

Face Shape Segmentation Mask Anonymization using a Generative Adversarial Network

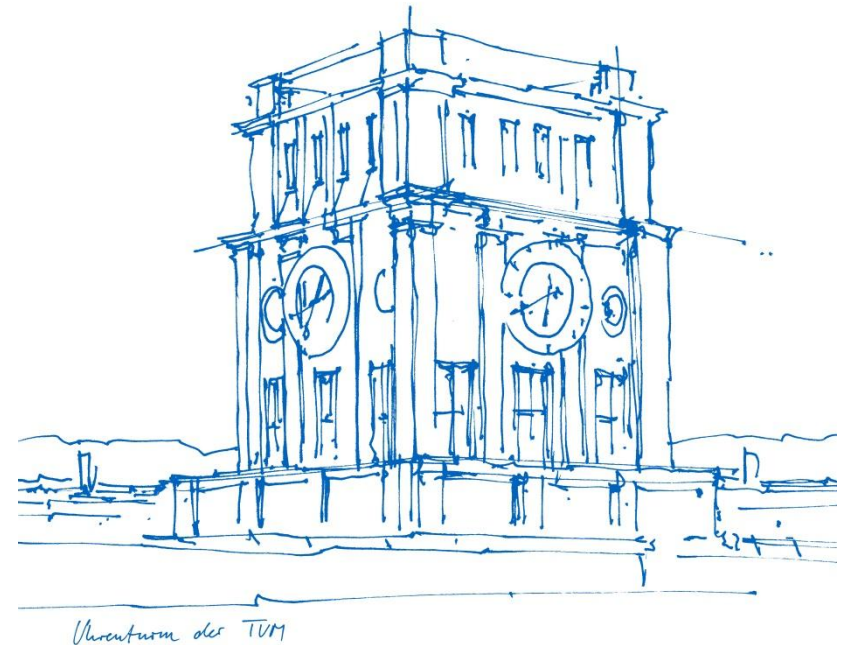
Candidate: Filippo Simonazzi

Supervisor: Maxim Maximov

Advisor: Prof. Dr. Laura Leal-Taixé

Technical University of Munich

Chair for Computer Vision and Artificial Intelligence



Introduction



Increased use of **face detection and tracking models** raises questions about **privacy**.

In most situations, it is not necessary to **identify** the subject, but it is sufficient to **detect** it.

How to perform face obfuscation?

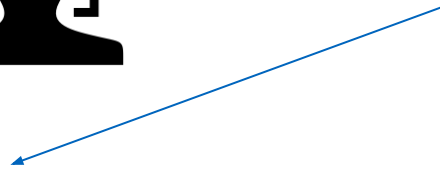
Related Work



Face Anonymization Task



Heuristic Methods



Related Work

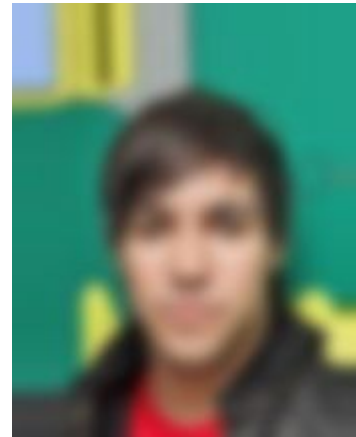


Face Anonymization Task



Heuristic Methods

- Blurring



Related Work

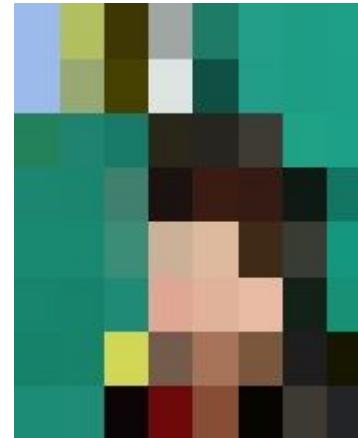


Face Anonymization Task



Heuristic Methods

- Blurring
- Pixelization



Related Work



Face Anonymization Task



Heuristic Methods

- Blurring
- Pixelization
- Masking



Related Work



Face Anonymization Task



Heuristic Methods

- Blurring
- Pixelization
- Masking



- Risk of identity leak
- Unrealistic results

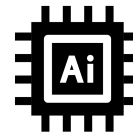
Related Work



Face Anonymization Task

Heuristic Methods

- Blurring
- Pixelization
- Black Box

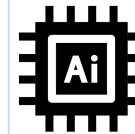
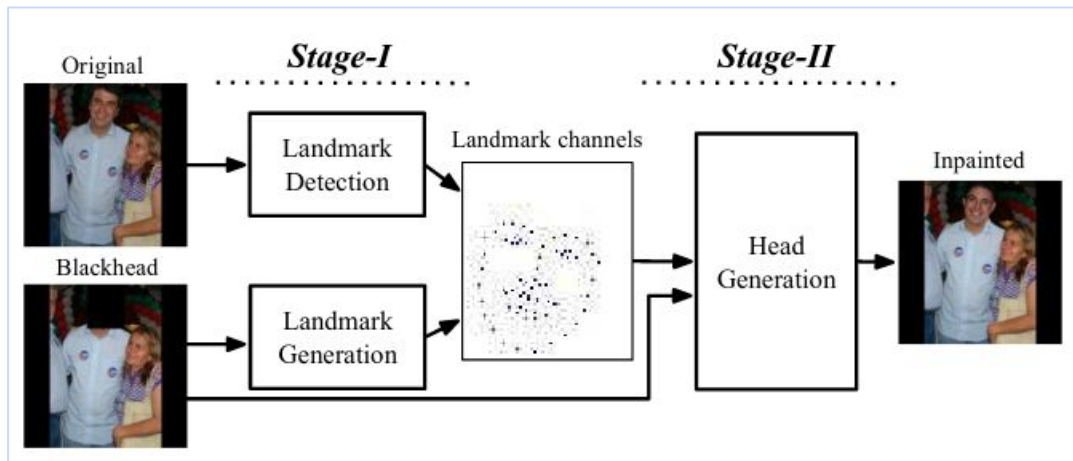


Data Driven Models

Related Work



Face Anonymization Task



Data Driven Models



Input Face Landmarks & Background

- Facial Landmark Generation
- Head Inpainting Conditioned on Facial Landmark

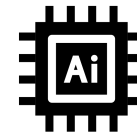


- *Natural and Effective Obfuscation by Head Inpainting*

Related Work



Face Anonymization Task



Data Driven Models

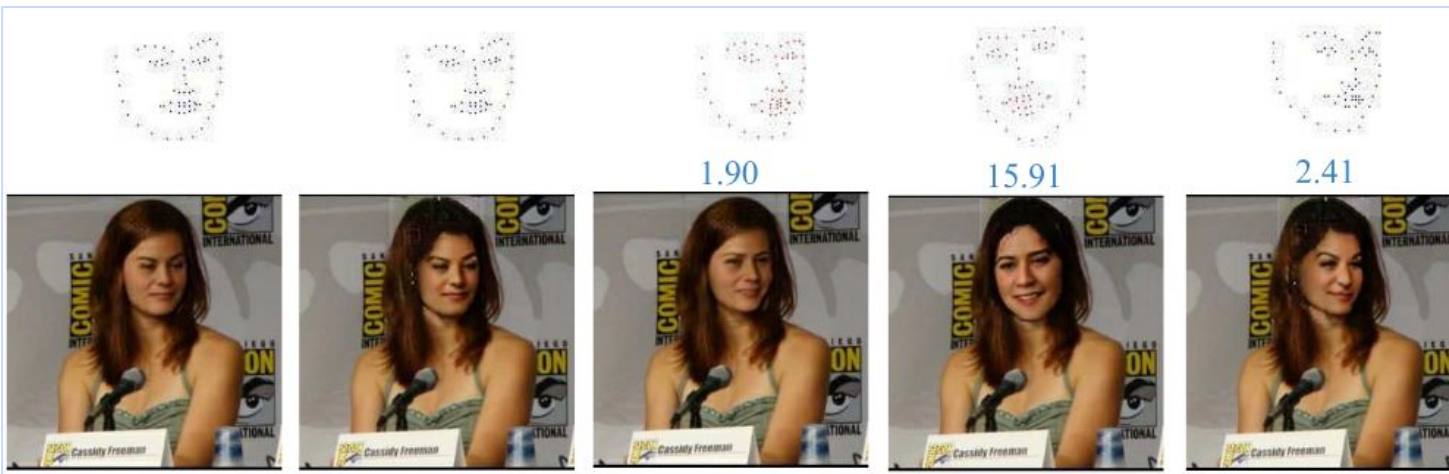


- **No control over the generated identity**
- **Generated faces may have artificial poses**
- **Computationally expensive**



Input Face Landmarks & Background

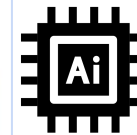
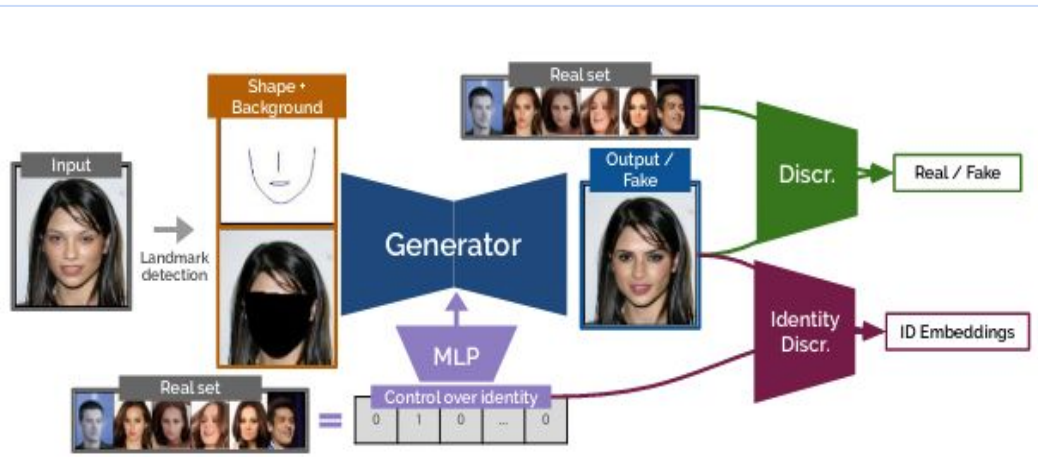
- *Natural and Effective Obfuscation by Head Inpainting*



