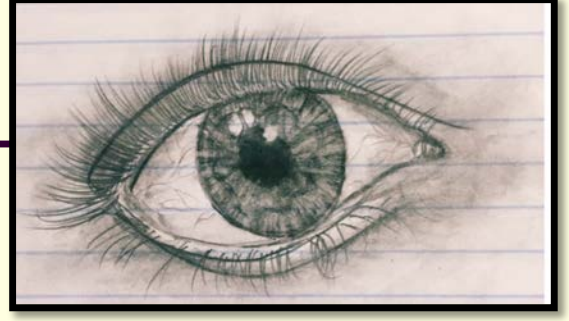


Privacy and Data Integrity in Biometrics

Arun Ross

Michigan State University

http://iprobe.cse.msu.edu/

The iPRoBe Lab

http://iprobe.cse.msu.edu

https://twitter.com/iPRoBeLab

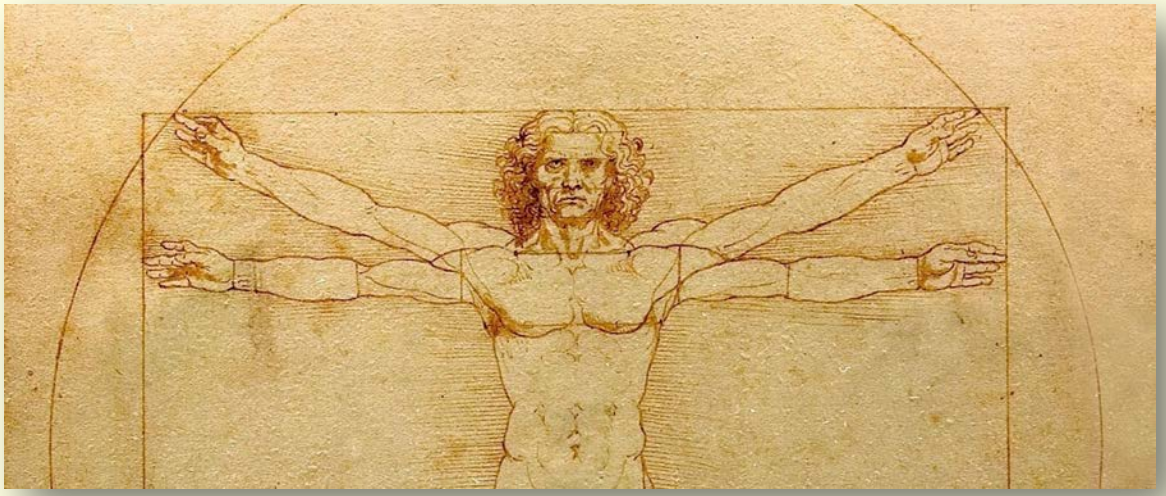
- Integrated Pattern Recognition and Biometrics Lab
- Currently: 7 PhD + 3 UG + 2 MS Students
- Graduated: 26 MS Thesis Students + 11 PhD Students

Research Theme

- **Adversarial Biometrics**
  - Spoofing Biometric Traits
  - Digitally Altered Biometric Data
  - Degraded Biometric Data
- **Privacy**
  - What Else Does Your Biometric Data Reveal?
  - Privacy Preserving Biometrics
- **Biometric Fusion**
  - Multiple Biometrics | Multispectral Biometrics
  - Biometrics + Demographics

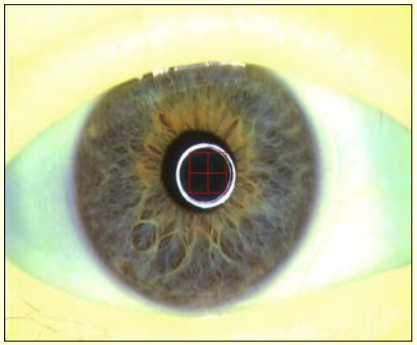
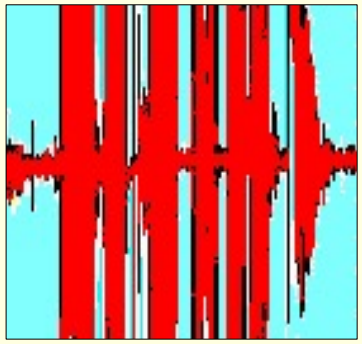
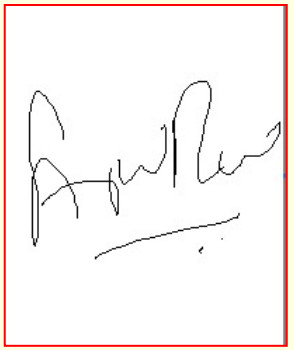
Biometrics

- Automated recognition of individuals based on their **biological** and **behavioral** characteristics
- Traits from which **distinguishing, repeatable** features can be extracted

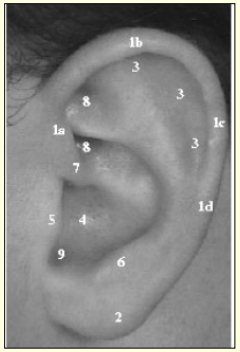


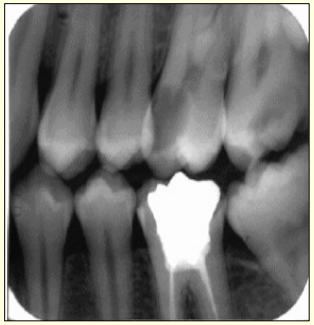
Biometric Traits







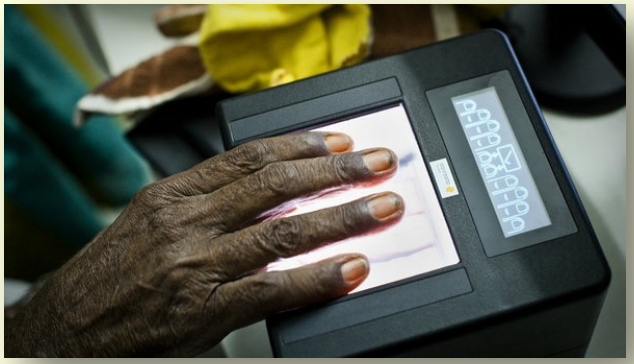


Biometric Applications

Iris: Health Care

Fingerprint: US OBIM

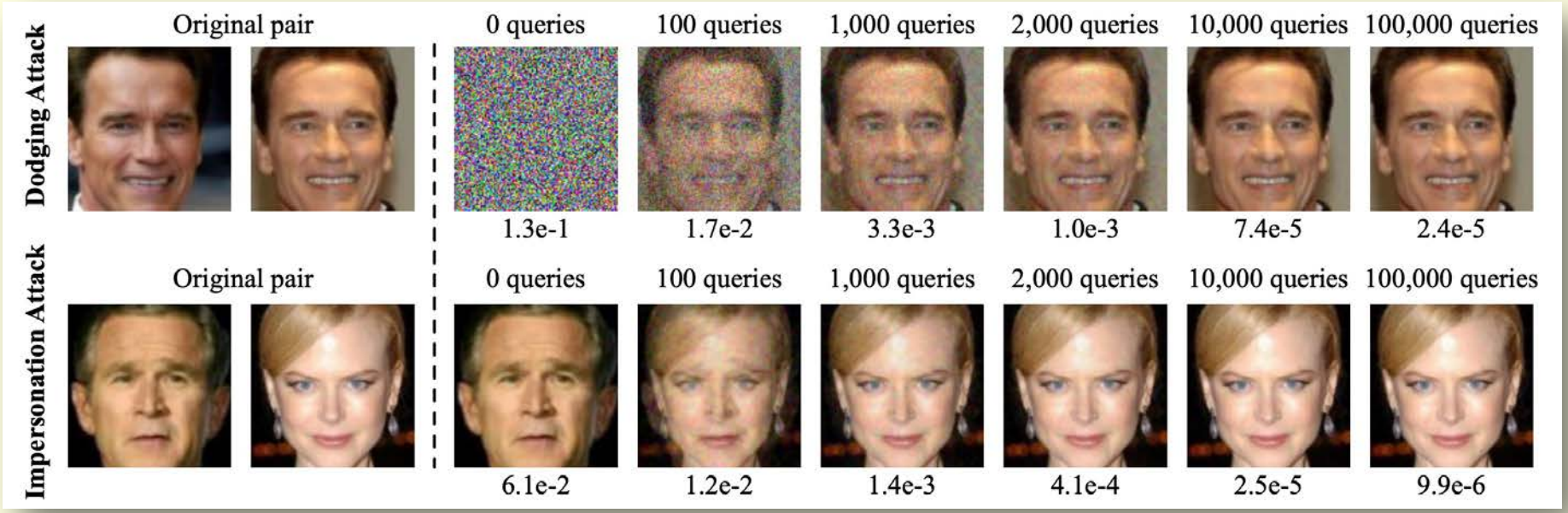
Face: Apple Face ID



Fingerprint: Refugee Services

Finger Vein: ATMs

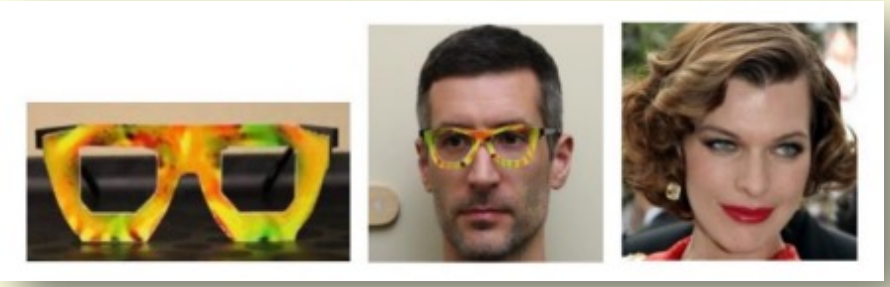
Altered Data: Blackbox Attacks



Dong et al, "Efficient decision-based black-box adversarial attacks on face recognition", CVPR 2019

Altered Data: Physical Attacks

- Presentation attacks: face masks
- 3D printed glasses: for dodging and impersonating others
  - Sharif et al., "Accessorize to a crime: Real and stealthy attacks on state-of-the-art face recognition, 2016
- Adversarial patches printed on T-Shirts to evade detectors
  - Thys et al., "Fooling automated surveillance cameras: Adversarial patches to attack person detection," CVPRW 2019



User **Target**

https://syncedreview.com/2019/04/24/now-you-see-me-now-you-dont-fooling-a-person-detector/

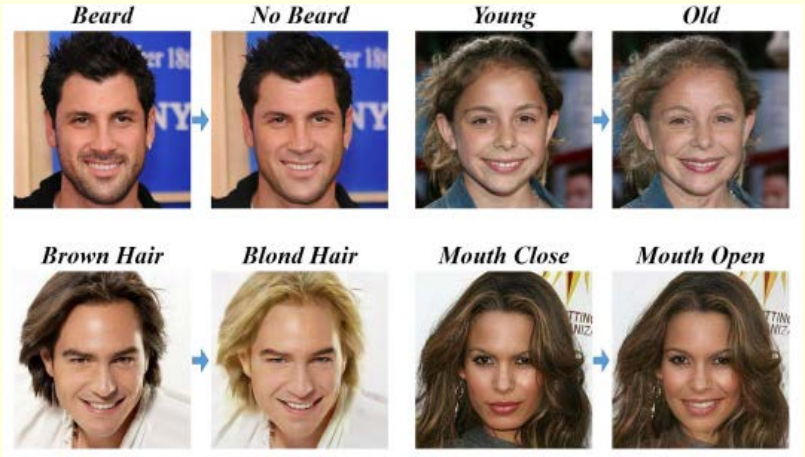
Real-world Challenges

Motivation – Why is the focus on biometric images?

- Widespread use of Photoshop and Snapchat filter on face images
- Deep learning-based manipulations are increasingly prevalent (attribute modifications, makeup transfer)

Media forensics

https://www.hindawi.com/journals/tswj/2013/795408/



https://arxiv.org/pdf/1711.10678.pdf

https://neurohive.io/en/news/adobe-trained-a-neural-network-that-detects-photoshopped-faces/

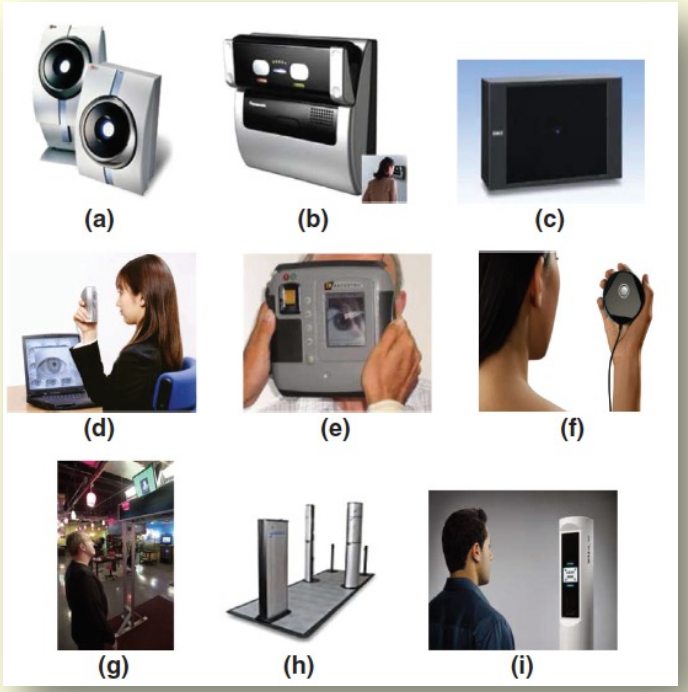
Image Forensics

- **Origin:** Which sensor produced this image?
- **Altered:** Is this an altered image?
- **Relationship:** How are these images related?

From Image to Sensor

IMAGE

SENSORS



Unit Level versus Brand Level

Banerjee, Ross, "Impact of Photometric Transformations on PRNU Estimation Schemes: A Case Study Using Near Infrared Ocular Images," IWBF 2018

PRNU: General Approach

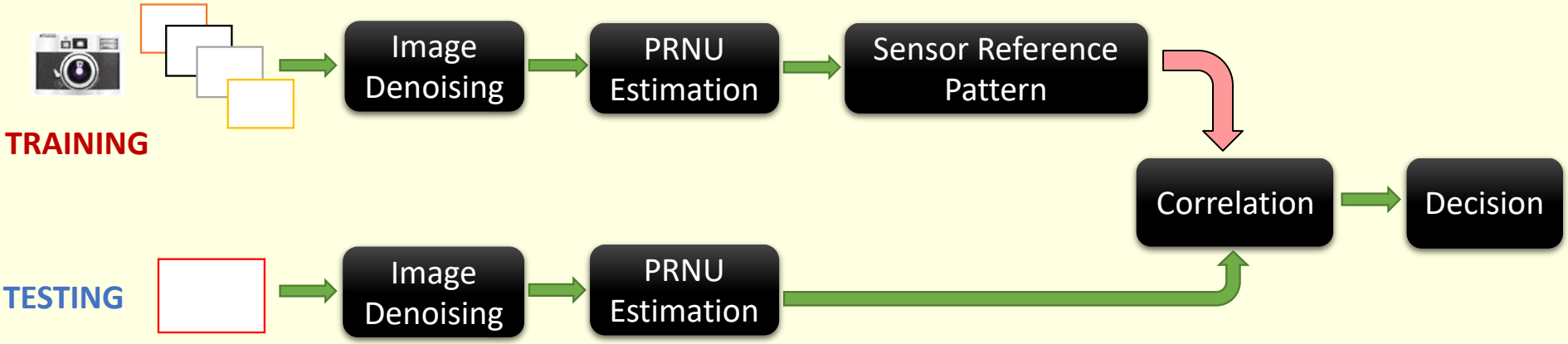
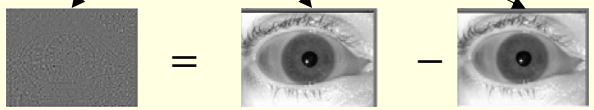


Image Denoising : Extract the PRNU, w_i from an image I_i using a denoising filter, $F(\cdot)$ to suppress scene influences

$$w_i = I_i - F(I_i)$$



$F(\cdot)$ can be wavelet-based filter

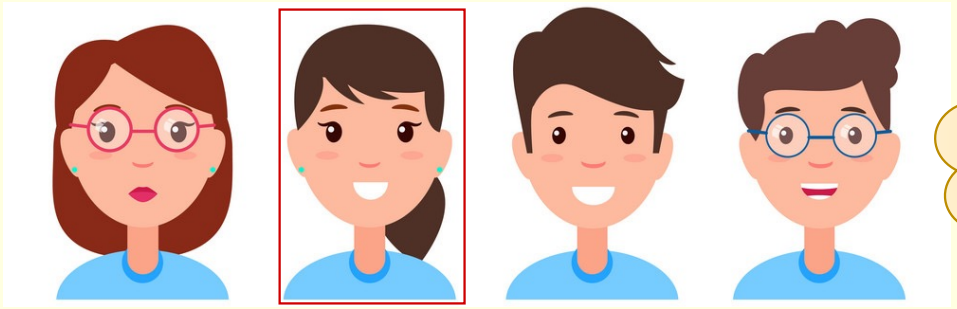
Lukas et al., "Digital camera identification from sensor pattern noise," TIFS 2006

PRNU: Privacy Concern

- Identify camera used to acquire an image → Link camera to owner

Identify smartphone camera (using PRNU)

It is a Moto G7



Eve has a Moto G7!

