Learning from synthetic data - Generation for learning

The INvicta school of VIsion, Computational intelligence, and patTern Analysis - INVICTA

Naser Damer

The content of this talk is largely based on works lead by:

Dr. Fadi Boutros

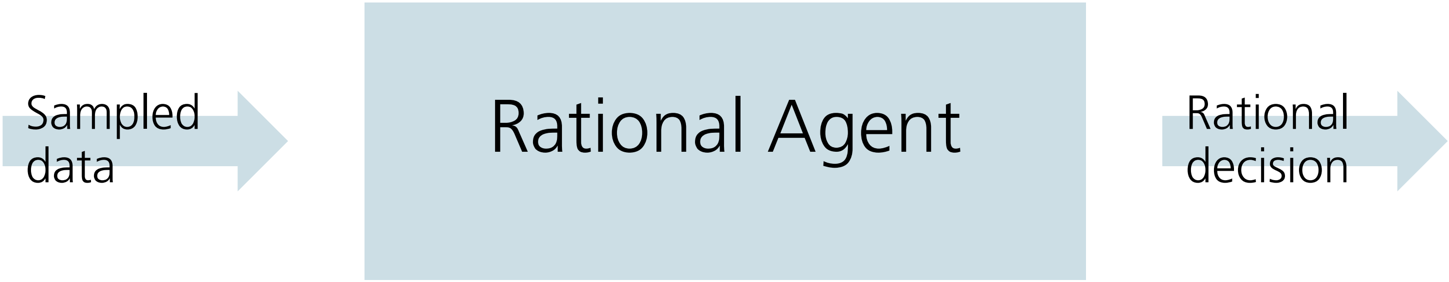
Fraunhofer IGD, Darmstadt, Germany and TU Darmstadt, Darmstadt, Germany

Why data?

What do we NEED to develop a rational agent?

Why data?

What does a rational agent do?



Why data?

What does a rational agent do?

Sampled data

Rational Agent

Rational decision

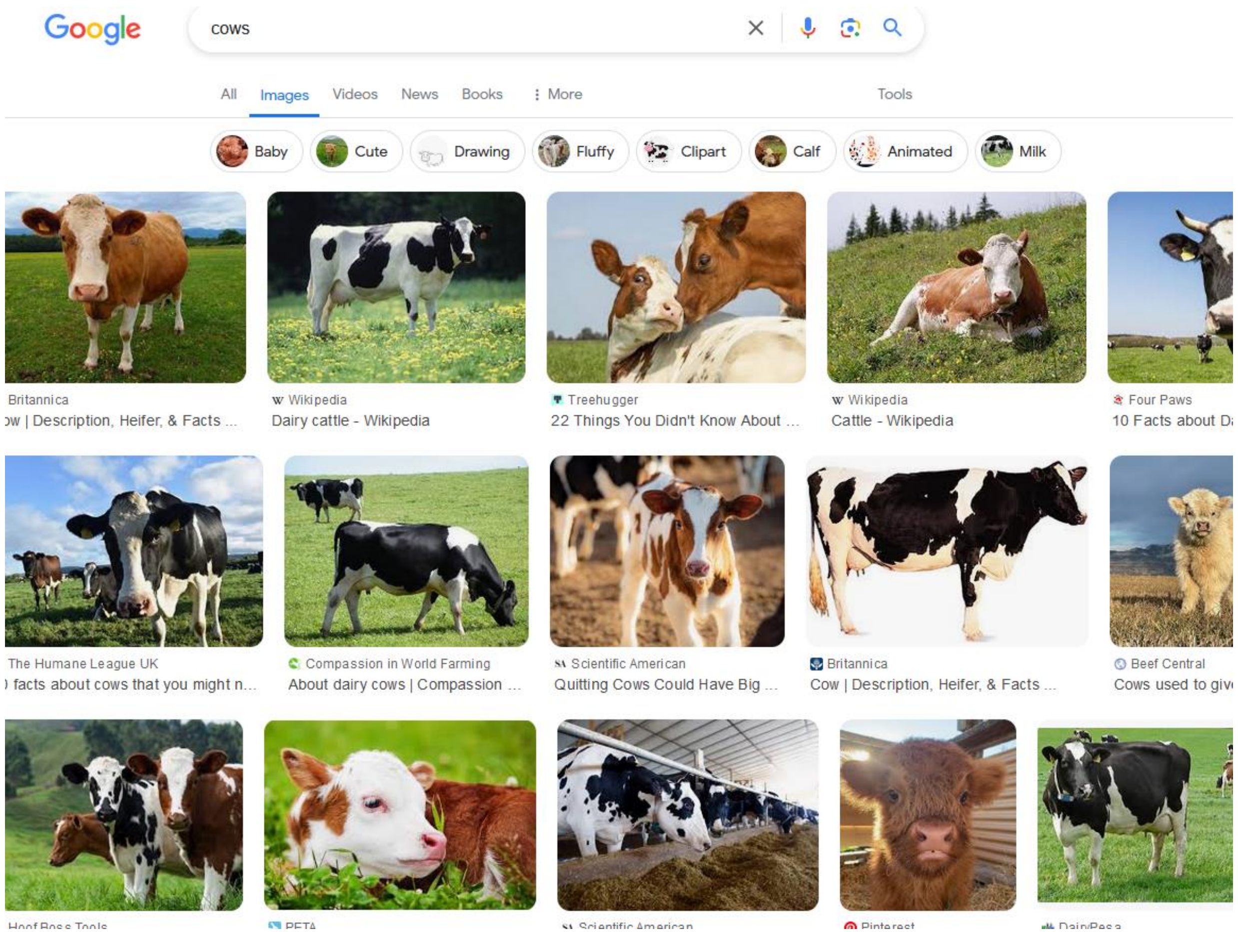
Cow

Why data?

What do we NEED to develop a rational agent?

Why data?

What do we NEED to develop a rational agent?



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Why data?

What do we NEED to develop a rational agent?

Why data?

What do we NEED to develop a rational agent?

1. Data that the agent expect to see in operation

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Why data?

What do we NEED to develop a rational agent?

1. Data that the agent expect to see in operation

Rational Agent

Coefficient

$$ax + b = 0$$

Variable

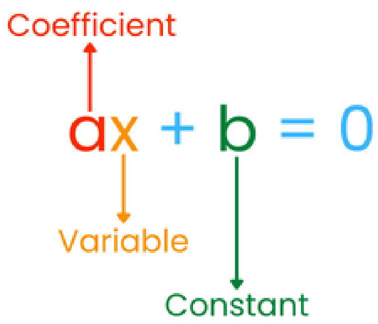
Constant

Why data?
What do we NEED to develop a rational agent?

1. Data that the agent expect to see in operation

2. The agent architecture (linear equation, or 1B parameter NN)

Rational Agent



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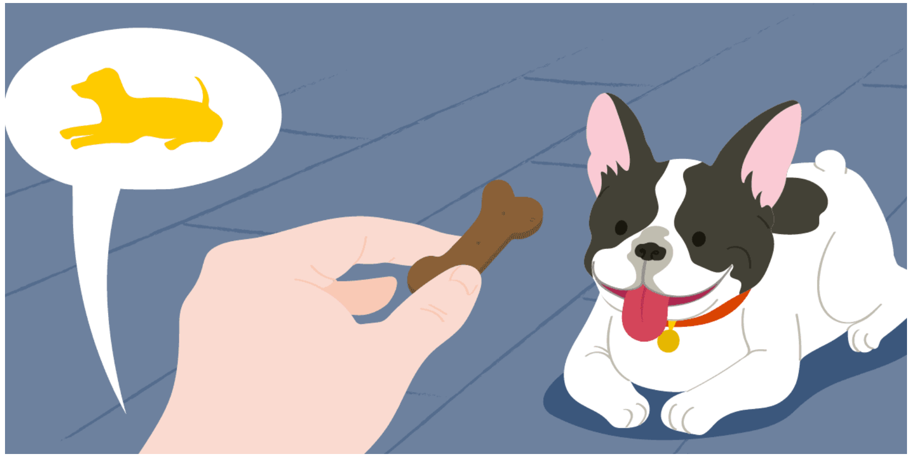


Rational Agent

Coefficient

$$\underbrace{\overset{\text{Coefficient}}{a}\,\underset{\text{Variable}}{x}}\; + \underset{\text{Constant}}{b} = 0$$

Variable

Constant

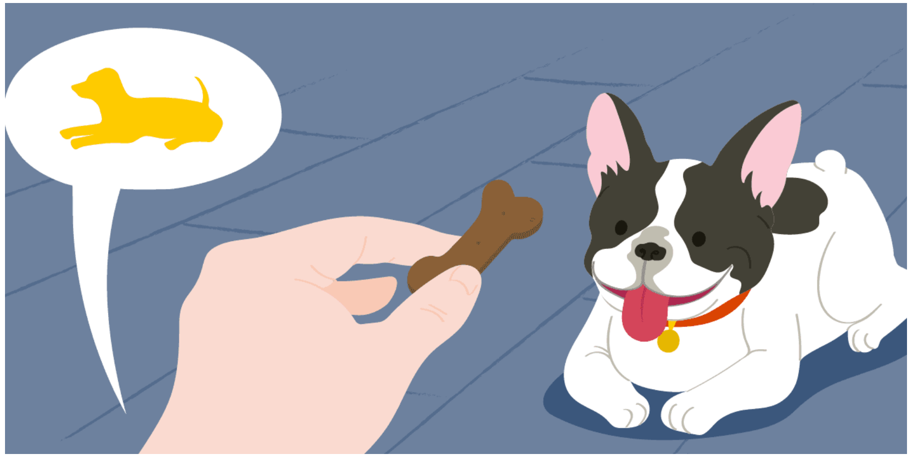
Why data?

What do we NEED to develop a rational agent?

1. Data that the agent expect to see in operation

2. The agent architecture (linear equation, or 1B parameter NN)

3. Targeted setting of parameters (a and b), i.e. loss



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Why data?

What do we NEED to develop a rational agent?

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4. In many cases, but not necessary, labels for the data to help the loss

Cow

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Why data?

What do we NEED to develop a rational agent?

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4. In many cases, but not necessary, labels for the data to help the loss

Why data?

What properties should this data have?

1. Data that the agent expect to see in operation
2. The agent architecture (linear equation, or 1B parameter NN)
3. Targeted setting of parameters (a and b), i.e. loss
4. In many cases, but not necessary, labels for the data to help the loss

Why data?

What do we NEED to develop a rational agent? -> **definitely DATA, and also probably labels for this data**

What properties should this data have?

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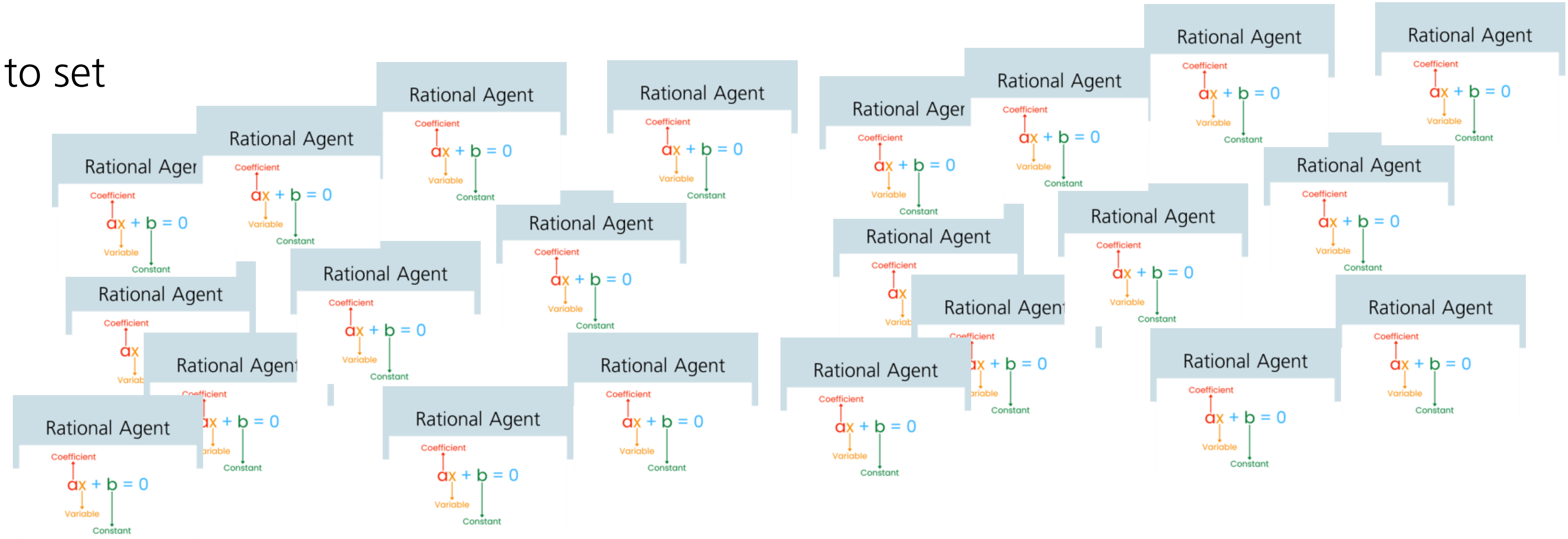
Why data?

What properties should this data have?

What properties should this data have?

- **Large amount of data**
  - Sooooo many parameters to set
  - Avoid overfitting



What properties should this data have?

- **Large amount of data**
- **Cover inter class variation**
  - All classes should be present
  - This “present” should also be similar

Why data?

What properties should this data have?

What properties should this data have?

- **Large amount of data**
- **Cover Inter class variation**
- **Cover Intra class variation**
  - Variation in the class should be present
  - This “present” should also be similar

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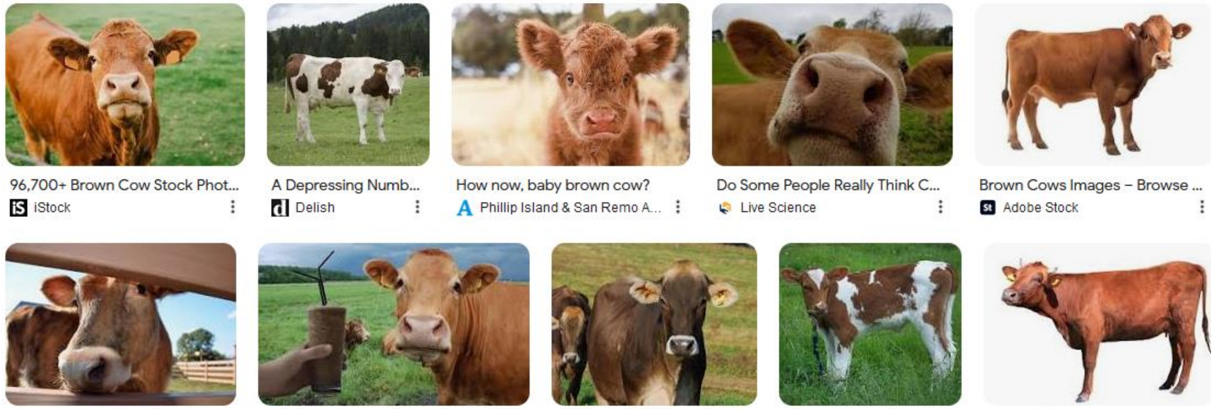

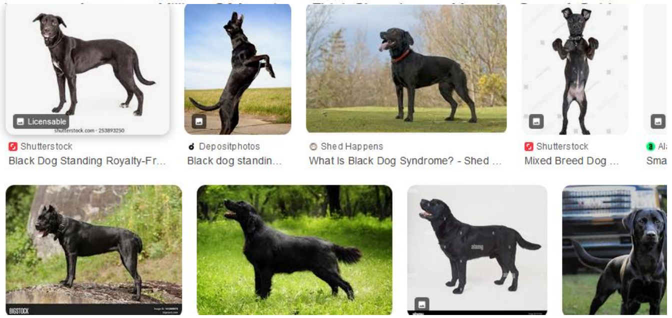

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Why data?

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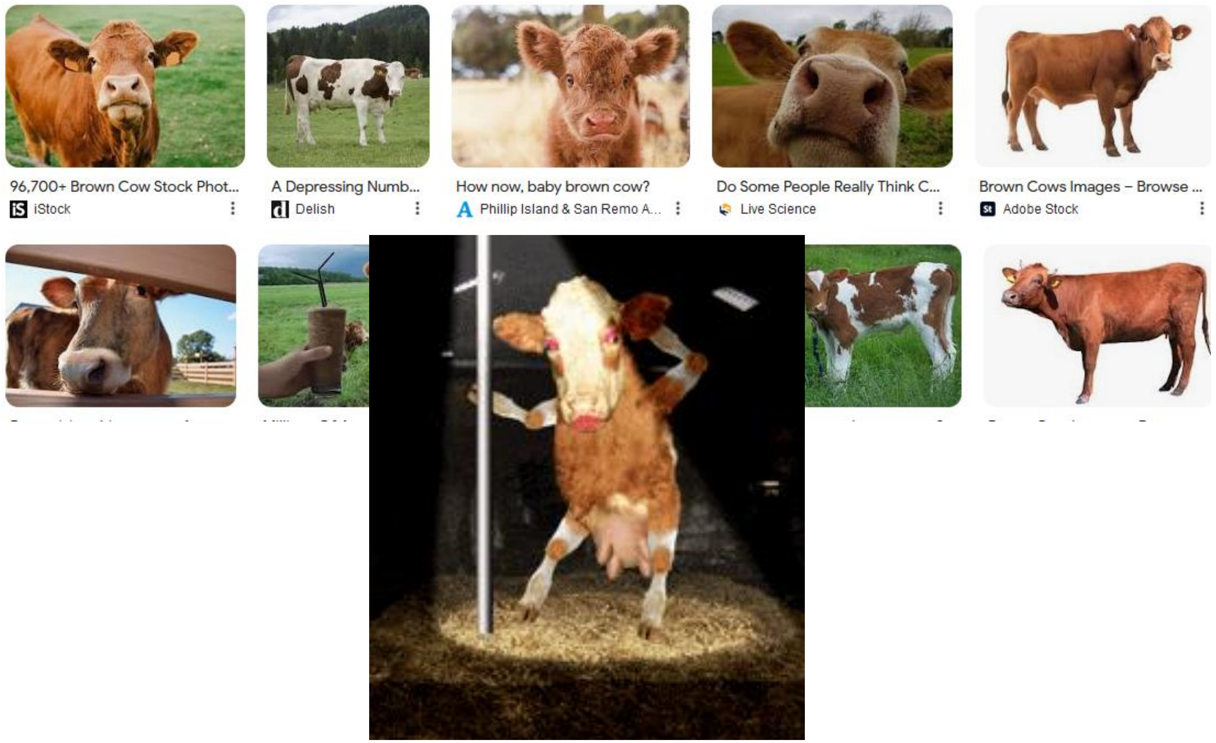

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Why data?

What properties should this data have?

What properties should this data have?

- **Large amount of data**
- **Cover Inter class variation**
- **Cover Intra class variation**
- **Labels needed (probably)**
  - Correct?

Dog

Why data?

So, why the data we can just capture does not fulfill this?

why the data we can just capture does not fulfill this?

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Why data?

So, why the data we can just capture does not fulfill this?

why the data we can just capture does not fulfill this?

- **Large amount of data - PROBLEM**
- **Cover Inter class variation - PROBLEM**
- **Cover Intra class variation – PROBLEM**
- **Labels needed (probably) - PROBLEM**

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Why data?

So, why the data we can just capture does not fulfill this?

why the data we can just capture does not fulfill this?

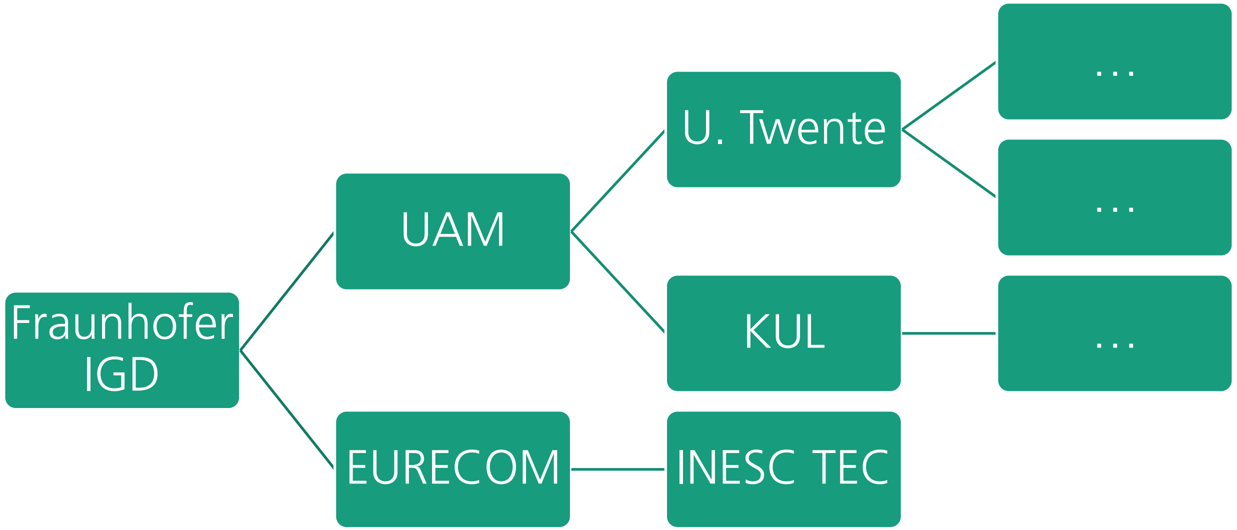
- **E.g. numerous legal obligations for biometric data controllers, including:**
  - the necessity to adhere to one of the exemptions of biometric data processing cumulatively with the choice of a suitable legal basis
  - the need to comply with the national law of the European Union (EU) Member State relating to the processing of biometric data, where applicable
  - the maintenance of processing records
  - the preparation of a data protection impact assessment and the appointment of a DPO, where applicable
  - comply with the mandatory obligations relating to automated individual decision-making, where applicable
  - assume the loss of any possibility of exemption with respect to the appointment of a representative in the EU for controllers and processors located outside the EU
  - …………

Why data?

So, why the data we can just capture does not fulfill this?

why the data we can just capture does not fulfill this?

- **Data sharing chain…**



How to fix data problems?
Options

How to fix our data problems?

How to fix our data problems? – discuss

- Large amount of data - **PROBLEM**
- Cover Inter class variation - **PROBLEM**
- Cover Intra class variation – **PROBLEM**
- Labels needed (probably) – **PROBLEM**
- Ethical / Legal – **PROBLEM**

How to fix data problems?
Synthetic data?

How to fix our data problems? – discuss

- **What about creating synthetic data that has the properties that we need?**

How to fix our data problems?

- **What about creating synthetic data that has the properties that we need?**
- **-> to discuss this we need an example -> Face data**

Why Face as an example?

- Large amount of data – **EXTREME PROBLEM**
- Cover Inter class variation - **EXTREME PROBLEM**
- Cover Intra class variation – **EXTREME PROBLEM**
- Labels needed (probably) – **EXTREME PROBLEM**
- Ethical / Legal – **EXTREME PROBLEM**

Why Face as an example?

- **Also because it is what we work on :)**

How to fix data problems?
Synthetic data?

How to synthesize data? – ABC of data synthesize

Data generator

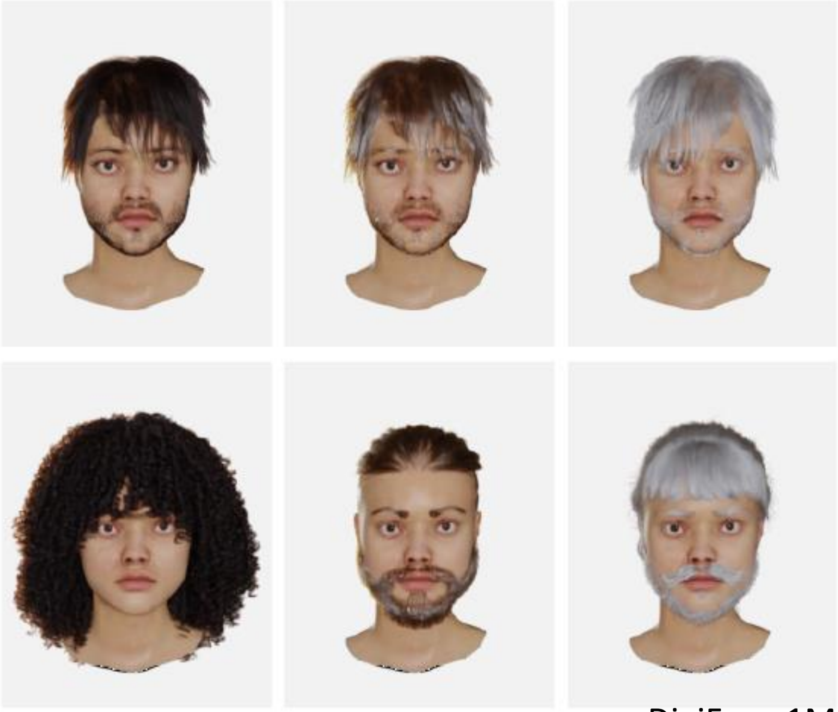
Synthetic data

How to synthesize data?

Graphics?

Graphics?

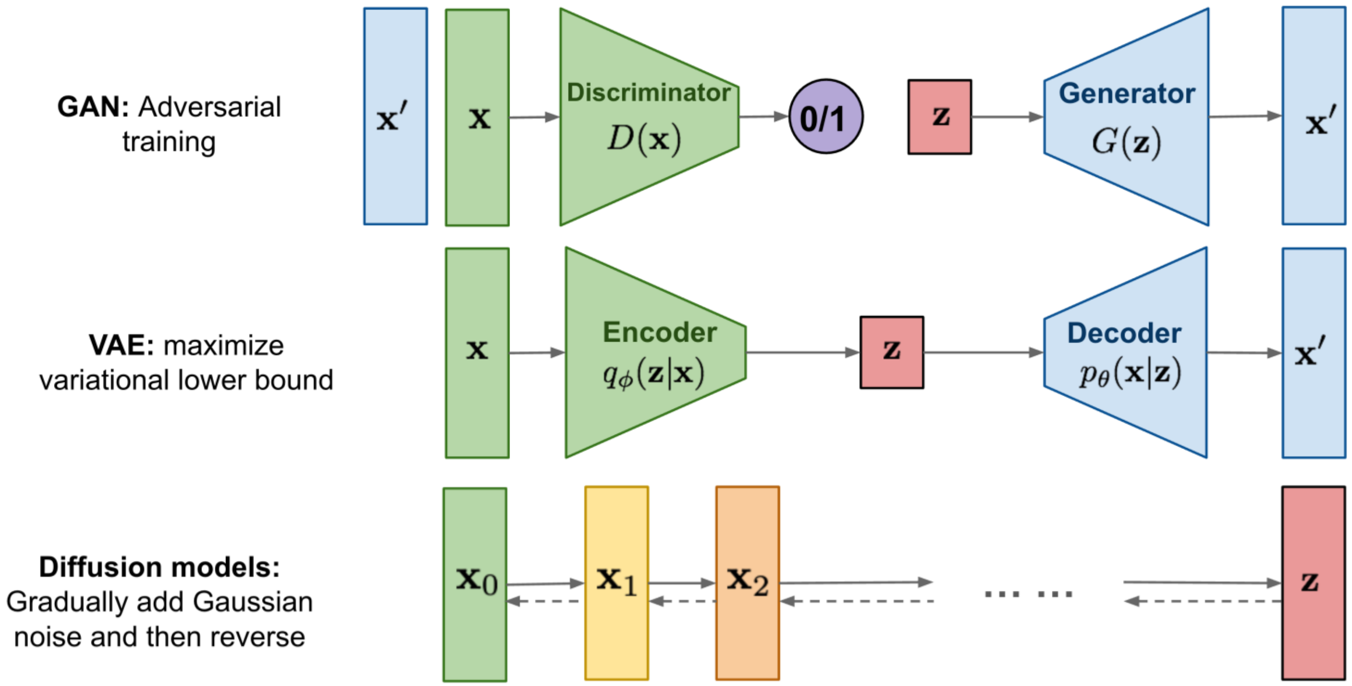
- Realistic appearance is a challenge
- A problem with limited variations
- So many parameters based on human opinion
- Computationally expensive
- ….



DigiFace-1M

Learn to generate?

- **Many options**

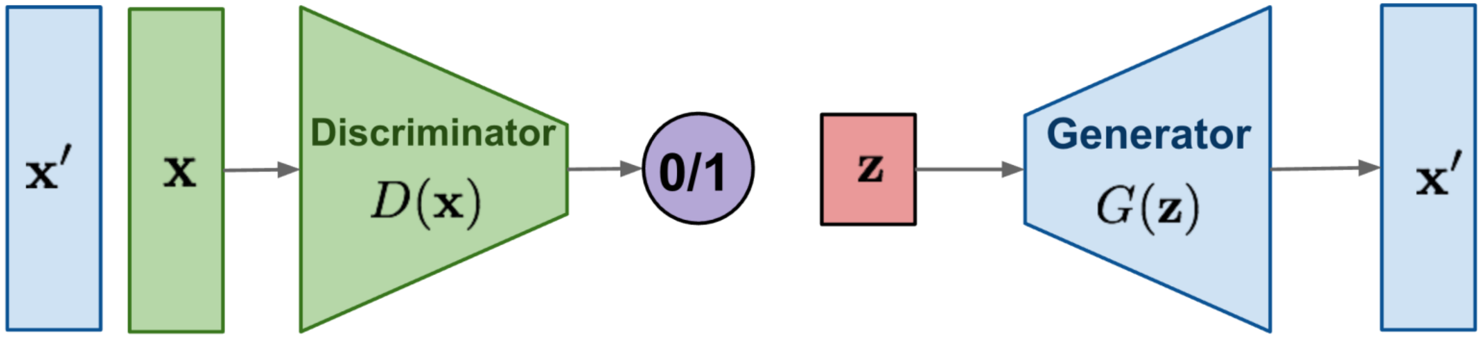


How to synthesize data?

Learn to generate by GANs

- **GANs**

GAN: Adversarial training



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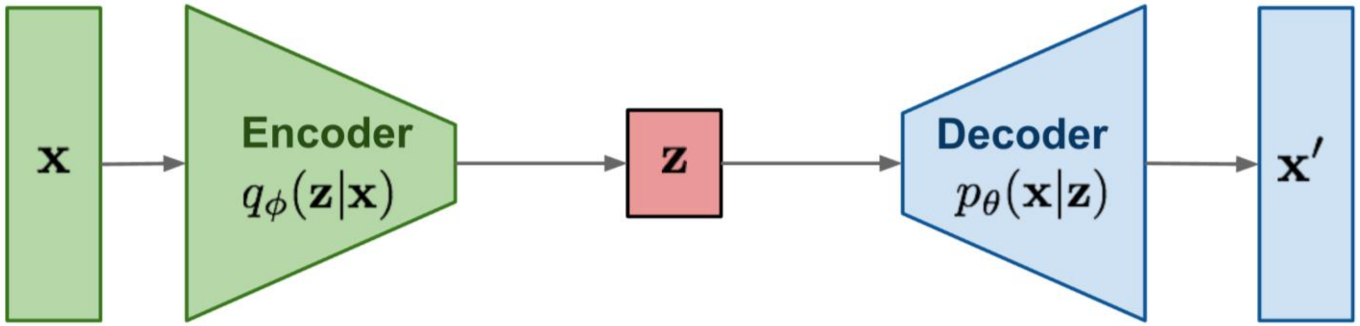
How to synthesize data?

Learn to generate by VAEs

- **VAEs**

VAE: maximize
variational lower bound



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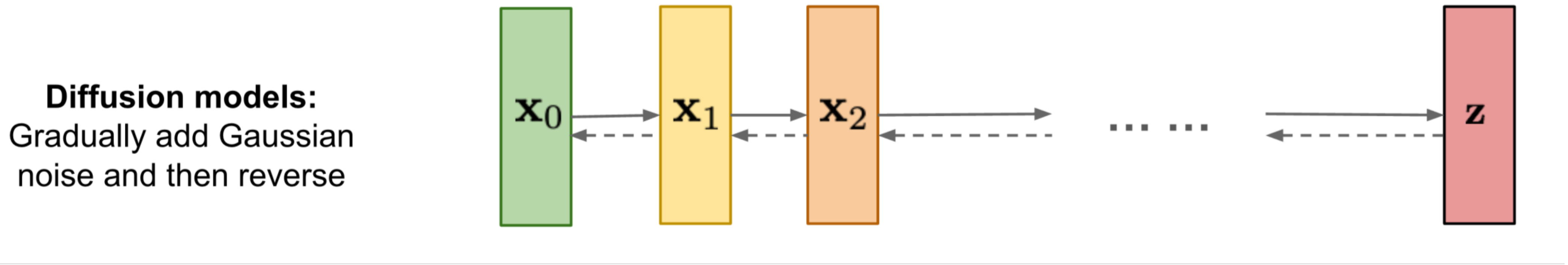
How to synthesize data?

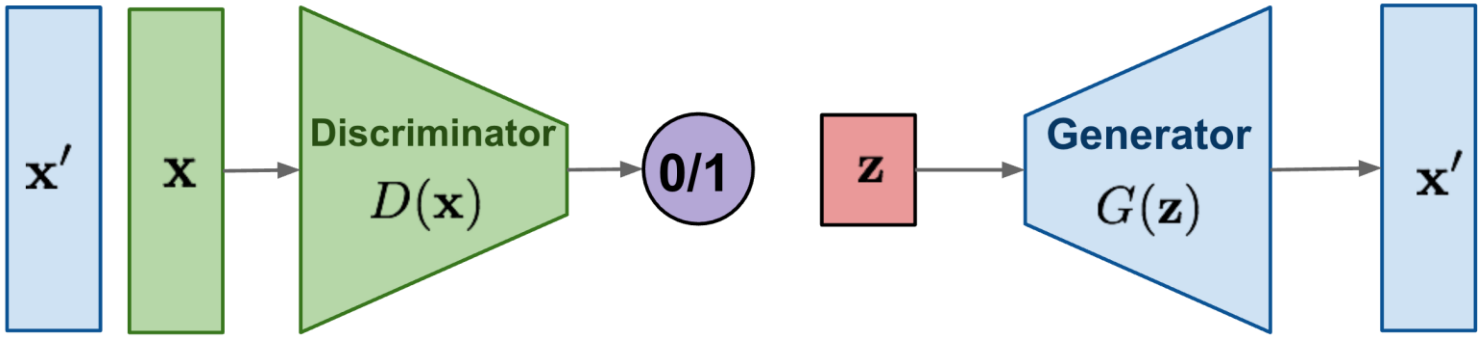
Learn to generate by Diffusion models

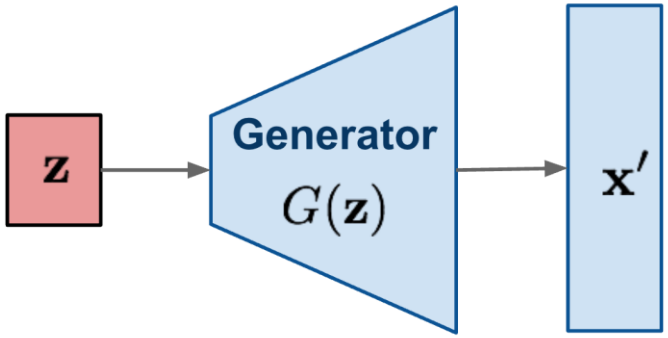
- **Diffusion models**



How to synthesize data?
e.g. Faces from GAN

GAN: Adversarial training





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How much of data problems did we solve?

