# Towards AI-Generated African Textile Patterns with StyleGAN and Stable Diffusion

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IARIA

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# Agenda

- Why this work?
- Wax patterns
- Background on GAN and StyleGAN
- Background on Stable Diffusion
- Experimentation
- Results
- Conclusion & Future Work

# Exploration

- How to use Generative AI to create African wax patterns?
- How can different training approaches manipulate design aspects like color, pattern, and texture?
- How to bridge communities and target global problems?

# Wax Fabric

## Wax

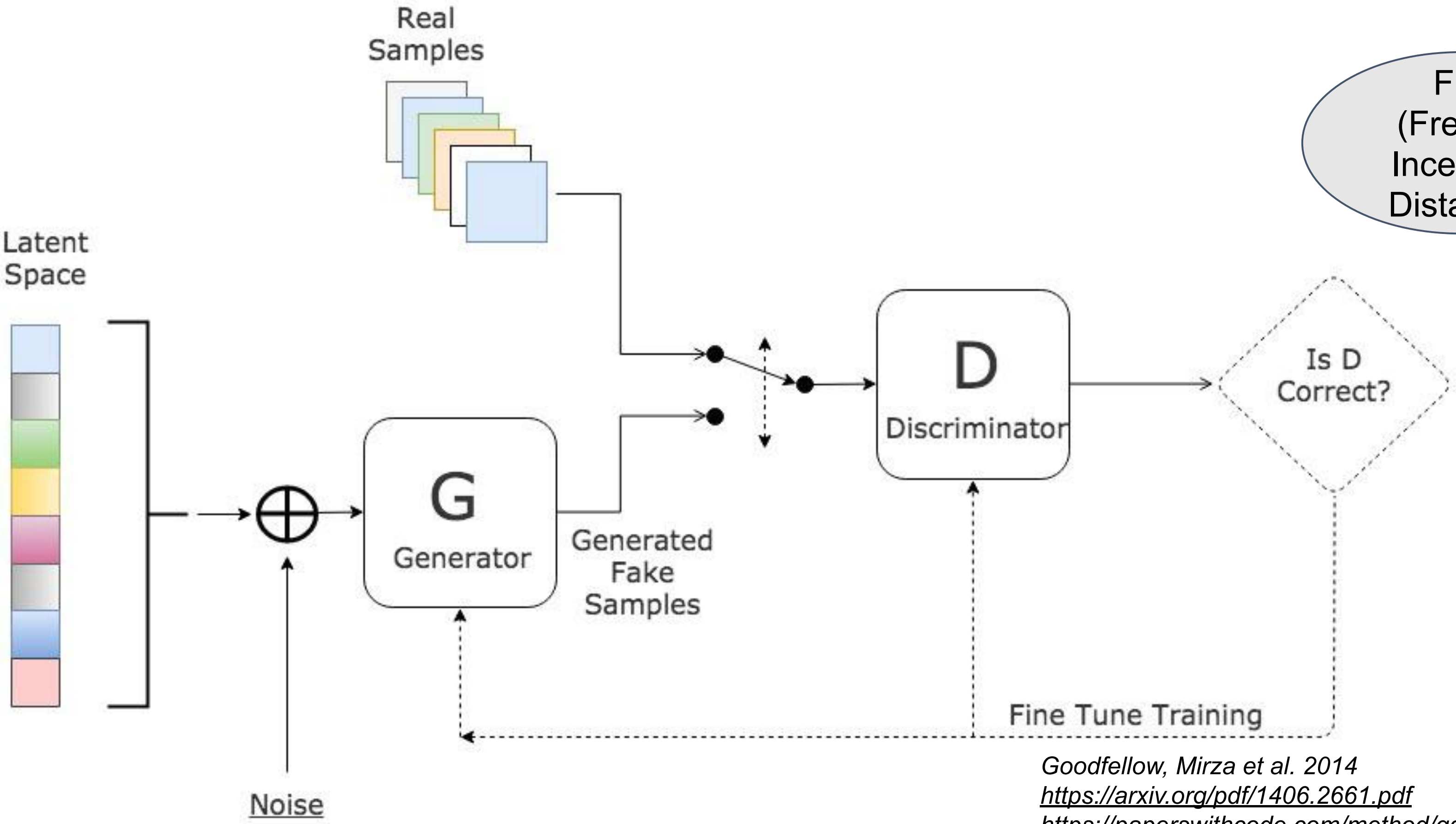
*Iwaria picture on Pexels. https://www.pexels.com/photo/close-up-photo-of-african-fabrics-8655023/*