Sensor De-identification

Original Image	PRNU Spoofed Image
 IP5 1 FRONT	 Galaxy S4 FRONT
 Galaxy S4 REAR	 IP5 2 REAR
 IP5 2 FRONT	 IP5 1 FRONT
 Galaxy S4 FRONT	 IP5 1 FRONT

Source Sensor

Target Sensor

Banerjee, Ross, "Smartphone Camera De-identification while Preserving Biometric Utility," BTAS 2019

Sensor De-identification

$$\begin{bmatrix} 5205.7 & 4300.5 & 3208.4 & 700.5 & 25.1 & 19.6 & -27.2 & 0.86 \\ 4927.6 & 1301.3 & 45.9 & -23.4 & 32.9 & 7.0 & 6.2 & -3.4 \\ 246.7 & 301.8 & 128 & 435 & 23.4 & 19.7 & 21.9 & 1.2 \\ 136.8 & 45.6 & -27.2 & 17.0 & 34.7 & 43.8 & -2.3 & 0.9 \\ 57.9 & 23.1 & 43.1 & 13.7 & 23.1 & 0.9 & 5.7 & 4.4 \\ 805.3 & -3.9 & 0.05 & 2.5 & 1.9 & -3.4 & 11.9 & 7.8 \\ -24.1 & 10.1 & 7.9 & -2.4 & 7.9 & 12.1 & 4.3 & 2.1 \\ 3.7 & -2.4 & 0.2 & 2.1 & 4.5 & -0.7 & 1.7 & 2.9 \end{bmatrix}$$

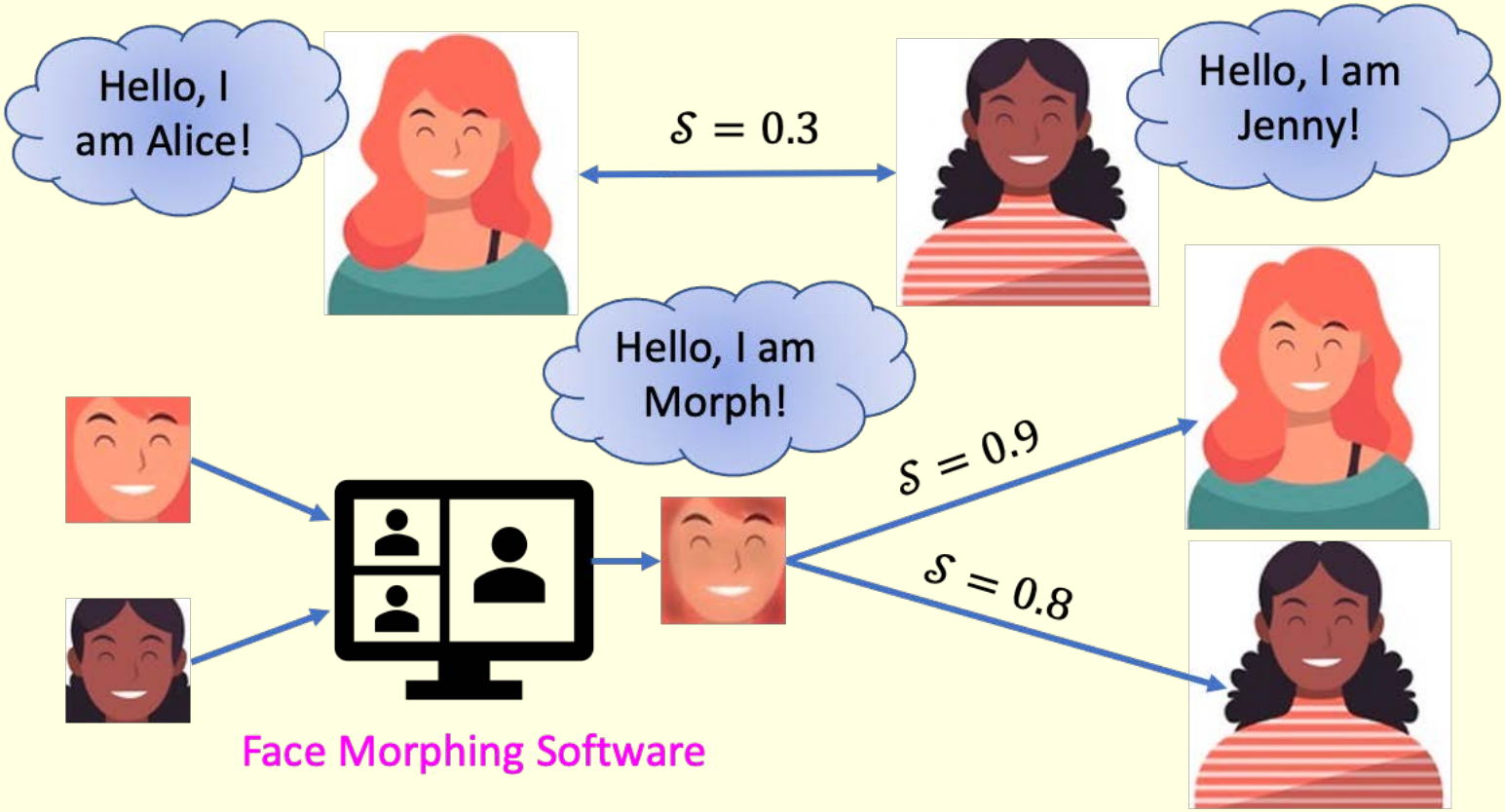
Modulating DCT coefficients

- **Sensor anonymization (~83% reduction in sensor identification)**
- **Sensor spoofing (~99.5% successfully spoofed)**
- **Without compromising matching performance (~1% deviation between pre and post perturbed images)**

Banerjee, Ross, "Smartphone Camera De-identification while Preserving Biometric Utility," BTAS 2019

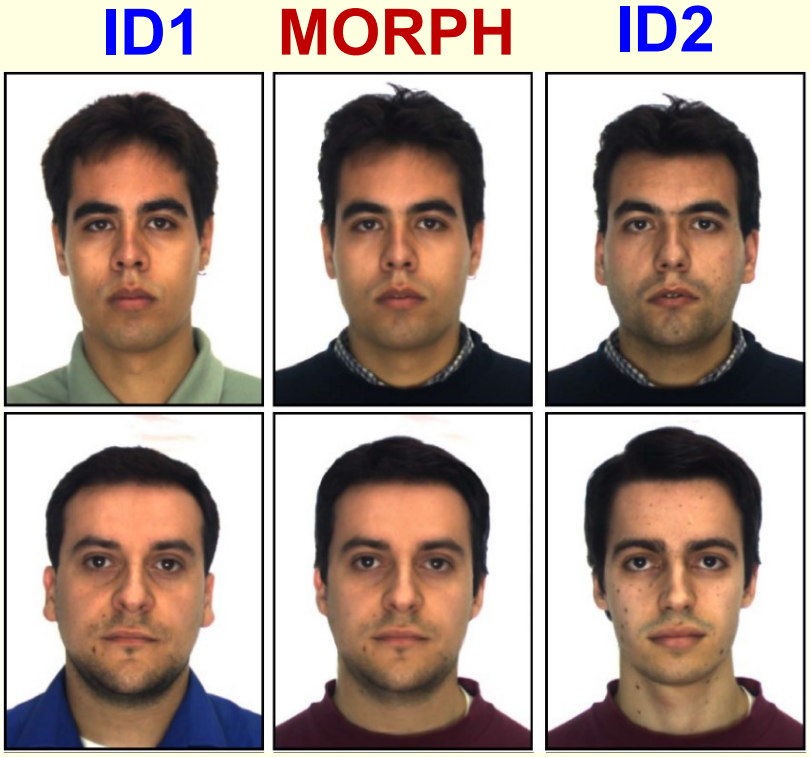
Digital Data: Morphed Faces

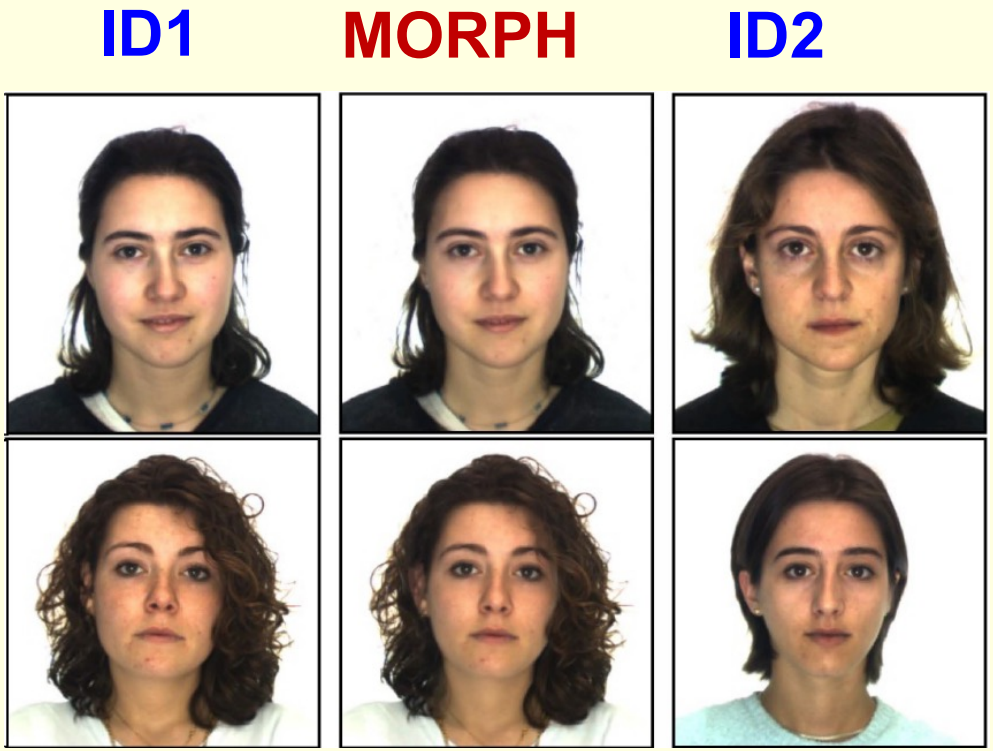
- Morphed Faces: Combining two face images



Morphed Faces: Examples

- Morphing combines face images from multiple identities
- Morphed face image matches all component identities

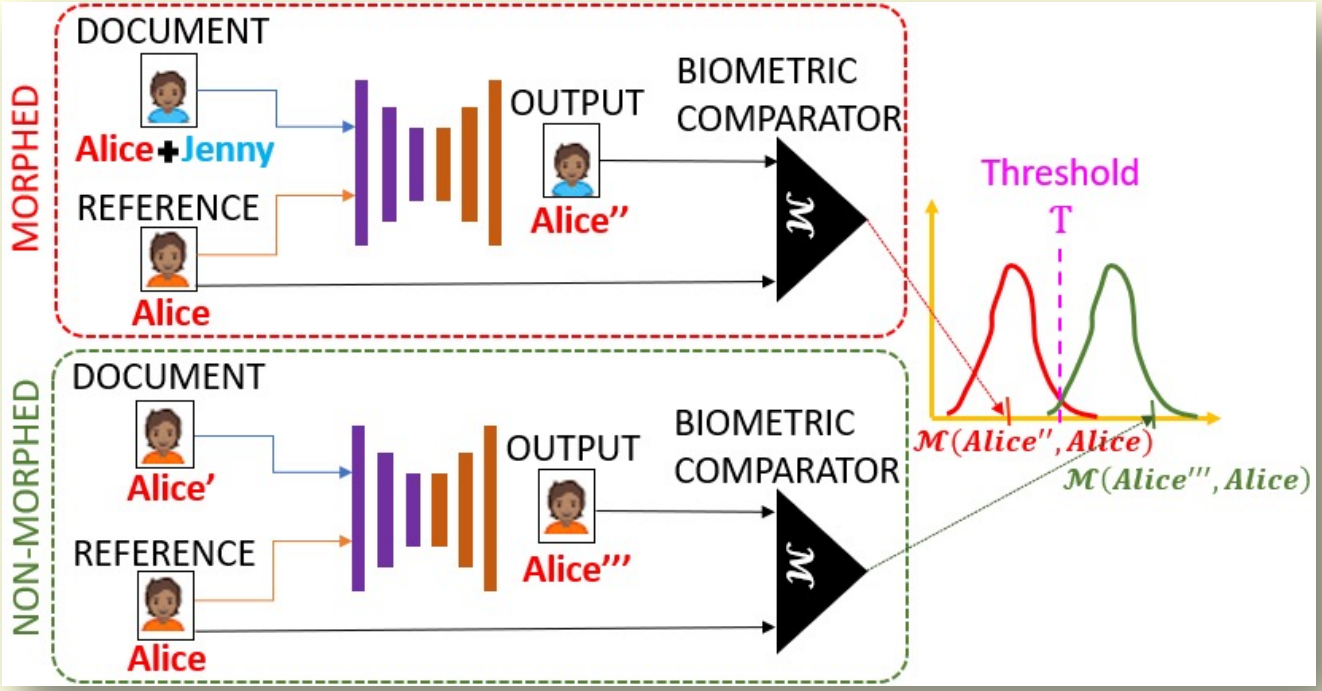




Ferrara et al, "The Magic Passport," IJCB 2014
Also see, Othman and Ross,
"Privacy of Facial Soft Biometrics: Suppressing Gender But Retaining Identity," ECCVW 2014

Detecting Morphed Faces

- We use a conditional generative network that translates the document image (morphed/non-morphed) to reference image (trusted live)
- Output of cGAN is compared with reference image, and score is used for decision

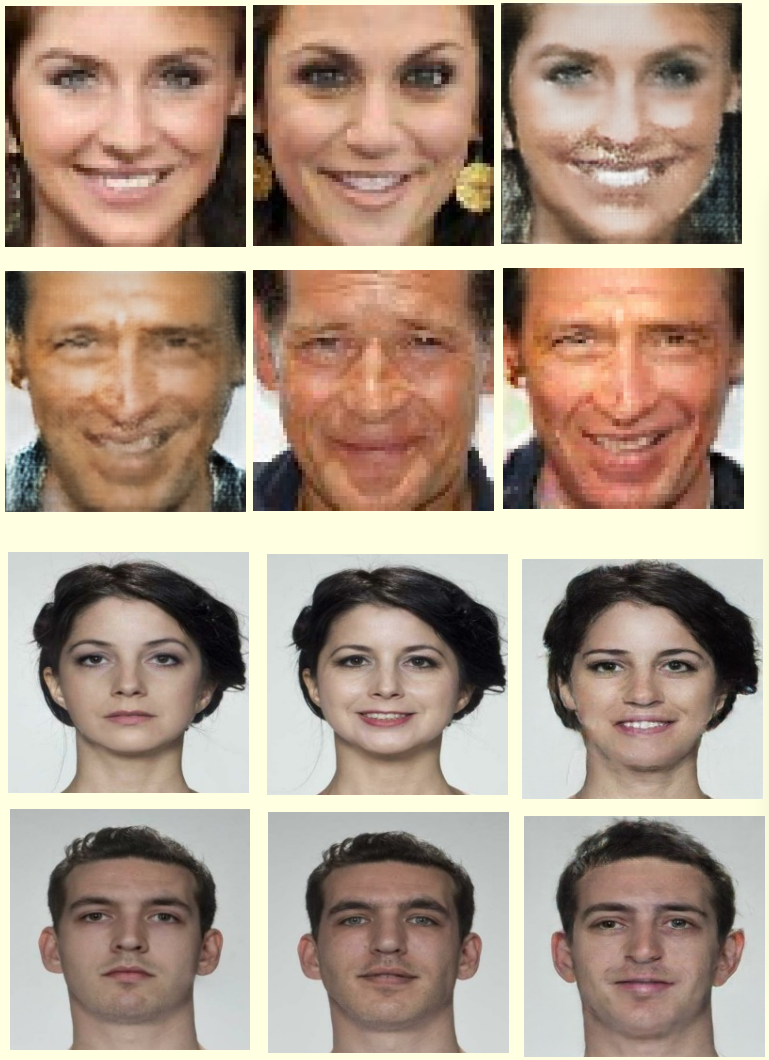


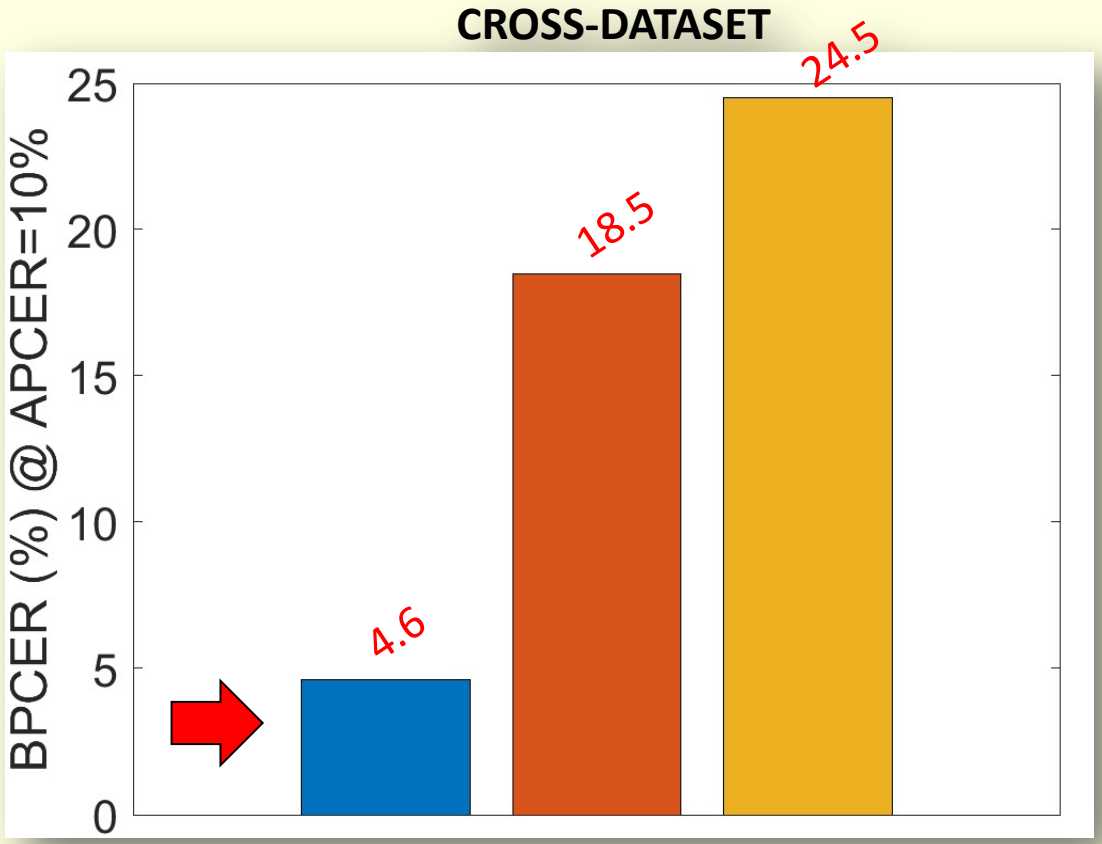
Hypothesis:
Output of cGAN will be more dissimilar to reference image in case of morphs, compared to non-morphs

Banerjee and Ross, Conditional Identity Disentanglement for Differential Face Morph Detection, IJCB 2021

Detecting Morphed Faces

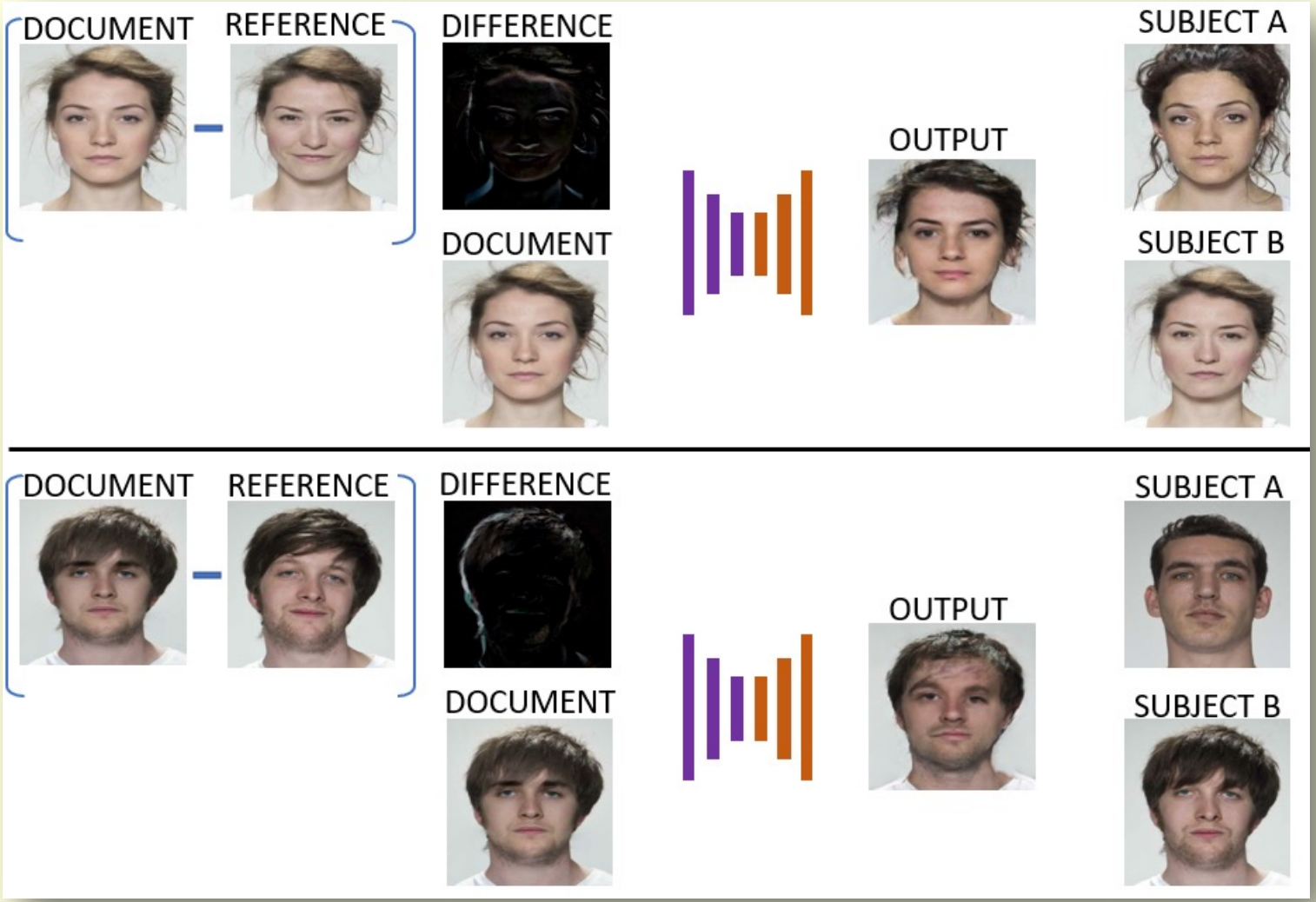
DOCUMENT REFERENCE OUTPUT





Banerjee and Ross, Conditional Identity Disentanglement for Differential Face Morph Detection, IJCB 2021

Deducing the Accomplice!