Synthetic data so far

How to fix our data problems? – synthesize

- **Large amount of data – SOLVED by SYNTHETIC DATA**
- **Cover Inter class variation - PROBLEM**
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- **Labels needed (probably) – PROBLEM**
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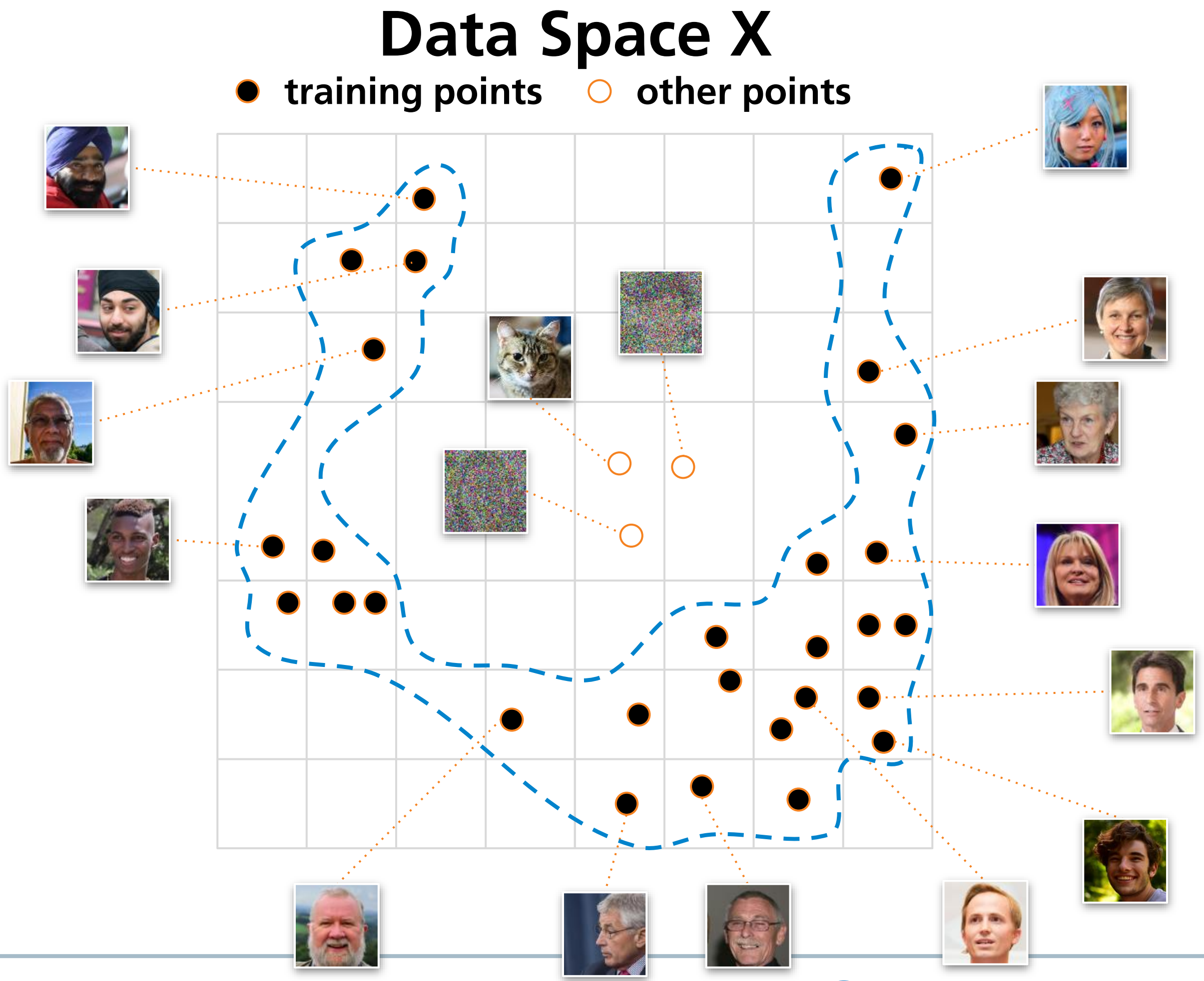
How to generate synthetic data?

Deep Generative Models

- ➔ learn data distribution p(x)
- ➔ e.g. GANs or diffusion models



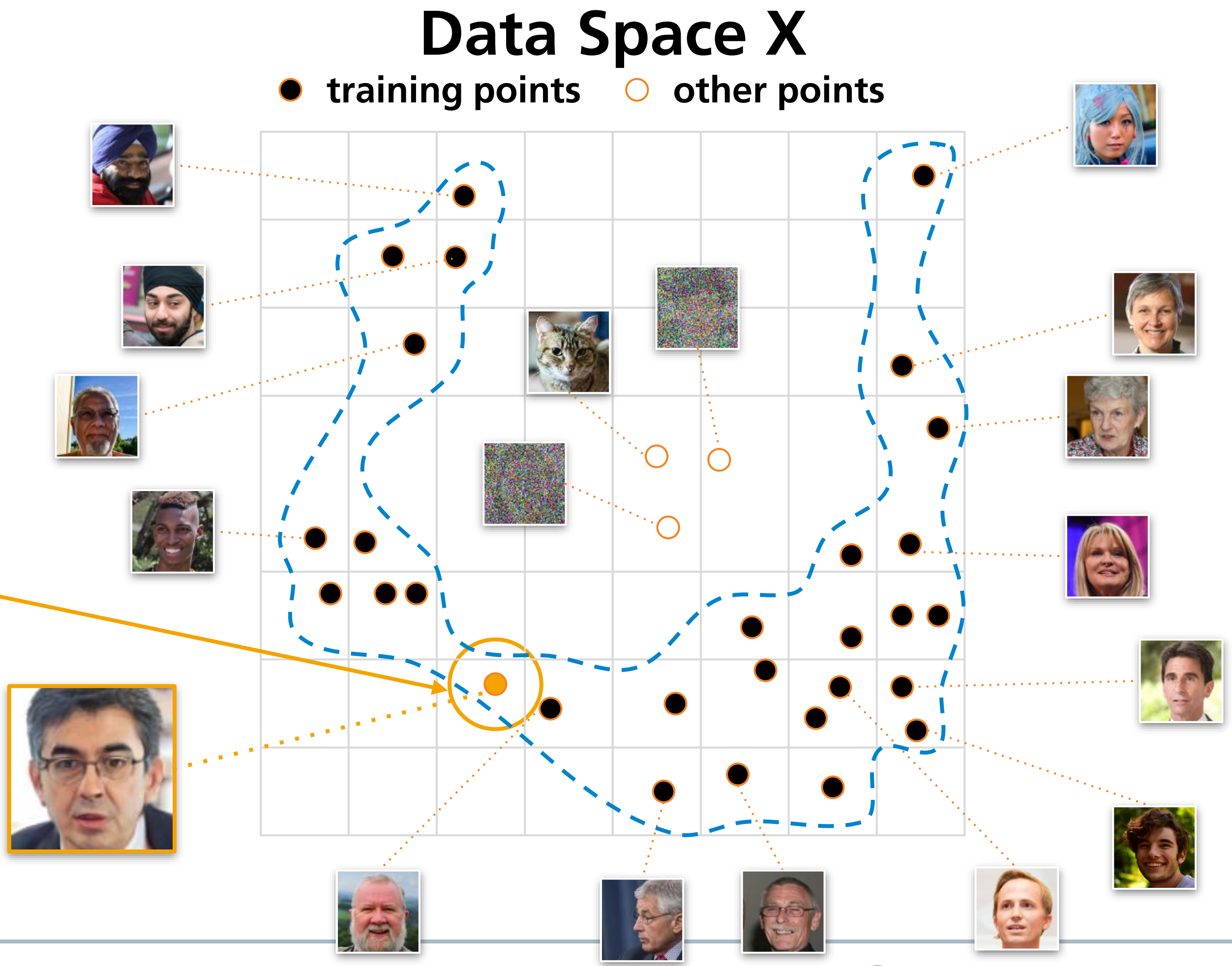
How to generate synthetic data?

Deep Generative Models

- ➔ learn data distribution p(x)
- ➔ e.g. GANs or diffusion models

We want to generate samples that

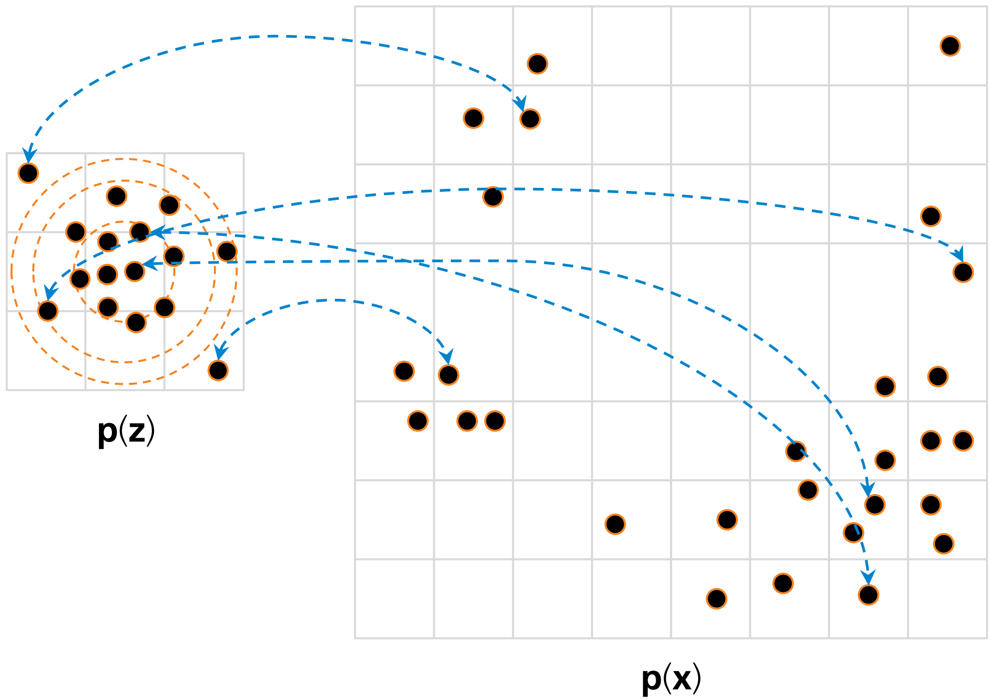
- ➔ are realistic but novel
- ➔ follow the training distribution



GANs vs. Diffusion Models

Generative Adversarial Networks

learn sample function: $z \rightarrow x$



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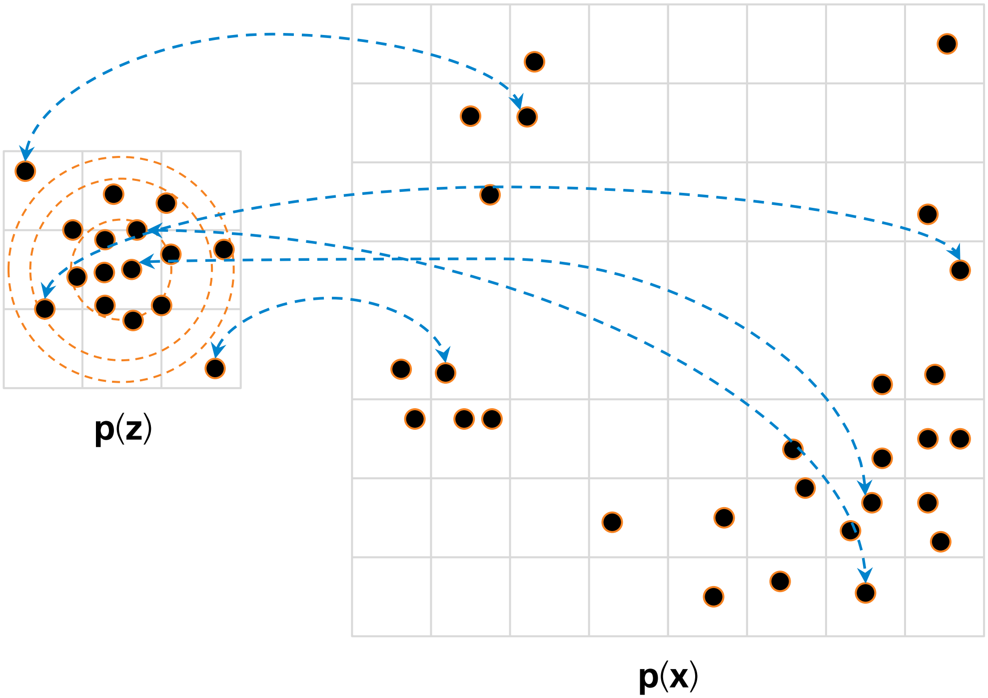
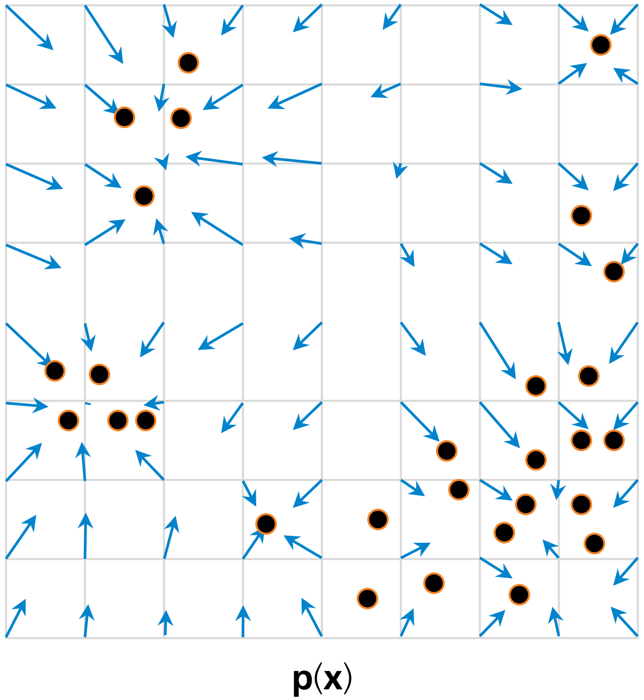


Diffusion Models

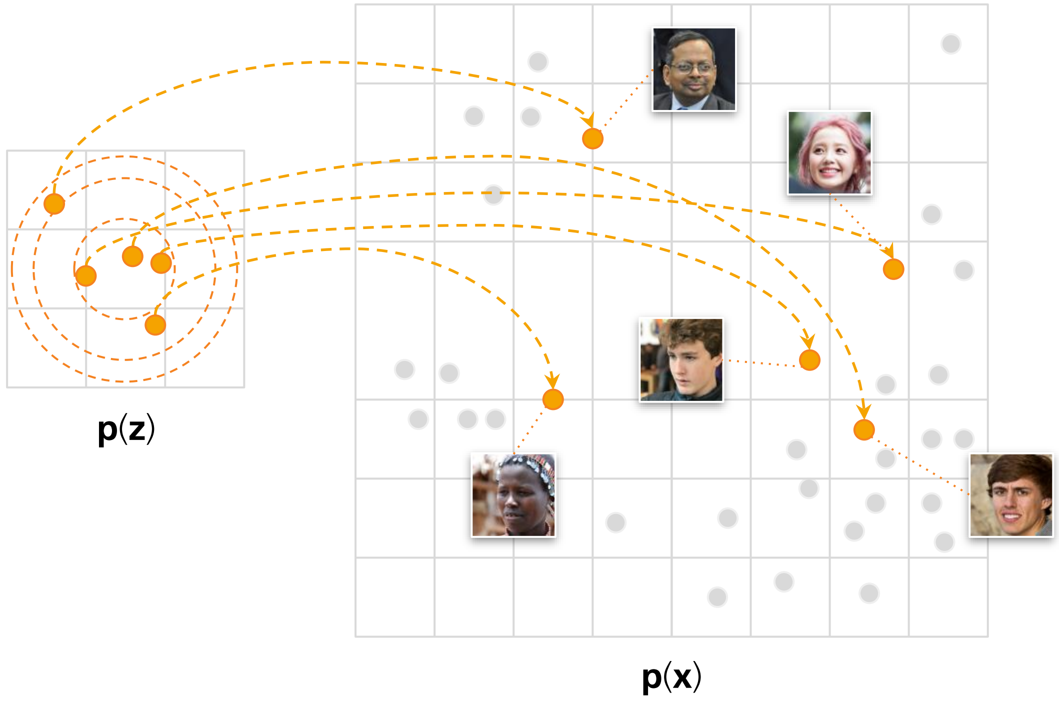
learn gradient of p(x)



GANs vs. Diffusion Models (Sampling)

Generative Adversarial Networks

learn sample function: z → x



Diffusion Models

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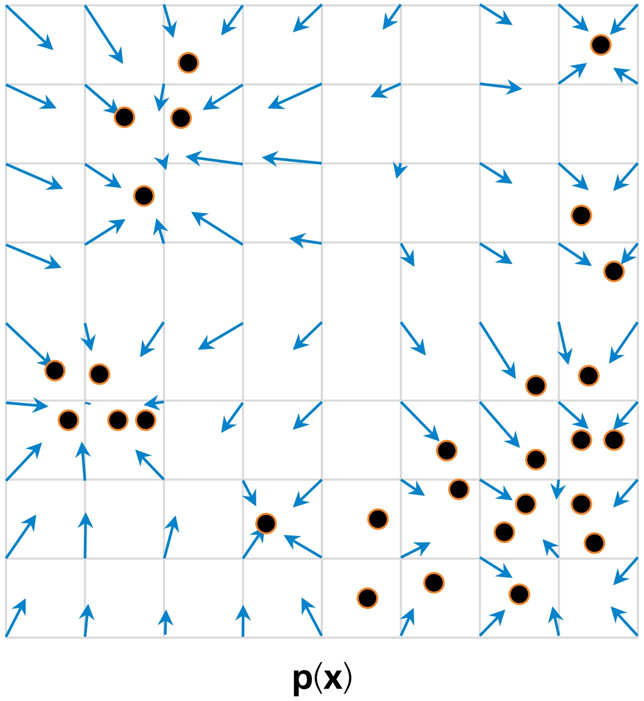
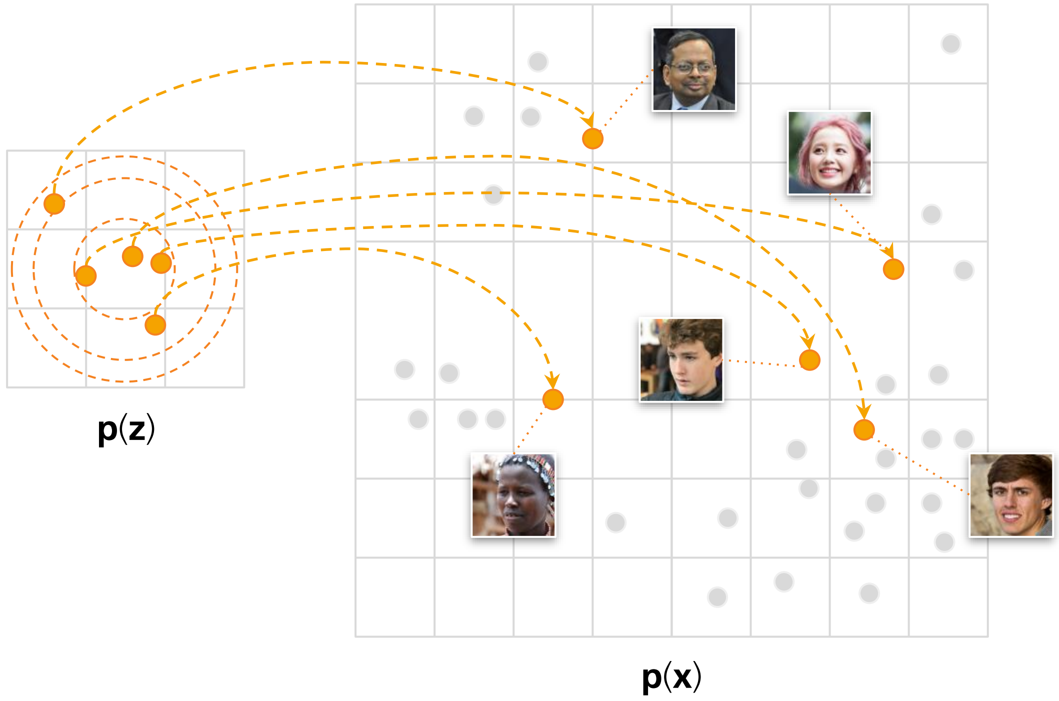


GANs vs. Diffusion Models (Sampling)

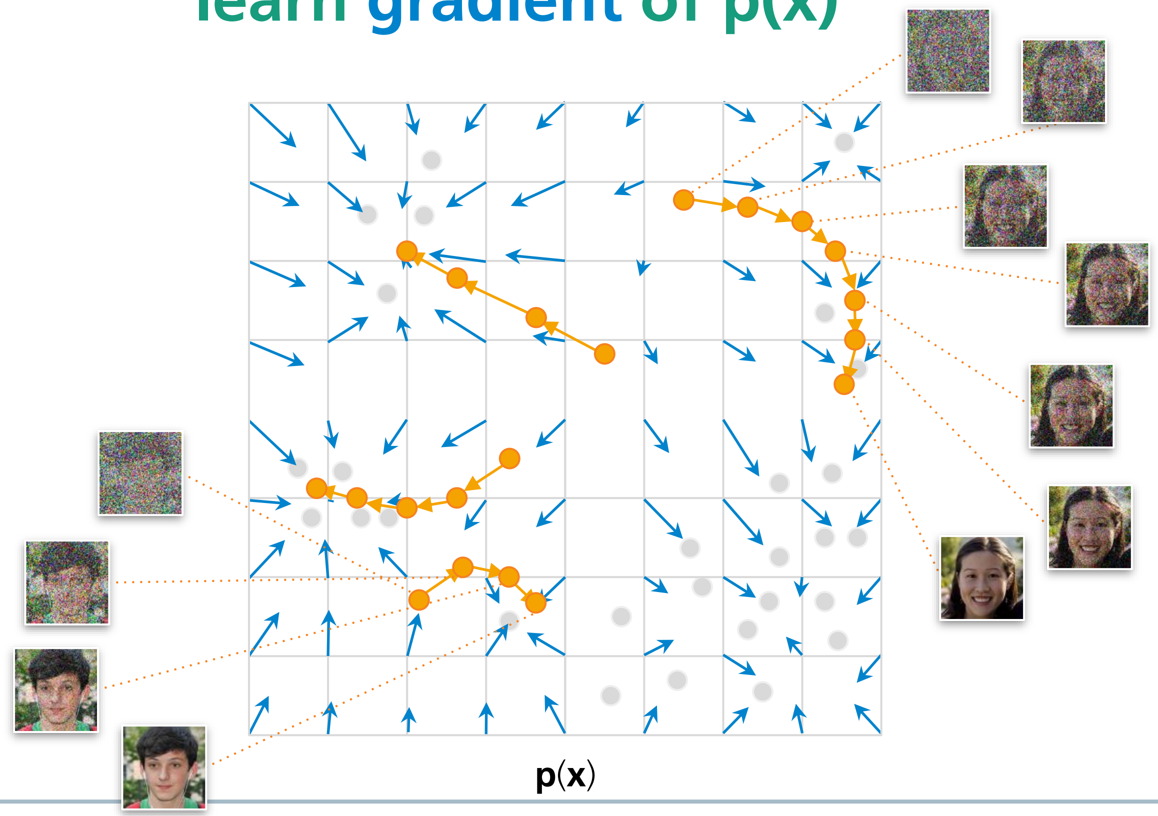
Generative Adversarial Networks

learn sample function: z → x



Diffusion Models

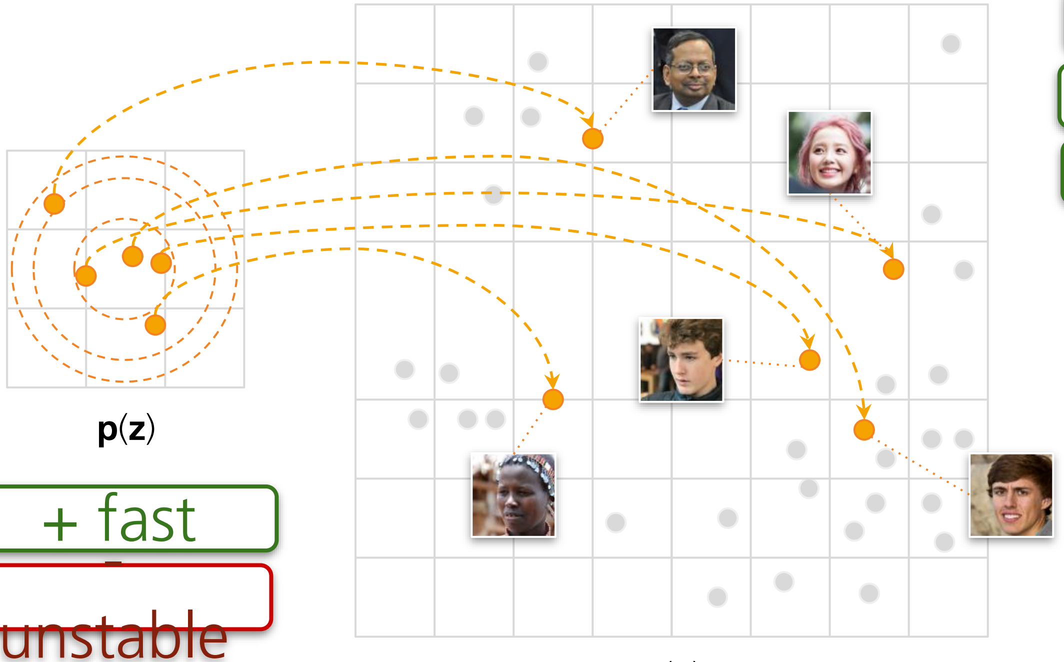
learn gradient of p(x)



GANs vs. Diffusion Models (Sampling)

Generative Adversarial Networks

learn sample function: $z \rightarrow x$



+ fast

- unstable

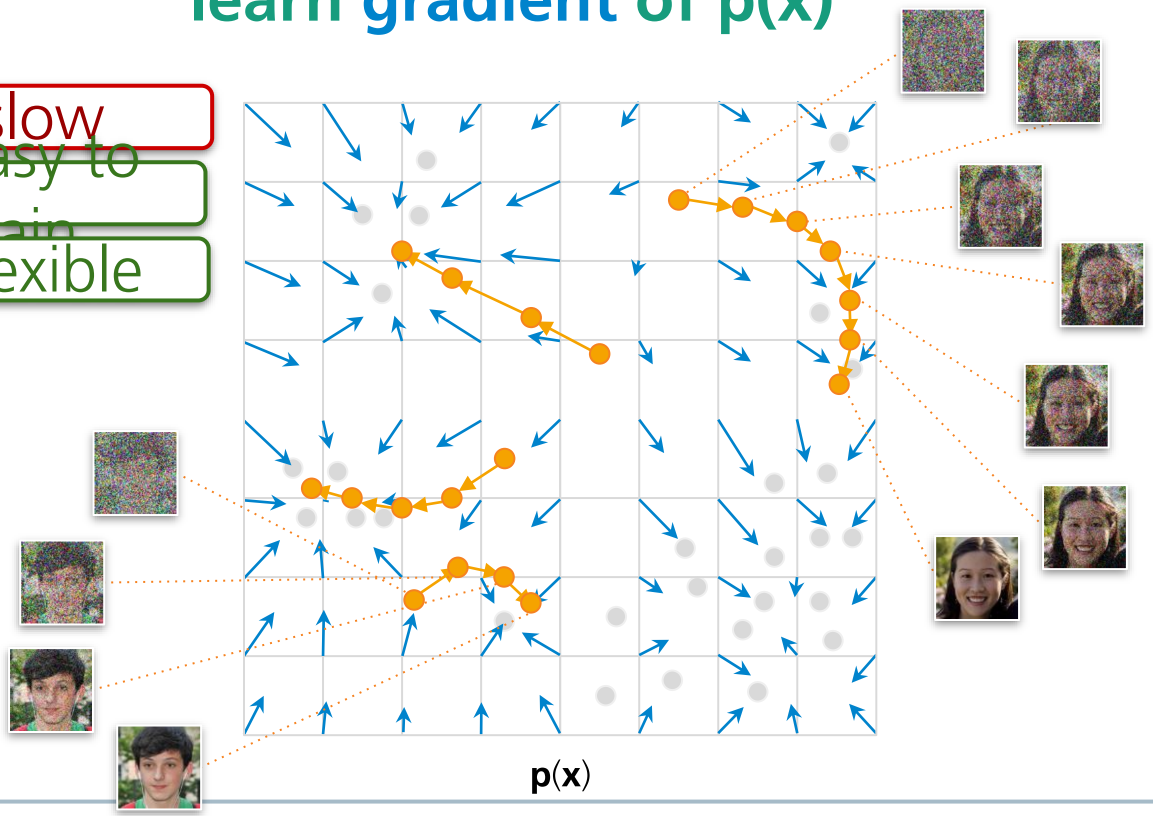
Diffusion Models

learn gradient of p(x)

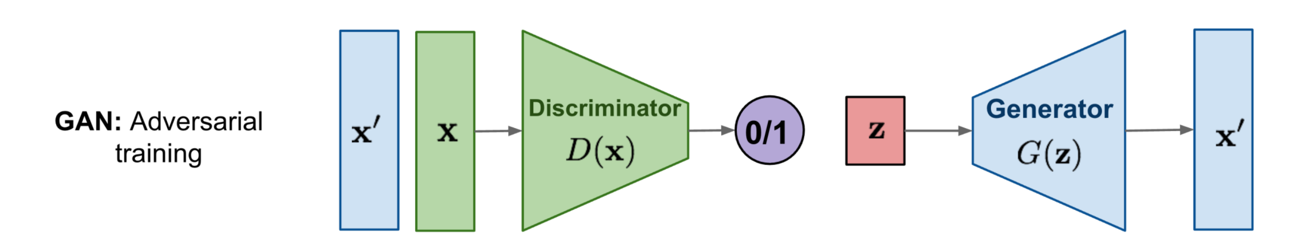
- slow

+ easy to train

+ flexible



Learning from synthetic data - Generation for learning – Part 1



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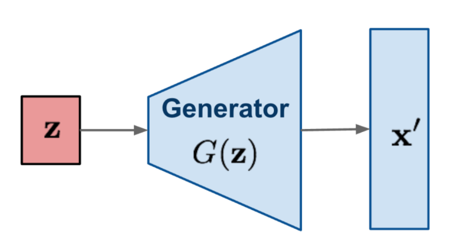

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Learning from synthetic data - Generation for learning – Part 2

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e.g. Faces from GAN

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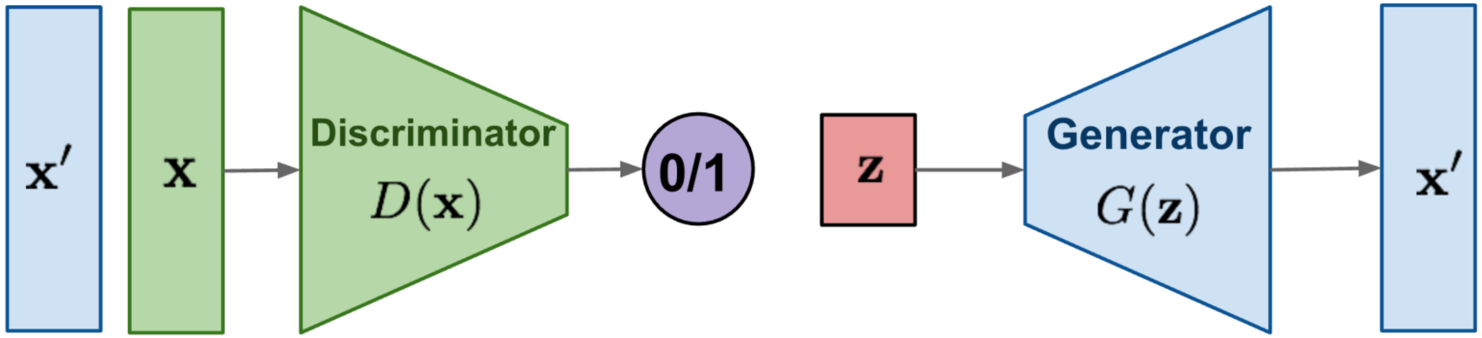

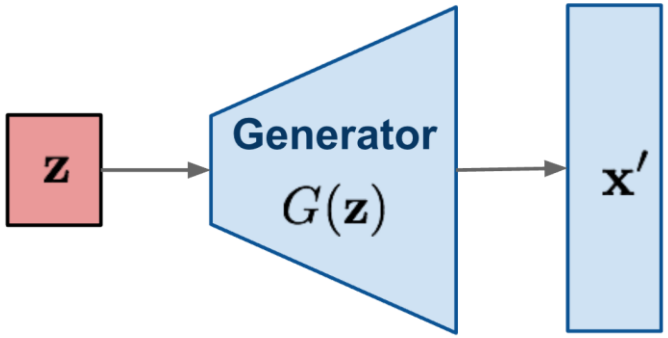

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How much of data problems did we solve?