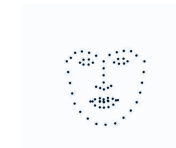
Related Work



Face Anonymization Task



Data Driven Models



Input Face Landmarks & Background



- Identity control on the generated output
- Little identity information given to the generator

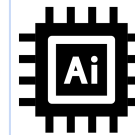
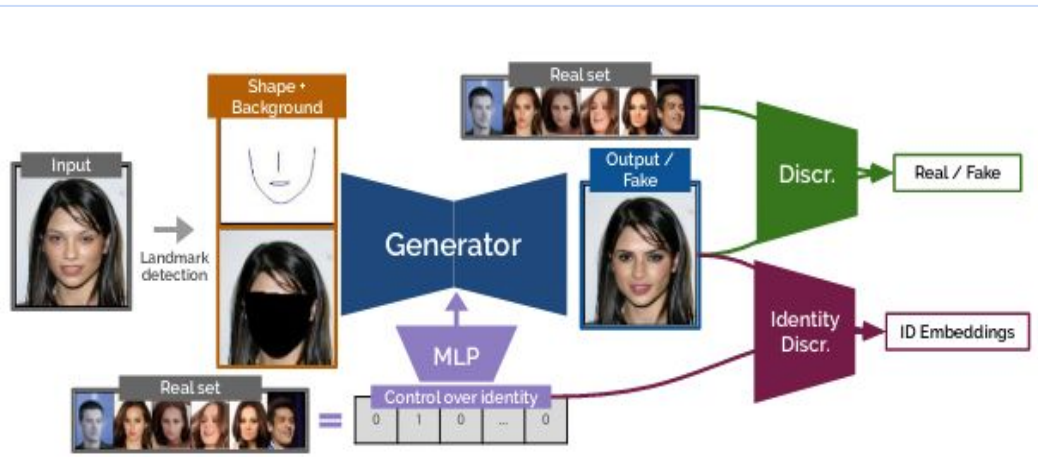
- *Natural and Effective Obfuscation by Head Inpainting*

- CIAGAN

Related Work



Face Anonymization Task



Data Driven Models



Input Face Landmarks & Background

- Identity control on the generated output
- Little identity information given to the generator

- *Natural and Effective Obfuscation by Head Inpainting*



No option to change the shape of the original face

- CIAGAN

Project Overview



**THESIS
INVESTIGATION**

Project Overview

Shape Appearance Anonymization

*Gain more control
over the generated
output by arbitrarily
changing the shape
of the original image*

**THESIS
INVESTIGATION**

Project Overview

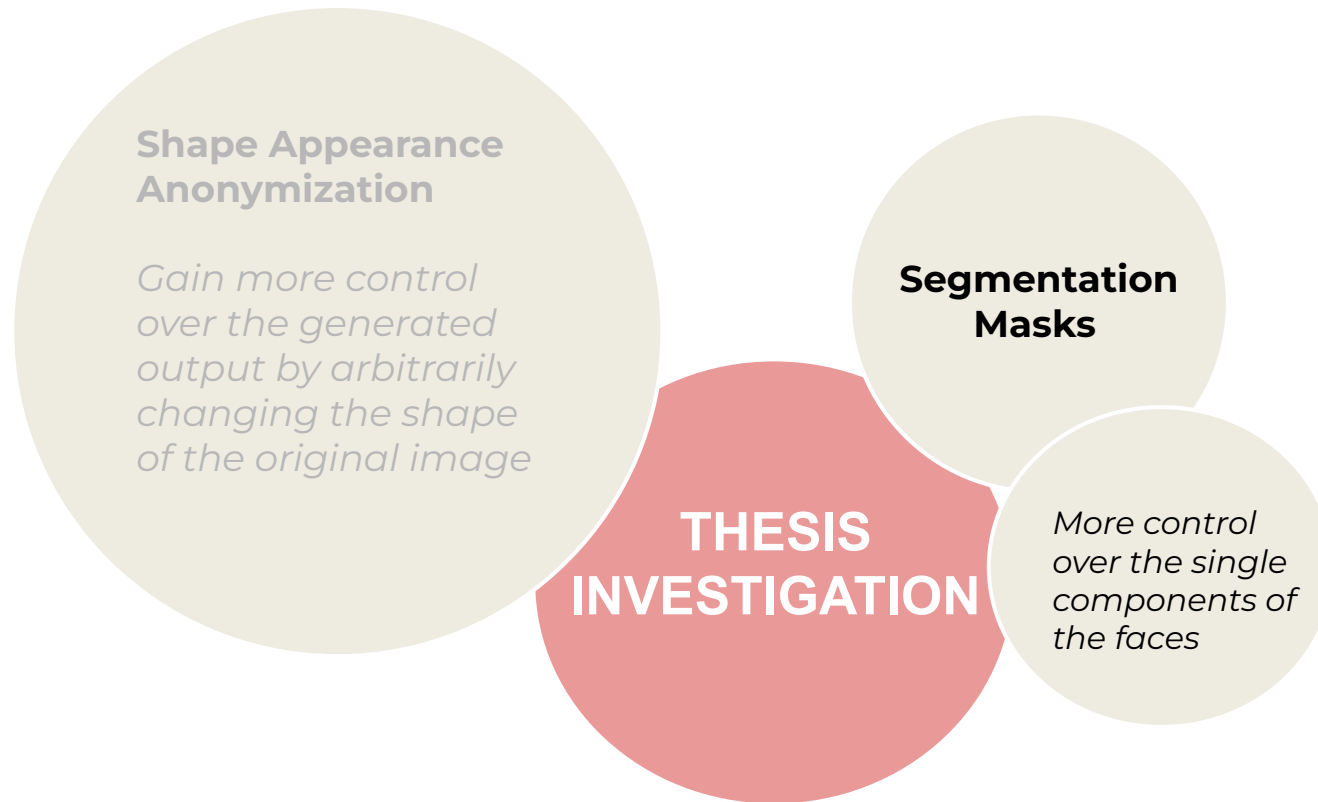
Shape Appearance Anonymization

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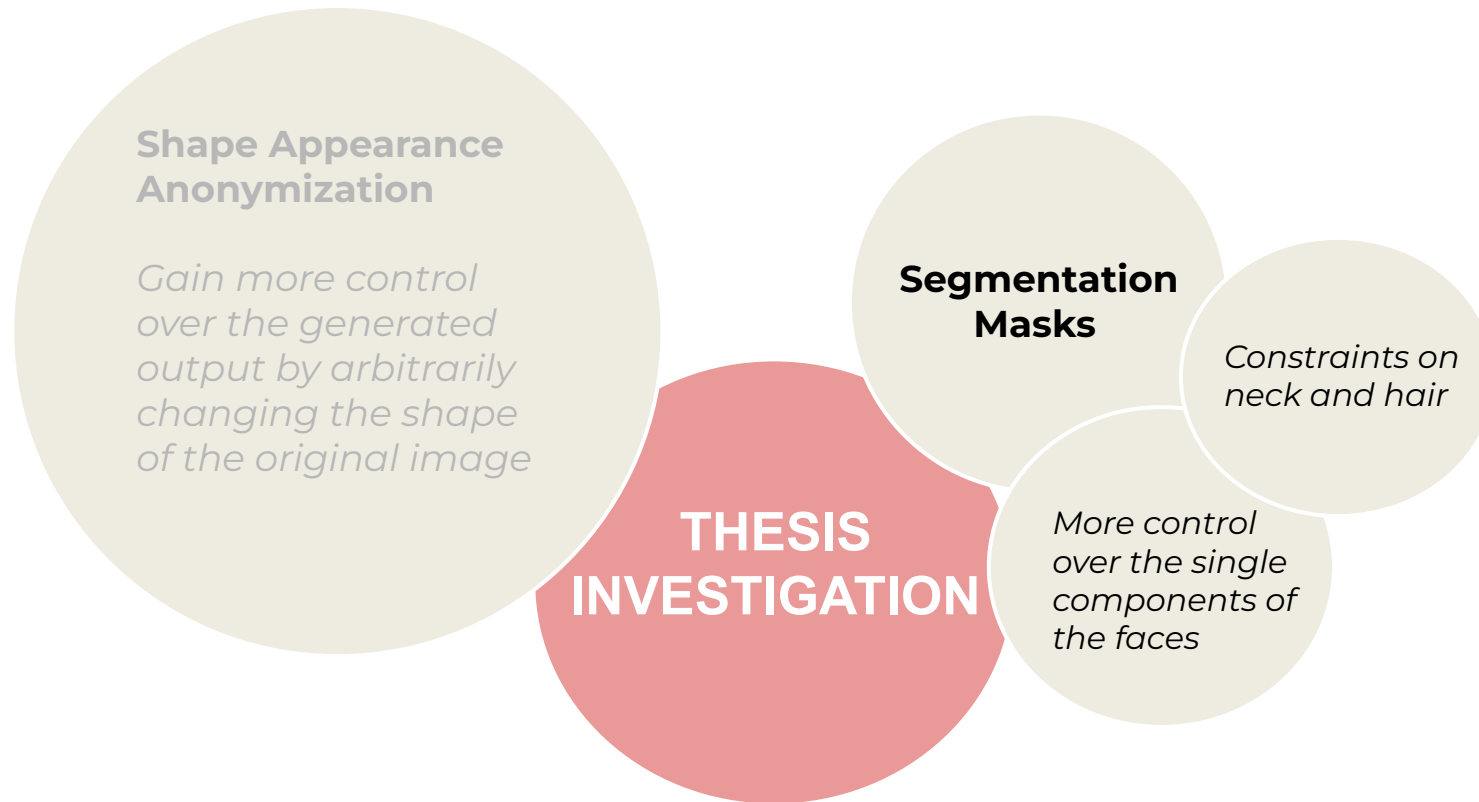
Segmentation Masks

