# Adversarial Learning in Face Recognition - Two Sides of the Security Coin

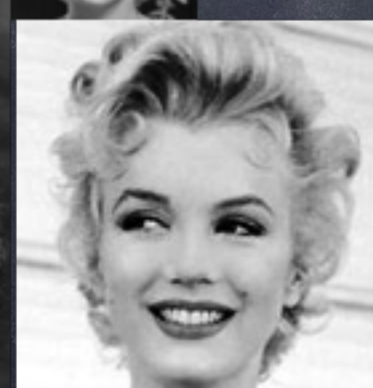

Mayank Vatsa
Infosys Center for AI @ IIIT-Delhi

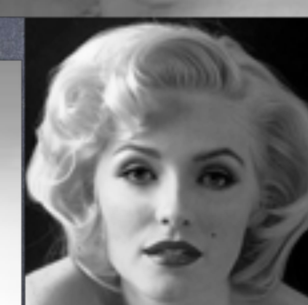
Let us start with some quick tests

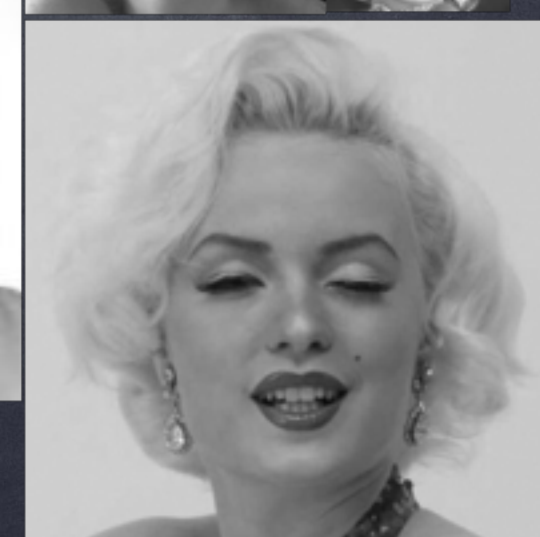
# Which of them are NOT Marilyn Monroe?