Matching output of cGAN with Second Subject is 23.4% higher than that of First Subject

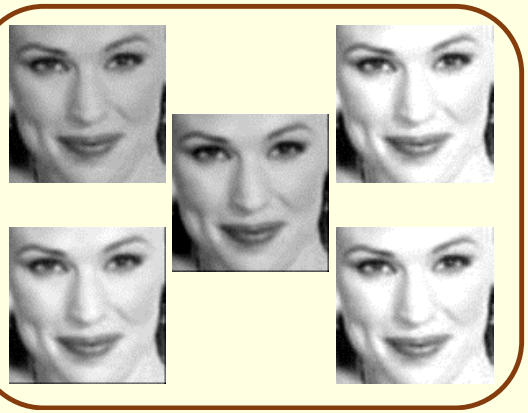
Biometric similarity is assessed in terms of TMR @FMR=1%

Banerjee and Ross, Conditional Identity Disentanglement for Differential Face Morph Detection, IJCB 2021

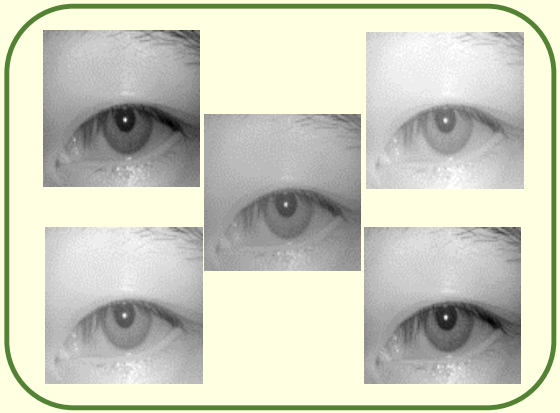
Digital Data: Near Duplicates

- Near Duplicates: Subtly Modified Images

Brightness adjustment



Gamma transformation

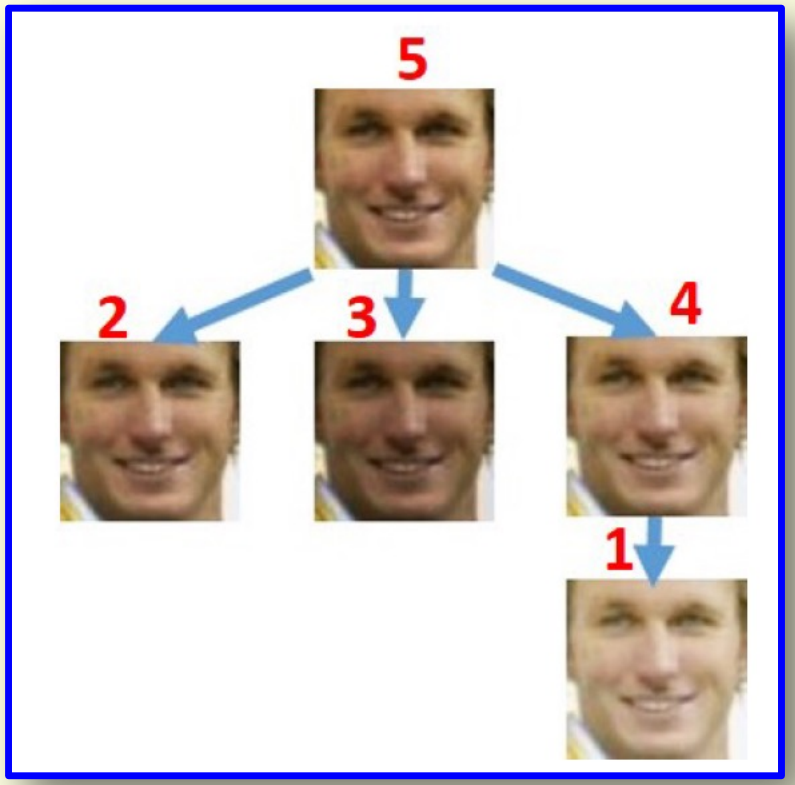


Rotation

S. Banerjee and A. Ross, "Face Phylogeny Tree Using Basis Functions," IEEE TBIOM, 2020

Relationship Between Images

- Phylogeny Tree: Relationship between near duplicate images



S. Banerjee and A. Ross, "Face Phylogeny Tree Using Basis Functions," IEEE TBIOM, 2020

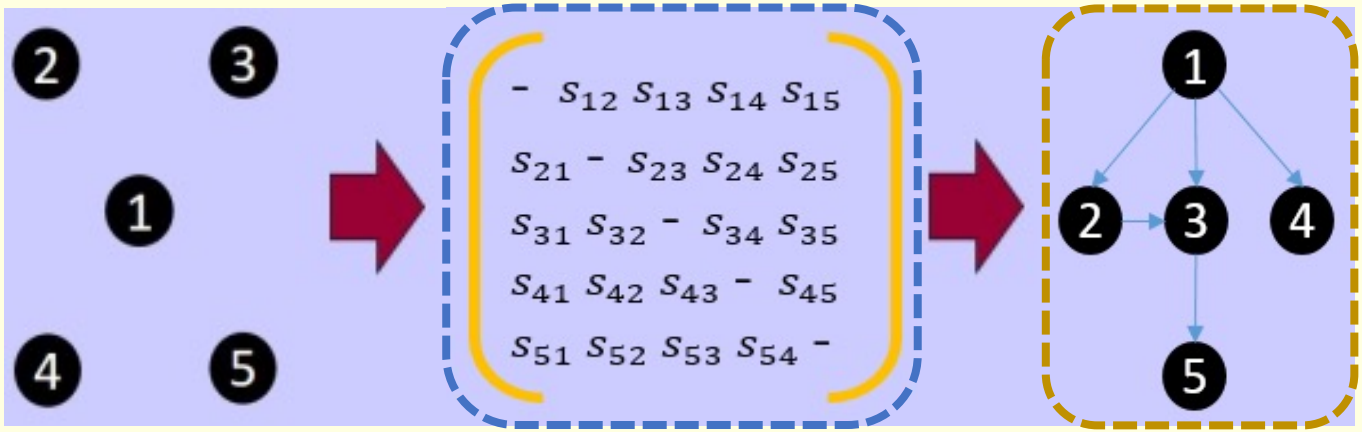
Importance of Problem

- Deduce whether a set of photometrically transformed images originated from a single source image or multiple sources
- Detection of image tampering hinted by significant photometric variation between two images
- Determination of transformation parameters relating two images

Forensics + Data Analysis

Image Phylogeny Tree (IPT)

- IPT construction is a 2-step process:
  - STEP I : Computing pairwise asymmetric measure
  - STEP II: Using a tree-spanning algorithm



Set of 5 near-duplicate photometrically related images	Compute an asymmetric similarity/dissimilarity matrix depicting pair-wise relationships	Use a tree-spanning algorithm to construct IPT

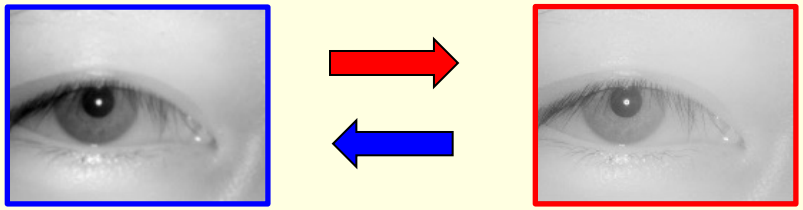
What are the Challenges?

- Photometric Transformations ▸ Large number
  - E.g., Brightness, Contrast, CLAHE, Gamma, Median, Gaussian

- Each Transformation ▸ multiple parameters
  - E.g., Gaussian: window size and variance

- Each Parameter ▸ multiple values
  - E.g., Window size: 3x3, 5x5, 9x9, 13x13, ….

- Need to distinguish between A→B and B→A

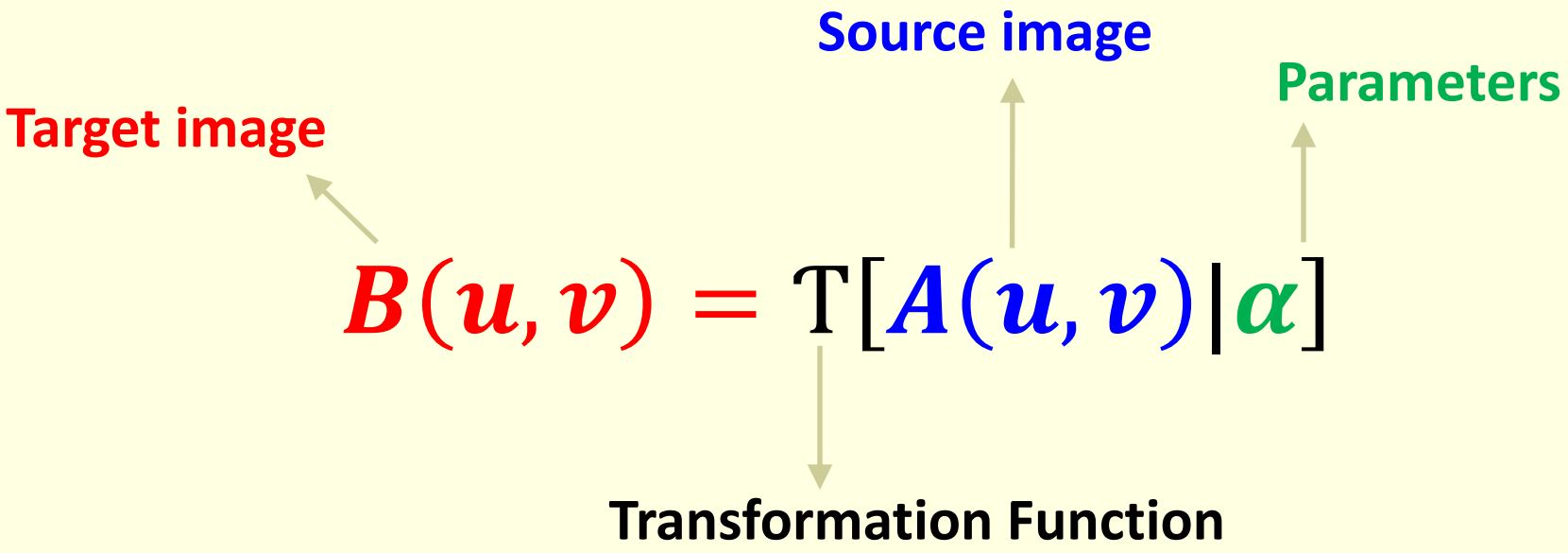


Our Approach

- Use a generic parametric transformation function to model the relationship between any two images
- Given two images, **A** and **B**, estimate the parameters of the function in both directions
- Use the likelihood of the parameters to determine which of the two cases is more likely, i.e., **A → B** or **B → A**

- **Banerjee and Ross, "Face Phylogeny Tree: Deducing Relationships Between Near-Duplicate Face Images Using Legendre Polynomials and Radial Basis Functions," BTAS 2019**
- **Banerjee and Ross, "Face Phylogeny Tree Using Basis Functions," IEEE TBIOM 2020**

Transformation Function



Transformation Function

- Model transformation from $\boldsymbol{A} \rightarrow \boldsymbol{B}$ such that the pair-wise photometric error (PE) is **minimized** for all pixels p

$$\min_{\boldsymbol{\alpha}} PE\ (\boldsymbol{A}, \boldsymbol{B}) = \min_{\boldsymbol{\alpha}} \sum_{p=1}^{N} \|\boldsymbol{B}(p) - \tau(\boldsymbol{A}(p); \boldsymbol{\alpha})\|_2^2$$

- We approximate transformations using a set of **basis** functions

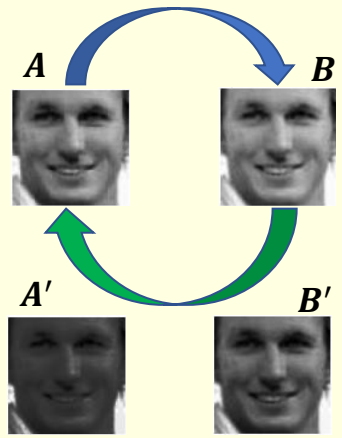
Basis Functions

Basis Functions		Utility	Formulation
Polynomials	Legendre	Used for image template matching and image reconstruction	$L_n(p) = 2^n \sum_{k=0}^{n} p^k \binom{n}{k} \binom{\frac{n+k-1}{2}}{n}$
	Chebyshev	Used for approximating complex functions (spectral convolutions)	$C_n(p) = p^n \sum_{k=0}^{\lfloor \frac{n}{2} \rfloor} \binom{n}{2k} (1 - x^{-2})^k$
Wavelets	Gabor	Used as texture descriptors, acts as bandpass filters	$\varphi(p, \theta, \lambda) = g(p, \lambda) \cdot w(p, \theta)$ $\lambda = \{2, 3, 4, 5\};\ \theta = \{0^\circ, 45^\circ, 90^\circ, 135^\circ\}$
Radial Basis Functions	Gaussian	Used for interpolation	$K(p) = exp\|p - \mu\|^2$
	Bump	Used as smooth cutoff functions	$K(p) = exp\left(-\frac{1}{1-p^2}\right)$

p: *Pixel intensity value* ; n: *Polynomial order* ; μ: *Mean pixel intensity value* ; λ: *Scale* ; θ: *Orientation*

Banerjee and Ross, "Face Phylogeny Tree: Deducing Relationships Between Near-Duplicate Face Images Using Legendre Polynomials and Radial Basis Functions," BTAS 2019

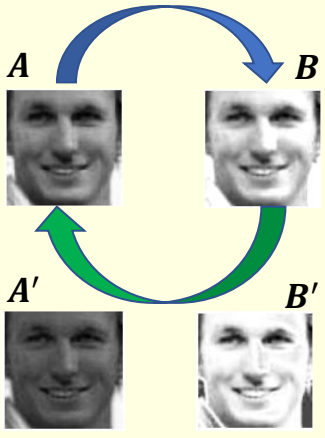
Basis Functions



Output of modeling $B \rightarrow A$

Output of modeling $A \rightarrow B$

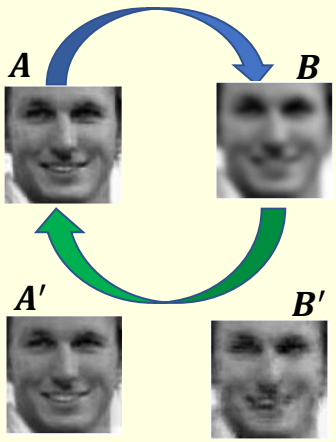
LEGENDRE



Output of modeling $B \rightarrow A$

Output of modeling $A \rightarrow B$

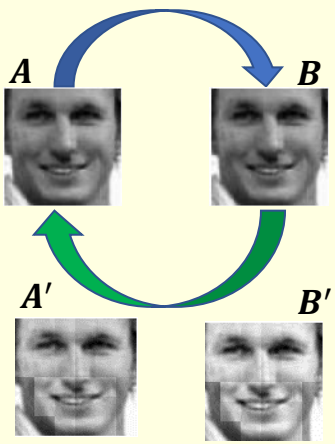
CHEBYSHEV



Output of modeling $B \rightarrow A$

Output of modeling $A \rightarrow B$

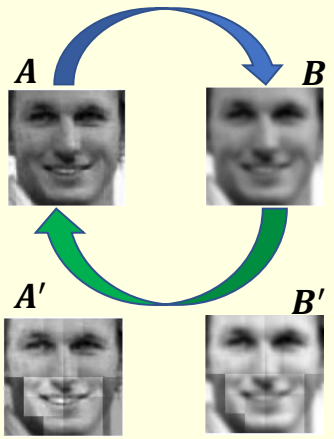
GABOR



Output of modeling $B \rightarrow A$

Output of modeling $A \rightarrow B$

GAUSSIAN RBF



Output of modeling $B \rightarrow A$

Output of modeling $A \rightarrow B$

BUMP RBF

- **Banerjee and Ross, "Face Phylogeny Tree: Deducing Relationships Between Near-Duplicate Face Images Using Legendre Polynomials and Radial Basis Functions," BTAS 2019**
- **Banerjee and Ross, "Face Phylogeny Tree Using Basis Functions," IEEE TBIOM 2020**