**THESIS
INVESTIGATION**

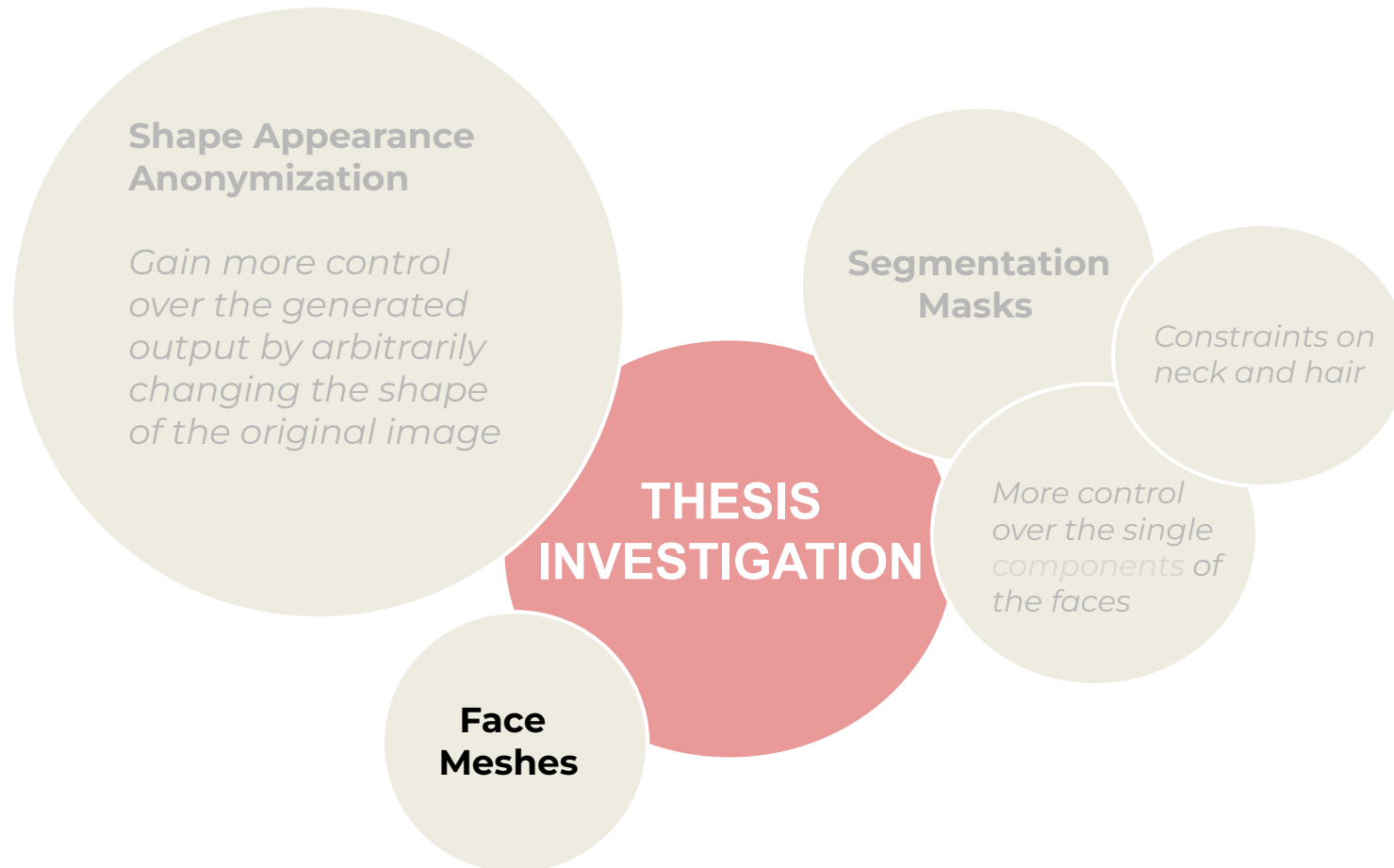
Project Overview



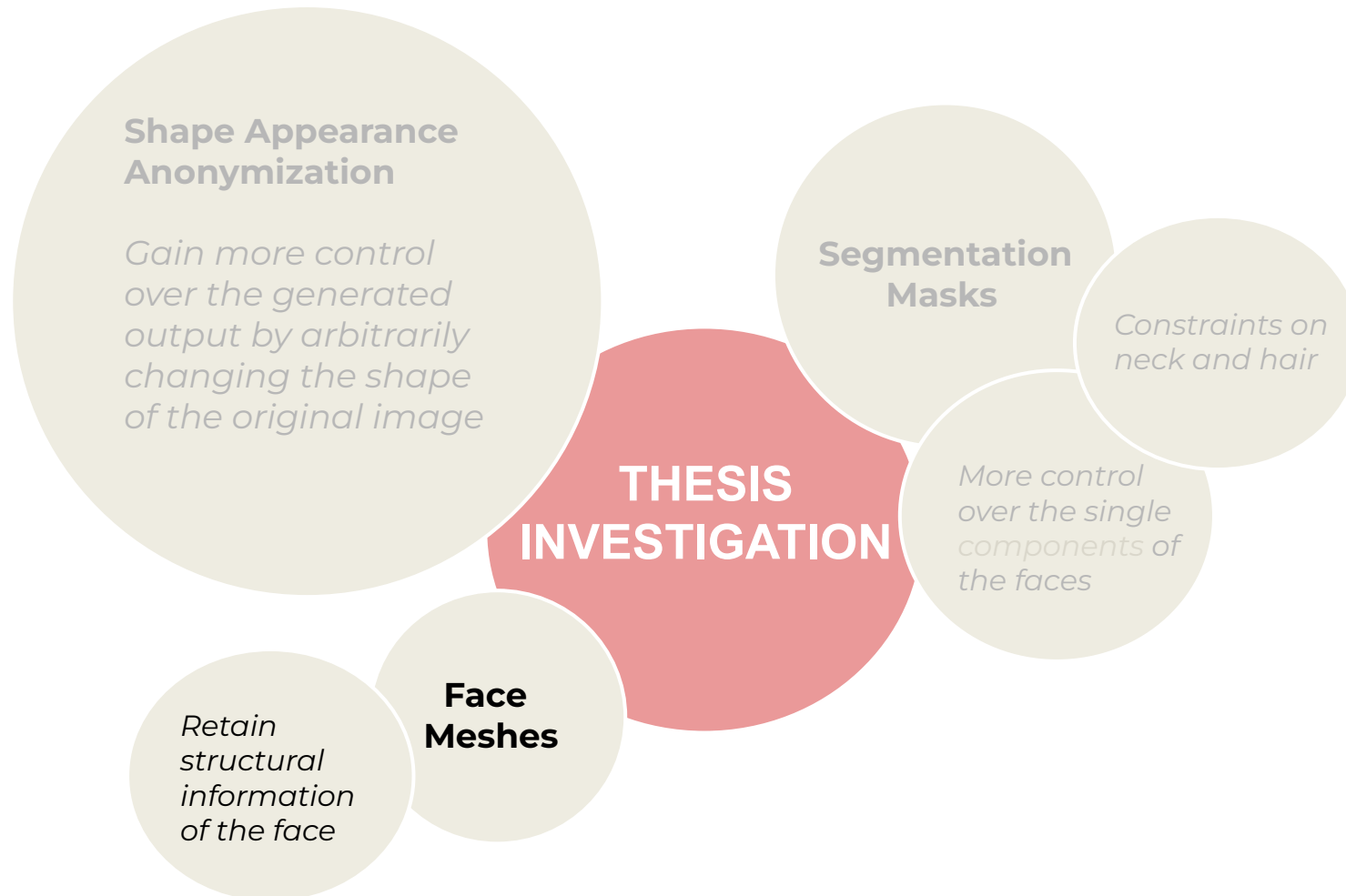
Project Overview



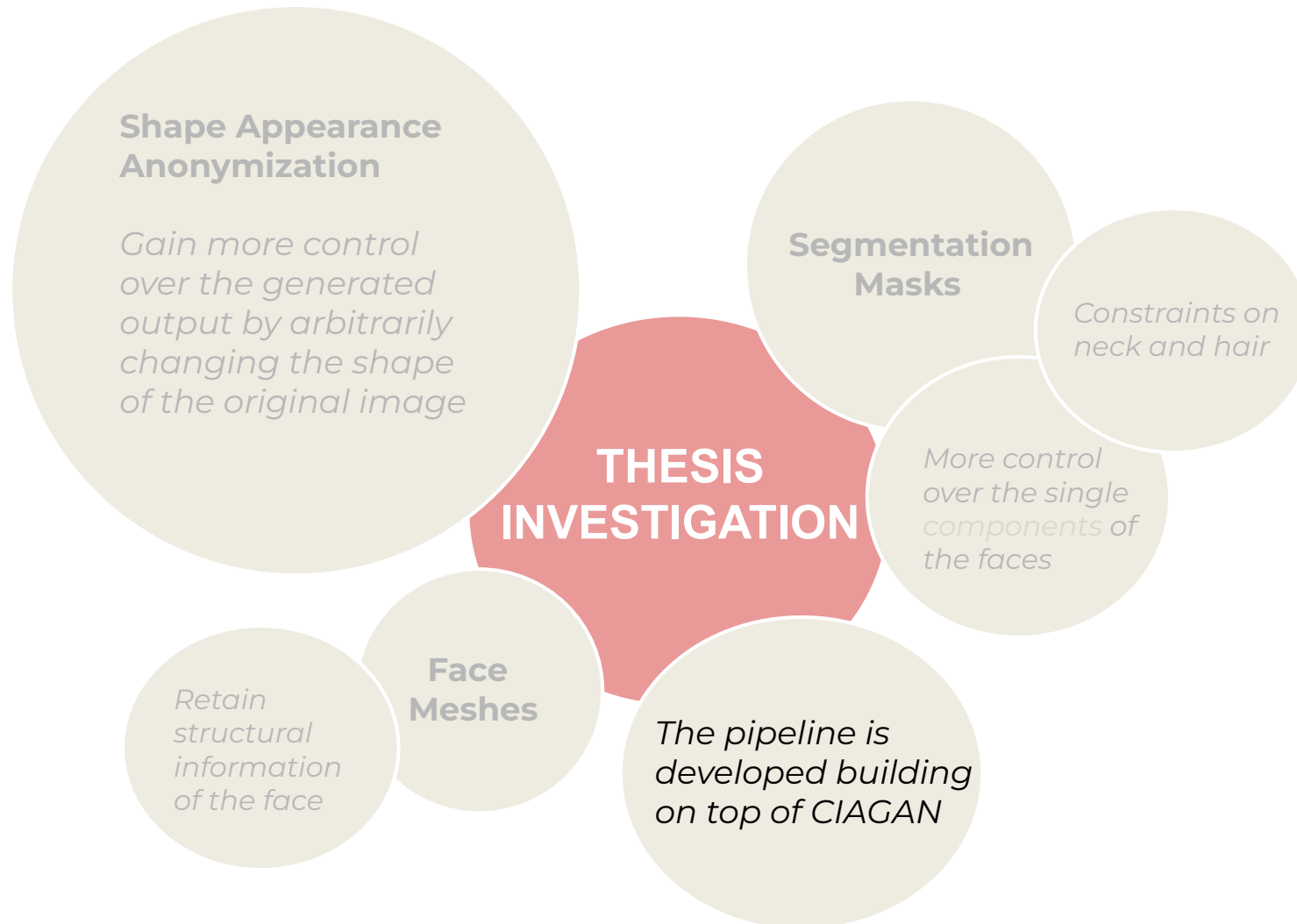
Project Overview



Project Overview



Project Overview



Project Overview

THESIS CONTRIBUTION

Full Anonymization Pipeline

- Any input size is supported