# Which of them are NOT Marilyn Monroe?

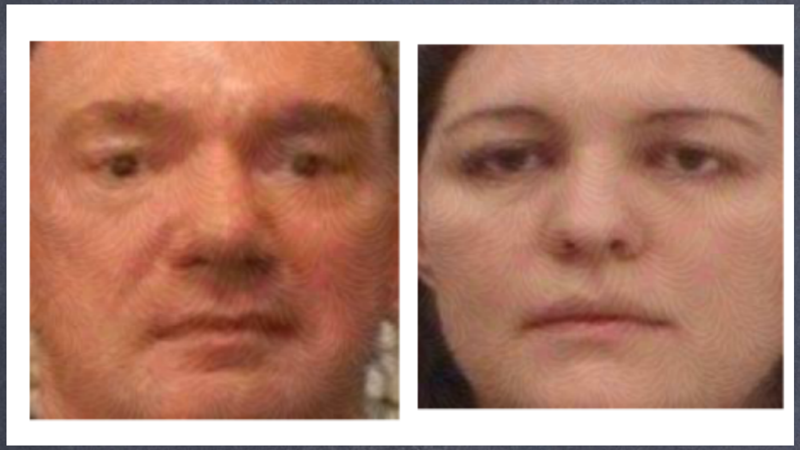
# Find Genuine Image Pairs

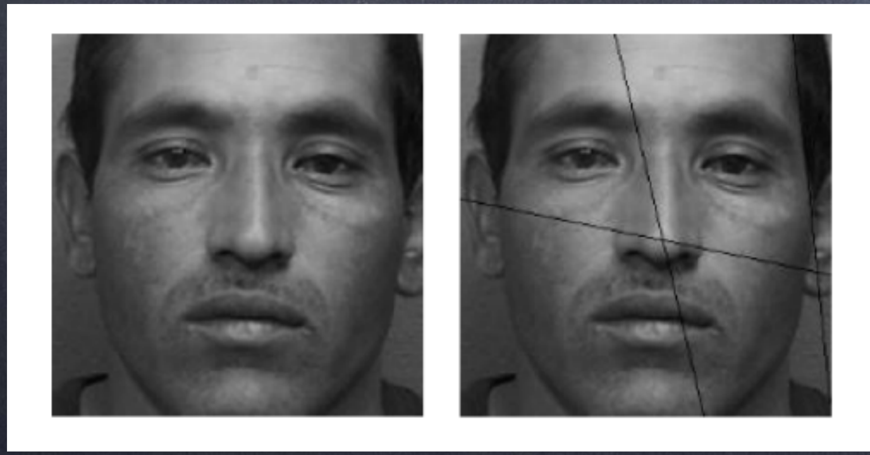
# All are Genuine





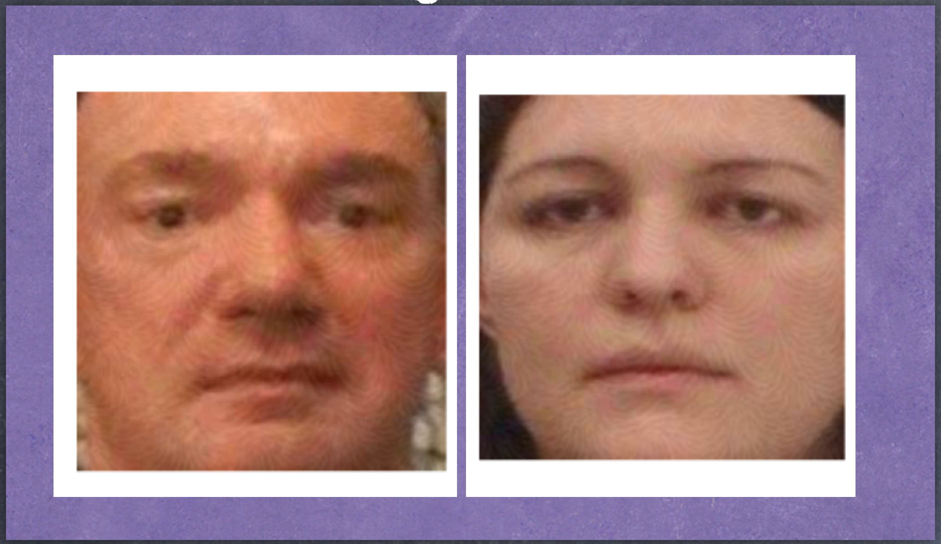