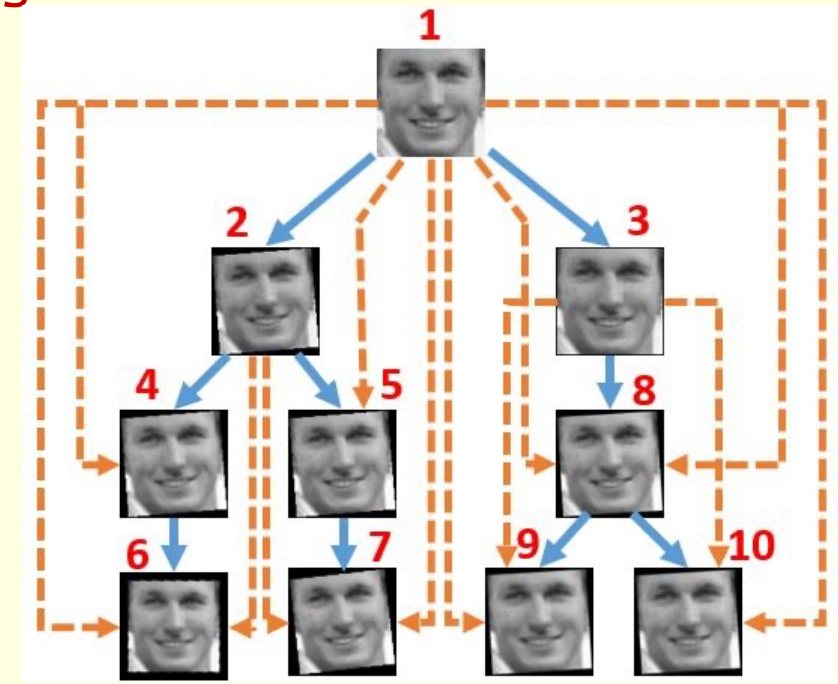
Asymmetric Measure

- Modeling the transformation in both directions results in two estimated parameter vectors $(\boldsymbol{\alpha}, \boldsymbol{\beta})$
- Compute the likelihood ratio $\left(\boldsymbol{\Lambda_\alpha} = \frac{p_f(\boldsymbol{\alpha})}{p_r(\boldsymbol{\alpha})}, \boldsymbol{\Lambda_\beta} = \frac{p_f(\boldsymbol{\beta})}{p_r(\boldsymbol{\beta})}\right)$ of the estimated parameters to obtain asymmetric measure
- Use depth first search to construct IPT

- Banerjee and Ross, "Face Phylogeny Tree: Deducing Relationships Between Near-Duplicate Face Images Using Legendre Polynomials and Radial Basis Functions," BTAS 2019
- Banerjee and Ross, "Face Phylogeny Tree Using Basis Functions," IEEE TBIOM 2020

Experiments

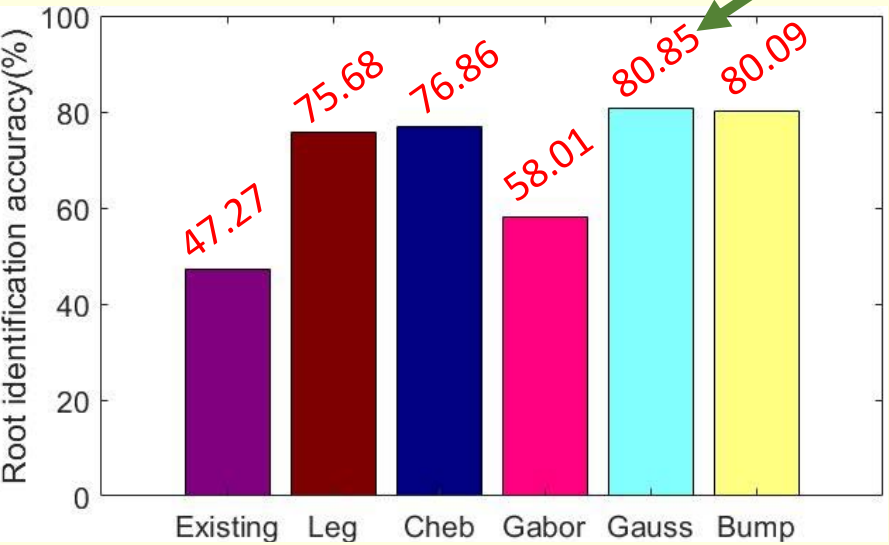
- We generated 2,727 IPTs by subjecting face images to random sequence of 4 transformations resulting in 27,270 images



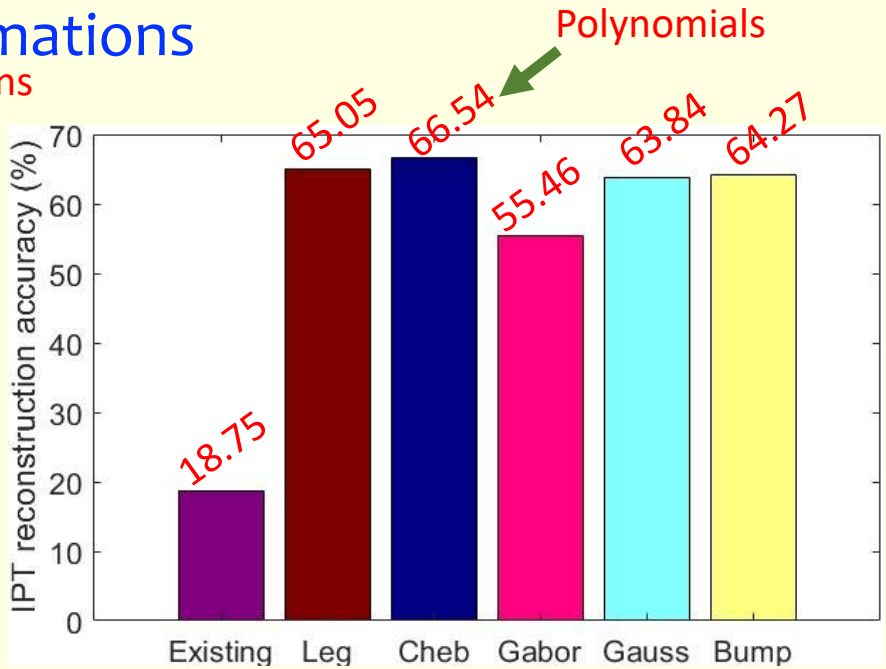
- Banerjee and Ross, "Face Phylogeny Tree: Deducing Relationships Between Near-Duplicate Face Images Using Legendre Polynomials and Radial Basis Functions," BTAS 2019
- Banerjee and Ross, "Face Phylogeny Tree Using Basis Functions," IEEE TBIOM 2020

Performance

- We compared the performance with an existing method
- The problem is a very challenging one:
  - face images vs natural scenes
  - subtle photometric transformations



ROOT IDENTIFICATION



IPT RECONSTRUCTION

Banerjee and Ross, "Face Phylogeny Tree: Deducing Relationships Between Near-Duplicate Face Images Using Legendre Polynomials and Radial Basis Functions," BTAS 2019

Generalizability

- **Unseen modalities:** 7,260 near-duplicate iris images from CASIA Iris V2 Device 2 dataset
- **Unseen transformations:** 175 near-duplicates using Photoshop and 1,080 near-duplicates using deep learning-based transformations

Experimental Settings		Root identification accuracy (%)	IPT reconstruction accuracy (%)
Unseen modality	Iris	95	68
Unseen transformations	Photoshop	90	100
	Deep learning-based	83	65

- Banerjee and Ross, "Face Phylogeny Tree: Deducing Relationships Between Near-Duplicate Face Images Using Legendre Polynomials and Radial Basis Functions," BTAS 2019
- Banerjee and Ross, "Face Phylogeny Tree Using Basis Functions," IEEE TBIOM 2020

Digital Data: DeepFakes

- DeepFakes: Synthetically Generated Images



https://thispersondoesnotexist.com/

DeepTalk: Speech Synthesis

Why do we need DeepTalk?

You want to listen to…

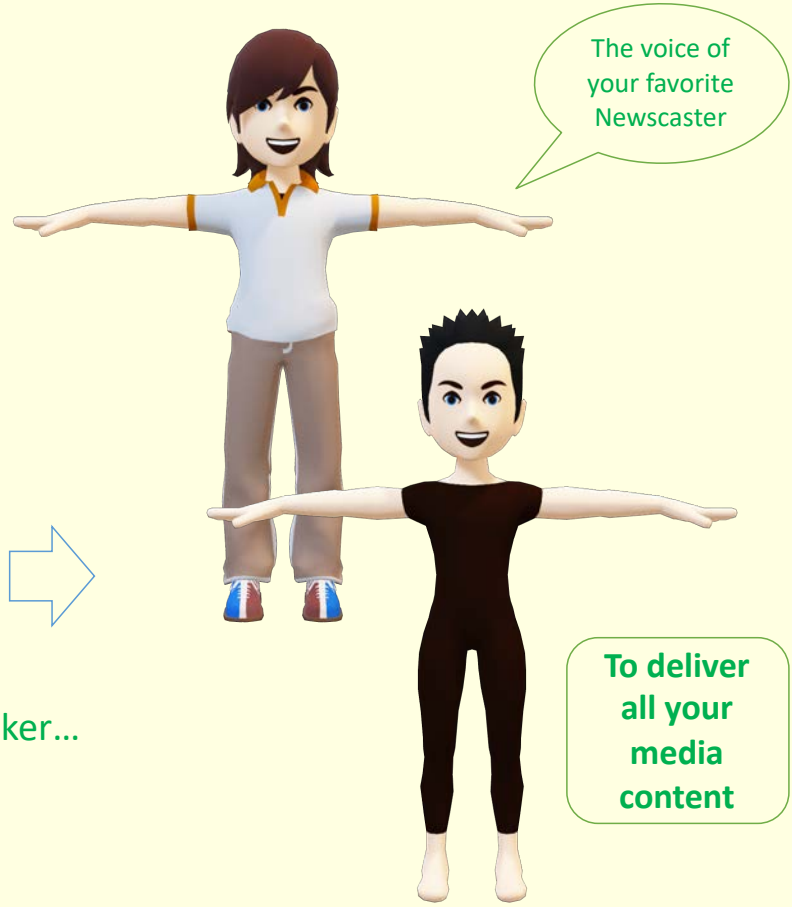
Morning News

Weather Update

Audiobook

From your smart speaker…

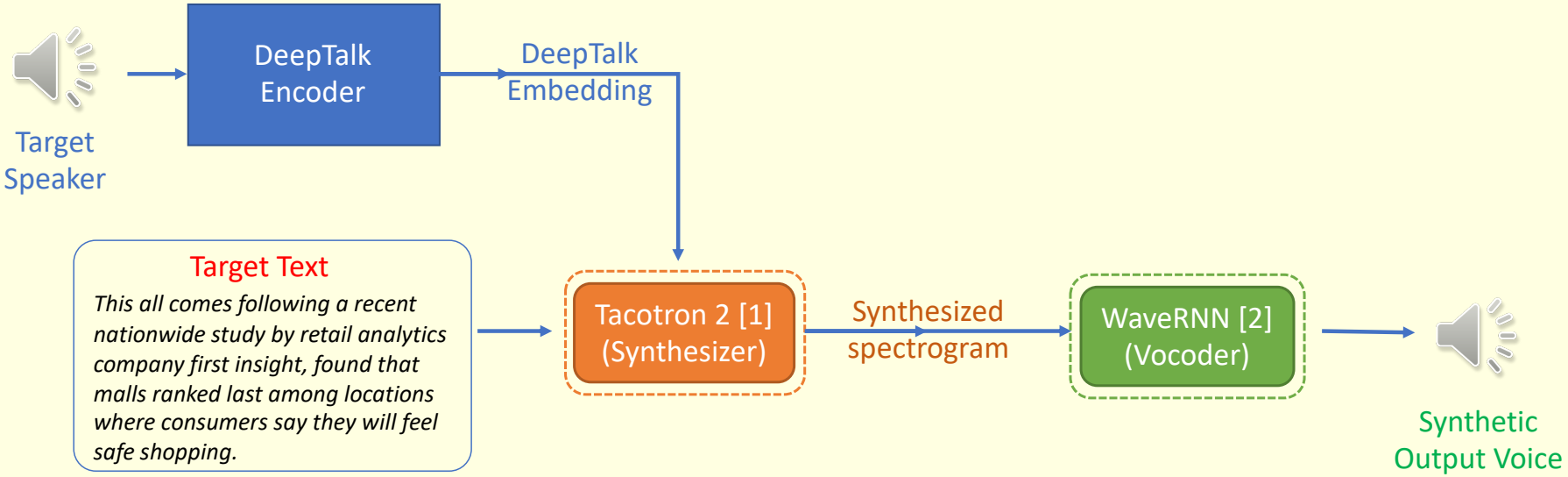
DeepTalk lets you choose…



All images taken from https://pixabay.com/

Chowdhury et al., "DeepTalk: Vocal Style Encoding for Speaker Recognition and Speech Synthesis,", ICASSP 2021

DeepTalk: Speech Synthesis



[1] Skerry-Ryan et al. "Towards end-to-end prosody transfer for expressive speech synthesis with tacotron." *arXiv preprint arXiv:1803.09047* (2018).
[2] Shen et al. "Natural TTS synthesis by conditioning wavenet on mel spectrogram predictions." In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 4779-4783. IEEE, 2018.

Chowdhury et al., "DeepTalk: Vocal Style Encoding for Speaker Recognition and Speech Synthesis,", ICASSP 2021

DeepTalk: Speech Synthesis

News Article

This all comes following a recent nationwide study by retail analytics company first insight, found that malls ranked last among locations where consumers say they will feel safe shopping.

Original Voice of Hannah

DeepTalk generated voice of Hannah after Phase 1

DeepTalk generated voice of Hannah after Phase 2

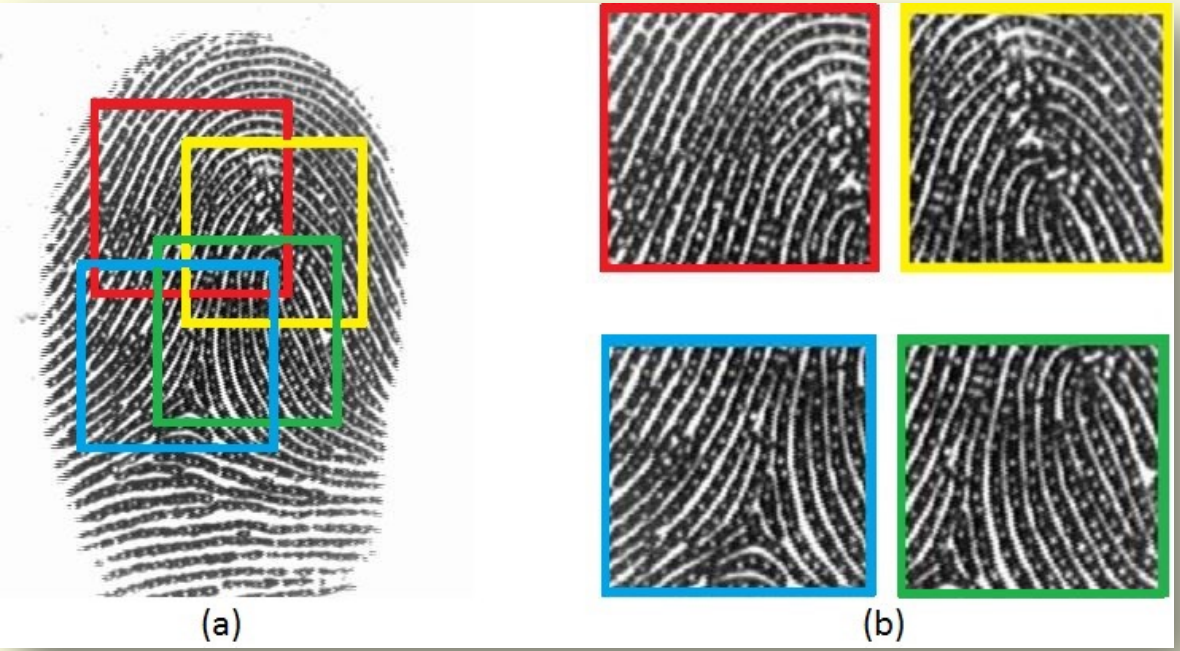
Original Voice of Ted

DeepTalk generated voice of Ted after Phase 1

DeepTalk generated voice of Ted after Phase 2

Chowdhury et al., "DeepTalk: Vocal Style Encoding for Speaker Recognition and Speech Synthesis,", ICASSP 2021

Partial Fingerprints



- Small sensors | Capture a limited portion of full finger
- Multiple partial fingerprints are captured | Enroll multiple fingers
- Access granted if the sensed partial fingerprint matches any one of the partial fingerprint of any enrolled finger

MasterPrints!

