

Deep Generative Models

Prepared by Dr. Sherif Mostafa

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Master of Science in Artificial Intelligence

Lecture 8



Advanced Generative Models

Introduction

StyleGAN

Weight Modulation and Demodulation

Path Length Regularization

No Progressive Growing

Outputs from StyleGAN2

StyleGAN: A Deep Dive

StyleGAN3 is a GAN architecture from 2018 that builds on the earlier ideas in the ProGAN paper. In fact, the discriminator is identical; only the generator is changed. Often when training GANs it is difficult to separate out vectors in the latent space corresponding to high-level attributes—they are frequently entangled, meaning that adjusting an image in the latent space to give a face more freckles, for example, might also inadvertently change the background color. While ProGAN generates fantastically realistic images, it is no exception to this general rule. We would ideally like to have full control of the style of the image, and this requires a disentangled separation of features in the latent space.

StyleGAN's Disentangled Features

StyleGAN achieves this by explicitly injecting style vectors into the network at different points: some that control high-level features (e.g., face orientation) and some that control low-level details (e.g., the way the hair falls across the forehead).

1. High-Level Features

Control aspects like face orientation, overall shape, and general appearance.

2. Low-Level Details

Influence specific details like hair texture, skin tone, and subtle facial expressions.

The StyleGAN Generator Architecture

The overall architecture of the StyleGAN generator is shown in Figure. Let's walk through this architecture step by step, starting with the mapping network.

1.Mapping Network

The mapping network takes a random noise vector as input and transforms it into a latent vector that represents the desired image style.

2.Adaptive Instance Normalization (AdaIN)

AdaIN layers are used to inject the style vectors into the generator network at different points, allowing for fine-grained control over the image's style.

3.Synthesis Network

The synthesis network takes the styled latent vectors and generates the final image, progressively building up the image from low-resolution to high-resolution.

Mapping Network: The Foundation of Style

The mapping network is a series of fully connected layers that takes a random noise vector as input and transforms it into a latent vector that represents the desired image style. This latent vector is then used to control the style of the image at different points in the generator network.

Random Noise

The mapping network starts with a random noise vector. This vector is essentially a random set of numbers that serves as the initial input to the network.

Mapping Network: The Foundation of Style

Fully Connected Layers

The noise vector is then passed through a series of fully connected layers. These layers learn to transform the random noise into a meaningful latent vector that represents the desired image style.