# Find Genuine Image Pairs





# Find Genuine Image Pairs

For Algorithms



For Human Eyes

For Human Eyes

For Algorithms

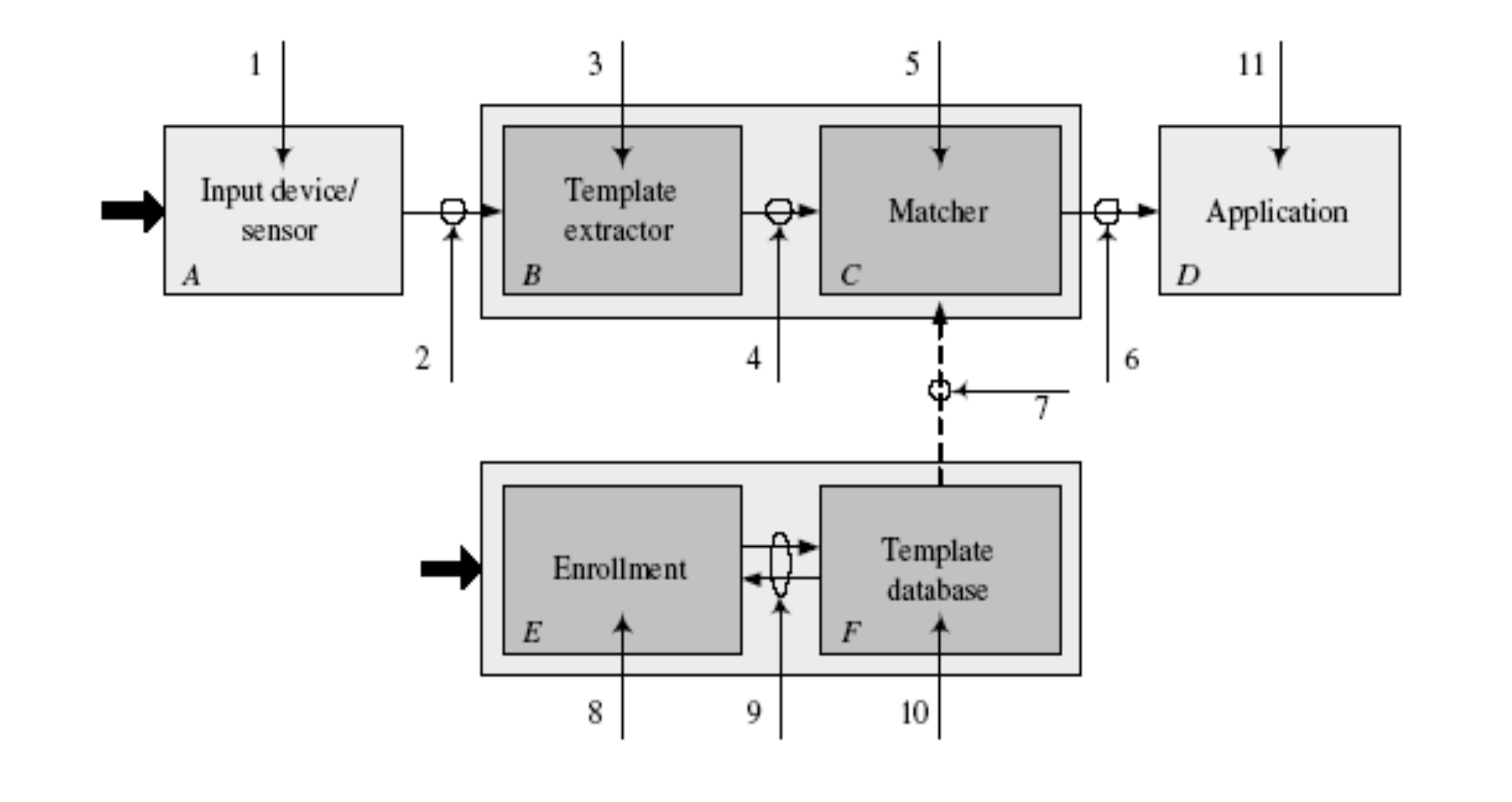
# These Examples Question Robustness of DL based Approaches

