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.

Hagenberg, June 27, 2023

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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

Around the thematic of neural style transfer or generating audios using neural networks, there exist a few proposed approaches that present rather good solutions. Some of these approaches 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 (spectrograms) and therefore call it explicitly audio style transfer. This is also because those solutions, are specifically defining a content and a style sound to combine, but more on that in section 2.2. Those methods who don't use 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/synthesizing novel sounds with the help of neural networks. The problem is similar and related to the field of audio style transfer. Like mentioned before, approaches in this domain differ in certain ways to neural style transfer. As a major difference, with 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 gets also a lot applied on whole audio samples or musical pieces, in synthesis the focus is more 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. On how different approaches are designed, which (machine learning) techniques and which results could be obtained, will be described in the following points.

Probably one of the most prominent solutions, in the field of neural audio synthesis, comes from *Engel et al.* [5]. 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. Not only they have proposed a system, but also a public available dataset called "NSynth" that contains a large scale of high quality musical notes.

The latter has been used for training 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. Nevertheless 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 their work the second technology using spectrograms is referenced/used as Baseline Model as they focus on the use of so called "WaveNet Autoencoders" that are trained on continuous time signal. With using the Autoencoder-Structure they make use of its ability in learning efficient encodings of the music data. These encodings are representing essential features from the original audio. To create new sounds they take the encoded data from the embeddding space of two instruments and interpolate them linearly. In addition they used the decoder part to reconstruct it back to audio data. Using this mechanisms they were able to create some new sounds which contain 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 not only got proven by the error scores for reconstructing the audios or auditory quality, but also through quantitative comparison with a pitch and quality classifier model. Nevertheless it also can be said that the spectral baseline model has a strong performance too.
The result regarding the WaveNet Autoencoder can be explored via their online AI-Experiment called "Sound Maker".[1].

In further publications and approaches, *Engel* continued the research on neural audio synthesis by using other network structures for this purpose. Especially mentioning for the use of generative adversarial networks (GANs) but also recurrent neural networks (RNNs), two more works have been published in the sake of neural audio synthesis. [4, 9] Similar to their work concerning WaveNet-style and convolutional autoencoder, they conducted experiments in (re)synthesizing audios but also e.g. interpolating extracted features has been done. Mentioning the results briefly, it can be said, that with those further works, the suitability of those kinds of networks for audio synthesis got proven, with also highlighting a major speedup in the computation of synthesized audio samples.

The work by *Natsious et al.* does not explicitly mention the term neural audio synthesis in its title, but deals with it throughout the article. [17] 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 possible improvements through additional techniques are measured. As they mention that with their work an exploration on musical timbre compression is made, the synthesis gets specifically refered as timbre synthesis. Because audio spectrograms exist with different scales, this approach uses in contrast to others, the log-mel scale. They prove it beneficial, as it already captures the most significant properties with the effect of consuming less memory and computational power. For the training they used the NSynth-Dataset proposed by *Engel et al.* [5], whereas just a

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

sub-sample consisting of samples of different instruments of one single pitch was considered. The model(s) that where used throughout their experiments, followed the general structure of an (stacked) convolutional autoencoder network, which consists 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). To measure the results of their experiments they were using error metrics such as root mean squared error (RMSE), structural similarity index (SSIM) but found out that those cannot accurately say something about the quality. Because of this reason, they also introduced a precision and recall score but also combined it in a F1_score. In order to generate from the spectrograms sounds, they were reusing 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 running these experiments 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 then with just convolution layers. Finally removing the fully connected / dense layer showed, that without it, the quality was significant better, as spatial information gets better preserved.