Latent Vector

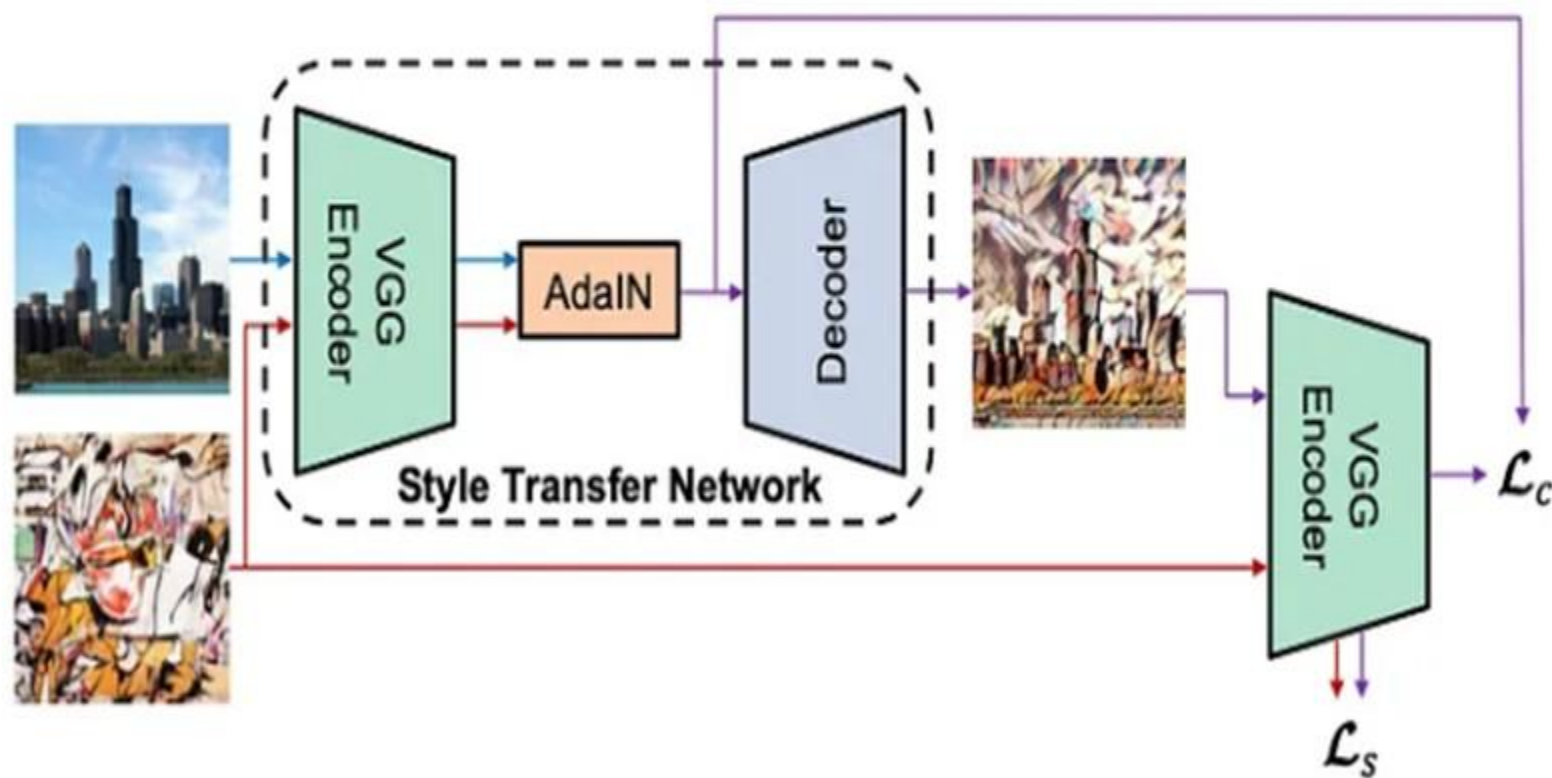
The output of the mapping network is a latent vector. This vector contains information about the desired image style, such as the overall shape, the presence of certain features, and the general appearance of the image.

Adaptive Instance Normalization (AdaIN): Injecting Style

AdaIN layers are used to inject the style vectors into the generator network at different points, allowing for fine-grained control over the image's style. AdaIN layers work by normalizing the input features to have zero mean and unit variance and then scaling and shifting the normalized features using the style vector.

Layer	Function
Normalization	Ensures that the input features have a consistent distribution, regardless of the input image.
Scaling and Shifting	The style vector is used to scale and shift the normalized features, allowing for fine-grained control over the image's style.

Adaptive Instance Normalization (AdaIN): Injecting Style



Synthesis Network: Building the Image

The synthesis network takes the styled latent vectors and generates the final image, progressively building up the image from low-resolution to high-resolution. This progressive approach allows the network to learn complex image structures and generate highly realistic images.

1.Low-Resolution Image

The synthesis network starts by generating a low-resolution image. This initial image is a rough representation of the final image, with basic shapes and features.

Synthesis Network: Building the Image

2. Progressive Upsampling

The network then progressively up samples the image, adding more detail and complexity at each stage. This process continues until the final, high-resolution image is generated.

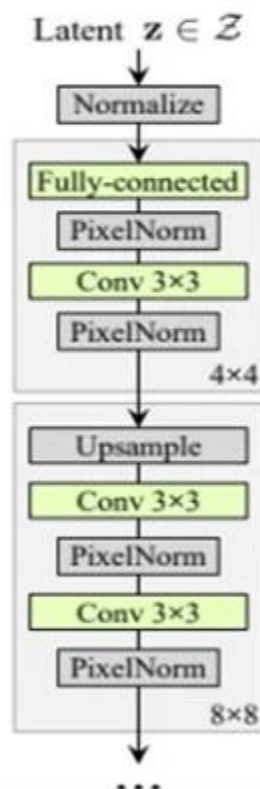
3. High-Resolution Image

The final output of the synthesis network is a high-resolution image that is highly realistic and captures the desired style.

