Interpolation Based Neural Audio Synthesis using Convolutional Autoencoders

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Declaration

I hereby declare and confirm that this thesis is entirely the result of my own original work. Where other sources of information have been used, they have been indicated as such and properly acknowledged. I further declare that this or similar work has not been submitted for credit elsewhere. This printed copy is identical to the submitted electronic version.

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Preface

Abstract

This should be a 1-page (maximum) summary of your work in English.

Kurzfassung

An dieser Stelle steht eine Zusammenfassung der Arbeit, Umfang max. 1 Seite. ...

Chapter 1

Introduction

Chapter 2

Related Works

There already exist a few good approaches around the thematic of neural style transfer or generating audios using neural networks, that present rather good solutions. Some of these studies have proven, that with neural networks it is possible to generate synthesized audio up to a certain quality. Those approaches can get categorized into different areas, as their principle and methodology differ in certain ways. As this field is related to the technique of image style transfer, a lot of works apply those methods to audio, and respective audio spectrograms and thus, call it explicitly audio style transfer. Secondly because those solutions, are defining a combination specifically of content and style. This topic will get discussed in more detail in section 2.2. All methods which do not include this principle of content and style, can get categorized to the technique of neural audio synthesis or simply just audio synthesis (see 2.1). Those methods incorporate mostly autoencoder networks.

2.1 Neural Audio Synthesis

Neural audio synthesis is the field of creating or synthesizing novel sounds with the help of neural networks. The approach is similar and related to the field of audio style transfer. As described before, approaches in this domain differ in certain ways to neural style transfer. As a major difference, with respect to neural audio synthesis, no content or style sound is specified, which means, that for the creation of novel sounds, two sound sources are used equally. While audio style transfer also gets frequently applied on whole audio samples or musical pieces, in audio synthesis the focus is more directed on the application for single notes. With a special look onto autoencoder networks, neural audio synthesis also includes the tasks of learning important sound features for compression and recreation of the input data. How different approaches are designed and which machine learning techniques and which results could be obtained, will be described as follows.

Probably one of the most prominent solutions, in the field of neural audio synthesis, comes from *Engel et al.* [6]. With their work "Neural Audio Synthesis of Musical Notes with WaveNet Autoencoders" they have proposed a system that is capable of synthesizing audio as well as interpolating/morphing encoded audio data of two instruments

to create new audio.In addition, there also exists a publicly available dataset called "NSynth" that contains a large scale of high quality musical notes. The dataset has been applied for training of the model in the course of this specific project. In their work regarding the synthesis, *Engel et al.* developed and compared two different approaches with two different kind of networks. Basically they have a similar structure, as they are both designed as autoencoders. but accept different formats of audio-data and thus have different components. While the one kind of network operates on time-continuous data the other one is trained on the spectral representation of audio samples. Throughout the work, the second technology using spectrograms is referenced as Baseline Model, by using so called "WaveNet Autoencoders", that are trained on continuous time signal. The Autoencoder-Structure enables learning efficient encodings of the music data, which are representing essential features from the original audio. In order to create new sounds they take the encoded data from the embeddding space of two instruments and interpolate them linearly. In addition they applied the decoder part to reconstruct audio data. As a result they were able to create new sounds with the characteristics of two different audio signals. Comparing the performance of the two different networks used, they found the WaveNet-style autoencoder to be advantageous. This was proven both by the error scores for reconstructing the audios or auditory quality and by quantitative comparison with a pitch and quality classifier model. Nevertheless it was also concluded that the spectral baseline model has a strong performance.
The results regarding the WaveNet Autoencoder can be explored via Engel's online AI-Experiment called "Sound Maker".[1].

In further publications and approaches, *Engel* continued the research on neural audio synthesis by applying other network structures for this purpose. With respect to generative adversarial networks (GANs) and recurrent neural networks (RNNs), two more works have been published in the field of neural audio synthesis. [5, 10] Similar to their work concerning WaveNet-style and convolutional autoencoder, they conducted experiments in (re)synthesizing audios, as an example interpolation of extracted features has been done. Eventually the discuessed works, show a suitability for audio synthesis and also highlight a major speedup in the computation of synthesized audio samples.

The work by *Natsiou et al.* does not explicitly mention the term neural audio synthesis in its title, but deals with it throughout the article. [20] In their work they do a research on the reconstruction capacity of (stacked) convolutional autoencoders in terms of log-mel-spectrograms and carry out experiments on different configurations. In their experiments they evaluate the effectiveness of autoencoders in terms of neural audio synthesis whereas also feasible improvements through additional techniques are measured. As well they mention, that their work makes an exploration on musical timbre compression. Here the synthesis gets specifically referred to timbre synthesis. As audio spectrograms exist with different scales, this approach uses, in contrast to others, the log-mel scale. This scale proves to be beneficial, as it already captures the most significant properties with the effect of consuming less memory and computational power. For the training the autors used the NSynth-Dataset proposed by *Engel et al.* [6], whereas

[1] "Sound Maker" https://magenta.tensorflow.org/nsynth-instrument

just a sub-sample, containing samples of different instruments of one single pitch, was considered. The model(s) that were used throughout their experiments, followed the general structure of a (stacked) convolutional autoencoder network, which is composed mainly of 2D convolutional layers. For experimental reasons, additional layers and techniques such as pooling layers, fully connected layers, dropout, kernel regularization got applied (added/removed). In order to measure the results of their experiments they applied error metrics such as root mean squared error (RMSE) and structural similarity index (SSIM). As a result these metrics cannot accurately say anything about the quality. Because of this reason, they also introduced a precision and recall score and combined it in a F1_score. In order to generate sounds from the spectrograms, they were utilizing the preserved phase information, unless there was no modification of the embedding. In the latter case, the Griffin Lim phase estimation algorithm was applied, as no phase information is present.
Regarding the results that could be obtained by reconstructing spectrograms (without modification in latent space), some interesting findings could be extracted. To their surprise, by reducing the size of the latent space, they found out that the smaller it is, more accurate spectrograms with a smoother distribution could be generated. Also, in some cases where kernel regularization got applied, the spectrograms were more accurate, while with dropout layers no improvement could be achieved. The use of (max) pooling also resulted in a more accurate time-frequency resolution with less noise than with just convolution layers. Finally, after the removal of the fully connected layers it showed that the quality was significant better, as spatial information got preserved better.

Regarding audio synthesis, *Colonel et al.* published a few works, where they investigated the suitability of autoencoder networks in connection with audio synthesis. [2, 3, 17] Starting in 2017 they proposed an autoencoder based audio synthesis through compression and reconstruction of audio spectrograms. [17] In contrast to the before mentioned approaches, this one is based on fully connected layers without convolutions. Also a self-made dataset was created, with their own synthesizer. In contrast to to e.G. the NSynth dataset, this one contains polyphonic notes and thus more complex harmonies. During the experiment they trained different parameterized networks, where they vary the depth and width of the network and its layers as well as the activation functions and different optimizers. As error metric in this work the mean squared error (MSE) was used. Comparing these scores regarding networks of one or two hidden layers on each side show, the network using the Adam optimizer worked out best in contrast to using Momentum as optimizer. These networks, based on sigmoid activation functions worked best when less compression is applied. The concept of 4 hidden layers, showed having a mix of ReLU and sigmoid activation functions worked out best. Additionally by applying regularization methods such as dropout and l2 penalty, the latter proved to be better, as the results where of better auditory quality. Further results showed that sigmoid activations led to fuller sound than with ReLU. Furthermore by using bias terms, it could be observed that noise was present in the results. As a consequence, despite of the better convergence, they chose to let them out. The authors concluded, that using a network with 4 hidden layers and a composition of sigmoid and ReLU worked out best also in terms of auditory quality.