Regarding audio synthesis, *Colonel et al.* proposed over the years a few works, where they investigated the suitability of autoencoder networks regarding this task. [2, 3, 15] Starting in 2017 they proposed an autoencoder based audio synthesis through compression and reconstruction of audio spectrograms. [15] In contrast to the before mentioned approaches, this one uses an autoencoder based on fully connected layers without convolutions. Also a different dataset was used, as they generated it themselves using an own synthesizer. A difference to e.G. the NSynth dataset used in other approaches, is that it also 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 used 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, that using the Adam optimizer worked out best in contrast to using Momentum as optimizer. These networks, just using sigmoid activation functions worked best when less compression is applied. Having 4 hidden layers, they found out, having a mix of ReLU and sigmoid activation functions worked out best. To mention here also, by applying regularization methods such as dropout and l2 penalty, that the latter was proven better as the results where of better auditory quality. Some more interesting results that could get obtained, where that having sigmoid activations led to fuller sound then with ReLU. Furthermore by using bias terms introduced noise in the results, whereas despite of the better convergence, they chose to let them out. In the end they came to the result, that using the 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 in this method to directly activate the latent space. Furthermore to improve the models convergence, the autoencoder was designed asymmetrically, via input augmentation. This means they padded the input magnitude data with different permutations (first/second order difference or mel-frequency cepstral coefficients (MFCC)). As in the previous work only MSE was contemplated as error metric, this one made use and comparison of several cost functions. To these cost functions the mean absolute error (MAE) as well the as spectral convergence cost function (SC) with L2 penalty was considered. An advantage in using the latter they found out that via the penalization of the total spectral power, the power in the output is more accurate then with the others. In comparison to their work from 2017, they also kept to leave out additional bias terms but decided to just use ReLU-activations instead of a mixture with sigmoid.
Coming to their results, overall can be said, that improvements to their previous previous could be achieved regarding the additional methods they 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 can be observed, that by padding with the MFCCs a different sound palette is present. In further comparison to their baseline, they introduced the possibility to omit the encoder part of the network. This enables to directly activate the innermost 8 neuron layer whereas the decoder can generate novel sounds. As no phase information is present, this one gets calculated/estimated by a method called real-time phase gradient heap integration in order to be able to generate a playable sound. In addition to this work, they 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 their previous works (that have been mentioned before). Referencing the previous work from 2018, they implemented a mechanism to directly activate and control the latent space of a trained autoencoder with a graphical tool, to synthesize sounds. They found out that this technique is proven to be difficult in terms of controlling the latent space. To overcome this issue and improve the work, they added in this approach chroma-based input augmentation to improve the reconstruction performance. The chroma-values are based on the 12 note (western) scale to represent the dominant note present in an audio sample. Besides of this input augmentation with chroma-values, 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, whereas the maximum value is set to one while all others to zero. For this work these one-hot encoded chroma representations tell e.g. the note played in a single-note audio. With this technique they can shape the timbre around a specific note

class. For the networks topologies, they decided, to vary the size of the "bottleneck"-layer (8, 3 or 2 neurons) but also the activation functions, input augmentation, the use of the chroma skip connection as well as different datasets. To mention they trained and experimented with the self generated dataset from their previous works containing five octaves of notes, a one octave subset of it but also with a separate violin note dataset. Concerning the results, they found out, that for the network with an eight neuron bottleneck, the version with the chroma-based input augmentation worked out best. Thus, for the rest of the experiments *Colonel et al.* were using this technique. Concerning the two neuron bottleneck network, using sigmoid activation functions and no skip connection worked out best for the one octave dataset. Using the skip connection turned out to work best for the violin dataset (sigmoid and two neurons). Finally with 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, also for the sake of audio synthesis. They 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 bound the values in the range of (0,1) as well as distributing the values in a more uniform manner. Also the skip connections lead to denser representation. By seeing this as 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 to be 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. [20] 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 their 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 they used for the DAE two and three layers on each side, for VAE just one version with two layers and one version of the LSTM-AE with one layer on each side. Concerning the size of the output from the encoder (latent space), they experimented with different values that reach 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 regarding the reconstruction error, 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 decreases faster when decreasing the dimension of the latent space.