## International Context

*[Dior, Cruise 2020 Collection, https://www.dior.com/en_us/fashion/womens-fashion/ready-to-wear-shows/cruise-2020-show]*

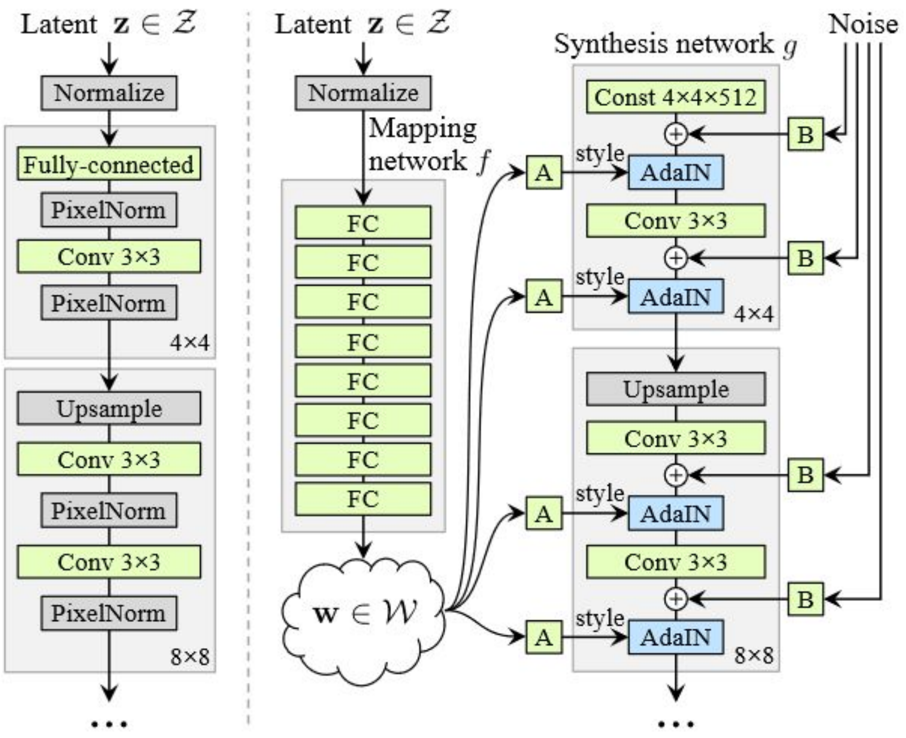
# Generative Adversarial Network

FID (Frechet Inception Distance)




*Goodfellow, Mirza et al. 2014*
*https://arxiv.org/pdf/1406.2661.pdf*
*https://paperswithcode.com/method/gan*

