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TH Köln

Cologne University of Applied Sciences
Faculty of Computer Science and Engineering Science

M A S T E R T H E S I S

Texture Asset generation through Transformer Models

Cologne University of Applied Sciences
Campus Gummersbach
Master Digital Sciences

written by:
Dennis Gossler
11140150

First examiner: Prof. Dr. Olaf Mersmann
Second examiner: Prof. Dr. Boris Naujoks

Abstract

This thesis explores the adaptation of Transformer architectures, traditionally used in natural language processing, for generating texture assets in digital environments, such as video games. The primary focus is on developing and evaluating two novel models: the Column Image Transformer (CIT) and the Spiral Image Transformer (SIT). Both models aim to generate texture assets from seed images, photos, or drawings.

The CIT model processes images by segmenting them into vertical columns and predicts subsequent pixels within a column using the context provided by previous pixels. In contrast, the SIT model analyzes pixels in a spiral pattern to capture a broader context within the image, which can be important for generating complex textures. These models were trained on a high-performance computing system, utilizing a dataset consisting of various game textures.

Experimental results indicate that both models have a basic understanding of the colors, positions, and space of texture assets. With further work, such as using a larger dataset and scaling up the models, high-quality images could be generated and produced. Additionally, future work could explore the integration of text descriptions to guide texture generation, potentially enhancing the models utility in real-world applications.

This study showcases a preliminary exploration into the feasibility of using Transformer models for graphic content generation and points to further research into their practical applications.

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1 Introduction

Transformers are widely used in the generation of text for large language models (LLMs), such as GPT (Radford et al., 2019), LaMMA (Touvron et al., 2023), among others. This thesis aims at extending the application of traditional Transformer-based architectures to generate texture assets, a significant departure from the conventional image-generating methods that primarily rely on stable diffusion techniques or Generative Adversarial Networks (GANs).

The primary objective of this study is to develop a model capable of continuously generating textures for a given seed image or drawing, thereby providing a simple method for video game prototyping to generate texture assets. This approach is analogous to text generation in LLMs, where the model expands upon an initial sentence. To realize this, two distinct models have been developed and trained, each incorporating unique adaptations to leverage the inherent advantages of Transformer-based models in texture generation.

The first model named the Column Image Transformer (CIT), processes images by segmenting them into vertical columns. This design allows the model to predict subsequent pixels within a column using the context information provided by previous pixels.

The second model, the Spiral Image Transformer (SIT), analyzes pixels in a spiral pattern. This approach enables the model to consider both the immediate neighborhood and the broader context of the image, potentially enhancing the texture generation process.

This thesis showcases the steps involved in collecting and preprocessing the data and developing the models. The models are trained on a high-performance computing system, and their effectiveness is evaluated using various metrics. The end of the thesis concludes with an evaluation of the strengths and weaknesses of each model, offering insights into potential areas for further improvement.

1.1 Research Questions

Building on the developed models, this thesis explores several research questions to assess the viability and effectiveness of the two mentioned models. The investigation begins by examining whether the Column Image Transformer (CIT) and Spiral Image Transformer (SIT) are technically feasible for generating texture assets for video games, including identifying specific challenges in adapting Transformer architectures from text to image texture generation.

The study also evaluates the performance of these models in producing coherent and continuous textures, identifying appropriate metrics for assessing their effectiveness and comparing these results to traditional methods such as stable diffusion and GANs. Further, it examines the scalability of the models and discusses their potential deployment on a local machine or cloud-based infrastructure.

Lastly, the possibility of further improvements is discussed. The final question will explore potential modifications to the model architecture that could enhance the model's performance and efficiency in generating textures for video games.

1.2 Related work

The exploration of machine learning models for image generation has been a significant area of research lately, with notable advancements from Generative Adversarial Networks (GANs) to state-of-the-art diffusion models like DALL-E, Midjourney and many more. This section reviews the seminal works and recent innovations in the field, particularly focusing on image/texture generation and the application of Transformer models in the context of images, laying the foundation for the current studies approach to image generating.

Generative Adversarial Networks (GANs): Since their introduction by Goodfellow et al. (Goodfellow et al., 2014), GANs have been a cornerstone in the field of generative models, especially for image generation tasks. Works by Radford et al. (Radford et al., 2016), introducing the DCGAN architecture, demonstrated the potential of GANs in producing high-quality images. The adaptability of GANs has been explored in various contexts, including texture synthesis (Xian et al., 2018), showcasing their capability to generate seamless textures for different materials.

Diffusion Models: Diffusion models represent a cutting-edge development in the field of generative models, that demonstrate remarkable capabilities in image generation by iterative denoising a random signal to produce detailed images. The process, initially introduced by Sohl-Dickstein et al. (Sohl-Dickstein et al., 2015), involves gradually adding noise to an image across several steps and then learning to reverse this process. Stable diffusion, a term often associated with these models, refers to the techniques ability to maintain stability throughout the noise addition and removal process, ensuring high-quality image synthesis. The paper "Diffusion Models Beat GANs on Image Synthesis" (Dhariwal & Nichol, 2021) further refined this concept with models like DDPM, showcasing exceptional fidelity in generated images. This approach contrasts traditional models by focusing on the controlled removal of noise, leading to the generation of coherent and visually impressive images.

Transformers in Image classification: The success of Transformer models in natural language processing, as seen with architectures like GPT (Radford et al., 2019) and LaMMA (Touvron et al., 2023), has inspired their application in image-related tasks. The Vision Transformer (ViT) by Dosovitskiy et al. (Dosovitskiy et al., 2021) marked a significant leap, applying Transformers directly to sequences of image patches for classification tasks.

Texture Generation with Transformers: TransGAN by Jiang et al. (Jiang et al., 2021) revolutionizes image generation with a Transformer-based GAN architecture, moving beyond traditional Convolutional neural network (CNN) approaches. It features a memory-efficient generator and multiscale discriminator, both utilizing transformer blocks. The TransGAN model produces high-quality images, showcasing the potential of Transformers

1.3 Infrastructure for Model Development

To develop and train the models in this thesis, a powerful computing infrastructure is necessary to manage the extensive datasets and the substantial computational requirements for model training. Unlike conventional development environments where a standard laptop or desktop may suffice, most of the models in this thesis demand a more capable infrastructure. Therefore, the high-performance computing system (NHR) at Zuse Institute Berlin (ZIP) is used for the model training processes. This system contains an array of (NVIDIA Tesla A100 80 GB) GPUs, (INTEL Ice Lake 8360Y) CPUs and a significant quantity of RAM. Such a configuration, especially the substantial GPU memory, enables the training and execution of larger models than would be possible on a home workstation. The development of these models is carried out using Python and PyTorch, with the code being developed in Visual Studio Code and managed through version control with Git. The model development and initial code testing are done on a local machine, reserving the high-performance system exclusively for the final training phases. This approach diverges from standard practices, where often both development and execution occur on the same development platform. Ensuring the code is free of errors prior to giving the task of training the model to the high-performance computing system is crucial, as discovering bugs in the training process can be exceedingly time-consuming. For instance, to endure a training session that extends for 24 hours, only to realize it terminated prematurely due to script errors.

1.4 Training Data and Data Analysis

This section describes the methods used for gathering, cleaning, and analyzing data for this thesis.

1.4.1 Data Acquisition

On the internet, a wide variety of game textures can be found, but not all of them are suitable for this task. The textures collected should be seamless, devoid of shadows, and free from any objects. Textures of floors, such as carpets, tiles, wood, concrete, and more, are utilized. Two approaches are employed to acquire the data for this thesis.

- Web Data Collection

  Some data for this project was obtained from various online sources. Numerous free texture providers are utilized for data acquisition. Due to the limitation of downloading one texture at a time from most websites, a series of scripts are developed to compile a list of suitable textures and automate the downloading process. These scripts are created using UiPath and Python.

- Video Game Textures

  The second approach involved using textures from video games. The advantage of this approach is that it allows for the acquisition of many textures simultaneously. However, a drawback is that these collections of textures include normal maps, height maps, and many other assets that are not suitable. And needed to be filtered and hand-sorted.

1.4.2 Data Cleaning

To ensure that the data is consistent and free from elements that could corrupt the model, various cleaning steps were applied. For example, all images containing 3D objects were removed. To obtain the cleaned textures from the video game sources, a Python script is used to discard images containing certain keywords like '_no.png', '_spec.png', and many others. Additionally, an image should contain a keyword like 'floor', 'wall', 'wood', or 'stone'. In summary, 129 good keywords and 56 bad keywords were utilized. The major challenge with this approach is that you can't filter with 100% accuracy, so all textures are manually checked. In addition, some textures are only usable as overlays for 3D models and aren't supposed to be flat 2D images on their own. So, these are also filtered out. In total, only 20-30% of textures from a video game are viable for use in this thesis.

In the case of web-gathered textures, the textures are often in different folder structures.

Therefore, it was necessary to standardize them across all data folders. Additionally, some of them had associated files that were irrelevant to this use case and needed to be discarded.

Finally, the images are cropped to 512x512 or 1024x1024 pixels. In total, 57454 images of size 512x512 were collected and 12600 being of size 1024x1024 pixels from 34 sources. The sources are summarized in Table 1.

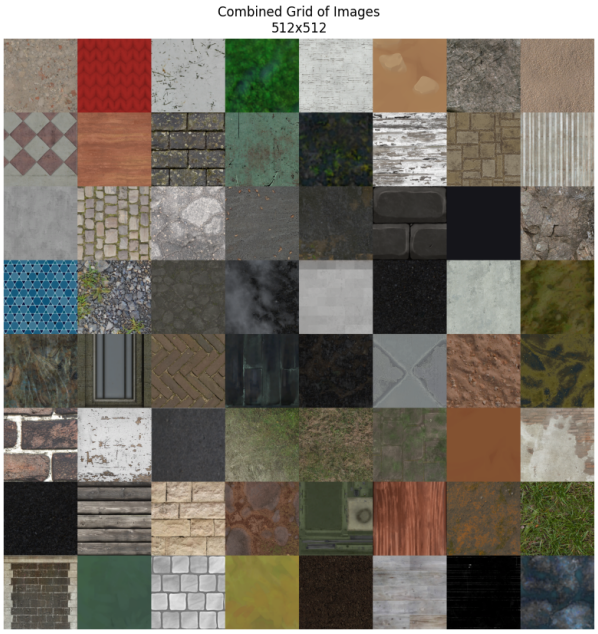


Figure 1: Combined Sources 512x512

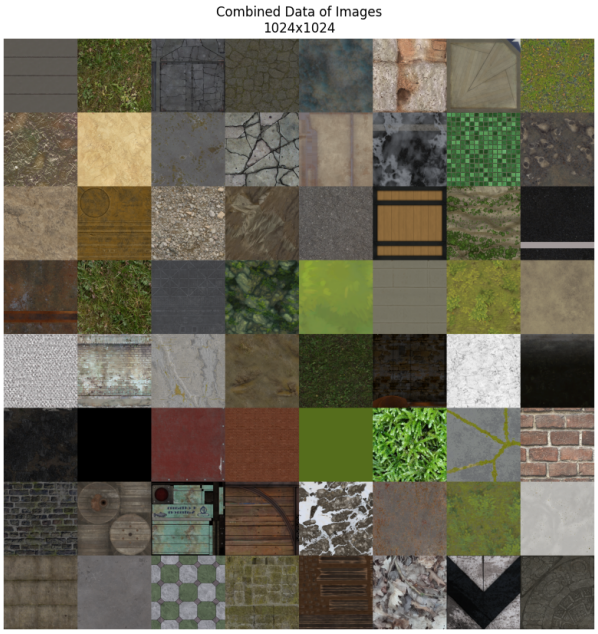


Figure 2: Combined Sources 1024x1024

Source	Type	Number of Images [size 512x512]	Number of Images [size 1024x1024]
0	Game assets	56	14
1	Game assets	3,236	809
2	Game assets	2,152	539
3	Game assets	184	46
4	Game assets	1808	452
5	Game assets	100	25
6	Game assets	309	71
7	Game assets	4154	809
8	Game assets	16	4
9	Game assets	1,084	271
10	Website	1,052	263
11	Game assets	102	20
12	Game assets	1,334	36
13	Game assets	409	24
14	Game assets	76	19
15	Game assets	5,789	628
16	Game assets	632	158
17	Game assets	1	—
18	Game assets	1,984	491
19	Website	196	49
20	Website	1,756	439
21	Game assets	643	110
22	Game assets	69	—
23	Game assets	1,656	414
24	Game assets	4,188	1,047
25	Game assets	24	6
26	Game assets	2,980	745
27	Game assets	996	14
28	Game assets	492	123
29	Game assets	2,096	524
30	Website	17,816	4,434
31	Game assets	8	2
32	Game assets	4	1
33	Game assets	52	13
Total	Game assets	36,634	7,415
	Website	20,820	5,185
Total		57,454	12,600

Table 1: The Dataset collected for this thesis

1.4.3 Patterns in the data

To examine whether the dataset encompasses a broad spectrum of colors, multiple plots are created. These plots illustrate the color distribution within the datasets, providing insights into the diversity of colors present. Prior to plotting, the colors of the pixels are counted across all images. For instance, if an image features 10 pixels of the color $(255, 0, 0)$, this count is added to a dictionary. Should the subsequent image in the dataset contain 5 pixels of the same color, these are also incorporated into the dictionary, cumulating a total of 15 for that specific color. This process is repeated for each color encountered,

aggregating the counts to yield the overall color frequency within the dataset.

```
color_counts = {}
for i, (data, _) in enumerate(dataset):
    # data is a tensor of shape (3, height, width)
    pixel_rgb_array = (data.view(3, -1).t() * 255).to(torch.int32)

    for pixel_color in map(tuple, pixel_rgb_array):
        if color in color_counts:
            color_counts[pixel_color] += 1
        else:
            color_counts[pixel_color] = 1
```

Figure 3: Python code to count the color frequency in a dataset

After analyzing the dataset through this method, visual representations of the color distributions were produced using Python, Seaborn and Matplotlib.