Even better results with over 23% improvement to PCA could be achieved by using LSTM-AEs which brought them to the concolusion, that its beneficial to use more complex architectures. Beneficial not at least, as more compression and thus a small latent space can be generated, which is important for sound-synthesis. Taking the results of the VAE into comparison, the reconstuction error lies between the one of the DAE and shallow AE/PCA. As the size of the latent space influences the reconstruction error, it can be said, that the bigger the size, the lower the error. Interesting here that 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 here are comparable to those with RMSE, with just the LSTM-AE having a slightly lower score (compared to RMSE). As in this work it also was investigated how the latent space values can be used to be controlled by musicians, the correlation between those values has been calculated. Averaged over all samples per model, it showed that the values from LSTM have the most correlation while VAE has the least. 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, having the latent space variables, they also showed how to use it 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, to linear interpolate 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 works in this section have in common that they all entitle their work, as audio style transfer. In their methodology they 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 at the end of this chapter (see 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. [6] This means that in the output image, the content image looks like 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). As in the image domain distinguishing content from style is already difficult, it is also a big or even bigger question that appears in the different approaches. Most of the time when defining the style of a certain audio, the authors define it as a musical instruments' timbre or even a musical genre. Alongside this a content might get defined as global music structure containing rhythmic constraints. [8] Those 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 as audio data, speech is considered, style and content also is different defined. 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. [19] In their approach they developed a neural network that is constructed as an (convolutional) autoencoder. As also the title says, they speak officially about their system as audio style transfer algorithm. The process of generating an audio containing characteristics of two audio signals is here slightly different as in the work of *Engel et al.* as they use in order 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 from the compressed data a spectrogram similar to the input of the network. For the training of the transformation network, the pre-trained weights of the loss network are used which speeds up training (just optimization towards low level features/style). Having the trained transformation network, it then is 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. By this procedure it is possible to pass a single spectrogram through the transformation network which in order outputs a new spectrogram containing the characteristics of itself (content) but also of one other style audio. To be also mentioned due to its architecture it also performs really fast and could be used for real-time use.

Verma et al. presented in their paper in 2018 a new machine learning technique for the purpose of generating novel sounds [21]. In this approach they tried to apply the method for artistic image style transfer, to audio where they specifically mentioned the approach proposed by Gatys et al.[6] (see section 2.3). Unlike to Gatys, they adapted and trained an AlexNet architecture on the classification of audio-samples. This kind of network is a so called convolutional neural network, whereas the audio therefore gets converted into spectrograms, as those can be seen as grey-scale images. An important note here is that in this work they used the log-magnitude data of the STFT output. Also to mention, they adapted the network to use a smaller receptive size (kernel) of 3x3 instead of the larger ones in the original network, as they claim that it retains the resolution of the audio. As in the image domain the stylised output image gets initialized with random noise, they also use here an input spectrogram consisting of a gaussian noise signal. The random noise spectrogramm afterwards gets iteratively optimized by minimizing the content- but also style loss via back-propagation. In the end this process creates a spectrogram containing the content of one audio with the style of one other audio sample. They also 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 in that field is coming from *Liu et al.* [16] which also explored the application of technologies given from the image domain for "mixing audio". This also means, that this approches focuses on using audio as spectrograms. As the previous work solely investigated on the one technique by Gatys et al. this one explores two more approaches in addition to compare the results. While one of those two additional is inspired by *Johnson et al.* which is a convolutional autoencoder coupled with a VGG classification network the other one uses an approach with (cycle)GAN (Generative Adversarial Network). In their work they called Gatys' approach specifically "slow transfer", as the iterative computation from gaussian noise was proven really slow. In contrast to the previous work by Verma et al., they used for the "slow transfer" method an adapted VGG network (1 input channel in first layer instead of 3) which has also been used in Gatys' image style transfer. The transfer process is also similar to the previous work, as they use a spectrogram initialized as gaussian noise to iteratively minimize the content loss (in the higher layers) and the style loss (lower layers). Using this one 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 as input the content spectrogram and outputting a spectrogram containing also the style features of a style spectrogram. Comparing it to other approaches this is very 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 is the initial spectrogram on which the content and style loss gets computed in the VGG network (just like previously with gaussian noise). The gradient descent then gets applied to the autoencoder network, resulting after few iterations, in a stylized spectrogram. They have proven that this approach is way faster than the one with gaussian noise. As mentioned before, for the third experiment they adapted a cycleGAN to accept 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. In the image domain the application of this method generates two images as transfer is done in both directions which means for audio that two new sounds get calculate. They also mentioned, that this approach generates the results in a shorter amount of time. For 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. Having the results, they state that with the baseline approach e.g. the harmonic is not clear and high frequencies get discarded. Also 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 already mentioned approaches are working on single notes/sounds, the experiment of *Grinstein et al.* has been implemented for whole audio samples [8]. Within their work they were adapting several other approaches, with neural networks from