Synthetic data so far

How to fix our data problems? – synthesize

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- **Cover Inter class variation - PROBLEM**
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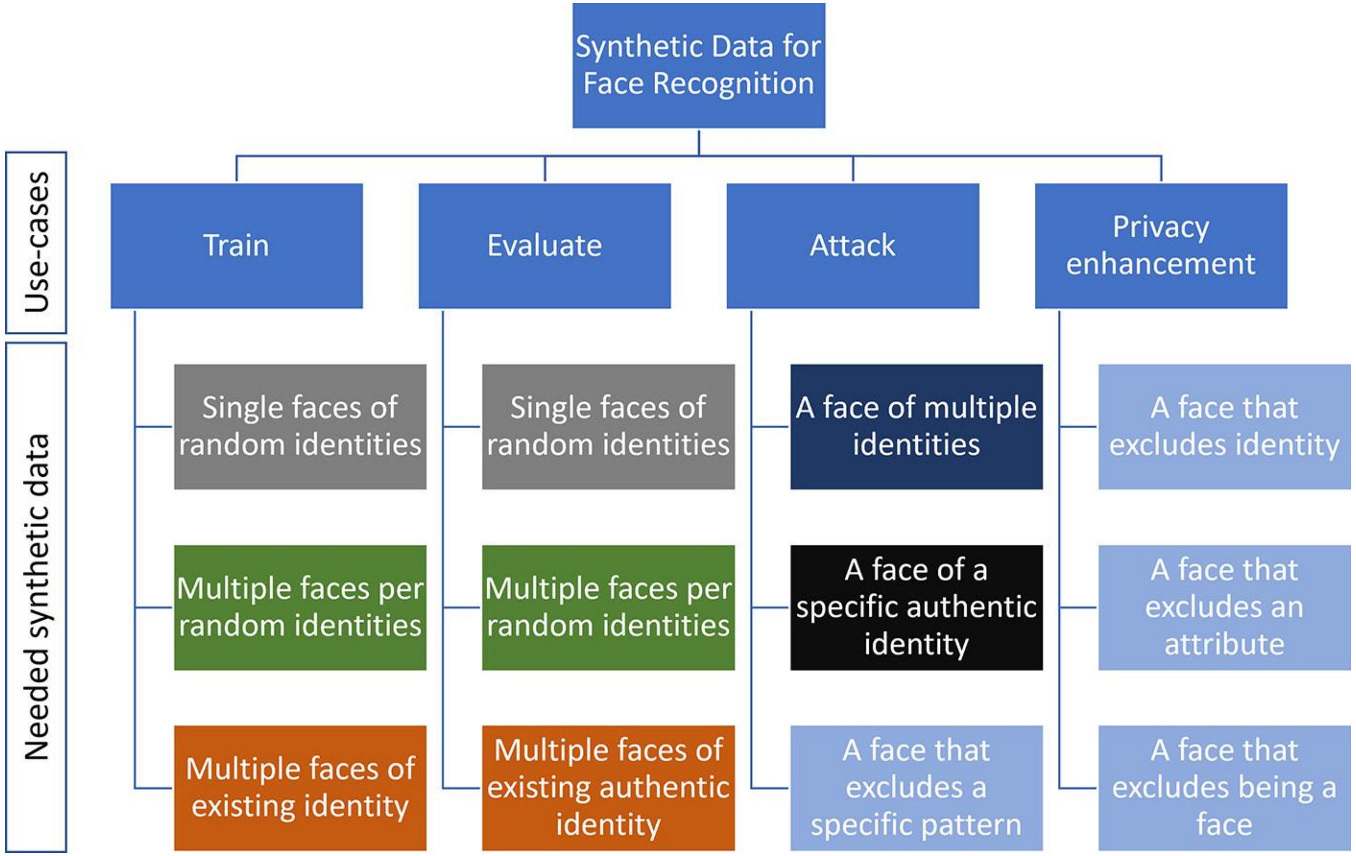
Synthetic data for face recognition

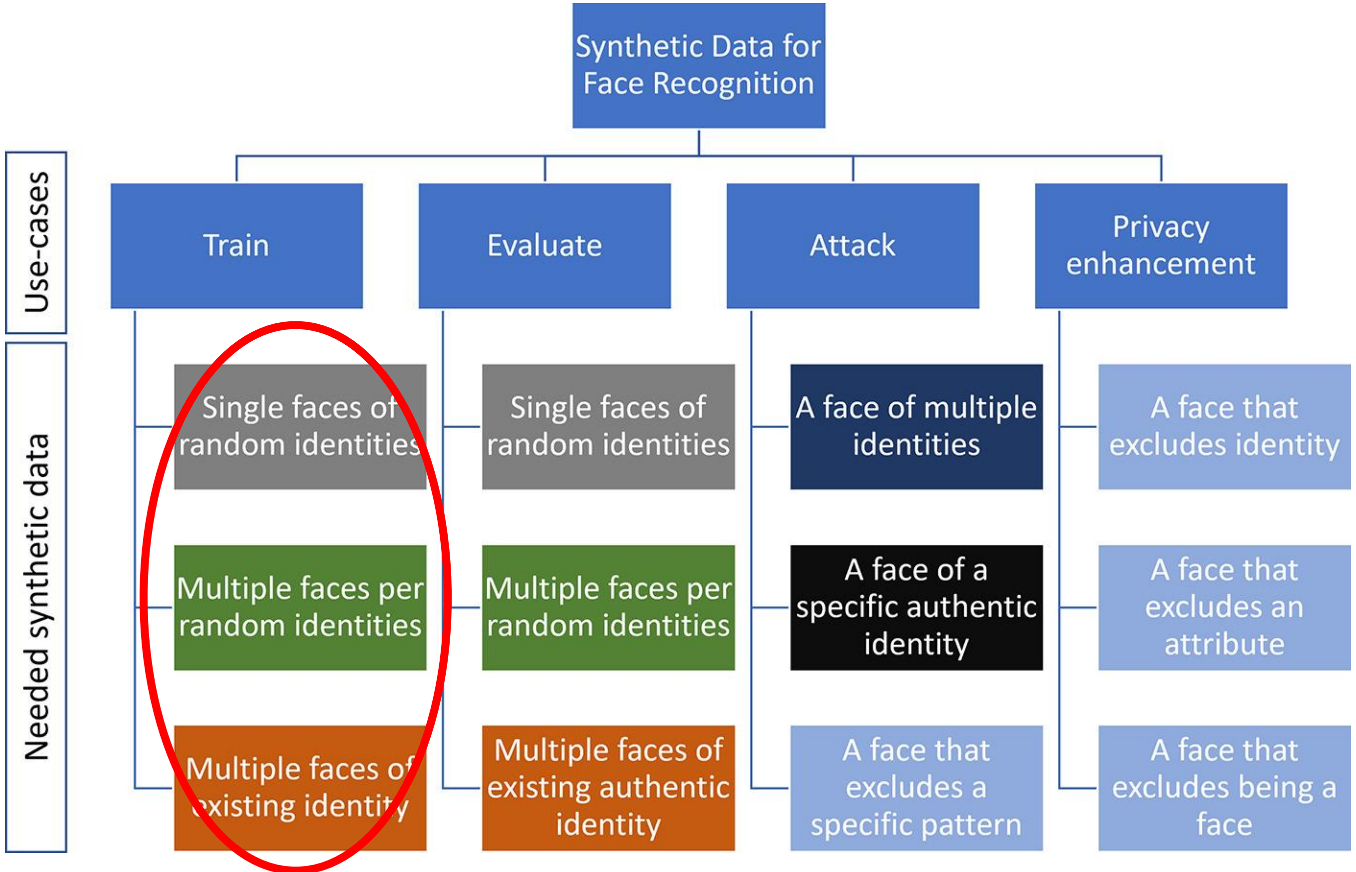
overview



Fadi Boutros, Vitomir Struc, Julian Fiérrez, Naser Damer: Synthetic data for face recognition: Current state and future prospects. Image Vis. Comput. (2023)

Synthetic data for face recognition

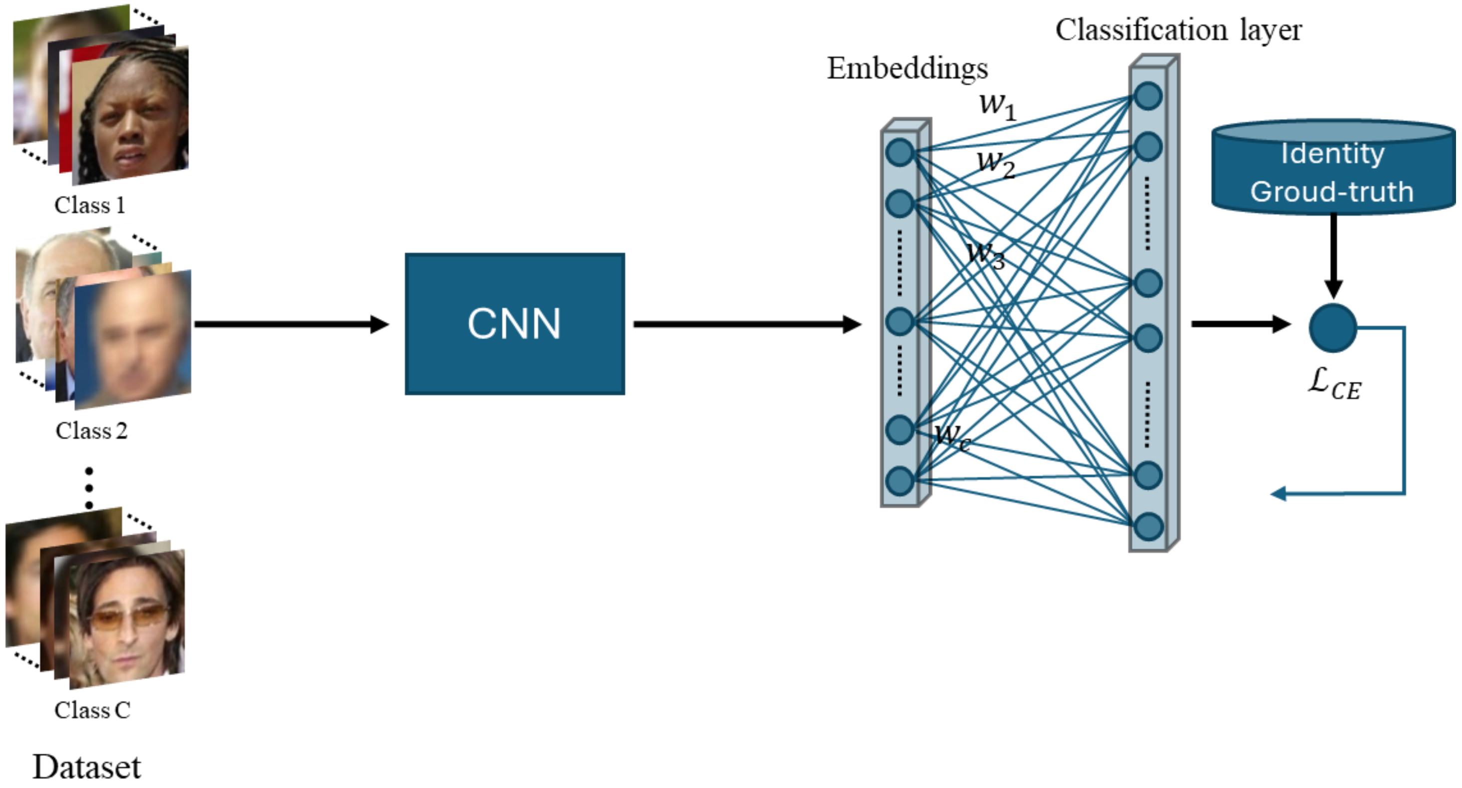
overview



Fadi Boutros, Vitomir Struc, Julian Fiérrez, Naser Damer: Synthetic data for face recognition: Current state and future prospects. Image Vis. Comput. (2023)

Focus out - How to train FR

How to train FR?



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How much of data problems did we solve?

The label problem

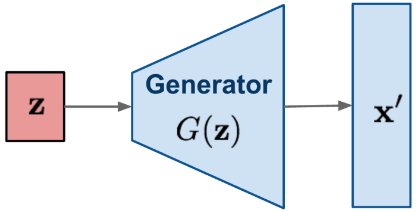
How to fix our data problems? – synthesize

- **Labels needed (probably) – PROBLEM**

The label problem
Discussion

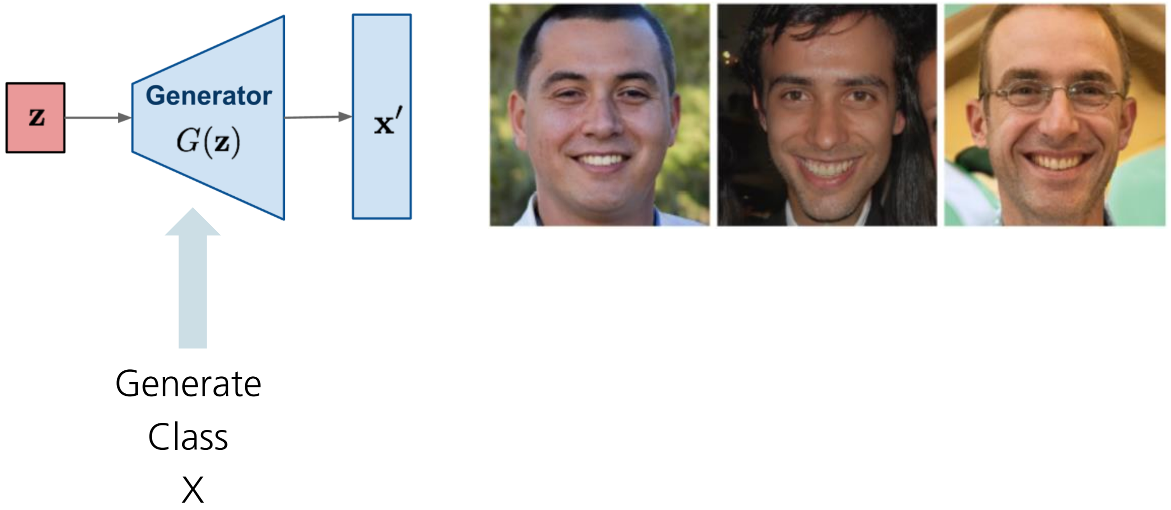
- **Inducing classes in the generation process**
    - Classes in FR are identities

Discussion



The label problem
Conditional label

- **Inducing classes in the generation process**



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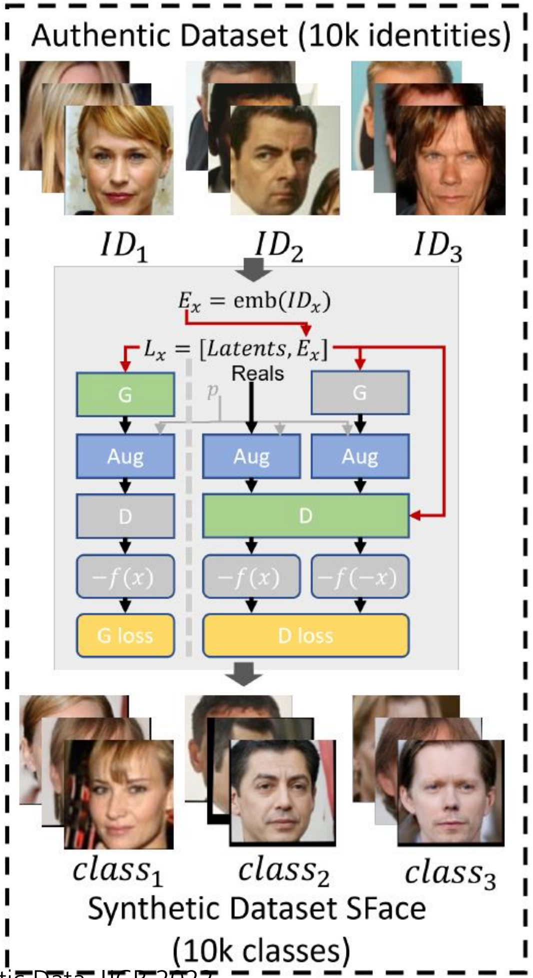
The label problem
SFace

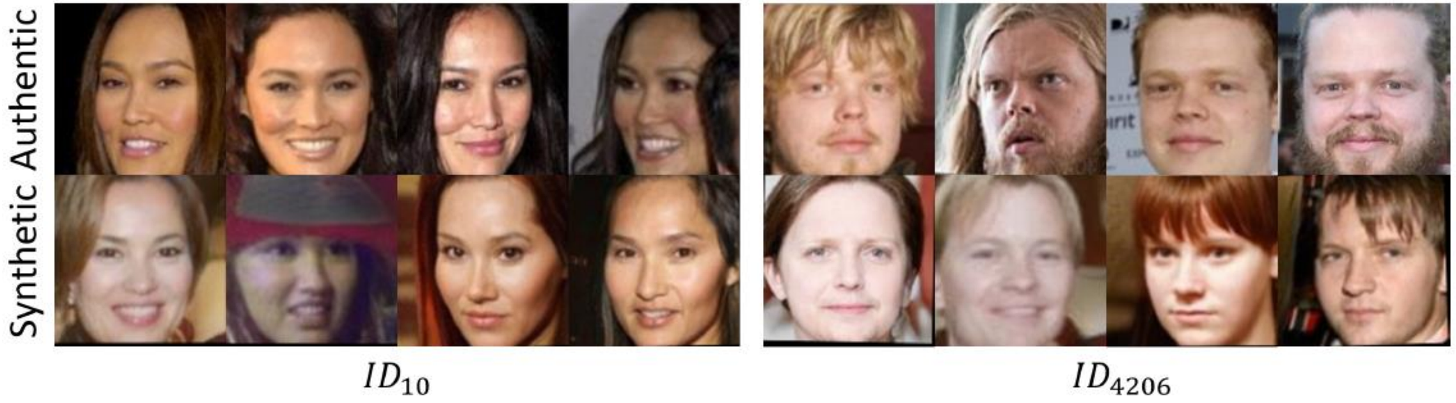
- **Inducing classes in the generation process**

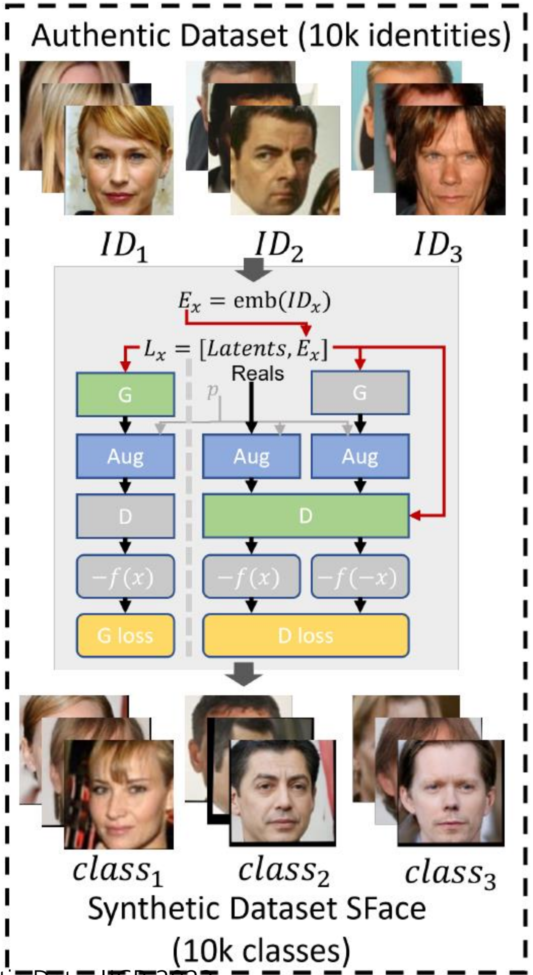


Fadi Boutros et al.: SFace: Privacy-friendly and Accurate Face Recognition using Synthetic Data. IJCB 2022

The label problem
SFace

- **Inducing classes in the generation process**





Fadi Boutros et al.: SFace: Privacy-friendly and Accurate Face Recognition using Synthetic Data. IJCB 2022

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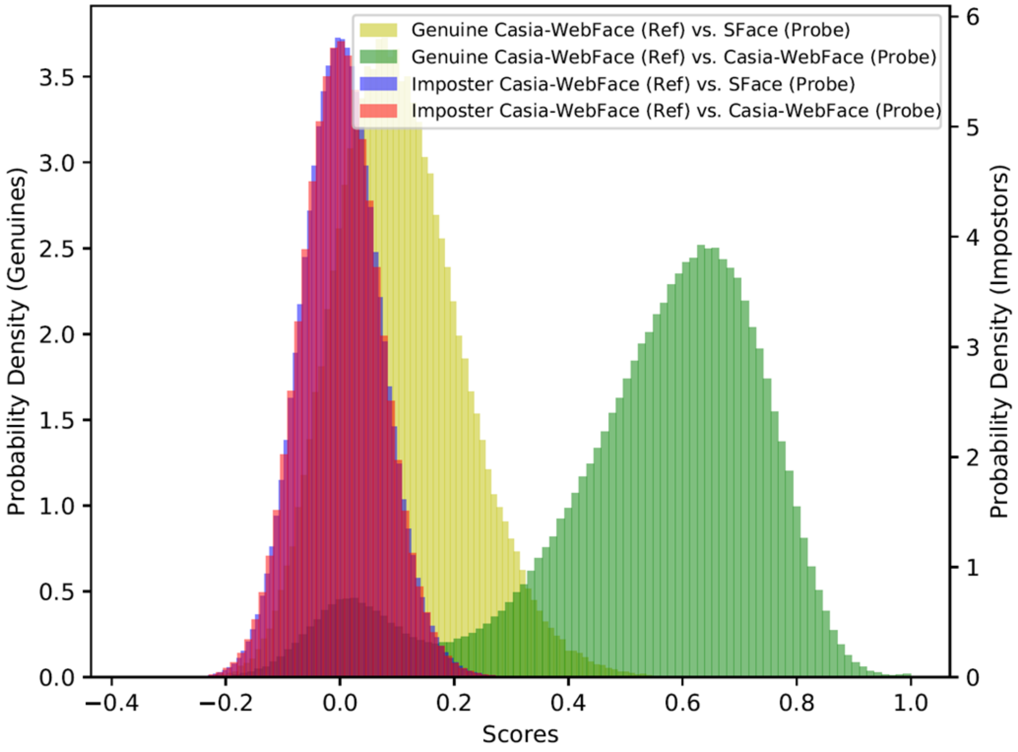
The label problem might be legal/ethical problem

SFace

" How strong is the link between the generation training data and the generated classes?"



- **Associating an identity of SFace to one of Casia-WebFace confidently is hardly possible.**
- **If operating at the FMR1000 threshold an authentic image, if compared to a 100 images of the same class in SFace using a top-performing FR solution will result in a (false) non-match decisions around 89 times.**

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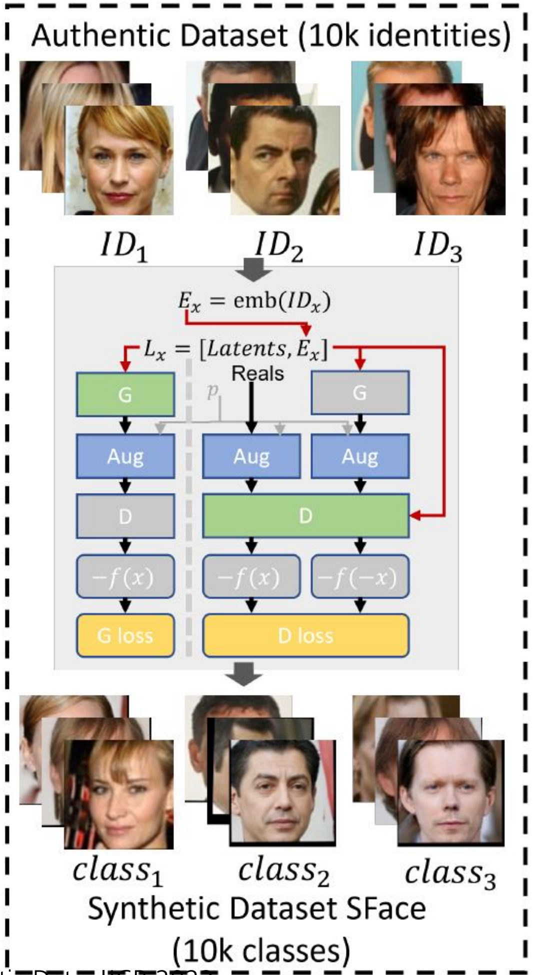
The label problem
SFace

- **Inducing classes in the generation process**
  - But the class separability is as strong as authentic data



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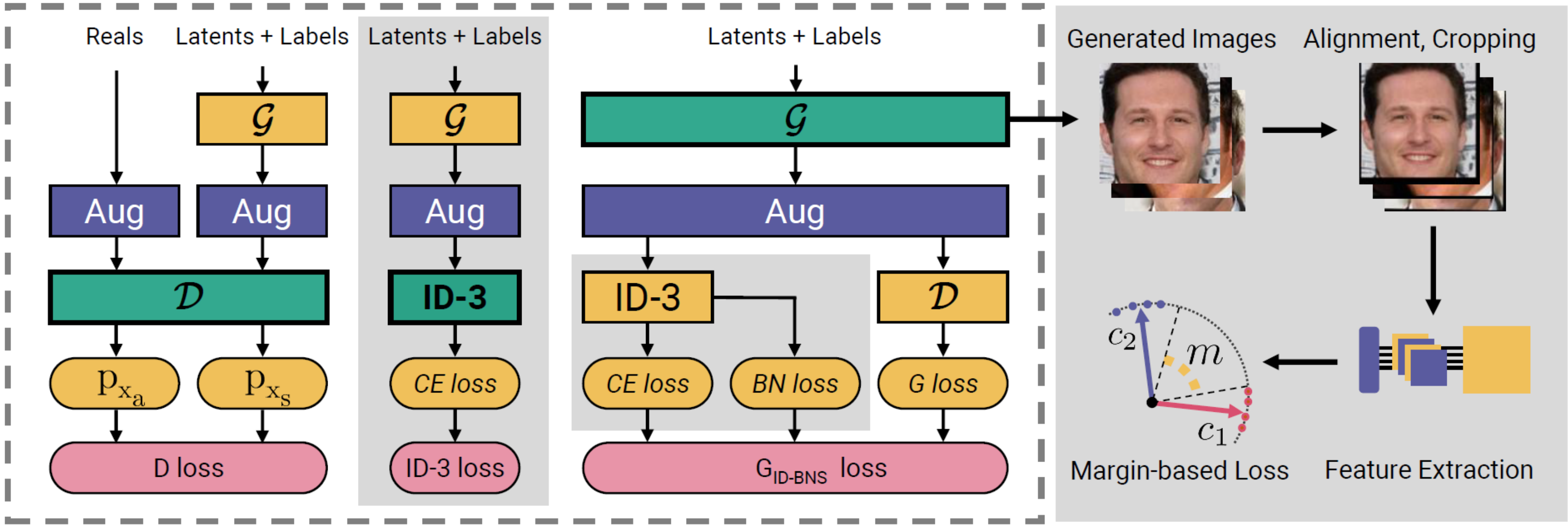
The label problem

Sface to IDNet

- **Inducing classes in the generation process**
  - But the class separability is not as strong as in authentic data -> so we force the generator to be identity consistent



Jan Niklas Kolf et al. Identity-driven Three-Player Generative Adversarial Network for Synthetic-based Face Recognition. CVPR Workshops 2023:

The label problem
Sface and IDNet

- **Inducing classes in the generation process**
  - Limited by the number of classes in the authentic data (might be legal/ethical problem)
  - Weak identity separability (inter class variation problem)
  - Level of identity intraclass variation is uncontrolled (intra class variation problem)

  - What to do?

Jan Niklas Kolf et al. Identity-driven Three-Player Generative Adversarial Network for Synthetic-based Face Recognition. CVPR Workshops 2023:

The label problem

Beyond: Sface and IDNet

- Limited by the number of classes in the authentic data (might be legal/ethical problem)
- Weak identity separability (inter class variation problem)
- Level of identity intraclass variation is uncontrolled (intra class variation problem)

- What we need?

    - Generate unlimited classes
    - Classes are realistically separable
    - Controlling the intraclass variation

Jan Niklas Kolf et al. Identity-driven Three-Player Generative Adversarial Network for Synthetic-based Face Recognition. CVPR Workshops 2023:

The label problem
Beyond: Sface and IDNet

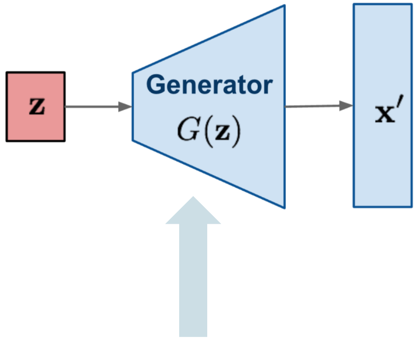
- What we need?

  - Generate unlimited classes
  - Classes are realistically separable
  - Controlling the intraclass variation

-> ExFaceGAN

Jan Niklas Kolf et al. Identity-driven Three-Player Generative Adversarial Network for Synthetic-based Face Recognition. CVPR Workshops 2023:

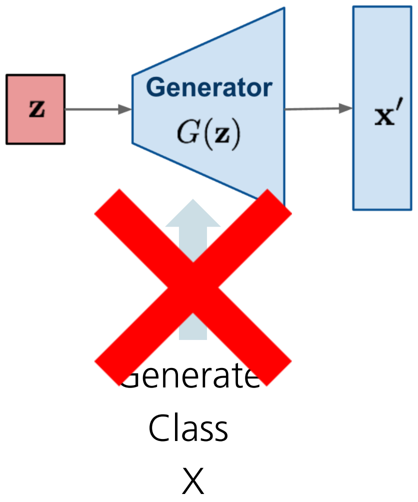
The label problem
ExFaceGAN



Generate
Class
X

Fadi Boutroset al. ExFaceGAN: Exploring Identity Directions in GAN's Learned Latent Space for Synthetic Identity Generation. IJCB 2023

The label problem
ExFaceGAN



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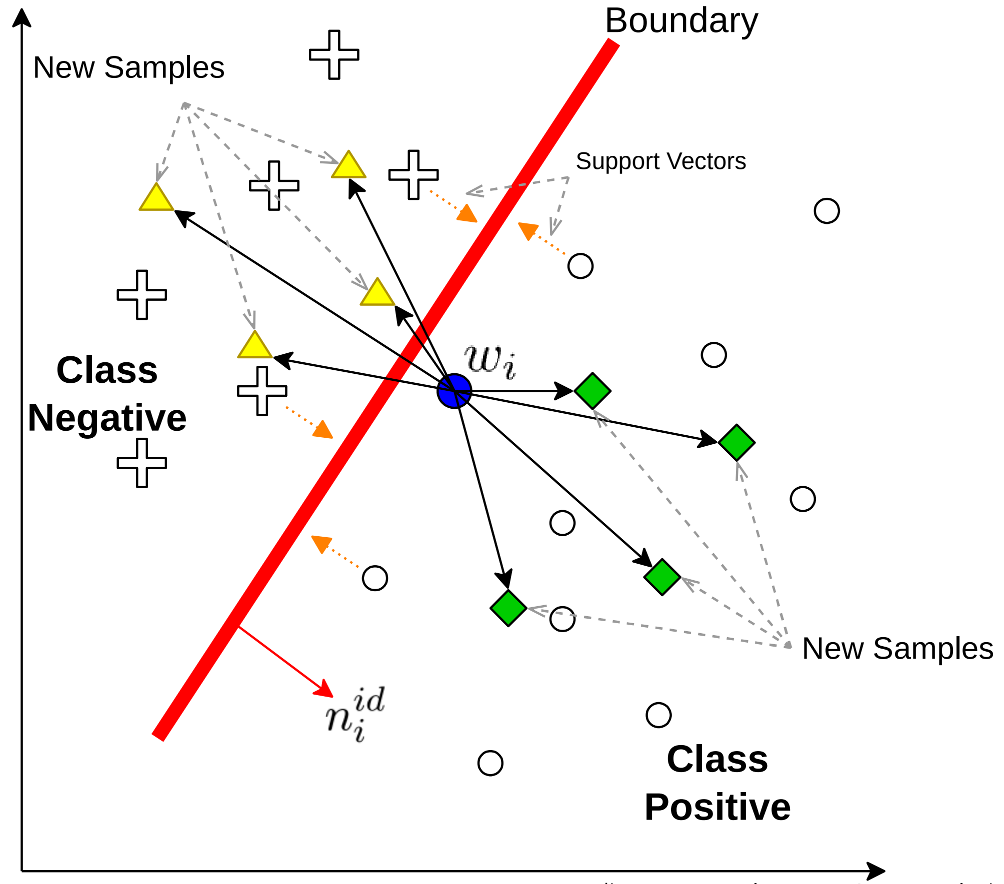
ExFaceGAN



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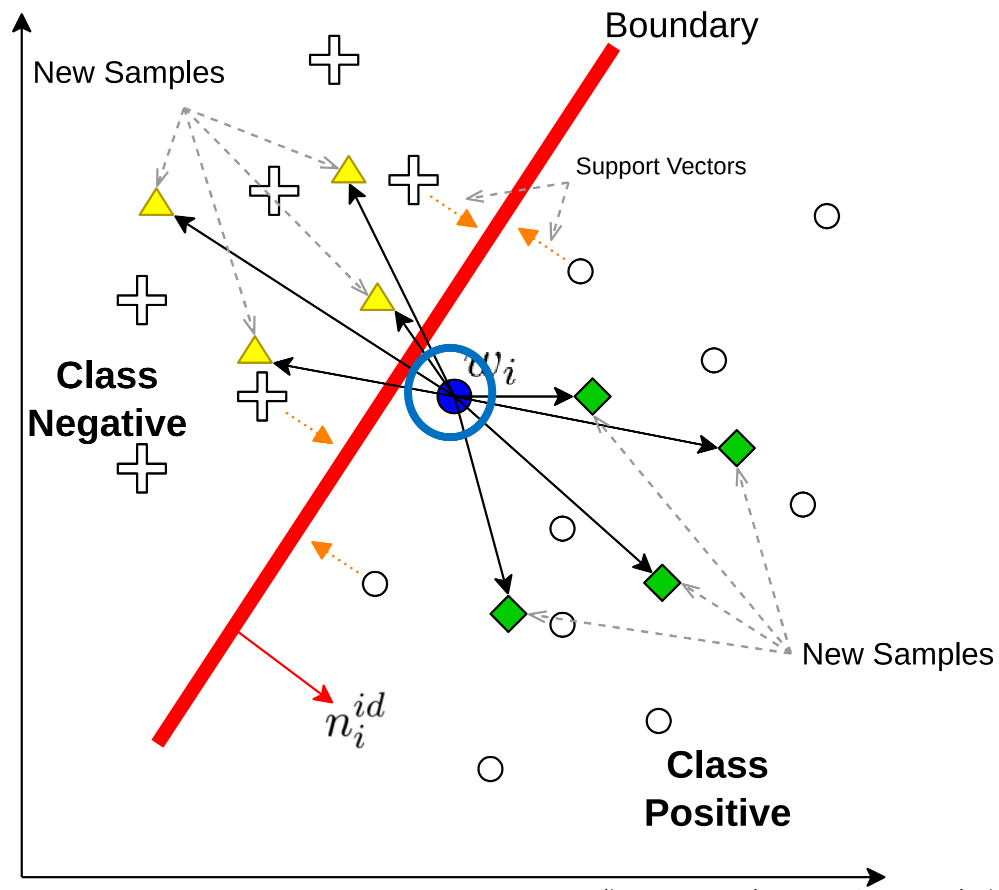

Reference

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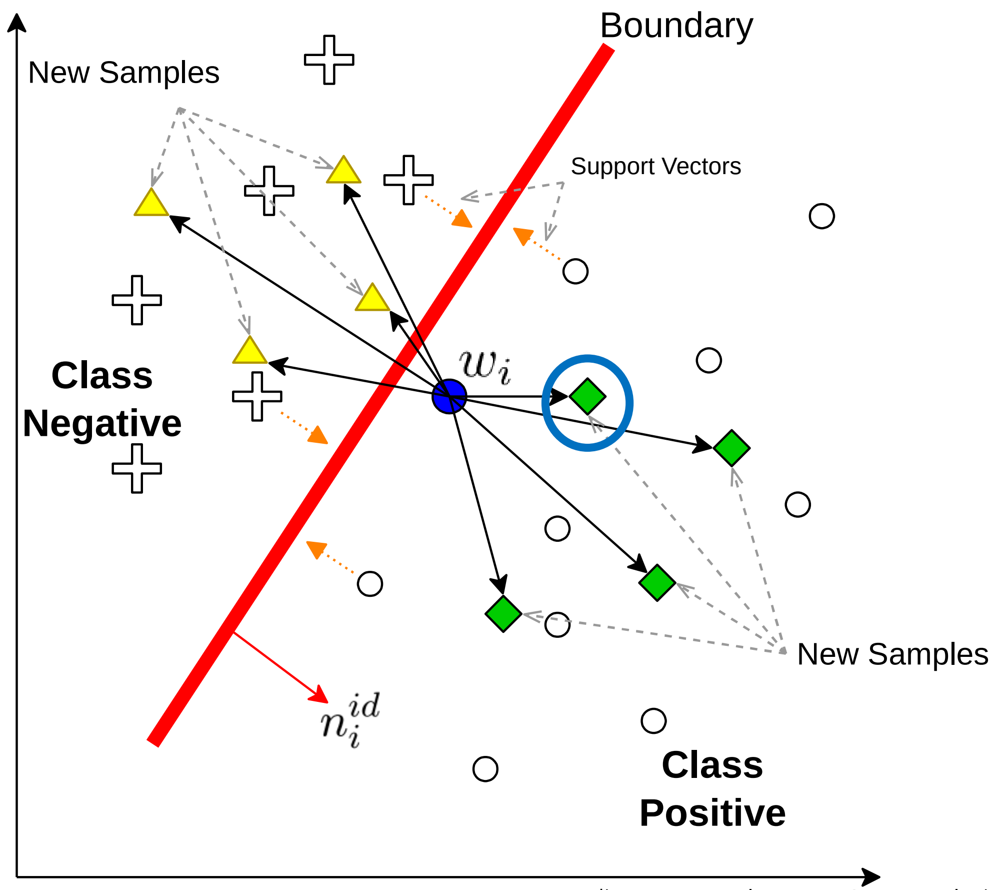