1.4.4 Data Lab plots

The following plot illustrates the color distributions of the whole dataset in the lab color spectrum.

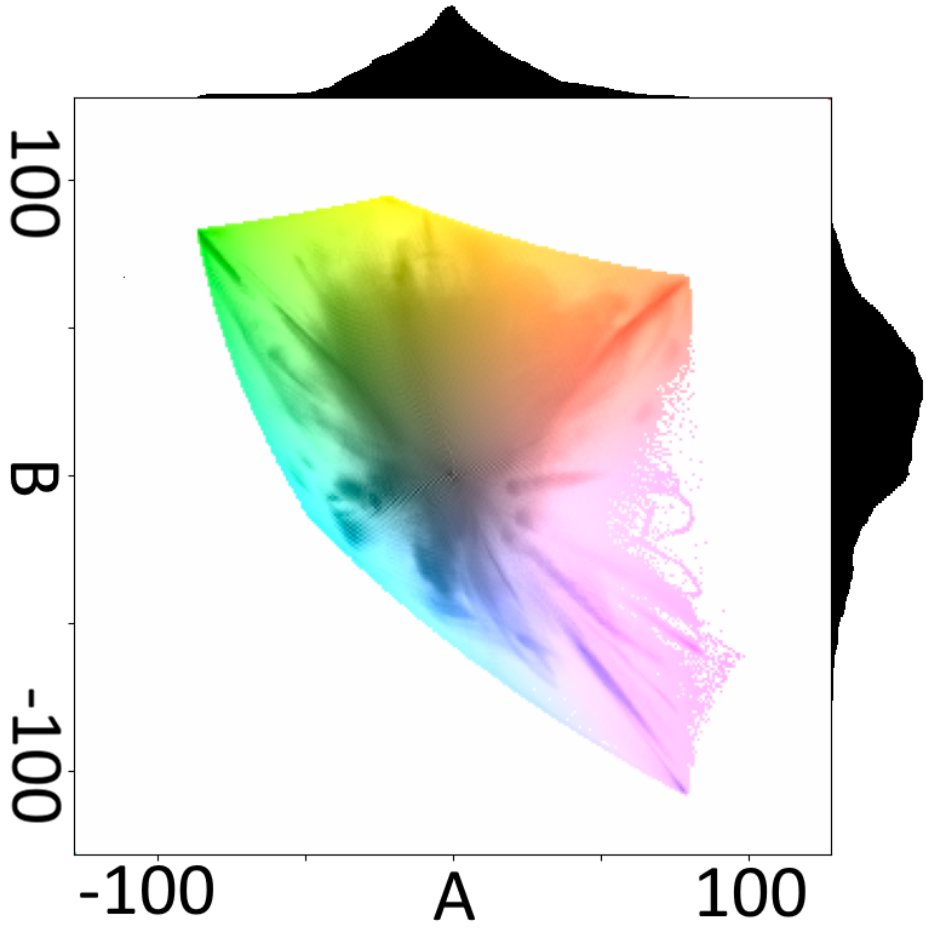


Figure 4: Color distribution of the dataset in the LAB color space

This visualization primarily consists of a central plot complemented by two histograms on its top and right sides. The central plot is a color map representing the distribution of colors from the original data in the CIELAB (Lab) color space, specifically focusing on the 'a' and 'b' components. The 'a' axis (horizontal) indicates the position between green and red colors, while the 'b' axis (vertical) shows the position between blue and yellow colors.

The color map itself is constructed by converting Lab color values back into the RGB color space for display. Colors are distributed across this plot based on their 'a' and 'b' values, with the lightness ('L' component of Lab) squeezed into the 2D plane. The areas with no data are shown in white.

The histograms on the top and right sides of the central plot provide additional context by showing the distribution of 'a' and 'b' values across the dataset. They are weighted by a logarithmic transformation of the count of colors. This logarithmic scaling helps to highlight patterns in the data without allowing very high or very low counts to dominate

the visualization.

The plot demonstrates that the dataset encompasses a broad array of colors, with a significant quantity of colors spread throughout the entire spectrum. However, the histograms on the sides suggest that the dataset primarily consists of colors in the middle of the spectrum, indicating that it is not overly colorful but leans more toward the white/gray/black spectrum. This could be attributed to the fact that most of the textures are floor textures, which are typically not very colorful. All the various sources are presented as a lab plot in the appendix; see Section A.1.

1.4.5 Data RGB plots

The second plots provide a three-dimensional view of the RGB color space, where the X, Y, and Z axes correspond to the red, green, and blue color values, respectively, each ranging from 0 to 255.

$$\text{size} = \log(\text{count of color}) \times 20$$

The size of each plotted point is determined by the logarithm of the color count, scaled by a factor of 20. See Figure 25 for the combined color distribution of all sources. There, it is also clearly visible that most of the sources are not very colorful, leaning more towards the white/gray/black color spectrum.

1.5 Image Transformers Models

This chapter explores the standard Large Language Models (LLMs) and their transformative applications, and later delves into the modifications required to process images and generate images. Furthermore, this chapter introduces the Column Image Transformer (CIT) and the Spiral Image Transformer (SIT) models, which are the primary focus of this thesis.

1.5.1 Large Language Models (LLMs)

Large Language Models (LLMs) are a class of machine learning models that have gained significant attention in recent years due to their ability to generate coherent and contextually relevant text. These models are trained on vast amounts of text data, enabling them to understand and generate human-like text. The GPT model by OpenAI (Radford et al., 2019) is a prominent example of an LLM, capable of generating human-like text and performing a wide range of language-related tasks. Like LLMs, the models developed in this thesis predict the next thing in a sequence. But instead of predicting the next word in a sentence, they predict the next pixel in an image. This is achieved by treating the image as a sequence of pixels and using the transformer architecture to predict the next pixel in the sequence.

1.5.2 Adapting Transformer Architecture for Image Prediction

The Transformer architecture, introduced by Vaswani et al. (Vaswani et al., 2023), has significantly impacted the field of natural language processing (NLP). Its widespread adoption across a variety of language tasks, such as machine translation and text generation, highlights its transformative influence. At the heart of the transformer's success is the self-attention mechanism, which allows the model to weigh different portions of the input data dynami-cally. This critical feature enables the detection of long-range dependencies and a deeper understanding of the context within the input, making the architecture highly effective for complex NLP tasks.

Building upon this foundation, this thesis explores the extension of the Transformer architecture from its traditional role in NLP to the domain of image prediction. This adaptation employs the architectures fundamental principles, especially the self-attention mechanism. By treating images as sequences of pixels, the Transformer architecture is applied to predict subsequent pixels in an image sequence, showcasing its potential versatility beyond text-based applications.

1.5.3 Column Image Transformer

In the context of this thesis, a model termed the Column Image Transformer (CIT) has been conceptualized and developed. This model embodies an adaptation of the conventional transformer architecture. Distinctively, the CIT model diverges from traditional image processing techniques by segmenting the image into vertical slices or columns of pixels. This segmentation allows for a method where each column is processed on its own.

The adaptation of self-attention for image prediction involves sequentially processing the image, similar to text in natural language processing. However, instead of words or characters, the sequence consists of pixels. In the Column Image Transformer (CIT) model, the image is divided into columns, and the self-attention mechanism is applied to understand the relationships between pixels within each column. This should enable the model to predict the properties of subsequent pixels in a column by considering the context provided by preceding pixels.

1.5.4 Spiral Image Transformer

The second approach is represented by the Spiral Image Transformer (SIT). Unlike its predecessor, the Column Image Transformer (CIT), the SIT model employs a contextually spiral pattern. This architecture enables the generation of images starting from a central point and expanding outward, see Section 2.3.2. In the SIT model, the batch dimensions correspond to distinct images, whereas the H dimension represents the spiral context. Similar to the CIT model, the C dimension denotes the color channels.

One of the pivotal enhancements of the SIT model is its ability to analyze adjacent pixels on the horizontal axis, in contrast to the CIT model's limitation to columnar pixel analysis. This feature is particularly beneficial for interpreting textures with intricate patterns, such as diagonal ones, thereby offering an advantage over the Column Image Transformer. However, it is important to note that the SIT model operates within a constrained area of the image due to its 2D context. This limitation necessitates the use of only a portion of the image area, specifically a sector determined by the square root of the total area available to the Column Image Transformer (CIT), with an equal context length.

In the Spiral Image Transformer (SIT) model, the self-attention mechanism is adapted to analyze pixels in a spiral pattern. This approach allows the model to evaluate the context in a manner that incorporates both the immediate neighborhood and the broader context of the image, facilitating the prediction of pixel properties in a way that captures complex, two-directional patterns and textures. The self-attention mechanism's ability to

dynamically focus on different parts of the spiral sequence should enable these models to generate coherent predictions for the next pixel, based on the learned importance of each pixel to the others.

2 Experiment

This section focuses on the implementation and the tests conducted to evaluate if the models work properly. This includes the data handling, logging, the training process, and the evaluation steps taken of the models.

2.1 The Foundation of the Models

To build the models, a set of Python libraries is utilized, mainly PyTorch, NumPy, TensorBoard, and Einops. PyTorch serves as the core tool for constructing and training the models.

The transformer models code discussed in this thesis is based on a Python script by A. Karpathy named NanoGPT (Karpathy, 2023a). This script implements a straightforward LLM (Large Language Model) approach, and it has been modified to meet the specific needs of the discussed models. However, the underlying transformer architecture remains unchanged.

2.1.1 Data Handling

For data management, a script named dataSetCombiner is developed to load and return a combined dataset from specified image folders with optional transformations. The function combines the 33 different sources from multiple directories into a single dataset, also offering the option to apply various image transformations.

It allows for the selection between the 512x512 and the 1024x1024 pixel dataset, depending on the use case. Parameters can be adjusted to tailor the dataset to specific needs, such as image size, the particular dataset to load, and the option to include multiple instances of the dataset. Furthermore, it can randomly flip images vertically or horizontally to augment the dataset, thereby preventing overfitting and improving model generalization. It also supports color jittering, allowing for random adjustments in image brightness, contrast, saturation, and hue, which introduces further variability into the dataset when needed. Additionally, an option to convert images to grayscale is available.

```
1    def getDataSet(path, dataset_name, size_x, size_y, repeatData=1,
     random_vertical_flip=False, random_horizontal_flip=False, crop_type='
     random', grayscale=False, color_jitter=False, jitter_brightness=0,
     jitter_contrast=0, jitter_saturation=0, jitter_hue=0):
```

Figure 5: Python function declaration: getdataset

2.1.2 Monitoring Training Progress

The training process is monitored using TensorBoard, a tool that helps visualize different aspects of training. In this thesis, TensorBoard is particularly useful for tracking training and validation loss through plots. It also allows for the viewing of the input images and the outputs generated by the models.