- Shape anonymization model
 - Flexible architecture
 - Ensures diversity
- Face Generator
 - Identity control as in CIAGAN
- Applicable to video frames

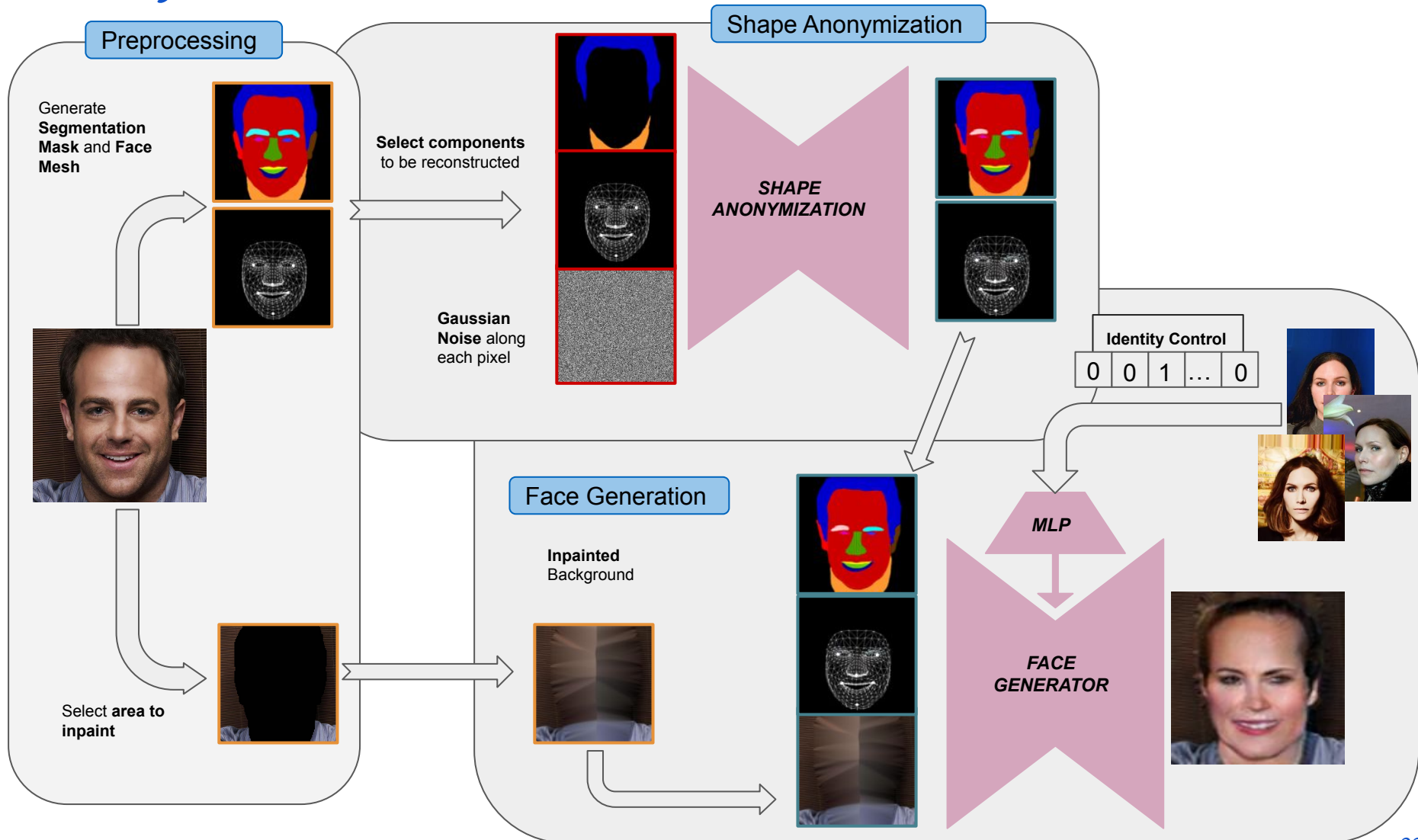
Shape Appearance
Anonymization

Gain more control
over the output
output
change
of the

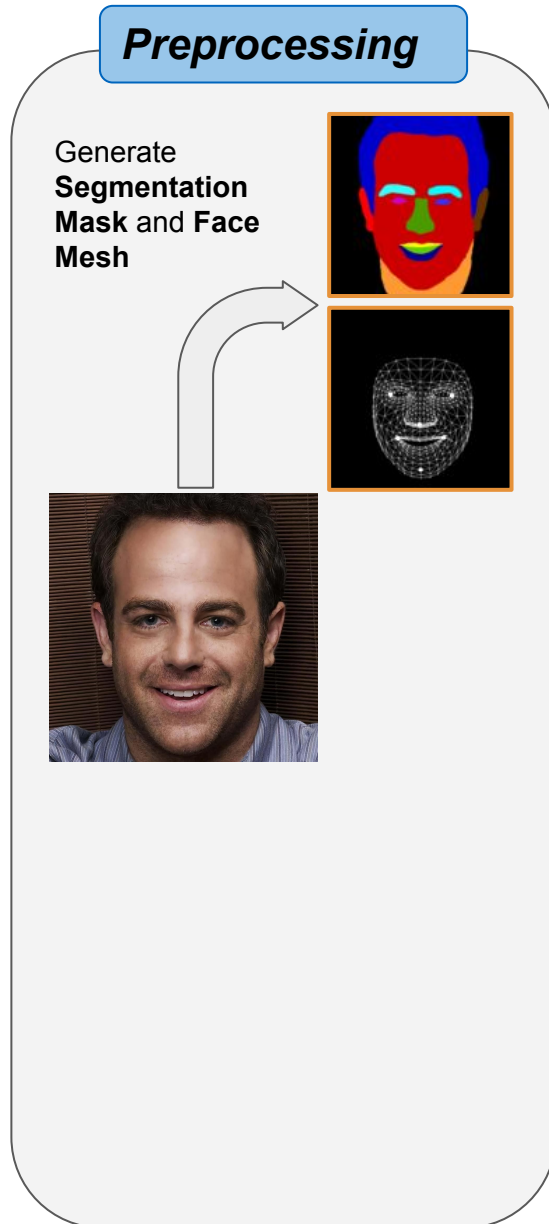
Retain
structure
information
of the face

