Image Synthesis

What are DeepFakes good for ?

INNOVATRICS

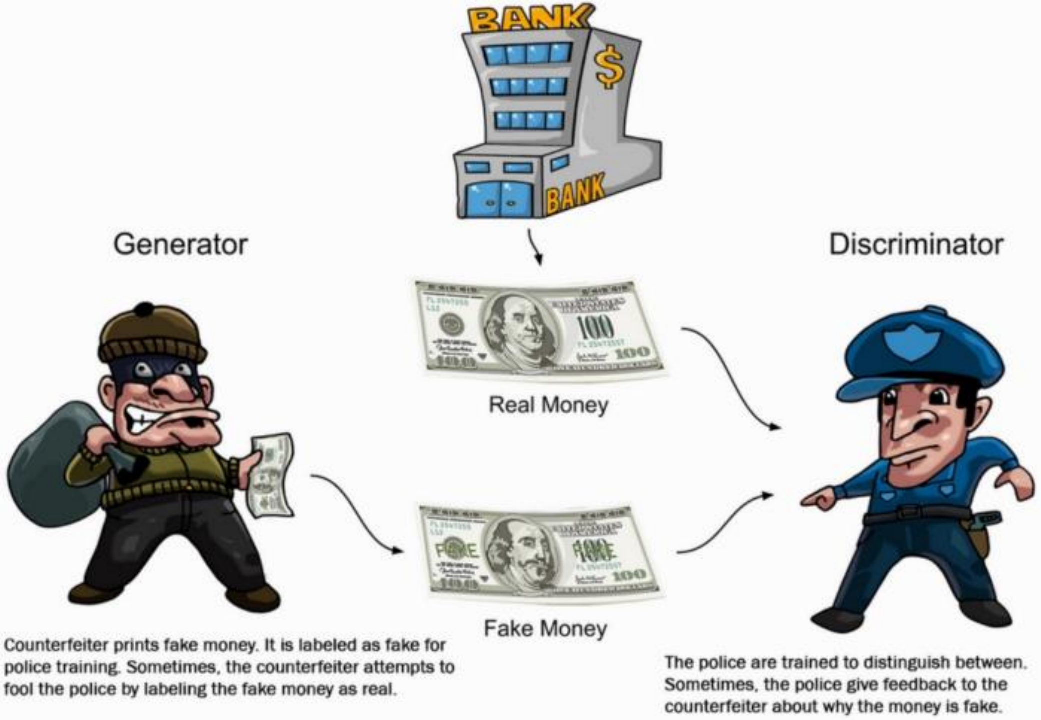
Overview

1. Data
2. Data synthesis @ Innovatrics
   - Faces
   - Fingerprints
   - Latent fingerprints
3. Future ideas

DeepFakes

DeepFakes

Generative Adversarial Networks - GANs

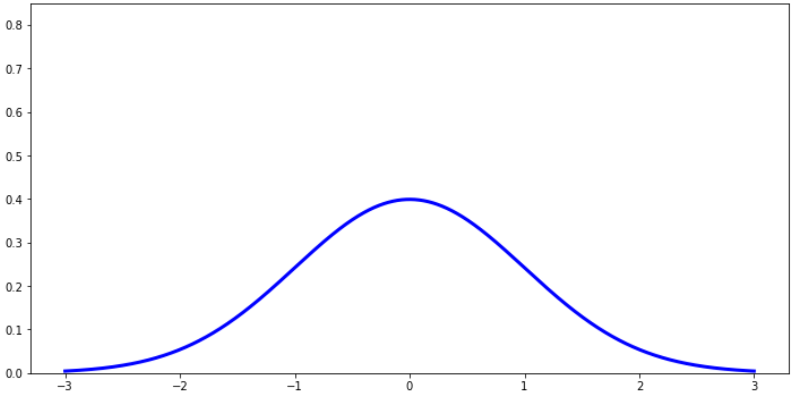


1. Data

“There is never enough data”

1. Data

Quantity and quality follows a distribution

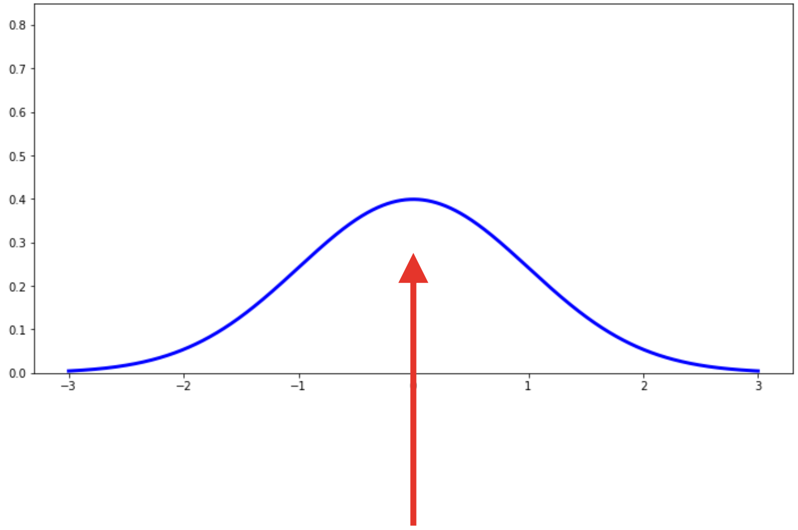


1. Data

Quantity and quality follows a distribution

Cover the majority of situations

- “Must have”



1. Data

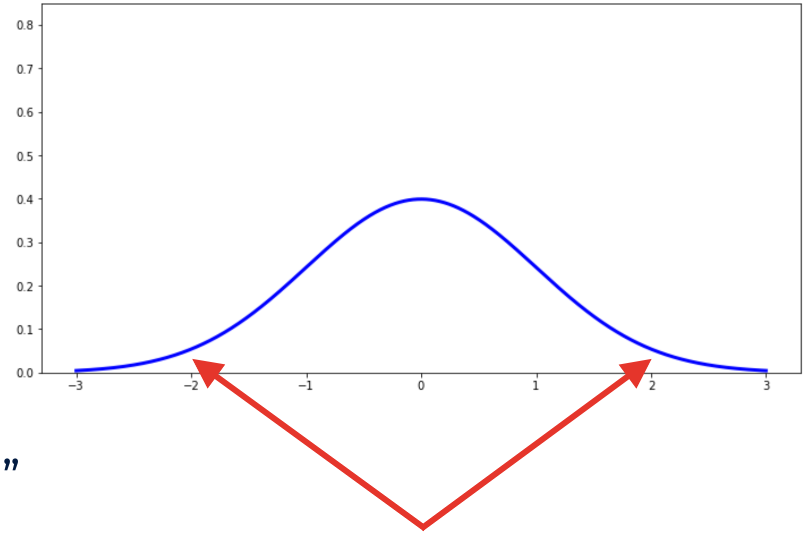
Quantity and quality follows a distribution

Cover the majority of situations

- “Must have”