Secondly, the training progress is monitored by logging the training process. This is helpful because the console output is not accessible until the training has finished on the external Slurm cluster. Logging is performed using the Python logging library. Additionally, all hyperparameters are logged to the log file at the start of the scripts.

2.1.3 Multi GPU Training

To enhance the training speed of larger models, utilizing multiple GPUs can be significantly more efficient. Consequently, the model's code is adapted to support multi-GPU training while maintaining the original core structure. Necessary adjustments were made to the data DataLoader, logger, and trainer. For distributed training across multiple GPUs, the PyTorch library Distributed-Data-Parallel (DDP) is used. This implementation draws on guidelines from the PyTorch documentation (Subramanian, 2023). The larger models are trained on an external Slurm cluster equipped with four A100 Tesla GPUs.

2.1.4 Generation of Assets

Similar to conventional text-based transformer models, this model generates assets pixel by pixel. Thus, the model is provided with some pixels, denoted as $\mathbf{x} = (x_1, x_2, \ldots, x_n)$. It then predicts the next pixel, x_{n+1}, based on the learned training data. During generation, the last predicted pixel is appended to the existing sequence, and the updated sequence is used for subsequent predictions.

$$\mathbf{x}' = \mathbf{x} \cup \{x_{n+1}\}$$

This process is repeated until the desired image size is achieved. Consequently, the model can generate assets of the specified size. This approach is utilized for both the CIT and the SIT models.

2.2 Column Image Transformer

The Column Image Transformer (CIT) is the first transformer-based model approach in this thesis. It processes input data in a columnar format as examined in the previous section in more detail see Section 1.5.3.

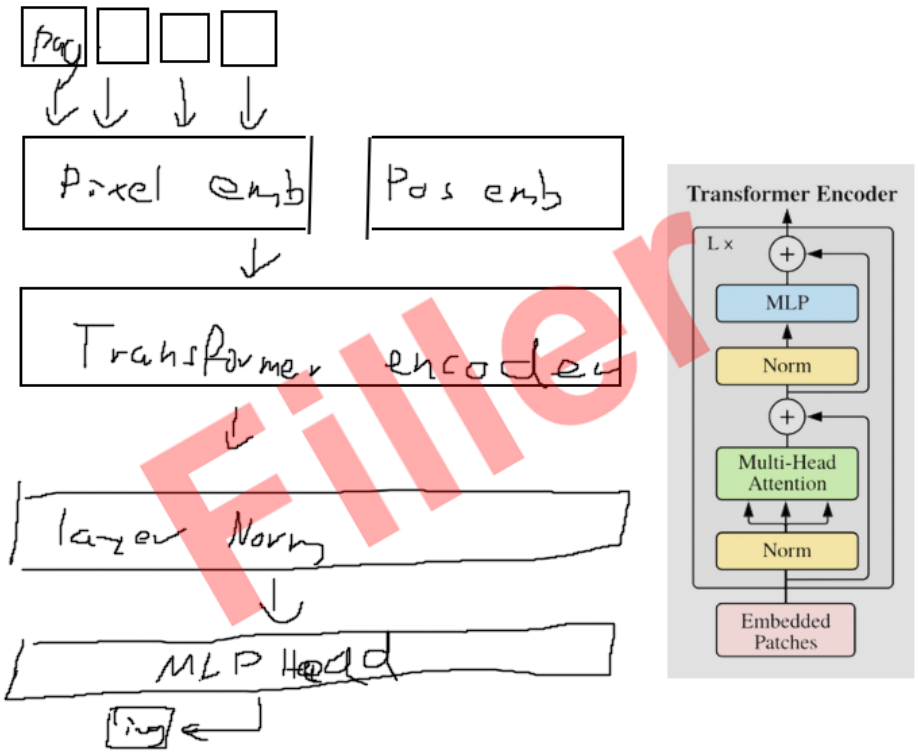


Figure 6: Column Image Transformer model structure

The image above shows the steps carried out by the CIT model. The input data is reshaped into a columnar format, which is then embedded into a higher-dimensional space. The positional embedding layer adds positional context to the input data. The transformer layer processes the data, and the output is then transformed back into a columnar format. After going through a final layer normalization and another MLP that converts back from the embedded layer to 3 colors, the model is trained using a Mean Squared Error (MSE) loss function.

2.2.1 Get Data as Columns

The data is loaded into a DataLoader object as described in Section 2.1.1 and iterated over to extract it as a 4-dimensional tensor (Batch, Color Channels, Height, Width). This data is reshaped into a columnar format, resulting in two tensors: the *source* and *targets*, both with the shape (Batch, Height, Color Channels). The target tensor is shifted one

pixel downwards to the prediction of subsequent pixels by the model. This reshaping and shifting method is commonly employed in transformer-style learning because it enables the model to process data more efficiently in terms of computational speed and resource utilization. The source tensor is then fed into the model, and its output is compared against the targets using the Mean Squared Error (MSE) loss function.

```
# data: (Batch, Color, Height, Width)
def get_batch(data):

    source = data[:, :BLOCK_SIZE, :BATCH_SIZE]
    targets = data[:, 1:BLOCK_SIZE+1, :BATCH_SIZE]

    source = rearrange(source, 'c h b -> b h c')
    targets = rearrange(targets, 'c h b -> b h c')

    return source, targets
```

Figure 7: Python function to convert data into a columnar format

2.2.2 Pixel Embedding

The *source* data is embedded into a higher-dimensional space using pixel embedding layers. This MLP is a straightforward linear layer that maps the input data to a higher-dimensional space, transitioning from 3 color channels to N_{EMBD}. This layer consists of a linear transformation followed by a ReLU activation function and is succeeded by a dropout layer.

Through testing and experimentation, it seems that the optimal configuration for the pixel embedding layer involves a sequence of dimensionality increases. The most effective pathway identified begins by scaling the dimensionality of the input from the original image channels C to one-fifth of N_{EMBD} ($\frac{1}{5}N_{\text{EMBD}}$), then increasing it to one-half of N_{EMBD} ($\frac{1}{2}N_{\text{EMBD}}$) until reaching N_{EMBD}. The pixel embedding layer is followed by a dropout layer with a dropout rate of 0.2. See Figure 8.

It is crucial to highlight the importance of not using a layer normalization (layernorm) layer in the initial few layers of the model. Incorporating a layernorm layer too early results in outputs that are predominantly black and white. This phenomenon occurs because the color channels C, which are comprised of red, green, and blue, are normalized by the layernorm layer to exhibit uniform values across these channels. As a consequence, this normalization process hinders the model's ability to learn the distinct colors of the pixels, relegating it to only wrong grayscale variations.

2.2.3 Positional Embedding

The positional embedding layer in this model utilizes a learnable embedding matrix of size BLOCK_SIZE times N_{EMBD}, where BLOCK_SIZE represents the context length, or the height of an image. This layer operates by assigning each position within this vertical context a unique embedding vector, thereby mapping the original pixel positions to a high-dimensional space characterized by N_{EMBD} dimensions. The integration of these positional embeddings is achieved through their direct addition to the output of the pixel embeddings, effectively enhancing the model's ability to maintain positional awareness across the image height.

```
class ColumnTransformer(nn.Module):
    self.pixel_embedding = nn.Sequential(
        nn.Linear(CHANNELS_IMG, N_EMBD//5, device = device),
        nn.ReLU(),
        nn.Linear(N_EMBD//5, N_EMBD//2, device = device),
        nn.ReLU(),
        nn.Linear(N_EMBD//2, N_EMBD, device = device),
        nn.Dropout(DROPOUT),
    )
    self.position_embedding_table = nn.Embedding(BLOCK_SIZE, N_EMBD)
    #[...]

def forward(self, source, targets=None):

    # tok_emb: (B, H, N_EMBD)
    tok_emb = self.pixel_embedding(source)

    # pos_emb: (H, N_EMBD)
    pos_emb = self.position_embedding_table(torch.arange(H))

    # x: (B,H,N_EMBD)
    x = tok_emb + pos_emb
    #[...]
```

Figure 8: Python code snippet for the positional / pixel embedding layers

2.2.4 Transformer Layer

The transformer layer forms the core of the model's architecture and is crucial for processing the data. It utilizes self-attention mechanisms (Vaswani et al., 2023) to weigh the importance of different pixels relative to each other, allowing the model to focus on relevant parts of the input when predicting the next pixel in a column.

In this model, each transformer layer receives the input from the previous layer. The layer then processes this input using a multi-head attention mechanism, which allows the model to capture various aspects of the input at different positions simultaneously. This is followed by a series of normalization and feed-forward layers. All are combined into a block that is repeated multiple times. See Section A.6 for the code snippet.

2.2.5 Output Layer

The output layer is like the pixel embedding a simple MLP that converts the data back to the original color space. It has the same structure but reversed like the Pixel Embedding layer but with the output dimensionality set to 3, representing the red, green, and blue color channels. After the shrinkage of the dimensionality, the output is passed through one final sigmoid to map the resulting colors to 0-1.

2.2.6 Sigmoid Compared to Clamp

Due to discoloration issues in the model output, the performance has been evaluated using two different activation functions: sigmoid and linear clamp. The sigmoid function typically maps input values to a range between 0 and 1. However, in the context of color values, this compression into the [0, 1] range can prevent achieving true black and white colors, as inputs need to be extremely large or small to reach the extremes of 0 or 1. Initially, the linear clamp function, which restricts input values to a specified range without compression, seemed to better preserve the distinct black and white colors. However, it has several notable disadvantages, such as the issue of vanishing gradients during backpropagation. A problem where gradients become so small during backpropagation that the model stops learning. This occurs because the derivative of the clamp function outside its bounds is zero, which stops the gradient flow and prevents weights from updating. Consequently, layers deeper in the network receive minimal or no updates, hindering the models training process.

In discussions about this problem, it was suggested that the lack of training data featuring significant black and white samples might be a contributing factor. After collecting more data and expanding the training set, the issue was resolved, and the model performance with the sigmoid activation function became very similar, showing improvement comparable to the clamp function.

2.2.7 Discoloration in the Model Output

The model faces similar discoloration issues as mentioned in section Section 2.2.6 with certain colors. When the model starts with a random pixel, it often struggles to consistently generate the intended pattern in that color or starting pattern. Some evidence

suggests that the training set may be too small, as the issue was less noticeable with a larger dataset. Generally, transformers require significantly more data to improve performance (Chen et al., 2022). However, this problem has not yet been resolved, and further research is needed.

2.2.8 Training the Model

The training process starts by selecting the hyperparameters and arguments for the model. To test the basic functionality of the model, the training process is kept simple, and they are trained on a single GPU. Most of the training is done via the Slurm cluster, which uses a batch script to configure the hardware and training parameters. All the relevant trained models [model 0-4] with their corresponding parameters can be found in detail in the appendix, see Section A.3.