constraints on
back and hair

Project Overview

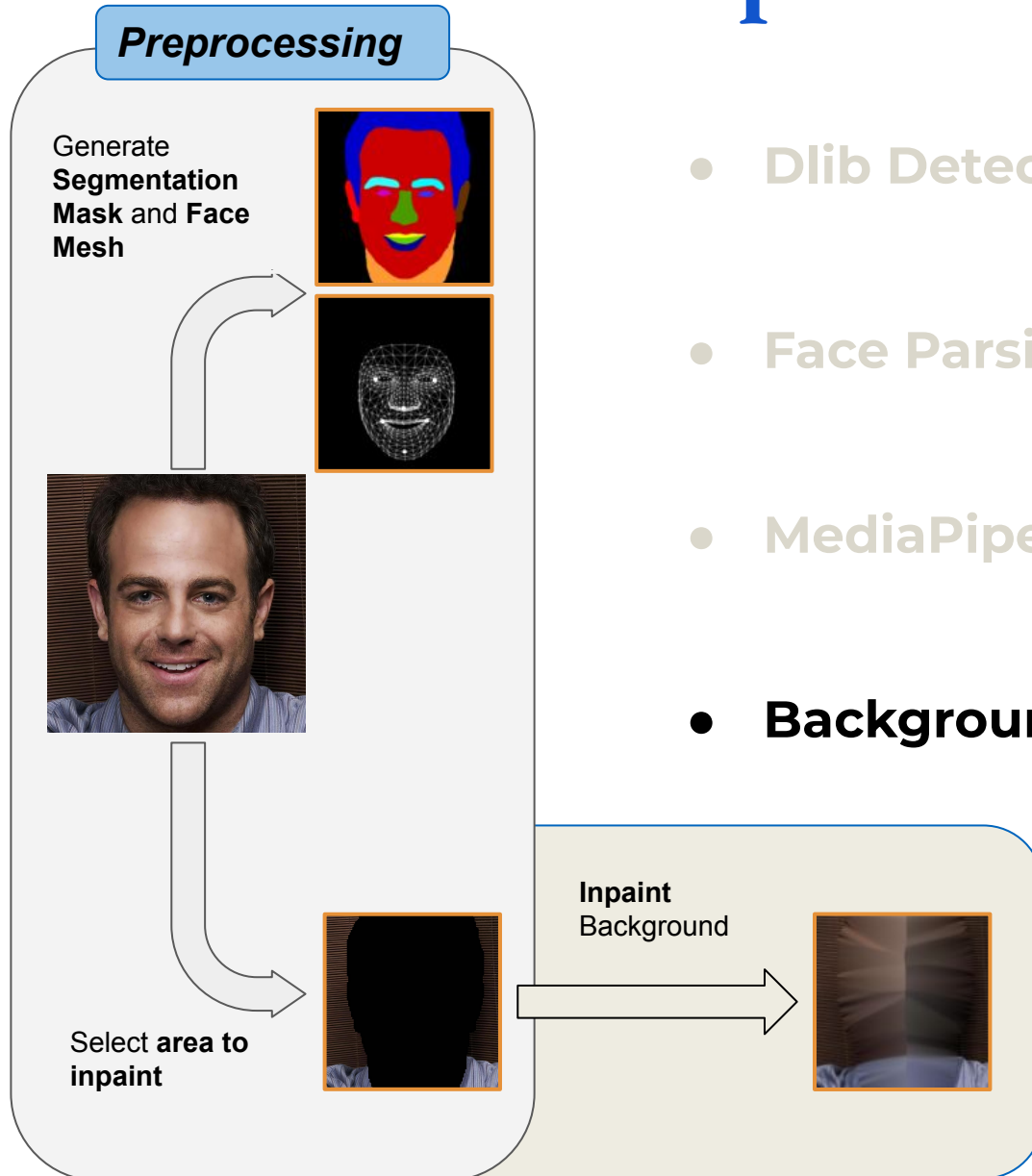


Preprocessing

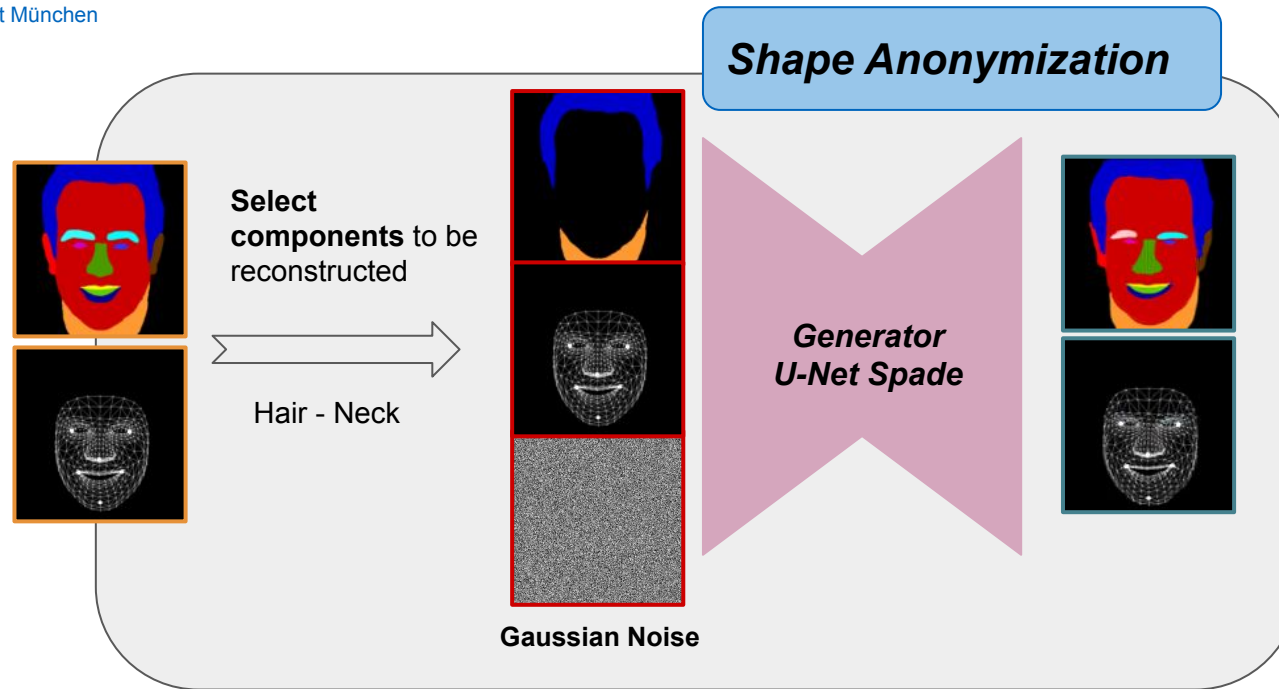


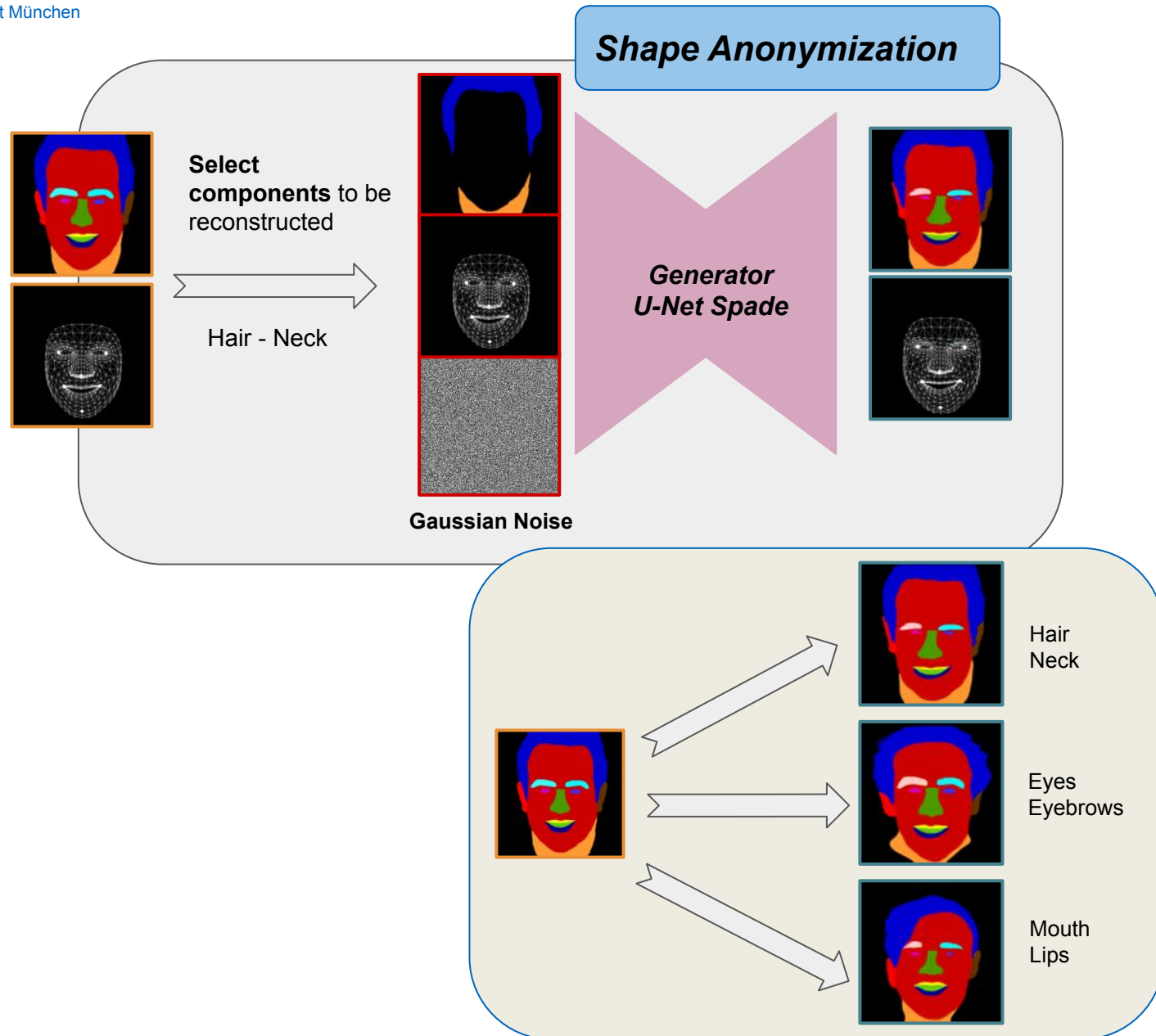
- **Dlib Detector**
- **Face Parsing**
- **MediaPipe**