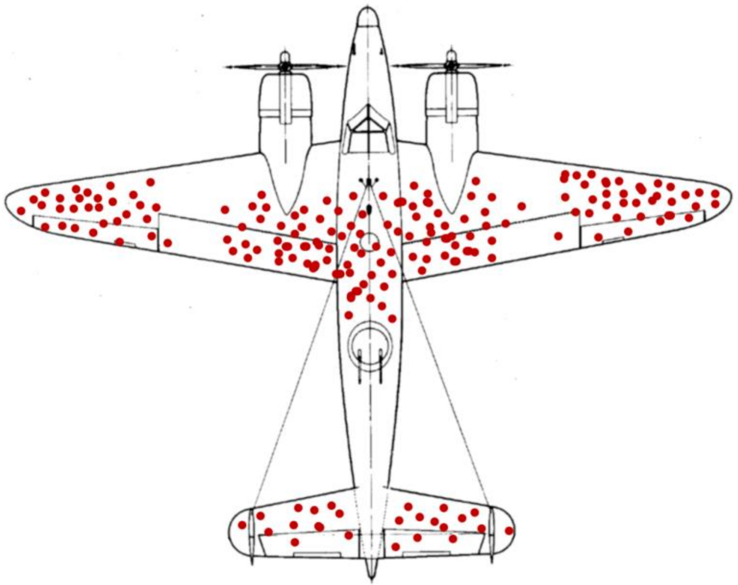
Deal with rare/unexpected events

- “State of the art”, “Life & death”



1. Data

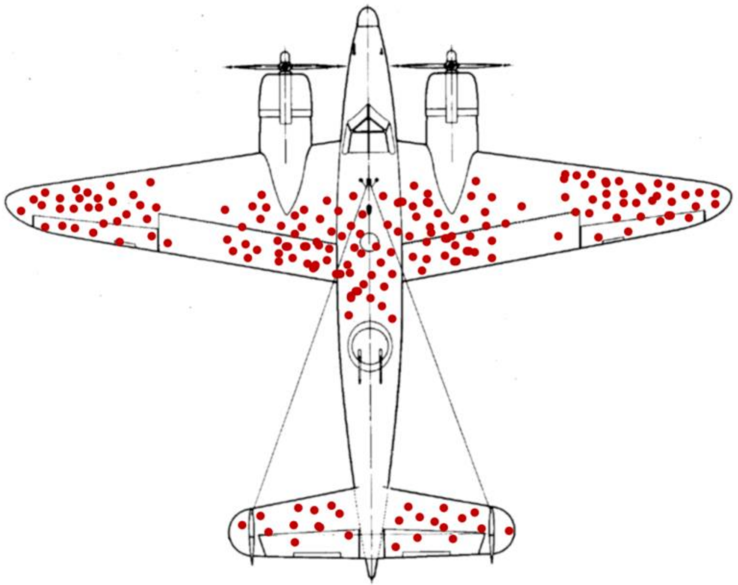
What parts of the aircraft should be reinforced ?



1. Data

What parts of the aircraft should be reinforced ?

Sometimes - the most important parts of information are in what is missing



2. Data Synthesis @ Innovatrics

"When data is scarce or difficult to get, DeekFakes come to the rescue."

“When data is scarce or difficult to get, DeekFakes come to the rescue.”

“Good enough to be useful”

2.1 Synthesis of Faces

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Liveness Detection

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Liveness Detection

Real person (3D) or printed facsimile?

Changes of perspective.

2.1 Synthesis of Faces

Liveness Detection - Generate Faces

StyleGAN

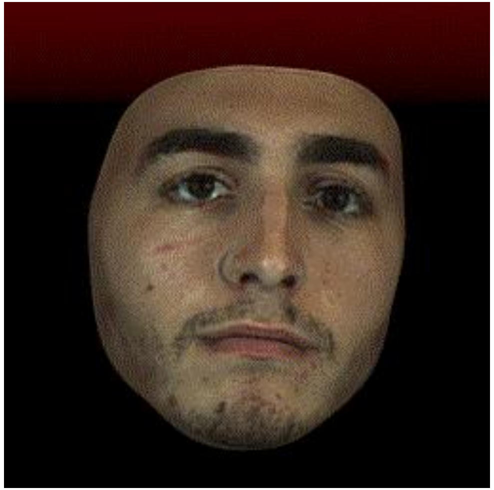
Generate and control synthetic faces of people

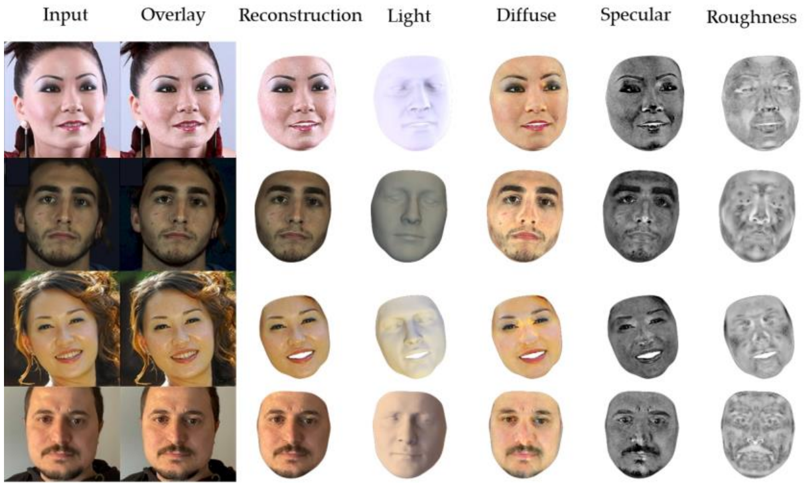
Karras, Laine, et. al. : Analyzing and Improving the Image Quality of StyleGAN, 2020

2.1 Synthesis of Faces

Liveness Detection - Extract 3D Model

3D model from single image

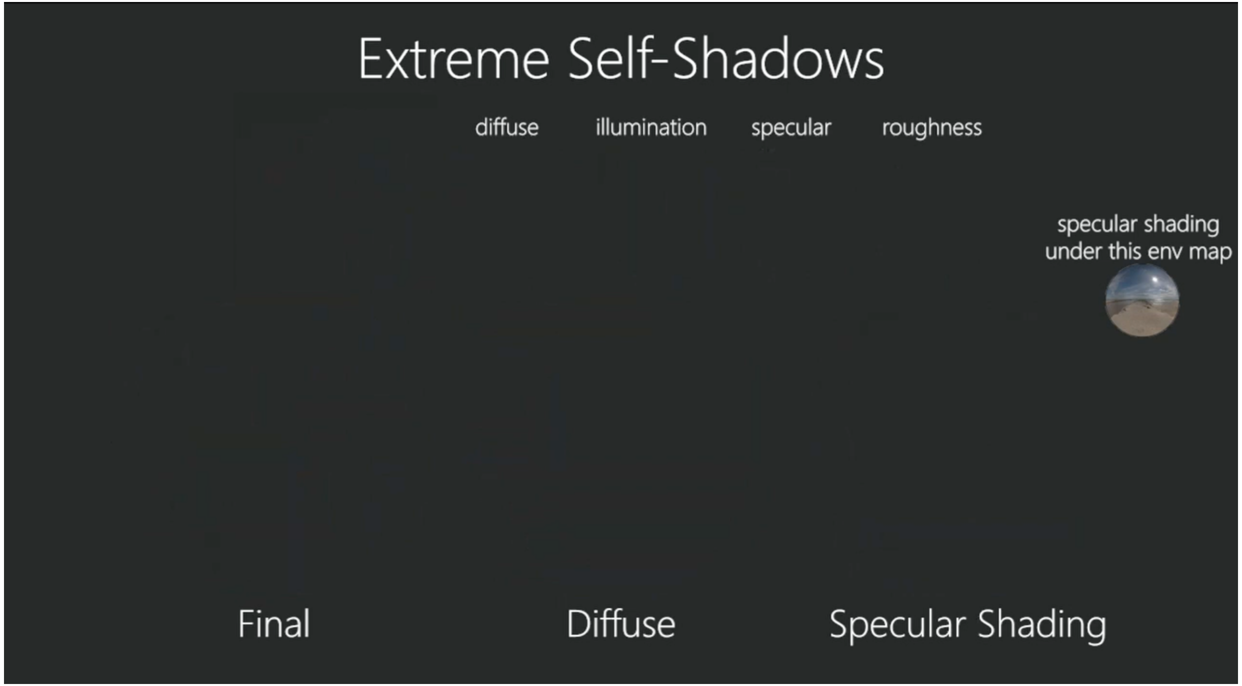




Dib, Bharaj et. al : Practical face reconstruction via differentiable ray tracing, 2021