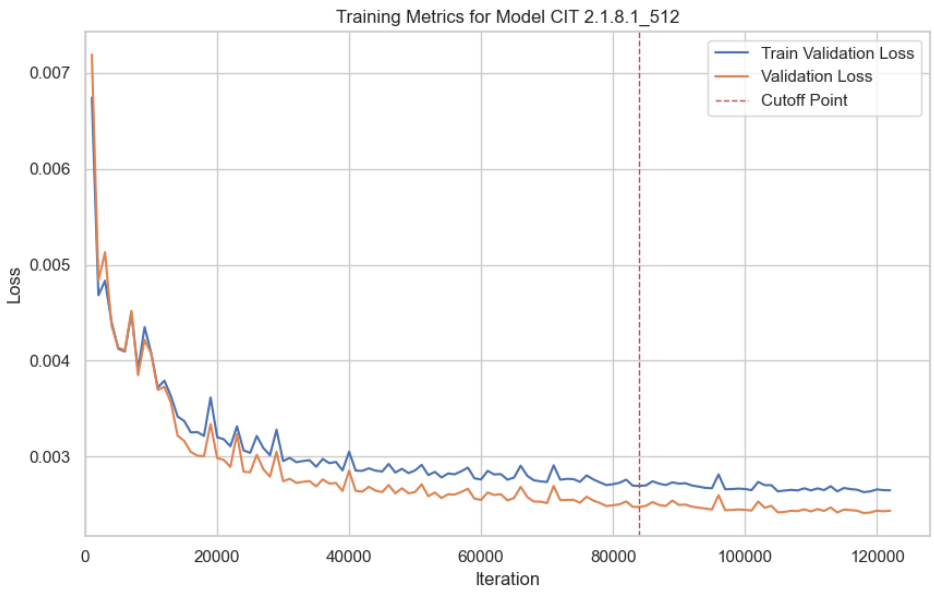


Figure 9: Loss plot of the CIT [model 4]

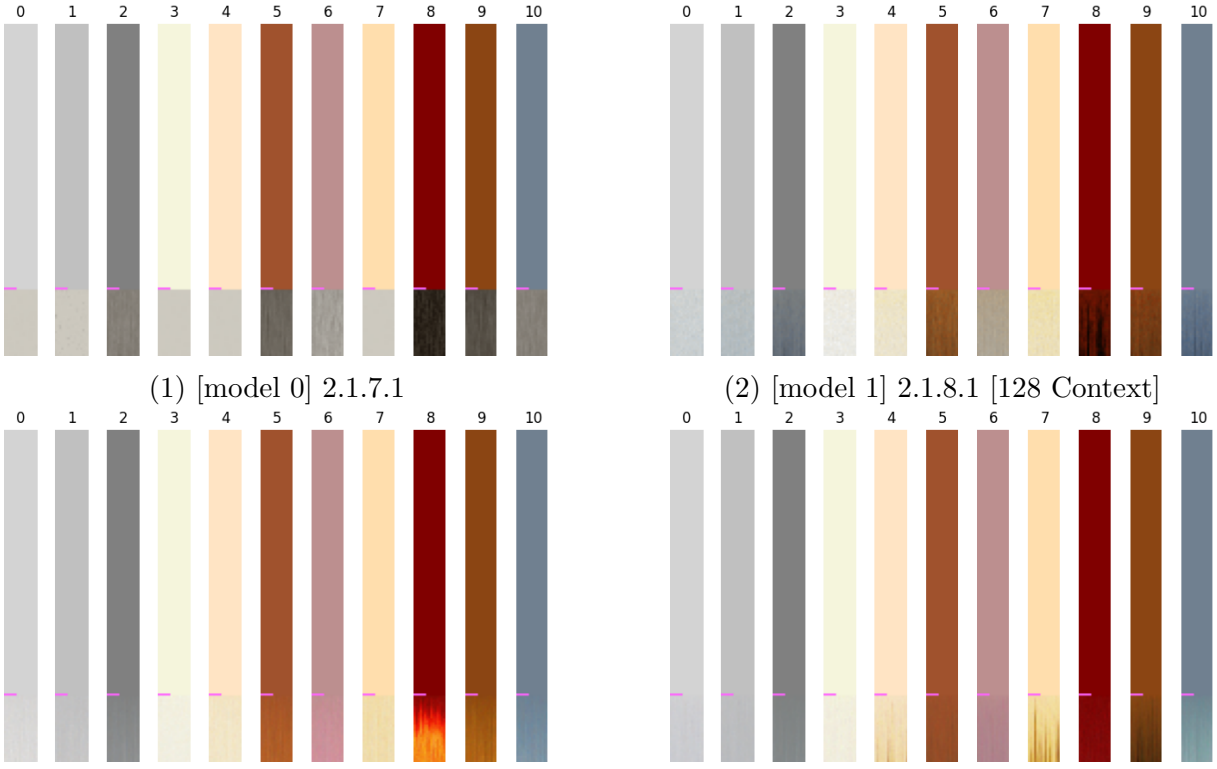
The figure above displays the training metrics for the Column Image Transformer [model 4] CIT 2.1.8.1_512, illustrating the loss over iterations during the training phase. The blue line signifies the training validation loss, and the orange line represents the validation loss throughout the training iterations. The graph shows a consistent decline in both metrics, indicating that the model is learning and improving its predictive accuracy over time. The 'Cutoff Point,' indicated by the dashed red line, marks the iteration at which the model is used in the examples presented in this thesis since it has not shown further improvement beyond this point. An unusual behavior observed is that the validation loss is lower than the training validation loss, which is uncommon. This could be the case due to various factors, such as a high dropout rate and needs further investigation.

2.2.9 Experimental Results

Multiple experiments are conducted to evaluate the performance of the CIT model. These experiments are designed to test the model's ability to generate images, the quality of the generated images, and the model's performance across different scenarios. The results are analyzed to identify the strengths and weaknesses of the model.

In each test, the end of the seed pixels are marked with a purple line on the left side of the image.

- **Color test:** To assess the model's capability to generate specific colors, it is challenged with 11 different images with a width of 32 and a height of 128 pixels. Each test image is composed of a single color filling 128 positions in the model's context. The model then generates the next 32 pixels for each image.



(1) [model 0] 2.1.7.1 (2) [model 1] 2.1.8.1 [128 Context]

(3) [model 2] 2.1.8.1 [256 Context] (4) [model 4] 2.1.8.1 [512 Context]

Figure 10: Color test with four different models

As shown in the images above, model [0] struggles to generate the correct colors due to the limited size of its old small dataset compared to Models [1-3]. Model [1] generally produces accurate colors but faces difficulties with some. Model [2] generates all colors correctly, but inconsistencies start appearing in column 8. The model may begin changing colors due to its training to recognize patterns such as flowers or carpets in the training data. Model [4] consistently generates the correct

colors but begins to create patterns in some columns, potentially indicating that the model is overfitting.

- **Zebra pattern test:** The second test assesses whether the model can generate a zebra pattern. The model is provided with both a vertical and a horizontal test image featuring black and white stripes, each stripe being 4 pixels wide. It then generates the next 32 pixels.

(1) [model 0] 2.1.7.1 (2) [model 4] 2.1.8.1 [512 Context]

Figure 11: Zebra test vertical with two different models

As shown in the images above, the model with the newer dataset model[4] generates the colors in the zebra pattern more accurately than the model with the older dataset model[0]. Models [0-2] perform similarly. The vertical test is particularly interesting to observe when the column model is altered to see pixels from both the left and the right sides of the current column, assessing whether it can still perfectly continue generating the pattern.

(1) [model 1] 2.1.8.1 (2) [model 4] 2.1.8.1 [512 Context]

Figure 12: Zebra test horizontal with two different models

Unfortunately, the model struggles to generate the zebra pattern horizontally. The

model with the newer dataset model [4] more accurately renders the colors in the zebra pattern than the model with the older dataset model [0], but both models struggle to correctly continue the pattern. Model [4] can recognize that the next pixel in the pattern should be dark but quickly loses context. This could be due to the dataset being too small or the model size being insufficient to fully understand the pattern. The images suggest that model [4] is better than model [1] but still fails to generate the pattern correctly.

2.2.10 Challenges and Limitations

The CIT model has some limitations and challenges that require attention. The primary issue is its limited context to only one column, which hampers its ability to generate complex patterns requiring a broader visual spectrum. Additionally, similar to some text-based Transformer models, the CIT model struggles with generating coherent long sequences, often using its recent outputs as a basis for predicting subsequent pixels. This can lead to errors accumulating over time, particularly evident in longer image sequences where the model fails to maintain the specific pattern.

To address these limitations, methods used in text-based models, such as scaling up the model size and expanding the training dataset, can be considered. Scaling the model could involve increasing the dimensionality of the embeddings or adding more layers, which might help the model capture more complex dependencies. However, expanding the dataset was not feasible in this thesis due to time constraints and the extensive duration of the dataset collection process.

Introducing a text prompt feature could significantly enhance the usability and flexibility of the CIT model. This feature would allow users to guide the generation process using descriptive language, making it easier to specify desired outcomes without relying solely on seed pixels. Such a capability would not only improve user interaction but could also potentially help the model deal with complex pattern generation by providing additional contextual information. Exploring this possibility could be a valuable direction for future research.

2.3 Spiral Image Transformer

The Spiral Image Transformer, as implied by its name, is a transformer-based model specifically designed to process image data by unrolling pixels in a spiral pattern. This approach stands in contrast to the CIT Model, which processes data using a column-by-column method.

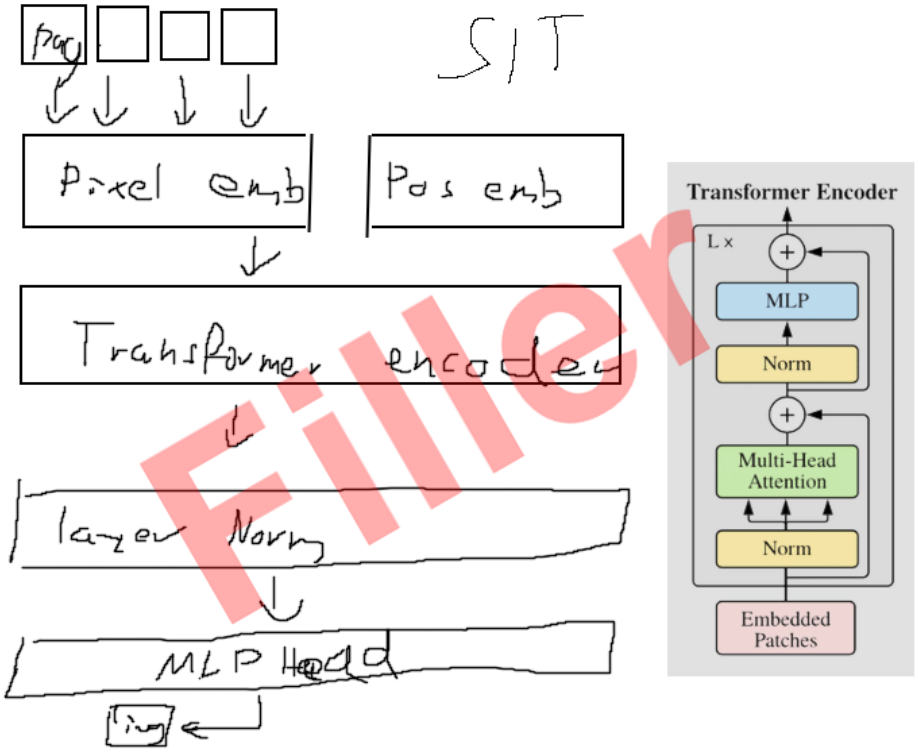


Figure 13: Spiral Image Transformer model structure

The visual representation above illustrates the operational steps of the SIT model. Similar to the CIT model, it begins by loading and converting the data. However, it diverges in its method by transforming the data into a spiral format, instead of using the columnar approach. Like its counterpart, this model embeds pixels, from 3 colors to a higher-dimensional embedding space represented by N_{EMBD}. Positional embeddings are then added. Similar to the CIT model, transformer layers are used to further process the data. The embedded data is finally processed by a (MLP), which converts it back into the original 3-color format. After this step, the spiral-formatted data is restructured into the original image layout.

2.3.1 Spiral Data Processing

To transform the data, which is loaded by the DataLoader and iterated over, into a spiral format, the width and height dimensions are first squeezed into a single dimension. This resulting tensor has the shape (Batch, Color Channels, Spiral Length). The next step involves indexing the data into the spiral form. For more detailed information on this indexing process, refer to Figure 16. The restructured tensor is then processed like how the data is handled in the Column Image Transformer model. The following code block illustrates the process used to convert the data into a spiral format.

```
def get_batch(data):
    # Batch_size, Color Channels, Height, Width
    B, C, H, W = data.shape

    spiral_data = torch.zeros_like(data.view(B, C, -1))

    spiral_data[:,:,spiral_indices.flatten()] = data.view(B, C, -1)

    source = spiral_data[:, :, :BLOCK_SIZE]
    label = spiral_data[:, :, 1:BLOCK_SIZE+1]

    source = rearrange(source, 'b c h -> b h c')
    label = rearrange(label, 'b c h -> b h c')

    return source, label

```

Figure 14: Python function to get data in a spiral form

2.3.2 Spiral generation

The conversion of data into a spiral form needs to be highly efficient because the code block will execute for every training step. Therefore, a simple nested for loop is insufficient to rearrange the data into the desired form. In this example, fancy indexing is used to convert the data into a spiral form. Thus, the data tensor is indexed with a flattened two-dimensional tensor containing the indices of the spiral form.