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

the image domain, for his idea. 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. Taking a closer look on their approach, especially with the neural networks, it can be said that they differ frome existing ones in several ways. On the one hand they do not use a random noise spectrogram, moreover they already use the content spectrogram which then gets stylised through their methods. On the second hand most/many approaches that deal explicitly with audio style transfer, are computing the result with a combined loss (function), that incorporates a style loss but also a 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.
With the neural network-based approach they 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/spectrogram. The style loss is equally computed as in Gatys' image style transfer approach, to a "style sound/spectrogram", at specific layers in the network that extract the style. Via back-propagation the loss gets minimized again at each layer, which results after a few iterations in a stylised content sound/spectrogram. 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, whereas 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 they used SoundNet which is Convolutional network learned on unlabeld videos including sounds. This type of network operates on the raw waveform wheras no generation of spectrograms has to be done in advance. As final network a wide-shallow-random network was used with audio spectrograms consisting of just one-layer CNN (like in the work of Ulyanov and Lebedev [23]). As the fourth and last method they used a handcrafted sound texture model that emulates the human auditory system. Even if its no neural network, it consists of three layers doing cochlear filtering, envelop extraction with compressive non-linearity and modulation filtering.
Having the results of their experiments using those approaches, a comparison could be made. While using the VGG network no meaningful results could be obtained (extremely noisy), the SoundNet yielded more relevant results despite also containing some noise. To their surprise the shallow random network performed best together with the sound texture model. for a better understanding, they provided their results online.[3]

When writing about audio style transfer, the work of Ulyanov and Lebedev has to be mentioned, as they are often referred to be one of the first, that explored transfer algorithms for audio. [23] 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

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

freuquency values as channels for the CNN. The network itself is 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 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 on the works of *Gatys et al.* as well as *Johnson et al.* as it has a relevance for this topic and is found to be important. [6, 13]
Gatys et al. were the first to implement a system of neural style transfer which gets applied on visual data. By using a convolutional network trained on object recognition and localization (VGG-19) in images, they were able to extract on the one hand the texture (style) but also the content of an image. They found that especially from higher layers in the network, just high-level features of the images, such as objects and their arrangements in the scene, without the exact pixel information, can get reconstructed, 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 on the basis of the former methodology an improved image style mechanism, that especially shows improvements regarding computational speed. For the computation of content and style losses they use a VGG network with 16 layers that is pre-trained on image classification. To this network they add a special transformation network, that is designed as autoencoder. This one takes a target image as input (which is also the content image) and (re)produces an image on which the style and content loss gets calculated in the VGG network instead of a random noise. By performing back-propagation just in the transformation network, the VGG network stays fixed, and makes the transformation network to produce a stylised image (after training). By comparing this to the method by *Gatys et al.*, this shows a significant improvement regarding computational speed but also yields promising results.
Having these methods in the image domain, they inspired significantly the development of audio style transfer algorithms, which are presented in section 2.2. Mentioning the works by [19] and [16] which 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. [11] 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).

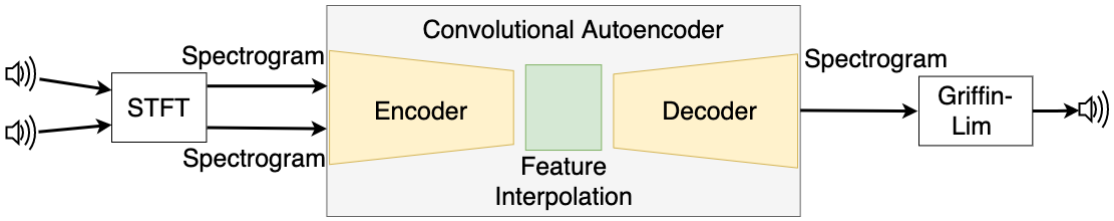
Out of those methodologies, when having the idea of using two instruments' characteristics, to generate audio, the approach of *Engel et al.* [5] using convolutional and WaveNet-style autoencoders yielded the most promising results. Promising especially in terms of output quality but also concerning 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.* [19], 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 [7] 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 [22] 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