Another work by *Colonel et al.* was proposed in 2018, which actually states an improvement of the method, described in their previous work from 2017. [2] Those improvements contain the use of a phase reconstruction method not used before, which allows a direct activation of the latent space. For an improved model convergence, the autoencoder was designed asymmetrically, via input augmentation. This means that they padded the input magnitude data with different permutations, being first or second order difference or mel-frequency cepstral coefficients (MFCC). Whereas in the previous work only MSE was contemplated as error metric, here, a comparison of several cost functions was used. Within the cost functions, the mean absolute error (MAE), as well the as spectral convergence cost function (SC) with L2 penalty, was considered. The penalization of the total spectral power, proves to be advantageous as the power in the output is more accurate as compared to others. In comparison to their work from 2017, they also left out additional bias terms, but decided to just use ReLU-activations instead of a mixture with sigmoid.
Eventually improvements to their previous results could be achieved regarding the additional methods, that were applied. Concerning the augmentation of the input data, a significant improvement regarding score could be reached, whereas augmenting with first order difference outperformed all other. With a look onto the generated sound, it could be observed, that by padding with the MFCCs a different sound palette was present. In another comparison to their baseline, *Colonel et al.* introduced the possibility to omit the encoder part of the network. This directly enables the activation of the innermost 8 neuron layer while the decoder can generate novel sounds. As no phase information was present, estimations were done via a method called real-time phase gradient heap integration, which enables the generation of a playable sound. In addition to this work, the authors implemented a small program including a GUI, where it is possible to directly interact and activate the innermost neurons (eight control values in latent space) to generate new sounds.

In a more recent work, *Colonel et al.* implemented and compared autoencoder networks with different topologies regarding their performances for musical timbre generation. [3] This work already utilizes findings and methodologies from previous works. Based on a study from 2018, they implemented a mechanism to directly activate and control the latent space of a trained autoencoder with a graphical tool. They found out that this technique proved to be difficult in terms of controlling the latent space. To overcome this issue and improve the work, they added chroma-based input augmentation to improve the reconstruction performance in this approach. The chroma-values are based on the 12 note (western) scale to represent the dominant note present in an audio sample. Besides this type of input augmentation, they also implemented a so-called skip connection, where the latent space gets conditioned with the chroma-value. In this work the chroma-values get represented via a one-hot encoded representation for each training sample, where the maximum value is set to one while all others to zero. Consequently these one-hot encoded chroma representations tell the note played in a single-note audio. With this technique the authors could shape the timbre around a specific note class. For the networks topologies, they varied the size of the “bottleneck”-layer (8, 3 or 2 neurons), the activation functions, the input augmentation, the use of the chroma skip connection, as well as different datasets. It should be mentioned that the

authors trained and experimented with the self-generated dataset from their previous works, containing five octaves of notes, a one octave subset of it and a separate violin note dataset.
As a result, the network with an eight neuron bottleneck, with the chroma-based input augmentation worked out best. Thus, for the rest of the experiments *Colonel et al.* were using this technique. In case of the two neuron bottleneck network, the sigmoid activation functions without skip connection worked out best for the one octave dataset. The skip connection turned out to work best for the violin dataset (sigmoid and two neurons). Finally in the case of three neurons also the variant with the skip connection worked out best for both datasets. By analyzing the latent spaces some interesting observations could be made for the sake of audio synthesis. The authors applied a clustering method to see the distribution of the values in the latent space concerning their note and timbre. Using sigmoid activations turned out to bind the values in the range of (0,1) as well as distributing the values in a more uniform manner. Also the skip connections led to a denser representation. By taking this as an advantage, and moving forward with just sigmoid activations, sampling of the latent space (with a mesh grid e.g. 350x350 for two neurons bottleneck) was done to generate a new timbre. In combination with setting the additional chroma conditioning vector to a given note class, the decoder generates the timbre that matches the chroma vector and thus, the desired note is present in the output sample.

A comparative work on autoencoders, in terms of music sound modeling, has been published by *Roche et al.* in 2019. [23] In this work they implemented four different types of autoencoder networks, that have been compared in terms of audio synthesis. Similar to the other techniques described earlier, this one also orientates itself on the principle of an autoencoder, to project the input data to a low-dimensional space, from which input can be (re)synthesized. In the described experiments, the proposed autoencoder networks consist of (shallow) autoencoers (AEs), deep autoencoders (DAEs), recurrent autoencoders (LSTM-AEs) and variational autoencoders (VAEs) which all got compared to principal component analysis (PCA) as baseline. As sound data for training and experimenting, they used a subsample of 10,000 different random selected notes from the public available NSynth dataset. The networks that where implemented got trained on the normalized log-magnitude spectra of those samples. Regarding the structure or the depth of the different networks, the researchers used two and three layers for the DAE on each side. In the case of the VAE just one version with two layers, and one version of the LSTM-AE with one layer on each side was applied. Regarding the size of the output from the encoder (latent space), they experimented with different values in a range from 4 to 100. The conducted experiments consist of an resynthesis-analysis where the reconstruction error (RMSE in dB) of the different methods got compared. Additionally to the RMSE so called PEMO-Q scores were introduced to calculate the objective measures of perceptual audio quality.
The results showed to their surprise, that PCA outperformed the shallow autoencoder network. Continuing with DAEs, the reconstruction performed almost 20% better than the shallow AE, having an encoding size of 12 and 16. Also the error decreased faster when the dimension of the latent space was decreased. Even better results with over 23% improvement compared to PCA could be achieved by using LSTM-AEs which

brought them to the concolusion, that it is feasible to use more complex architectures. The fact that more compression and thus a small latent space can be generated, is even more important for sound-synthesis. In comparison the reconstuction error from the VAE was lying between the one of the DAE and shallow AE/PCA. As the size of the latent space influences the reconstruction error, it can be stated, that the bigger the size, the lower the error. Interestingly PCA outperforms all models having an encoding size of 100. In addition to the RMSE score, the perceptual audio quality got measured with te PEMO-Q score. The results are comparable to those with RMSE, with just the LSTM-AE having a slightly lower score as compared to RMSE. In this context it was also investigated how the latent space values can be used to be controlled by musicians, and thus, the correlation between those values has been calculated. Averaged over all samples per model, it was shown that the values from LSTM have the most correlation while VAE has the worst. Having less correlation makes VAE the better candidate in terms of using the latent values as control values for synthesis (less redundancy and clear perceptual meaning). In terms of audio synthesis, including the latent space variables, *Roche et al.* also demonstrated how it could be applied for sound interpolation like in the Work of *Engel et al.*. For this task they selected the latent space vectors of two sounds with different characteristics and linearly interpolated each value. By decoding and in addition, applying the inverse STFT and Griffin Lim, new interesting sounds could be generated.