2.1 Synthesis of Faces

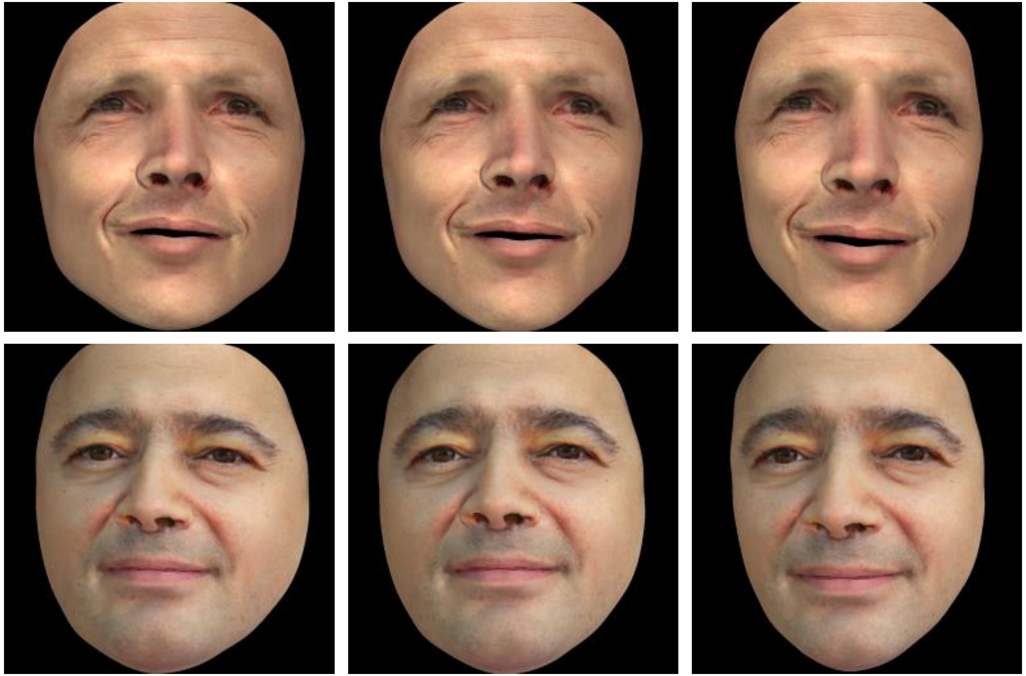
Liveness Detection - Adjust Properties of 3D Model



Dib, Bharaj et. al : Practical face reconstruction via differentiable ray tracing, 2021

2.1 Synthesis of Faces

Liveness Detection - Rendering with Perspective



2.1 Synthesis of Faces

Detection of Synth. Images / Tampering / Morphing

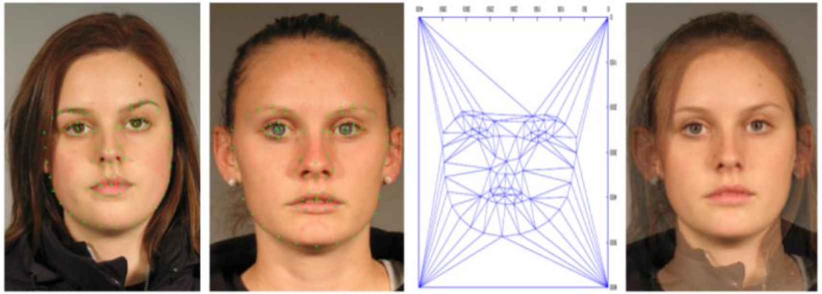
Is x a real person or synth ?

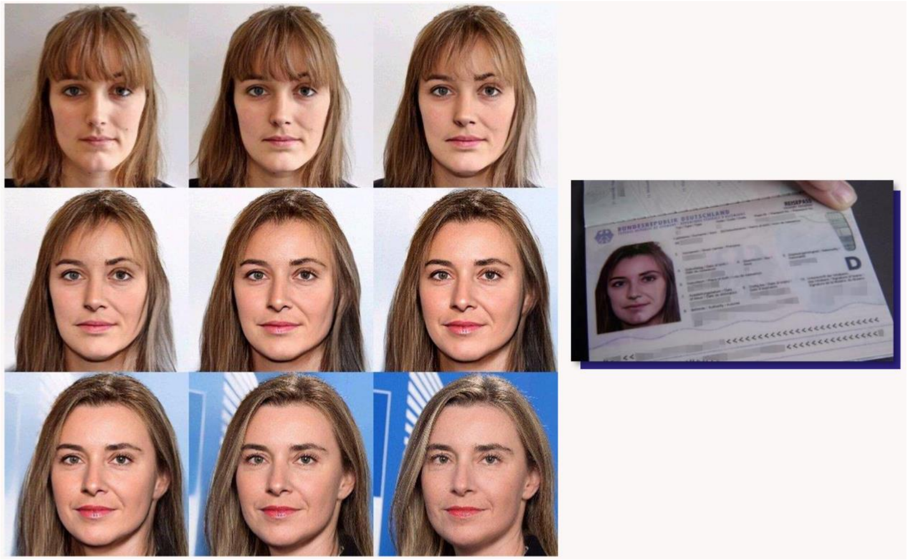
Karras, Laine, et. al. : Analyzing and Improving the Image Quality of StyleGAN, 2020

2.1 Synthesis of Faces

Detection of Synth. Images / Tampering / Morphing

Does $\mathcal{X}$ exhibit traces of morphing ?





Torkar : Morphing Cases in Slovenia, German Biometric Working Group, 2021

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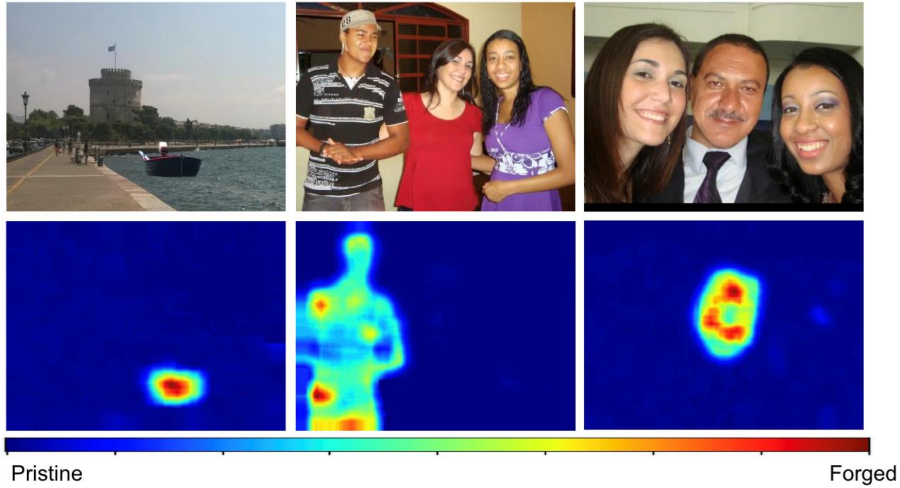