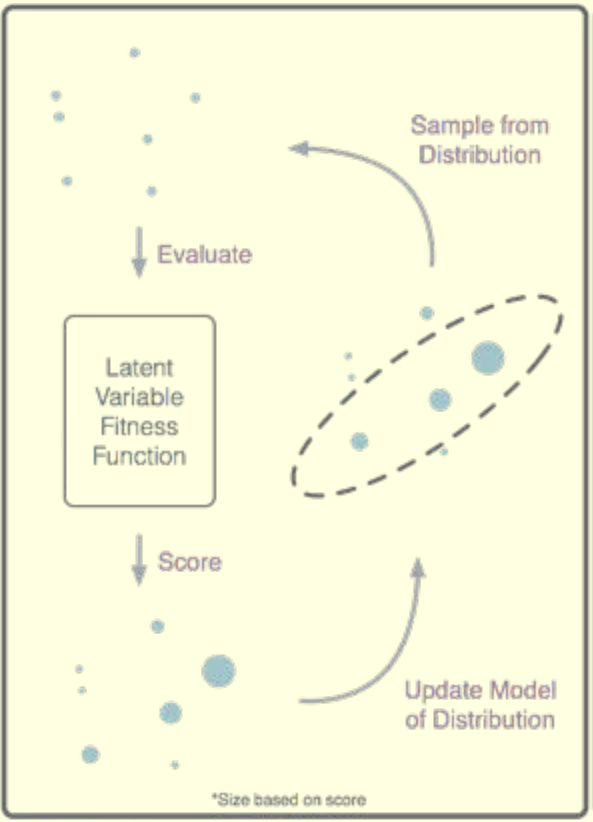
- Fingerprints that match with a large proportion of the fingerprint population
- Could be either full prints or partial prints

Roy, Memon, Ross, "MasterPrint: Exploring the Vulnerability of Partial Fingerprint-based Authentication Systems," TIFS 2017

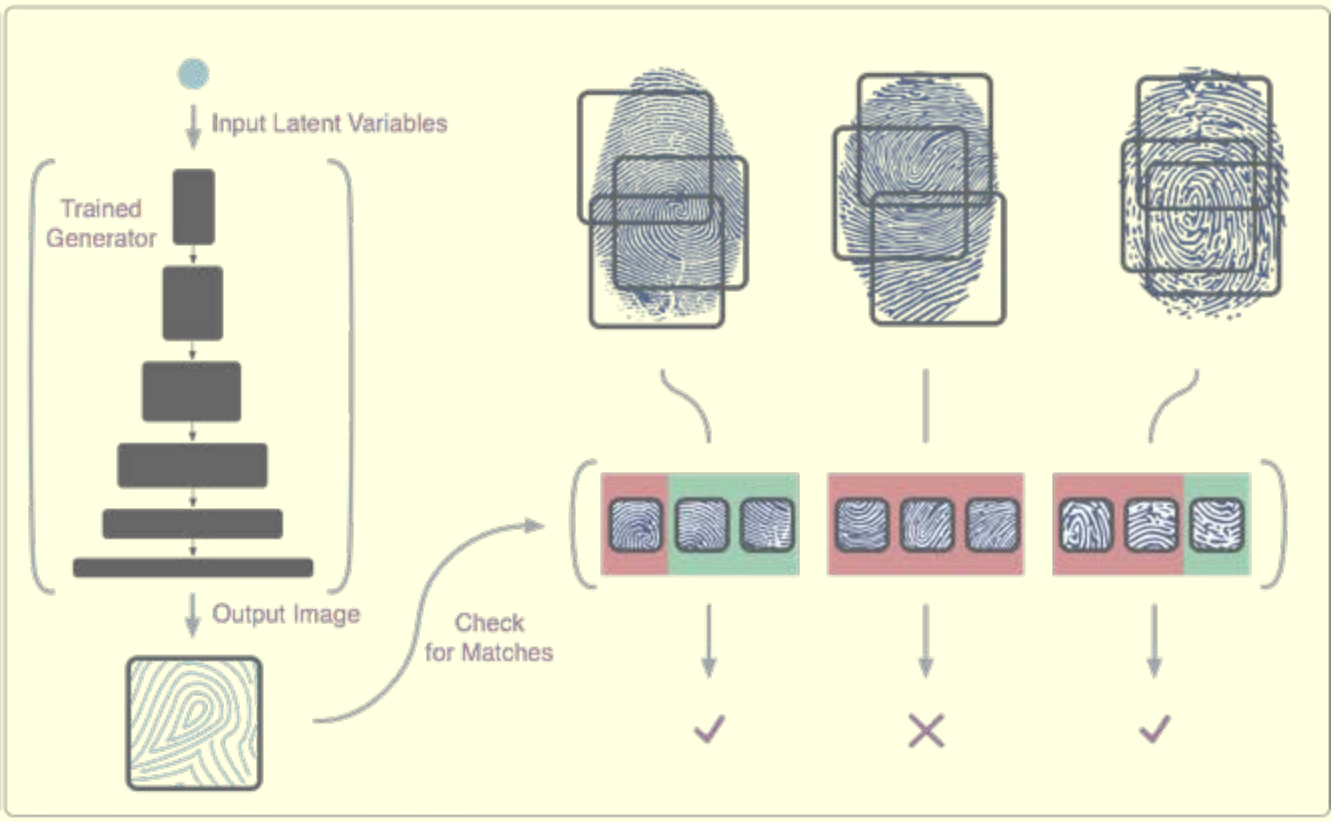
“MasterPrints”

Roy, Memon, Ross, “MasterPrint: Exploring the Vulnerability of Partial Fingerprint-based Authentication Systems,” TIFS 2017

Latent Variable Evolution



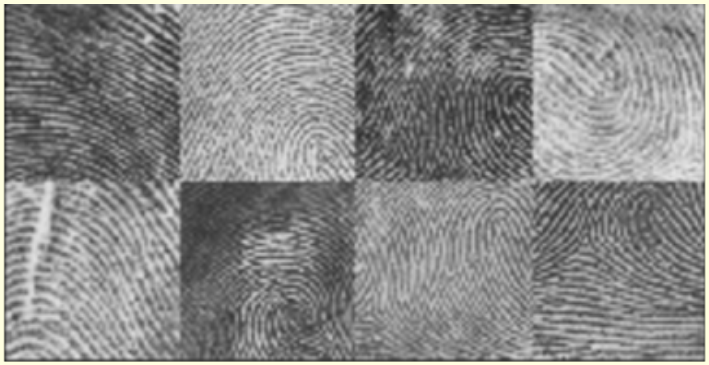
CMA-ES Optimization

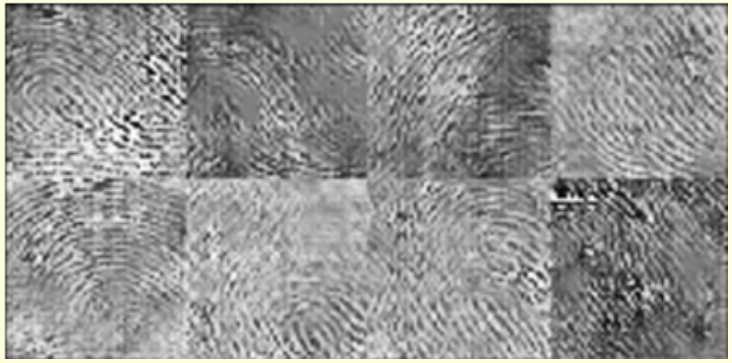


Latent Variable Fitness Function

Bontrager et al., "DeepMasterPrints: Generating MasterPrints for Dictionary Attacks via Latent Variable Evolution," BTAS 2018

GAN-based DeepMasterPrints





Increases vulnerability of small sensors to dictionary and spoof attacks

Bontrager et al., "DeepMasterPrints: Generating MasterPrints for Dictionary Attacks via Latent Variable Evolution," BTAS 2018

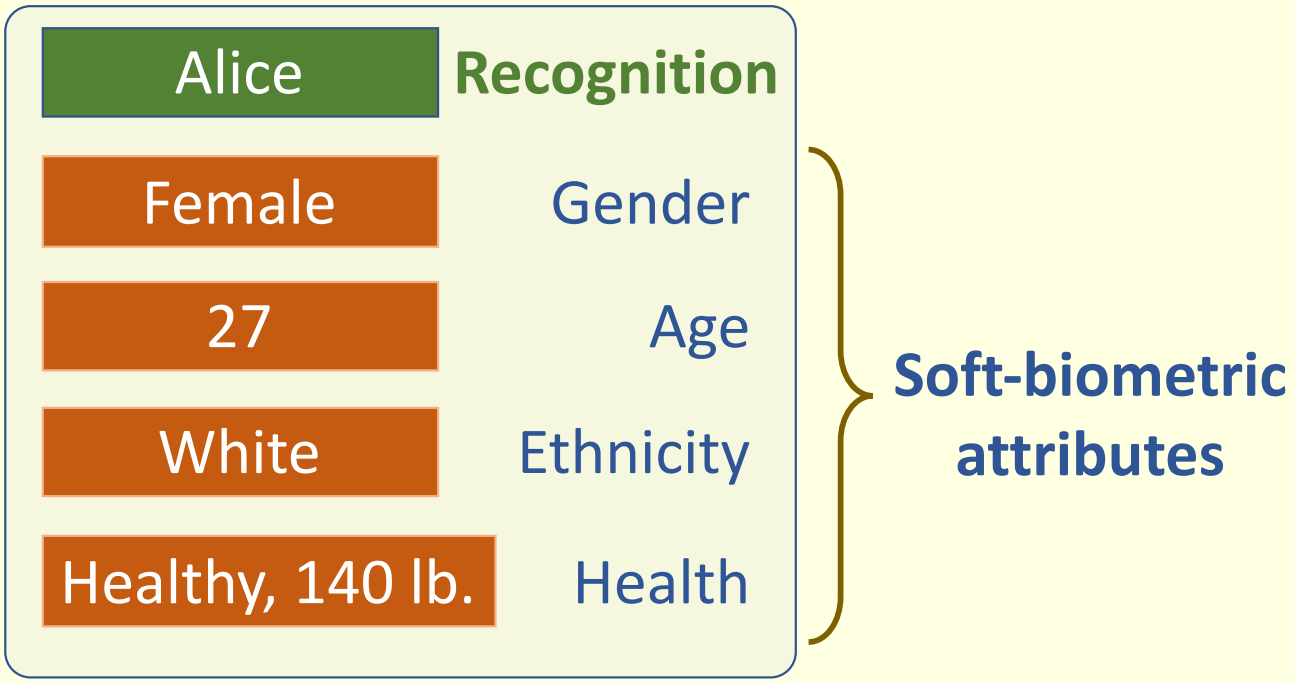
Attack Success Rate

	0.01% FMR	0.1% FMR	1% FMR
Single MasterPrint	1.88%	6.60%	33.40%
Multiple MasterPrints	6.88%	30.69%	77.92%
Single DeepMasterPrint	**1.11%**	**22.50%**	**76.67%**

Experiments on FingerPass DB7 Dataset using VeriFinger Matcher

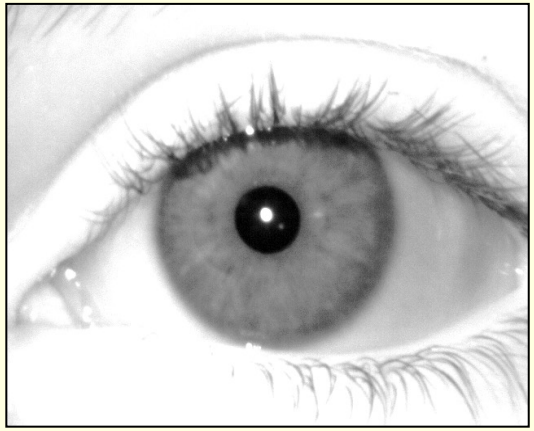
Bontrager et al., "DeepMasterPrints: Generating MasterPrints for Dictionary Attacks via Latent Variable Evolution," BTAS 2018

Soft Biometrics



- Age, Gender, Ethnicity, can be **automatically derived** from the face image
- That is, a **trained classifier or a regressor** may be used to automatically deduce certain soft biometric attributes

Biometrics + Forensics



- Subject is a Male (90% Confidence), White (85% Confidence)
- Image taken using an Aoptix camera
- Iris stroma is plain textured
- Highly constricted pupil suggests strong ambient illumination

Bridges the gap between human and machine description of data

OR

Compromises privacy?

Face2Gene

MEGAN MOLTENI SCIENCE 01.09.17 01:00 PM

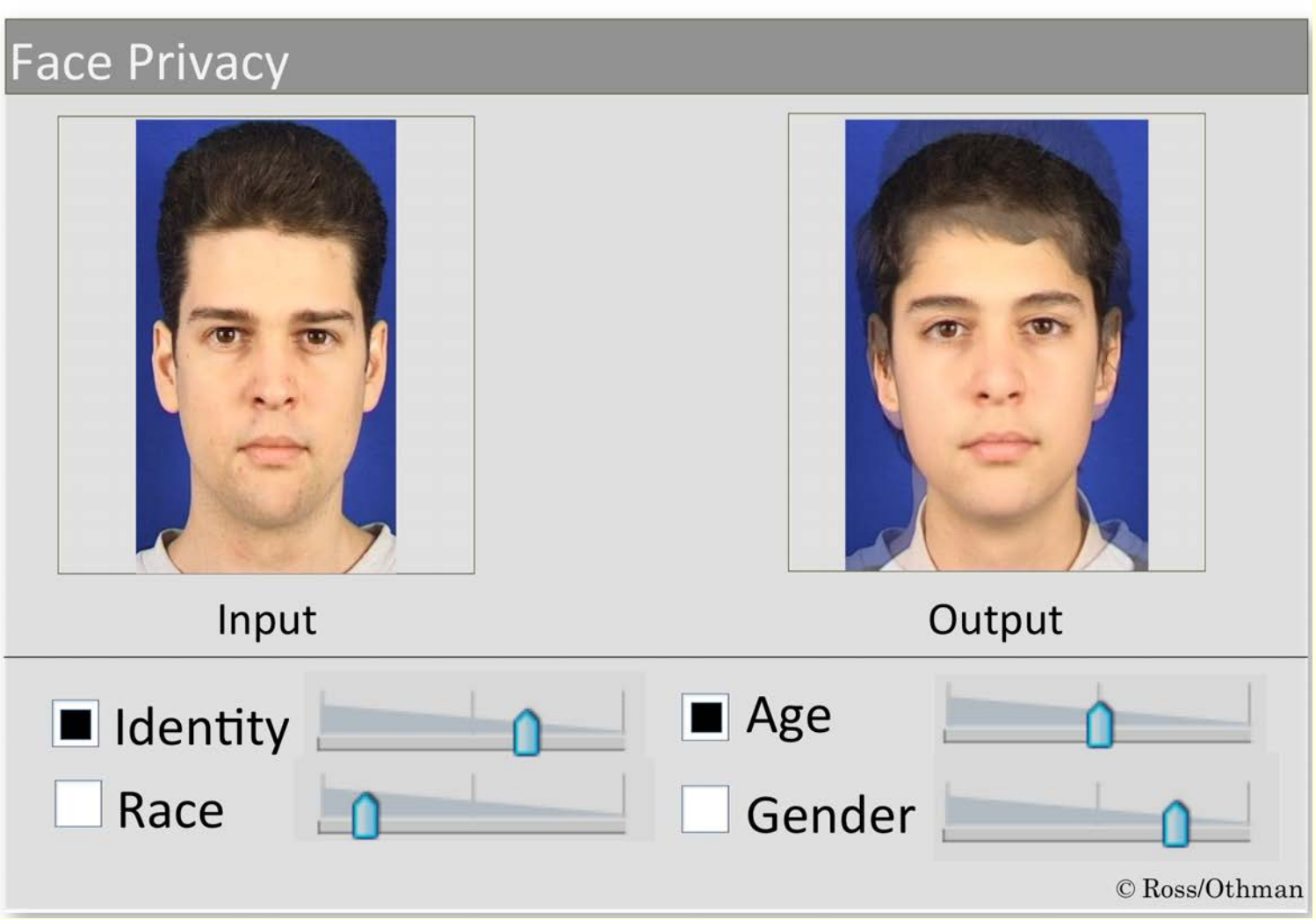
THANKS TO AI, COMPUTERS CAN NOW SEE YOUR HEALTH PROBLEMS

"In hindsight it was all clear to me," says Gripp, who is chief of the Division of Medical Genetics at A.I. duPont Hospital for Children in Delaware, and had been seeing the patient for years. "But it hadn't been clear to anyone before." What had taken Patient Number Two's doctors 16 years to find took Face2Gene just a few minutes.

Face2Gene is a suite of phenotyping applications that facilitate comprehensive and precise genetic evaluations.

"Deep learning algorithms build syndrome-specific computational-based classifiers (syndrome gestalts). Proprietary technology converts a patient photo into de-identified mathematical facial descriptors (facial descriptors). The patient's facial descriptor is compared to syndrome gestalts to quantify similarity (gestalt scores) resulting in a prioritized list of syndromes with similar morphology." – From face2gene.com

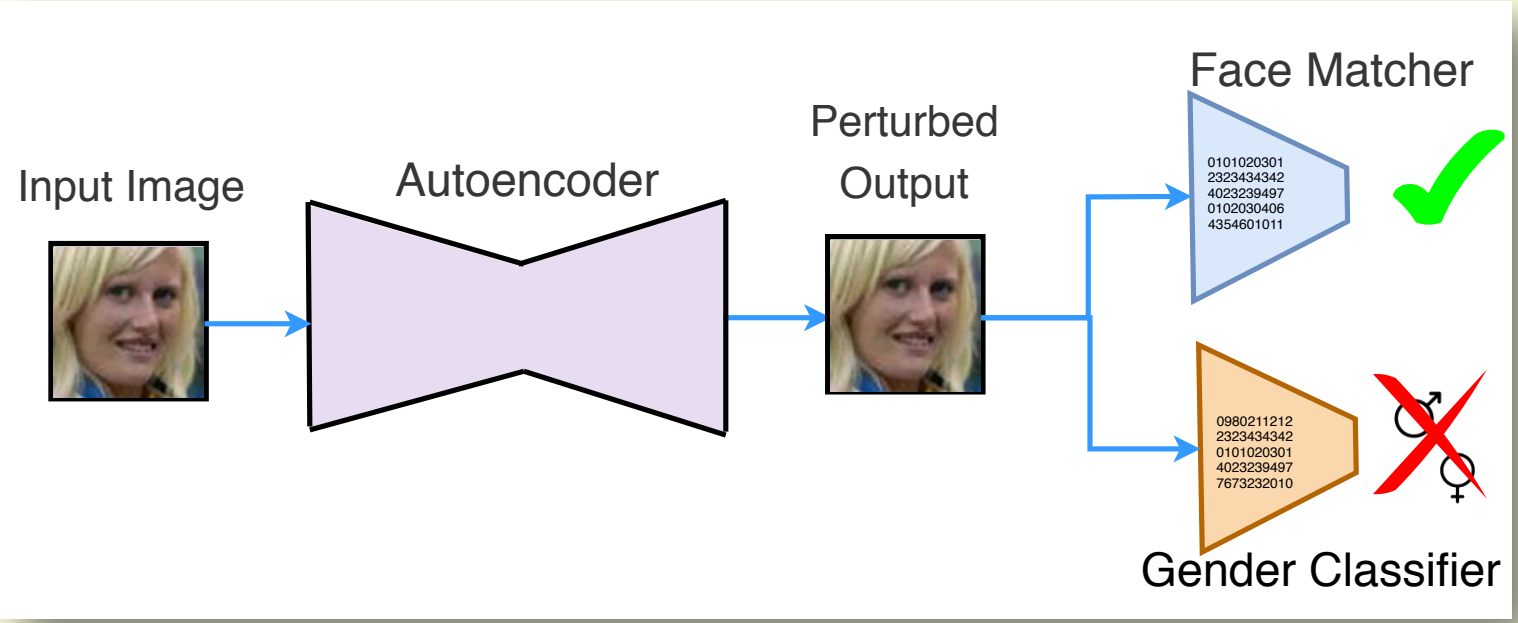
Controllable Privacy



Othman and Ross, "Privacy of Facial Soft Biometrics," ECCVW 2014

Semi-Adversarial Networks (SAN)

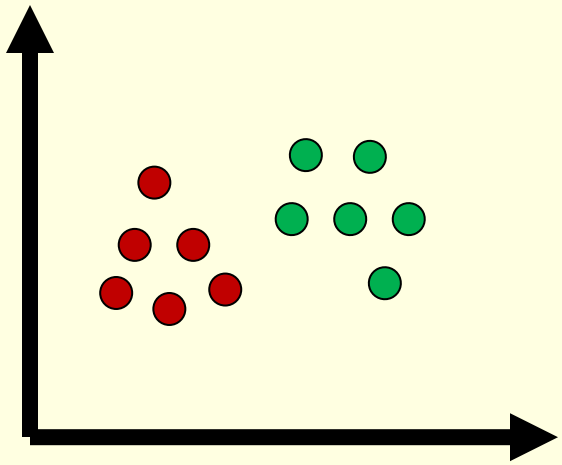
- Design a transformation model to:
  - Confound gender attribute ➔ gender classifiers will <u>not</u> work
  - Retain recognition capability ➔ face matchers will still work