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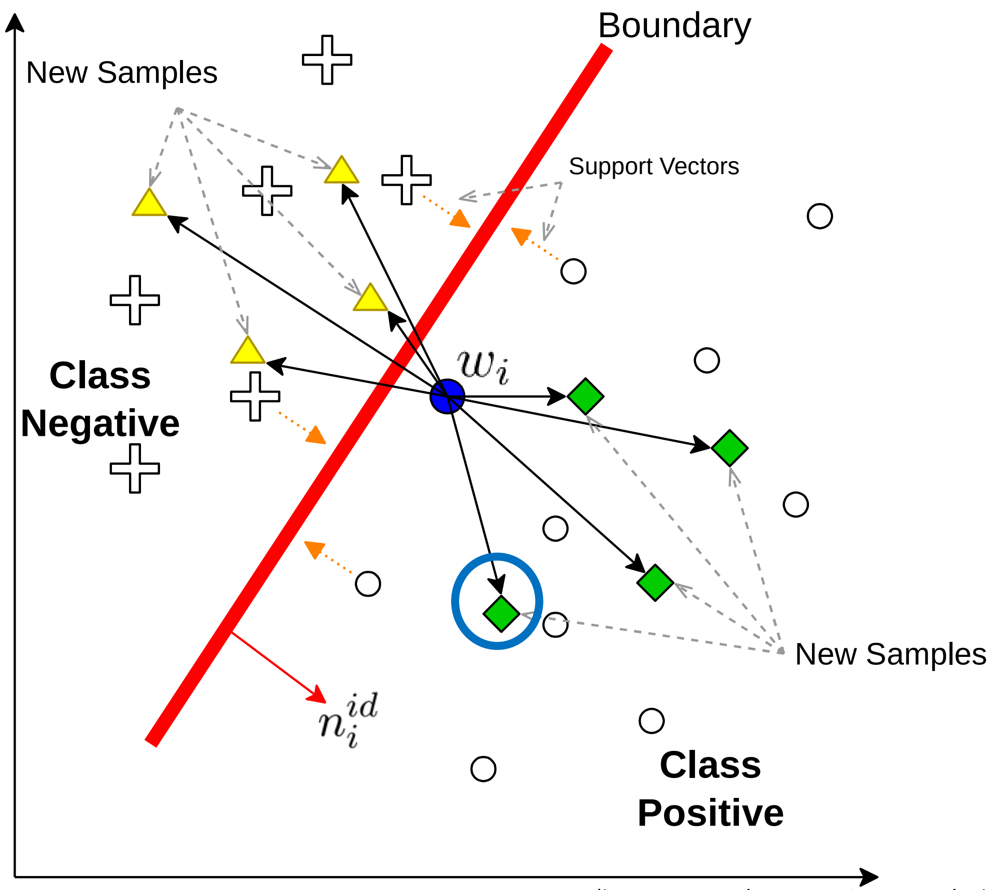
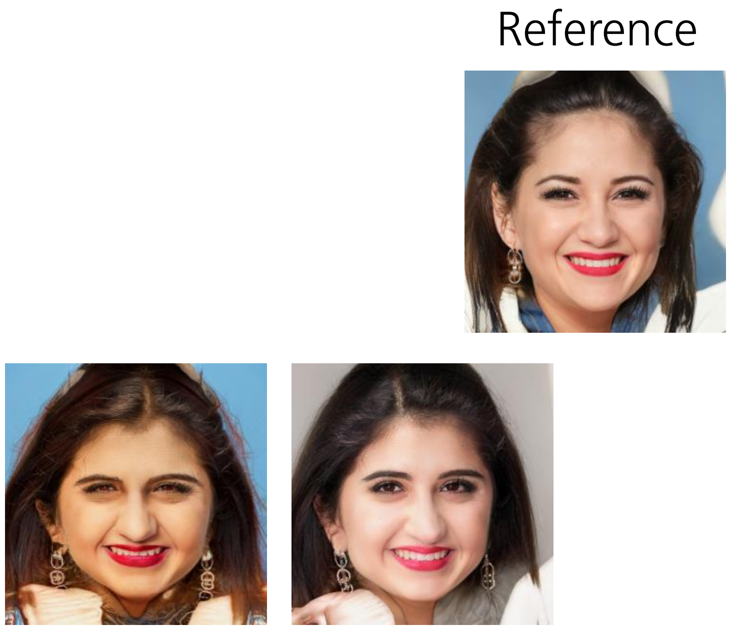
ExFaceGAN





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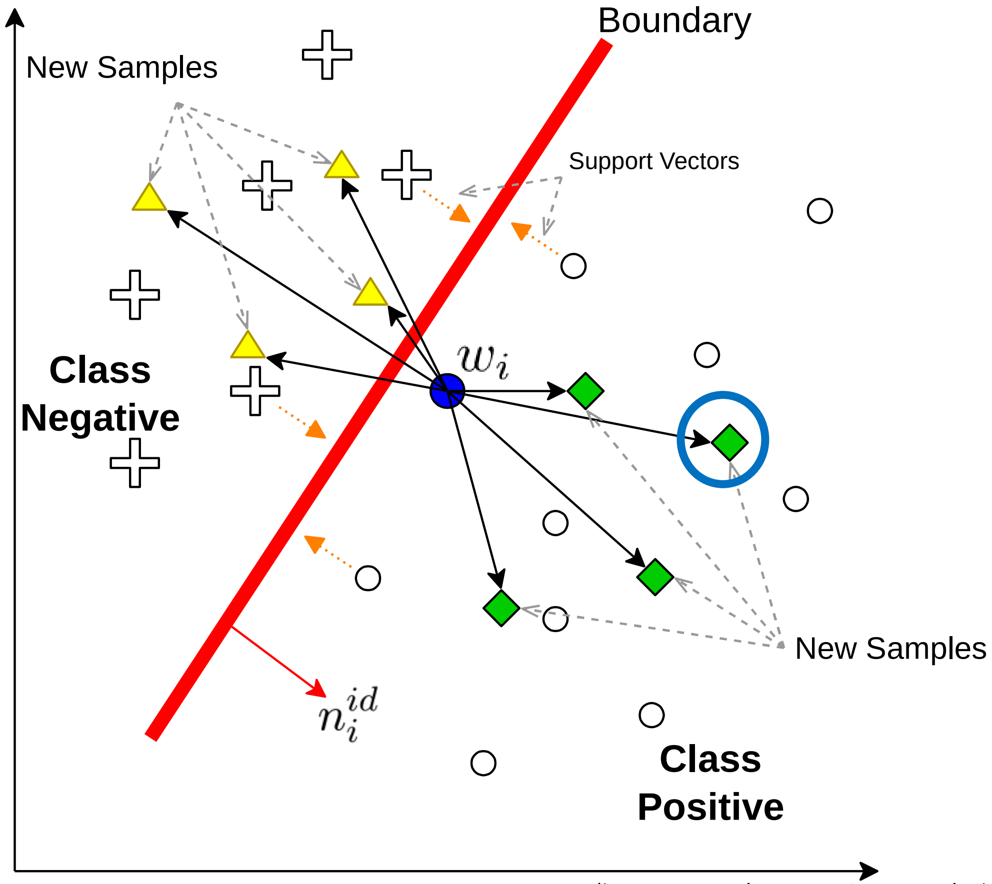
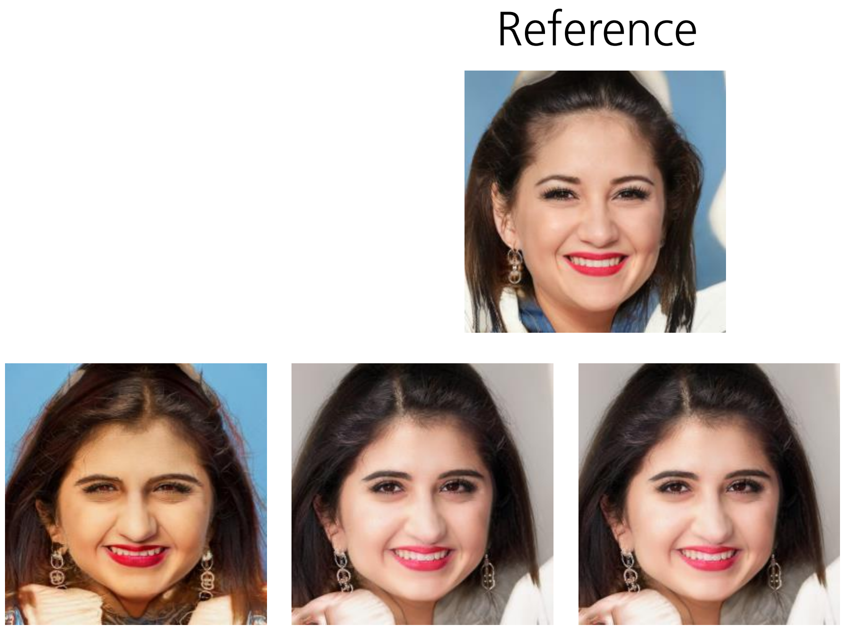
ExFaceGAN





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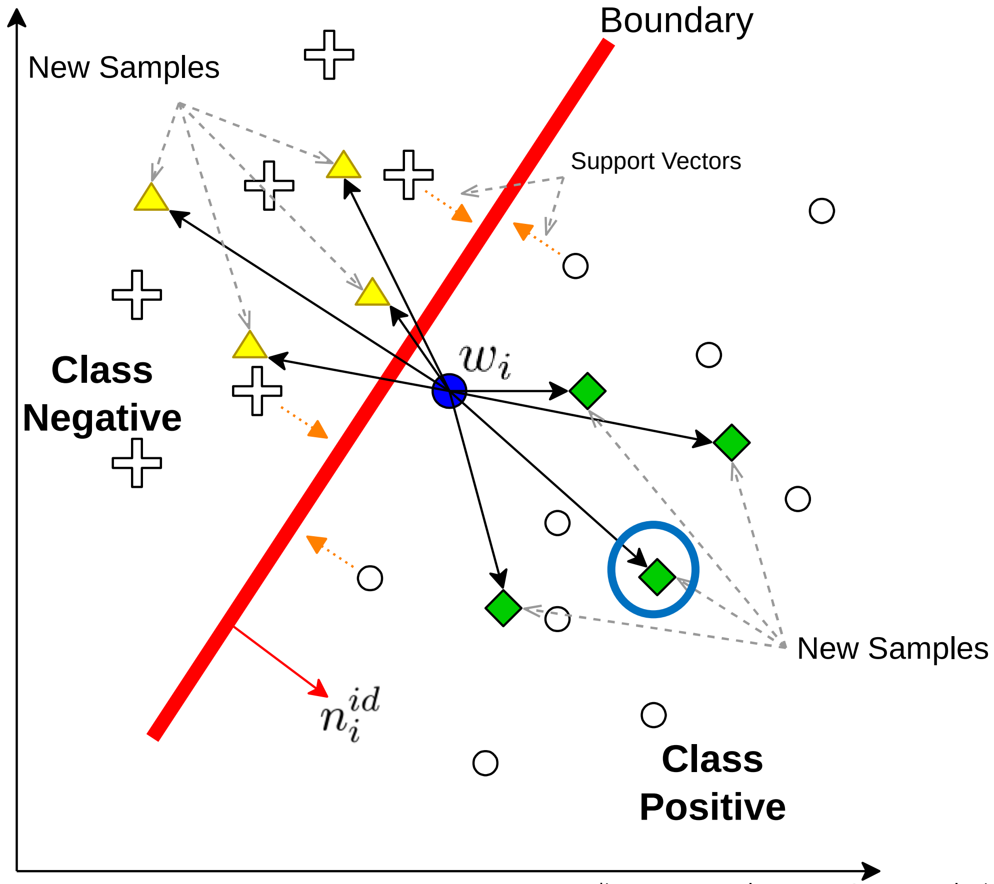
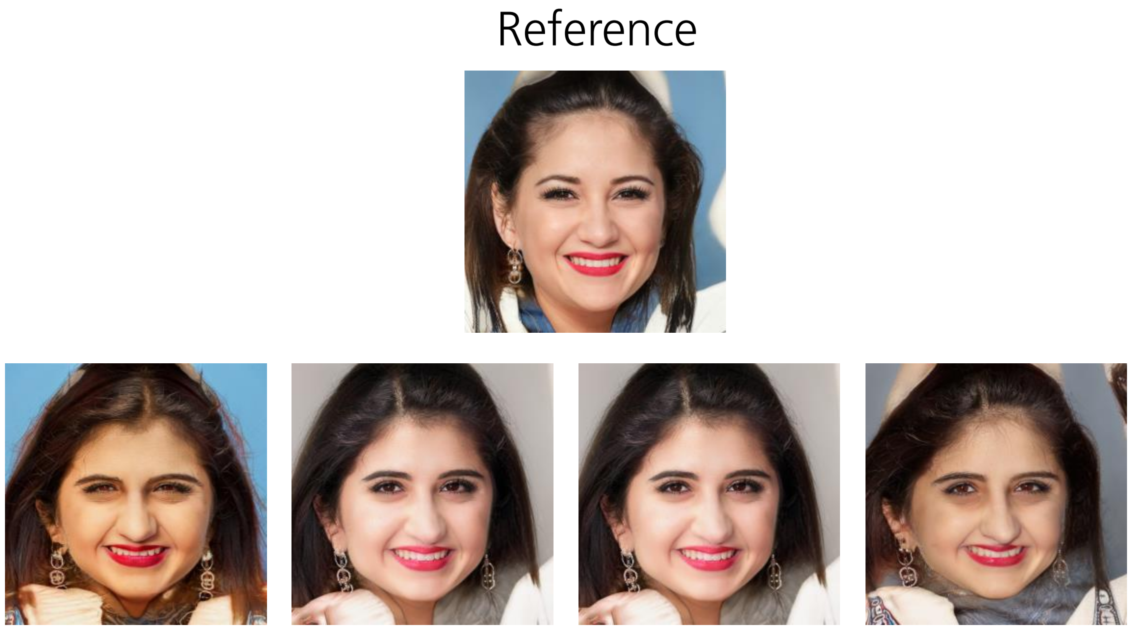
ExFaceGAN





Fadi Boutroset al. ExFaceGAN: Exploring Identity Directions in GAN's Learned Latent Space for Synthetic Identity Generation. IJCB 2023

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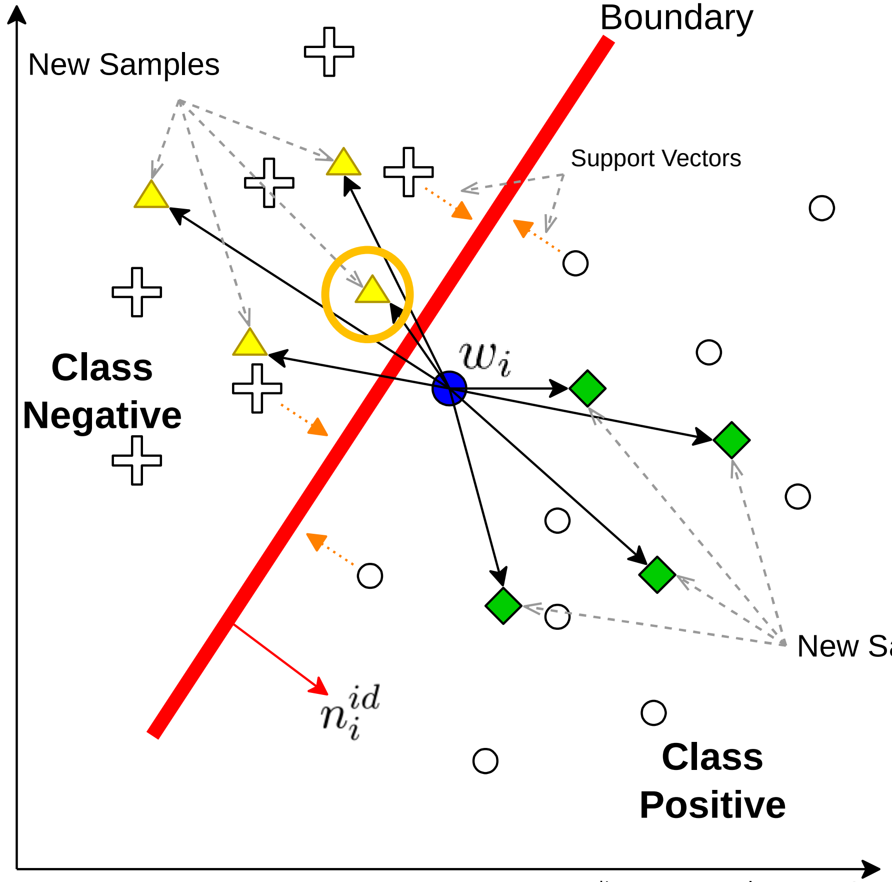

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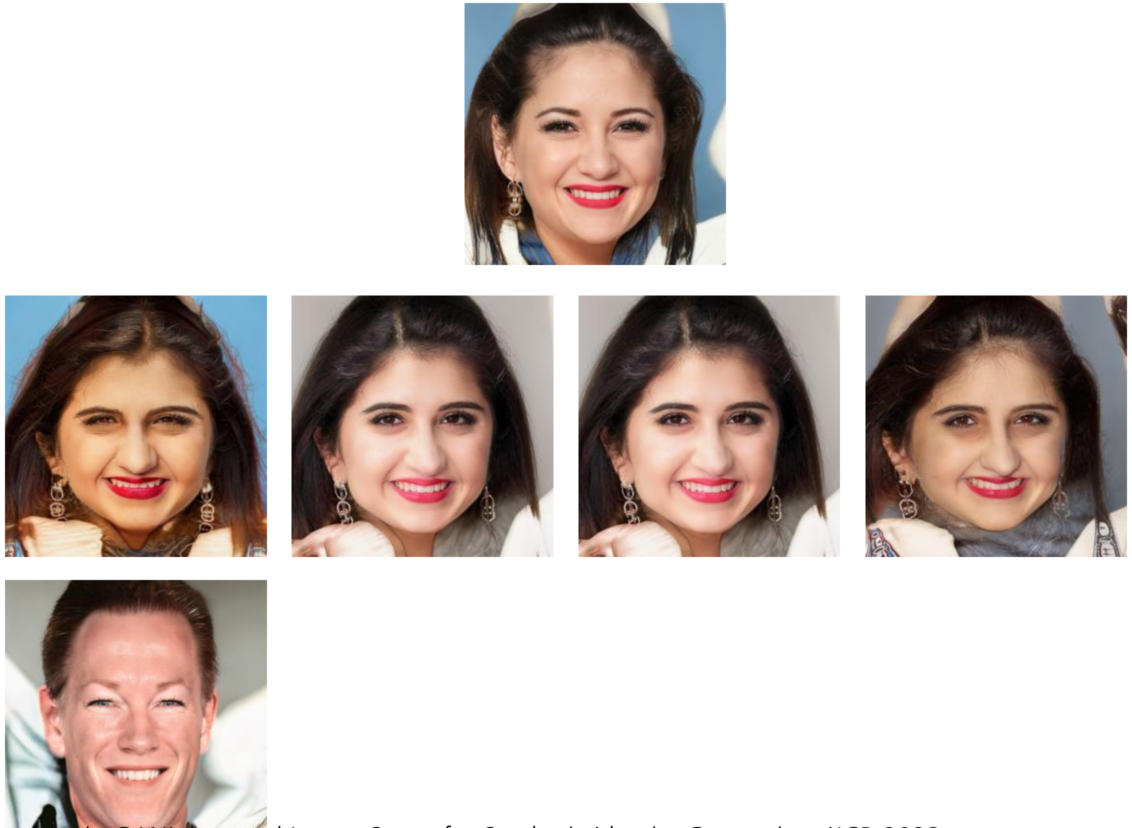
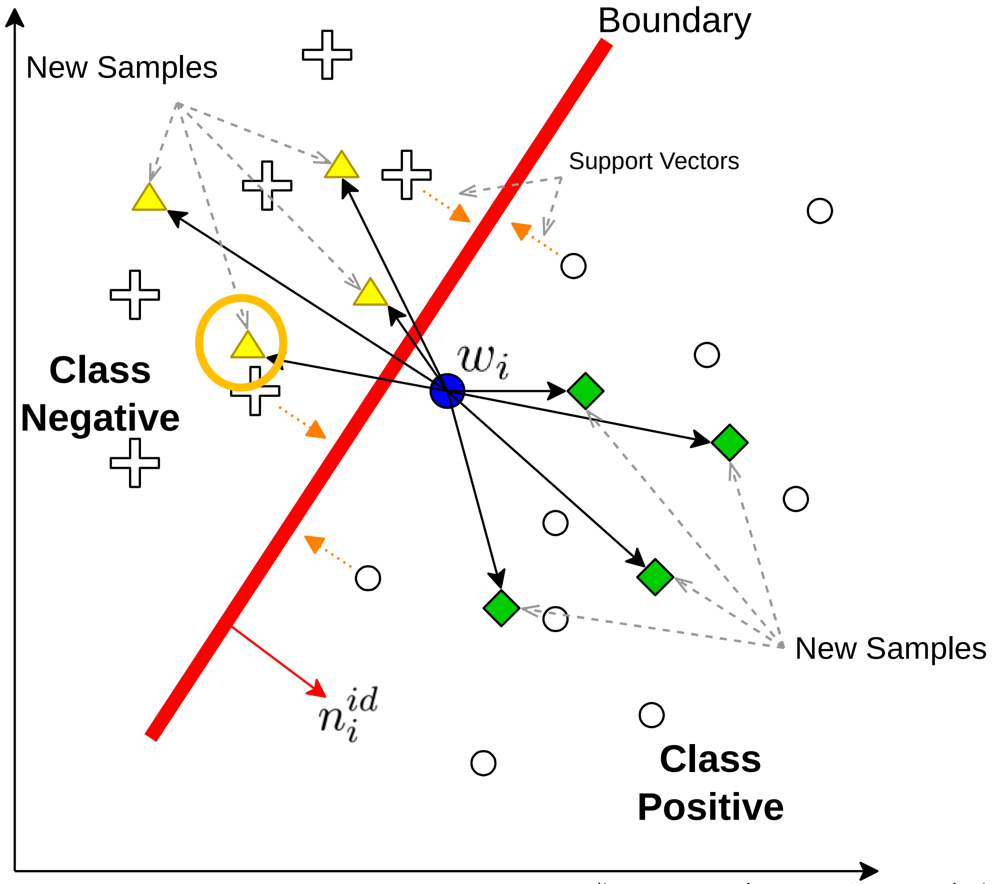
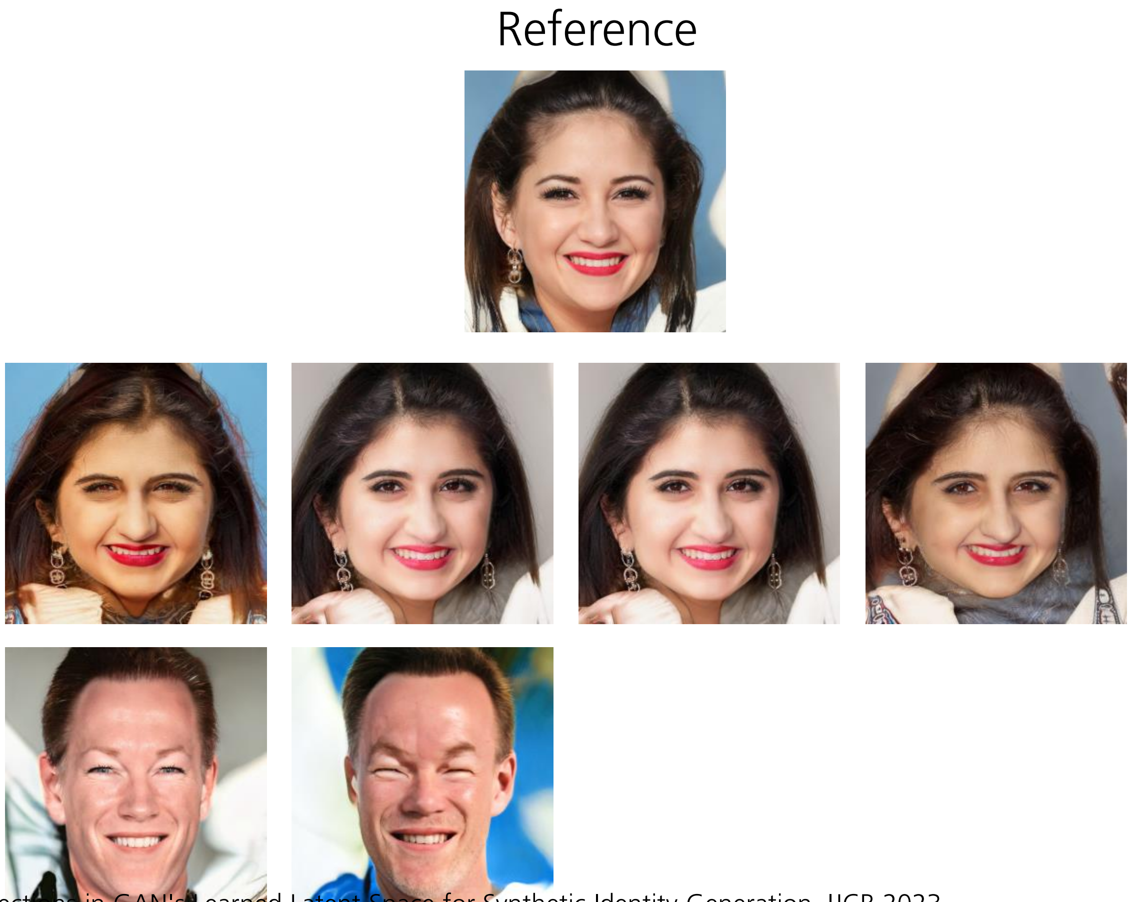


Fadi Boutroset al. ExFaceGAN: Exploring Identity Directions in GAN's Learned Latent Space for Synthetic Identity Generation. IJCB 2023

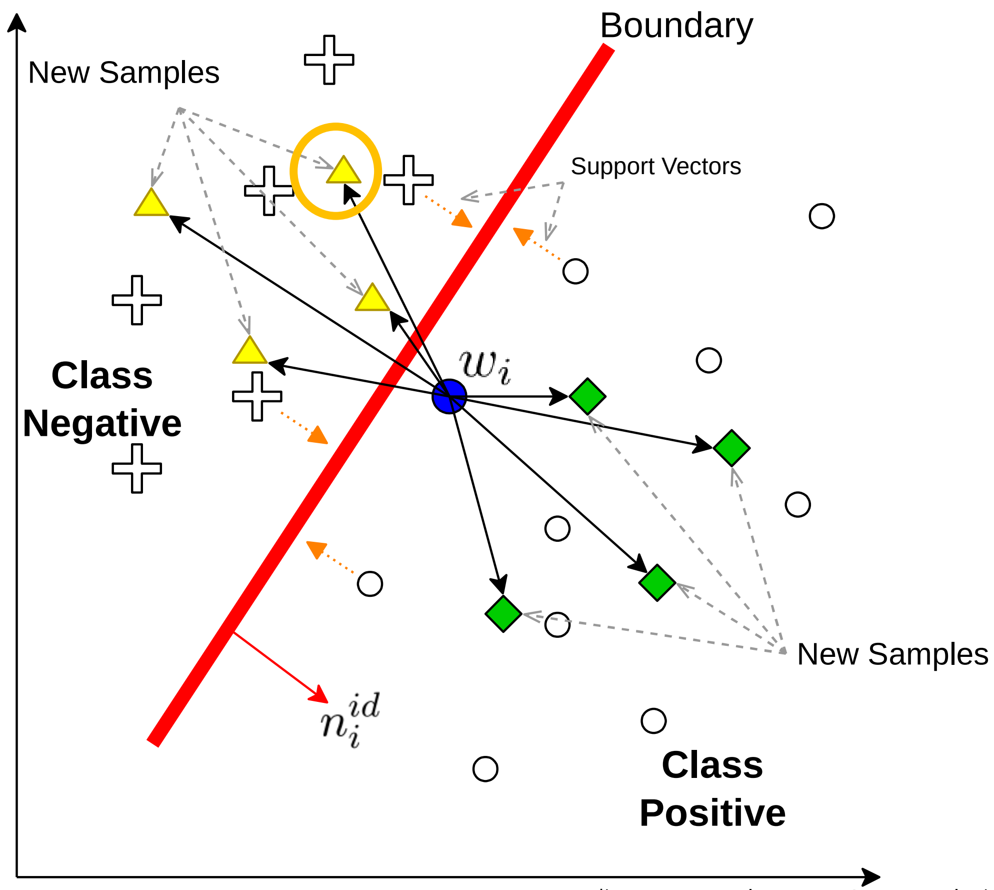
ExFaceGAN

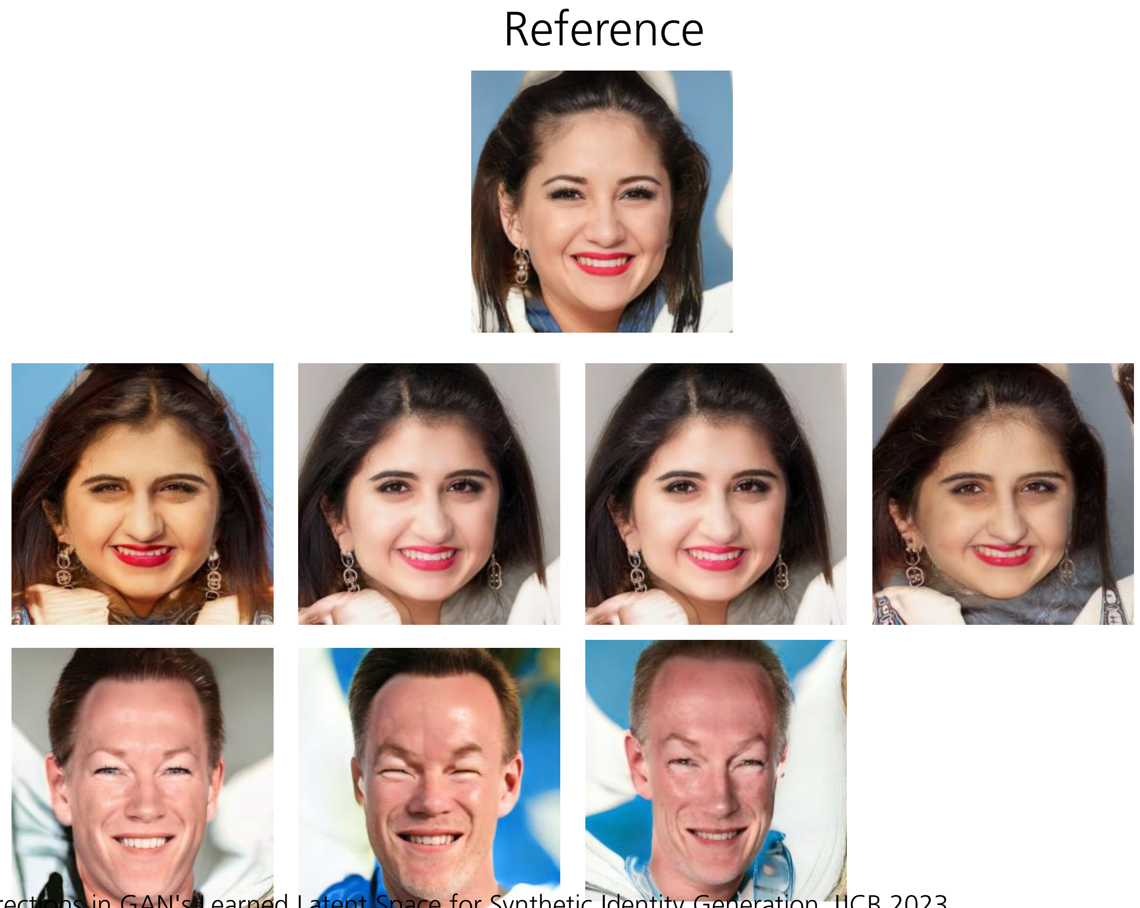




Fadi Boutroset al. ExFaceGAN: Exploring Identity Directions in GAN's Learned Latent Space for Synthetic Identity Generation. IJCB 2023

ExFaceGAN





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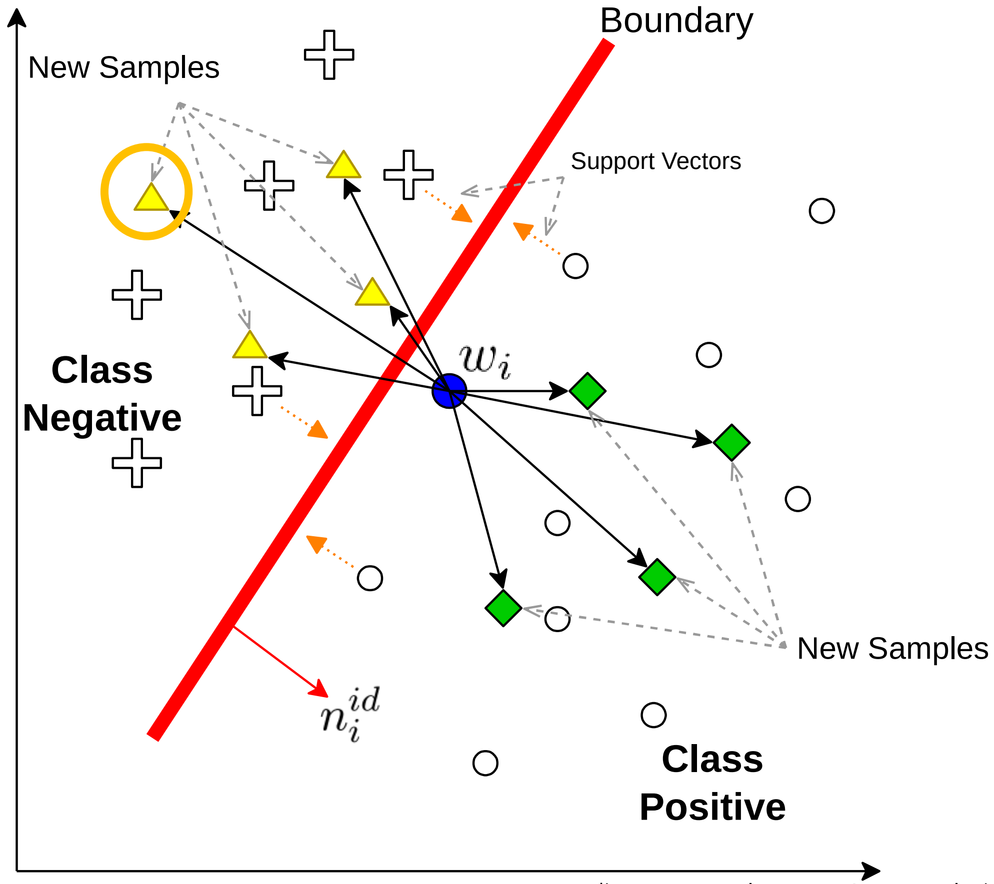
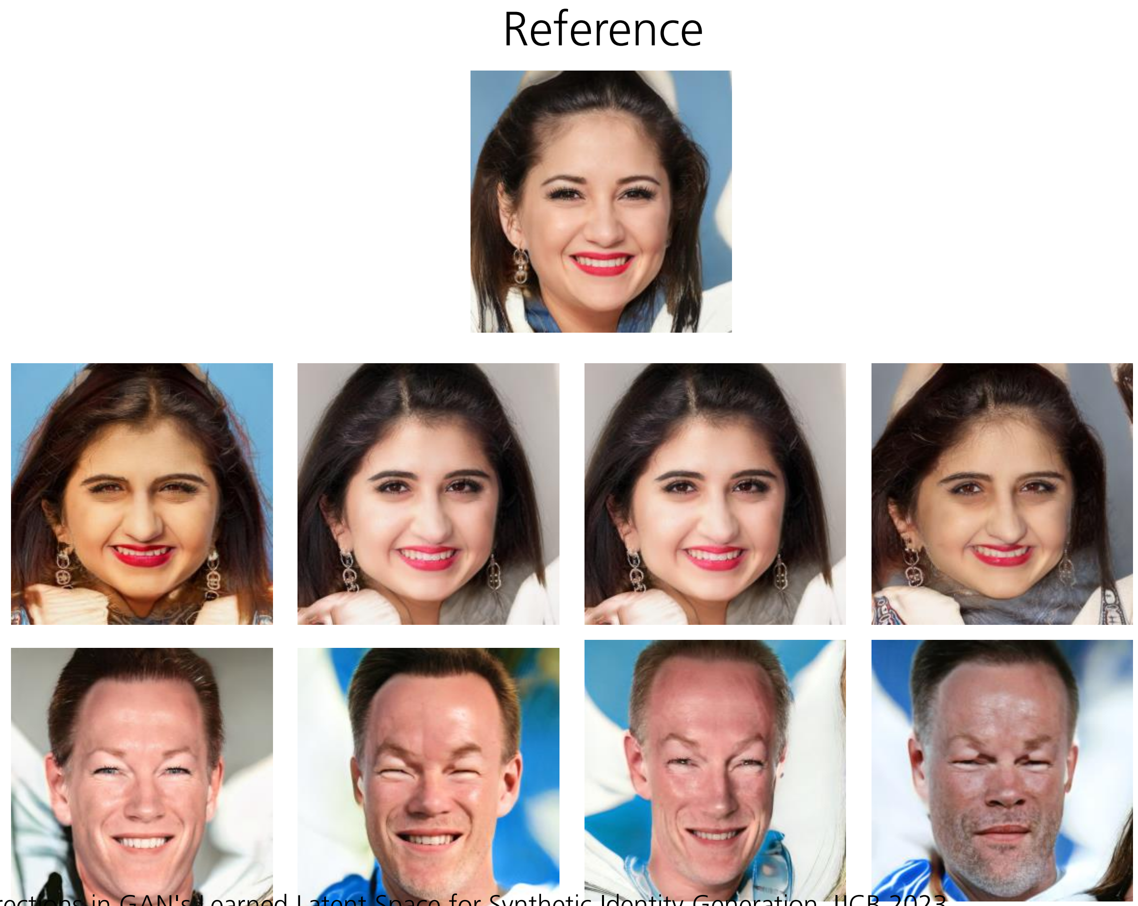
ExFaceGAN