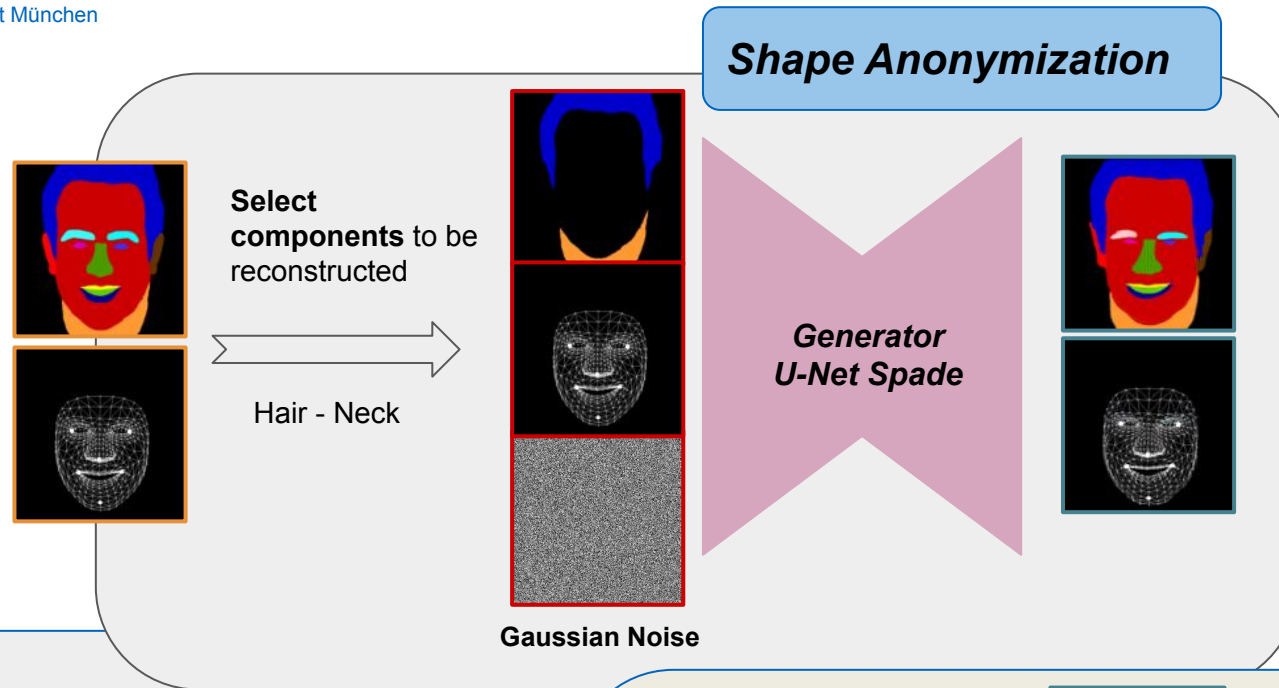
Preprocessing



- Dlib Detector
- Face Parsing
- MediaPipe
- **Background Inpainting**





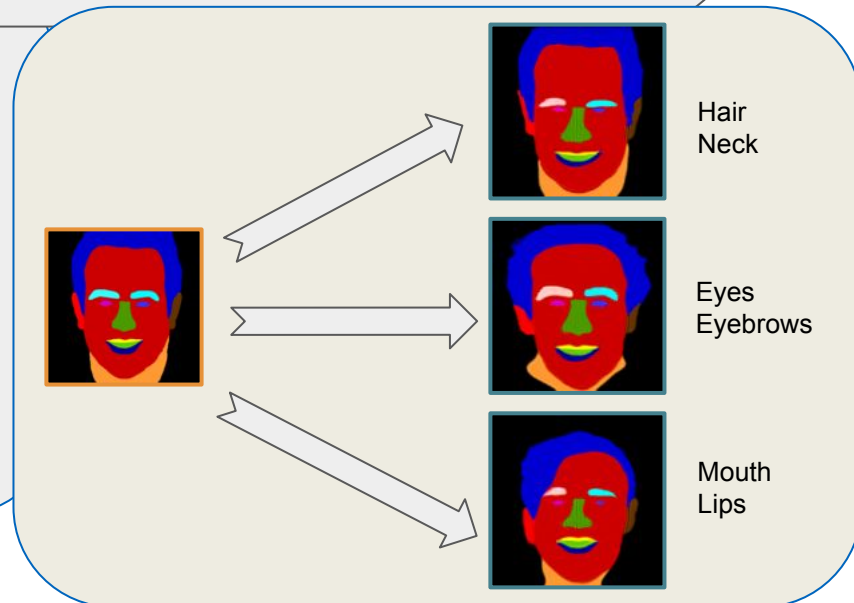


I. GAN Loss

II. L1 Loss

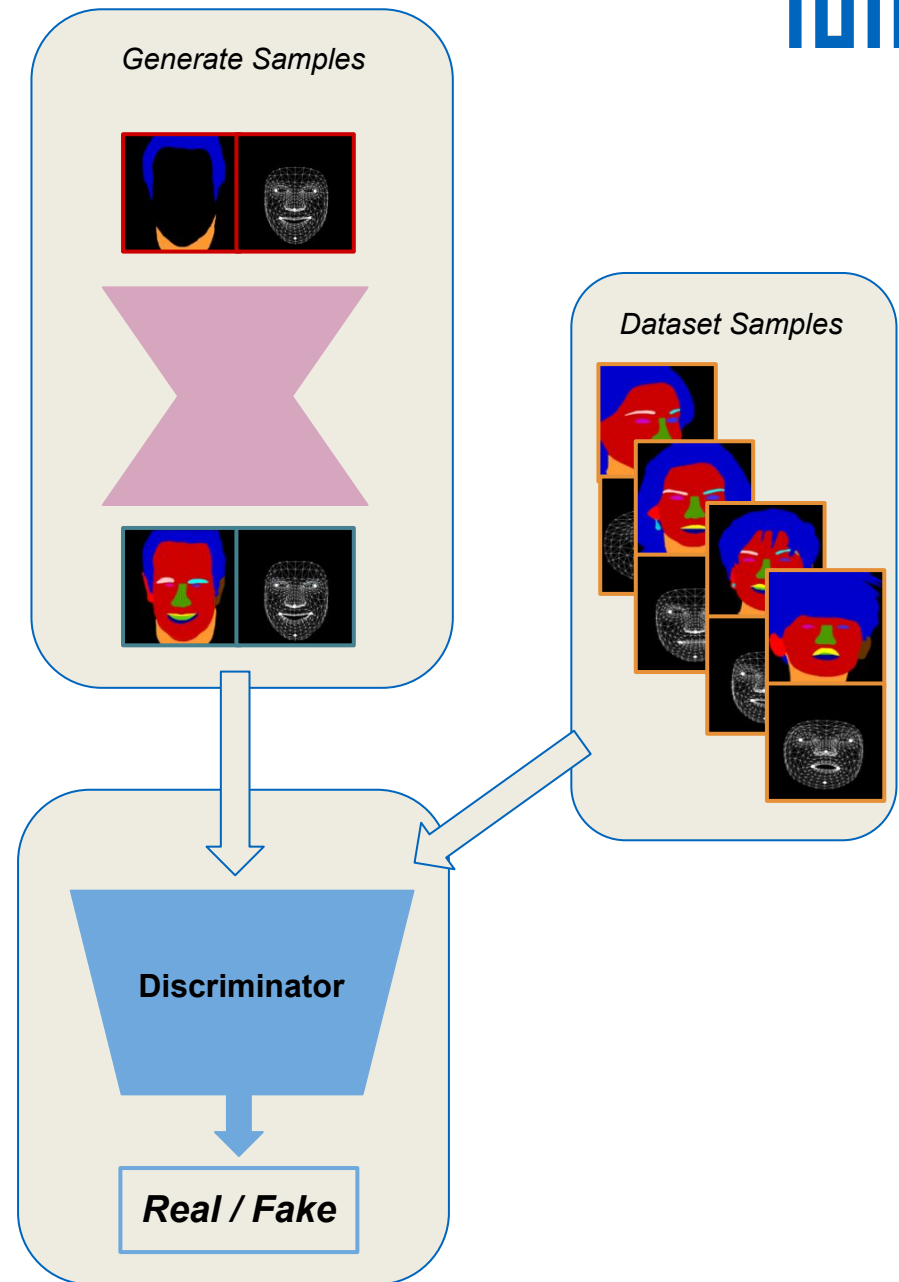
- Reconstruction
- Negative Reconstruction
- Hair Excess