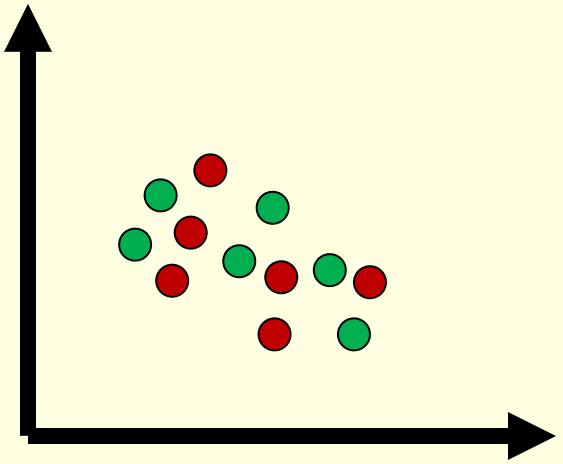
Mirjalili et al., Semi-Adversarial Networks: Convolutional Autoencoders for Imparting Privacy to Face Images, ICB 2018

Semi-Adversarial Networks (SAN)

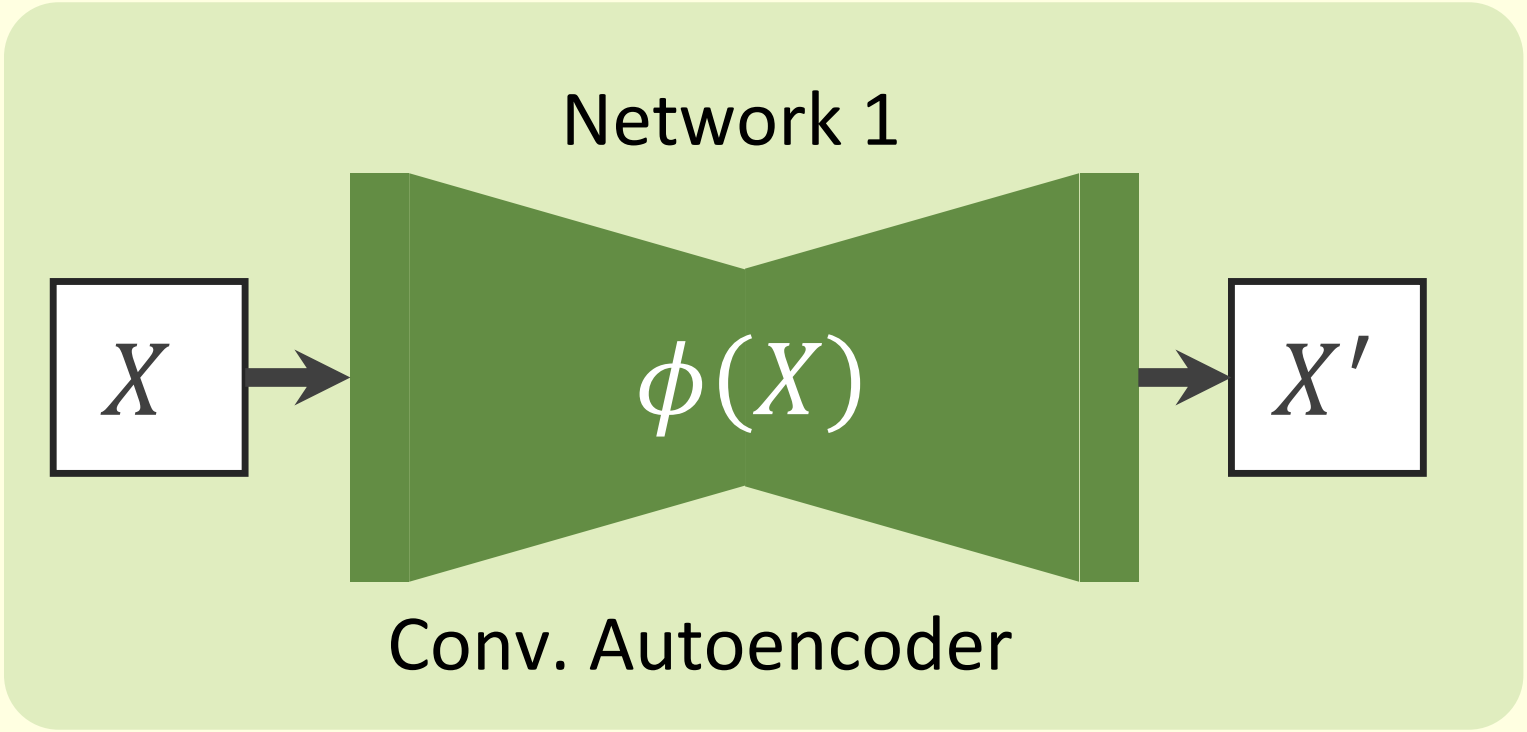
Original Image Space



Transformed Image Space

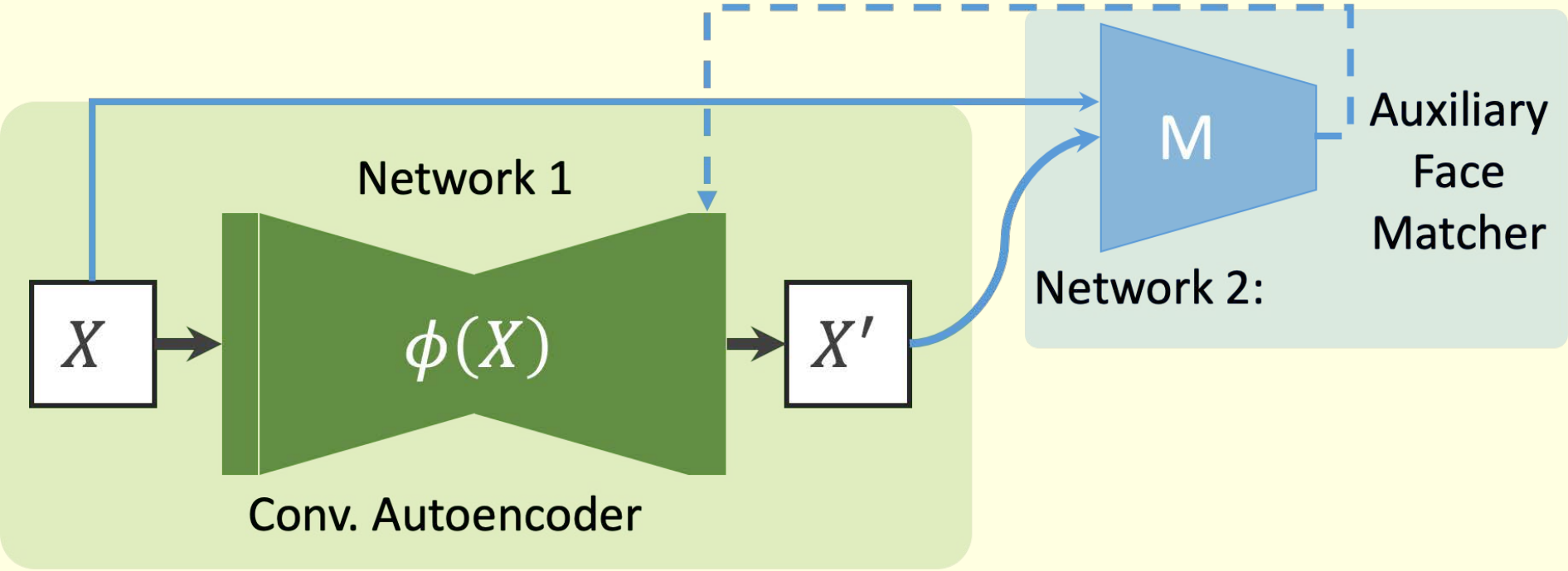


General Architecture of SAN Model



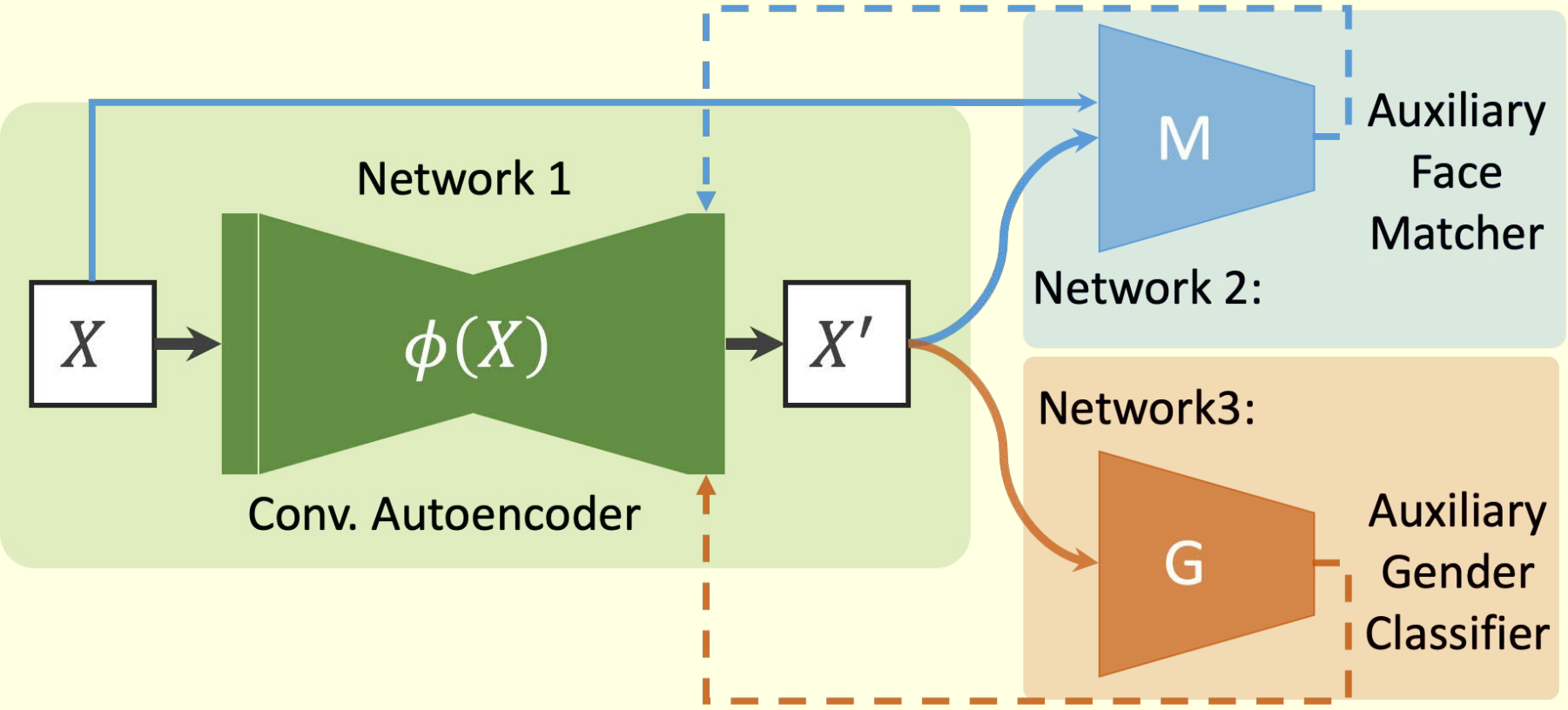
Mirjalili et al., Semi-Adversarial Networks: Convolutional Autoencoders for Imparting Privacy to Face Images, ICB 2018

General Architecture of SAN Model



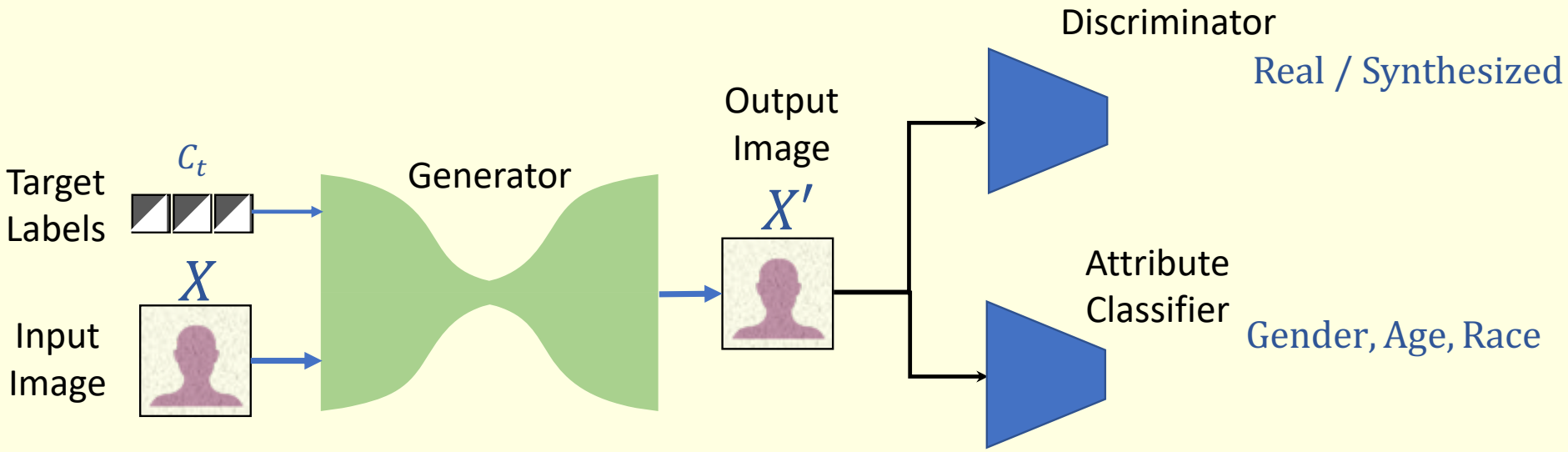
Mirjalili et al., Semi-Adversarial Networks: Convolutional Autoencoders for Imparting Privacy to Face Images, ICB 2018

General Architecture of SAN Model



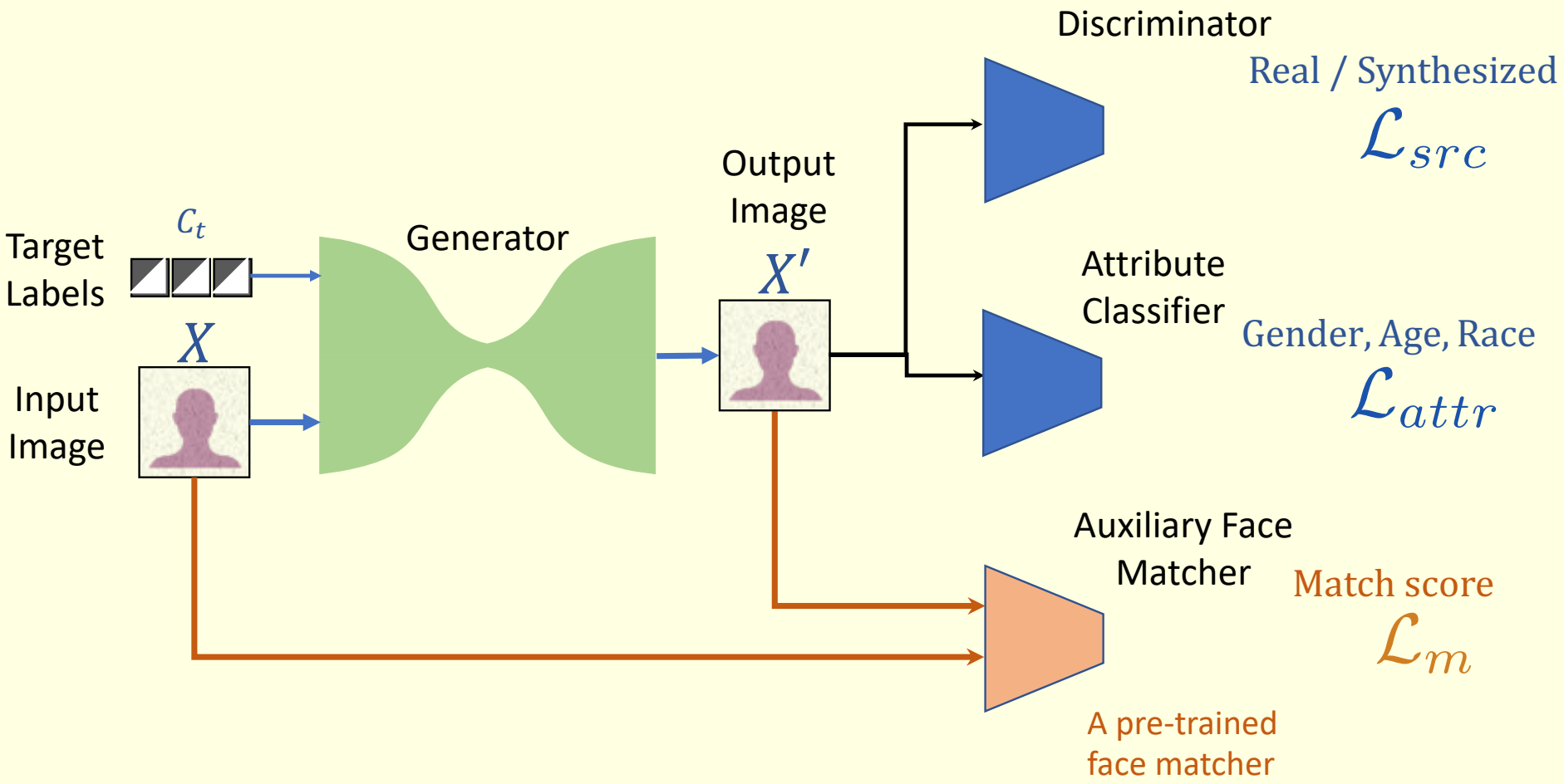
Mirjalili et al., Semi-Adversarial Networks: Convolutional Autoencoders for Imparting Privacy to Face Images, ICB 2018

Multi-attribute Privacy



- Input image X from original label c_0
- A regular cycle-GAN that generates output image X' for a given input image X and target label vector c_t.

Multi-attribute Privacy



- Auxiliary Face Matcher derives the matching-loss term to ensure that the output image X' matches with input X.

