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

Texture Asset generation through Transformer Models

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Abstract

Blob

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1 Introduction

Transformers are predominantly utilized in generating text for Large Language Models (LLMs) like GPT (Radford et al., 2019) and LaMMA (Touvron et al., 2023). This thesis aims to explore the application of conventional Transformer-based architectures for the generation of texture assets, diverging from the traditional image generation methods primarily relying on stable diffusion techniques or Generative Adversarial Networks (GANs).

To achieve this, three distinct models are developed and trained, each incorporating unique modifications to harness the principal benefits of Transformer-based models for image texture generation. The dataset required for training these models is compiled from a variety of sources, necessitating thorough cleaning and analysis to ensure usability. The objective is for these trained models to be capable of generating basic floor textures suitable for use as assets in video games. These developed models are compared using a specific set of metrics. Furthermore, the development process will be briefly outlined, highlighting the differences from conventional programming workflows typically encountered.

1.1 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. 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 study's approach to image generating.

Generative Adversarial Networks (GANs): Since their introduction by (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., 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., 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 technique’s 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., 2021) marked a significant leap, applying Transformers directly to sequences of image patches for classification tasks. This idea was extended to image generation through architectures like the VideoGPT by (Yan et al., 2021), which demonstrated that Transformer models could generate coherent and detailed videos.

Texture Generation with Transformers: TransGAN by (Jiang et al., 2021) revolutionizes image generation with a Transformer-based GAN architecture, moving beyond traditional CNN approaches. It features a memory-efficient generator and a nuanced, multiscale discriminator, both utilizing transformer blocks. With advanced training techniques to overcome common GAN challenges, TransGAN produces high-quality images, showcasing the potential of Transformers in this new domain.

1.2 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, a high-performance computing system situated in Berlin 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 that would be possible on a home workstation. The development of these models is carried out using Python and PyTorch, with the code being crafted 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 30 hours, only to realize it terminated prematurely due to script errors.

1.3 Data

This section describes the methods used for gathering, cleaning, and analyzing data for this thesis. Essential for training a machine learning model, the data is carefully collected from various sources, cleaned to maintain uniformity, and examined for patterns, with a focus on color distribution.

1.3.1 Data Retrieval

On the internet, a wide variety of textures can be found, but not all of them are suitable for this task. The textures should be seamless, devoid of shadows, and free from any objects. Textures of floors, such as carpets, tiles, wood, concrete, and more, were utilized. Two approaches were 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 were utilized for data acquisition. Due to the limitation of downloading one texture at a time from most websites, a series of scripts were developed to compile a list of suitable textures and automate the downloading process. These scripts were 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.

1.3.2 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 the 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, and 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, as these are the sizes used in this thesis. In total, 57454 images of size 512x512 were collected and 12600 being of size 1024x1024 pixels. The sources are summarized in Table 1.