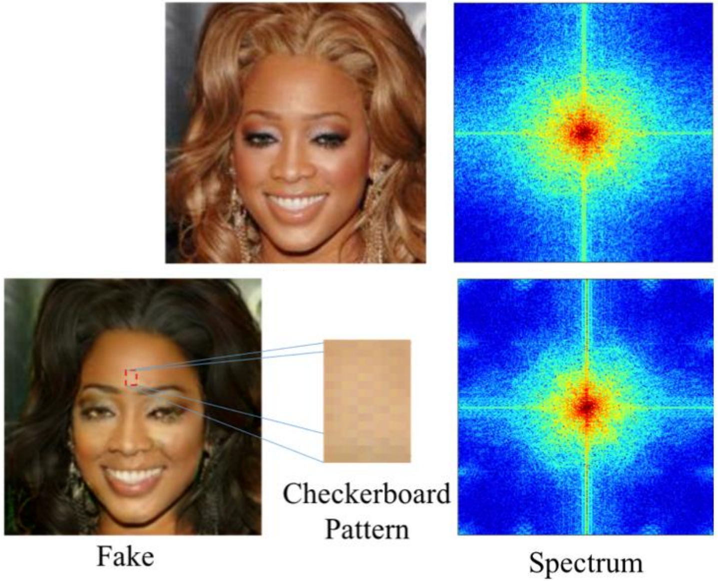

Image: Luisa Verdoliva

Zhang, et. al. : Detecting and Simulating Artifacts in GAN Fake Images (Extended Version), 2019

2.2 Fingerprints

2.2 Fingerprints

- Sensitive, private data
- Protected by laws and regulations
- Lots of data exists - access is very limited

2.2 Fingerprints

Case 1 - Performance Evaluation

Stress-test a large-scale system

- Database of 200 million persons
- Demonstrate peak performance

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SFINGE - generator

1) Selection of the singularities

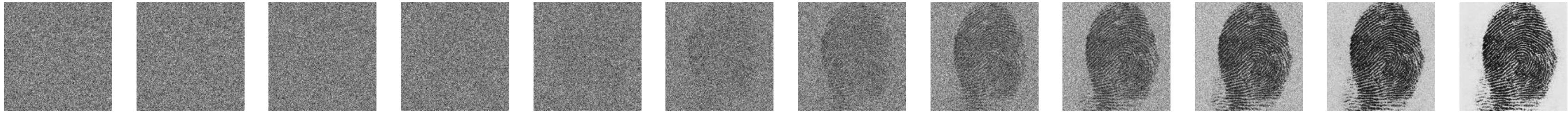
2.2 Fingerprints

Case 1 - Performance Evaluation

Stress-test a large-scale system

- Database of 200 million persons
- Demonstrate peak performance

Deep learning - generator



2.2 Fingerprints

Case 1 - Performance Evaluation

2.2 Fingerprints

Case 2 - Accuracy Evaluation

Demonstrate accuracy on different NFIQ quality levels

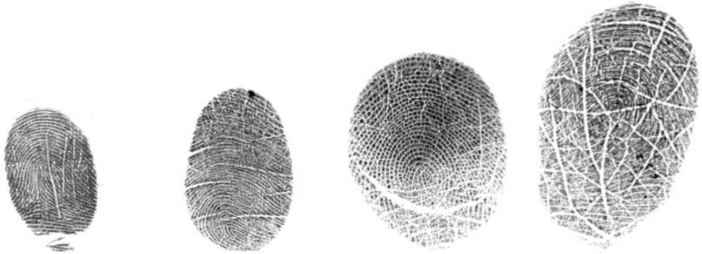
- Local clarity score
- Orientation certainty level
- Orientation flow
- Ridge valley uniformity
- Minutiae count
- Minutiae quality
- Region of interest
  - Area mean, orientation map coherence sum

NIST Fingerprint Image Quality 2, July 2021

2.2 Fingerprints

Case 2 - Accuracy Evaluation

(a) Score = 97 **(b)** Score = 87 **(c)** Score = 77 **(d)** Score = 67 **(e)** Score = 57 **(f)** Score = 47 **(g)** Score = 37



(h) Score = 27 **(i)** Score = 17 **(j)** Score = 7 **(k)** Score = 0

NIST Fingerprint Image Quality 2, July 2021

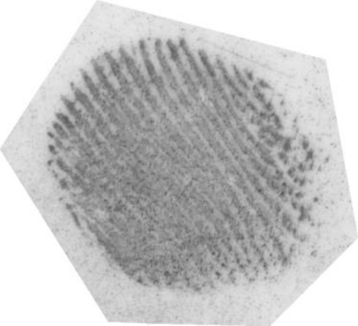
2.2 Fingerprints

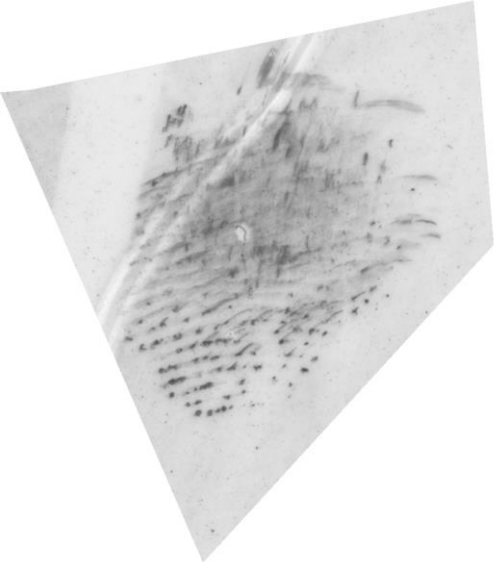
Case 3 - More robust detection

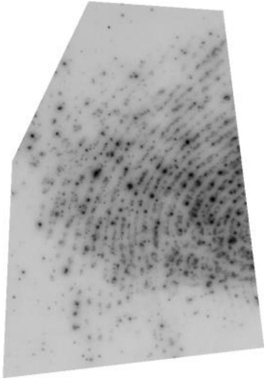
Same identity

Same appearance

2.3 Latent Fingerprints







2.3 Latent Fingerprints

Very little public data

Extremely little pairs of matching latent and non-latent fingerprints

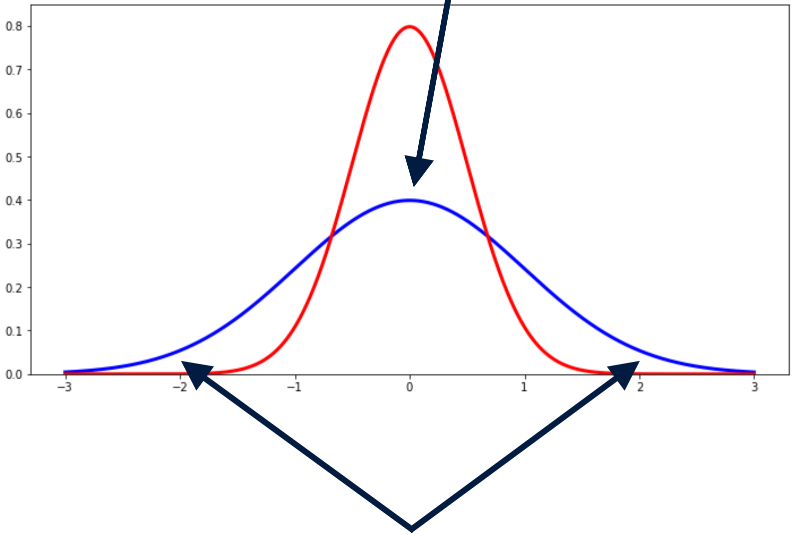
Very diverse domain

- Many kinds of techniques of acquiring latent fingerprint images
- Perspective correction
- Many kinds of surfaces to capture fingerprints from