At the start of the model training script, one indexing spiral is created to be used for all images in the dataset. The following code block illustrates the creation of the spiral index tensor.

```python
def create_spiral(n): # n = width and height

    matrix = [[0] * n for _ in range(n)] # Initialize n x n matrix

    x, y = 0, 0
    # Direction vectors (right, down, left, up)
    dx = [0, 1, 0, -1]
    dy = [1, 0, -1, 0]
    direction = 0

    for i in range(n * n - 1, -1, -1):  # Start (35 for 6x6)
        matrix[x][y] = i
        nx = x + dx[direction]
        ny = y + dy[direction]

        # Change direction if the next position: out of bounds or filled
        if nx<0 or nx>=n or ny<0 or ny>=n or matrix[nx][ny]!=0:
            direction = (direction + 1) % 4  # Change direction
            nx = x + dx[direction]
            ny = y + dy[direction]

        x, y = nx, ny

    return torch.tensor(matrix)
```

Figure 15: Python function to create a spiral index tensor

The code above generates a square matrix of size n by n, then fills it with numbers in a spiral pattern, starting from the outer edge and spiraling inwards clockwise. Each cell of the matrix is assigned a unique number, beginning from the highest value in the top-left corner and decreasing by one with each step along the spiral path until reaching zero at the center or the end of the spiral. The spiral formation is achieved by moving right, then down, then left, then up, and repeating this sequence, adjusting direction whenever the next step would go out of bounds or into a cell that is already been filled.

The generated spiral index tensor is then used to index the data tensor, effectively converting it into a spiral form. The following image illustrates the process of converting a 7x7 image.

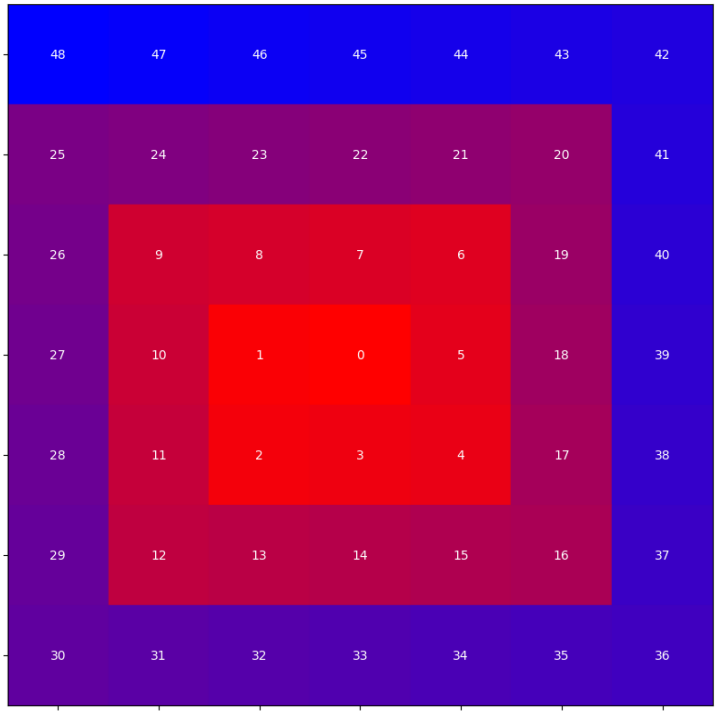


Figure 16: 7x7 image with a spiral index overlay

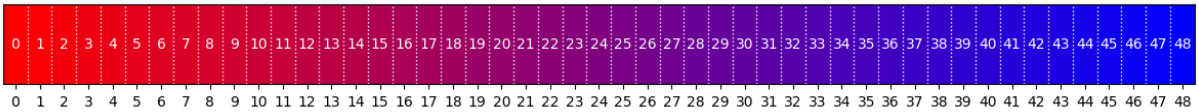


Figure 17: 7x7 Image flattened into the spiral form

As shown in Figure 16, the pixels of the image are labeled with their respective indices 0, . . . , 48. The image is then unrolled into a single dimension, as shown in Figure 17. The centering pixel is the first element of the spiral, and the spiral continues counterclockwise from there. In the model script, the dimensions for width and height typically exceed a width of 7, yet the underlying process remains unchanged.

2.3.3 Model Architecture

Similar to the CIT model, the addition of positional embeddings is handled in the same manner. This is because the data is transformed into a spiral pattern, allowing the addition of positional embeddings to remain unchanged. Additionally, the transformer layer operates identically. For more information on the transformer layer, see the CIT model Section 2.2.4.

2.3.4 Training the Model

This model is trained using the Adam optimizer with a learning rate of 3×10^{-5}. The loss function used is the Mean Squared Error (MSE) loss. Both training sizes of the model are trained for 4 epochs with a batch size of 8 for the small model and 4 for the big model. The model is trained on the x512 dataset. All the relevant trained SIT models [model 5-6] with their corresponding parameters can be found in detail in the appendix, see Section A.3.

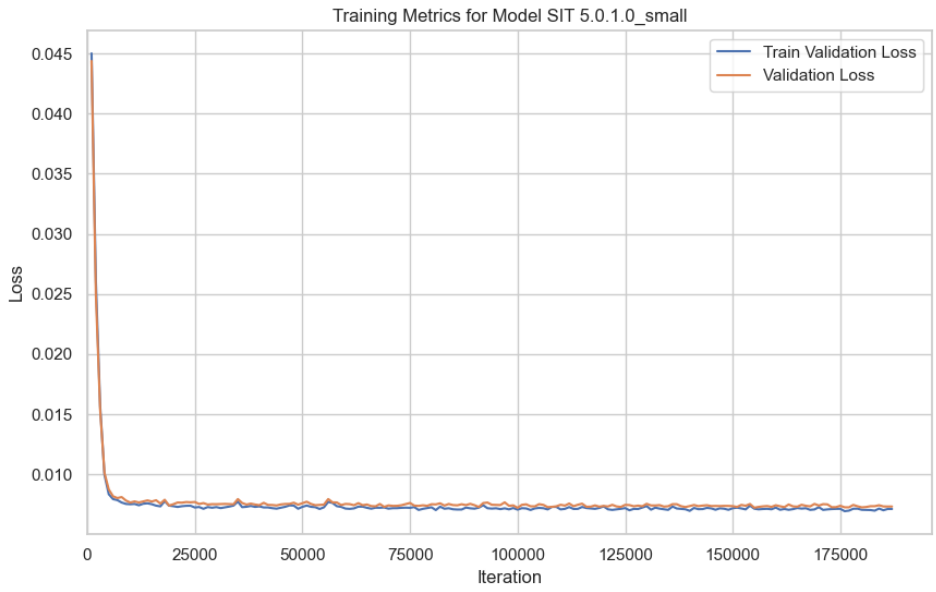


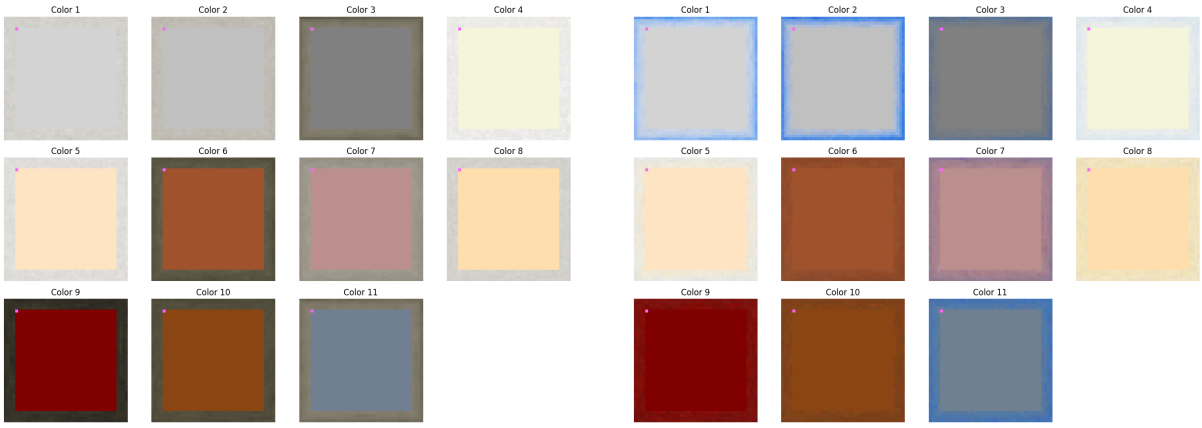
Figure 18: Loss plot of the SIT [model 5]

2.3.5 Experimental Results

A series of experiments were carried out to assess the capabilities of the Spiral Image Transformer (SIT) model like the CIT Model. The outcomes of these experiments provide insights into the efficacy of the SIT model and highlight potential areas for improvement.

In each of the tests, the end of the seed pixels is marked with a purple pixel indicating the beginning of the generation.

- **Color test:** To evaluate the color capabilities of the model, a test image with a solid color with a size of 36x36 pixels is provided to the model. The model is then tasked with generating a new image that is 42x42 pixels in width. The test is conducted using two different models, one small and one large.



(1) [model 5] 5.0.1.0 small (2) [model 6] 5.0.1.0 big

Figure 19: Color test with two different model sizes

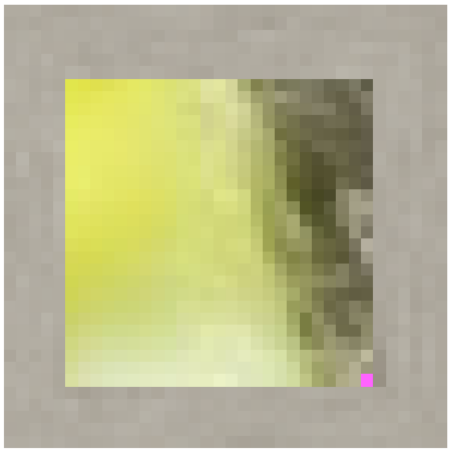
As depicted in the images above, the smaller model cannot even come close to the desired color output. The larger model performs somewhat better but still struggles to produce the correct color output, especially with the lighter gray shades.

- **Image Continuation Test:** The image continuation test is designed to evaluate the model's ability to expand an image. The model is provided with a test image measuring 25 pixels, see Figure 20 and is tasked with generating around it to a width of 44 pixels.

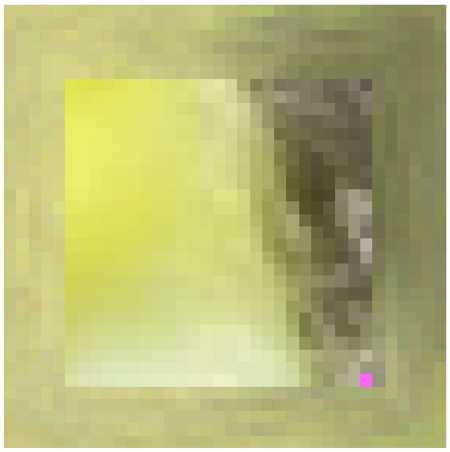
Figure 20: Initial test image

Figure 21: Test image flattened into spiral form

Figure 21 shows the test image flattened into the spiral form.



(1) [model 5] 5.0.1.0 small



(2) [model 6] 5.0.1.0 big

Figure 22: Image continuation test with two different model sizes

As depicted in Figure 22, the smaller model has difficulty producing the correct color output, focusing primarily on the last gray pixels. In contrast, the larger model performs better, generating a color closer to the desired output. It is important to note that the big model correctly captures that the image should be a light green color on the left side and a gray/dark green color on the right side. This indicates that the model can understand the positional context within the image. However, the model still struggles to generate a clear output.

- **Spiral Pattern Test:** The third test evaluates whether the model can accurately generate colors in a rainbow spiral pattern. This test is conducted in a manner very similar to the previous test but provides a more detailed perspective on certain problems. The model starts generating in the upper left corner and continues downwards, then to the right in a counterclockwise motion. The purple pixel indicates the beginning of the generation. The test image is rotated 90 degrees four times to give the model four different starting locations.