PrivacyNet: Loss Functions

- Losses for training the discriminator D_{src} and D_{attr}:

  1. Source term (real vs. synthesized)

$$\mathcal{L}_{D,src} = \mathbb{E}_X\left[-\log(D_{src}(X))\right] + \mathbb{E}_{X,c_t}\left[-\log(1 - D_{src}(G(X, c_t)))\right]$$

  2. Attribute term

$$\mathcal{L}_{D,attr} = \mathbb{E}_{X,c_0}\left[-\log(D_{attr}(c_0|X)\right]$$

- Losses for training the generator $G(X, c_t)$:

  1. Source term

$$\mathcal{L}_{G,src} = \mathbb{E}_{X,c_t}\left[\log(D_{src}(G(X, c_t))\right]$$

  2. Attribute term

$$\mathcal{L}_{G,attr} = \mathbb{E}_{X,c_t}\left[-\log(D_{attr}(c_t|G(X, c_t))\right]$$

  3. Matching term

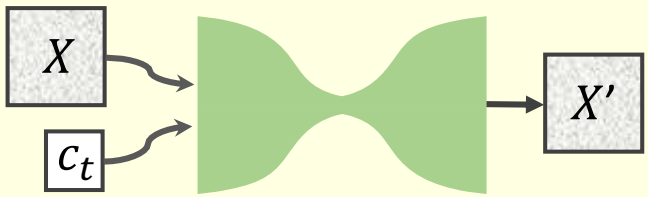
$$\mathcal{L}_{G,m} = \mathbb{E}_{X,c_t}\left[\|R(X) - R(G(X, c_t))\|_2^2\right]$$

  4. Reconstruction loss (cycle-consistency)

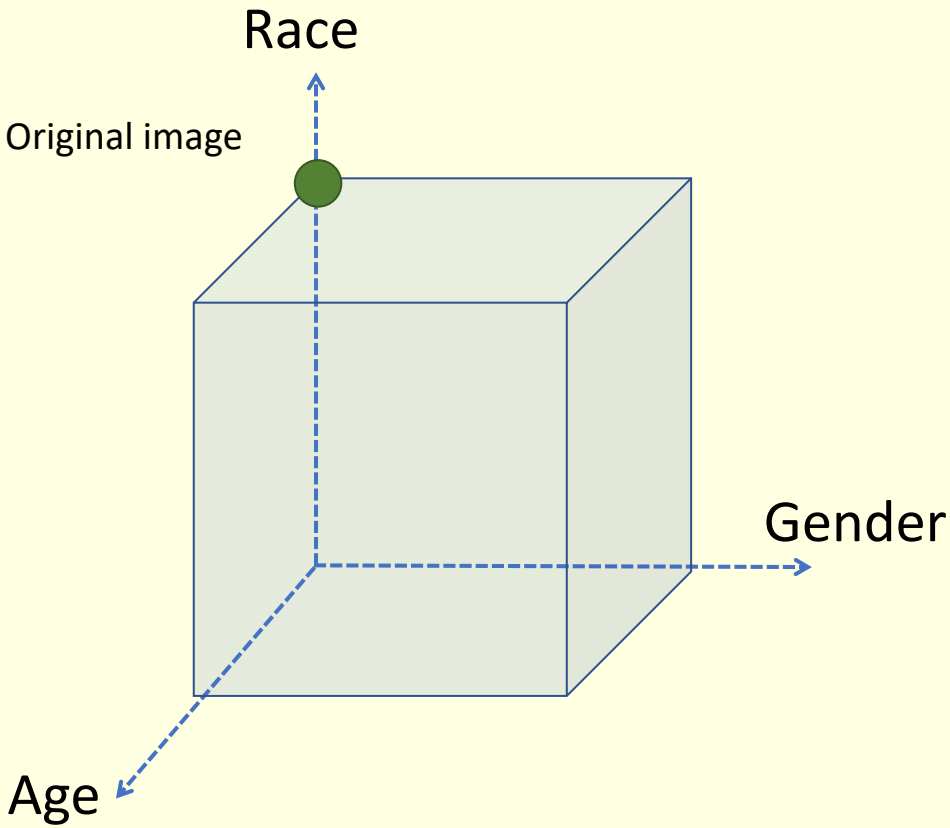
$$\mathcal{L}_{rec} = \mathbb{E}_{X,c_0,c_t}\left[\|X - G(G(X, c_t), c_0)\|_1\right]$$

Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

Face Transformation Using PrivacyNet

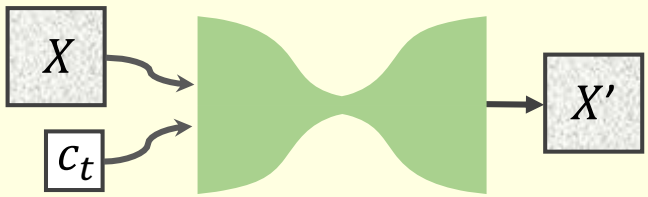


Original Label c_0: [0, 1, 1]
[Female, Middle-aged, Caucasian]



Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

Face Transformation Using PrivacyNet



Original Label c_0: [0, 1, 1]
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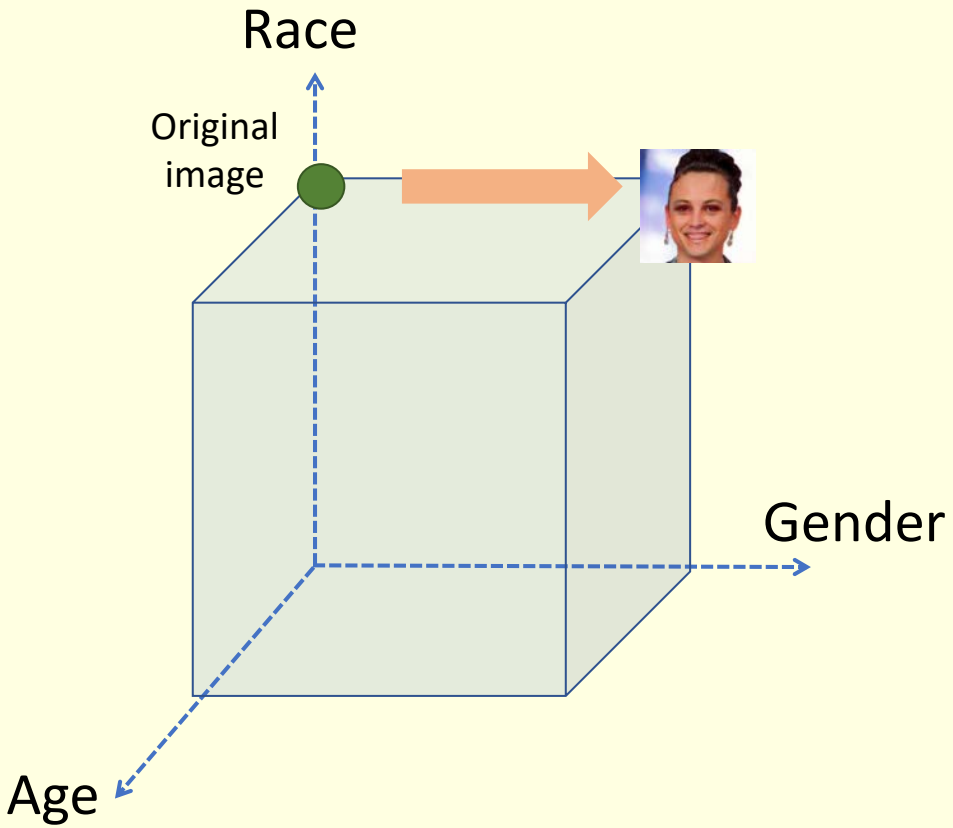
c_t

[Male, Mid-age, Cauc.]



Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

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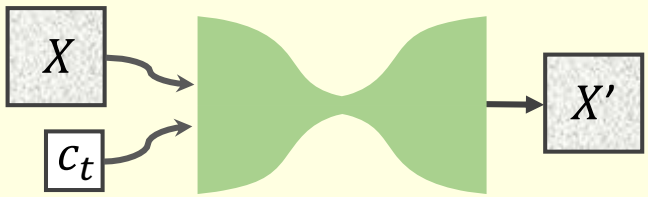

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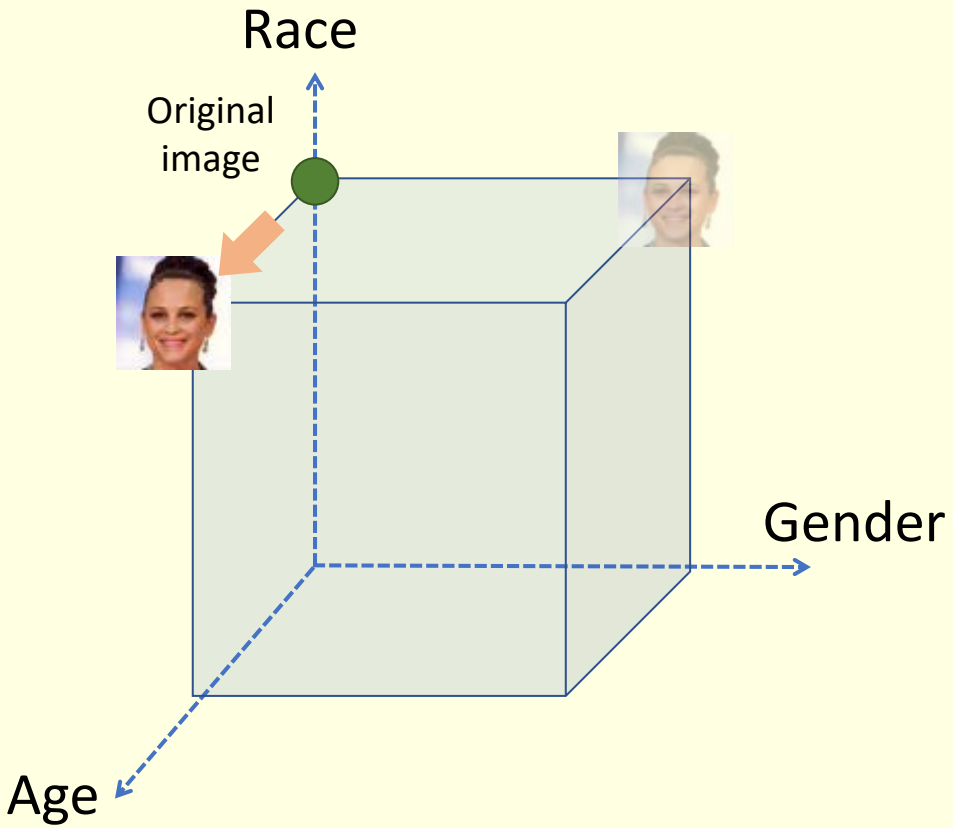
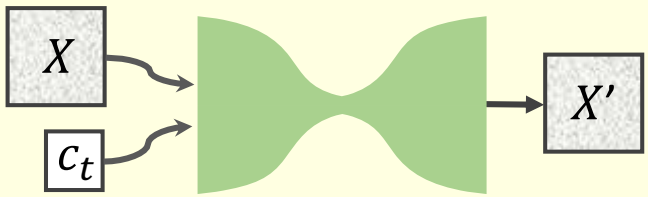
[Female, Old, Cauc.]



Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

Face Transformation Using PrivacyNet



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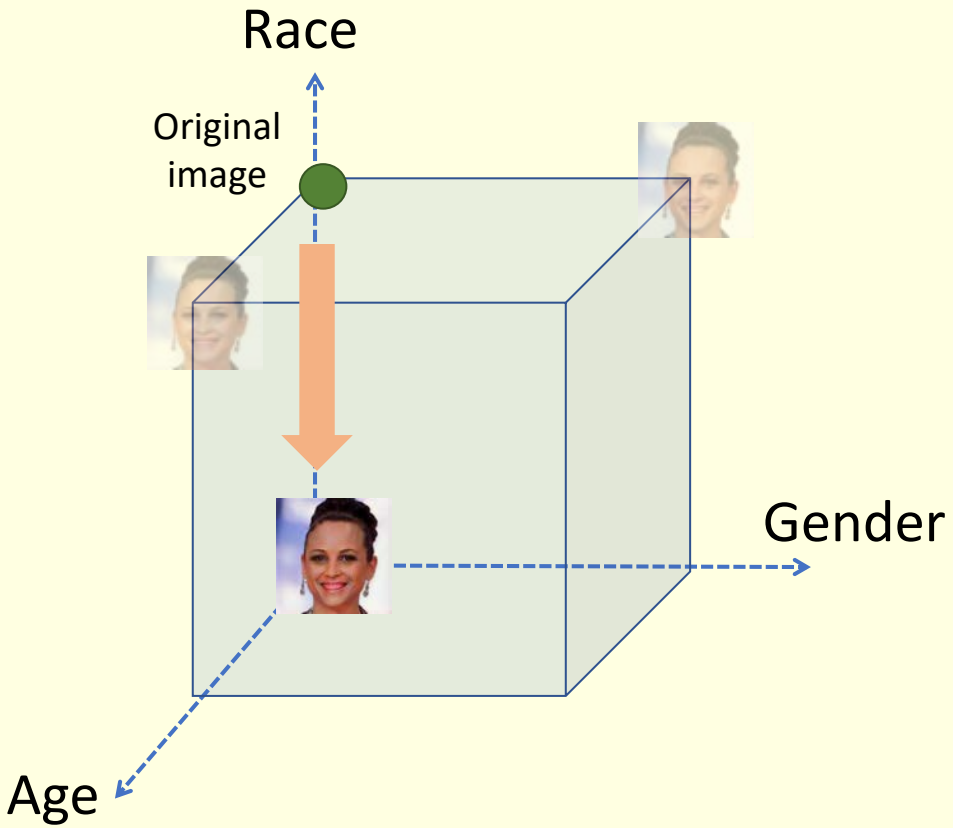
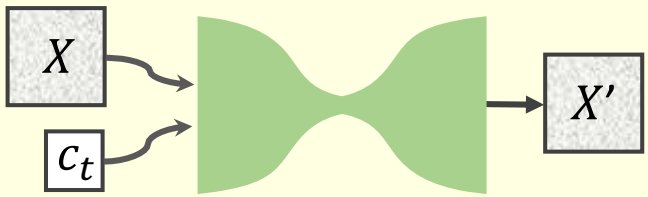


Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

Face Transformation Using PrivacyNet



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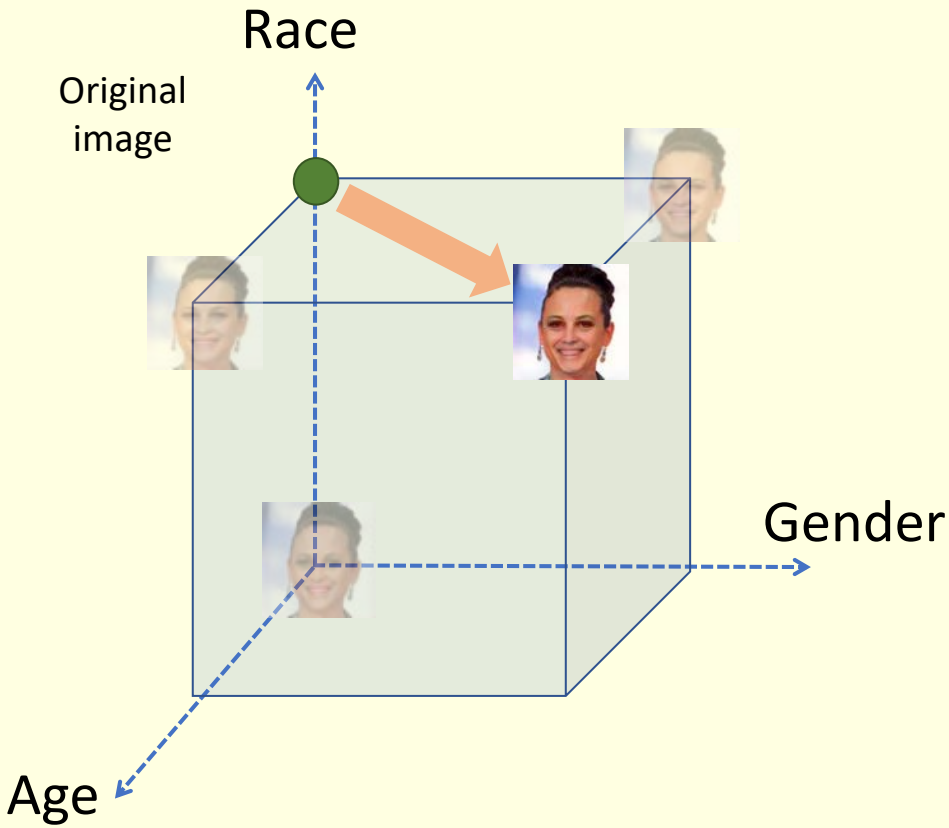

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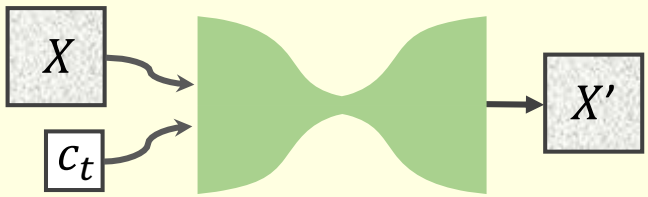

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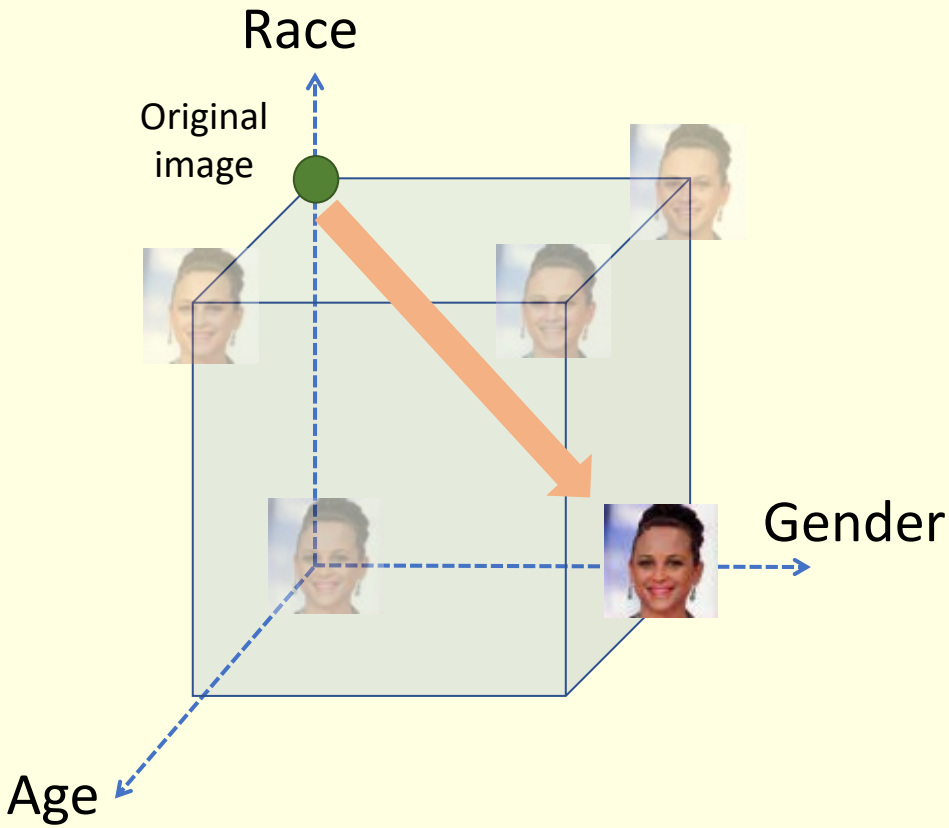
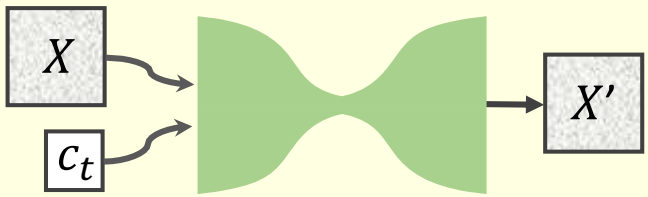


Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

Face Transformation Using PrivacyNet



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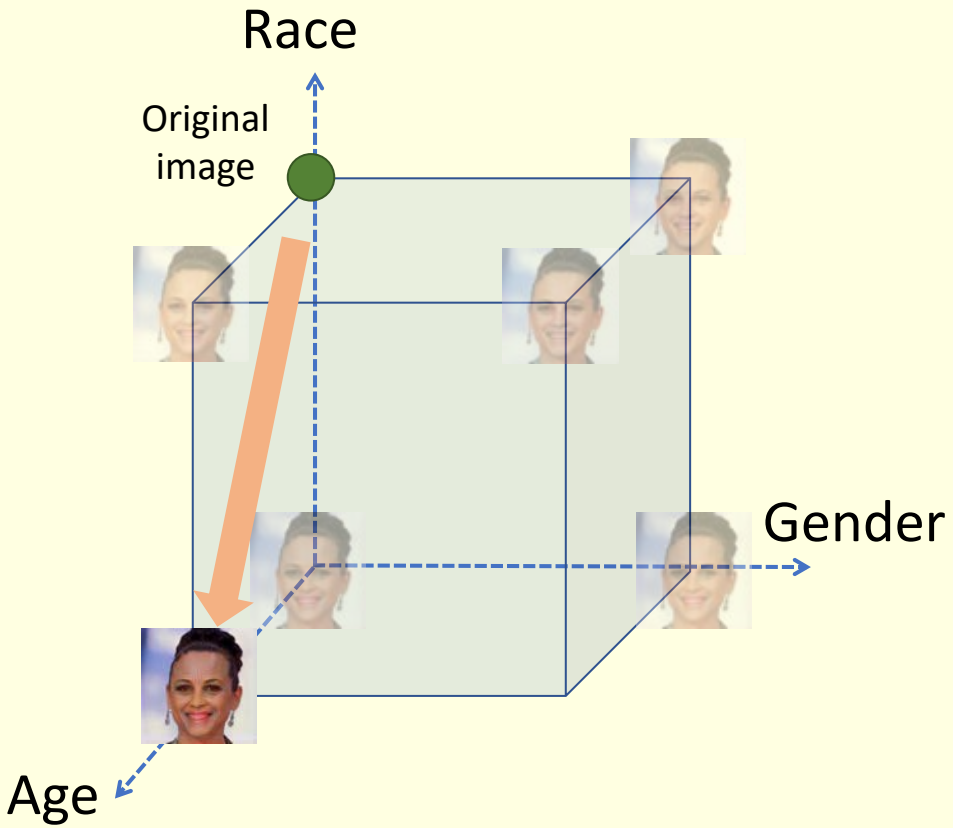
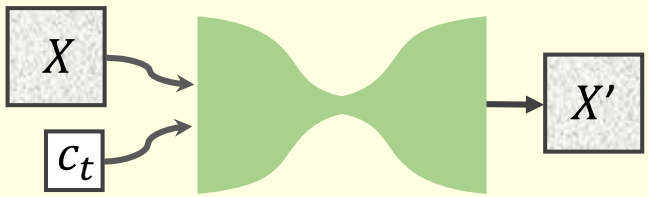


Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

Face Transformation Using PrivacyNet



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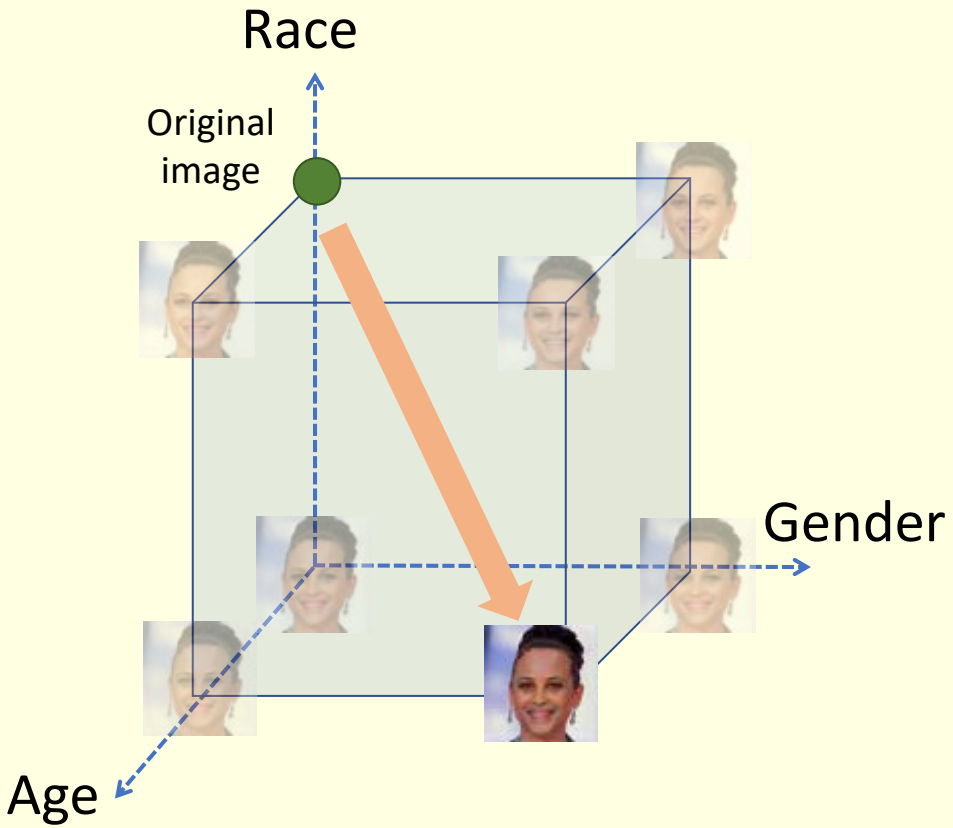
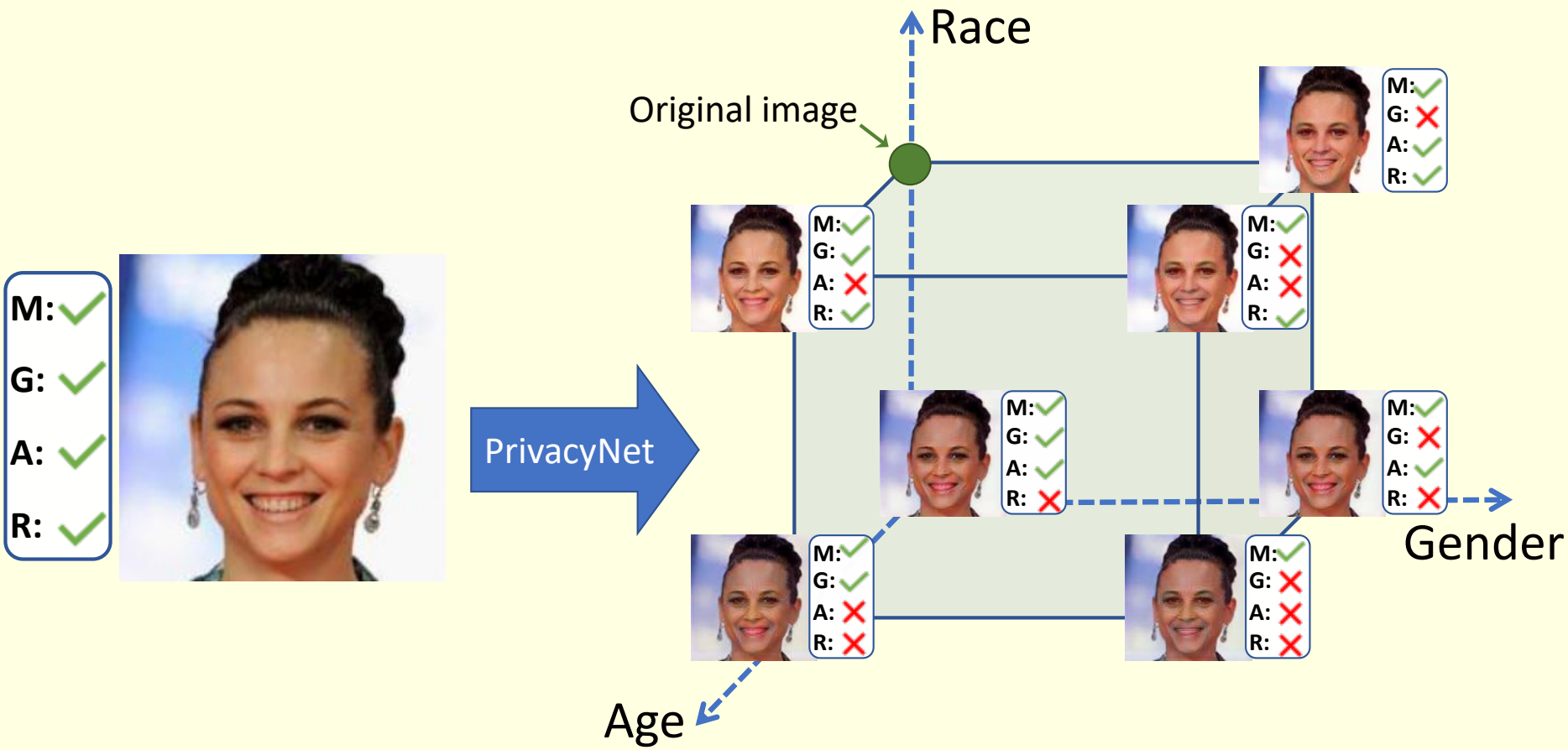


Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

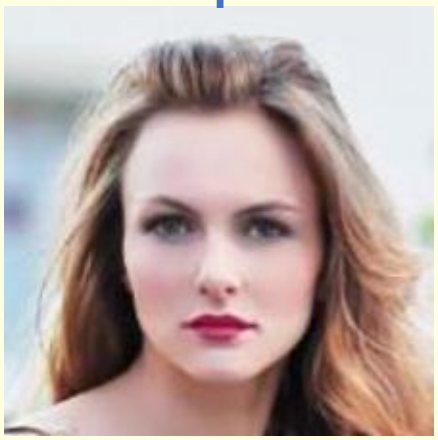
Face Transformation Using PrivacyNet



Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

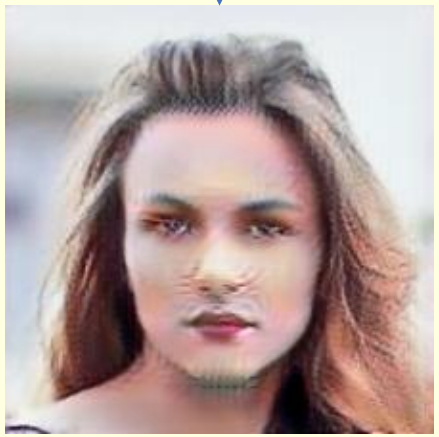
Face Transformation Using PrivacyNet

Original Image



G R

PrivacyNet



GAN

Match Scores with original image:

M-COTS:	0.99	0.41 ↓
DR-GAN:	0.93	0.69 ↓
SE-ResNet-50:	0.72	0.14 ↓

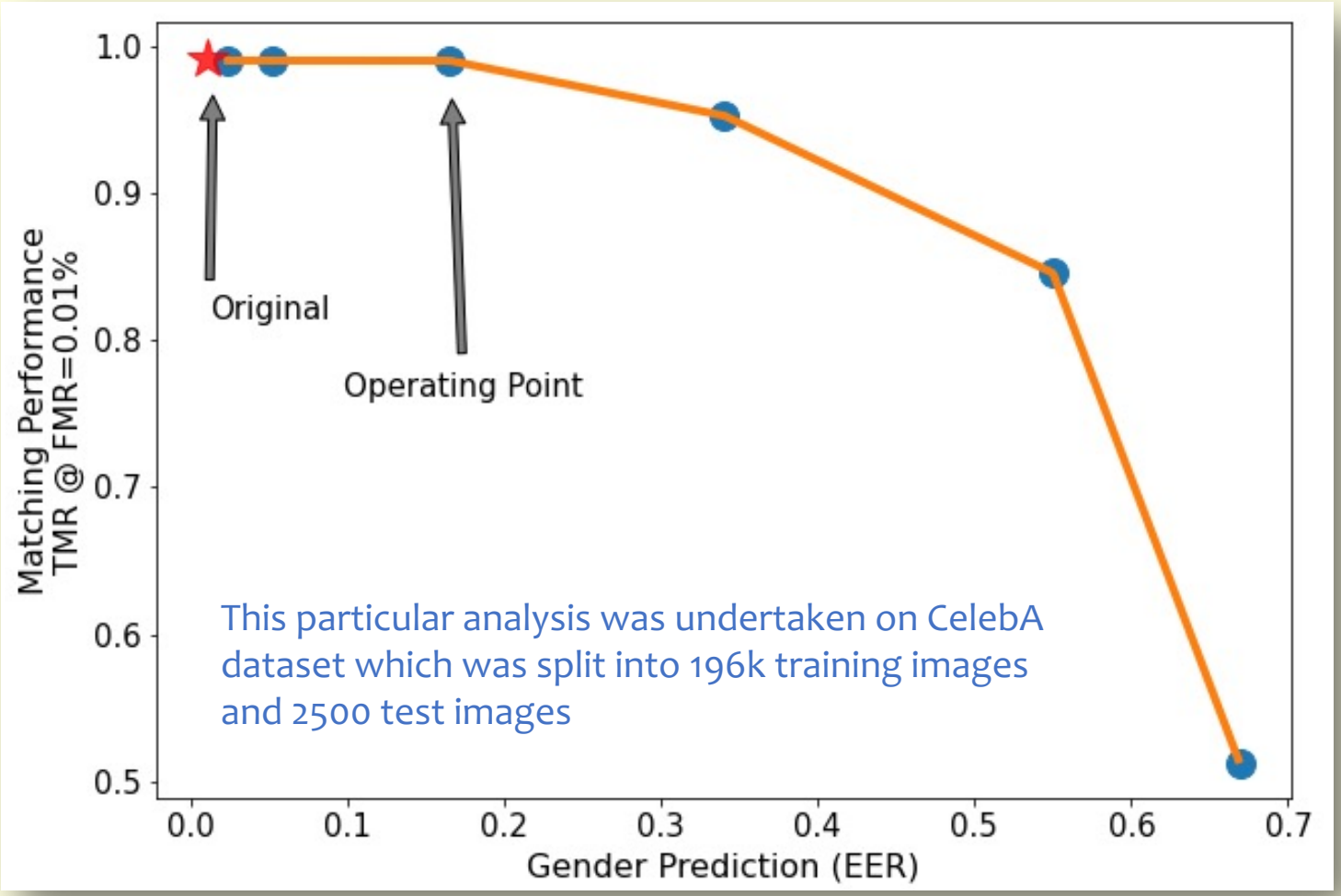
Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

Face Transformation Using PrivacyNet

Match Scores with original image:	PrivacyNet	GAN
M-COTS:	0.99	0.39 ↓
DR-GAN:	0.93	0.74 ↓
SE-ResNet-50:	0.81	0.31 ↓

Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

Experimental Results



Mirjalili et al., PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy, IEEE TIP 2020

Summary

- Altered and Synthetic Data
  - Sensor Privacy
  - Morph Attacks
  - Deep MasterPrints
- Digital Image Forensics
  - Which sensor did this image come from?
  - Has this image been digitally tampered?
  - What is the relationship between a set of images?
- Privacy
  - Semi-adversarial Networks (SAN): Controllable Privacy

Digital Image Forensics

- El-Naggar, Ross, "**Which Dataset is this Iris Image From?,**" WIFS 2015
- Kalka, Bartlow, Cukic, Ross, "**A Preliminary Study on Identifying Sensors from Iris Images,**" CVPRW 2015
- Banerjee, Ross, "**From Image to Sensor: Comparative Evaluation of Multiple PRNU Estimation Schemes for Identifying Sensors from NIR Iris Images,**" IWBF 2017
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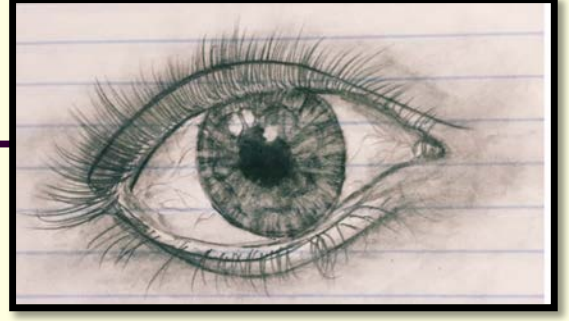
- Banerjee, Ross, "**Face Phylogeny Tree: Deducing Relationships Between Near-Duplicate Face Images Using Legendre Polynomials and Radial Basis Functions,**" BTAS 2019
- Banerjee, Ross, **"Face Phylogeny Tree Using Basis Functions,"** IEEE TBIOM 2020

SAN and Privacy

- V. Mirjalili, S. Raschka, A. Ross, "**PrivacyNet: Semi-Adversarial Networks for Multi-attribute Face Privacy**," IEEE TIP 2020.
- V. Mirjalili, S. Raschka, A. Ross, "**FlowSAN: Privacy-Enhancing Semi-Adversarial Networks to Confound Arbitrary Face-Based Gender Classifiers**," IEEE Access, 2019.
- V. Mirjalili, S. Raschka, A. Ross, "**Gender Privacy: An Ensemble of Semi Adversarial Networks for Confounding Arbitrary Gender Classifiers**," BTAS 2018
- V. Mirjalili, S. Raschka, A. Namboodiri, A. Ross, "**Semi-Adversarial Networks: Convolutional Autoencoders for Imparting Privacy to Face Images**," ICB 2018
- V. Mirjalili and A. Ross, "**Soft Biometric Privacy: Retaining Biometric Utility of Face Images while Perturbing Gender**," IJCB 2017
- A. Othman and A. Ross, "**Privacy of Facial Soft Biometrics: Suppressing Gender But Retaining Identity**," ECCVW 2014

Related Resources

- A. Ross et al., "**Some Research Problems in Biometrics: The Future Beckons**," ICB 2019
- A. K. Jain, K. Nandakumar, A. Ross, "**50 Years of Biometric Research: Accomplishments, Challenges, and Opportunities**," Pattern Recognition Letters, Vol. 79, pp. 80 - 105, August 2016.
- A. Dantcheva, P. Elia, A. Ross, "**What Else Does Your Biometric Data Reveal? A Survey on Soft Biometrics**," IEEE Transactions on Information Forensics And Security (TIFS), Vol. 11, No. 3, pp. 441 - 467, March 2016.
- A. K. Jain and A. Ross, "**Bridging the Gap: From Biometrics to Forensics**," Philosophical Transactions of The Royal Society B, Vol. 370, Issue 1674, August 2015.
- A. K. Jain, B. Klare, A. Ross, "**Guidelines for Best Practices in Biometrics Research**," Proc. of 8th IAPR International Conference on Biometrics (ICB), (Phuket, Thailand), May 2015.



Privacy and Data Integrity in Biometrics

Arun Ross

Michigan State University

http://iprobe.cse.msu.edu/