2.2 Audio Style Transfer

The below discussed works, all orientate themselves on the techniques of image style transfer. As those techniques have a significant impact on the development of audio style transfer algorithms, two important works get discussed in section 2.3. Applying the method of image style transfer to audio also means, as audio is a time-continuous signal, that it has to be brought into a similar shape, which will be done mostly by generating spectrograms out of signals. As for image style transfer, a content and a style picture is needed, this principle also gets applied to audio style transfer. In image style transfer, the style (e.g. brush strokes, colors) and content of an other image (e.g. contours, scenery) get combined, to form a new stylised image. [7] This means that in the output image, the content image looks painted with a certain “style”. Mapping this principle to the audio domain, this means, that there has to be a specific content sound (sample) that gets stylized with a certain style of a sound (e.g. style of a specific instrument). In the image domain it is difficult to distinguish content from style, whereas it is a bigger question that appears in the different approaches. Most authors define the style as a musical instruments’ timbre or even a musical genre. Alongside, the content might get defined as global music structure with rhythmic constraints. [9] Those scientific questions also might be influenced if whole audio samples/musical pieces might be taken to get stylised or just some single notes from an instruments. Furthermore if speech is considered as audio data, style and content differently defined as well. Here, style could be e.g. the emotion of the voice or the speakers identity and content the spoken words in an sample. The following works show different solutions specific to the problem of Audio Style transfer in which they also get compared and assessed.

One approach that applies this principle, is the solution proposed by Ramani et al. in 2018. [22] In their study they developed a neural network that is constructed as an (convolutional) autoencoder. Here they described officially their system as audio style transfer algorithm. In this case the process of generating an audio containing characteristics of two audio signals is slightly different as in the work of *Engel et al.*. They worked with two networks, namely a transformation network and a loss network. This architecture and methodology is especially inspired by the neural style transfer algorithm by *Johnson et al.*. Both networks have the same structure and composition of layers. The loss network is trained to compress input spectrograms to lower dimensions, which means that the encoder part learns to preserve the high level features of the input. In addition, the decoder learns to reconstruct a spectrogram similar to the input of the network from the encoded data. For the training of the transformation network, the pre-trained weights of the loss network are used which speeds up the learning process. This means just optimization towards low level features/style has to be made. The trained transformation network, is then able to transform an input spectrogram into a stylised spectrogram. The loss network is subsequently used to calculate the style-loss but also content-loss between the respective spectrograms and the output from the transformation network. This loss gets minimized by back- propagation to the transformation network. Through this procedure it is possible to pass a single spectrogram through the transformation network. In the following the network outputs a new spectrogram containing the characteristics of itself (content) but also of one other style audio. Due to its architecture it also performed really fast and could be used for real-time use.

Verma et al. presented a new machine learning technique for the purpose of generating novel sounds, in their paper in 2018 [24]. In this approach they tried to apply the method for artistic image style transfer, into audio and they specifically mention the approach proposed by *Gatys et al.*[7] (see section 2.3). Unlike Gatys image style transfer approach, they adapted and trained an AlexNet architecture on the classification of audio-samples. This kind of network is a so called convolutional neural network, where the audio gets converted into spectrograms, which can be seen as grey-scale images. An important aspect is, in this work they used the log-magnitude data of the STFT output. It also should be mentioned, that they adapted the network towards a receptive size (kernel) of 3x3 instead of the larger ones in the original network, as it retains the resolution of the audio. Similarly to the image domain, the stylised output image gets initialized with random noise. Thus an input spectrogram consisting of a gaussian noise signal is utilized. This one gets iteratively optimized by minimizing the content, but also style loss via back-propagation. In the end this process creates a spectrogram combining the content of one audio with the style of one other audio sample. Additionally they found out that including additional loss terms for temporal and frequency energy envelopes, helped to improve the quality, as otherwise temporal dynamics would not get incorporated. For their experiments they imposed the style of a tuning fork onto a harp sound and also transferred the style of a violin sound onto a sample of a singing voice. In this way they developed a novel method for achieving cross-synthesis by using image style transfer methods.

More work was published by *Liu et al.* [19] exploring the application of technologies given from the image domain for "mixing audio". This means, that this approch focuses on using audio as spectrograms. As the previous study solely focused on the one technique by *Gatys et al.* this experimient explores two more approaches. While one inspired by *Johnson et al.*, a convolutional autoencoder coupled with a VGG classification network, the other one uses an approach with (cycle)GAN (Generative Adversarial Network). In this work they call Gatys' approach specifically "slow transfer", as the iterative computation from gaussian noise was proven to be really slow. Different to the previous work by Verma et al., the authors adapted a VGG network (1 input channel in first layer instead of 3) for the "slow transfer" method. This approach has also been used in Gatys' image style transfer. The transfer process is also similar to the previous work, as Liu uses a spectrogram initialized as gaussian noise in order to iteratively minimize the content loss in the higher layers, and the style loss in the lower layers. Setting this transfer process as a baseline model, they also adapted a faster style transfer method by coupling the VGG network with a convolutional autencoder network. The purpose of this network is to take the content spectrogram as input and in the following outputting a spectrogram containing also the style features of a style spectrogram. Comparing the described work to other approaches, this proves to be similar to the one of Ramani et al. having a transformation network. The only difference is the second network as here they are using a VGG classification network and no second autoencoder. Having the output of the autoencoder network (also called generative network) this one serves as the initial spectrogram on which the content and style loss gets computed in the VGG network. The gradient descent then gets applied to the autoencoder network, resulting after few iterations, in a stylized spectrogram. The researchers have proven that their approach is faster than the one with gaussian noise. As mentioned before, for the third experiment they adapted a cycleGAN, which accepts audio spectrograms instead of images. In the image domain, this kind of network is able to apply style transfer to only a portion of the input images. Secondly the application of this method generates two images as transfer is done in both directions, which means in case of audio that two new sounds get calculated. As another result, this study showed that their approach generate te results in a shorter amount of time. For the purpose of evaluation, they listen to the outcome, but also apply objective mechanisms like visual assessment of spectrograms, consistency tests with classification and examination of signal clusters. Eventually the authors state that with the baseline approach features like the harmonic is not clear and high frequencies get discarded and that the faster transfer emphasizes on lower frequencies but is missing out on beginnings of the notes. With cycleGAN also the lower frequencies get emphasized while higher ones get discarded. The listenable results of each approach are provided online.[2]

As the above mentioned approaches are working on single notes, the experiment of *Grinstein et al.* has been implemented for whole audio samples [9]. Within their work they were adapting several other approaches, with neural networks from the image domain. Besides of neural networks, they also implemented a handcrafted sound texture model which got compared to the neural approaches. The latter one is composed of three sound processing steps, that in combination emulates the human auditory system. Tak-