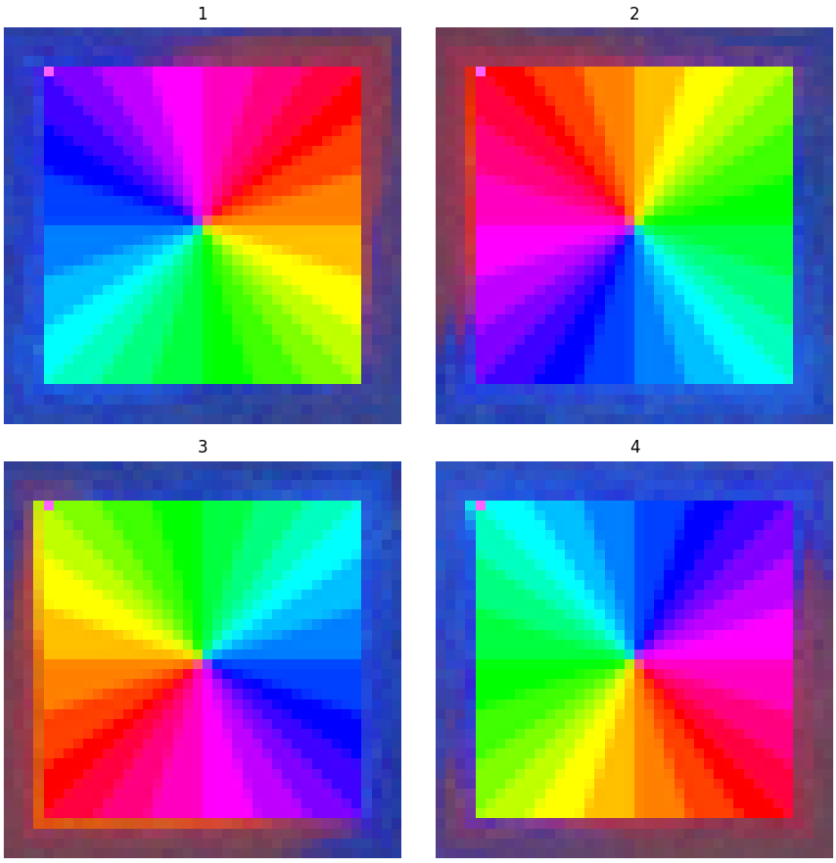


Figure 23: Rainbow spiral pattern test SIT [model 6]

As demonstrated in Figure 23, the model tends to favor the generation of blue or red colors while avoiding yellow, purple, and especially green colors. However, it is noticeable in Image No. 4 that the model generates red accents, although this color is on the opposite side of the starting point. The issues could be due to a lack of training data or the model's size, which needs further investigation.

2.3.6 Challenges and Limitations

As revealed in the experimental section, the Spiral Image Transformer (SIT) model faces difficulties in accurately generating the intended color outputs. This challenge could be anticipated, given that the SIT model's task is inherently more complex than that of the Column Image Transformer (CIT) model. A pattern that progresses one dimensional in a single column is far simpler to learn than one that spirals in two dimensions. The smaller SIT model has an equivalent number of parameters to the smallest CIT model and was trained on an identical dataset, yet its performance is noticeably inferior. Similarly, the larger SIT model holds a parameter count on par with the mid-sized CIT model but falls short in the color tests.

The limitations experienced by the SIT model could be partially attributed to the in-

sufficiently diverse training dataset. Expanding the dataset, introducing more variance in the training examples, and scaling up the model's complexity could potentially fix its current deficiencies. Moreover, equipping the model with additional contextual data, such as the precise location of a random crop, might improve its capacity for understanding and interpreting the broader context of an image.

Incorporating a text prompt feature presents could result in a big improvement. By translating descriptive language into visual cues, a text prompt could guide the SIT model toward generating more accurate outputs, potentially reducing or even eliminating the need for seed pixels in some cases.

Nevertheless, the current iteration of the SIT model is considerably resource-intensive. Its inability to generate multiple pixels parallel translates into lengthy runtimes when operated on consumer-grade GPUs.

3 Conclusion

In conclusion, this thesis demonstrates the feasibility and potential of using transformer-based models for texture generation in video game development and use. The Column Image Transformer (CIT) and Spiral Image Transformer (SIT) represent initial approaches and potential ways in which traditional Transformer architectures can be extended beyond text to graphical content generation. Each model offers unique benefits and poses different challenges. Both models require further development to become fully user-friendly and capable of generating assets efficiently.

3.1 Evaluation of the Models

As a general conclusion, the data suggest that it is possible to quickly generate new assets through this approach. Especially the CIT model can generate new assets in a short amount of time because it does not process the whole image at once and is highly parallelizable. However, this is also a significant disadvantage because it is unable to envision the whole context. In contrast, the Spiral Model, which can see the entire image at once, is unable to generate new assets quickly due to the fact that a context window will become exponentially large (width * height) and because the pixels depend on each other so each pixel needs to be generated after another. The best approach might be to find a middle ground between the two models. For example, using a wider width than in the CIT model or feeding additional information to the model, such as the x position of the pixel to be generated.

Another addition to the model could be the use of text input as additional information. This would be an easy approach to generate more specific assets and it would be easier to start from no or a smaller amount of seed pixels, similar to DALL-E or Midjourney.

3.1.1 Quality

The following images show generated assets from the CIT and the SIT model.

3.1.2 Performance

A key question that arises is whether it is feasible to generate assets for video games using the developed models. This question can be divided into two distinct parts. The first considers the pre-generation of assets during the development cycle, while the second evaluates whether the models are efficient enough to generate assets in real-time on a local machine.

The following table provides a detailed overview of the performance metrics for the CIT

and SIT models, tested on both GPU and CPU. It is noteworthy that the Tokens column refers to the number of tokens used for generating the image. The CIT model utilizes a batch size of 32 and a context length of 32 tokens, while the SIT model uses a batch size of 1 and a context length of 1024 tokens. Both models generate a resulting image of 32x32 pixels. Each model was tested on a local workstation equipped with an NVIDIA GeForce RTX 3090 GPU and an AMD Ryzen 9 7900X CPU.

Model	**Platform**	**Total Time (sec)**	**Avg Time per Token (sec)**	**Tokens**
CIT [1] 128	GPU	0.511	0.000499	32x32
	CPU	0.494	0.000483	
CIT [3] 256	GPU	0.725	0.000708	32x32
	CPU	2.851	0.002784	
CIT [4] 512	GPU	0.899	0.000877	32x32
	CPU	4.489	0.004384	
SIT [5] Small	GPU	9.388	0.009168	1x1024
	CPU	30.709	0.029989	
SIT [6] Big	GPU	15.773	0.015403	1x1024
	CPU	114.394	0.111713	

Table 2: Performance metrics for CIT and SIT models [local workstation]

The results indicate that the SIT model is significantly slower than the CIT model, especially when running on the CPU. This is because generating a bigger image in the batch dimensions is far more efficient than in the token dimension. For a detailed visualization of the performance scaling across these dimensions, refer to Figure 26 for batch dimension scaling and Figure 27 for context dimension scaling on the CIT [model 4].

It can be observed that both methods could be somewhat viable in a development environment where developers generate assets during the prototyping or development cycle. As shown in Figure Figure 26, the expected optimal runtime per pixel for the CIT model is 2.51 milliseconds. This would result in an approximate runtime of roughly 11 minutes for a 512x512 image on an RTX 3090 GPU.

However, this could pose a challenge when considering running these models on an average gaming-capable machine. Due to the large amount of data and the size of the models, substantial video memory is required. Only 27.17% of users have more than 8 GB of VRAM, and 49.37% have at least an NVIDIA GeForce RTX 2060, according to the Steam Hardware Survey of March 2024 (Valve, 2024). This could be problematic for the SIT model, which demands considerable memory to operate effectively. The CIT model could run on most machines, but the size/context length of the generated images would be compromised, and any enhancements to the model could further increase system

requirements. Thus, a cloud-based solution might be a better approach for this case, when the created games should be capable of generating assets on the fly.

3.2 Further research

The following sections outline potential areas for further research that could lead to significant improvements in model performance and usability and extend their applicability in real-world applications.

3.2.1 Discriminator

To achieve better results, a discriminator could be used to enhance the output of the model. In this context, a discriminator is a type of neural network trained to distinguish between real data and artificially generated data. The goal of the discriminator is to accurately classify data as either real from the actual dataset or fake, created by another neural network called the generator, in this case, the CIT or SIT Model. The discriminator's performance helps improve the generator, leading to more realistic synthetic data over time. In a perfect scenario, the discriminator cannot distinguish between the generated content and the original content, and the loss will balance out at 0.5 for the discriminator. This is the point where the generator is creating content indistinguishable from the original content.

Some tests have been conducted with a discriminator and the CIT model, where the CIT model was pretrained to learn basic generation and then further trained with the discriminator. The tests indicated that the performance of the CIT model could be slightly improved and needs further investigation.

3.2.2 Incorporating Text Input

Integrating text input into an image generation model like the CIT or SIT could significantly enhance its functionality and usability by allowing the model to generate images based on descriptive text prompts. Unfortunately, due to time constraints, this feature was not implemented in this thesis, but it could be a valuable addition to the models. To implement this, all the data would need to be additionally labeled with text descriptions. Most of the images already contain basic descriptions in their names, such as "concrete floor" or "oak wood tiling," but further labeling and more data would be required. This would allow the model to generate images based on text input. The text input could be used to generate more specific assets or to create assets from scratch without any seed pixels. This would make the model more usable in the development process of video games. Therefore, this could be a valuable addition to the models.

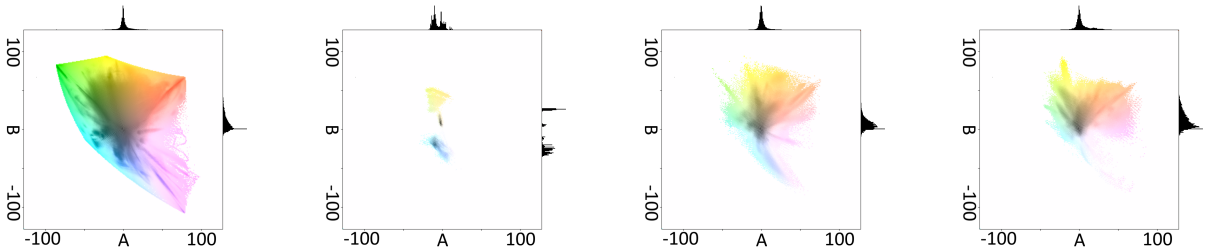
3.2.3 LLM Scaling Laws

As often mentioned in this thesis, the lack of training data and potentially the small size of the models could be reasons for the models not performing perfectly. The scaling laws of LLMs (Kaplan et al., 2020) could potentially be applied to the CIT and SIT models to improve their performance. The scaling laws of LLMs suggest that the performance of a model can be improved by increasing the model's size and the amount of training data. This could be achieved by increasing the model's parameter count and the amount of training data. One way would be to increase the number of attention heads or the size of the feedforward network, or the model could be enhanced by adding more transformer layers.

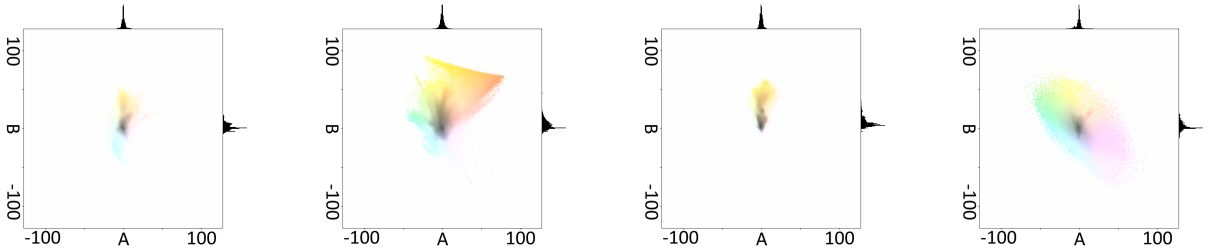
The amount of training data could also be increased by using more video game assets. In this thesis, 30 video games are used. Scaling up the training dataset and increasing the parameter count resulted in better outcomes, especially for the SIT model.

