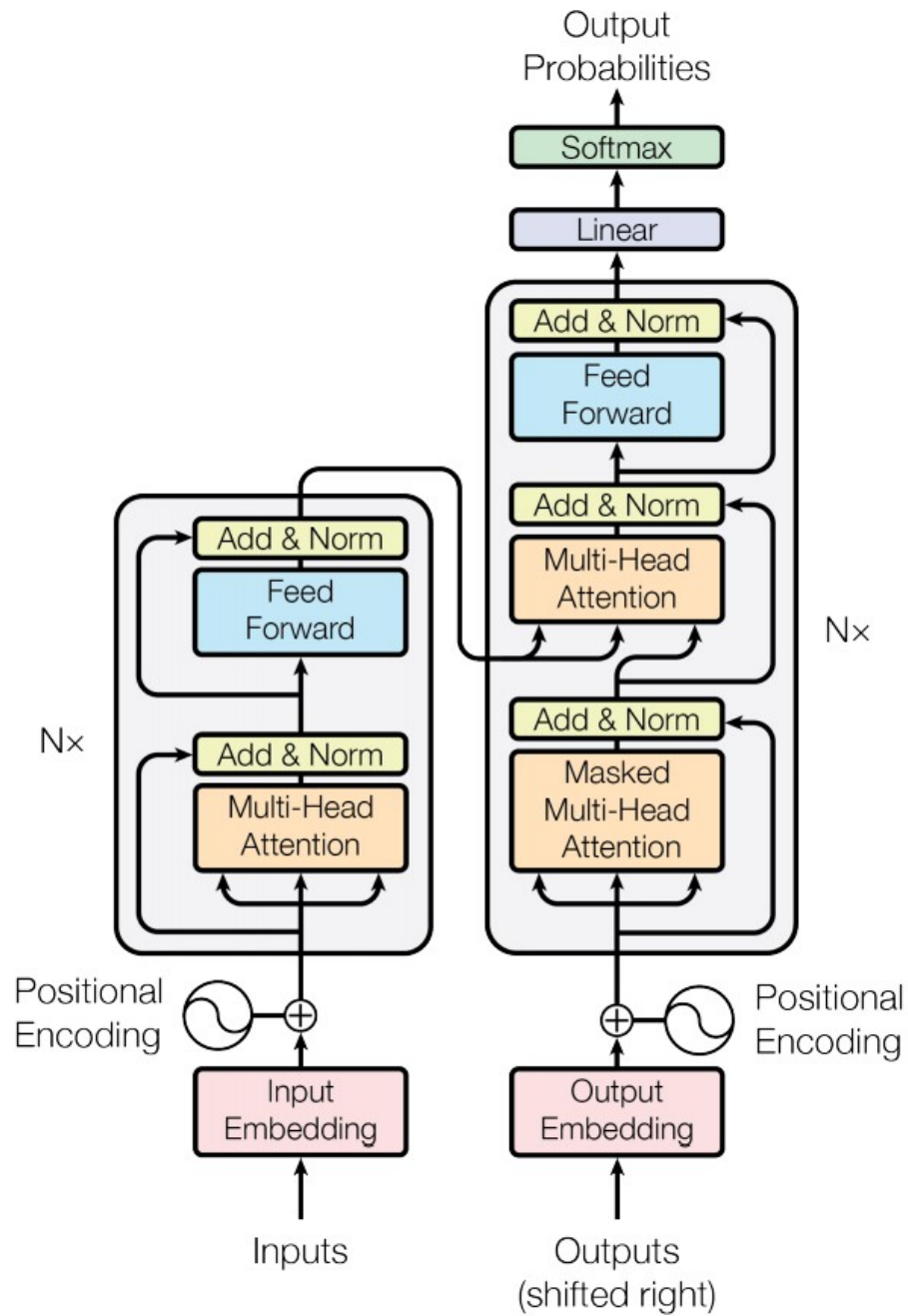Source: Cheng-Zhi Anna Huang et al.'s paper [36]

Figure 4: Transformer architecture
Source: Ashish Vaswani et al.'s paper [28]

train the model with all the possible combinations of parameters. However, the number of iteration grow exponentially with the number of hyper-parameters.

It has been showed that a random-search algorithm is in average faster and better than a grid search,

Another possibility is to implement a Bayesian optimization [73, 74]. It is a sequential design strategy for global optimization of black-box functions that doesn't require derivatives. It uses GP to learn a unknown function. Since the number of hyper-parameters in my very high, (at some point, I was trying to tune over 20 parameters), I implemented a script to do a Bayesian search over them. To do so I used the library scikit-optimize [75]. The main advantages of a Bayesian optimization over a grid or a random search are:

- It requires less iterations

- The domain of search for a specific parameter value is not discrete but continuous.