[2] https://www.xuehaoliu.com/audio-show

ing a closer look on their work, especially on the neural networks, it can be said that they differ from existing ones in several ways. On the one hand, they do not use a random noise spectrogram, but use the content spectrogram which then gets stylised through their methods. On the other hand many audio style transfer approaches, explicit are computing the result with a combined loss function, that incorporates both style and content loss. *Grinstein et al.* do not make use of this concept, as they already initialize the future stylized spectrogam with the content spectrogram, like mentioned previously. On this target spectrogram, just the style loss gets optimized, as the content is already present. To mention here, they proved this method to have compelling results, as the global structure of the content sound gets preserved.
In detail the neural network-based approach the authors investigated the use of three different network architectures for the purpose of audio style transfer. Concerning all three network types, they minimized the style loss on the content sound respective spectrogram. This style loss is equally computed as in Gatys' image style transfer approach. It gets calculated by minimizing the error to a "style sound or spectrogram", at specific layers in the network that extract the style. Via back-propagation the loss gets minimized again at each layer, which results in a stylised content sound or spectrogram, after a few iterations. This workflow was applied to all three different network types and compared in the end. As first network they used a VGG-19 network like Gatys, where the input spectrogram was replicated three times in order to mach the input shape (RGB-like). By averaging all three channels in the end, they were able to obtain the final stylised spectrogram. The second network is called SoundNet, which is a convolutional network learned on unlabeled videos including sounds. This type of network operates on the raw waveform where no generation of spectrograms has to be done in advance. Finally a wide-shallow-random network was investigated with audio spectrograms consisting of just one-layer CNN (like in the work of Ulyanov and Lebedev [26]). As the fourth and last method they made trials with a handcrafted sound texture model that emulates the human auditory system. Even it is no neural network, it consists of three layers doing cochlear filtering, envelop extraction with compressive non-linearity and modulation filtering.
Eventually the authors came to the following experimental conclusions: While using the VGG network no meaningful results could be obtained due to the noisiness. In comparison the SoundNet yielded more relevant results despite also containing some noise. Surprisingly the shallow random network performed best together with the sound texture model. For a better understanding, the results were provided online.[3]

The work of Ulyanov and Lebedev has to be mentioned here, as they are often referred to be one of the first, that explored transfer algorithms for audio. [26] In fact, they took the architecture used in image style transfer by Gatys et al. and adapted it for the use on audio spectrograms. Rather then seeing the spectrogram as a picture, with the dimensions of frequency x time, they took the freuquency values as channels for the CNN. The network itself was designed as a shallow network (1-layer) using 1D-Convolutions with random weights. To obtain a final spectrogram containing content and style, an optimization is made on random noise, to minimize the loss values to a

[3] https://egrinstein.github.io/2017/10/25/ast.html

style and a content spectrogram. Instead of applying it on single notes, this approach also uses longer samples or music snippets.

2.3 Image Style Transfer

In the previous sections it has been written about neural audio synthesis as well as neural audio style transfer. A lot of these works especially those proposing solutions for neural audio style transfer, took their inspirations from the image domain. For this reason this section makes a short excursion relevant image style transfer works of *Gatys et al.* as well as *Johnson et al.*. [7, 15] *Gatys et al.* were the first to implement a system of neural style transfer applied on visual data. By using a convolutional network trained on object recognition and localization (VGG-19) in images, they were able to extract the texture as style but also the content of an image. They found that especially from higher layers in the network, high-level features of the images, can get reconstructed. This includes objects and their arrangements in the scene, without the exact pixel information, which will be used as content representation further on. Using a special feature space for texture synthesis, the style of a content image can get extracted by using the feature responses at certain layers in the network. By combining these two principles, respective style losses and content loss can get computed which will be used for the style transfer. The generation of the target image starts by initialization of a random noise image, on which those losses get minimized by using gradient descent.
Johnson et al. developed an improved image style mechanism on the basis of the former methodology, that particularly shows improvements regarding computational speed. For the computation of content and style losses they use a VGG network with 16 layers and pre-trained on image classification. Here they added a special transformation network, that is designed as autoencoder. This one takes a target image as input (content image) and synthesizes an image on which the style and content loss gets calculated in the VGG network instead of a random noise. Back-propagation was performed just in the transformation network, while the VGG network stayed fixed. As a consequence the transformation network produced a stylised image after training. By comparing Johnson's work to the method by *Gatys et al.*, it shows a significant improvement regarding computational speed but also yields promising results.
Previously described image domain methods significantly inspired the development of audio style transfer algorithms, which are presented in section 2.2. Finally, it should be noted that works by [22] and [19] adapted and applied the method of *Johnson et al.* while all other in section 2.2 mainly used the methodology proposed by *Gatys et al.*.

Chapter 3

Approach

In the last section a few approaches have been outlined and discussed, that have successfully implemented methods regarding the creation of audios/music with a neural network approach. As seen, these have been mainly categorized in neural audio synthesis and neural audio style transfer. There current work has its main influence from the area neural audio synthesis, and can be categorized as such, as the methodology and workflow is strongly related to those works. Nevertheless regarding certain components, it has also its influence from the style transfer methods, despite not defining a specific content or style audio respective loss functions.

This chapter will therefore dive into the methodology and exact workflow of this works' solution, to the problem that also will help to derive the answers to the defined research questions. First an Overview/Motivation should provide the reader with the intended idea and an overview of the applied methods, to get a general understanding of the idea (see section 3.1. Later on the single steps and components that are needed, in order reach the desired functionalities, are going to get described in detail, starting with the pre processing. Further on the ML-Model (neural network) will get described, as well as the step that is done to synthesize new sounds. Further on, the required steps for (re)generating a listenable audio as well as an description of the used dataset for training and also all experiments conducted later on (see chapter 4).

3.1 Motivation

Like mentioned in the beginning of this thesis, this work aims to explore the possibilities of machine learning techniques such as neural networks, to apply in the audio domain for sound generation. This idea is mainly inspired by the idea of taking two distinct audio sources and mixing their characteristics in order to generate a new sound. As seen in the previous chapter, this idea is strongly related to the image domain, where the "synthesis" of a new pictures based on two source images, is commonly known as image style transfer (point 2.3). This technique, of having a content image to be stylised with a certain style from another image, would mean for the application in the audio, to have a style sound to be transferred onto a content/target sound. Such approaches are specifically known as audio style transfer and can either be applied to single notes or also whole audio samples or songs. Having the principle of content and style this would mean, that of one sound the global structure and rhythmical components get preserved while imposing style (e.g. the timbre) on it to generate audios. The details to these approaches, have already been outlined in the previous chapter, when describing some existing work around this topic.

Neural audio synthesis is another method for neural sound generation, which does not apply the principles of style and content audio. In the previous chapter, some insights could be gained, how neural audio synthesis can look like, as well as how it can be achieved using different methods and neural networks. Most of those methods, were showing promising results, either concerning the auditory quality but also the possibilities that arise in experimenting and designing sounds. Those methods were using most of the time so called autoencoder networks, that can be used for dimensionality reduction of input data, as they have a so called "bottleneck" in the middle. [12] Because of this structure, the compressed data in this "bottleneck" represents essential features that either can be combined/interpolated or directly synthesized. To generate synthesized audio, the solutions described in section 2.1 used the "decompressing part" of the network to generate in order audio data. The exact workflow and methodologies for sound creation, have already been mentioned in the chapter related works (see chapter 2, point 2.1).