A Appendix

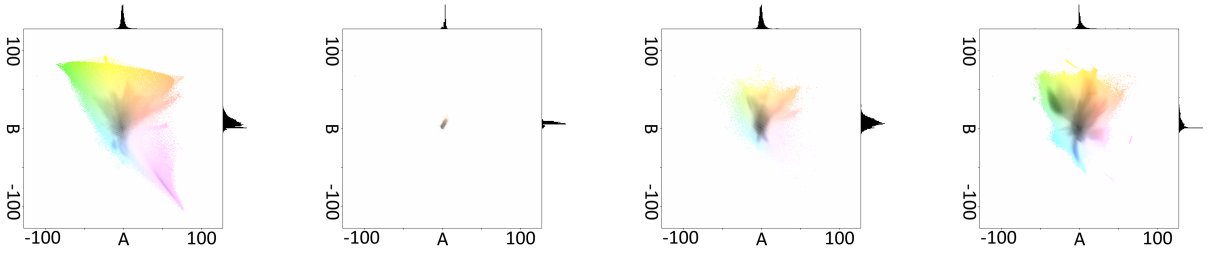
A.1 Dataset Plots in the Lab Color Space



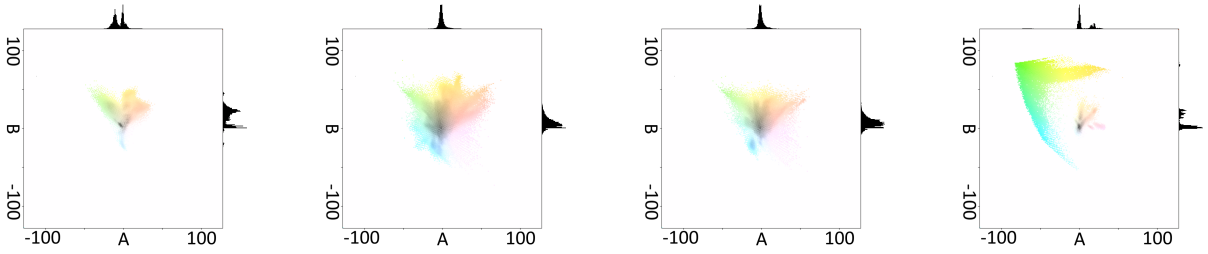
(1) All Data (2) source 0 (3) source 1 (4) source 2



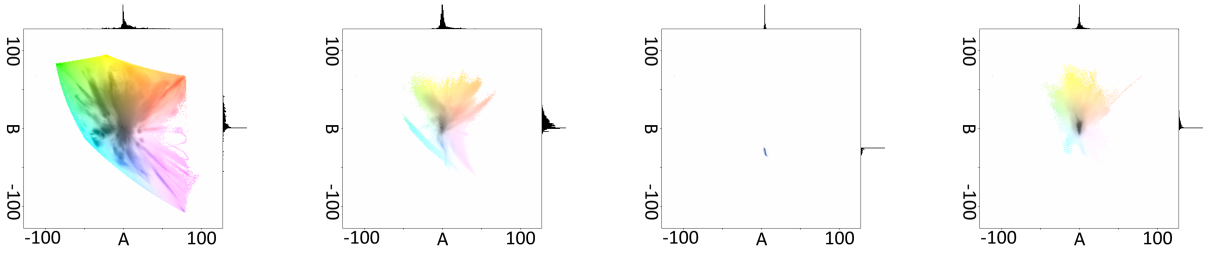
(5) source 3 (6) source 4 (7) source 5 (8) source 6



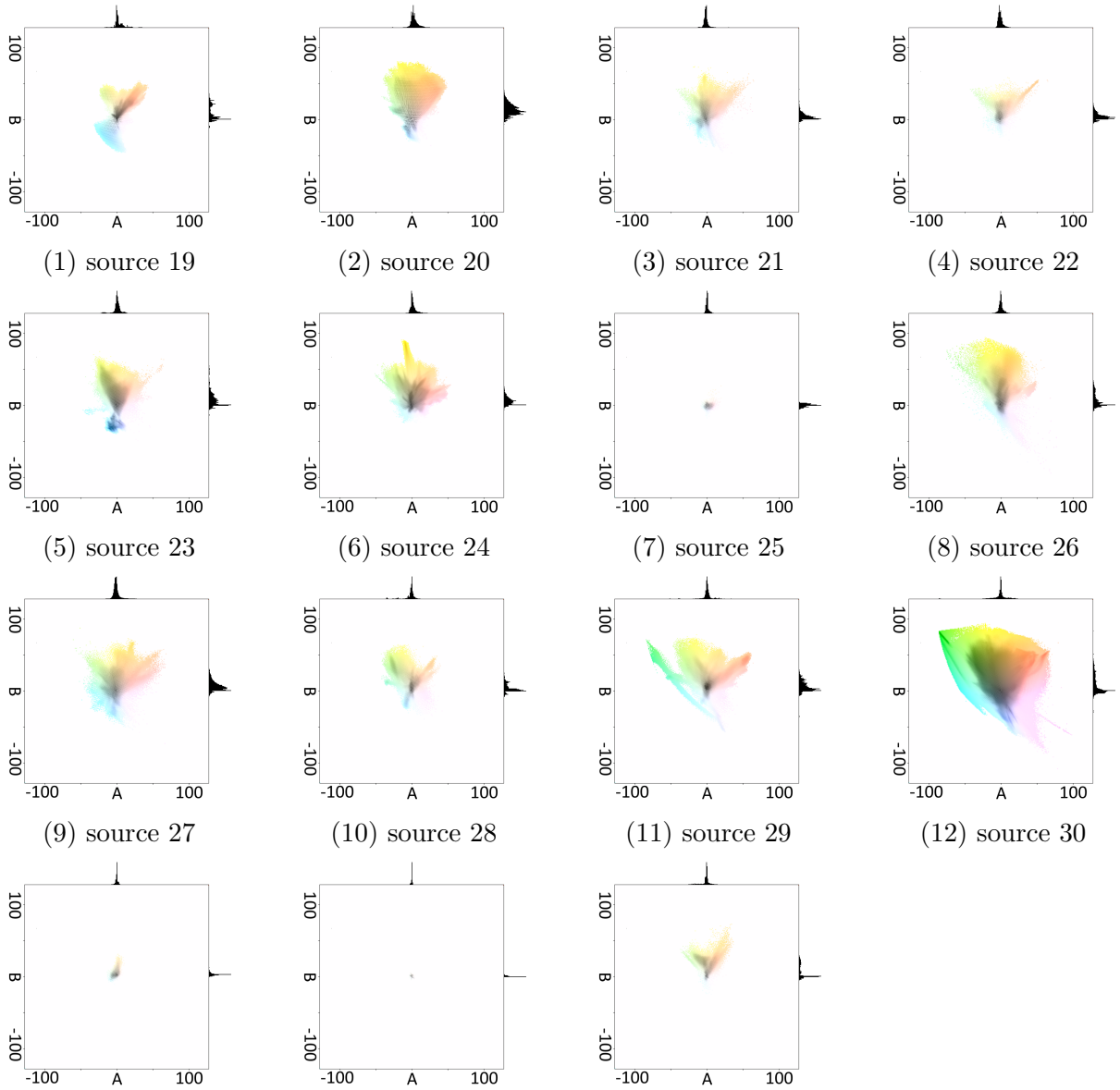
(9) source 7 (10) source 8 (11) source 9 (12) source 10



(13) source 11 (14) source 12 (15) source 13 (16) source 14



(17) source 15 (18) source 16 (19) source 17 (20) source 18



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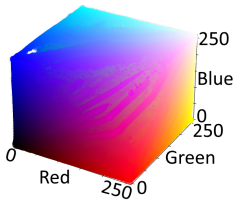
(5) source 23 (6) source 24 (7) source 25 (8) source 26

(9) source 27 (10) source 28 (11) source 29 (12) source 30

(13) source 31 (14) source 32 (15) source 33

Figure 24: Visualization of datasets plotted in the LAB color space

A.2 Dataset Plots in the RGB Color Space



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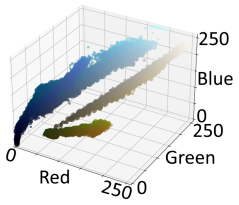

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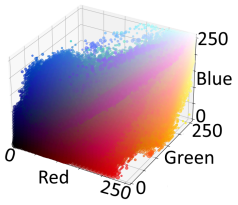
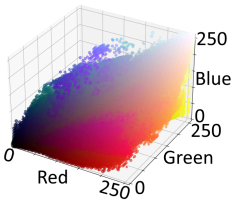
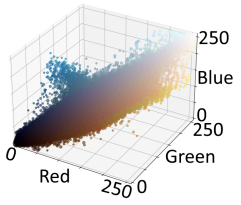


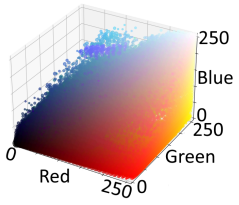
(3) source 1



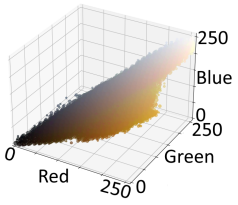
(4) source 2



(5) source 3



(6) source 4



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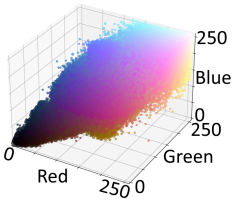
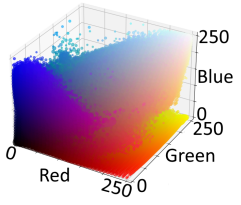


(8) source 6



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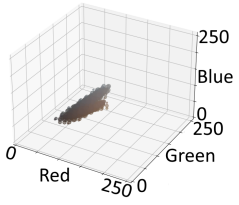

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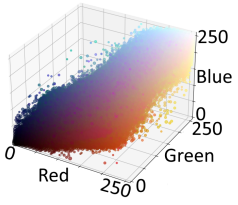

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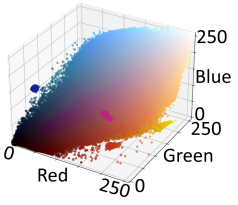

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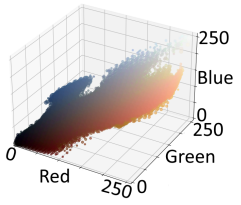

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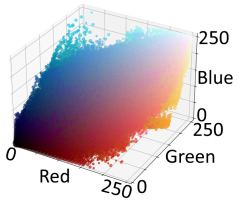

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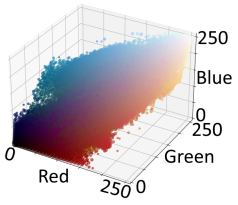
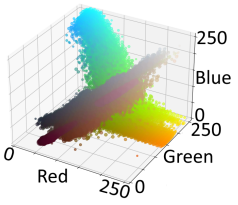


(15) source 13



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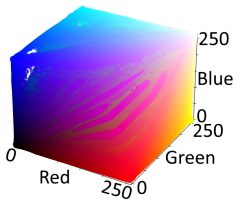
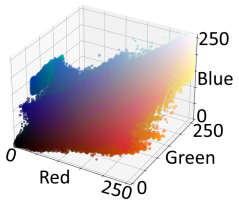


(17) source 15



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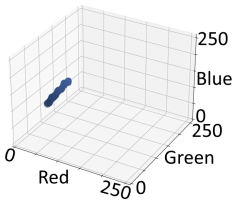

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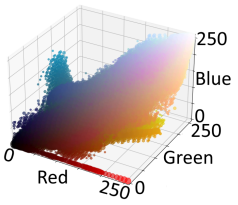