Figure 1: Combined Sources 512x512

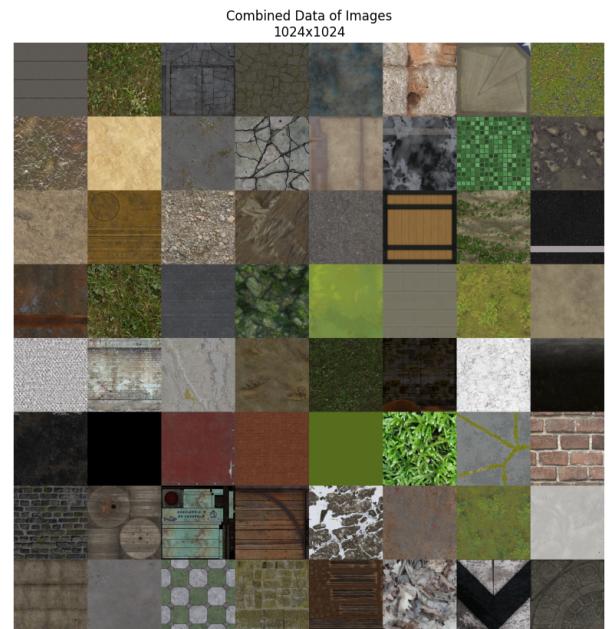


Figure 2: Combined Sources 1024x1024

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

1.3.3 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, a comprehensive pixel count across all images is conducted. 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.

```
1 color_counts = {}
2 for i, (data, _) in enumerate(dataset):
3     # data is a tensor of shape (3, height, width)
4     pixel_rgb_array = (data.view(3, -1).t() * 255).to(torch.int32)
5
6     for pixel_color in map(tuple, pixel_rgb_array):
7         if color in color_counts:
8             color_counts[pixel_color] += 1
9         else:
10             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.

1.3.4 Data Lab plots

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

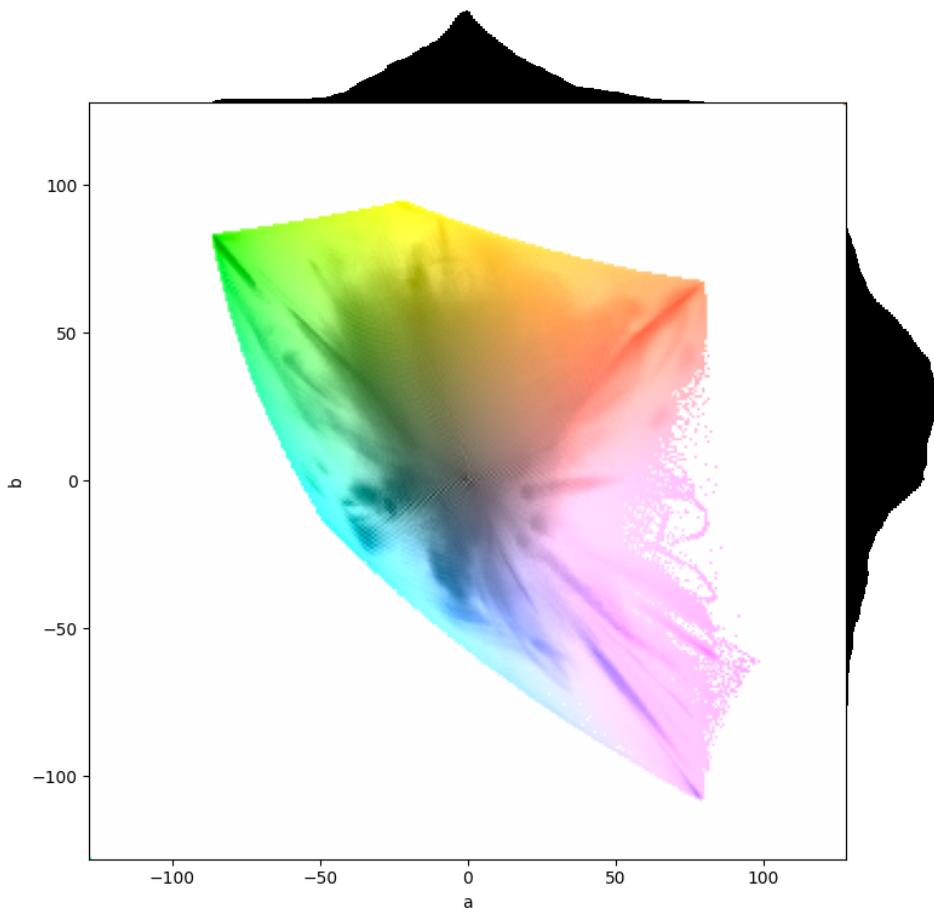


Figure 4: Color distribution of the dataset in the LAB color space

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 in highlighting 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 subsection A.1.

1.3.5 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 12 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.

1.3.6 Data Synchronization

In the thesis, a manual data synchronization routine is established to maintain data consistency between the supercomputer located in Berlin and the local workstation.

1.4 Models

(LLMs, basic idea, roll model, spiral model)

1.4.1 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 models 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.

1.4.2 Adapting Transformer Architecture for Image Prediction

The Transformer architecture, introduced by (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 dynamically. 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 architecture's 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.

1.4.3 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, following the "B" batch dimension in the model's structure.

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.

1.4.4 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 ...). 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

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 models discussed in this thesis are based on a Python script by A. Karpathy named NanoGPT (Karpathy, 2023). This script demonstrates a straightforward and accessible GPT implementation.

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 such as cropping, flipping, gray scaling, and color jitter.

It allows for the selection between 512x512 and 1024x1024 pixel datasets, 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.

2.2 Column Image Transformer

The Column Image Transformer is a transformer-based model that processes input data in a columnar format as examined in detail see subsubsection 1.4.3.

2.2.1 Get Data as Columns

The data is loaded as a DataLoader object, which is then iterated over to obtain the data in (Batch, Color, Height, Width) format. The data is then reshaped into a columnar format, resulting in a tensor of shape (Batch, Height, Color). This reshaping is achieved by indexing the data tensor as follows:

```

1
2 # data: (Batch, Color, Height, Width)
3 def get_batch(data):
4
5     x = data[:, :, :BLOCK_SIZE, :BATCH_SIZE]
6     y = data[:, :, 1:BLOCK_SIZE+1, :BATCH_SIZE]
7
8     x = rearrange(x, 'c h b -> b h c')
9     y = rearrange(y, 'c h b -> b h c')
10
11    return x, y

```

Figure 6: Python function to convert data into a columnar format

The resulting tensor x is the input to the model, and the tensor y is the target output. The y tensor is shifted by one position to the right so that the model can learn to predict the next column based on the previous columns.

2.2.2 Pixel Embedding

The input part of the data x 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 was discovered that the optimal configuration for the pixel embedding layer involves a specific 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} ($\frac{1}{5}N_{EMBD}$), then increasing it to one-half of N_{EMBD} ($\frac{1}{2}N_{EMBD}$) until reaching N_{EMBD} . The pixel embedding layer is followed by

a dropout layer with a dropout rate of 0.2.

It is crucial to highlight the importance of excluding a layer normalization (layernorm) layer in the initial few layers of the model. Incorporating layernorm early on 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

2.2.4 Classification or Regression

2.2.5 Discriminator

2.3 Spiral Image Transformer

(explanation, Data to Spiral form, positional embedding,)

As explained in the previous section (see Section 1.4.4), the spiral model is a transformer-based model that employs a spiral architecture to process input data.

2.3.1 Spiral

To convert the 3-dimensional data (color channels, image height, image width) into a spiral form, the data must be unrolled into one dimension, resulting in an output format of (color channels, spiral length). Consequently, the data width and the height dimensions must be squeezed into a single dimension. This new form can then be utilized similarly to the data in the Column Image Transformer. As the data is flattened into a single dimension, it allows for an easy addition of positional embedding.

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 image (batch) in the dataset. Therefore, a simple nested for loop is insufficient. In this example, fancy indexing is used to convert the data into a spiral form. Thus, the data tensor is indexed with a 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.