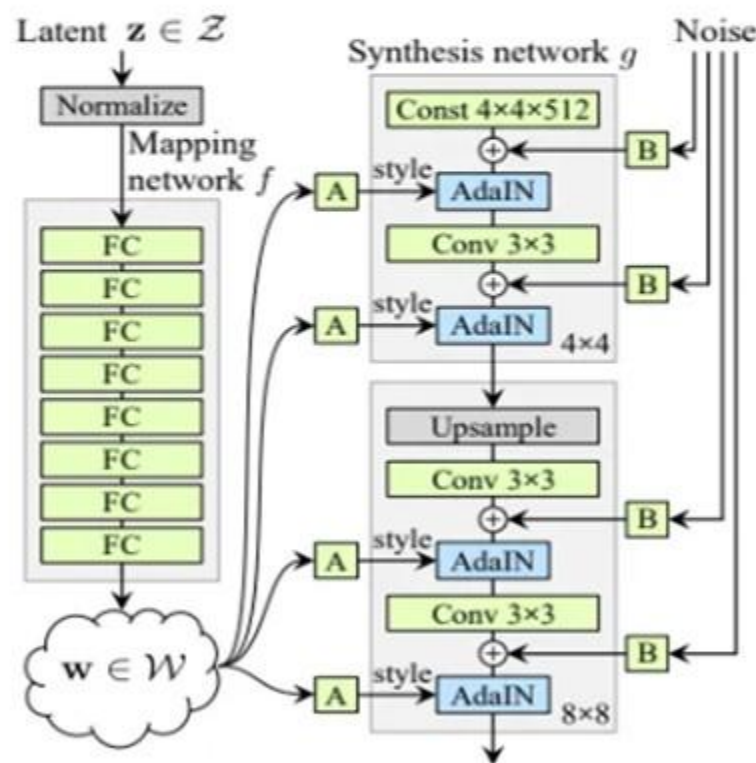
Adaptive Instance Normalization (AdaIN): Injecting Style



Traditional



StyleGAN



StyleGAN's Impact on Image Generation

StyleGAN has had a significant impact on the field of image generation. It has enabled the creation of highly realistic and diverse images, and it has opened up new possibilities for creative applications.

Artistic Expression

Artists can use StyleGAN to create unique and expressive artwork, exploring different styles and concepts.

Game Development

Game developers can use StyleGAN to generate realistic characters, environments, and assets, enhancing the visual fidelity of their games.

Film and Animation

Filmmakers and animators can use StyleGAN to create realistic characters, environments, and special effects, pushing the boundaries of visual storytelling.

StyleGAN: A Powerful Tool for Image Generation

StyleGAN is a powerful tool for image generation that has revolutionized the field. Its ability to disentangle features in the latent space and provide fine-grained control over image style has opened up new possibilities for creative applications.

Realistic Images

StyleGAN generates highly realistic images that are indistinguishable from real photographs.

Diverse Styles

StyleGAN can generate images in a wide range of styles, from photorealistic to abstract.

Control over Features

StyleGAN allows users to control specific features of the generated images, such as the pose, expression, and lighting.

Future of StyleGAN

StyleGAN is a rapidly evolving technology, and its future is bright, Researchers constantly working to enhance its capabilities and explore new applications, while also highlighting the need to address the ethical concerns associated with this technology.

Improved Realism:

Researchers are working to improve the realism of StyleGAN-generated images, making them even more indistinguishable from real photographs.

Future of StyleGAN

New Applications:

StyleGAN is being explored for a wide range of new applications, such as medical imaging, scientific visualization, and even art restoration.

Ethical Considerations:

As StyleGAN becomes more powerful, it is important to consider the ethical implications of its use, such as the potential for misuse in creating deepfakes or generating harmful content.

Style Transfer: A Deep Dive

In the fascinating world of deep learning, style transfer has emerged as a powerful technique that enables us to seamlessly blend the artistic style of one image onto the content of another.

This process often involves a two-step approach, employing separate networks for style extraction and content generation.

The text delves into the architecture and mechanisms behind these networks, exploring the intricacies of style transfer and its remarkable capabilities.

The Mapping Network: Unraveling Style

The mapping network serves as the initial stage in style transfer, tasked with extracting and representing the stylistic essence of a given image. It takes a noise vector, often drawn from a random distribution like Gaussian noise, as input. This random input serves as a starting point for the network to explore the style space.

The network's architecture typically consists of multiple fully connected or convolutional layers that learn to process the input noise vector and transform it into a structured representation of the style, referred to as the style space.

This latent style space captures the essential stylistic features of the input image, allowing the network to generate a meaningful representation of the style, which can then be passed on to the synthesis network for the style transfer process.