# StyleGAN

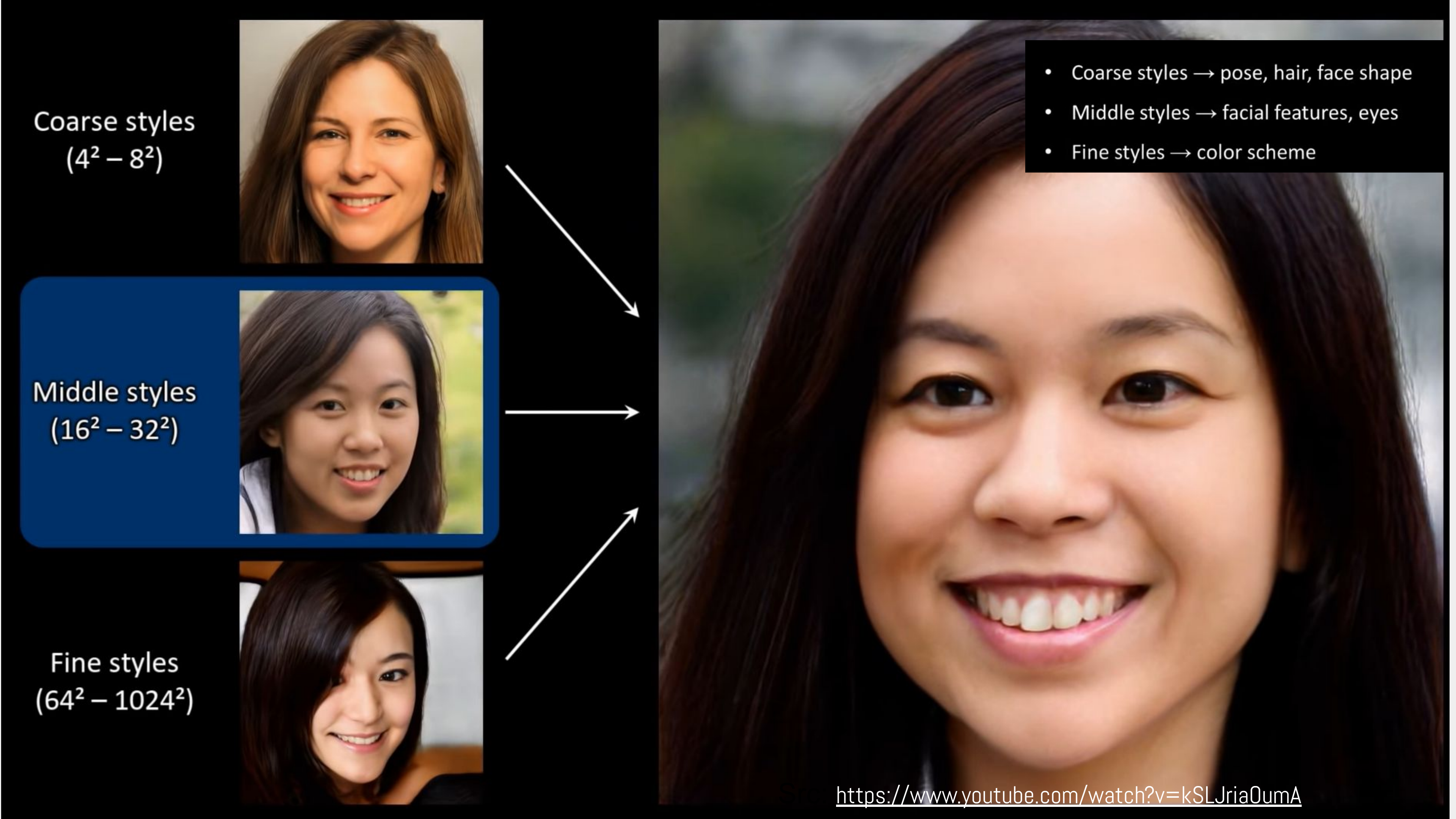



(a) Traditional (b) Style-based generator

Multiple levels of style

FID (Frechet Inception Distance)

*Karras et all , NVIDIA 2018*
*https://arxiv.org/pdf/1812.04948.pdf*


Coarse styles
($4^2 - 8^2$)
Middle styles
($16^2 - 32^2$)
Fine styles
($64^2 - 1024^2$)
• Coarse styles ⟶ pose, hair, face shape
• Middle styles ⟶ facial features, eyes
• Fine styles ⟶ color scheme
https://www.youtube.com/watch?v=kSLJriaOumA

StyleGAN

StyleGAN2

StyleGAN2-ADA

StyleGAN3

# Evaluation of Generated Images

- Frechet Inception Distance (FID) is a metric used to evaluate the quality and diversity of generated images in GAN.
- Lower FID suggests that the generated images are more similar to the real images in terms of their overall appearance and statistical properties.
- FID calculates the distance between the distributions of real and generated images in a feature space learned by an InceptionV3 neural network.

# FID

- FID has several limitations: unique application to images, insensitivity to certain fine-grained details, subjectivity, and requirements on image  preprocessing (scale, cropping and normalization).
- FID and other evaluation metrics should be coupled with Subject Matter Expert (SME) evaluation to judge the realism and details of generated images.

# Stable Diffusion

- Stable Diffusion models (e.g., Stability AI SDXL) produce images guided by textual descriptions
- They rely on a Variational Autoencoder (VAE) to map images to and from this latent space, producing a randomized initialized noise, and a Denoising Diffusion Probabilistic Model (DDPM) to iteratively refine these image

Ho et all, 2020, https://arxiv.org/pdf/2006.11239.pdf

# Dataset

Synthetic dataset

- **2000 1024x1024** images collected from **OpenAI DALL·E 2** using prompt engineering, capturing various shapes, colors, objects
- **Preprocessing:** Image normalization and data augmentation