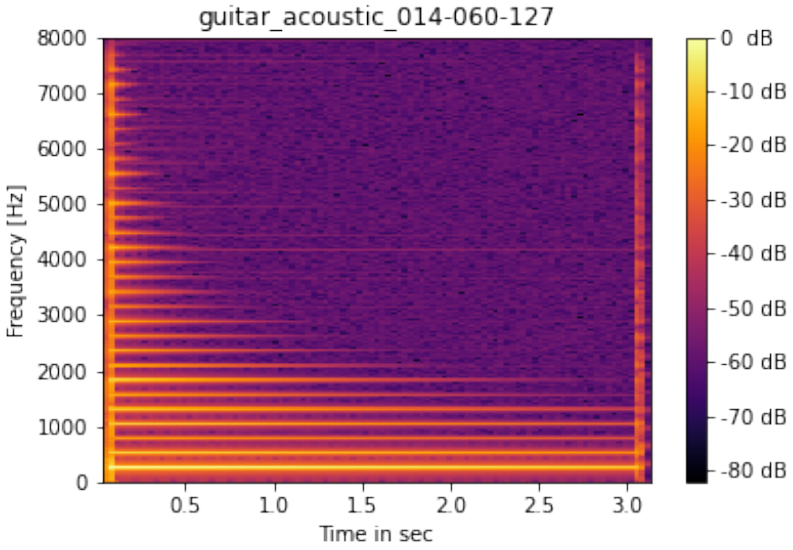
defines how much audio values are between the beginning of the first and the following frame. This means that when defining this parameter to `n_fft/2` this would yield in a 50% overlap of the following frame. Modifying this parameter, would mean to either increase or decrease the overlap and also the 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). [10] 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. [10] 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. [14] 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. [12] The latter involves a so called input-output function which is also commonly known as activation function (e.G. ReLU, Sigmoid ...). 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. 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).[18] More on that

3.4.2

<convergence?, learning rate,

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

References

Literature

[1] Keunwoo Choi et al. *A Tutorial on Deep Learning for Music Information Retrieval*. 2018. arXiv: 1709.04396 [cs.CV] (cit. on p. 14).

[2] Joseph Colonel, Christopher Curro, and Sam Keene. *Autoencoding Neural Networks as Musical Audio Synthesizers*. 2018. eprint: 2004.13172 (eess.AS) (cit. on pp. 4, 5).

[3] Joseph T Colonel and Sam Keene. "Conditioning Autoencoder Latent Spaces for Real-Time Timbre Interpolation and Synthesis". In: *2020 International Joint Conference on Neural Networks (IJCNN)*. 2020, pp. 1–7. DOI: 10.1109/IJCNN48605.2020.9207666 (cit. on pp. 4, 5).

[4] Jesse H. Engel et al. "GANSynth: Adversarial Neural Audio Synthesis". *CoRR* abs/1902.08710 (2019). arXiv: 1902.08710. URL: http://arxiv.org/abs/1902.08710 (cit. on p. 3).

[5] Jesse H. Engel et al. "Neural Audio Synthesis of Musical Notes with WaveNet Autoencoders". *CoRR* abs/1704.01279 (2017). arXiv: 1704.01279. URL: http://arxiv.org/abs/1704.01279 (cit. on pp. 2, 3, 13).

[6] Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge. "Image Style Transfer Using Convolutional Neural Networks". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2016, pp. 2414–2423. DOI: 10.1109/CVPR.2016.265 (cit. on pp. 7, 8, 11).

[7] D. Griffin and Jae Lim. "Signal estimation from modified short-time Fourier transform". *IEEE Transactions on Acoustics, Speech, and Signal Processing* 32.2 (1984), pp. 236–243. DOI: 10.1109/TASSP.1984.1164317 (cit. on p. 14).

[8] Eric Grinstein et al. "Audio Style Transfer". In: *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. 2018, pp. 586–590. DOI: 10.1109/ICASSP.2018.8461711 (cit. on pp. 7, 9).

[9] Lamtharn Hantrakul et al. "Fast and Flexible Neural Audio Synthesis." In: *ISMIR*. 2019, pp. 524–530 (cit. on p. 3).

[10] Gerhard Heinzel, Albrecht Rüdiger, and Roland Schilling. "Spectrum and spectral density estimation by the Discrete Fourier transform (DFT), including a comprehensive list of window functions and some new at-top windows" (2002) (cit. on p. 16).