The Mapping Network: Unraveling Style

The image provides an overview of the key components in a style transfer neural network:

Input Noise:

The network's journey begins with a noise vector drawn from a random distribution, which provides a foundation for the network's exploration of the style space.

Mapping Network Layers:

The network's core lies in its layers, typically fully connected or convolutional, which learn to process the input noise vector. These layers gradually transform the random noise into a structured representation of the style.

Output Style Vector:

The network's final output is a style vector, a compact representation of the extracted style. This vector captures the essential stylistic features of the input image, ready to be passed on to the synthesis network.

Disentanglement: Separating Style and Content

The mapping network plays a crucial role in disentangling the style from the content of an image. This disentangling process is essential for allowing the style transfer process to selectively apply a specific style to any desired content type. The disentangling achieved through the mapping network enables the separation of the style-choosing process from the image generation process.

Disentanglement: Separating Style and Content

1. Style Variation:

The mapping network enables the exploration of a wide range of artistic styles by manipulating the input noise, generating different style vectors corresponding to various styles. This allows for flexibility in style selection, catering to diverse artistic preferences.

2. Independent Control:

The mapping network facilitates independent control over the style. The style vector generated by the network can be used to adjust the style of the output image without altering the content. This provides a powerful mechanism for manipulating the style of an image.

Disentanglement: Separating Style and Content

3. Content Preservation:

By disentangling style from content, the mapping network enables the preservation of the original image's content while applying a new style. This ensures that the content of the image remains intact, while its visual appearance is transformed by the chosen style.

The image also features an abstract, swirling pattern, which complements the informative text about the disentanglement process in image generation.

the Synthesis Network: Building style-infused images

The Synthesis Network takes a central role in the style transfer process, responsible for generating the final image with the desired style. It receives the style vector from the mapping network and utilizes it to guide the image generation process.

The synthesis network's core lies in its ability to incorporate the style vector into its internal operations, effectively transforming the content of the image while preserving its structural integrity.

the Synthesis Network: Building style-infused images

The synthesis network often consists of multiple convolutional layers, each responsible for processing different levels of detail in the generated image. The network incorporates AdaIN layers, which allow for dynamic adjustment of the image's features based on the style vector.

1. Input Content:

The synthesis network receives the content image as input, which serves as the foundation upon which the desired style will be applied.

2. Style Injection:

The style vector from the mapping network is injected into the synthesis network at specific layers, influencing the image's feature maps.

3. Synthesis Layers:

The synthesis network's layers process the content image and the injected style, gradually building the final image with the desired style.

Adaptive Instance Normalization : Style Injection

Adaptive Instance Normalization (AdaIN) plays a pivotal role in enabling the seamless integration of style into the image generation process. It allows for dynamic adjustment of the image's features based on the style vector, effectively transforming the image's appearance while preserving its underlying structure.

AdaIN works by normalizing the features of the image, ensuring a consistent distribution across different layers. This normalization is crucial for stabilizing the training process and preventing overfitting.

The key to style transfer lies in the adaptive nature of AdaIN, which allows for adjustments to the normalized features based on the extracted style.

Adaptive Instance Normalization : Style Injection

Normalizing Feature:

AdaIN first normalizes the features of the image, ensuring a consistent distribution across layers.

Scaling and Bias:

The AdaIN layer then applies a scaling and bias operation based on the style vector, adjusting the normalized features to match the desired style.

Style Transaction:

These scaling and bias operations effectively transform the image's features, aligning them with the stylistic characteristics captured by the style vector.

This explains how the AdaIN layer plays a crucial role in the style injection process, enabling the integration of the desired style into the generated image.

Style Vector Injection: Shaping the Image's Features

The style vector, carrying the essence of the chosen style, is injected into the synthesis network at different points. These injection points are strategically placed within the network, targeting specific layers that process different levels of detail in the generated image.

Each injection point corresponds to a densely connected layer, which generates two vectors: a bias vector and a scaling vector. These vectors define the specific style that should be injected at this point in the network.

Style Vector Injection: Shaping the Image's Features

The bias vector acts as a shift, adjusting the mean of the features, while the scaling vector acts as a stretch, adjusting the variance of the features. By manipulating these vectors, the style vector controls the specific style characteristics that are injected into the image at each layer.

This approach allows for fine-grained control over the style transformation, enabling the network to adapt the style to different content images and achieve a wide range of stylistic variations.