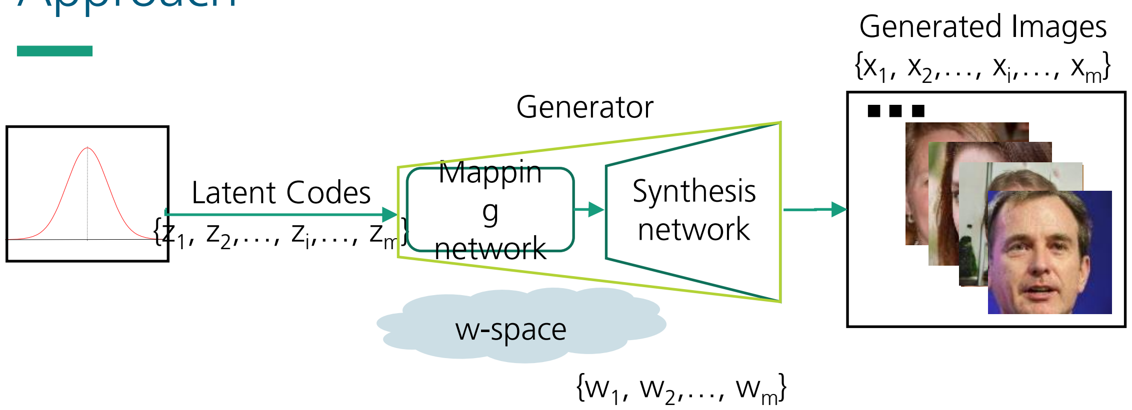


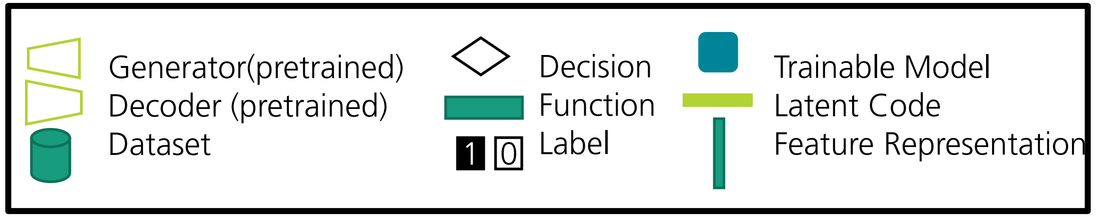


Fadi Boutroset al. ExFaceGAN: Exploring Identity Directions in GAN's Learned Latent Space for Synthetic Identity Generation. IJCB 2023

ExFaceGAN

Approach

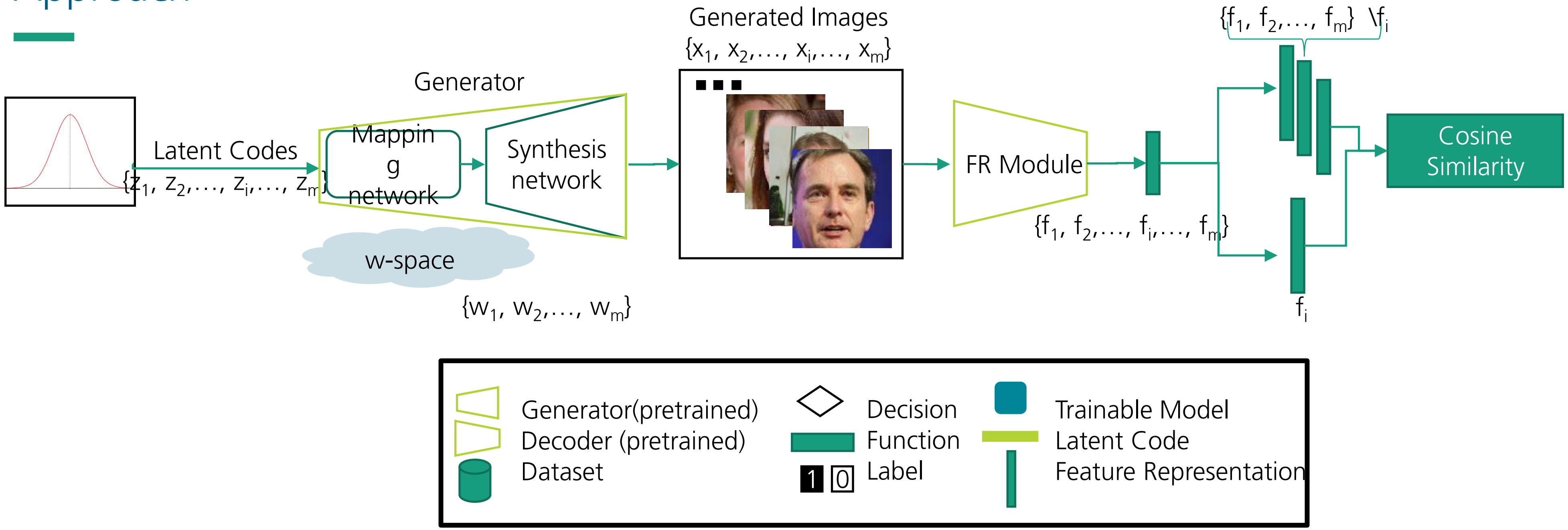




Fadi Boutroset al. ExFaceGAN: Exploring Identity Directions in GAN's Learned Latent Space for Synthetic Identity Generation. IJCB 2023

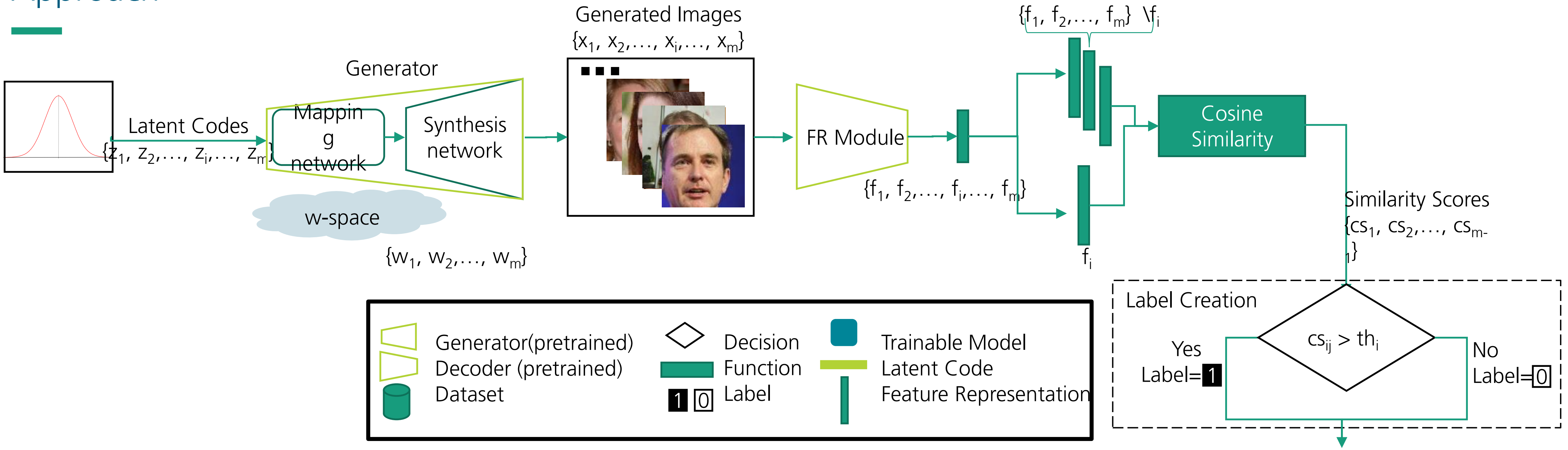
ExFaceGAN

Approach



Fadi Boutroset al. ExFaceGAN: Exploring Identity Directions in GAN's Learned Latent Space for Synthetic Identity Generation. IJCB 2023

ExFaceGAN
Approach



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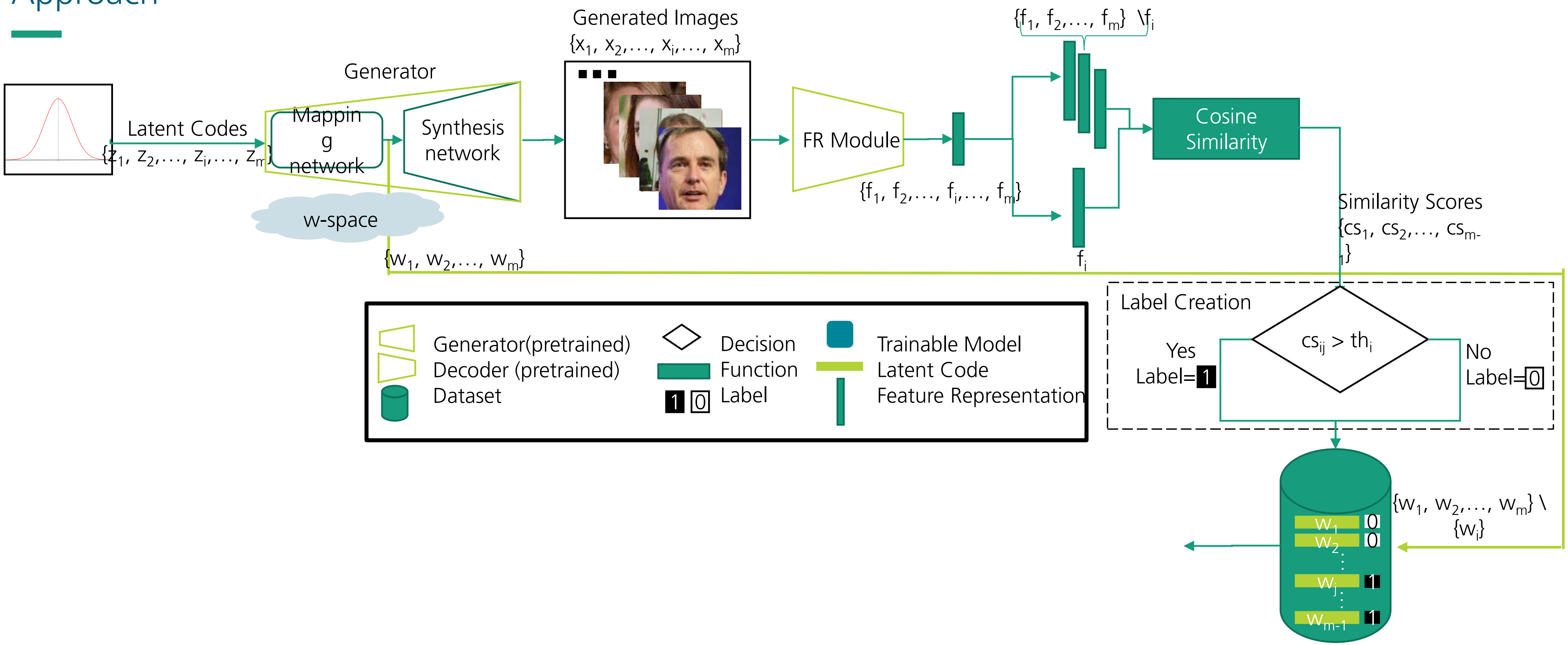
ExFaceGAN

Approach



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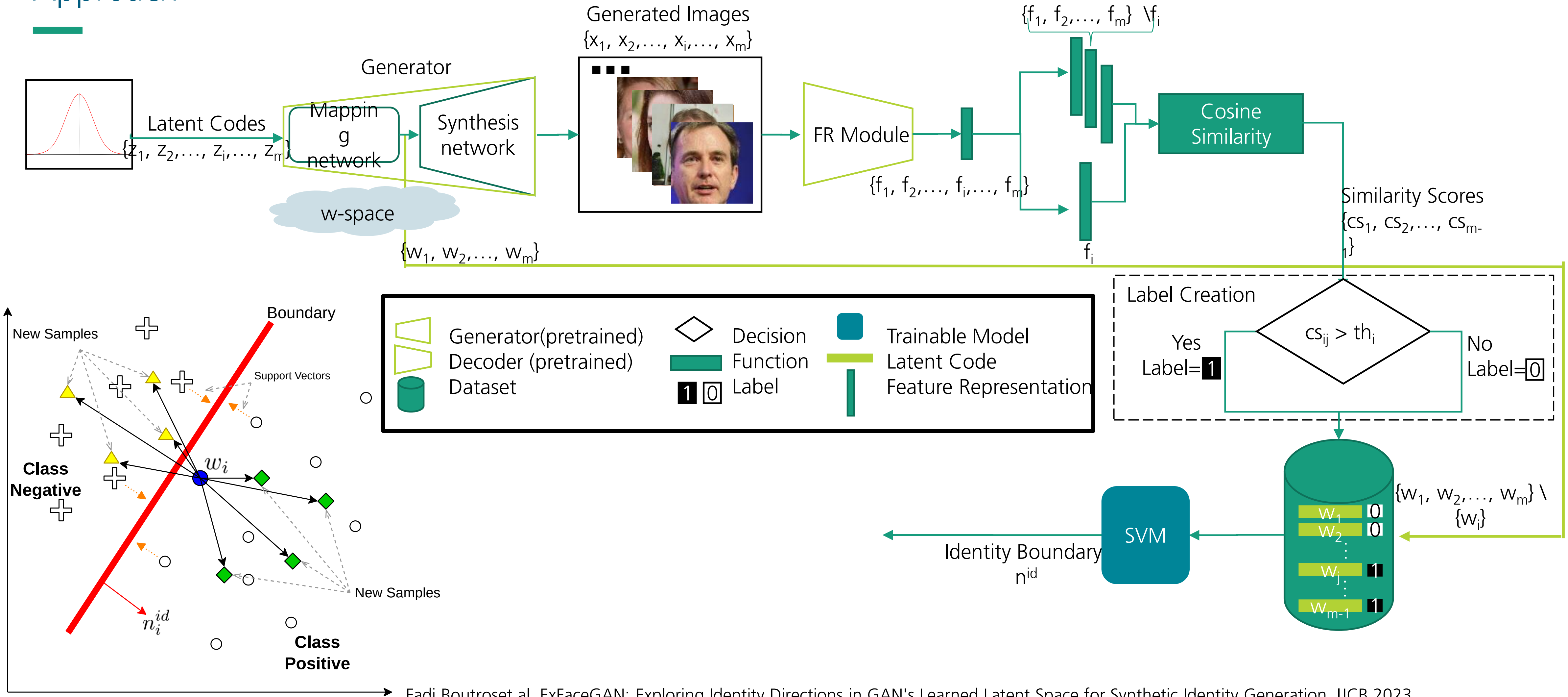
ExFaceGAN

Approach



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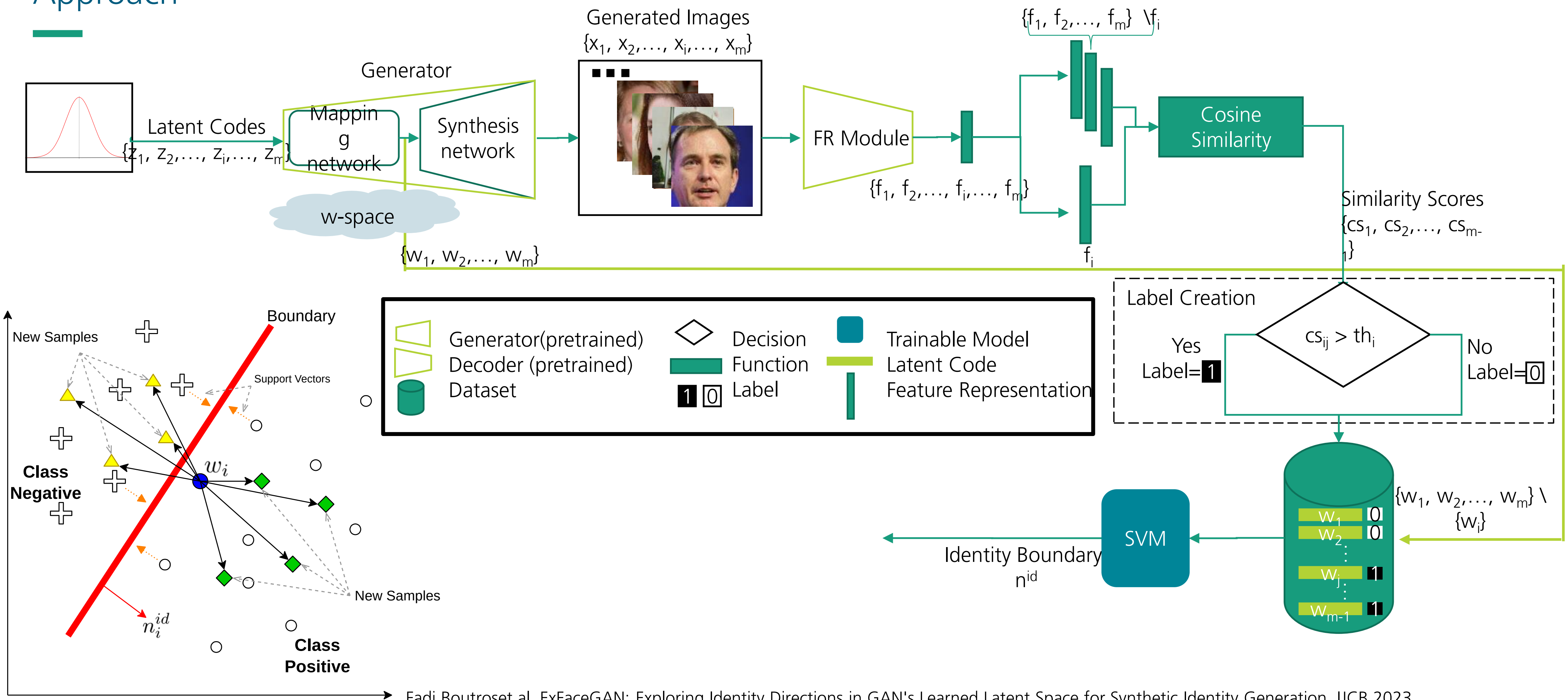
ExFaceGAN
Approach



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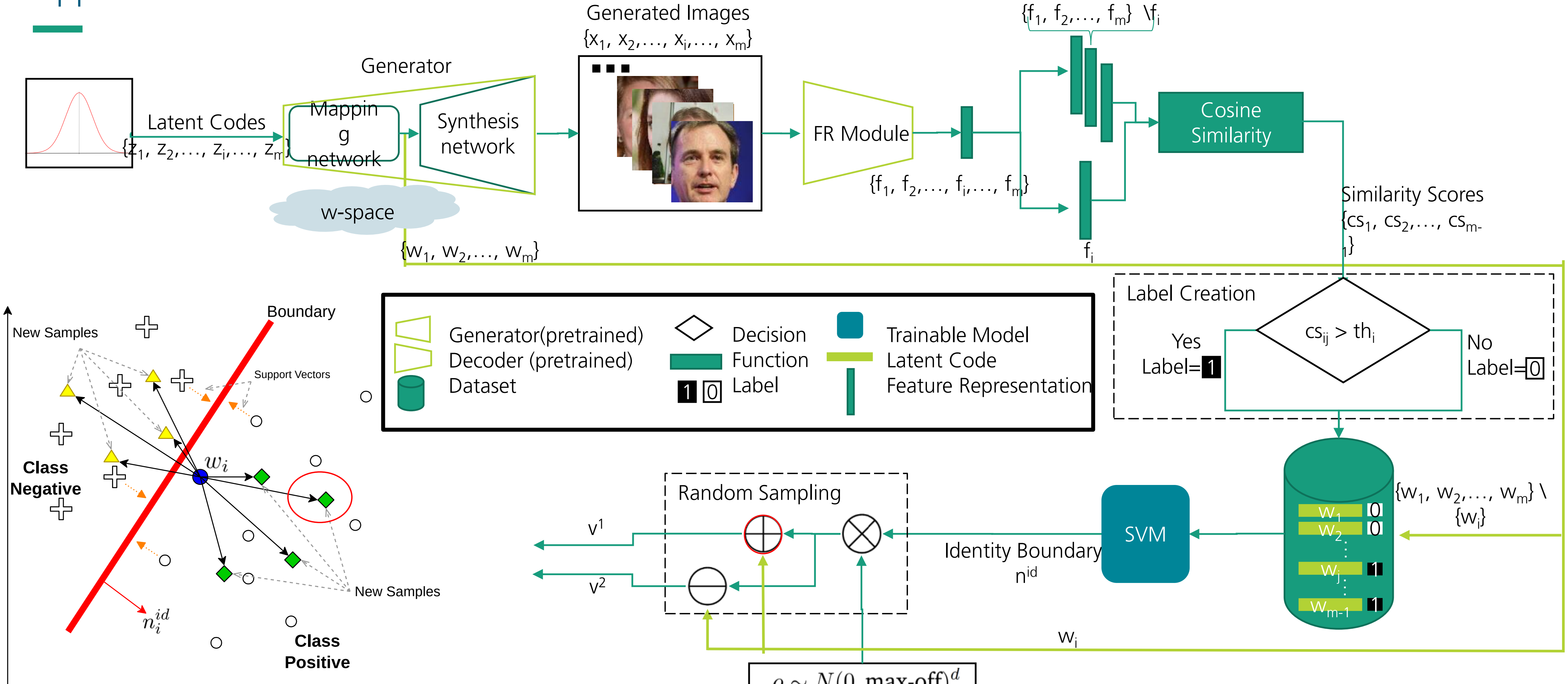
ExFaceGAN

Approach



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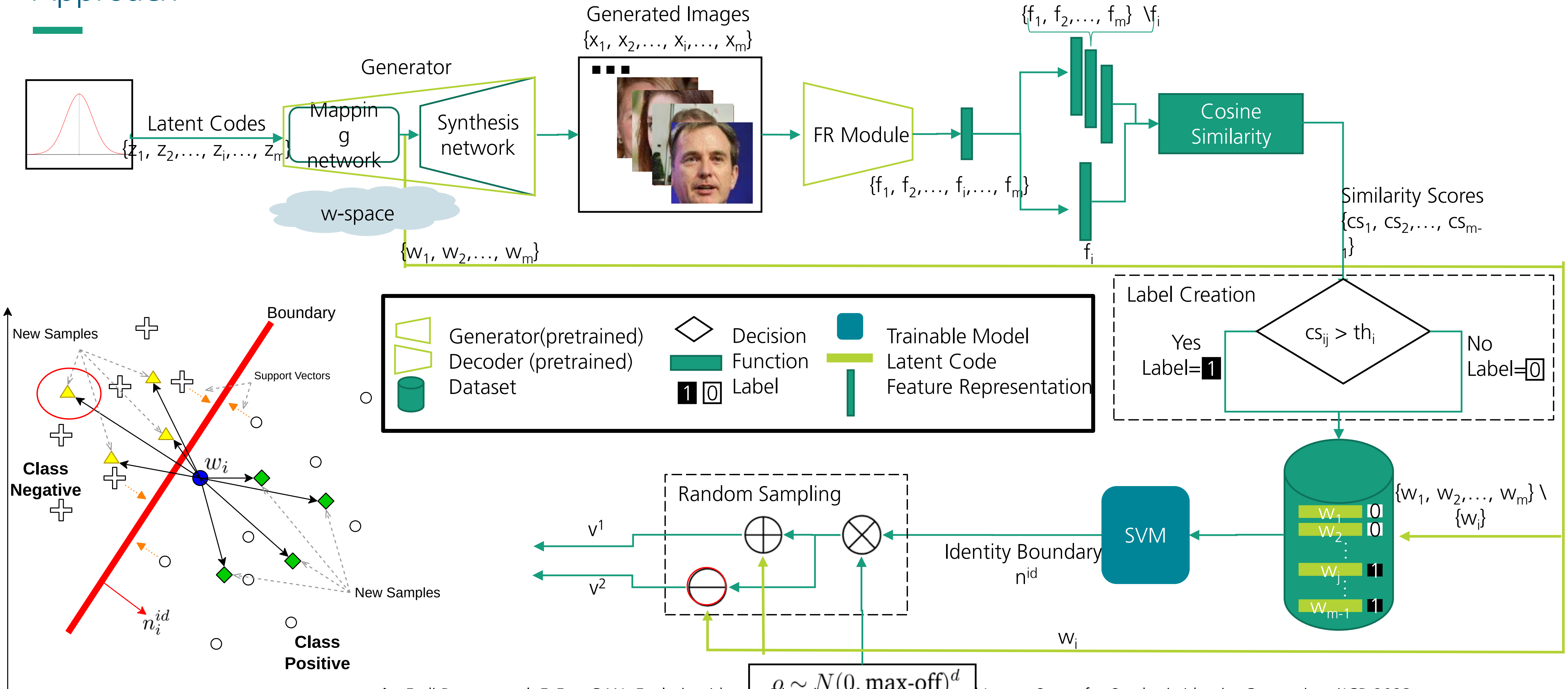
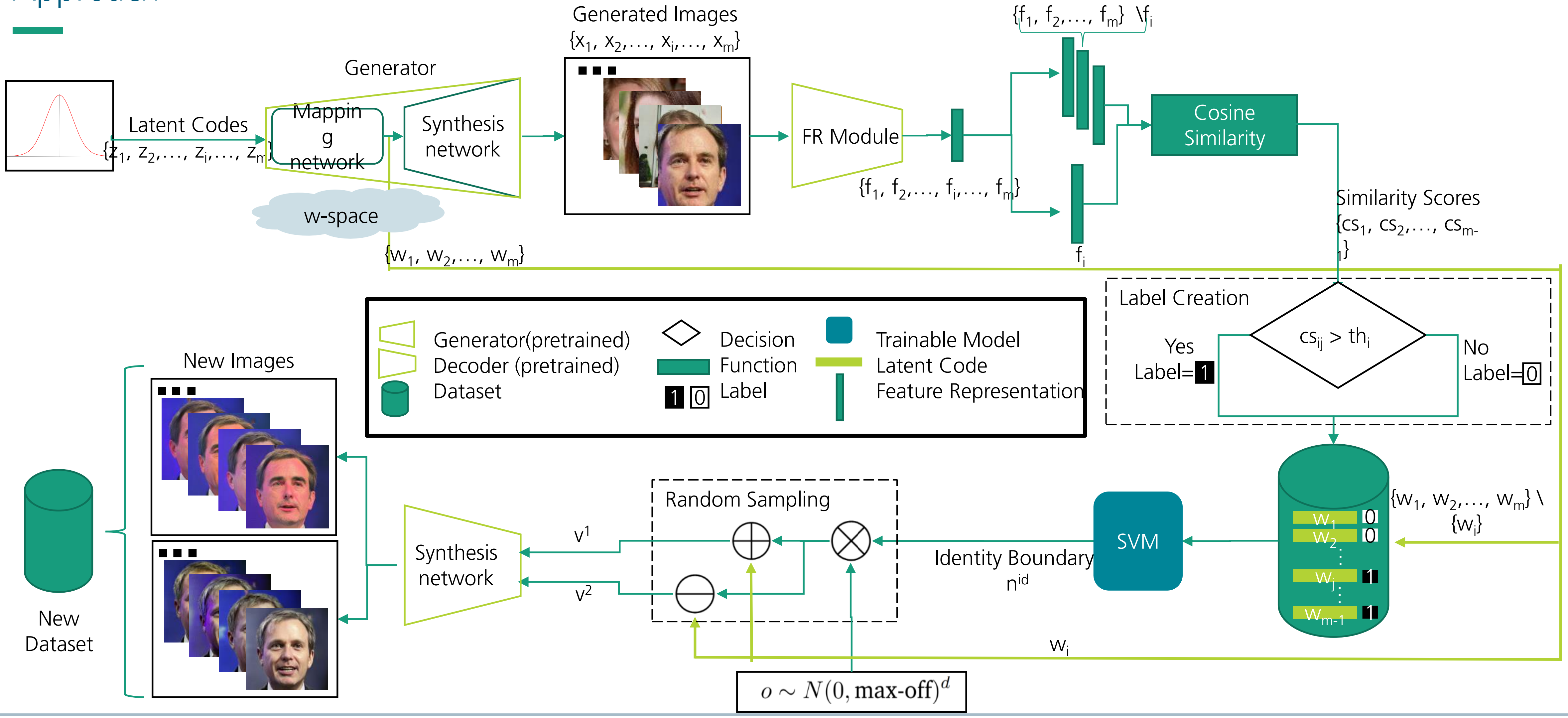
ExFaceGAN
Approach



Fadi Boutros et al. ExFaceGAN: Exploring Identity Directions in GAN's Learned Latent Space for Synthetic Identity Generation. IJCB 2023

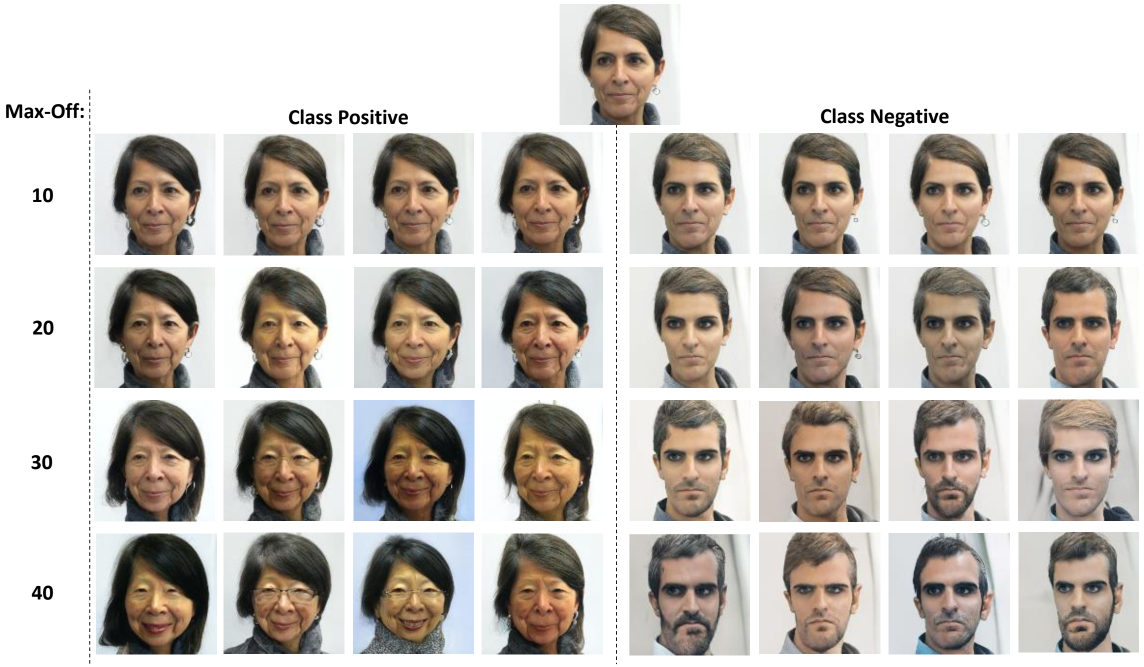
ExFaceGAN

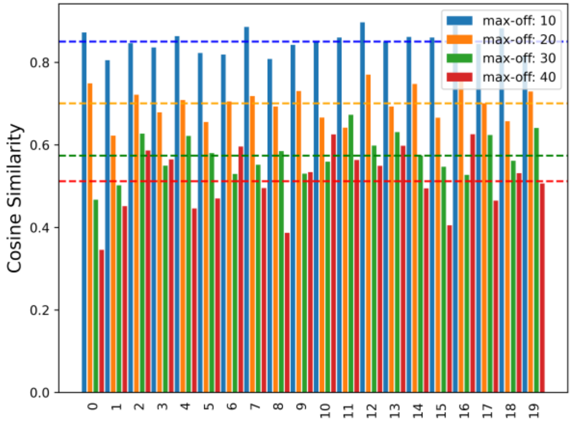
Approach



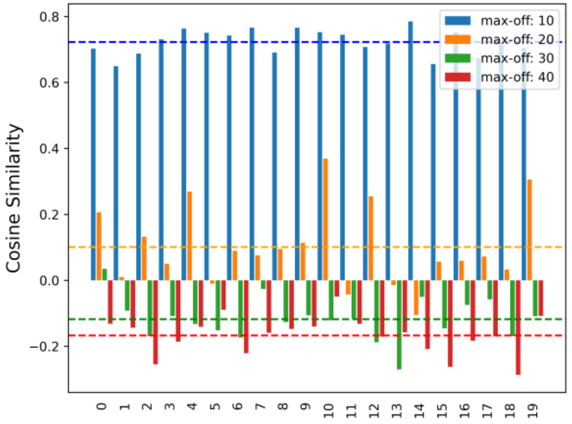
ExFaceGAN

Identity-similarity between reference images and samples generated with different max-off values





Class Positive



Class Negative

Fadi Boutroset al. ExFaceGAN: Exploring Identity Directions in GAN's Learned Latent Space for Synthetic Identity Generation. IJCB 2023

The label problem
ExFaceGAN

- What we need?
  - Generate unlimited classes ✓
  - Classes are realistically separable ✓
  - Controlling the intraclass variation ✓

Jan Niklas Kolf et al. Identity-driven Three-Player Generative Adversarial Network for Synthetic-based Face Recognition. CVPR Workshops 2023:

Did synthetic data fix data problems?