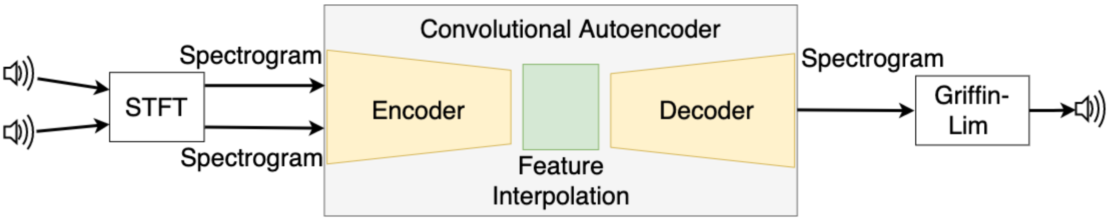
Out of those methodologies, when having the idea of using two instruments' characteristics, to generate audio, the approach of *Engel et al.* [6] using convolutional and WaveNet-style autoencoders yielded the most promising results. Promising especially in terms of output quality but also concerning its implementation/reproducability. With a provided interactive web application, the results of this solutions can be explored, whereas different sounds can be mixed based with a certain ratio. The results in the web application are based on the WaveNet-style autoencoder but according to the scientific article, the convolutional (baseline) also provides strong results. Implementing an approach with a WaveNet-style network would also go beyond the scope, not least also the computational costs would be too high. As also some audio style transfer methods, especially the approach by *Ramani et al.* [22], are using convolutional autoencoders, this kind of network was chosen to be preferable, to be applied in this work/research.

3.2 Overview

Based on the motivation and existing approaches, this work aims to propose a system, that uses a convolutional autoencoder network, for the task of neural audio synthesis. This systems' goal is to take two distinct audio samples as input, wheras the significant features, of those get extracted and interpolated, to in order (re)generate a novel sound in the end. In figure 3.1 the general workflow of the toolchain is depicted in order to get an understanding, how this system is built up.

Starting on the very left, two audios are taken and have to be brought into a suitable representation for this type of network. As audio is in its raw form a time-continuous signal and the input for convolutional networks are of a different shape (e.g. images) some pre-processing has to be done. In this case the short-term Fourier transform (STFT) is applied in order to generate a spectrogram, that shows the frequency spectra over the time. The frequency spectra contains on the one hand the magnitude (power) of the frequencies but also the phase information. For this purpose, only the magnitude

Figure 3.1: Overview of the proposed solution



data gets used, as its found to contain the most characteristic features of an audio. The ML-model (autoencoder) then takes the magnitude data as input, from which a compressed representation with the essential features gets generated with the lefthand (encoder) side. Having those features of two different audio samples, those get linearly interpolated, to generate one feature vector representing the “mixed” features of two instruments. This new vector, gets passed through the righthand (decoder) side of the network, which regenerates again spectral magnitude data of the same dimension as the input. In order to obtain a “playable” audio sound, it gets transformed back into time-domain with the Griffin-Lim algorithm [8] for phase estimation or the inverse short-term Fourier transform (ISTFT). The latter will be applied if there was no interpolation in the embedded space, as the phase information can be reused. Corresponding terminologies as well as a detailed insight into each step and its functionalities are given down below in the following points.

3.3 Pre-processing

Pre-processing is the task of preparing raw data for a specific purpose. Moreover it is an important component of machine learning techniques such as for training neural networks. Deciding which pre-processing technique(s) to use on the one hand depends heavily on the type of ML-problem that has to be solved or even the training method that is chosen, but of course also on the type of data itself. As written before, for this work a neural network consisting of convolutional layers, has been chosen to be applied to the problem of neural audio synthesis. As convolutional neural networks are known for image processing tasks, they also can be applied for audio data, which has already been outlined in recent works in this field (see chapter 2). In contrast to image data which most of the time has a 3D shape (width x length x RGB-colors), a raw audio has a different structure in its data representation, as it is a time-continuous signal (1D-shape). To in order bring the audio data in a similar shape, it has to undergo some pre-processing steps. Some representations of audio that have a image-like shape and can be used for deep learning tasks, include e.g. log-magnitude spectrograms or Mel-spectrograms but also Chromagrams and Constant-Q Transform (as stated by [1]). Taking the methods of recent works concerning neural audio synthesis into account, this work chooses to use the first two representation whereas in the experimental part of this work, they are going to be compared concerning the synthesis task and the performance of the neural network. <Maybe mention that spectrograms are found beneficial as they contain most essential data>

As the practical part of the project to this thesis is implemented in python, whereas a special library was used for the pre-processing part. For this part the library librosa [25] was being used, as it provides practical functions for audio processing, that were considered as useful for this work. Special to mention here are the functionalities as calculating spectrograms (STFT) but also transforming spectral data back into time domain to generate playable audio data (ISTFT, Griffin-Lim).

3.3.1 Spectrograms and STFT

Spectrograms represent a 2D-representation of an time-continuous signal, which essentially shows the presence of certain frequency bands over time. Like previously said, there exist different forms of spectrograms e.G. log-magnitude and log-mel spectrograms. Especially speaking of the log-magnitude spectrogram whose calculation is based on the short-time Fourier transform (STFT) and thus on the Fourier transform. The Fourier transform, takes a frame of N values of an (audio) signal and transforms it from the time domain into the frequency domain. Generally said, that the bigger the frame, the better is the frequency resolution. What this means in terms of calculating the spectrogram, will get outlined shortly. Whats also important to mention at this point is, that the result of the Fourier transform, consists of an array of N complex numbers, which are mirrored in the middle. Every complex number in this array stands for a so called frequency bin in the signal. The real part of these numbers would represent the power/magnitude of this “bin” and the imaginary part gives information about the phase. Coming back to the frequency resolution, this for example means that when taking a one-second signal with a sampling rate SR and performing the Fourier transform with length $N = SR$ on it this would yield an array of N values. The first value in the result depicts the signal’s offset whereas all values from 1 to N/2 are the frequency bins with a resolution of 1Hz per bin. This means that each of this bin shows the magnitude and also phase of each frequency from 1 to N/2 Hz. The ongoing values in the result, show the same values except they are mirrored, as they depict the negative frequencies. (maybe some more explanation or citation) Because of this behaviour, the second part can be omitted for further use. Now these values just show the frequency spectra of one time frame and do not incorporate more information about the change. To overcome this shortcomming, the Fourier transform can get applied to a series of frames of the signal in order to obtain multiple frequency spectras over time that can be depicted as a spectrogram.