The Power of Style Transfer: Artistic Fusion

Artistic Expression:

Style transfer allows artists to experiment with different artistic styles, creating unique and captivating works of art.

Image Enhancement:

Photographers can utilize style transfer to enhance their images, applying artistic filters and special effects to elevate their work.

The Power of Style Transfer: Artistic Fusion

User Interface Design:

Designers can leverage style transfer to create visually appealing user interfaces, enhancing the user experience with unique aesthetics.

Content Personalization:

Style transfer can be used to personalize content, allowing users to customize their visual experiences based on their individual preferences.

Beyond the Basics: Exploring Advanced Techniques

Style transfer, highlighting the emergence of new techniques that expand the capabilities and address various challenges.

Neural Style Transfer:

This technique employs deep neural networks to learn the style from an image and apply it to a content image, offering a more sophisticated approach to style transfer.

Multi-Style Transfer:

Multi-style transfer allows for the simultaneous application of multiple styles to a single image, creating intricate and visually captivating results.

Beyond the Basics: Exploring Advanced Techniques

Real-Time Style Transfer:

Real-time style transfer enables the application of styles to images in real-time, facilitating interactive experiences and applications for live video processing.

These advanced techniques aim to refine the style transfer process, improving its accuracy, efficiency, and creative potential, as the field of style transfer continues to evolve with active research and development.

The Future of Style Transfer: Unlocking New Possibilities

The future of style transfer holds immense promise, with ongoing research and development pushing the boundaries of this powerful technique.

Advancements in deep learning and computer vision are expected to further enhance the capabilities of style transfer, unlocking new possibilities for creative expression and technological innovation.

The Future of Style Transfer: Unlocking New Possibilities

Style transfer is poised to play a significant role in shaping the future of visual content creation, empowering artists, designers, and developers to explore uncharted territories of visual aesthetics.

As the style transfer technique continues to evolve, we can anticipate exciting developments and applications that will revolutionize the way we create, manipulate, and interact with visual content.

Adaptive Instance Normalization (AdaIN) for style transfer

Adaptive Instance Normalization (AdaIN) is a powerful technique used to enable neural networks to effectively separate content and style information in images, allowing for the manipulation of style while preserving the original content. This method leads to impressive results in image generation and artistic transformations.

AdaIN layer: Adjusting Mean and Variance

AdaIN layer is a type of neural network layer that adjusts the mean and variance of each feature map with a reference style bias b and scale s , which are vectors of length equal to the number of channels output from the preceding convolutional layer in the synthesis network.

This allows for the manipulation of the style information in images while preserving the original content.

Style Vector Injection: Controlling Feature Transformations

the adaptive instance normalization layers ensure that the style vectors injected into each layer only affect the features at that particular layer, preventing any style information from leaking through between layers. This results in the latent vectors being significantly more disentangled than the original vectors.

Progressive Training: Controlling Style at Different Levels of Detail

Since the synthesis network is based on the ProGAN architecture, it is trained progressively. This means that the style vectors at earlier layers in the network (when the image resolution is lowest, around 4×4 to 8×8) affect the coarser features, while the style vectors at later layers (when the resolution is higher, 64×64 to 1024×1024) affect the finer details.

The key point is that this progressive training approach provides complete control over the generated image through the latent vector, as well as the ability to switch the vector at different points in the synthesis network to change the style at a variety of levels of detail.

Style Mixing: Breaking Correlations for Disentangled Styles

“Style mixing” technique used to ensure that the styles injected at each layer are as disentangled as possible.

Instead of sampling only a single latent vector, two latent vectors (Z_1 , Z_2) are sampled, corresponding to two style vectors (W_1 , W_2).

At each layer, either W_1 or W_2 is randomly chosen to be injected, breaking any possible correlation between the style vectors.

This approach allows the generator to learn disentangled styles, preventing it from exploiting any correlations between adjacent styles during the training process. The goal is to achieve more independent and versatile style manipulations in the generated images.

The background image suggests the application of this technique in a creative or artistic context, where controlling and mixing disentangled styles can lead to compelling visual results.

AdaIN: A Key Component in Style Transfer

Content Preservation:

AdaIN allows for the transfer of style without altering the original content of an image. This is achieved by separating the content and style representations within the neural network.

Style Control:

The ability to inject style vectors at different layers of the network provides granular control over the style of the generated image, enabling fine-grained adjustments.