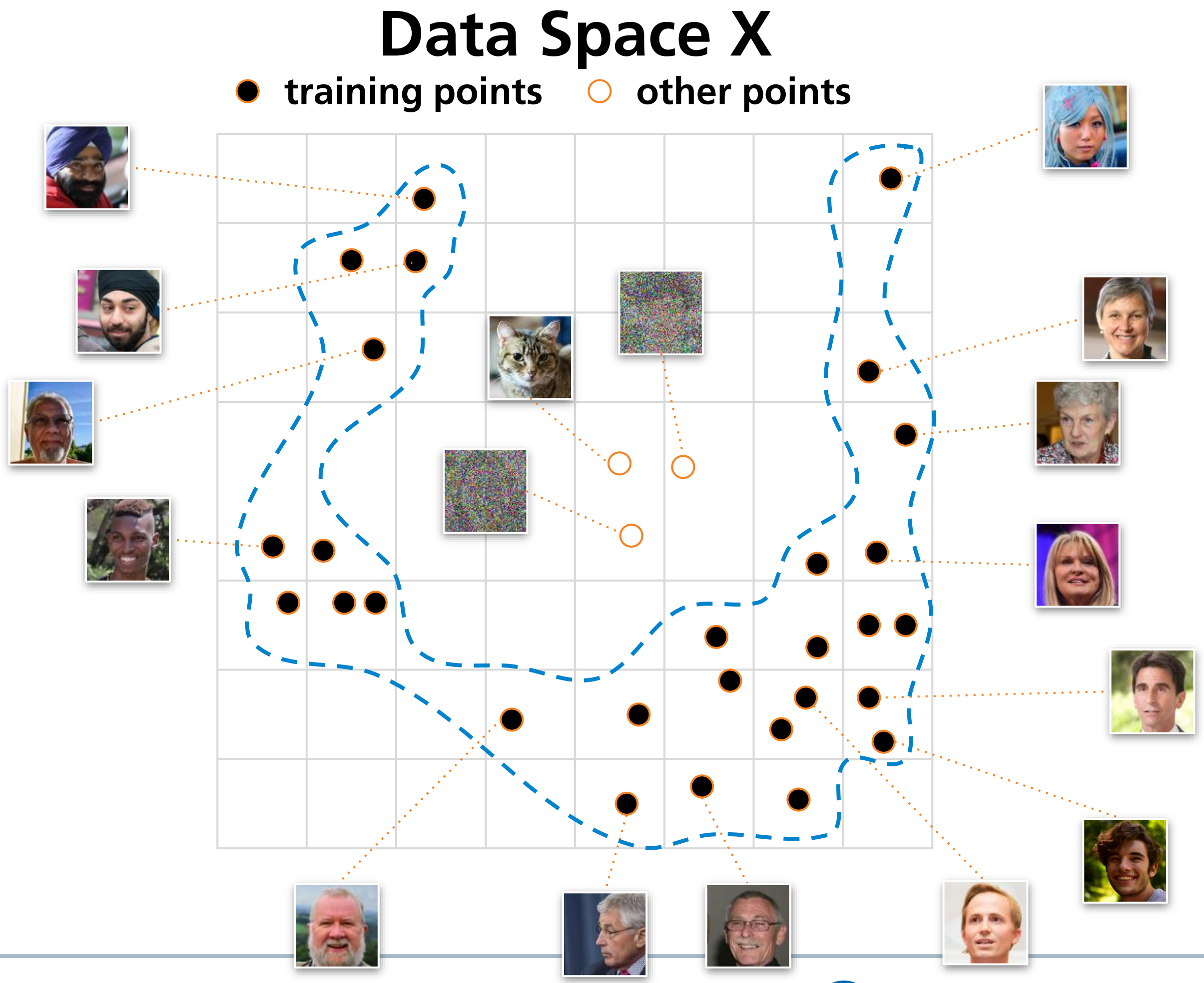
- Large amount of data – No PROBLEM
- Cover Inter class variation - No PROBLEM
- Cover Intra class variation – No PROBLEM
- Labels needed (probably) – No PROBLEM
- Ethical / Legal – No PROBLEM
- But all can be made better – e.g. more realistic images through Diffusion

GANs and Diffusion models in data generation

How to generate synthetic data?

Deep Generative Models

- ➔ learn data distribution p(x)
- ➔ e.g. GANs or diffusion models



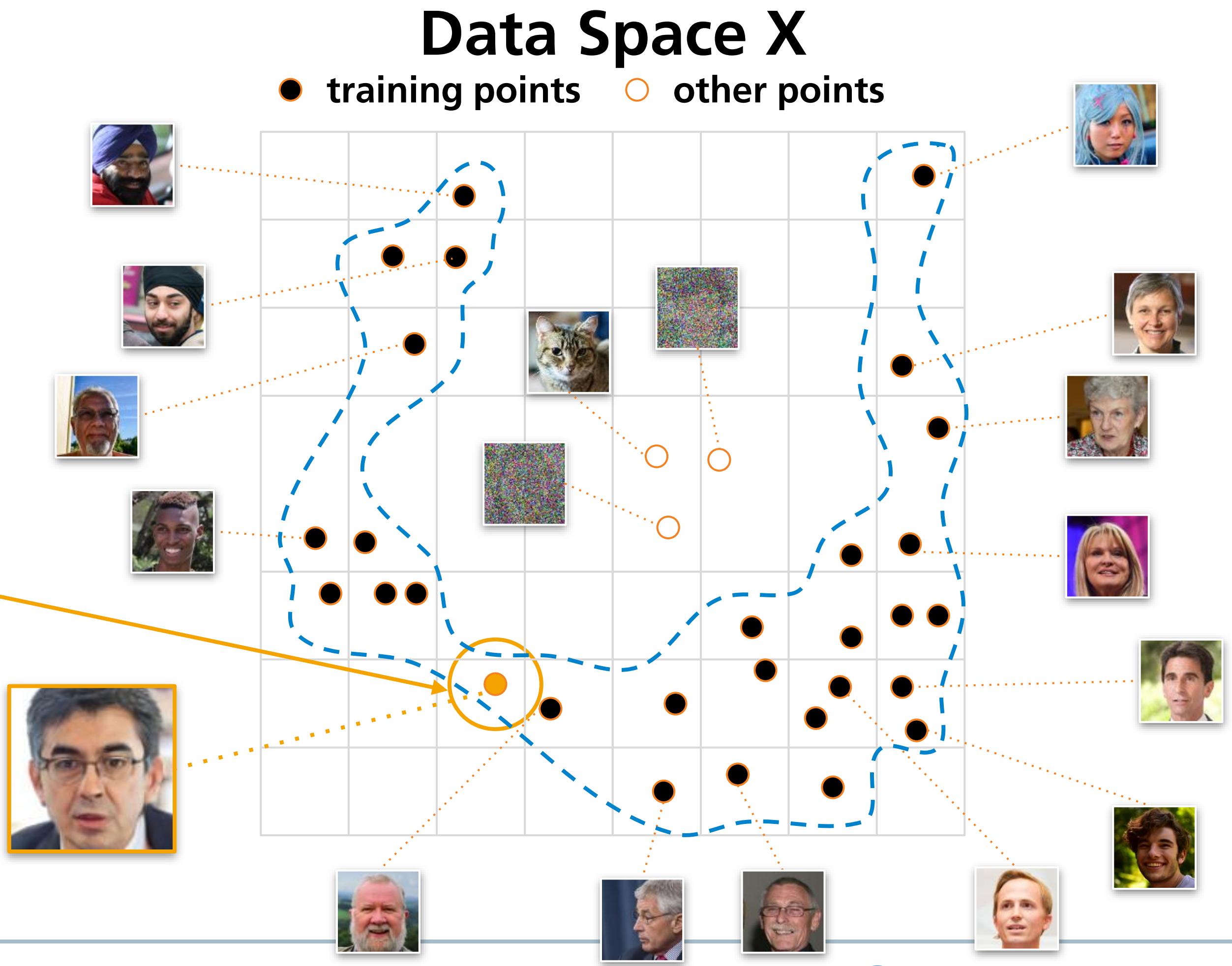
How to generate synthetic data?

Deep Generative Models

- ➔ learn data distribution p(x)
- ➔ e.g. GANs or diffusion models

We want to generate samples that

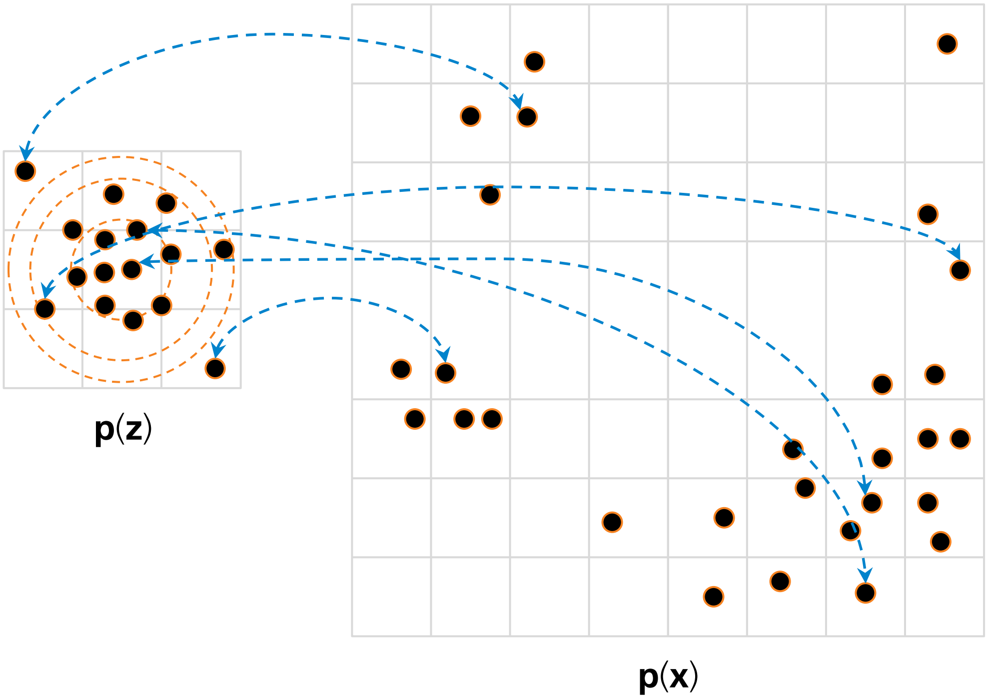
- ➔ are realistic but novel
- ➔ follow the training distribution



GANs vs. Diffusion Models

Generative Adversarial Networks

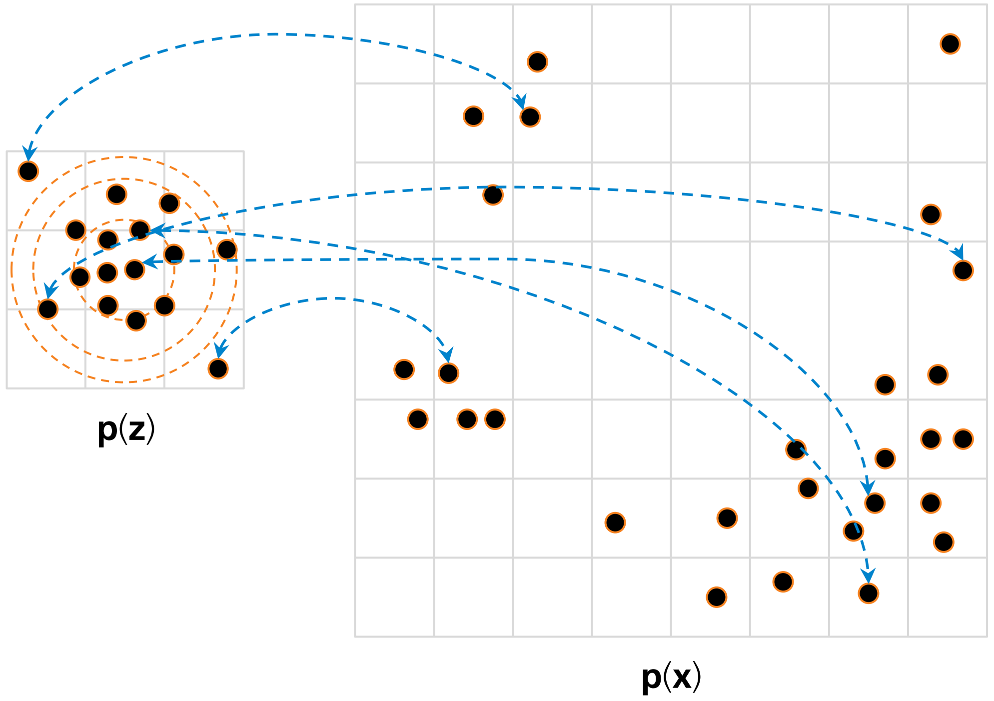
learn sample function: z → x



GANs vs. Diffusion Models

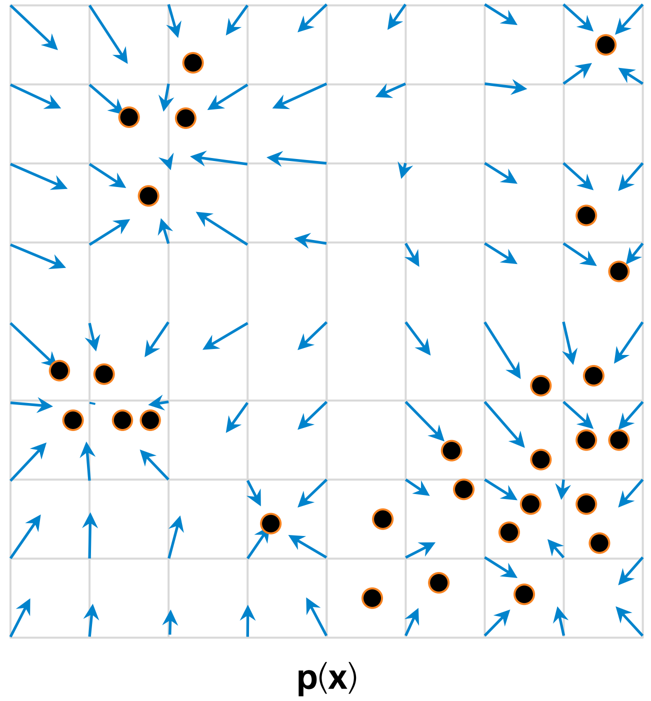
Generative Adversarial Networks

learn sample function: z → x



Diffusion Models

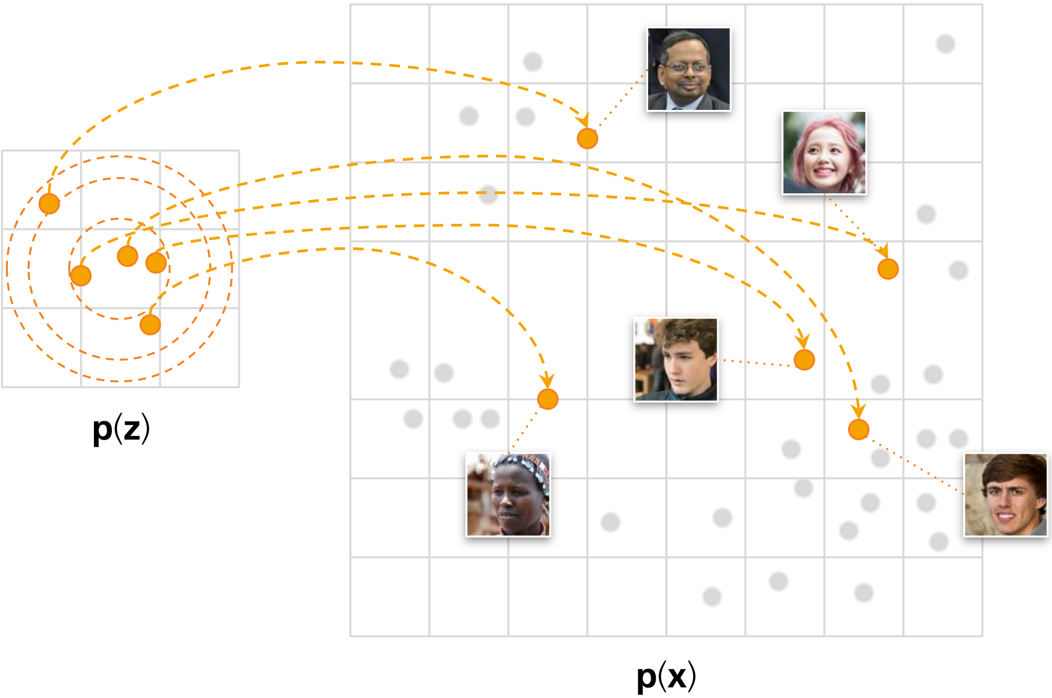
learn gradient of p(x)



GANs vs. Diffusion Models (Sampling)

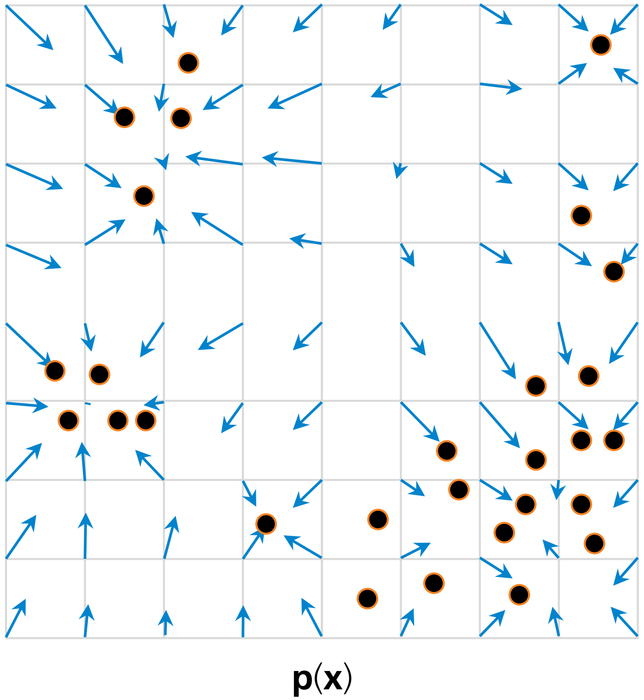
Generative Adversarial Networks

learn sample function: $z \rightarrow x$



Diffusion Models

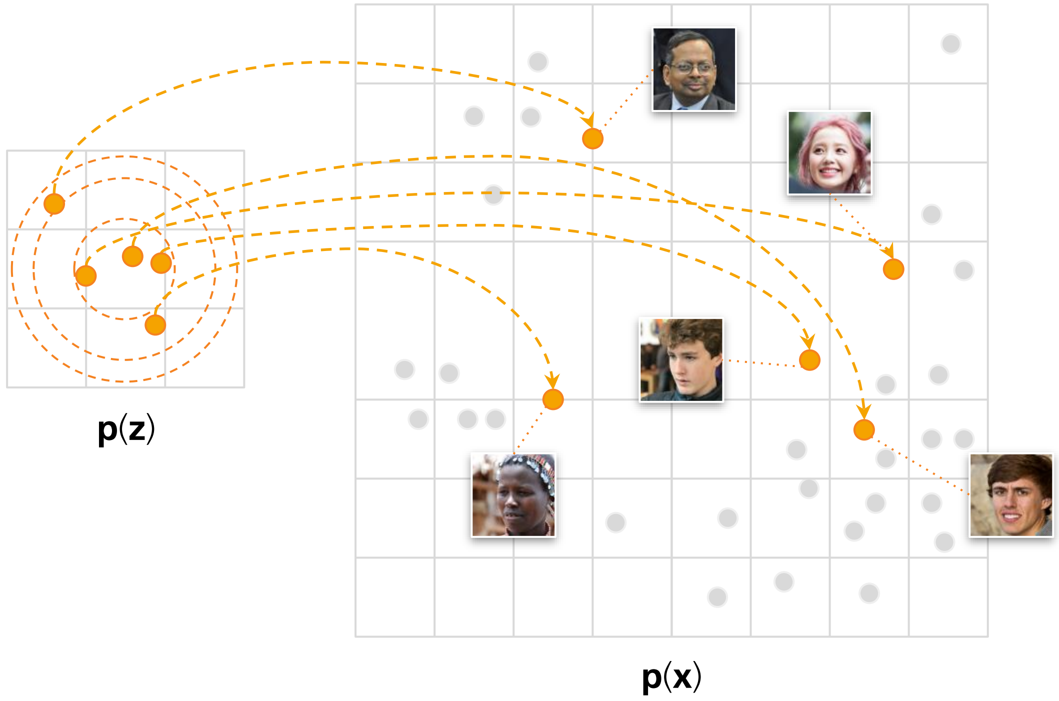
learn gradient of p(x)



GANs vs. Diffusion Models (Sampling)

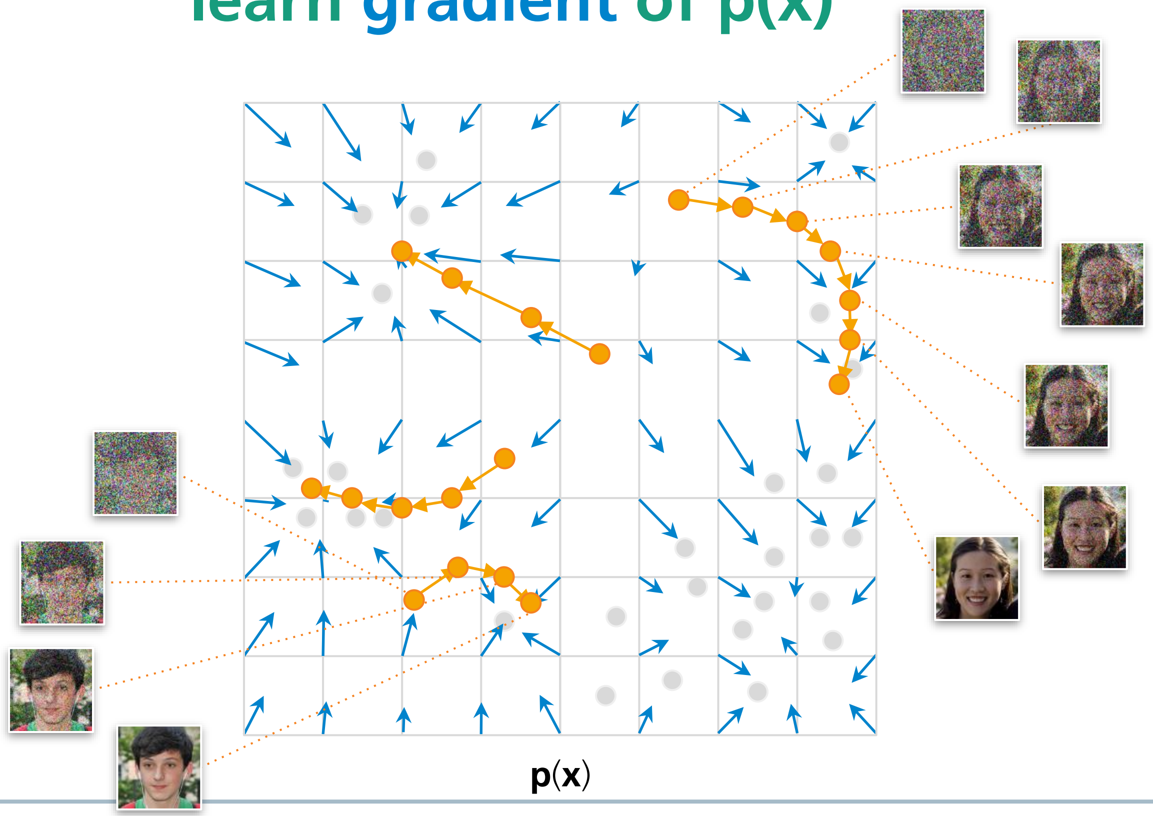
Generative Adversarial Networks

learn sample function: $z \rightarrow x$



Diffusion Models

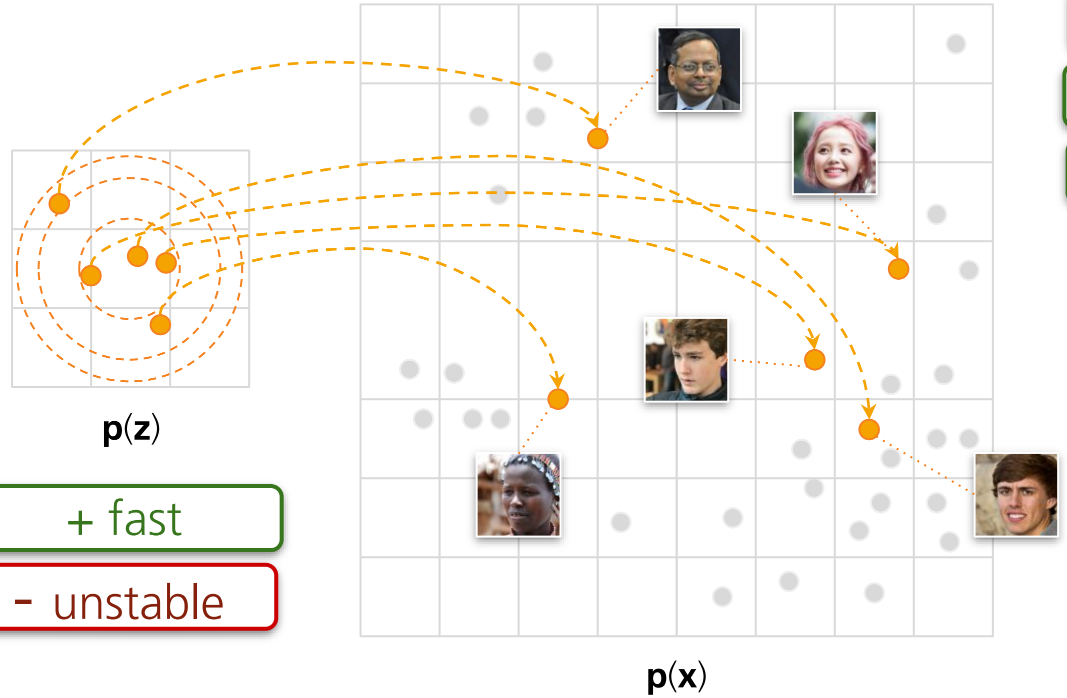
learn gradient of p(x)



GANs vs. Diffusion Models (Sampling)

Generative Adversarial Networks

learn sample function: $z \rightarrow x$



+ fast

- unstable

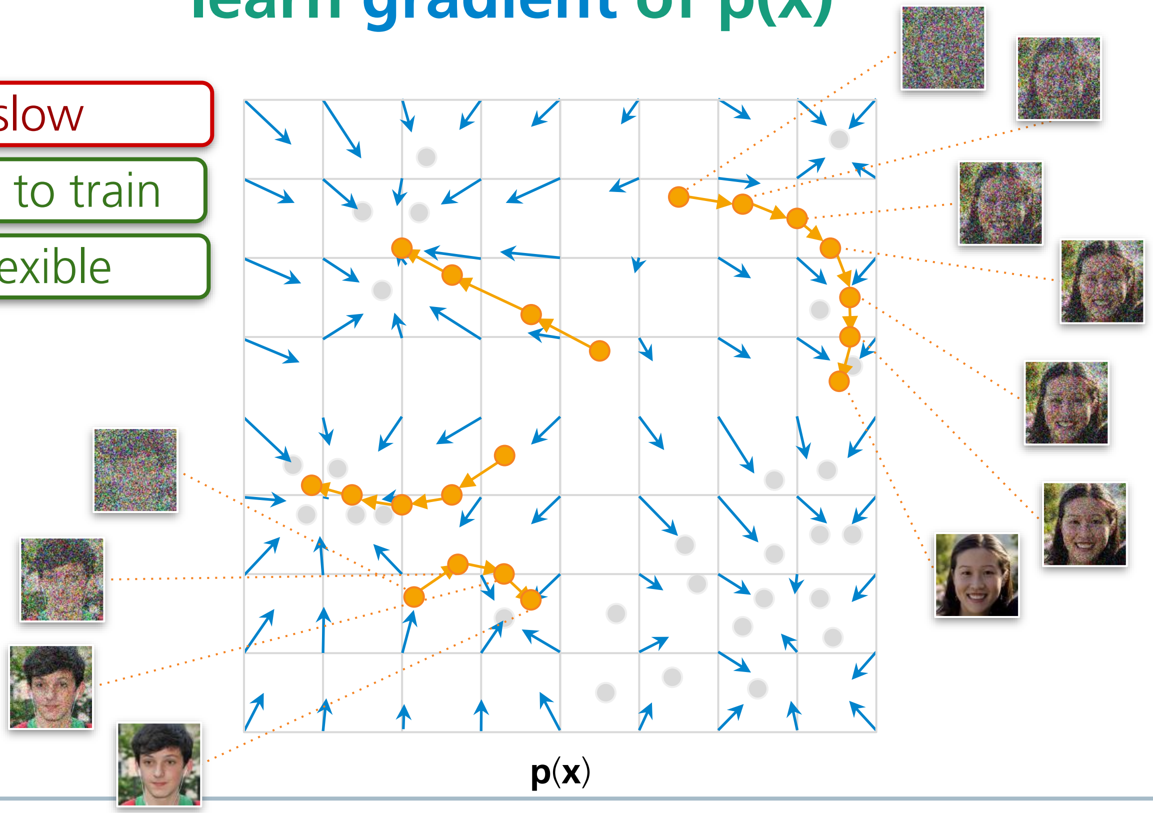
Diffusion Models

learn gradient of p(x)

- slow

+ easy to train

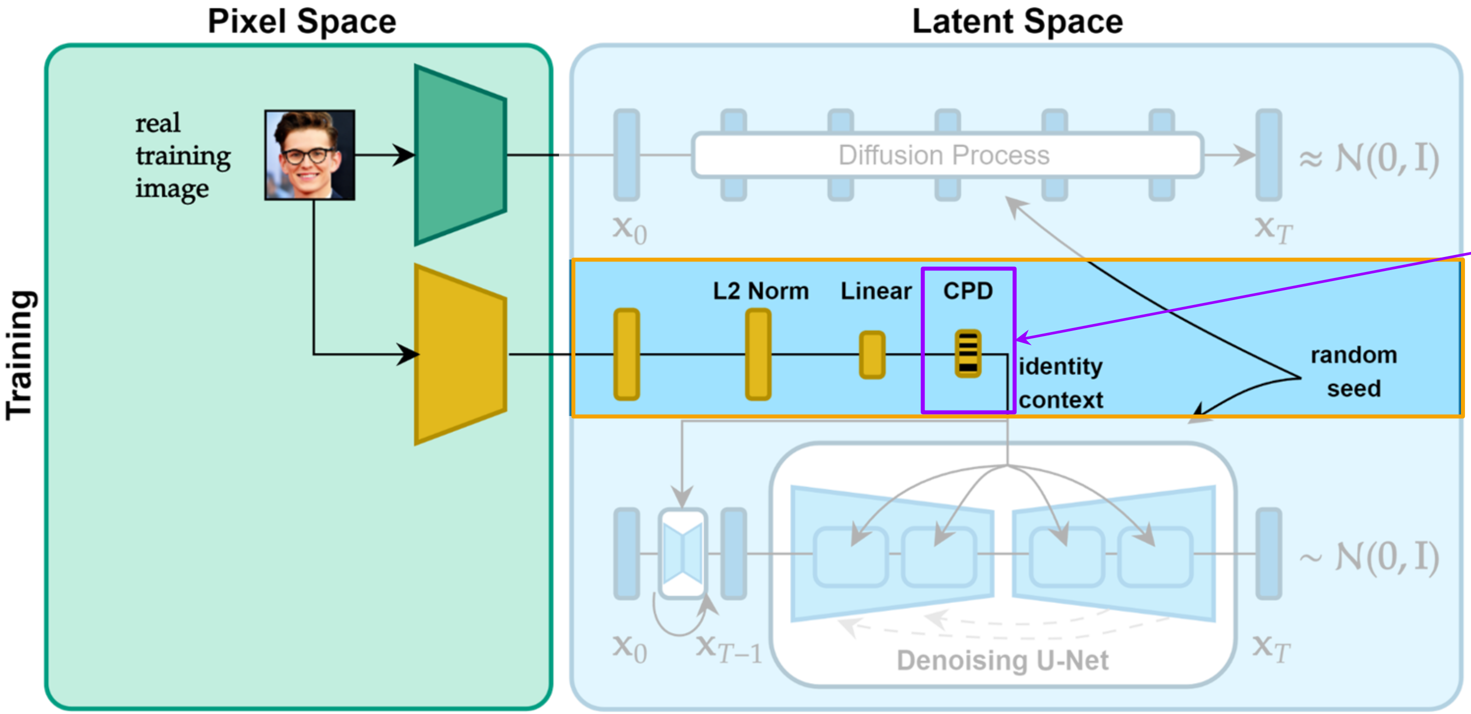
+ flexible



Back to Synthetic data for FR training

This Thesis: IDiff-Face

Training phase

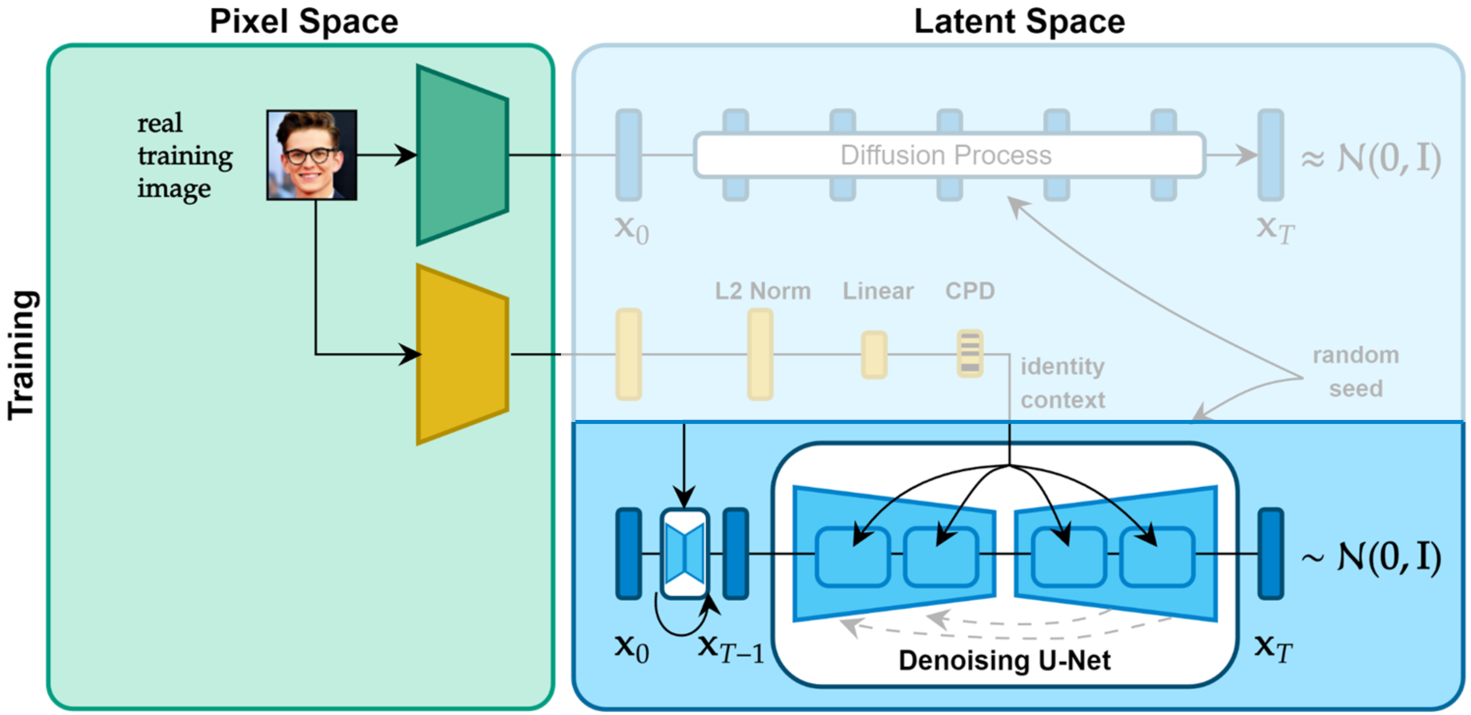


Contextual Partial Dropout

identity condition

IDiff-Face

Training phase

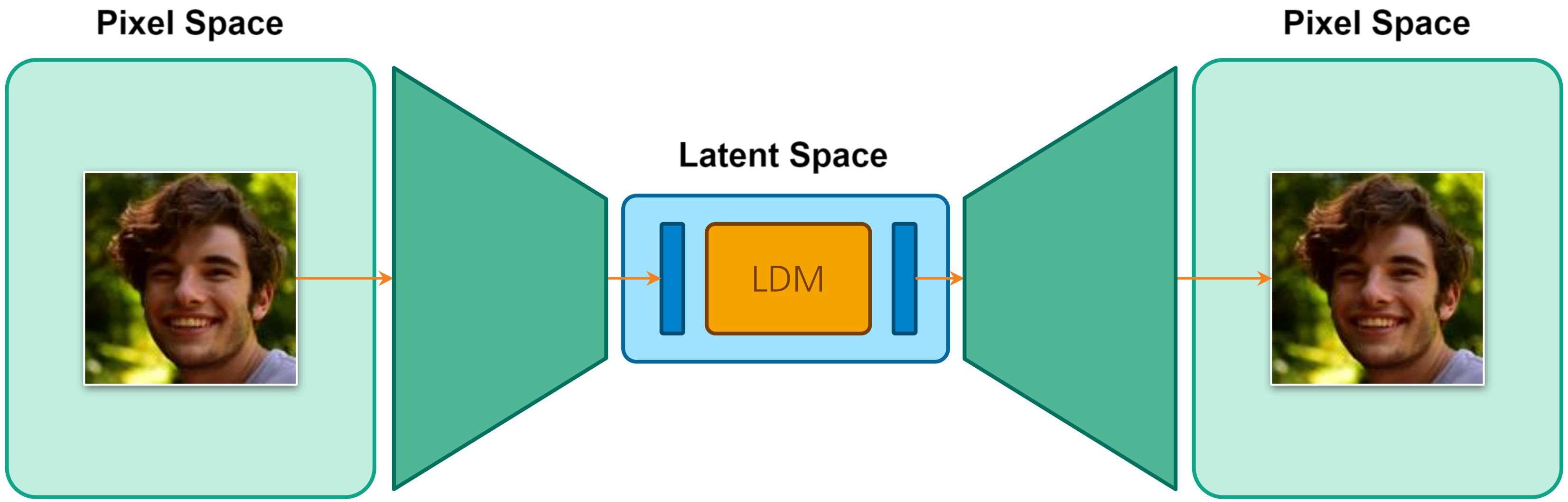


trained model

Fadi Boutros et al. IDiff-Face: Synthetic-based Face Recognition through Fizzy Identity-Conditioned Diffusion Models. ICCV 2023:

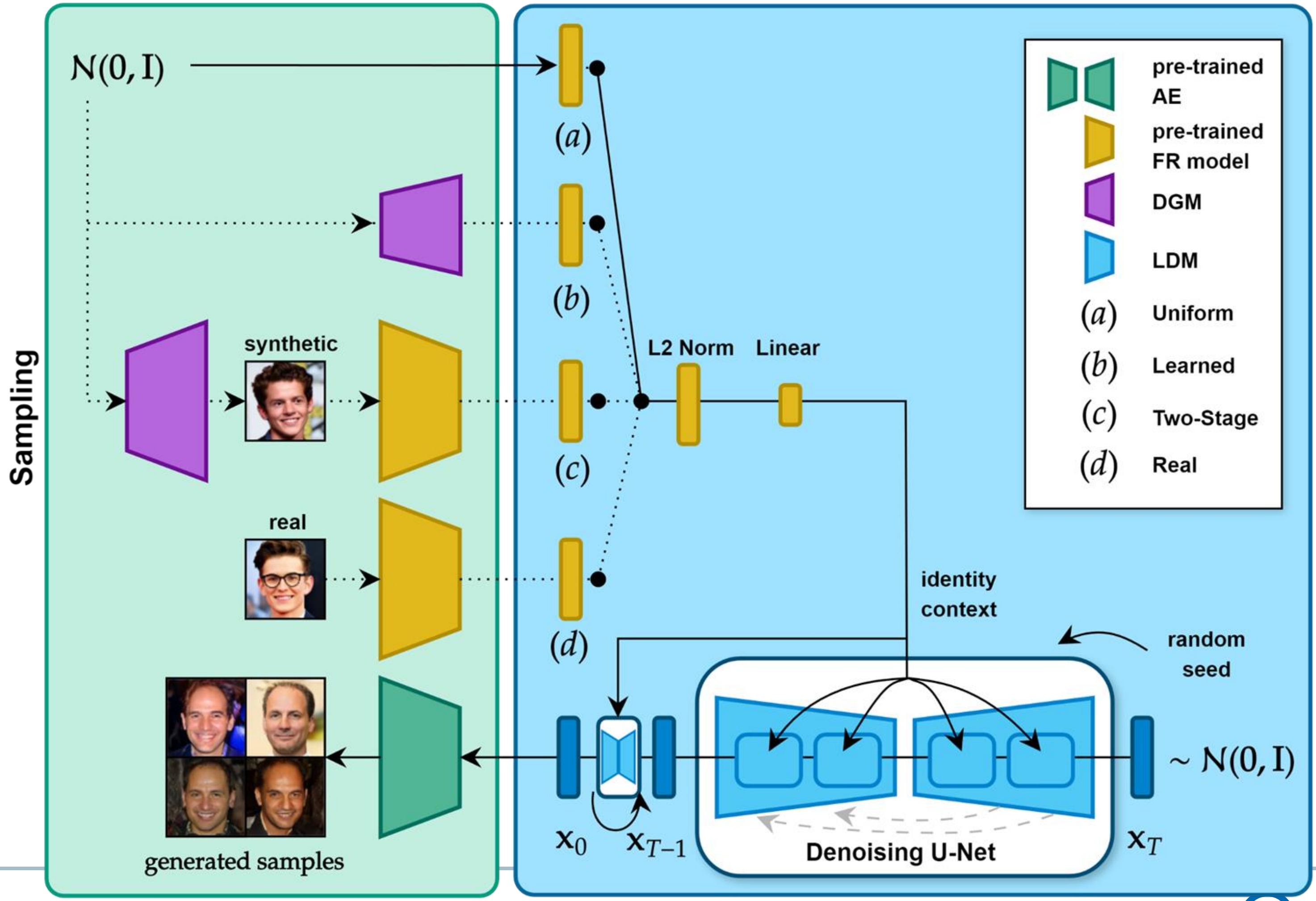
Latent Diffusion

Rombach et al. "High-Resolution Image Synthesis with Latent Diffusion Models"
https://doi.org/10.48550/arXiv.2112.10752



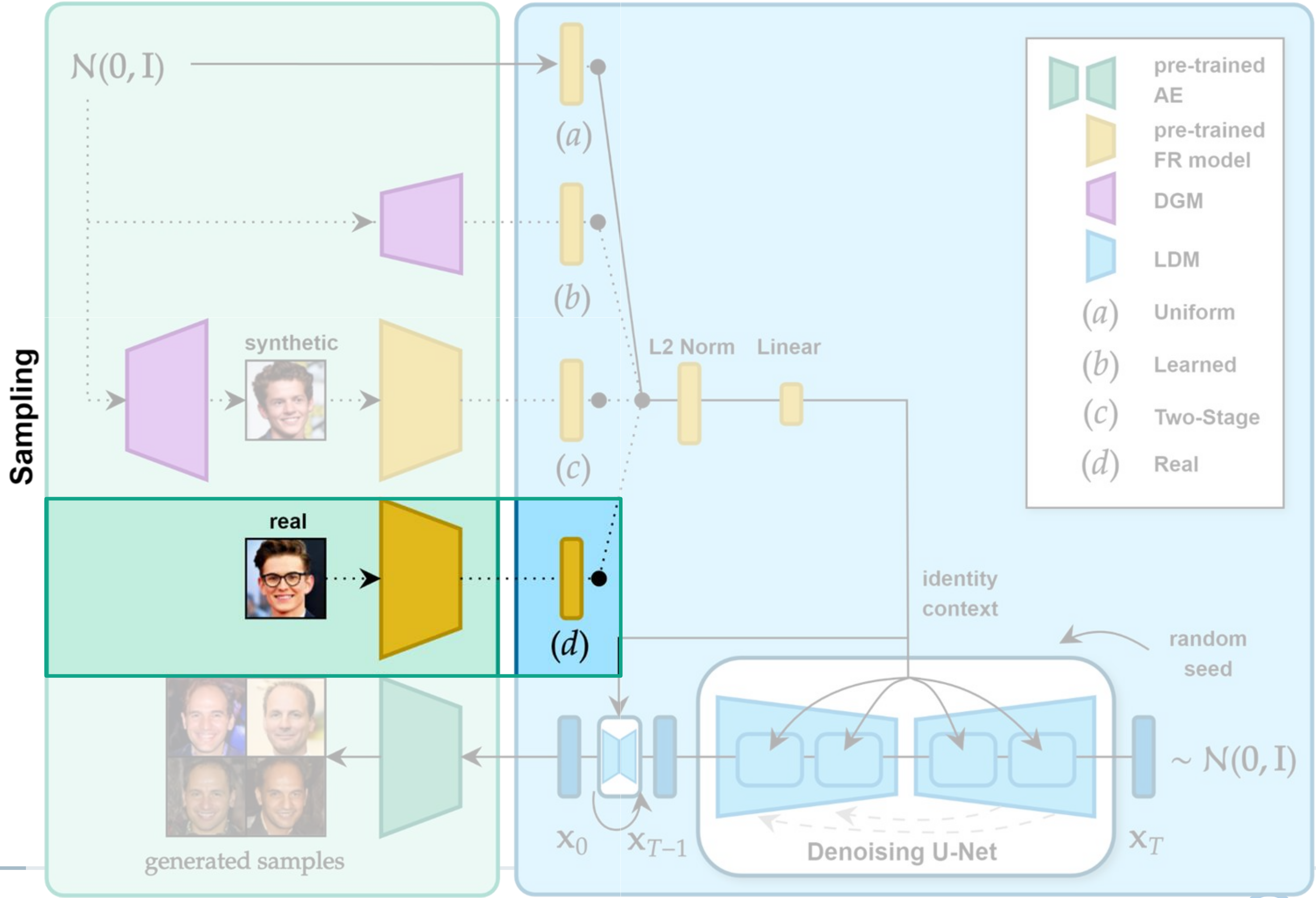
→ pre-trained powerful **autoencoder**
→ diffusion training in **lower-dimensional latent space**

IDiff-Face - Sampling Phase



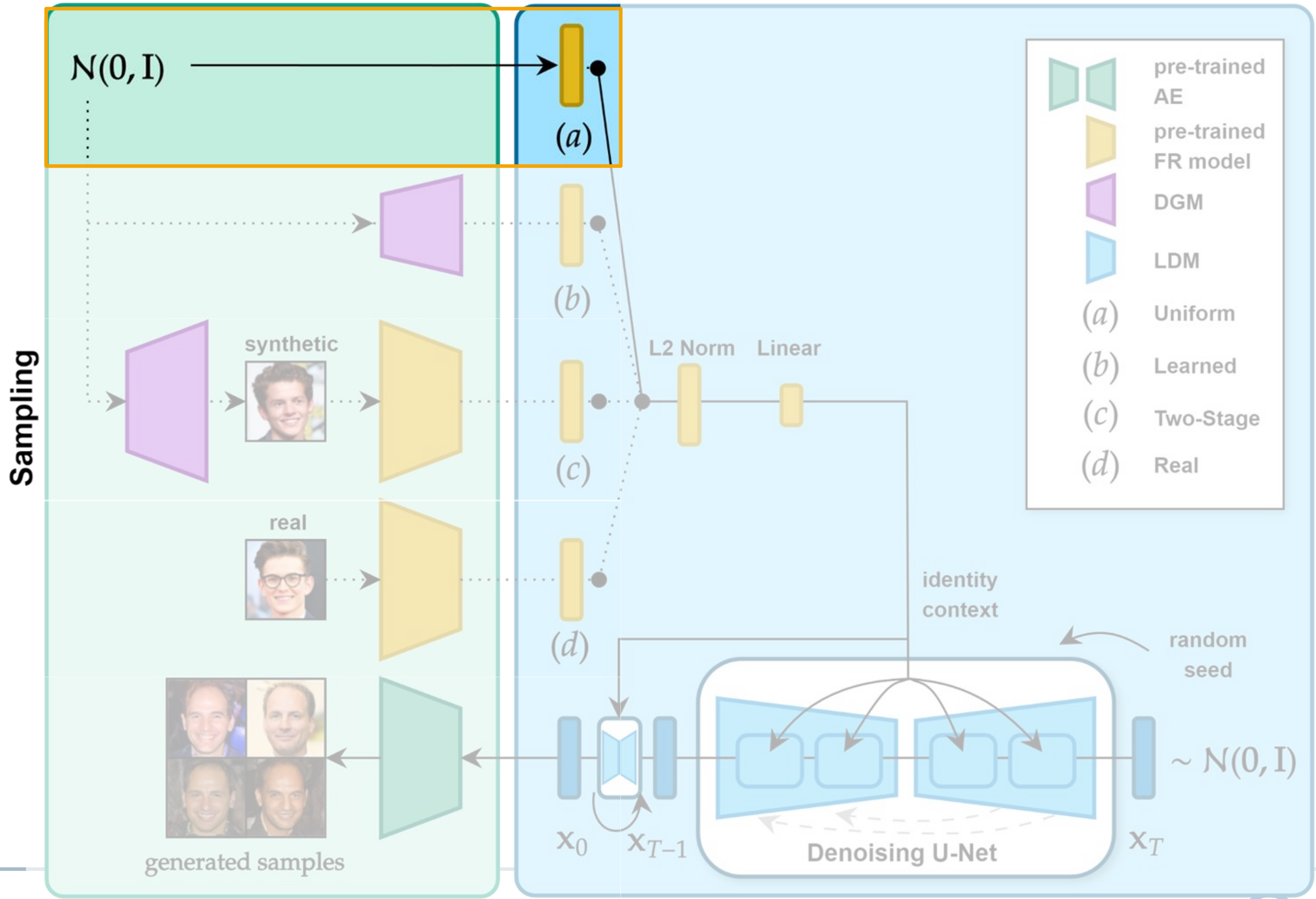
IDiff-Face - Sampling Phase

Real Embedding



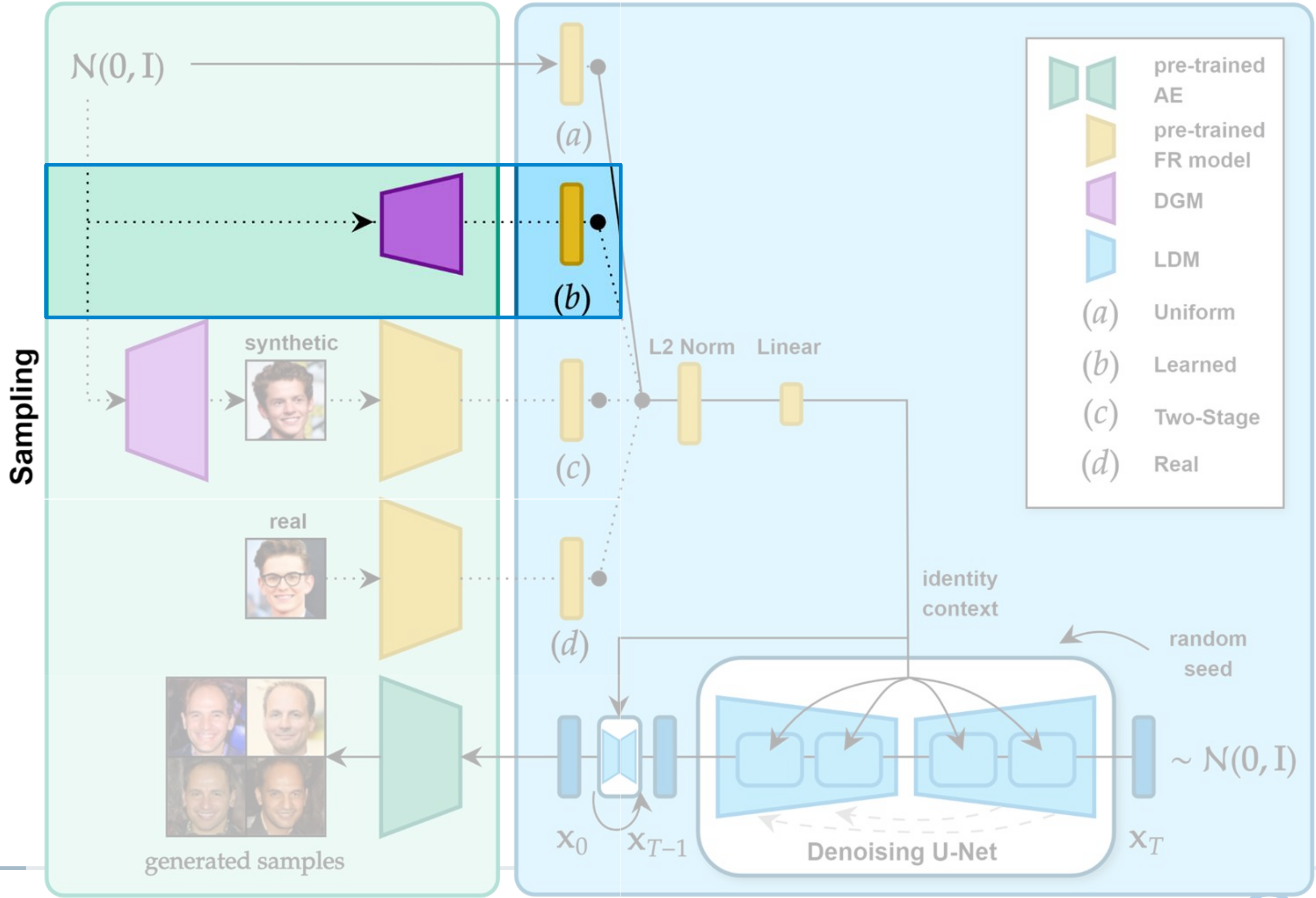
IDiff-Face - Sampling Phase

Synthetic Uniform



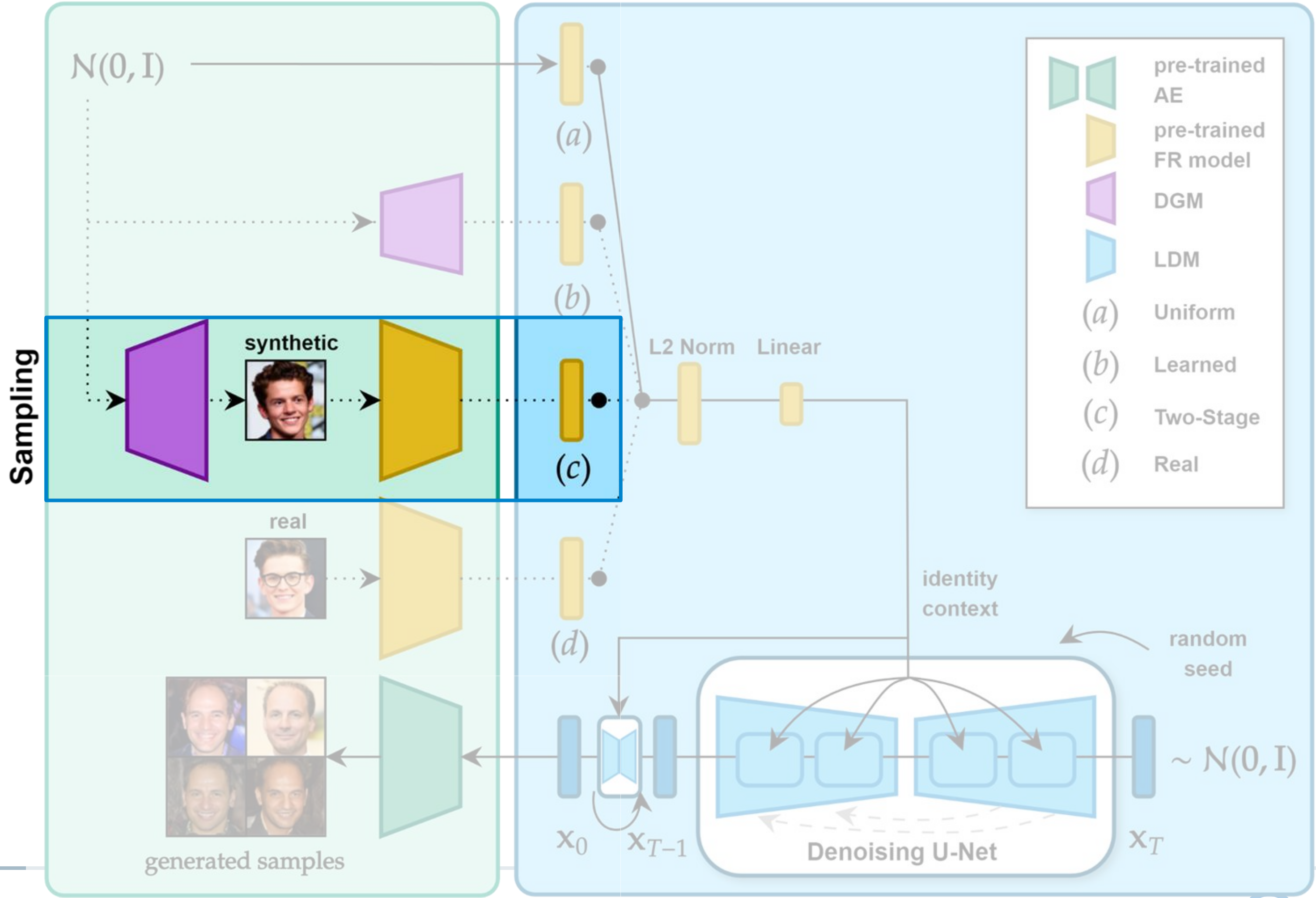
IDiff-Face - Sampling Phase

Synthetic Learned

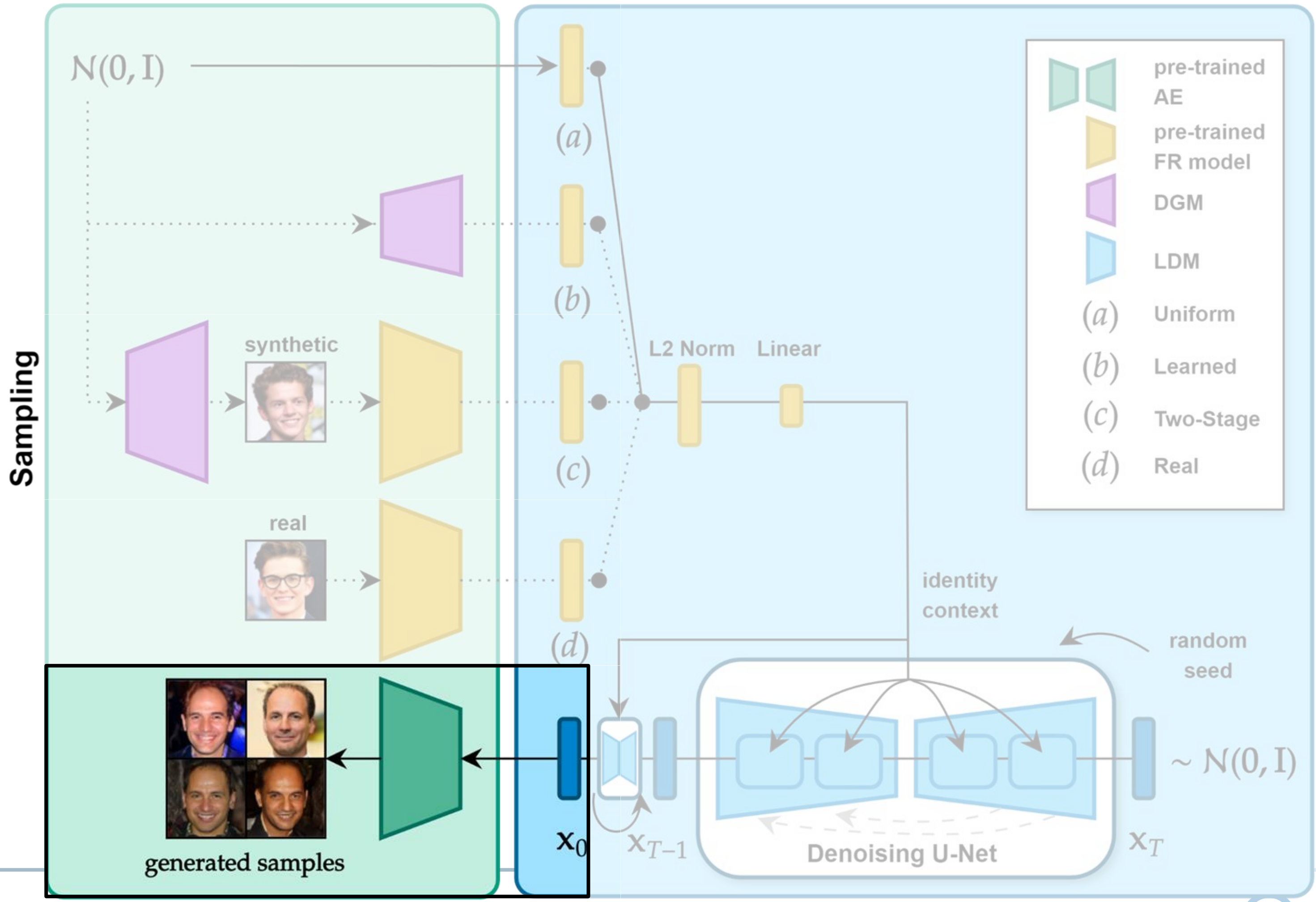


IDiff-Face - Sampling Phase

Synthetic Two-Stage

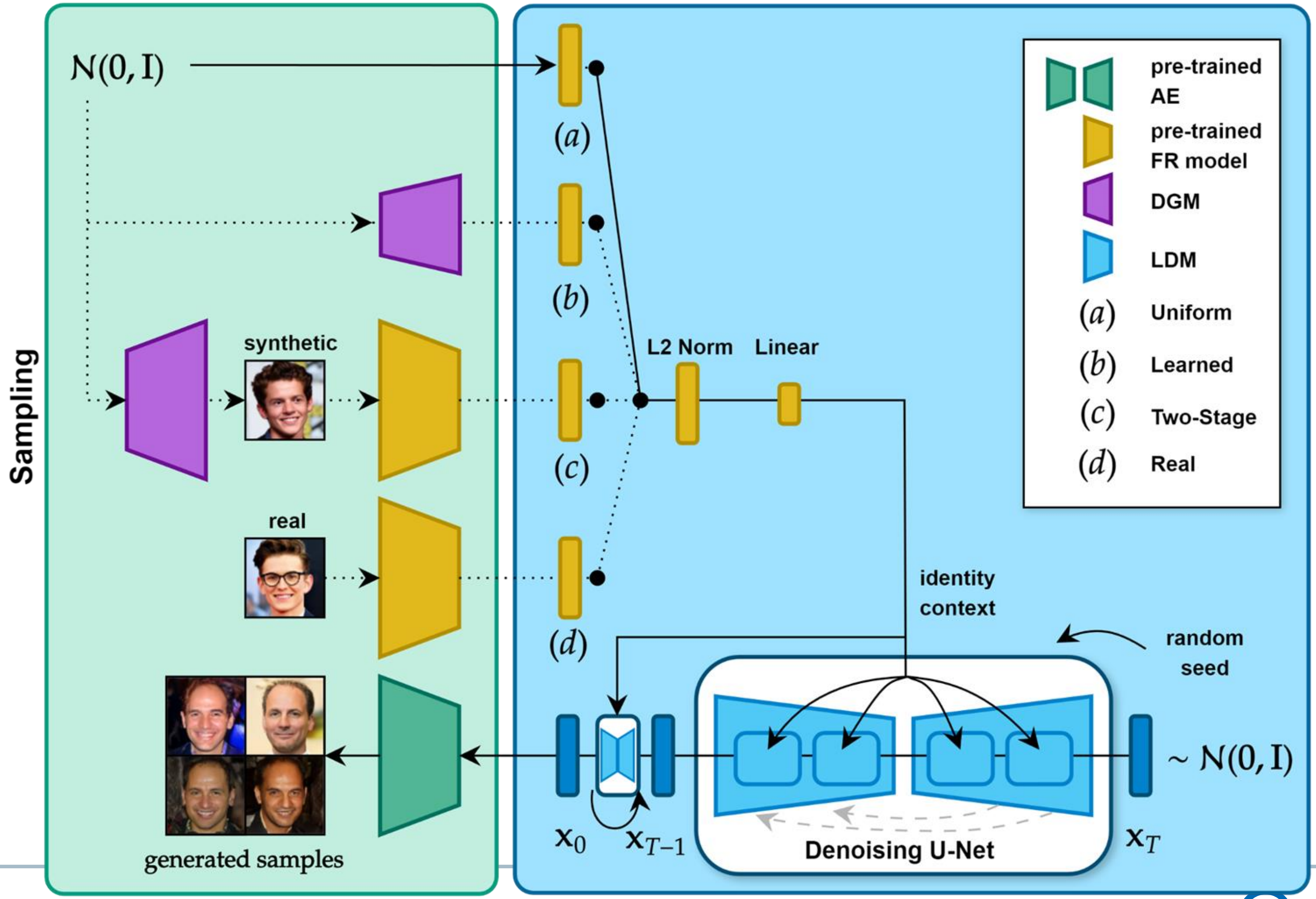


IDiff-Face - Sampling Phase



Decoding Samples

IDiff-Face - Sampling Phase



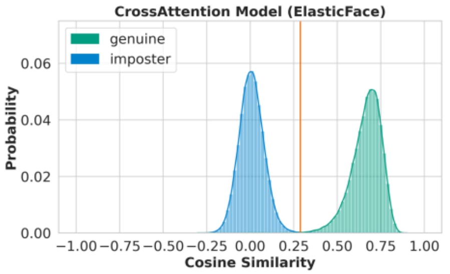
FHG-SK: Offen

Can IDiff-Face successfully generate realistic variations of existing identities?

Real Training ← **Variations** →

Identity-Separability

0%



Increase of CPD

FHG-SK: Offen

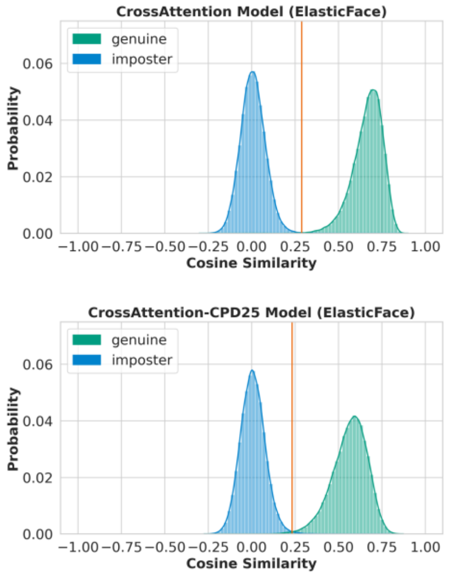
Can IDiff-Face successfully generate realistic variations of existing identities?

Real Training ← Variations → **Identity-Separability**

Increase of CPD

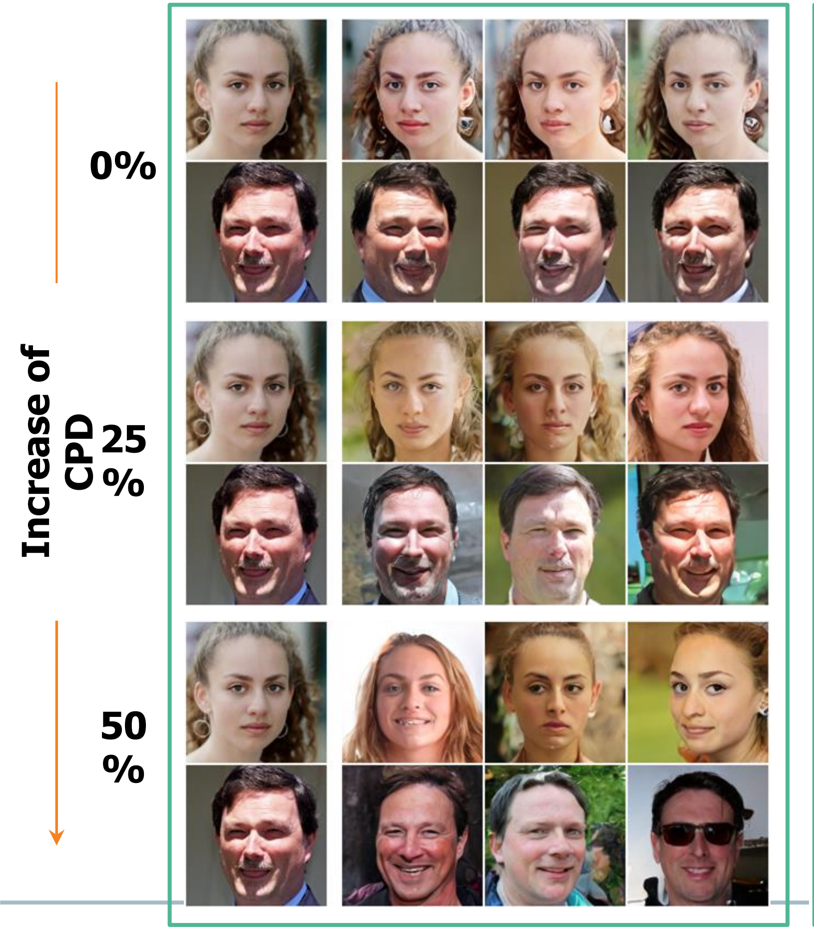
0%

25 %

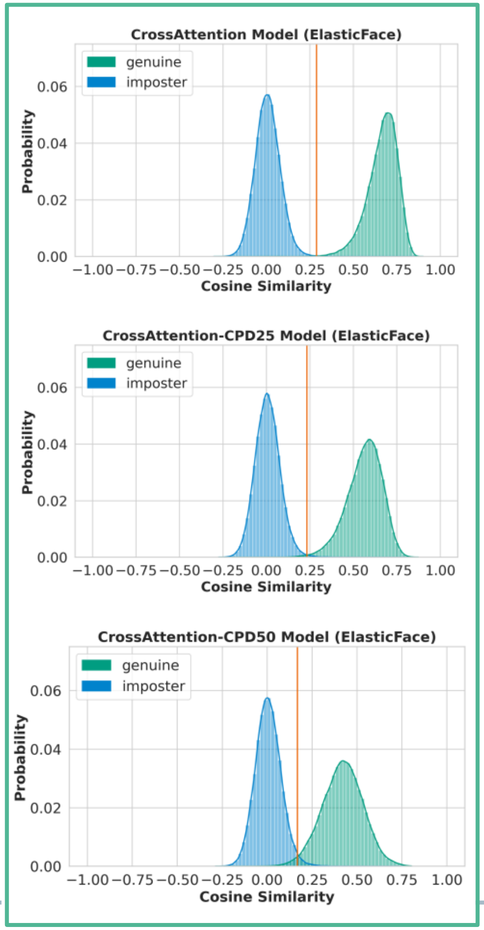


Can IDiff-Face successfully generate realistic variations of existing identities?