2.3 Latent Fingerprints
GAN approach

Requires lots of images

Lots of data
- realistic results

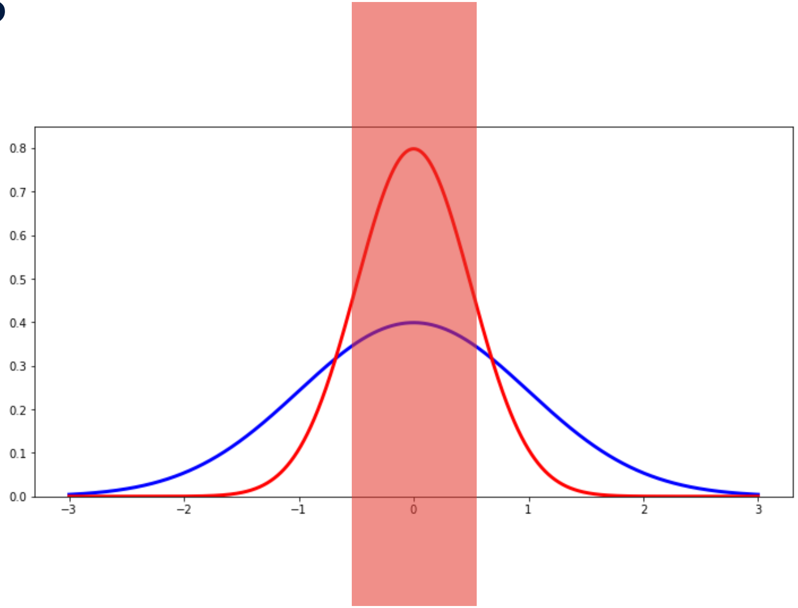


Little data
- poor quality results

2.3 Latent Fingerprints

GAN approach

More realistic, less diverse

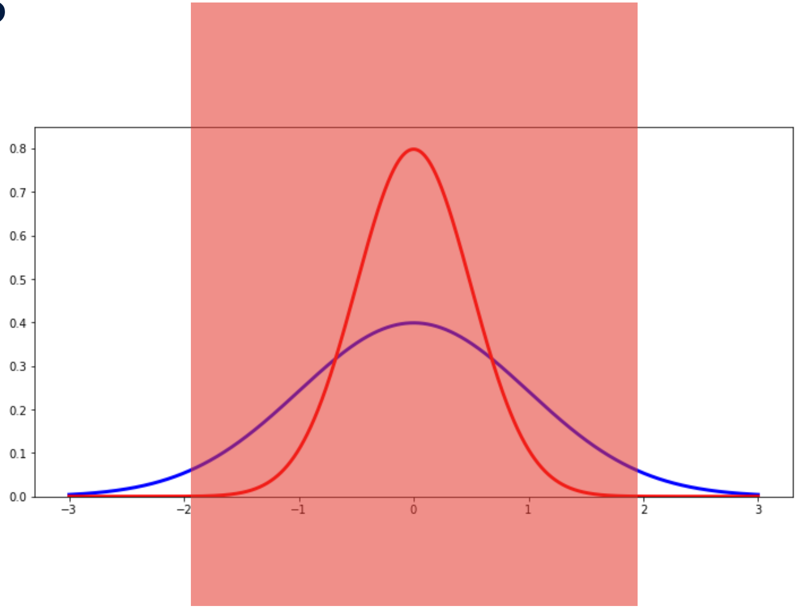


Sampling interval

2.3 Latent Fingerprints

GAN approach

Less realistic, more diverse

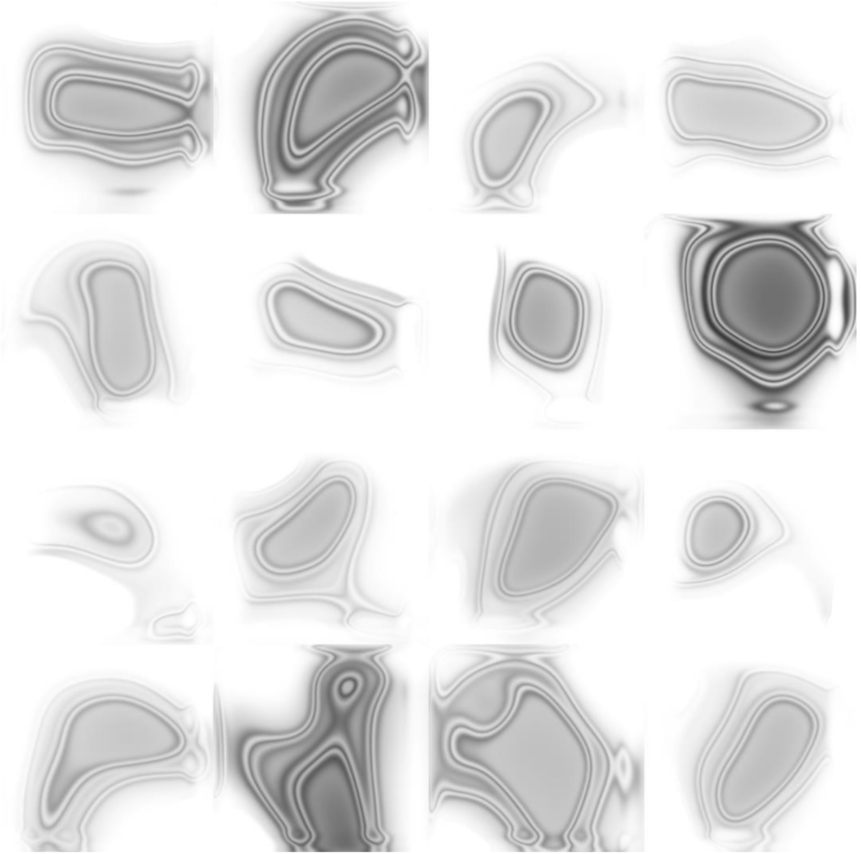


Sampling interval

2.3 Lat. FPs