AdaIN: A Key Component in Style Transfer

Disentangled Representations:

Style mixing techniques ensure that the style vectors are disentangled, preventing unwanted correlations and leading to more expressive and controllable style transfer.

Progressive Training:

The progressive training approach allows for the control of style at different levels of detail, enabling the creation of images with both global and local style variations.

Applications of AdaIN

Artistic Style Transfer:

Transforming images into different artistic styles, such as painting, photography, or graphic design.

Image Generation:

Creating new images with specific styles and content, enabling the generation of realistic and stylized images.

Image Editing:

Modifying the style of existing images, allowing for creative adjustments and enhancements.

Advantages of AdaIN

Improved Control:

AdaIN provides fine-grained control over the style of generated images, allowing for precise adjustments and creative exploration.

Disentangled Representations:

Style mixing techniques ensure that the style vectors are disentangled, leading to more expressive and controllable style transfer.

Efficient Training:

AdaIN is computationally efficient and can be trained effectively on large datasets, enabling the development of powerful style transfer models.

Future Directions for AdaIN

Exploring new techniques for style disentanglement:

Future research in AdaIN could focus on exploring new methods to improve the disentanglement of style information, leading to more expressive and controllable style transfer.

Improving the efficiency of style transfer:

Ongoing research aims to develop more efficient style transfer models, enabling the creation of powerful and versatile image generation and manipulation tools.

Developing novel applications:

The potential for AdaIN to revolutionize image generation and manipulation is vast, and further research is likely to lead to even more impressive and creative results in various applications.

Stochastic Variation in Generative Adversarial Networks

GANs have revolutionized the field of image synthesis, enabling the creation of remarkably realistic and diverse images.

One key aspect of this success is the ability of GANs to incorporate stochastic variation into their image generation process.

Stochastic variation introduces random elements into the network's output, contributing to the rich diversity and natural variability seen in real-world images.

The Role of the Noise

A key element in StyleGAN's stochastic variation strategy is the injection of noise after each convolutional layer. This noise, passed through a learned broadcasting layer (B), simulates the presence of minute, stochastic details that are often imperceptible to the naked eye but contribute to the subtle nuances and variations that make real-world images so compelling.

These subtle details, such as variations in hair placement, uneven texture of a surface, or randomness in a background of an image. These details, collectively captured as "noise" by the network, are crucial in creating the realistic look and feel of the generated images.

The Role of the Noise

Noise Depth and Control:

The depth at which noise is injected into the network affects the scale and impact of its influence. Deeper layers capture larger-scale features, while shallower layers influence subtle aspects like texture and microstructure.

Learned Constant Inputs:

The inclusion of noise at various levels within the network allows StyleGAN to start with a simple, learned constant as the initial input to the synthesis network. This constant serves as a starting point, and the stochasticity inherent in the style inputs and the noise inputs themselves provides enough variation to generate a wide range of distinct images.

StyleGAN in Action: Merging Styles

One of the most remarkable features of StyleGAN is its ability to merge styles between different images. This capability where two generated images, Source A and Source B, are created from distinct input vectors.

The merging process involves passing the Source A vector through the synthesis network, but at a specific point, switching to the Source B vector. This switch point determines the level of detail at which the styles are merged, allowing for seamless blending of the visual elements from the two input sources.

In other words, StyleGAN can generate images that combine the styles and characteristics of different input vectors, enabling the creation of novel and unique visual compositions by leveraging the strengths of multiple source images.

StyleGAN in Action: Merging Styles

Early Switch:

Switching later in the network, at higher resolutions, results in the transfer of only fine-grained details from Source B onto Source A. This might involve merging colors, texture variations, or microstructural features of the face, while preserving the coarse features of Source A. This creates an image with the overall structure and shape of Source A, but with subtle details borrowed from Source B.

StyleGAN in Action: Merging Styles

Late Switch:

Switching early in the network, at lower resolutions like 4x4 or 8x8, merges the coarse features from Source B onto Source A. This means that aspects like pose, face shape, and the presence of glasses from Source B are transferred, while Source A retains its original fine-grained details. The result is a blended image where the overall shape and structure are taken from Source B, but the finer details remain from Source A.

In summary, the Early Switch and Late Switch mechanisms allow StyleGAN to selectively transfer coarse or fine-grained visual elements from one source image to another, enabling the creation of unique and compelling hybrid images.