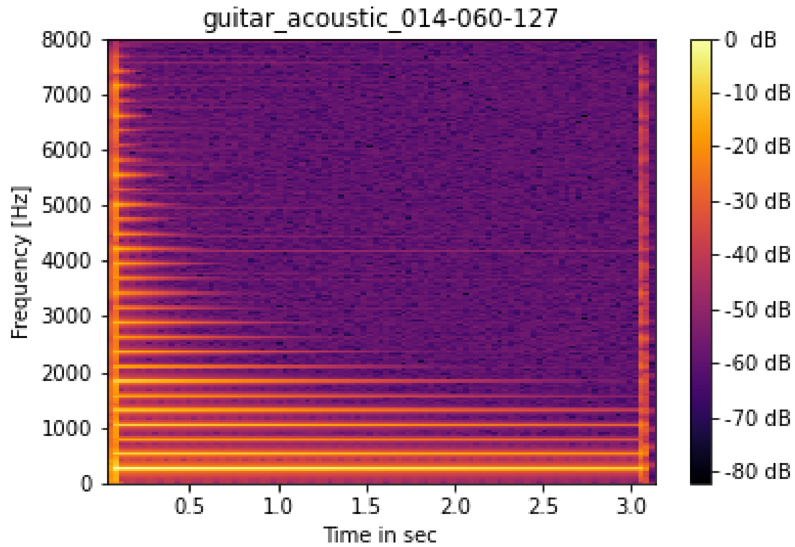
The calculation of multiple frequency spectras over time is the so called short-time Fourier transform. This form of calculation is widely used for pre-processing of audio data for ML-Tasks (for example see chapter 2). When applying this transform, a few parameters have to be considered, as those influence the result but also the quality for the later workflow. One of the the most important parameters is `n_fft` as it specifies the actual length of the signal-frame, on which the FFT (fast Fourier transform) gets applied to. This parameter therefore influences therefore, the frequency- but also time-resolution in the final spectrogram. To be mentioned regarding the official Librosa documentation, this should be a value of a power of two, as it speeds up the computation of the FFT behind. Another important parameter would be the `hop_length`, which defines how much audio values are between the beginning of the first and the following frame. This means that when defining this parameter to `n_fft/2` this would yield in a 50% overlap of the following frame. Modifying this parameter, would mean to either increase or decrease the overlap and also the amount of time columns as more overlapping frames occur. The overlap of the frames is also coherent with the chosen window function for the STFT. As every time when the FFT gets applied to a frame, this one gets multiplied with a so called "window". Multiplying a signal frame with a window has to be done, as the FFT assumes, that the transformed signal is periodic (repeating itself infinitely). [11] This gets problematic when the input signal does contain frequencies that may not directly fall into a frequency bin, due to the FFT's frequency resolution. Due to the assumed cyclic continuation the Fourier transform will 'think' that there is a discontinuity and will spread therefore the power over all the spectrum. There exist multiple window functions such as "Hann", "Hamming", "Blackman", etc. which start at (almost) zero, rises to a maximum in the middle but falls again to (almost) zero at the end (symmetric). Multiplying the signal frame with such a window function helps to overcome this issue as it removes the discontinuity. On which window to chose, depends on the usecase of the application, whereas throughout this work a "Hann"-window was chosen all the time. Coming back to the relation with the window overlap, if no overlap would be used a lot of information of the signal would get lost. This is because when multiplying the signal frames with the window functions, this would bring very little or zero values at the beginning and end of the frame. [11] When having overlapping frames this issue would get corrected. Important here is again the amount of overlap as this is dependent on the window and its wideness. Using the "Hann"-window a common value for the overlap would be 50% which was also considered throughout this work. This value is also beneficial later on, when performing the inverse transformation, back into time domain, but more on that in section 3.5. Beside of these parameters some more exist, for example for specifying the padding of the signal whereas in this work a constant padding on both sides of the signal has been used, which is also the default setting.

Now having the knowledge of the STFT and its parameters, it can be applied onto a signal, to generate a spectrogram. For example by using an audio sample with a sample rate of 16 kHz and applying the STFT with a n_fft value of 1024 and a hop-length of 512 this would result in a spectrogram with a frequency resolution of 15,625 Hz but time resolution of 64 ms. As explained before, the values of the result, consist of complex numbers which contain the magnitude but also the phase at each frequency bin. By setting this result absolute, or calling the function `librosa.magphase(spectrogramm)` the real magnitude data can be obtained, whereas the latter also retrieves phase information in a separate vector. The magnitude here displays the energy values of the spectrogram, whereas for further processing and also to be better displayable those get converted into a dB-scale. [1] As this function also takes a reference value that gets set to 0 dB, which in this case will be the maximum value of the magnitude spectrum. As for post-processing when converting the dB-scaled data back into energy, also a reference value is needed, this one gets preserved, in order to get the same scaling as in the original input. Finally when having the log-mag spectrograms in dB, those were considered for

[1] normally the magnitude would need to get squared to obtain the power, but in this case magnitude without squaring was taken

the training of the neural network afterwards. An example of a log-mag spectrogram can be seen in figure 3.2. As also the phase information also was obtained when calculating the magnitude data, this one was also preserved next to the energy reference value for the recreation of signals, as it is needed there (this will mainly affect the recreation of single samples, without interpolation in embedded space, but more on that later on).

Figure 3.2: STFT log-mag spectrogram of a guitar note



This section describes the general workflow of the pre-processing from taking a signal and converting it into a spectral representation. This workflow is a basis on which different experiments with different parameterization (size of n_fft, etc.) of the calculation of the spectrograms but also with additional steps (log-mel scale, additional framing, etc.) are being made. Those steps will get mentioned later on in chapter 4 when describing the experimental part of the thesis.

3.4 ML-Model

The main or core component of every machine learning project is of course the model itself, as it achieves the main task of prediction or inference to a given problem. Those models exist as different technologies that perform regression tasks or even classification tasks. Dependent on the usecase, but also the kind of data that is present, different models are better suited or not. To count technologies, there exist the KNN-Algorithm, Decision-Trees, Random Forests, Support-Vector-Machines (SVM) but also neural networks which can be applied in a variety of usecases. Especially the latter, the neural networks, are able to achieve a variety of different tasks, as they are highly adaptive regarding their topology, used layers, but also the size and shape. Those variety of different tasks spread across different domains, so also for images and audio.

3.4.1 Neural Networks - Introduction

Generally said a neueral network can be seen as a graph of connected nodes with numeric values that can achieve transformations between patterns using message-passing algorithms. [16] Those nodes are commonly structered in layers, where there especially exist certain nodes or even layers that are seen as input nodes/layers and some as output nodes/layers. Between the input and the output there can also exist some so called hidden layers, expanding the depth of the network. The links between the nodes, that get also called neurons, are connected via links, that are parameterized with weights, that get optimized using learning algorithms. Each neuron receives its weighted input (activities) of its connected predecessors, which get converted into a single output that gets broadcast to all its connected successors. [13] The latter involves a so called input-output function which is also commonly known as activation function (e.G. ReLU, Sigmoid, Softmax ...). Also important to know, is that the weights on the connections define how much this value influences the input of the connected node. When a neural network gets trained to a specific problem (e.g. classifying certain images), using predetermined training data, the output of the neural network gets compared with the desired one, resulting in a certain error (metric). To minimize this error, the weights in the network get adapted by back-propagating the error through all the layers, to the beginning. On this way it changes the influence of certain connections and therefore the overall outcome. This procedure gets repeated on all training data over several iterations, until the error gets low to produce the desired output. Depending on the problem to solve / what's the desired output, neural networks can be trained using labeled data (supervised) but also just by minimizing a cost function (unsupervised).[21] More details on the learning will get mentioned later on when explaining the model itself.