StyleGAN 2 model

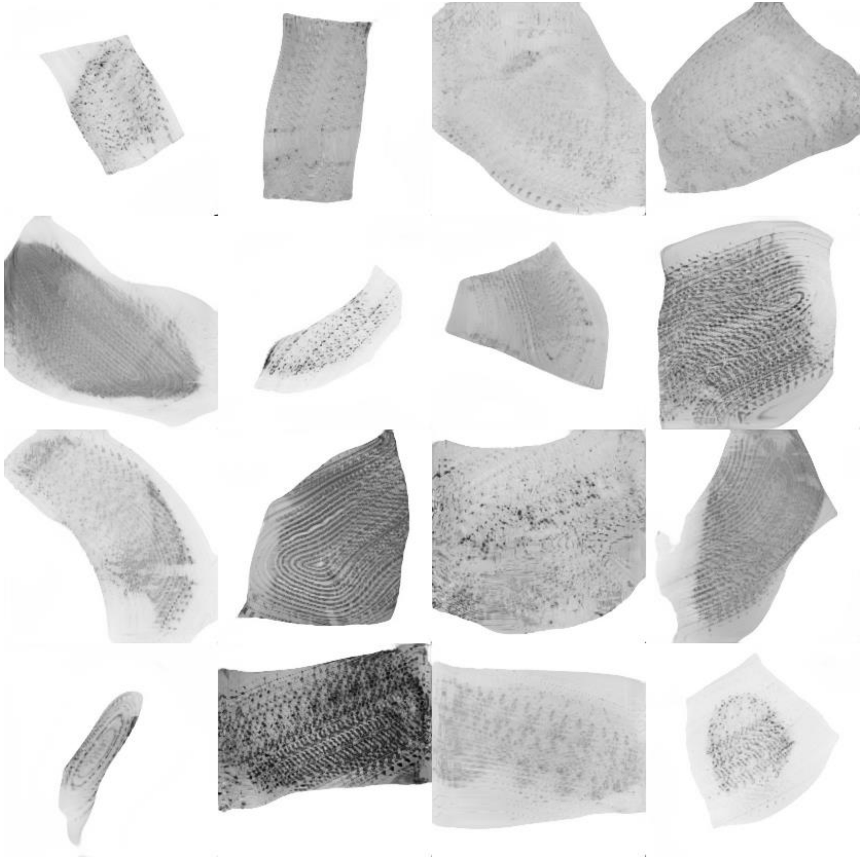
4 hours of training



2.3 Lat. FPs

StyleGAN 2 model

1 day of training



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StyleGAN 2 model

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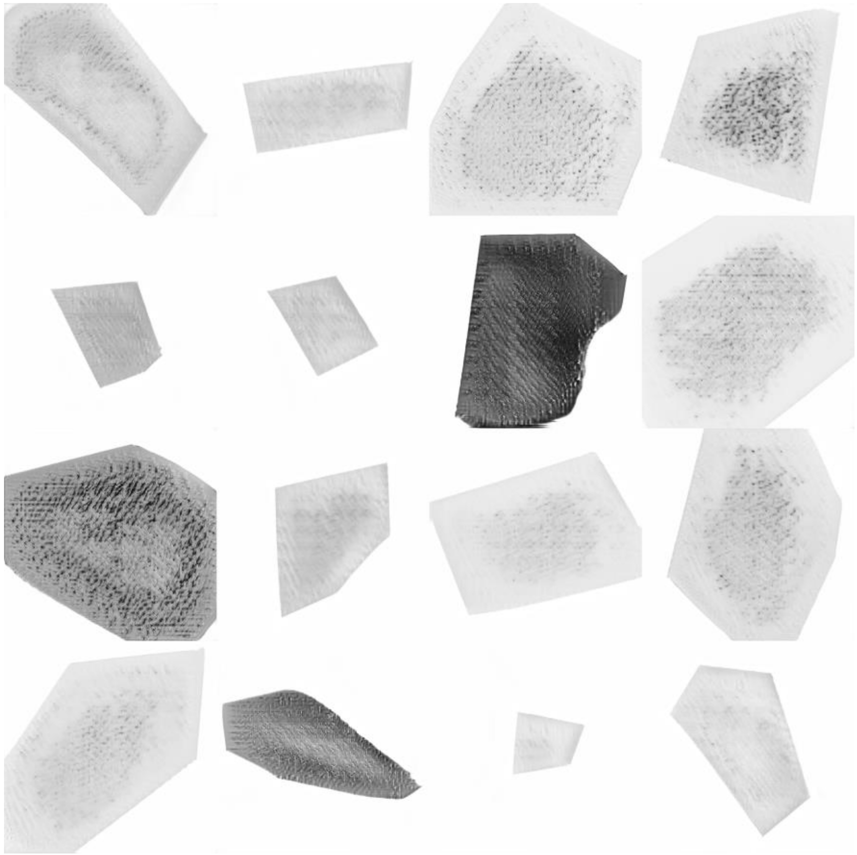


2.3 Latent Fingerprints

Diffusion Generative Process

Exploded after 2020

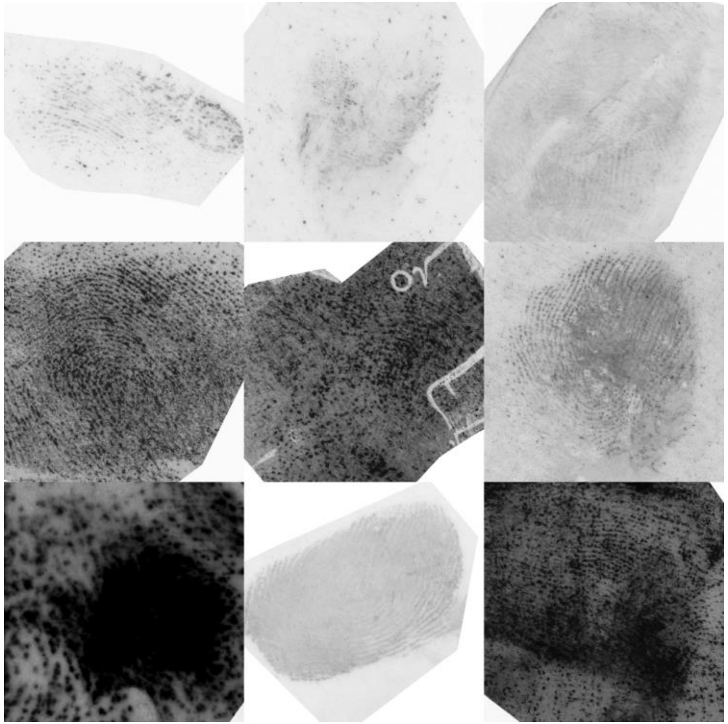
State of the art in fidelity and variety