III. Diversity Contrastive Loss



Loss Functions

I. GAN Loss

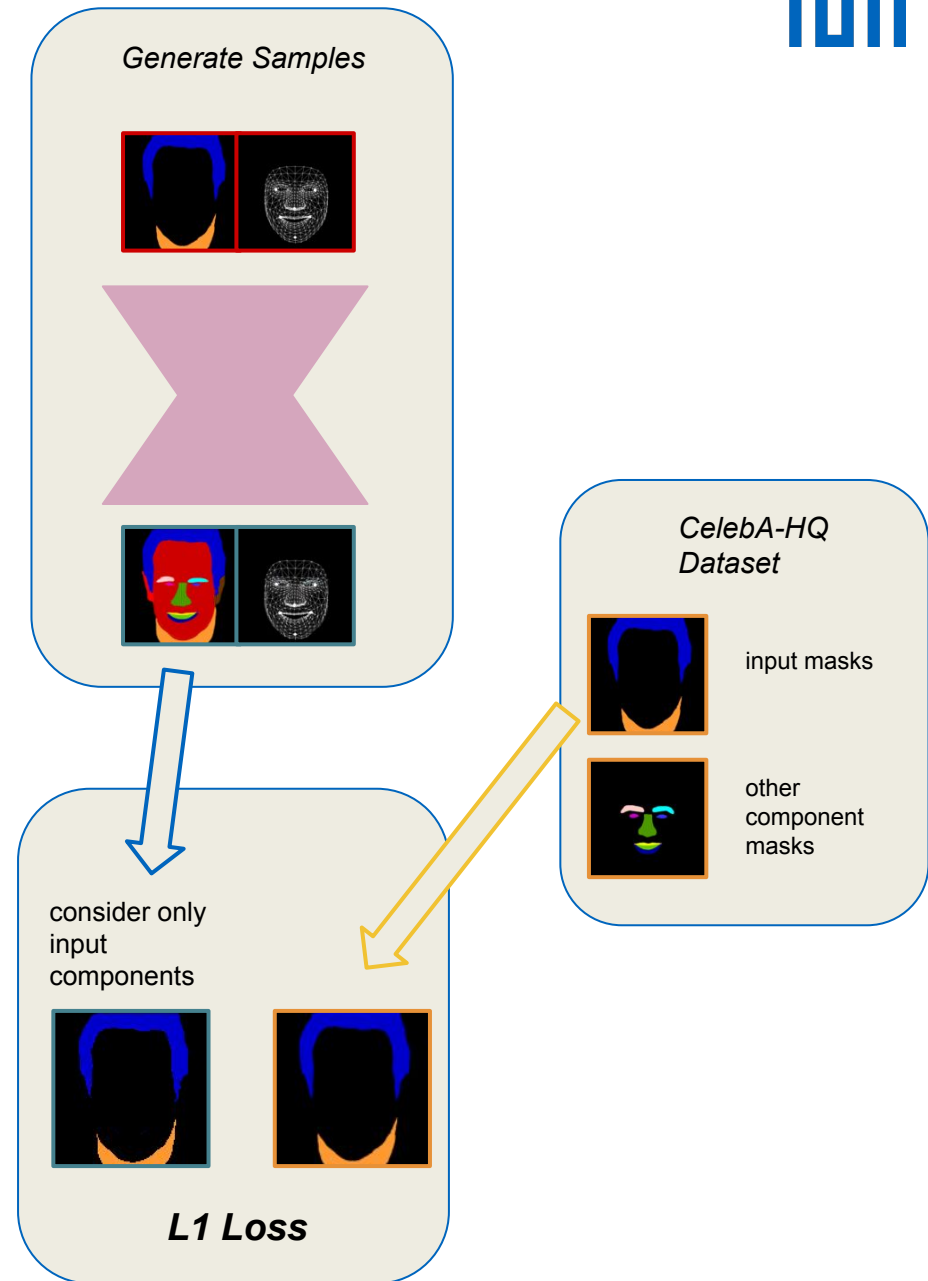


Loss Functions

I. GAN Loss

II. L1 Losses

1. Reconstruction Loss

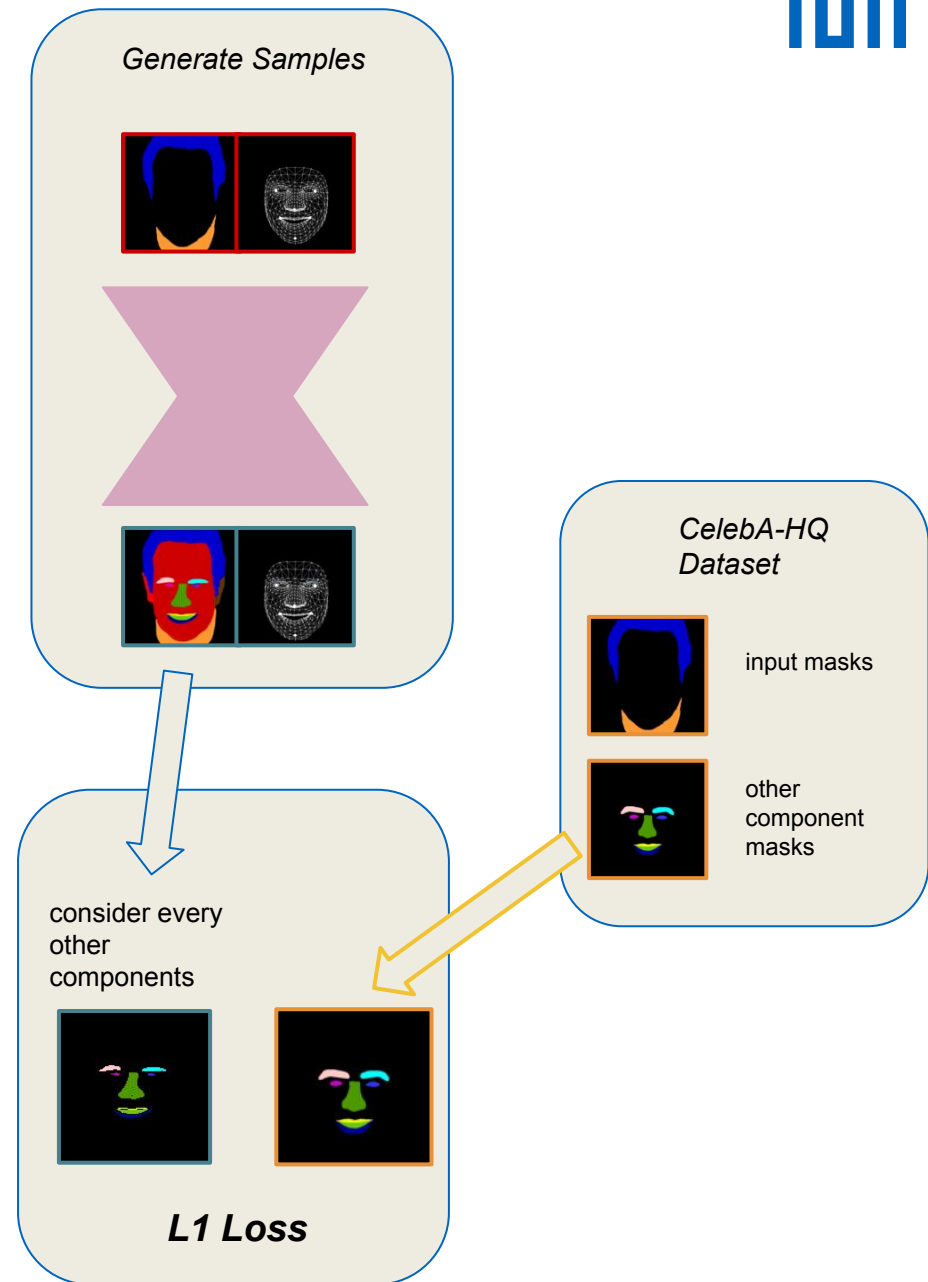


Loss Functions

I. GAN Loss

II. L1 Losses

1. *Reconstruction Loss*
2. *Negative Reconstruction Loss*



Loss Functions

I. GAN Loss

II. L1 Losses

- 1. Reconstruction Loss*
- 2. Negative Reconstruction Loss*
- 3. Hair Excess Loss*