3.4.2 Convolutional Neural Networks

In this approach, due to the promising usage in existing solutions, a convolutional neural network has been chosen as model. Convolutional neural networks are a type of networks, that get primarily used for tasks in the image-domain for example to recognize patterns in pictures or classification, but also like seen in chapter 2 for image style transfer. They have the advantage over traditional neural networks, that they can cope with the dimensionality of pictures (width x height x colors/depth). The layers containing convolutional nodes have as learnable parameters, so called kernels. [21] Those kernels, if taking a 2D-Convolutional layer, are normally small in width and height (e.g. 3x3) but span the whole depth (channels) of the input (in the case of RGB-pictures depth of three). Those kernels calculate the skalar-product for each value contained in the kernel and the input map. This yields, having e.g. a 3x3 kernel operating on a 3x3 field, in a single value. This value is the weighted sum of the kernel's values and from those of the input vector. This operation will be applied to each 3x3 field along the spatial dimension of the input, resulting in a smaller activation map. One can also apply padding around the input, to preserve the dimensionality. Furthermore a stride can be defined, which defines how much these convoluted fields overlap, as using a bigger stride would result in a smaller overlap. Having also a smaller overlap would result in a much smaller activation map. For example taking a 7x7 input, by applying a 3x3 kernel with no strides and also no padding, this would yield an output field of 5x5. With a padding of 1x1 the output would be of the same size. Finally if the stride would be 2, the output field would be of 3x3. Through training of the network and back-propagating the error, those values in the kernel get adapted in order to learn certain/important features or patterns on which a classification or pattern recognition can be made (easier). As it got here described for 2D-convolutions, depending on the input dimensionality it can be also be applied as 1D-convolutions or even 3D-convolution.

With the knowledge, that such convolutions are successful on image data, those can be also applied on audio provided in the shape of a spectrogram. As described in the previous section (see 3.3) spectrograms can be described in a "picture-like" shape having the dimensions of frequency x time with a depth of one. Speaking of that, the spectrogram can therefore be seen as a grey-scale image. The energy in different frequency bands over time with its variations, can be seen as "recognizable" patterns. Taking a 2D-convolution, the kernel (e.g. 3x3) takes a 3x3 frame of frequency x time which results in one value. Summed up, this results in an activation map smaller or equal (if zero padding is used) than the input. After training on different samples and iterating several times, those activation map would contain the most significant features or characteristics of the spectrogram (e.g. when training on classification). Depending on the chosen hyper parameter for the amount of output channels (depth), the resulting activation map can be of depth one or even deeper.

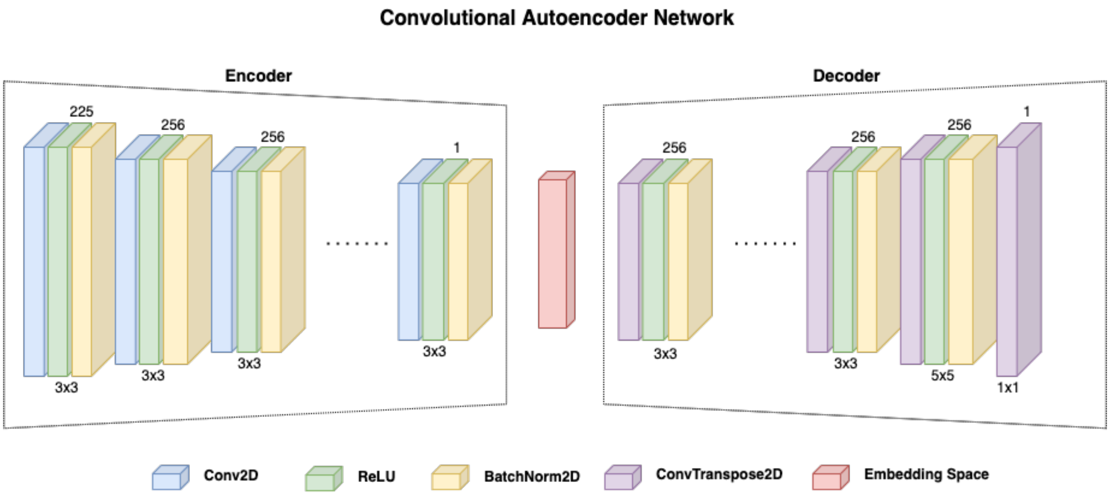
As mentioned before, each neuron in a neural network has an activation function, which is also the case for convolutional neural networks. As there exist different kinds of activation functions, for this approach mostly ReLU (Rectified Linenar Unit) activation functions got used but also LeakyReLU. Additional to this activation function, Batch-Normalization gets applied after each convolutional and ReLU non-linearity component. The choice is mainly based on already existing approaches like from *Ramani et al.*[22] and *Engel et al.*[6], as it was proven to yield promising results in combination. According to *Ioffe ad Szegedy* [14] applying Batch Normalization also improves the training speed (number of iterations/epochs) and enables use much higher learning rates. Also it acts a regularizer, so that overfitting-reducing technologies, such as Dropout, can be omitted.

3.4.3 Autoencoder

Neural networks exist in different shapes and compositions, depending on desired work it should fulfill. Whereas some networks e.g. for classification of a given input, might reduce the width of the layers towards the end, some are designed to have a so called "bottle neck". This means, that this kind of network, contains a smaller central layer then the input, but at the end again a bigger layer (eventually same size of input layer). [12] Those networks are called autoencoder, in which the first part of the network (until the smaller central layer) gets called "encoder" and the second part beginning at the small central layer which is getting bigger towards the end gets called "decoder". These parts are called this way, as for the encoder part, it "encodes" the high-dimensional input data to a low-dimensional representation (output of small central layer). The counterpart is therefore called "decoder" as it decodes the low-dimensional data, to bring it again to a higher-dimensional representation (mostly same as input). The lower dimensional output of the small central layer, can be named differently for example "code", as *Hinton et al.* does when describing the work of autoencoders in his publication [12]. Some other common names would be e.g. latent space, embedding space, encoding or embedded data. This principle of dimensionality reduction, therefore means, that the encoder part extracts the most important or characteristic data, from which the decoder is able to reconstruct the input data.

In the related works chapter (2) a few works have made use of this principle to extract “characteristic” features for audio data and synthesize audio from it. This knowledge encouraged this work to also make use of this principle to synthesize audio by using autoencoders. Especially when having the extracted audio features as encodings, those can be modified easier, to in order synthesize novel sounds using the decoder part of the network. Combined with the knowledge to apply convolutional networks to audio spectrograms and capabilty of autoencoers to bring input-data into a more controllable form, the model in this work is designed as convolutional autoencoder. Also the works of *Ramani et al.* or *Engel et al.* made use of these kind of network to generate novel sounds. Figure 3.3 shows the basic autoencoder network structure which is used throughout this thesis work.