```

1 def create_spiral(n): # n = width and height
2
3     matrix = [[0] * n for _ in range(n)] # Initialize n x n matrix
4
5     x, y = 0, 0
6     # Direction vectors (right, down, left, up)
7     dx = [0, 1, 0, -1]
8     dy = [1, 0, -1, 0]
9     direction = 0
10
11    for i in range(n * n - 1, -1, -1): # Start (35 for 6x6)
12        matrix[x][y] = i
13        nx = x + dx[direction]
14        ny = y + dy[direction]
15
16        # Change direction if the next position: out of bounds or filled
17        if nx < 0 or nx >= n or ny < 0 or ny >= n or matrix[nx][ny] != 0:
18            direction = (direction + 1) % 4 # Change direction
19            nx = x + dx[direction]
20            ny = y + dy[direction]
21
22        x, y = nx, ny
23
24    return torch.tensor(matrix)

```

Figure 7: 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's already been filled.

2.4 Fancy Indexing into the Spiral form

The 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.

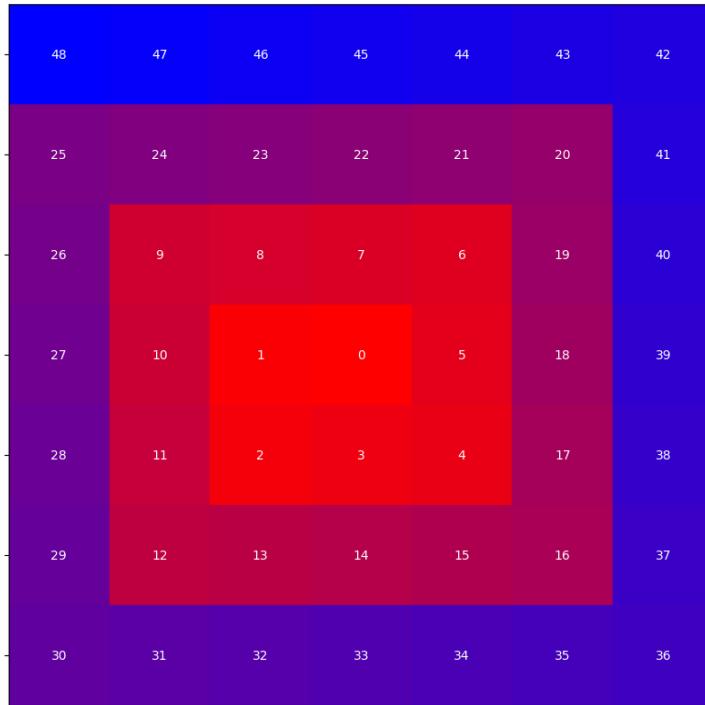


Figure 8: Image representation

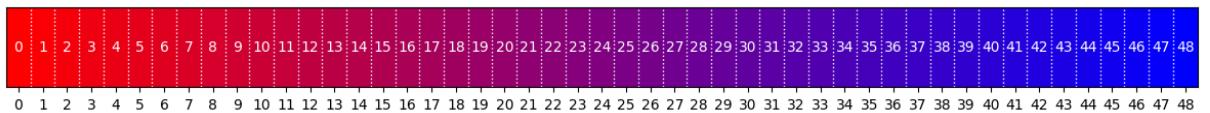


Figure 9: 7x7 Image flattened into a spiral form

As you can see in Figure 8, the pixels of the image are labeled with their respective indices $0, \dots, 43$. The image is then unrolled into a single dimension, as shown in Figure 9. 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 7, yet the underlying process remains unchanged.