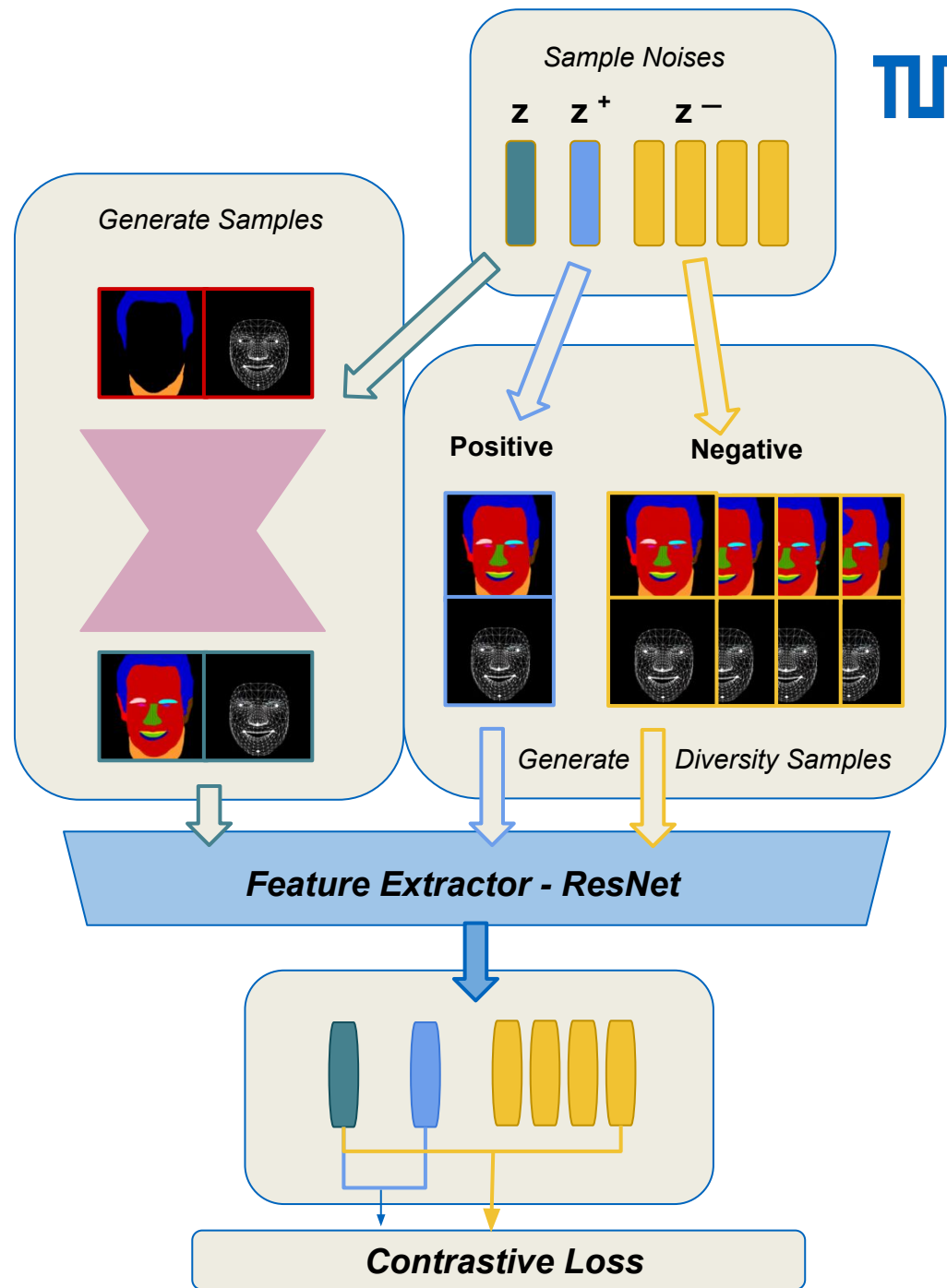
Loss Functions

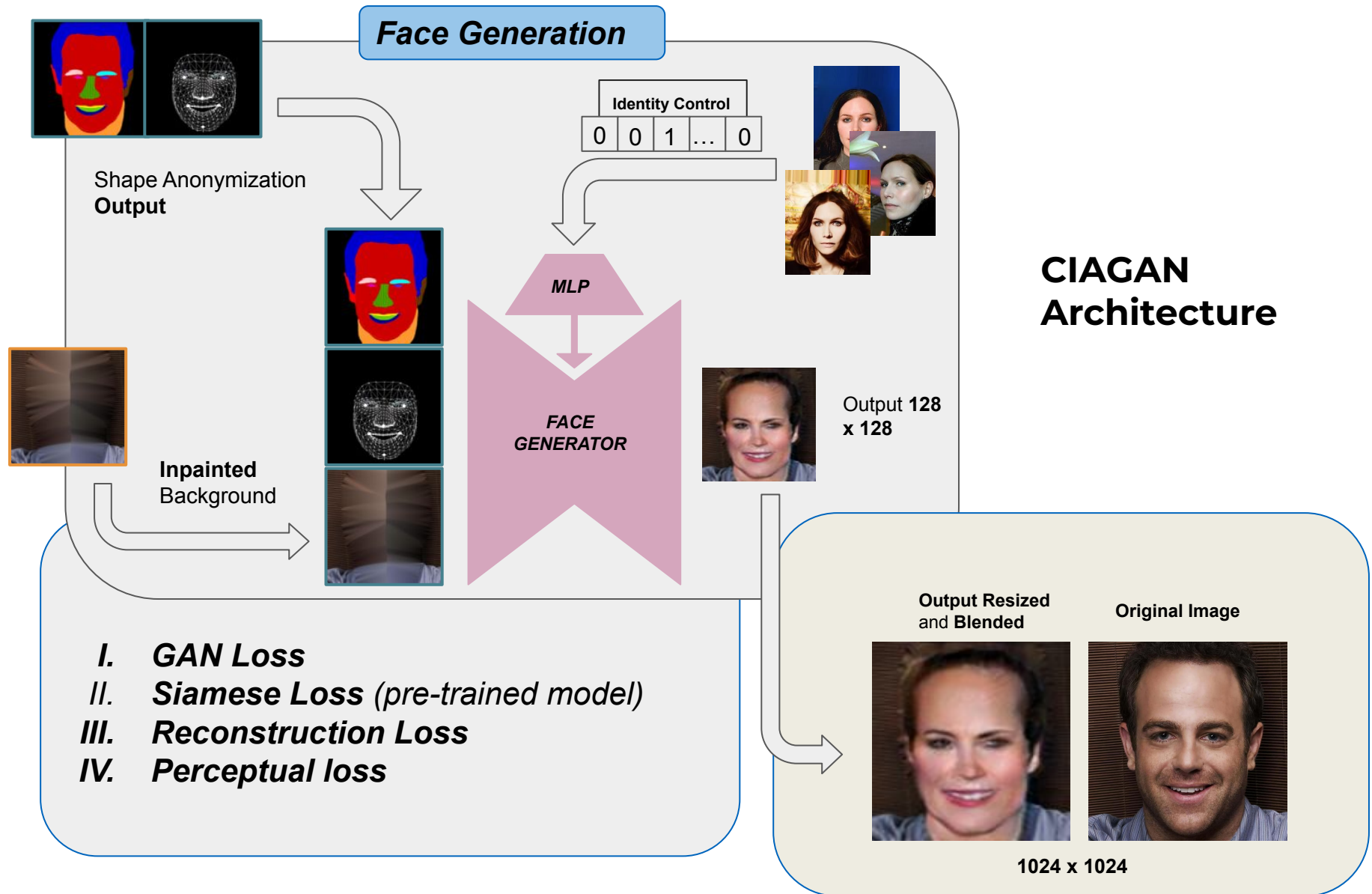
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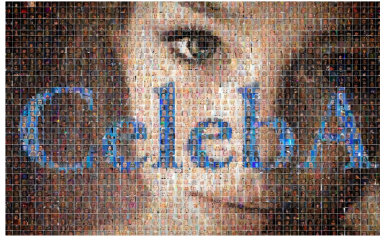
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Datasets



- Aligned and cropped images
- Resolution 178 x 218
- Only identities with at least 30 images

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- 30.000 High Quality images selected from CelebA (1024 x 1024)
- Corresponding facial segmentation masks with 19 classes (512 x 512)



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Face Forensics ++



- 1.000 video sequences
- Trackable face without occlusions

Results

Hair - Neck

Identity

Source



Results

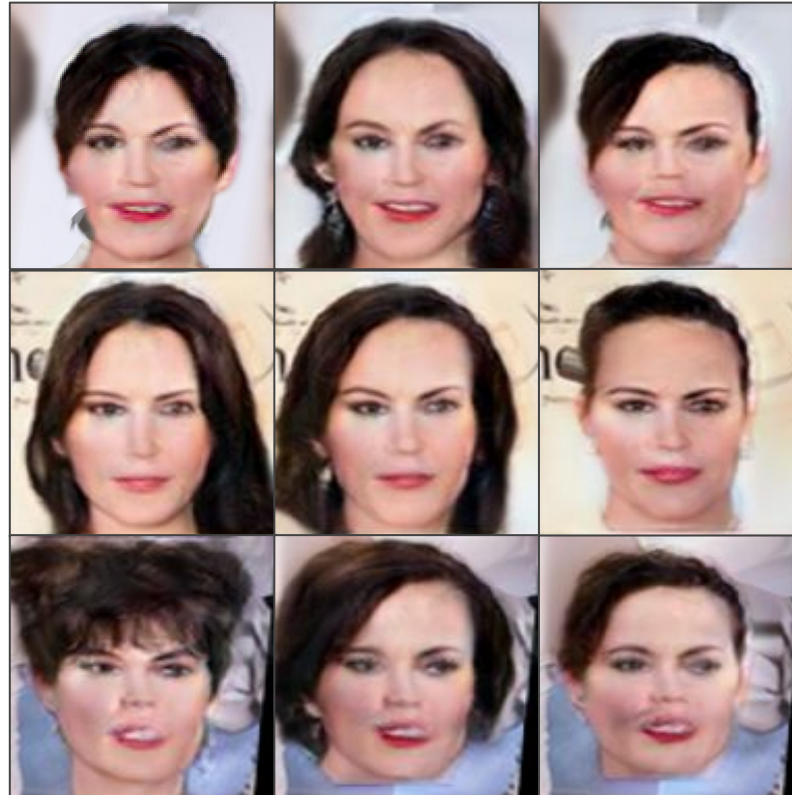
Constraints

Source

Hair
Neck

Eyes
Eyebrows
Nose

Mouth
Lips



Evaluation - Main Results

Models	Detection (\uparrow)		Identification (\downarrow)
	Dlib	SSH	FaceNet
Original	100	100	95.44
Pixelization 8 by 8	0	0	0.43
Blur 9 by 9	93.58	33.87	73.34
Blur 17 by 17	82.05	0.33	24.67
CIAGAN Baseline	99.73	54.38	2.94
Thesis Model	99.80	65.43	1.20

Evaluation - Main Results

Wanted Parts	Detection (\uparrow)		Identification(\downarrow)	FID (\downarrow)	LPIPS(\uparrow)
	Dlib	SSH	FaceNet		
Hair, Neck	99.80	65.43	1.20	67.11	0.025
Mouth, Lips	99.61	72.10	1.08	94.77	0.141
Eyes, Eyebrows	99.85	72.15	0.82	83.94	0.214
Everything	99.78	69.89	1.27	68.85	0.021
Nothing	99.72	67.14	0.73	88.44	0.226
CIAGAN Baseline	99.73	54.38	2.85	71.95	0.107

Evaluation - Ablation Study

Models Evaluation on Neck, Hair	Detection (↑) Dlib	Identification (↓)	FID (↓)	LPIPS (↑)
Thesis Model	99.80	1.20	67.11	0.025
Full Segmentation Mask	99.18	1.20	71.70	0.049
No Face Mesh	1.09	0.22	142.72	0.229
No Orientation Landmarks	99.59	0.46	71.93	0.103
No Reconstruction Loss	0.41	0.33	274.77	0.225
No Inverse Reconstruction Loss	99.61	1.15	72.77	0.065
No Diversity Loss	99.92	0.29	85.55	0.045

Evaluation - Ablation Study

Models Evaluation on Neck, Hair	Hair, Neck		Mouth, Lips		Eyes, Eyebrows		Everything		Nothing	
	FID (↓)	LPIPS (↑)	FID	LPIPS	FID	LPIPS	FID	LPIPS	FID	LPIPS
Thesis Model	67.11	0.025	94.77	0.141	83.94	0.214	66.85	0.021	88.44	0.226
Full Segmentation Mask	71.70	0.049	72.11	0.050	72.35	0.051	74.60	0.051	75.00	0.051
No Face Mesh	142.72	0.229	204.33	0.356	266.22	0.362	132.93	0.134	253.08	0.345
No Orientation Landmarks	71.93	0.103	89.75	0.173	86.66	0.192	73.02	0.074	85.53	0.196
No Reconstruction Loss	274.77	0.225	277.76	0.277	274.21	0.278	274.98	0.213	274.34	0.282
No Inverse Reconstruction Loss	72.77	0.065	95.09	0.095	85.13	0.144	71.75	0.036	85.36	0.147
No Diversity Loss	85.55	0.045	106.39	0.035	91.46	0.048	100.42	0.018	96.58	0.064

Evaluation - Video

Models	PSNR (\uparrow)	LPIPS (\downarrow)	tOF (\downarrow)	tLP (\downarrow)
Evaluation on Neck, Hair				
Thesis Model	21.66	0.133	1.02	5.97
CIAGAN Baseline	25.99	0.077	0.22	1.65

Conclusion

- Full Anonymization Pipeline
- Good detection and de-identification rates
- Flexible shape anonymization model to improve control over the generated images, including on neck and hair
- The pipeline generates realistic faces, however the blending step could be improved

THANK YOU

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