The Impact of Stochasticity: Realism and Diversity

There is a crucial role that stochastic variation plays in the realism and diversity of images generated by StyleGAN. The random noise introduced at various levels in the network creates subtle variations that mimic the inherent randomness found in real-world images. This translates into a wider range of outputs, with each generated image exhibiting unique details. The stochastic variation allows StyleGAN to capture the nuances and unpredictability that are characteristic of natural images, resulting in a more realistic and diverse set of generated outputs.

In essence, the inclusion of this stochastic variation is a key factor that enables StyleGAN to produce images that feel authentic and true to the real world, rather than appearing overly uniform or synthetic. This diversity and realism are hallmarks of the StyleGAN approach to image generation.

The Impact of Stochasticity: Realism and Diversity

Hair Placement and Texture:

Noise injection contributes to the realistic rendering of hair, capturing the subtle variations in hair placement, thickness, and texture that differentiate individual strands.

Surface Texture and Microstructure:

The noise component helps create natural-looking textures on surfaces, capturing the fine-grained variations and irregularities that give objects a realistic appearance.

Background Complexity and Depth:

Stochastic variation can also be used to generate complex and realistic backgrounds, simulating the random arrangement of objects and details that contribute to the depth and richness of a scene.

Controlling Stochasticity: Fine-tuning Image Generation

While stochastic variation is essential for generating realistic and diverse images, it is also crucial to have control over the level of randomness introduced into the generation process. StyleGAN provides mechanisms that allow users to fine-tune the level of stochastic variation at different layers within the network.

This gives users a greater degree of control over the specific types of variations that are incorporated into the final generated images. By allowing adjustments to the noise level at different layers, StyleGAN enables users to precisely manage the balance between realism and the desired characteristics of the generated outputs.

In other words, StyleGAN's capabilities go beyond simply introducing stochastic variation, but also provide the tools for users to precisely tailor the level and nature of that variation to suit their specific needs or preferences. This fine-tuning capability is an important aspect of the StyleGAN framework, allowing for greater flexibility and customization in the image generation process.

Controlling Stochasticity: Fine-tuning Image Generation

Three key mechanisms for controlling the level of stochastic variation in the image generation process:

Noise Strength: Adjusting the overall level of stochasticity introduced into the network. Higher noise levels lead to greater variations in the generated images, while lower noise levels result in more deterministic and less varied outputs.

Noise Filter: By applying filters to the noise, users can influence the types of variations introduced into the network. For example, filters can be used to emphasize certain frequency ranges within the noise, leading to specific types of variations in the generated image.

Noise Frequency: Adjusting the frequency of the noise allows users to control the scale of the variations introduced into the network. Higher frequencies result in finer-grained variations, while lower frequencies lead to larger-scale variations in the generated image.

Applications of Stochastic Variation in GANs

The incorporation of stochastic variation into GANs has opened up a wide range of applications across various domains, from image synthesis and manipulation to data augmentation and training, as well as artistic exploration and creativity.

Image Synthesis and Manipulation:

The ability to control stochasticity in GANs has become a powerful tool for generating high-quality images, manipulating existing images, and creating new visual styles. This has led to applications in art generation, photo editing, and even the creation of personalized avatars.

Applications of Stochastic Variation in GANs

Data Augmentation and Training:

The ability to generate realistic synthetic data using GANs is a boon for machine learning, especially in domains where real data is limited or expensive to acquire. Stochastic variation ensures that the synthetic data generated is diverse and representative of real-world variations, leading to more robust and accurate machine learning models.

Artistic Exploration and Creativity:

By introducing random elements into the creative process, stochastic variation has enabled artists and designers to explore new styles, create unique visuals, and push the boundaries of artistic expression. This has led to the development of innovative artistic tools and techniques powered by GANs.

Future Directions in Stochastic Variation

The field of stochastic variation in GANs, with researchers exploring new ways to enhance the realism, diversity, and controllability of the generated images and content.

Noise Models:

Developing more advanced noise models that capture the intricate details and variations present in real-world scenes.

Style Transfer:

Improving techniques for style transfer and manipulation, enabling users to seamlessly blend and transfer styles between different images.

Future Directions in Stochastic Variation

High-Resolution Synthesis:

Extending stochastic variation to generate high-resolution images with intricate details and realistic textures.

3D Scene Generation:

Exploring the use of stochastic variation to generate complex 3D scenes, including realistic objects, environments, and lighting.



Thank You