[11] G. E. Hinton and R. R. Salakhutdinov. “Reducing the Dimensionality of Data with Neural Networks”. *Science* 313.5786 (2006), pp. 504–507. DOI: 10.1126/science.1127647. eprint: https://www.science.org/doi/pdf/10.1126/science.1127647 (cit. on p. 13).

[12] Geoffrey E Hinton. “How neural networks learn from experience”. *Scientific American* 267.3 (1992), pp. 144–151 (cit. on p. 18).

[13] Justin Johnson, Alexandre Alahi, and Li Fei-Fei. “Perceptual losses for real-time style transfer and super-resolution”. In: *European conference on computer vision*. Springer. 2016, pp. 694–711 (cit. on p. 11).

[14] Michael I. Jordan and Christopher M. Bishop. “Neural Networks”. *ACM Comput. Surv.* 28.1 (Mar. 1996), pp. 73–75. DOI: 10.1145/234313.234348 (cit. on p. 18).

[15] joseph colonel joseph, christopher curro christopher, and sam keene sam. “improving neural net auto encoders for music synthesis”. *journal of the audio engineering society* (Oct. 2017) (cit. on p. 4).

[16] Xuehao Liu, Sarah Delany, and Susan Mckeever. “Sound Transformation: Applying Image Neural Style Transfer Networks to Audio Spectograms”. In: Aug. 2019, pp. 330–341. DOI: 10.1007/978-3-030-29891-3_29 (cit. on pp. 9, 11).

[17] Anastasia Natsiou, Luca Longo, and Sean O’Leary. *An investigation of the reconstruction capacity of stacked convolutional autoencoders for log-mel-spectrograms*. 2023. DOI: 10.48550/ARXIV.2301.07665 (cit. on p. 3).

[18] Keiron O’Shea and Ryan Nash. *An Introduction to Convolutional Neural Networks*. 2015. arXiv: 1511.08458 [cs.NE] (cit. on p. 18).

[19] Dhruv Ramani et al. “Autoencoder Based Architecture For Fast & Real Time Audio Style Transfer”. *CoRR* abs/1812.07159 (2018). arXiv: 1812.07159. URL: http://arxiv.org/abs/1812.07159 (cit. on pp. 8, 11, 13).

[20] Fanny Roche et al. *Autoencoders for music sound modeling: a comparison of linear, shallow, deep, recurrent and variational models*. 2019. arXiv: 1806.04096 [eess.AS] (cit. on p. 6).

[21] Prateek Verma and Julius O Smith. “Neural style transfer for audio spectograms”. *arXiv preprint arXiv:1801.01589* (2018) (cit. on p. 8).

Software

[22] Brian McFee et al. *librosa/librosa: 0.9.1*. Version 0.9.1. Feb. 2022. DOI: 10.5281/zenodo.6097378 (cit. on p. 15).

Online sources

[23] Dmitry Ulyanov and Vadim Lebedev. *Audio texture synthesis and style transfer*. 2016. URL: https://dmitryulyanov.github.io/audio-texture-synthesis-and-style-transfer (visited on 03/14/2023) (cit. on p. 10).

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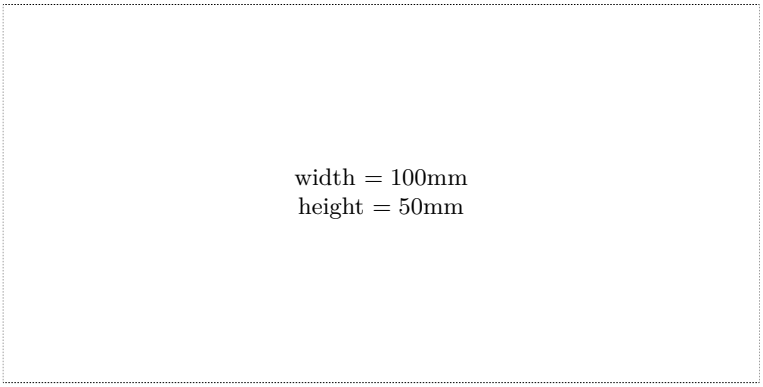

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