Figure 3.3: Basic autoencoder structure used throughout this thesis



In this figure, the depicted autoencoder, gives an insight of which components and layers it is composed. The amount of layers as well as the parameters shown in this sketch, are just an example, as throughout the experimental part, those get varied. Therefore, the dotted lines in this figure, act as a placeholder for possible more layers on each side in the network. The numbers above the individual layers represent the amount output channels and those on the bottom, represent the kernel size. Some paragraphs before, it has been mentioned, that in this approach the convolutional layer gets equipped with ReLU activation function and BatchNormalization. This also gets visualized in this figure, where each layer is shown as combination of sub-layers that incorporate those three components. Speaking of the composition of the layers, it can be seen in the decoder part, that instead of a convolutional layer, a convolutional transpose layer is used. This because of the nature of convolutions, as its output is always smaller or equal sized, which has been mentioned under point 3.4.2. As the decoder part

generates output that is bigger than its input, the layers have to perform upsampling. In convolutional nets this is typically done via the convolutional transpose layer.
This transposed convolution is not the reverse operation of a convolution, but it is more a operation to recover the shape from the convolutions input. [4] Taking the convolution example from above, by taking as input a 5x5 field and applying the transposed convolution, with a kernel of 3x3 this would result in a field in 7x7. The equivalent of this operation would be a convolution with the same kernel, on an input of 5x5, with 2x2 padding (padded input = 9x9), as this would result in a 7x7 output too. When in the convolution, striding was applied, this also works for the transposed convolution. Again when having the 3x3 input, by applying a 3x3 kernel with a stride of 2, this again results in a 7x7 output field. To be mentioned, the striding parameter for the transposed convolutions, defines how much zeros are added between the values of the input. This means, when taking the previous example, that the 3x3 input gets one column respective one row of zeros inserted after each value to result in a 5x5 field.

With this knowledge, convolutional transpose layers are best suited to be in the decoder part of convolutional autoencoder networks. Coming back to the architecture of the convolutional autoencoder in figure 3.3, those convolutional transpose sublayers are also coupled with ReLU activations and BatchNormalization, with an exception to the last layer.

Having this kind of autoencoder for this approach and the idea to extract features of spectrograms using convolutions, this models task is to encode and decode spectral audio data. The network is therefore configured, to produce an output of the same dimensionality as the input of the encoder. Like mentioned above, the output should be a reconstruction of the input, that gets inferred, by decoding the extracted features in the embedded space. To achieve this goal of reconstructing the input, the network has to be trained, through minimizing a specific error. In some cases also maximization is desired, but is dependent on the error score and the desired outcome. In the case of an autoencoder, this works by comparing the output of the decoder with the input of the encoder, by calculating the difference. Generally said, depending on the outcome and the goal of a training, there exist different metrics like mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE) but also more specific formulas. Throughout the literature, those error or error functions are also often called cost (functions) or loss (functions). For the experimental part of this work, the choice has been made to use MSE as error metric, as it has been used successfully by some existing works. To minimize this error an optimization of the network has to be made, which will be done through back-propagating the error score. Through this step, the parameters (weights, bias, convolutional kernels, etc.) get adapted according the error, which in the best case, improves the score and thus the output of the network. In this work the output of the network are reconstructions of spectral data for example slices of spectrogram. As having the encoder decoder structure, those output data get reconstructed through the decoder, which takes the encoder output as input. As mentioned before, this generated data of the encoder, is a compressed vector, consisting of the most significant extracted from the input. Depending on the configuration of the network, especially the encoder part, this vector also called encoding, can be of different size. This is because, when using more convolutional layers with strides, the output of each layer gets more downsampled, which results in a smaller encoding. As a consequence, the decoder part has to learn to regenerate spectral data from this encoded vector. This vector therefore is a compressed representation of the models input, which contains the most significant characteristics, of this specific spectrogram and further on, of the sound. Altering this encoded data, therefore also means, that the output of the decoder is different, and thus will be a novel, synthesized sound. More on how it should get altered, gets discussed later on. Choosing the right compression, is also an important part, that influences the outcome and thus the quality of the desired model output. Too much compression, may lead to the fact, that the decoder has too less information to infer the spectral output, which in order results in poorer quality of the resulting audio. On the other hand having, less compression, results in embeddings being not significantly smaller then the input, containing less important data too (e.g. noise). It also may gets more difficult to alter those encoded vectors. Throughout this work, different amounts of compression have been applied in the experimental part, which get discussed later, including the impacts and observations made on that. Knowing this this behaviour of the autoencoder model, this also one of the main reasons, this architecture got chosen, to synthesize audio.

3.4.4 Optimizer

For this optimization, different strategies exist, where hyper-parameters such as learning-rate or weight-decay play an essential role. Those optimizations are on a large scale stochastic gradient-based techniques, to which algorithms such as stochastic gradient descent (SGD) or Adam can be counted. Those algorithms influence and improve the convergence which means to find a minimal error. Throughout this implementation the Adam optimizer [18] has been chosen, as it is used widely in recent publications where promising results, could be achieved. Also regarding the training process in this work, Adam optimizer was proven to be advantageous. The parameters that have been found to have the most impact on the optimization process during training, are the previous mentioned learning-rate and weight-decay. To be mentioned, the learning-rate specifies how “fast” the model actually learns while weight-decay works as a penalty for the weights optimization to prevent overfitting. If the learning rate is chosen rather big, then the network learns faster, but because of its big steps or jumps, it could miss out the optimal solution in the solution space. Also it could happen, that when optimum is found, that it “jumps” out again. In this case a smaller learning rate would be desirable, as it makes smaller steps. Choosing it too low, would end up in a slow training where also large areas of the solution space are not visited. The latter leads to get stuck in a local minimum. Therefore it is important to choose the right size of learning rate, but this issue depends also on the problem size and type of network. In this work different learning rates have been applied throughout the experimental part where also different findings could be made, but this will be shown and discussed, later on, in this thesis.

With this knowledge, it can be stated, that a high learning rate, could be advantageous at the beginning of the training process, in order to rather find a global optimum and explore the solution space. In order to prevent, to jump out of minimum, a smaller learning rate would be desirable later on in the training. For this case, there exist some mechanisms to decrease the learning rate, later on in the training, especially when de-

tecting “oscillating” due to too large learning rate.
In this works’ implementation, for the start of the training a specific starting learning rate has been set, while throughout the training, it gets adapted, when no more optimization and eventual oscillation gets detected.

3.5 Post Processing

3.6 Interpolation in latent space

3.7 Dataset

Chapter 4

Experiment

Chapter 5

Results

Chapter 6

Discussion/Evaluation

Chapter 7

Conclusion

Chapter 8

Future Work

Appendix A

Technical Details

Appendix B

Supplementary Materials

List of supplementary data submitted to the degree-granting institution for archival storage (in ZIP format).

B.1 PDF Files

Path: /

thesis.pdf . . . . Master/Bachelor thesis (complete document)

B.2 Media Files

Path: /media

*.ai, *.pdf . . . . Adobe Illustrator files
*.jpg, *.png . . . . raster images
*.mp3 . . . . audio files
*.mp4 . . . . video files

B.3 Online Sources (PDF Captures)

Path: /online-sources

Reliquienschrein-Wikipedia.pdf **WikiReliquienschrein2022**

Appendix C

Questionnaire

Appendix D

LaTeX Source Code

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