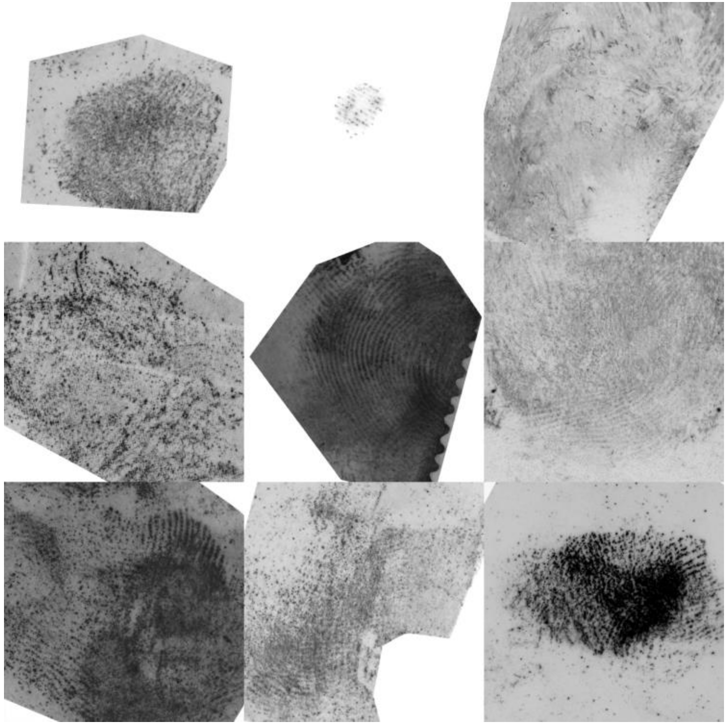
DALL-E 2

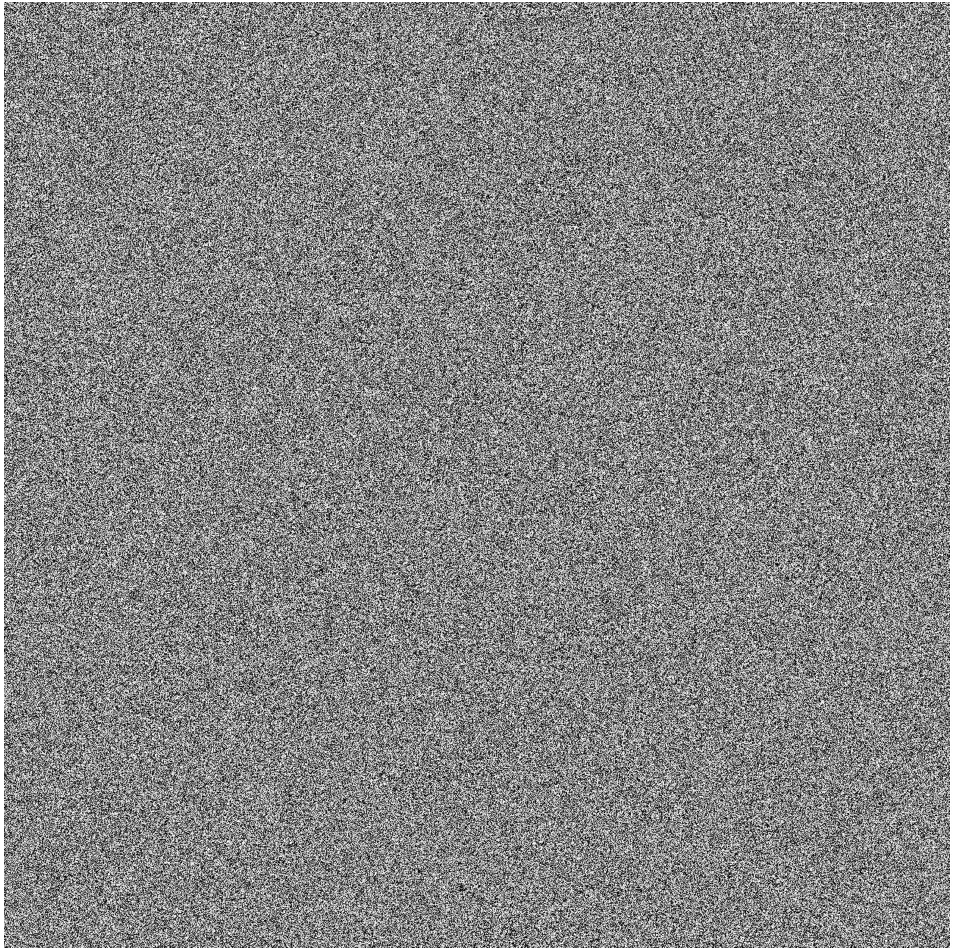
a dolphin in an astronaut suit on saturn, artstation

Ramesh, Dhariwal, et. al. : Hierarchical Text-Conditional Image Generation with CLIP Latents, 2022

2.3 Latent Fingerprints







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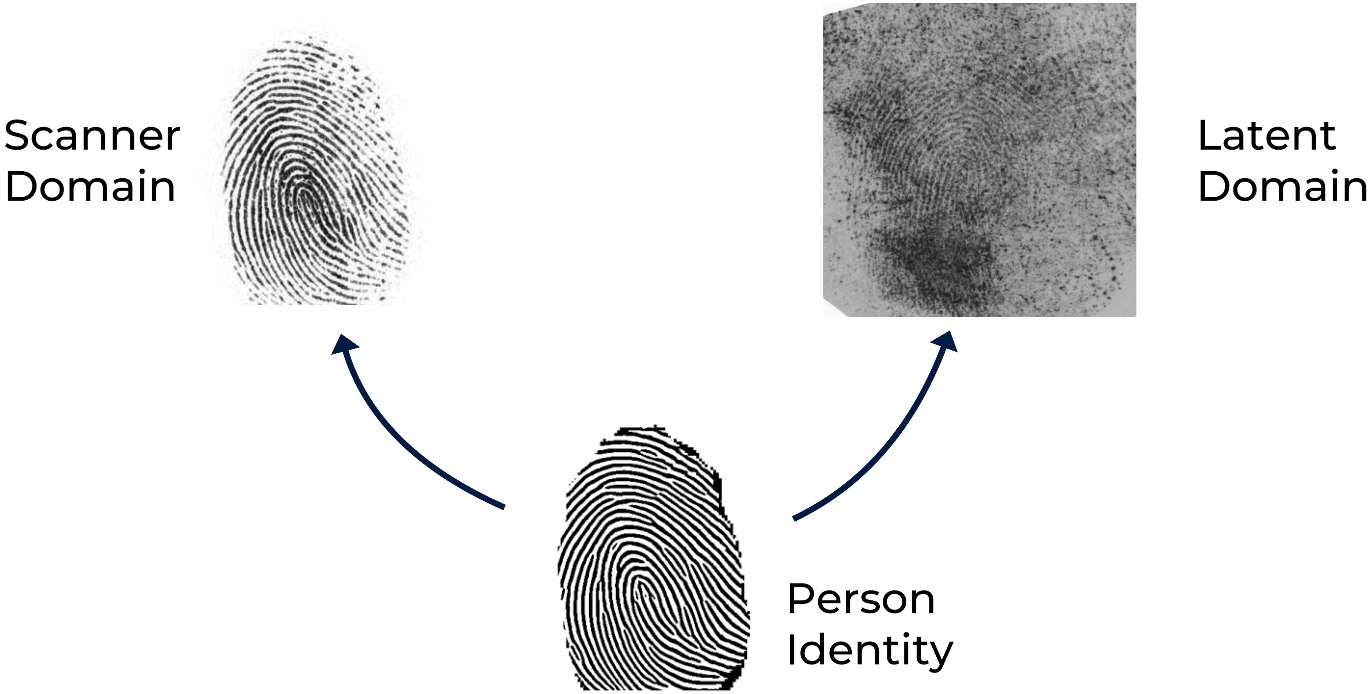

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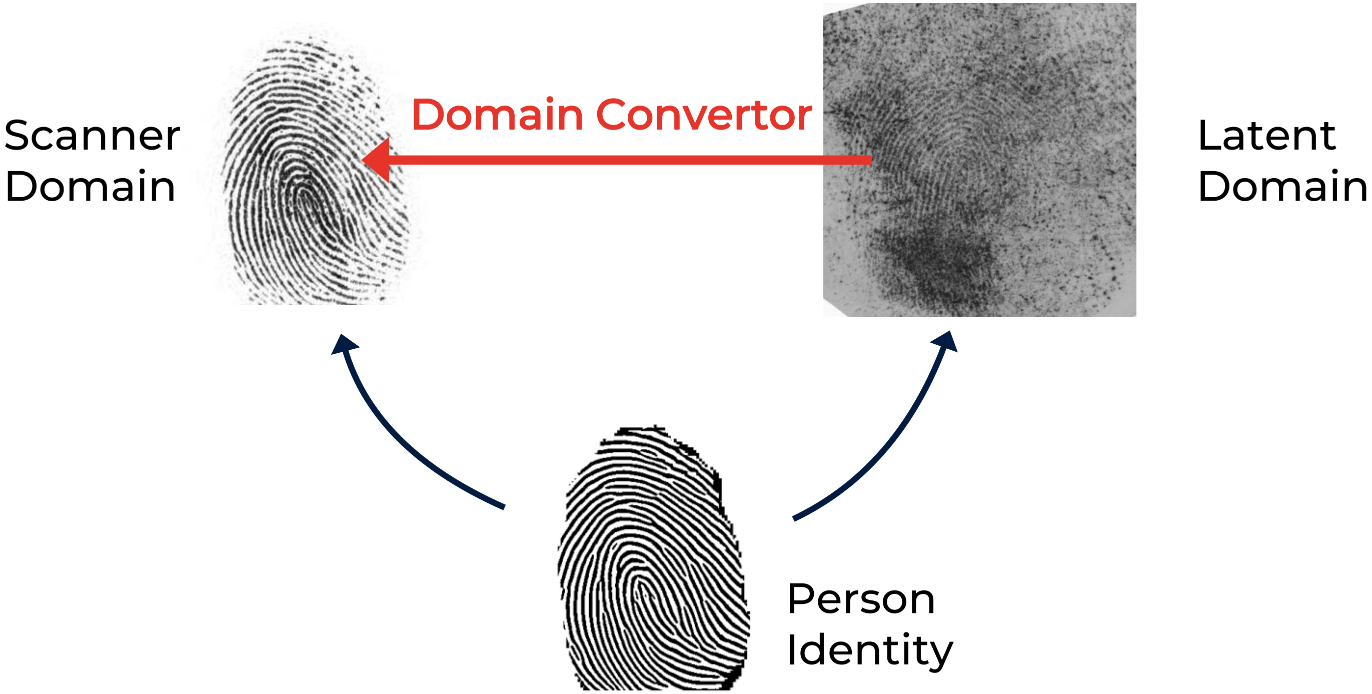