(20) source 18

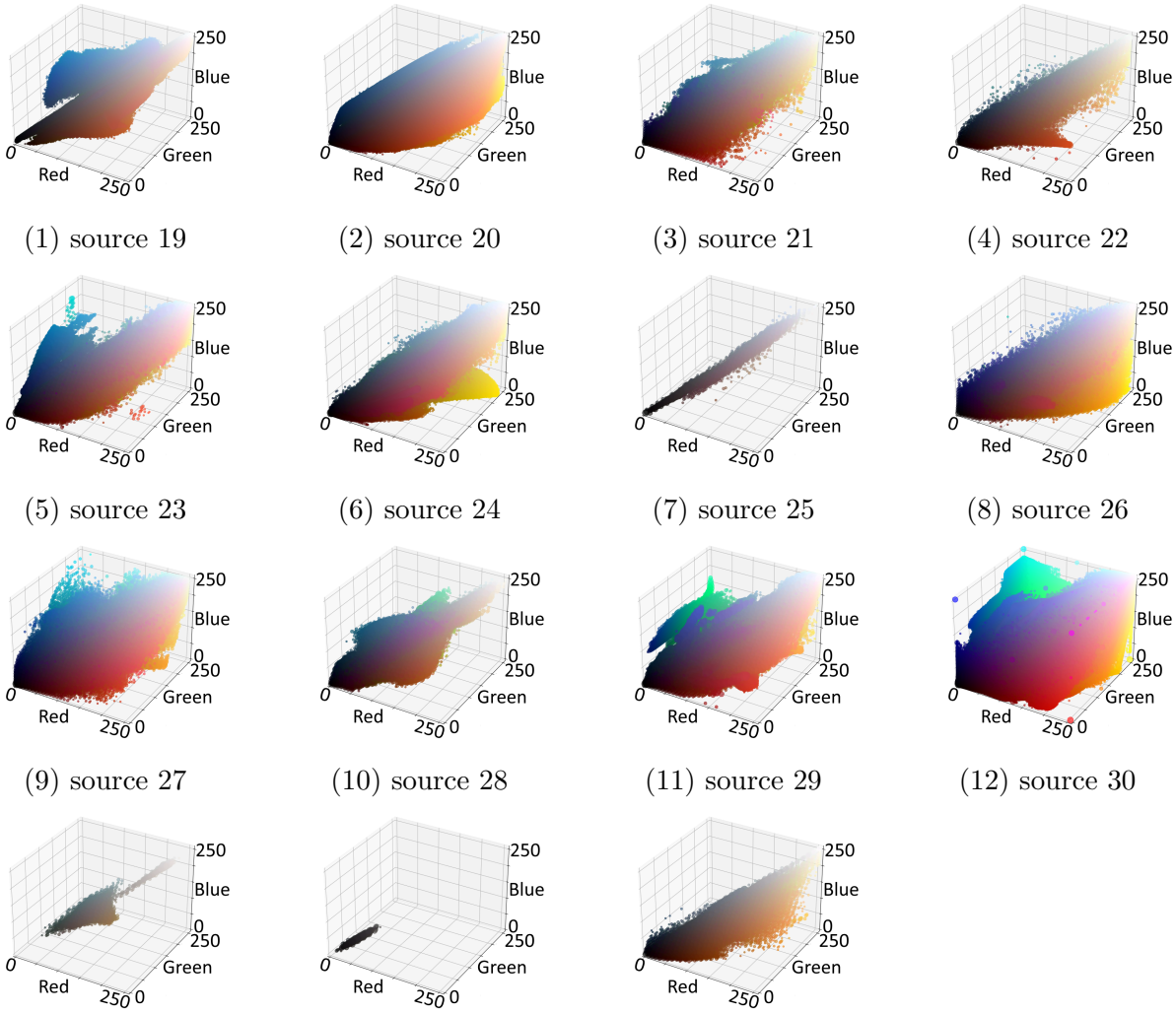

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Figure 25: Visualization of datasets plotted in the RGB color space

A.3 Trained Models with hyperparameters

Table 3: Model Configuration Overview

MODEL	Nr.	VER.	BATCH_SIZE	BLOCK_SIZE	N_EMBD	N_HEAD	N_LAYER	PARAMETER*	GPUS	DATASET	VAL_LOSS**
CIT	0	2.1.7.0	128	128	128	6	6	1.22 m	1	old Dataset	0.0082
	1	2.1.8.0	64	64	128	6	6	1.21 m	1	x512 Dataset	0.0035
	2	2.1.8.0 Classify	64	64	128	6	6	1.25 m	1	x512 Dataset	1.841
	3	2.1.8.0	64	256	512	8	8	25.66 m	4	x512 Dataset	0.0025
	4	2.1.8.0	32	511	640	9	9	45.09 m	4	x512 Dataset	0.0024
SIT	5	5.0.1.0	8	4,095	128	6	6	1.73 m	1	x512 Dataset	0.0074
	6	5.0.1.0	4	4,095	512	8	8	27.62 m	1	x512 Dataset	0.0027

* Figures in millions

** Average of the last 5 validation loss values

A.4 Local workstation setup

Component	Specification
Operating System	Microsoft Windows 11 Pro
CPU	AMD Ryzen 9 7900X 12 cores, 4.7 GHz
GPU	NVIDIA RTX 3090
RAM	64 GB (DDR5-6000)
SSD	2TB Samsung 990 PRO M.2 PCIe 4.0

Table 4: Local workstation setup

Component	Specification
CPU	2x Intel Xeon "Ice Lake" Platinum 8360Y (36 cores per socket, 2.4 GHz)
GPU	4x Nvidia A100 (80GB HBM2, SXM)
RAM	1 TB RAM (DDR4-3200)
SSD	7.68 TB NVMe local SSD

Table 5: Single slurm compute node

A.5 Performance metrics average time per token

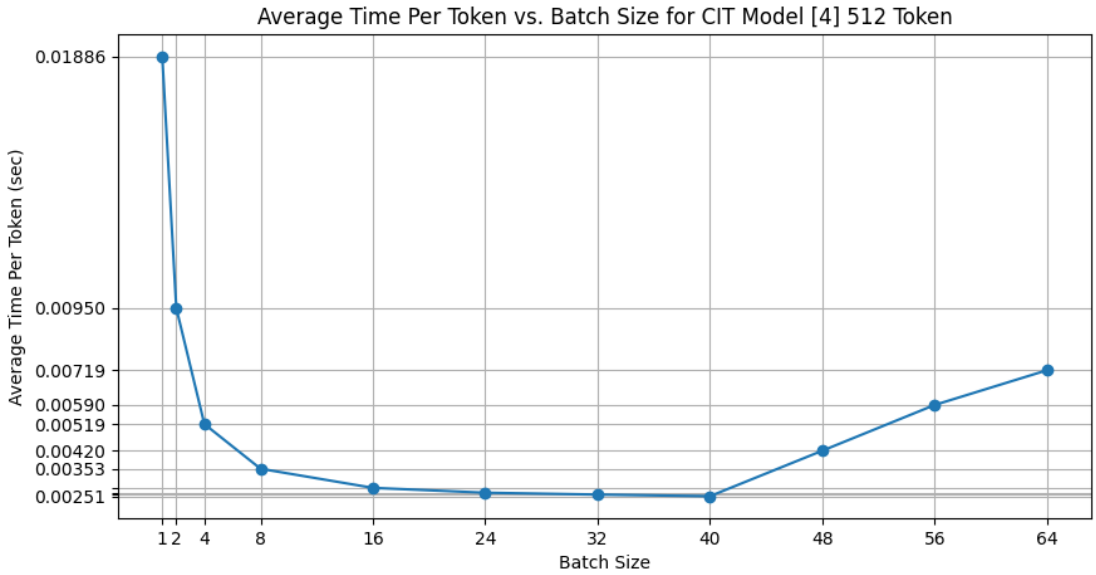

Figure 26: Average time per token vs. batch size for CIT model [4] 512 token

As illustrated in Figure 26, the batch size is plotted against the average time per generated token. The test was conducted on a local workstation equipped with an NVIDIA RTX 3090 GPU. Notably, the average time per token decreases logarithmically as the batch size increases. However, upon reaching a batch size of 40, the GPUs 24GB of memory becomes fully utilized, resulting in a noticeable linear increase in processing time. This slowdown occurs because PyTorch begins to utilize an additional 32GB of shared system memory to manage the increased data load.

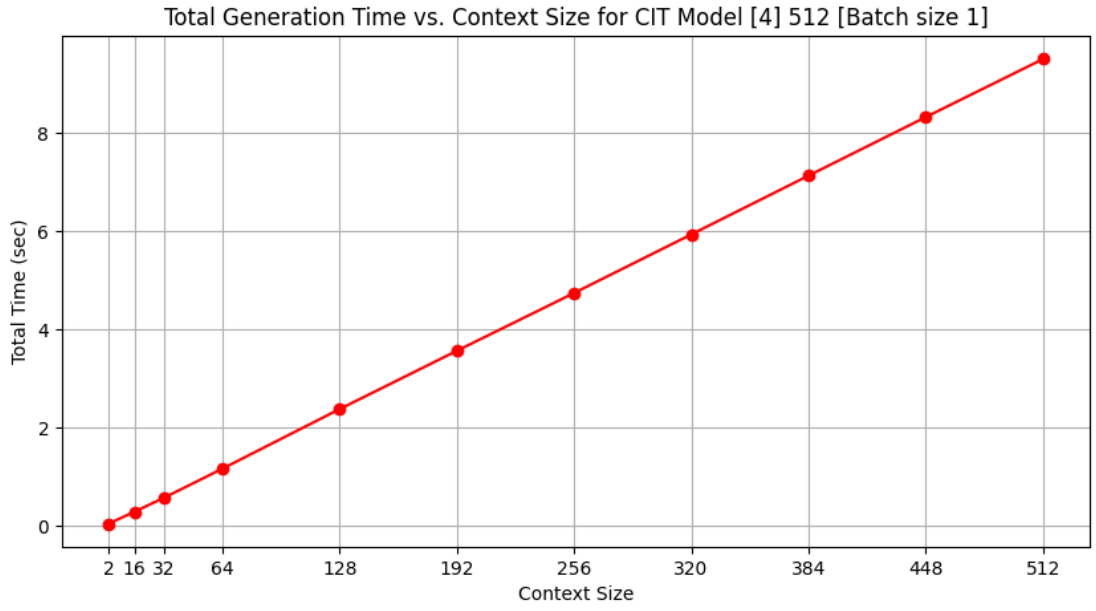

Figure 27: Total generation time vs. context size for CIT model [4] 512 token

A.6 Transformer layer implementation

```
class Head(nn.Module):
""" one head of self-attention """

    def __init__(self, head_size):
        super().__init__()
        self.key = nn.Linear(N_EMBD, head_size, bias=False)
        self.query = nn.Linear(N_EMBD, head_size, bias=False)
        self.value = nn.Linear(N_EMBD, head_size, bias=False)
        self.register_buffer('tril', torch.tril(torch.ones(BLOCK_SIZE, BLOCK_SIZE)))

        self.dropout = nn.Dropout(DROPOUT)

    def forward(self, x):
        # input of size (batch, time-step, channels)
        # output of size (batch, time-step, head size)
        B,T,C = x.shape
        k = self.key(x)   # (B,T,hs)
        q = self.query(x) # (B,T,hs)
        # compute attention scores ("affinities")
        wei = q @ k.transpose(-2,-1) * k.shape[-1]**-0.5 # (B, T, hs) @ (B, hs, T) -> (B, T, T)
        wei = wei.masked_fill(self.tril[:T, :T] == 0, float('-inf')) # (B, T, T)
        wei = F.softmax(wei, dim=-1) # (B, T, T)
        wei = self.dropout(wei)
        # perform the weighted aggregation of the values
        v = self.value(x) # (B,T,hs)
        out = wei @ v # (B, T, T) @ (B, T, hs) -> (B, T, hs)
        return out

class MultiHeadAttention(nn.Module):
""" multiple heads of self-attention in parallel """

    def __init__(self, num_heads, head_size):
        super().__init__()
        self.heads = nn.ModuleList([Head(head_size) for _ in range(num_heads)])
        self.proj = nn.Linear(head_size * num_heads, N_EMBD)
        self.dropout = nn.Dropout(DROPOUT)

    def forward(self, x):
        out = torch.cat([h(x) for h in self.heads], dim=-1)
        out = self.dropout(self.proj(out))
        return out

```

```
class FeedFoward(nn.Module):
""" a simple linear layer followed by a non-linearity """

    def __init__(self, n_embd):
        super().__init__()
        self.net = nn.Sequential(
            nn.Linear(n_embd, 4 * n_embd),
            nn.ReLU(),
            nn.Linear(4 * n_embd, n_embd),
            nn.Dropout(DROPOUT),
        )

    def forward(self, x):
        return self.net(x)

class Block(nn.Module):
""" Transformer block: communication followed by computation """

    def __init__(self, n_embd, n_head):
        # n_embd: embedding dimension, n_head: the number of heads we'd
    like
        super().__init__()
        head_size = n_embd // n_head
        self.sa = MultiHeadAttention(n_head, head_size)
        self.ffwd = FeedFoward(n_embd)
        self.ln1 = nn.LayerNorm(n_embd)
        self.ln2 = nn.LayerNorm(n_embd)

    def forward(self, x):
        x = x + self.sa(self.ln1(x))
        x = x + self.ffwd(self.ln2(x))
        return x
```

This code snippet shows the implementation of the transformer layer in the Column Image Transformer and the Spiral Image Transformer. The code above is heavily inspired by the implementation of the script by A. Karpathy named NanoGPT (Karpathy, 2023a) (Karpathy, 2023b)

B Eidesstattliche Erklärung

Ich versichere, die von mir vorgelegte Arbeit selbständig verfasst zu haben. Alle Stellen, die wörtlich oder sinngemäß aus veröffentlichten oder nicht veröffentlichten Arbeiten anderer entnommen sind, habe ich als entnommen kenntlich gemacht.
Sämtliche Quellen und Hilfsmittel, die ich für die Arbeit benutzt habe, sind angegeben. Die Arbeit hat mit gleichem Inhalt bzw. in wesentlichen Teilen noch keiner anderen Prüfungsbehörde vorgelegen.

(Ort, Datum, Unterschrift)

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