Real Training ← **Variations** →



Identity-Separability



Can IDiff-Face successfully generate realistic variations of existing identities?

Real Training ⟵ Variations ⟶

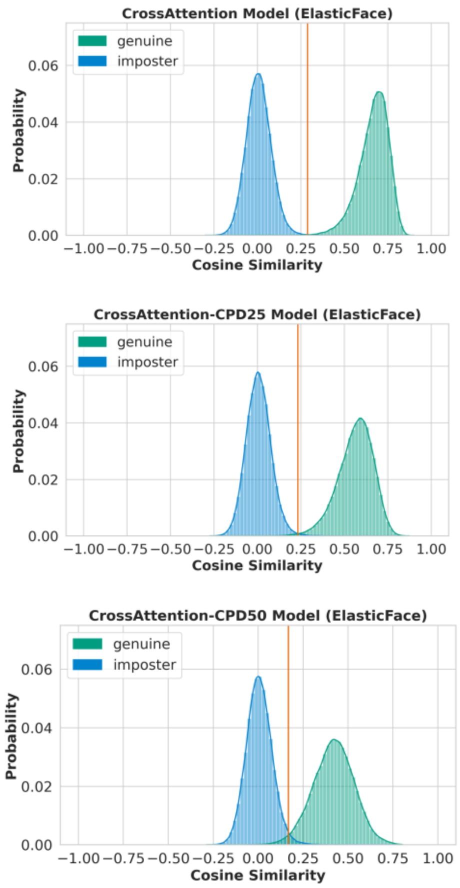
Increase of CPD

0%

25 %

50 %

Identity-Separability



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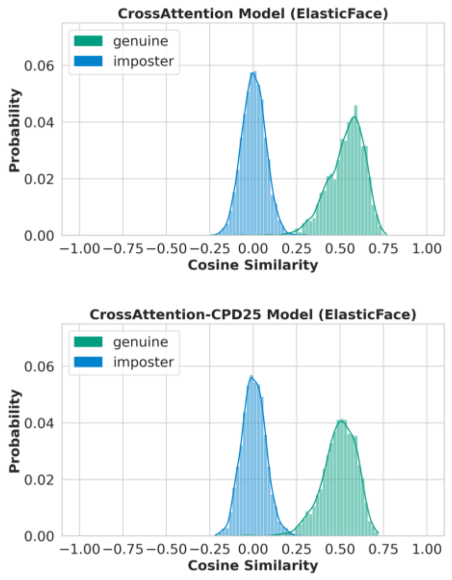
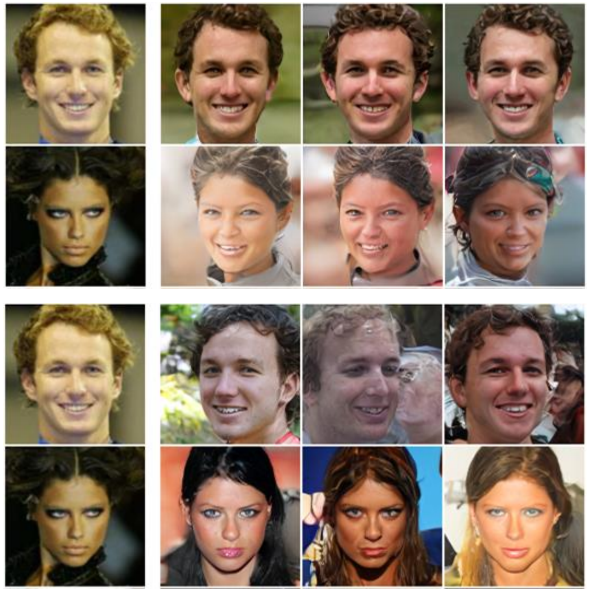


Real LFW ⟵ Variations ⟶



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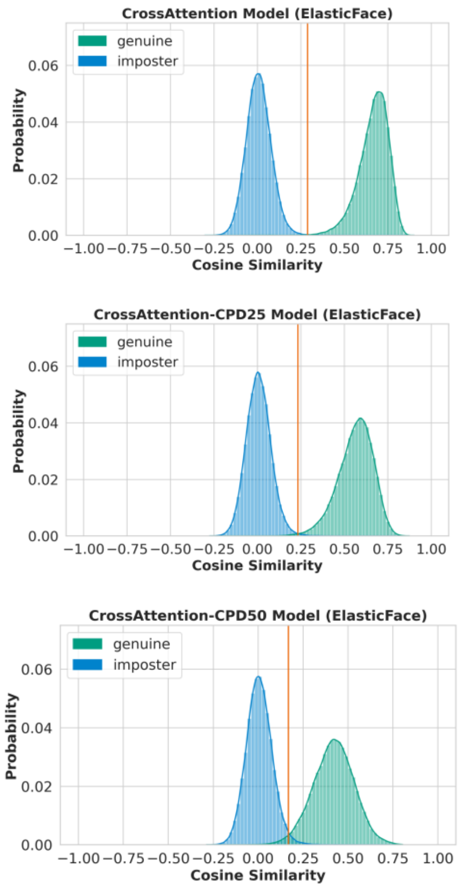

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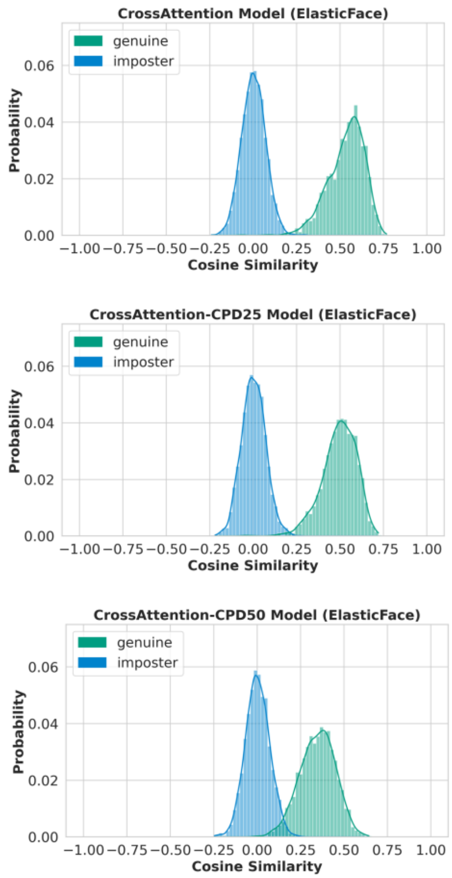

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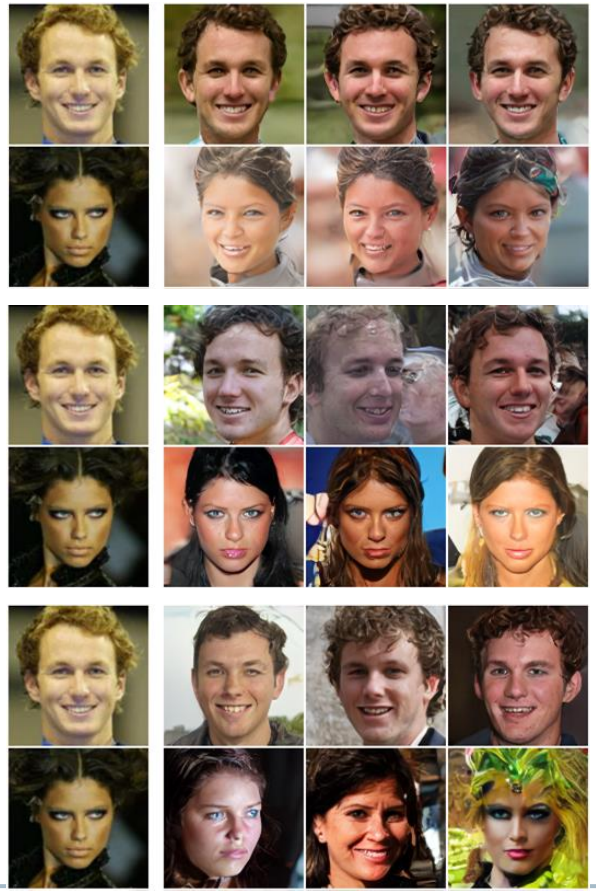
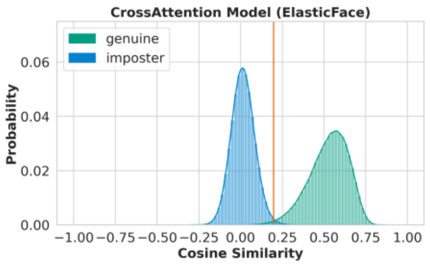


Can IDiff-Face successfully generate realistic variations of synthetic identities?

Synthetic Uniform **Identity-Separability**

0%



Increase of CPD

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Synthetic Uniform

Identity-Separability

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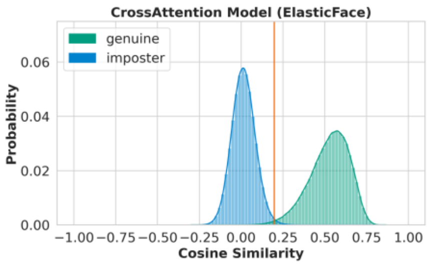
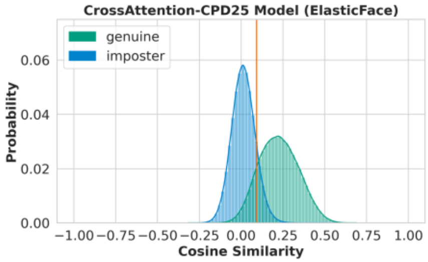
Increase of CPD

25 %





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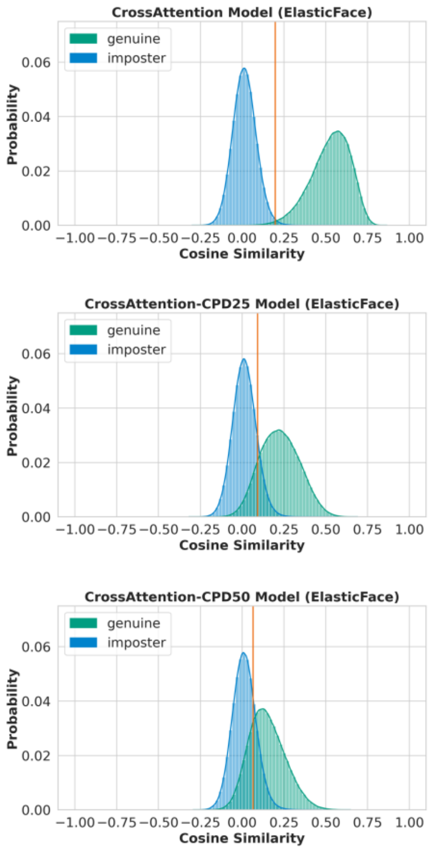

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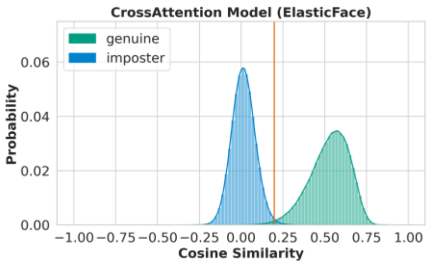
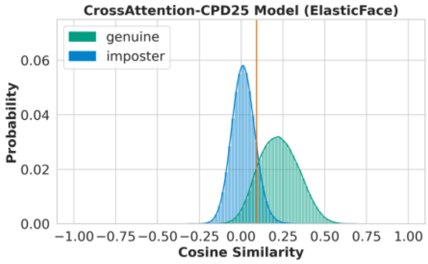
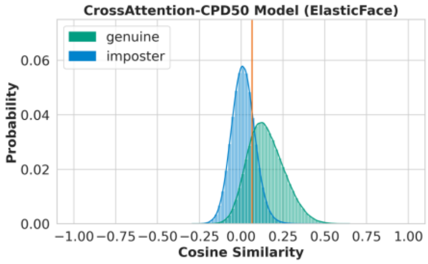
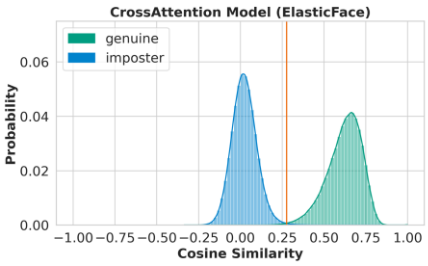






Identity-Separability



Synthetic Two-Stage

Can IDiff-Face successfully generate realistic variations of synthetic identities?

Increase of CPD

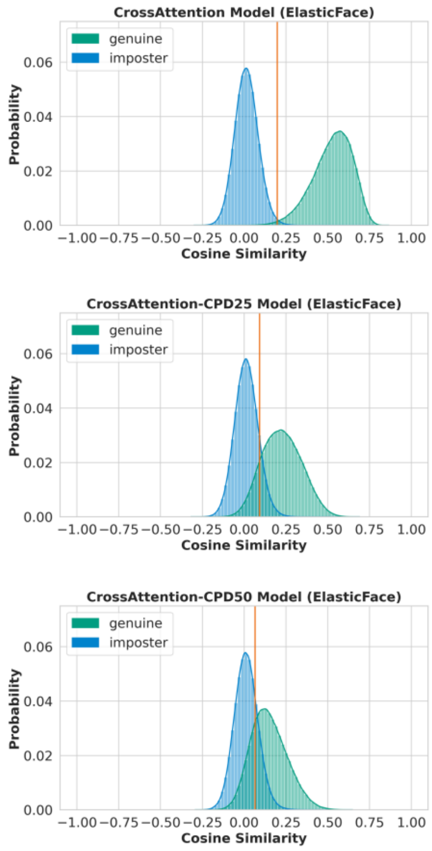
0%

25 %

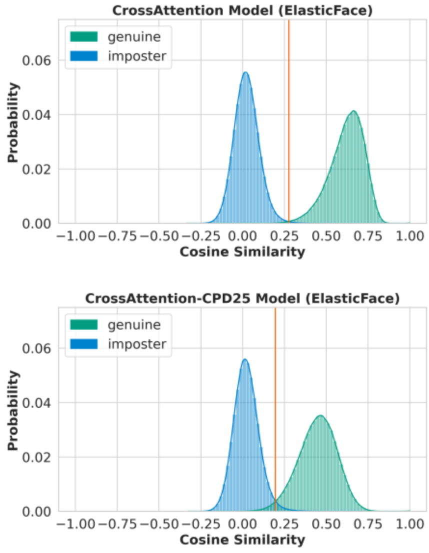
50 %

Synthetic Uniform

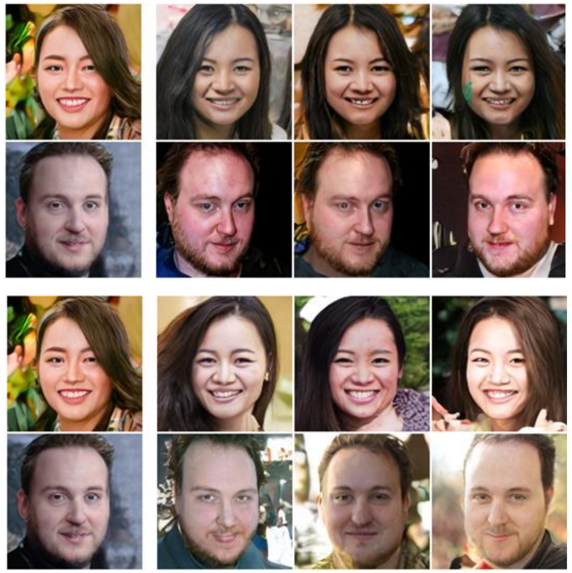
Identity-Separability



Identity-Separability



Synthetic Two-Stage



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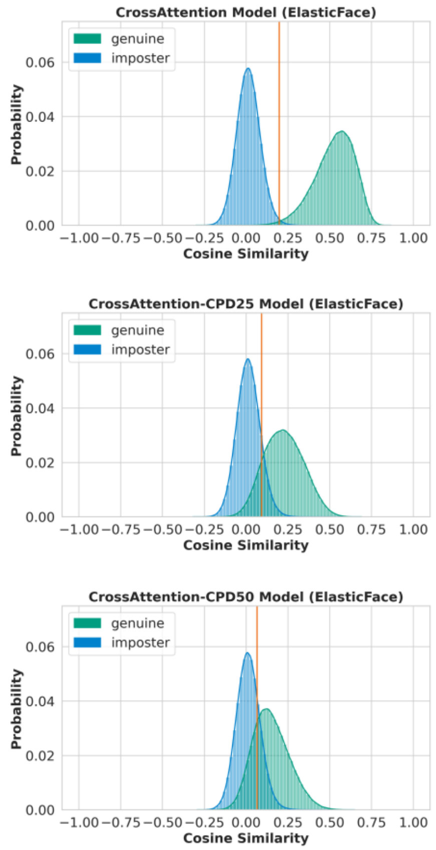
Identity-Separability



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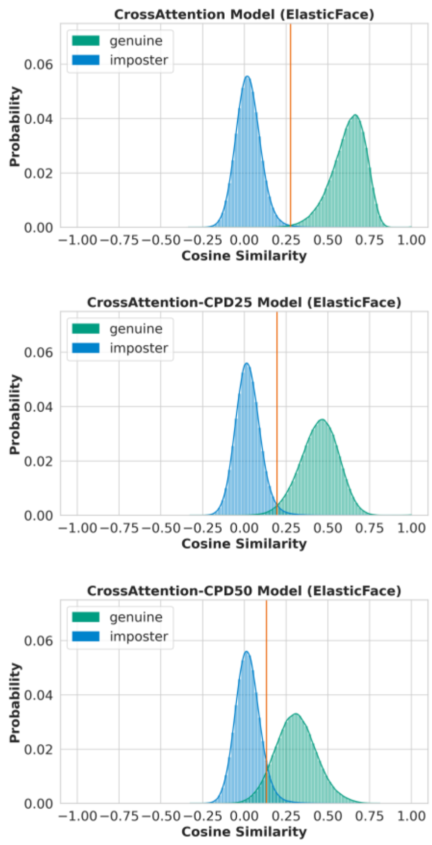

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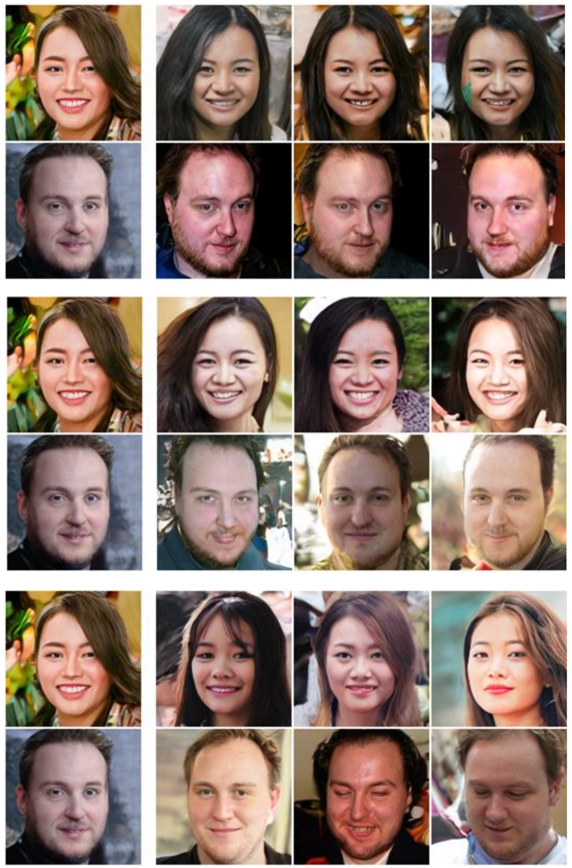

Solving the label problem

Do we necessary need labels?

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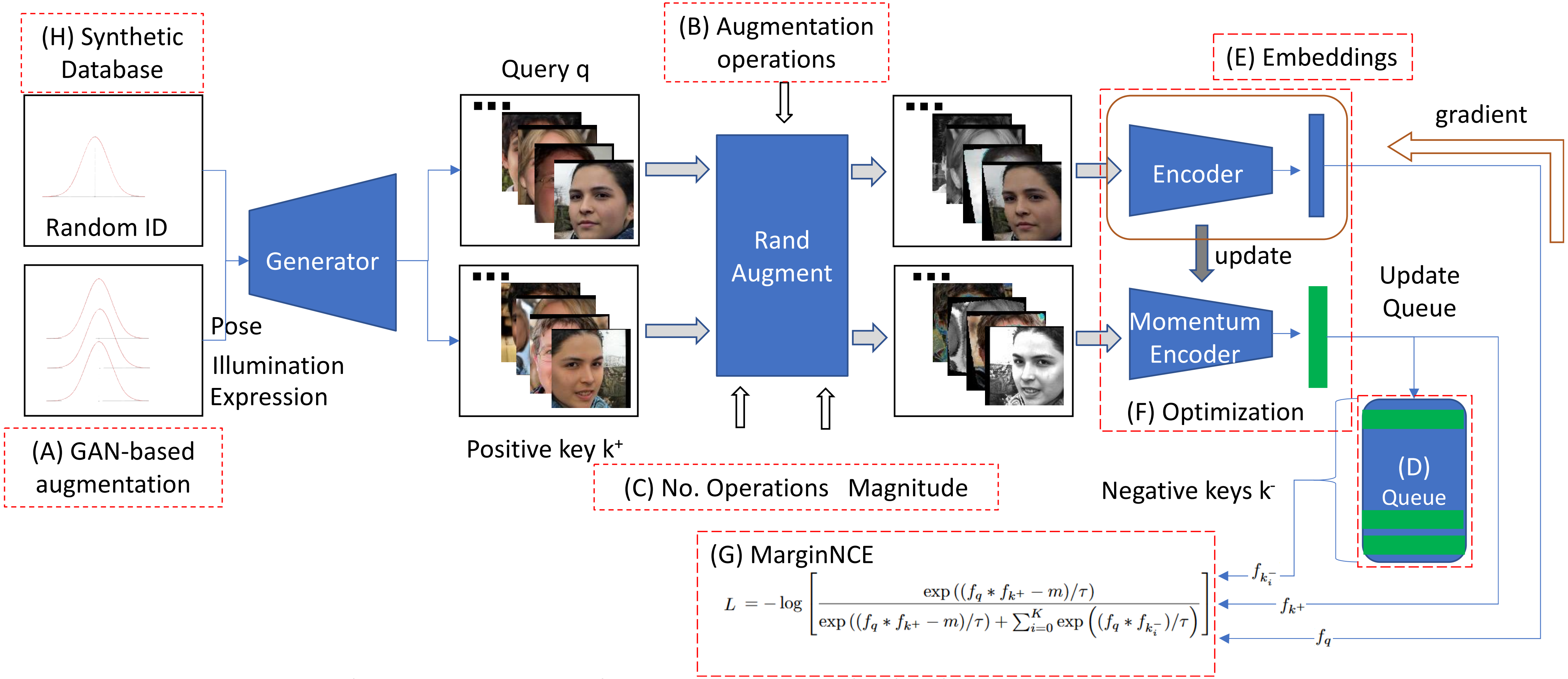
Fadi Boutros et al.: Unsupervised Face Recognition using Unlabeled Synthetic Data. FG 2023

Solving the label problem

Do we necessary need labels?



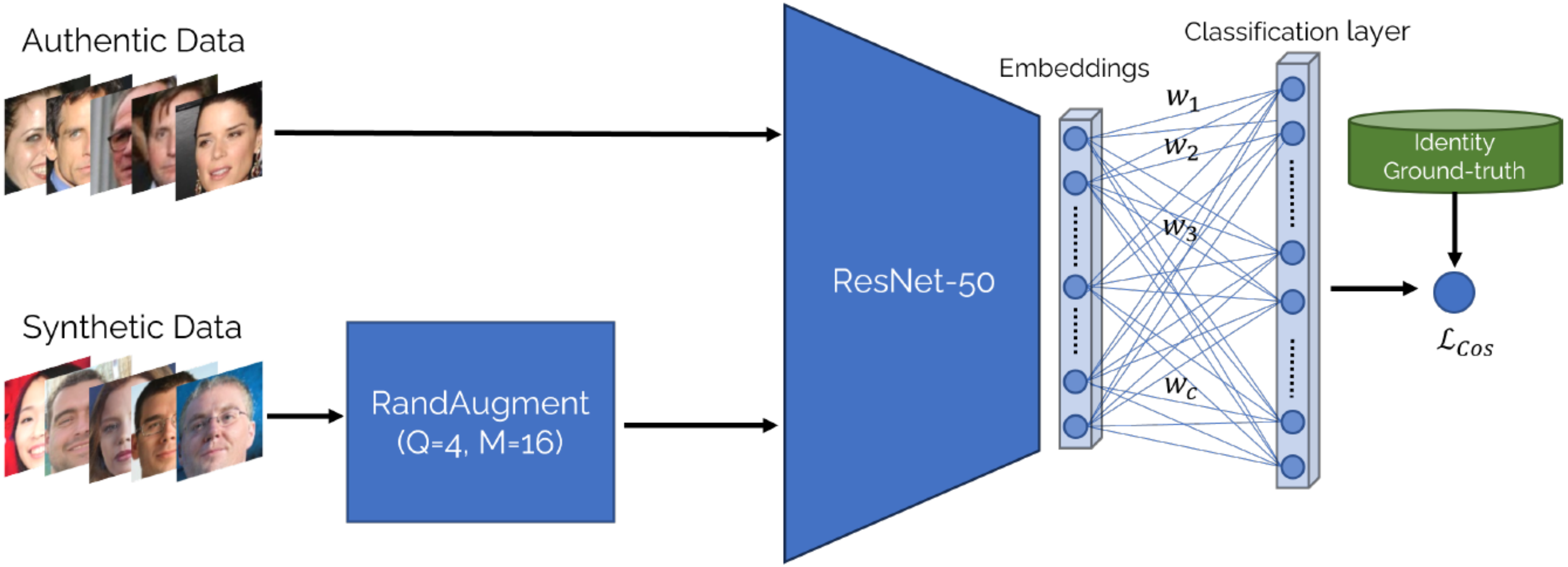
Fadi Boutros et al.: Unsupervised Face Recognition using Unlabeled Synthetic Data. FG 2023

How far did we come with synthetic-based FR?

Method	Data generation	Id/Img.	LFW	AgeDB-30	CFP-FP	CA-LFW	CP-LFW	Avg
CASIA-WebFace [59]	Authentic	10.5K/ 46	99.55	94.55	95.31	93.78	89.95	94.63
IDiff-Face [51]	Diffusion model	10K/50	98.00	86.43	85.47	90.65	80.45	88.20
DCFace [52]		10K/50	98.55	89.70	85.33	91.60	82.62	89.56
DigiFace-1M [50]	Digital Rendering	10K/50	95.40	76.97	87.40	78.62	78.87	83.45
SynFace [37]	GAN-Based	10K/50	88.98	-	-	-	-	-
SynFace (w/IM) [37]		10K/50	91.93	61.63	75.03	74.73	70.43	74.75
USynthFace [45]		400K/1	92.23	71.62	78.56 (1)	77.05	72.03	78.30
IDnet [47]		10.5K/50	92.58	73.53	75.40	79.90	74.25 (2)	79.13
GAN-Control [43], [49]		10K/50	93.22	77.60 (2)	73.03	82.25 (3)	70.80	79.38 (3)
ExFaceGAN(SG3) [49]		10K/50	90.47	72.85	72.70	78.60	69.27	76.78
ExFaceGAN(Con) [49]		10K/50	93.50 (3)	78.92 (1)	73.84	82.98 (2)	71.60	80.17 (2)
SFace [46]		10.5K/60	91.87	71.68	73.86	77.93	73.20 (3)	77.71
SFace2 (ours)		10.5K/60	94.62 (2)	74.37	76.24 (3)	81.57	72.18	79.20
SFace2+ (ours)		10.5K/60	95.60 (1)	77.37 (3)	77.11 (2)	83.40 (1)	74.60 (1)	81.62 (1)

Fadi Boutros et al.: SFace2: Synthetic-Based Face Recognition With w-Space Identity-Driven Sampling. TBIOM 2024

Can we use synthetic data to support limited authentic data?



Andrea Atzori et al.: If It's Not Enough, Make It So: Reducing Authentic Data Demand in Face Recognition through Synthetic Faces. FG 2024

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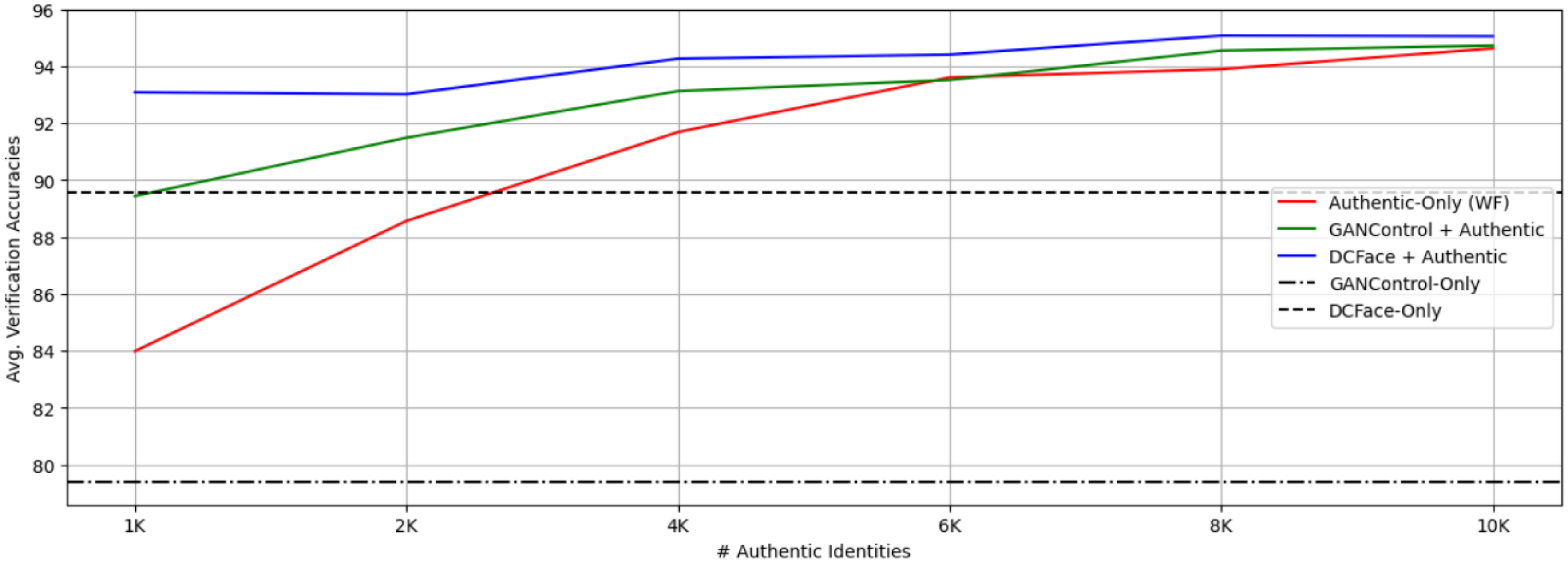

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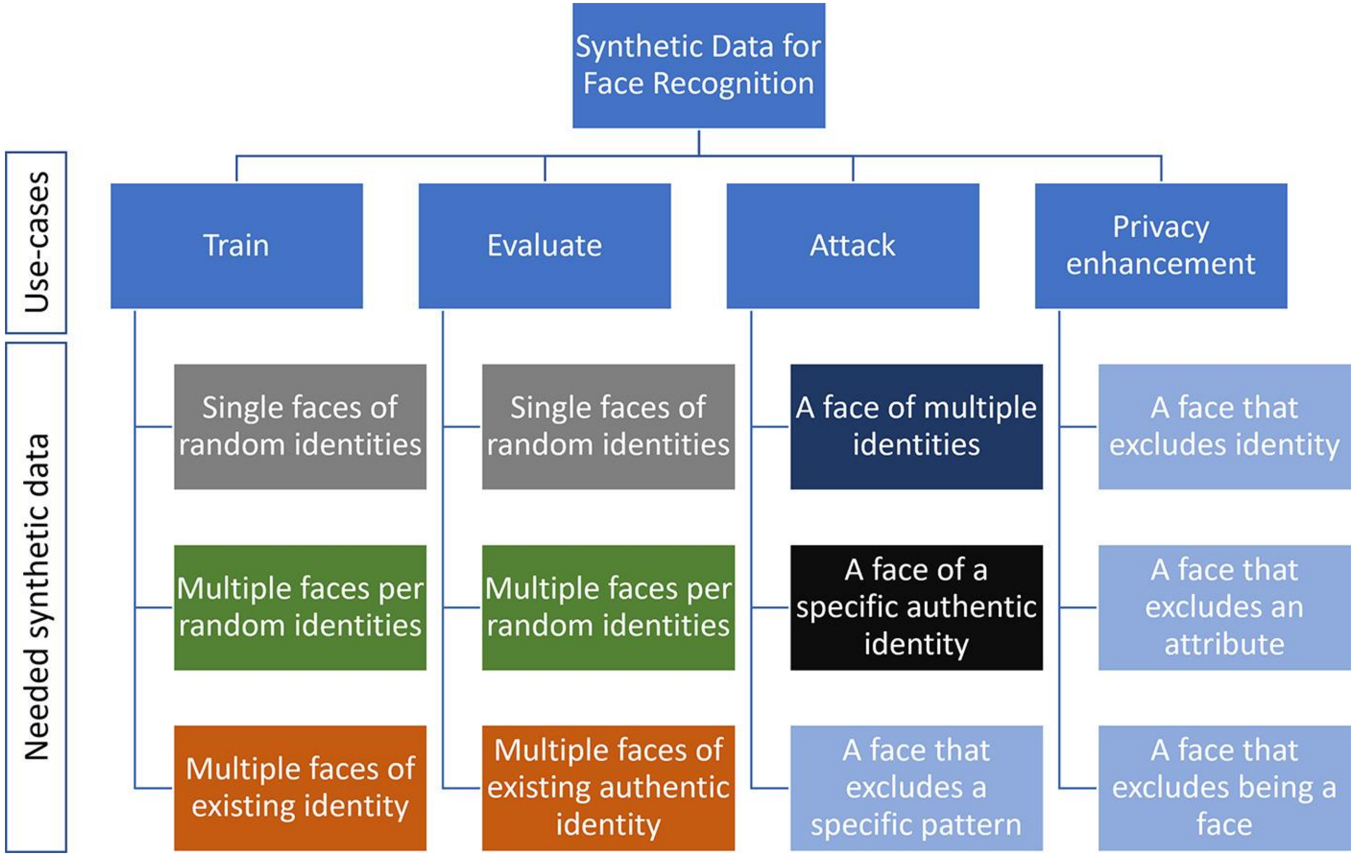
Synthetic data for face recognition

overview



Fadi Boutros, Vitomir Struc, Julian Fiérrez, Naser Damer: Synthetic data for face recognition: Current state and future prospects. Image Vis. Comput. (2023)

Learning from synthetic data - Generation for learning – Part 2

The INvicta school of VIsion, Computational intelligence, and patTern Analysis - INVICTA

Naser Damer

The content of this talk is largely based on works lead by:

Dr. Fadi Boutros

Fraunhofer IGD, Darmstadt, Germany and TU Darmstadt, Darmstadt, Germany