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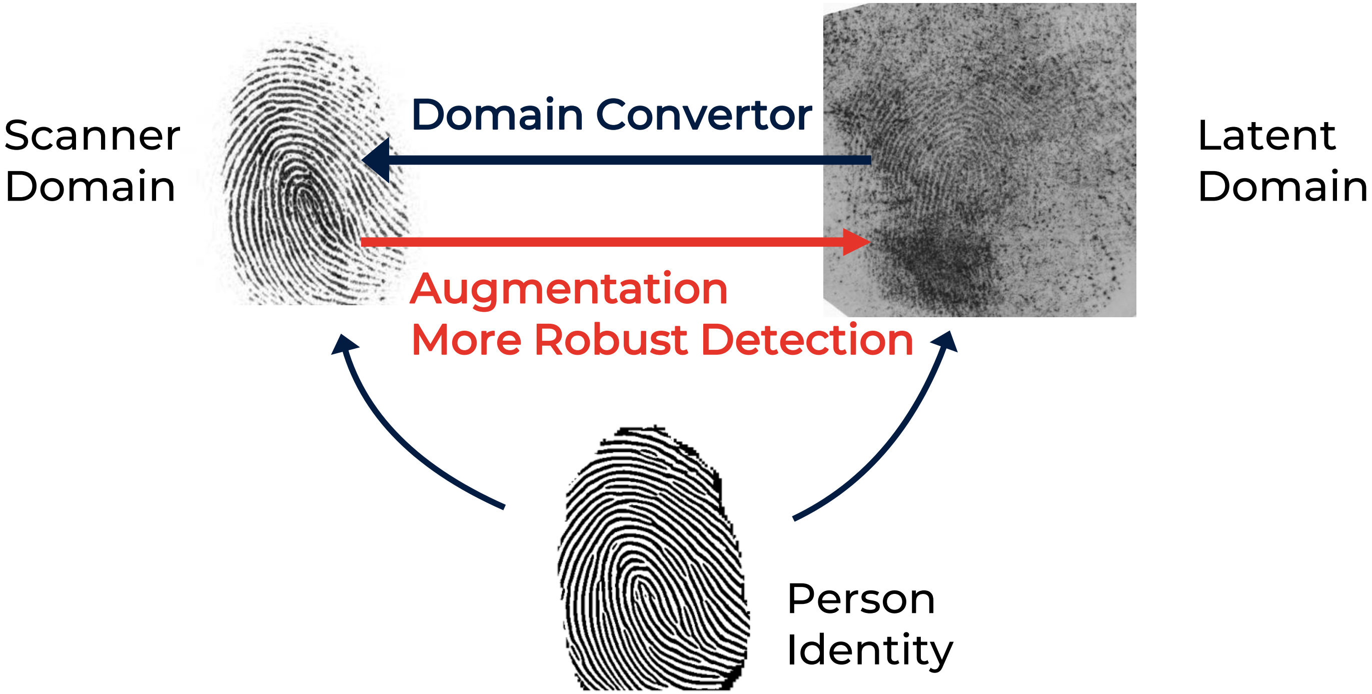
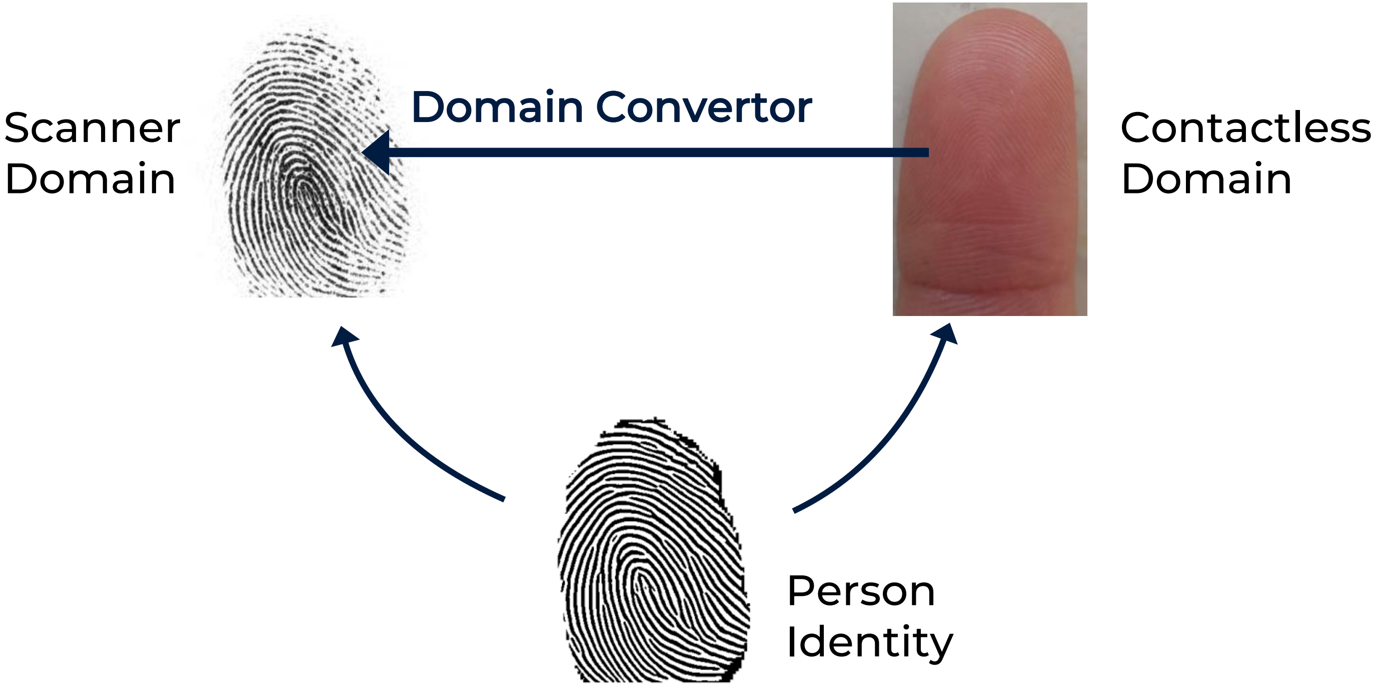


3. Future Ideas

2.3 Latent Fingerprints



Thank you!

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