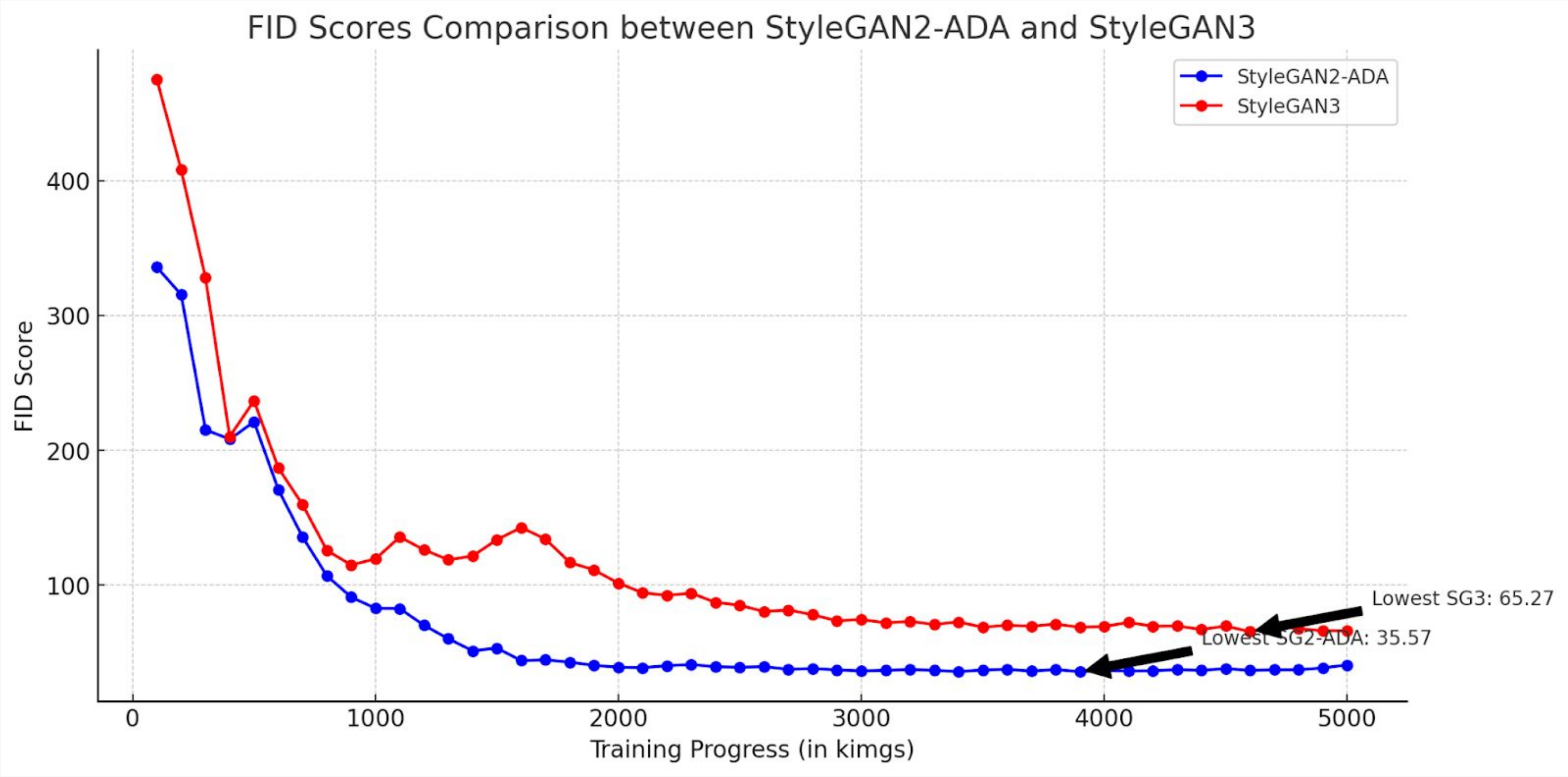



# StyleGAN2-ADA versus StyleGAN3

HPC on 2 nodes. Each node is a 2x Intel(R) Xeon(R) Gold 6136 CPU @ 3.00GHz (24 cores total), 384GB RAM and 3x Nvidia Tesla V100 GPUs

FID 35.57

FID 65.27




Training Progress of StyleGAN2-ADA and StyleGAN3 in Kimgs Depicting FID.

# StyleGAN2ADA versus Stable Diffusion

Prompt: "Afwapa, beautiful african wax pattern with blue and black designs"

FID 35.57

# Results

- Varied performances and nuances in the production of the generated images.
- StyleGAN models are dedicated to learn and mimic complex distributions from training data. They capture global and local patterns.
    - Quality of generated images dependent of the diversity and size of the training dataset, the alignment of images, the model capacity, and the specifics of the training data
- Stable Diffusion models leverage the characteristics of these patterns more directly throughout the image generation process.
    - Higher fidelity to the specific overall style of African wax patterns

# Conclusion & Future Work

- StyleGAN2-ADA generated designs diverse in colors, shapes and details with some symmetry and repetition.
- Stable Diffusion was stronger with symmetry and repetition, but it generated less details.

- Importance of human involvement in the process
- Refinement of the styles - geometry, symmetry, symbols etc.

- **Broader impact:** Diversity of the problems to tackle and solve; bridge between communities

# THANKS

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Thanks to all involved in the project

Credits: This presentation template was created by Slidesgo, including icons by Flaticon, and infographics & images by Freepik.

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