```
1 spiral_indices = torch.tensor(create_spiral(IMAGE_SIZE))
2
3 # [...]
4 # Batch_size, Color_channels, Height, Width
5 B, C, H, W = data.shape
6
7 spiral_data = torch.zeros_like(data.view(B, C, -1))
8
9 spiral_data[:, :, spiral_indices.flatten()] = data.view(B, C, -1)
10
11 # [...]
```

Figure 10: Fancy indexing to convert data into a spiral form

2.4.1 Positional embedding

2.5 Problems

(layer norm(sigmoid vs clamp), color shift to gray (illustrations of average color), Text tokens vs imgs tokens)

3 Conclusion

3.1 Roll model

(strength, weaknesses)

3.2 Spiral model

(strength, weaknesses)

3.3 LLM Scaling Laws

3.4 Stable diffusion/ GANs with convolutional neural network

3.5 Further research

A Appendix

A.1 Dataset Plots in the Lab Color Space

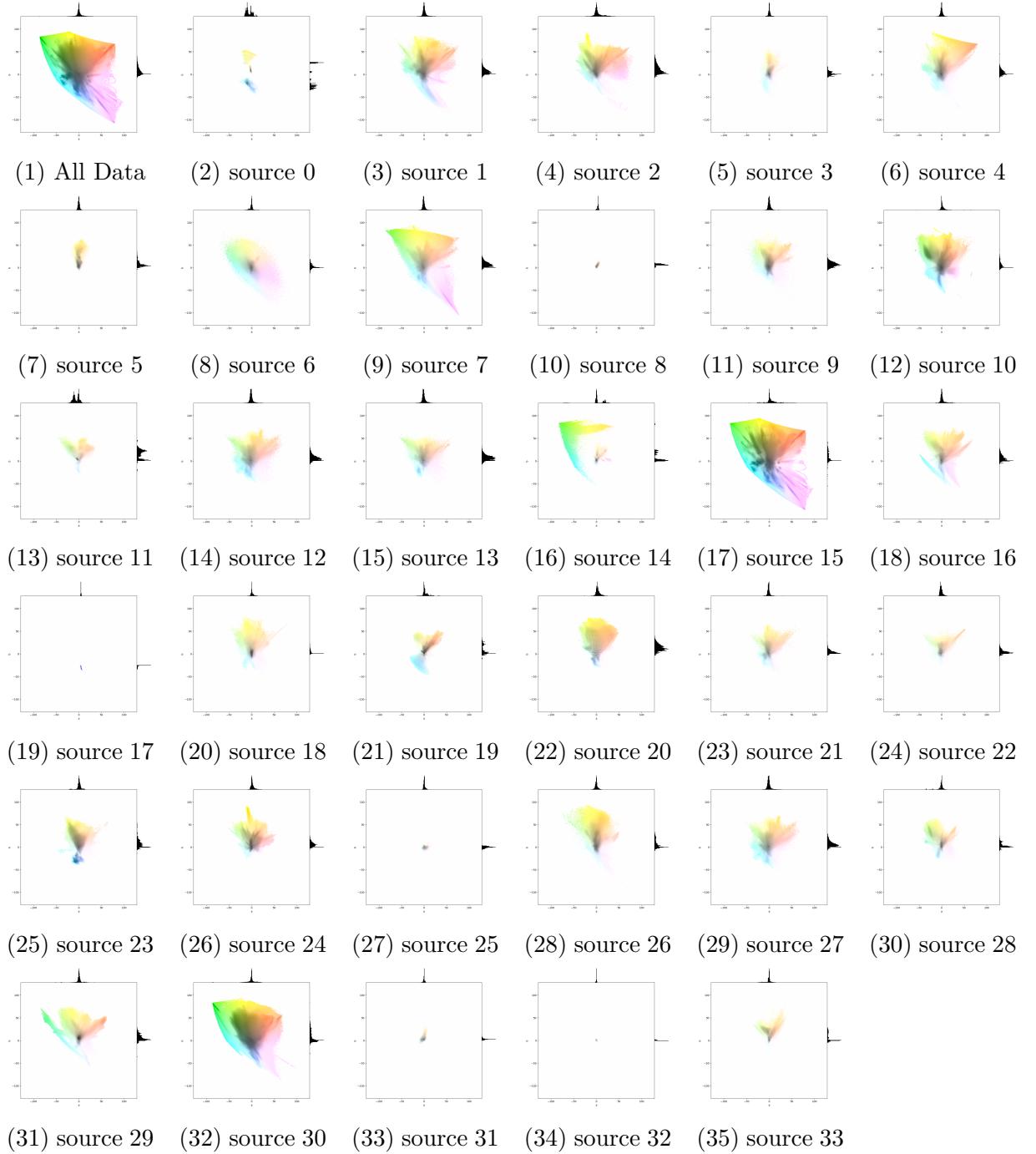


Figure 11: Visualization of datasets plotted in the LAB color space

A.2 Dataset Plots in the RGB Color Space

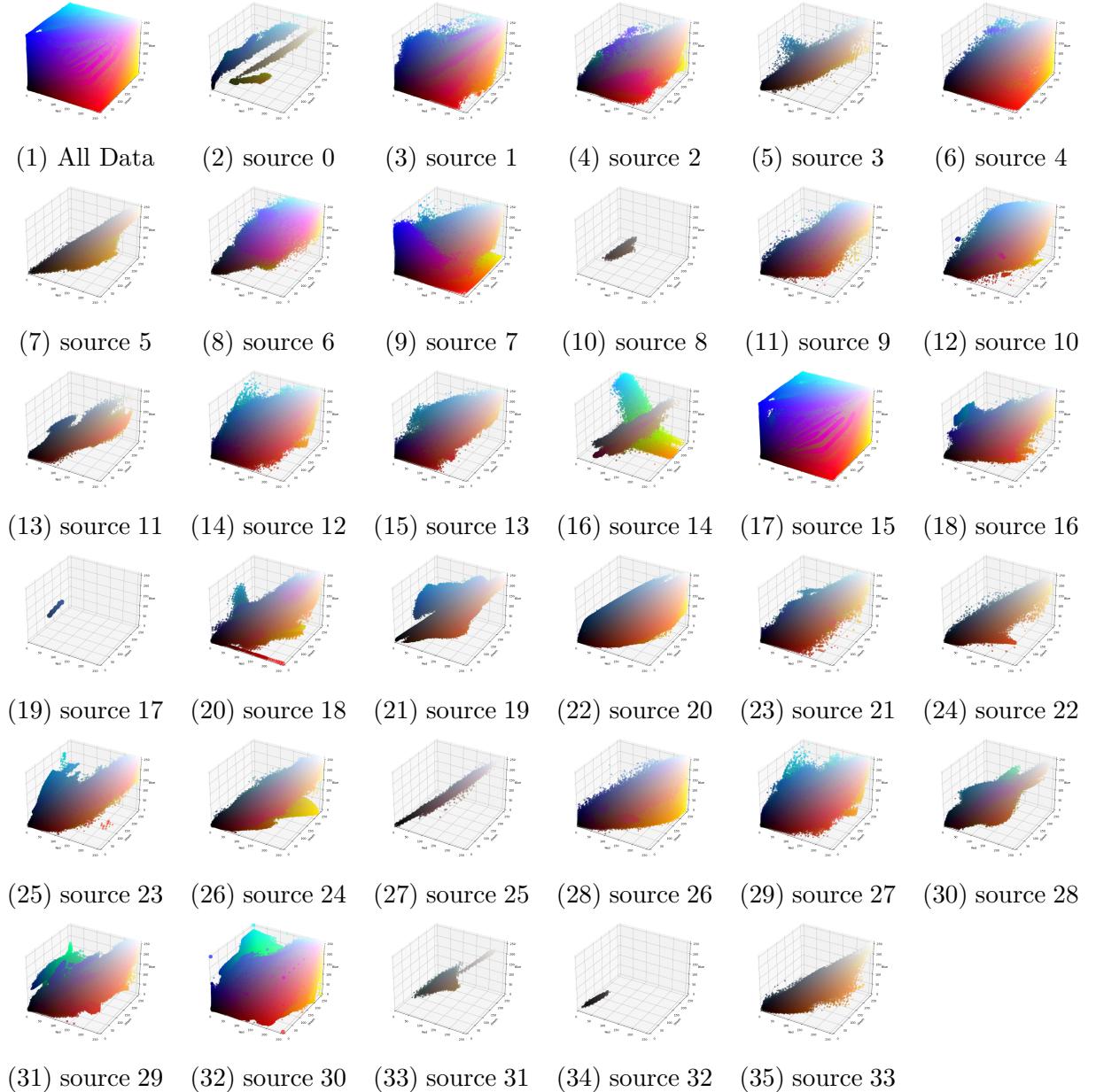


Figure 12: Visualization of datasets plotted in the RGB color space

A.3 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 2: 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 3: Single compute node

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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