- Generalization and Robustness are important for ML/DL algorithms
- Sensitivity towards "distribution drift" is a research challenge
- DL models have some singularities and limitations
- These can be exploited by an adversary to "fool" a ML/DL system

# Structure of the Tutorial

- Motivation and classification of attacks
- How to attack a system/algorithm using adversarial perturbation?
- How to detect these adversarial perturbations (attacks)?
- How to mitigate the effect of adversarial perturbation?
- Is adversarial perturbation always bad?

# Shallow Learning Attack Model (Pre-DL Era)




Formidable adversaries:

Thieves

Hackers

Users

Customers

Employees

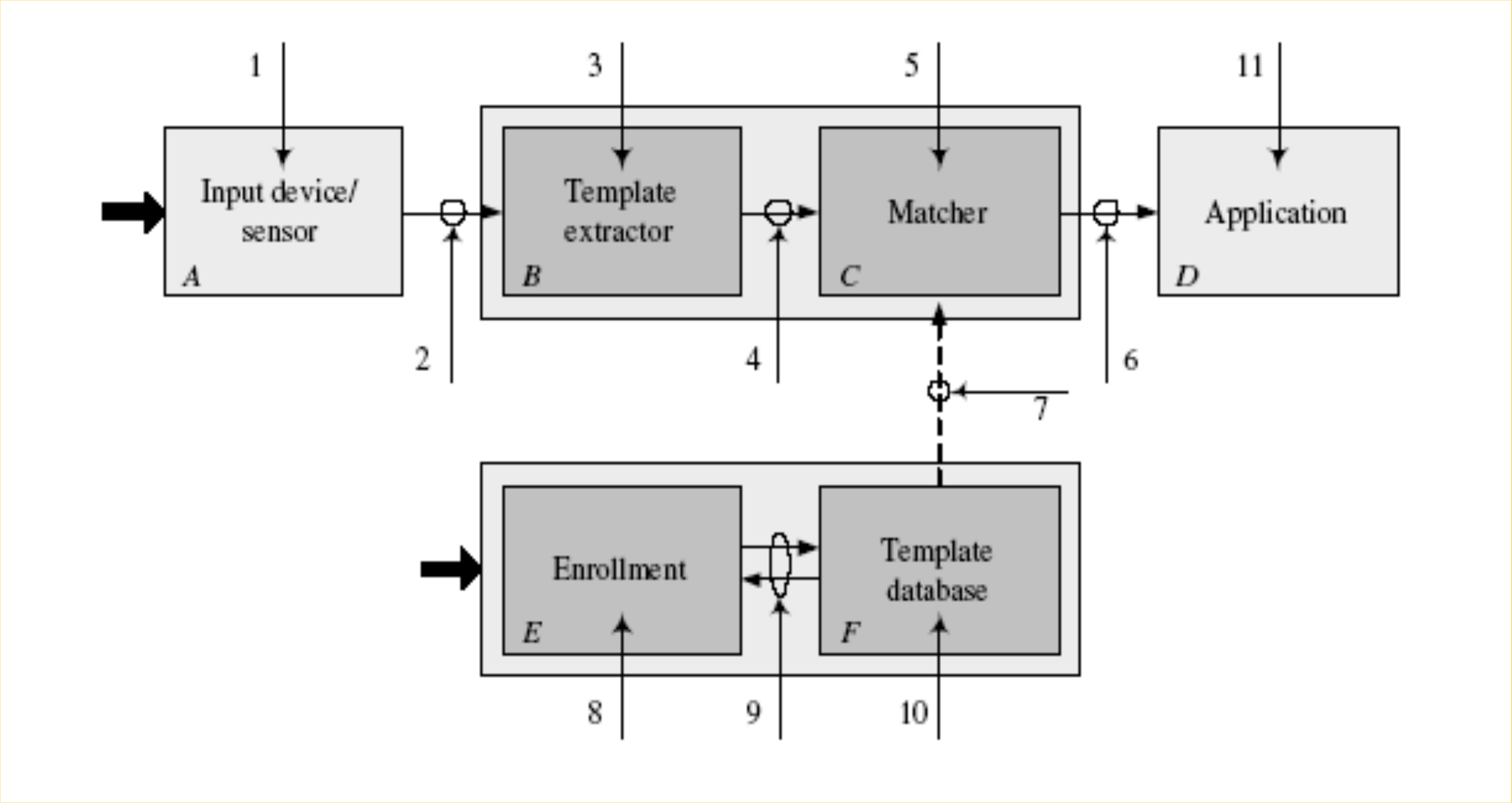
Merchants

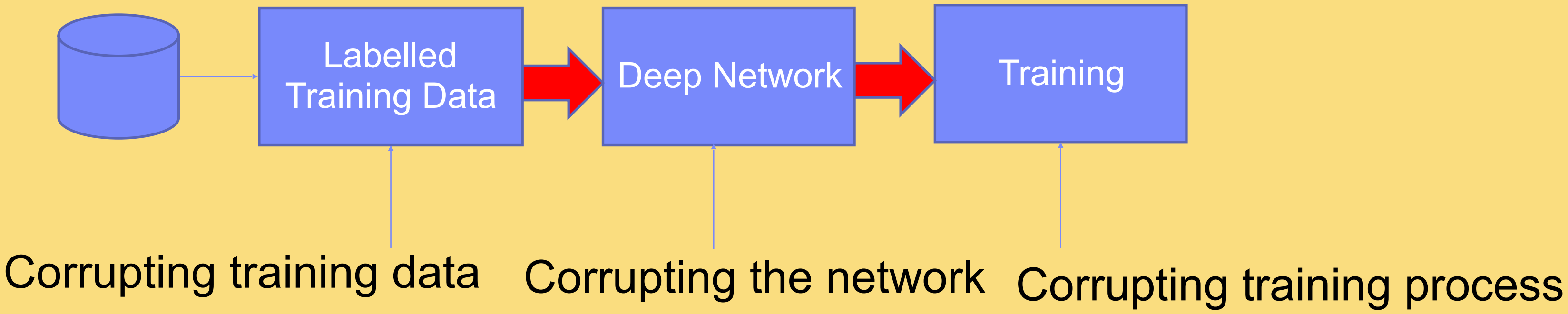
Competitors

Competitors' governments

Ratha et al. 2003

# Deep Learning Attack Models (DL Era)




Formidable adversaries:

Thieves

Hackers

Users

Customers

Employees

Merchants

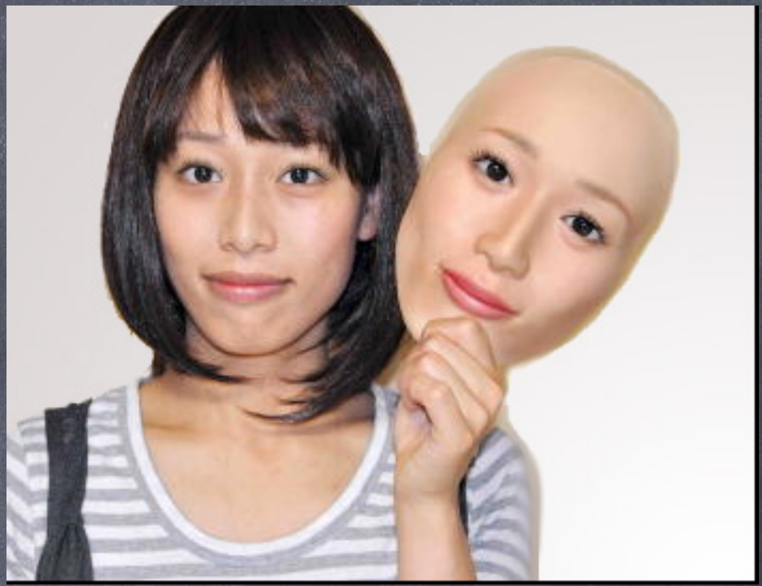
Competitors

Competitors' governments

# Classification of Attacks

- Physical attacks
- Digital attacks

# Physical Adversarial Attacks




# Physical Adversarial Attacks

# Physical Adversarial Attacks

**Black robbers used $2,000 white masks to fool victims in $200,000 'Town'-style stickup, prosecutors say**

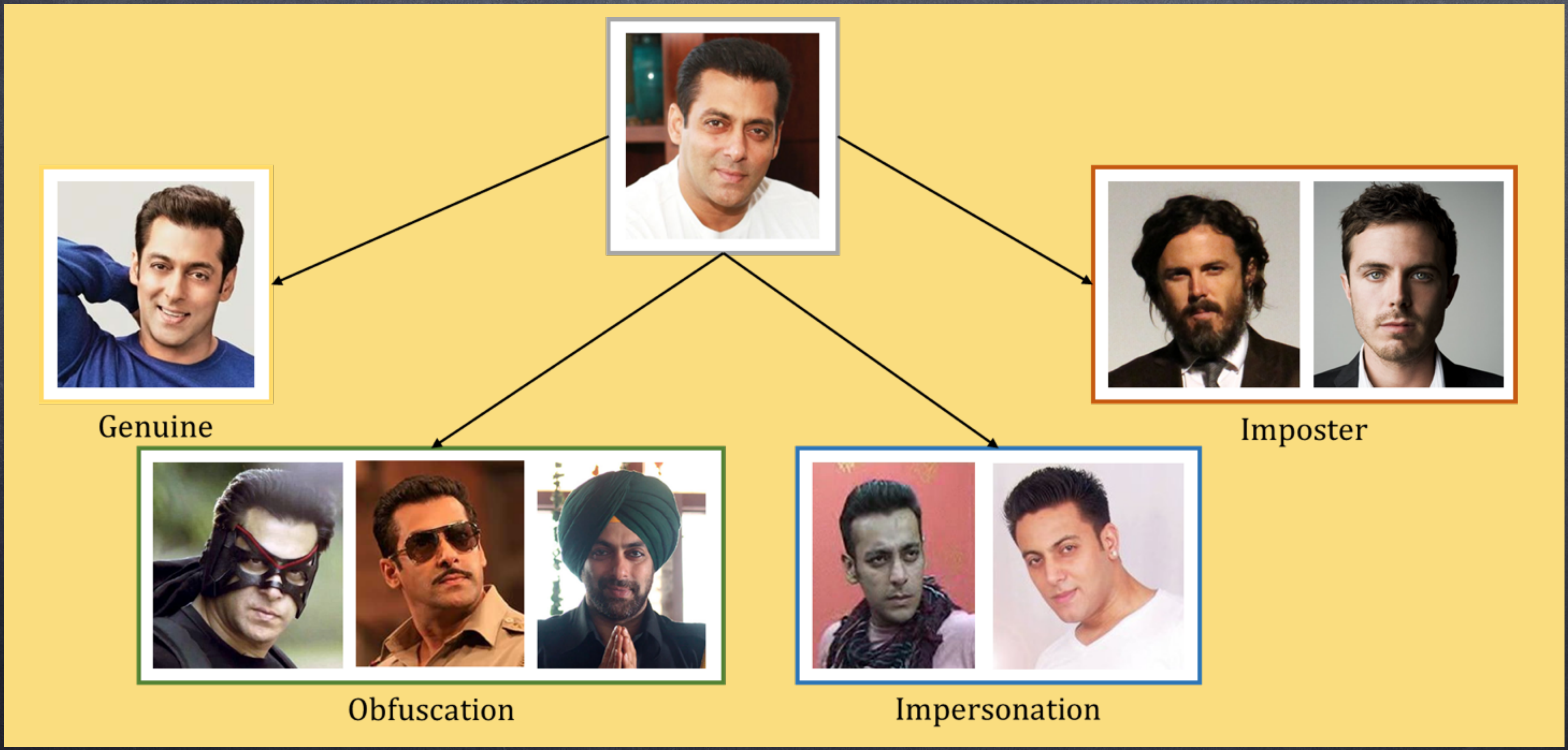
By Selim Algar July 31, 2013 | 4:00am

**The white robber who carried out six raids disguised as a black man (and very nearly got away with it)**

By DAILY MAIL REPORTER
**UPDATED:** 16:11 GMT, 1 December 2010

Manjani et al., Detecting Silicone Mask based Presentation Attack via Deep Dictionary Learning, IEEE T-IFS 2017

# Physical Adversarial Attacks

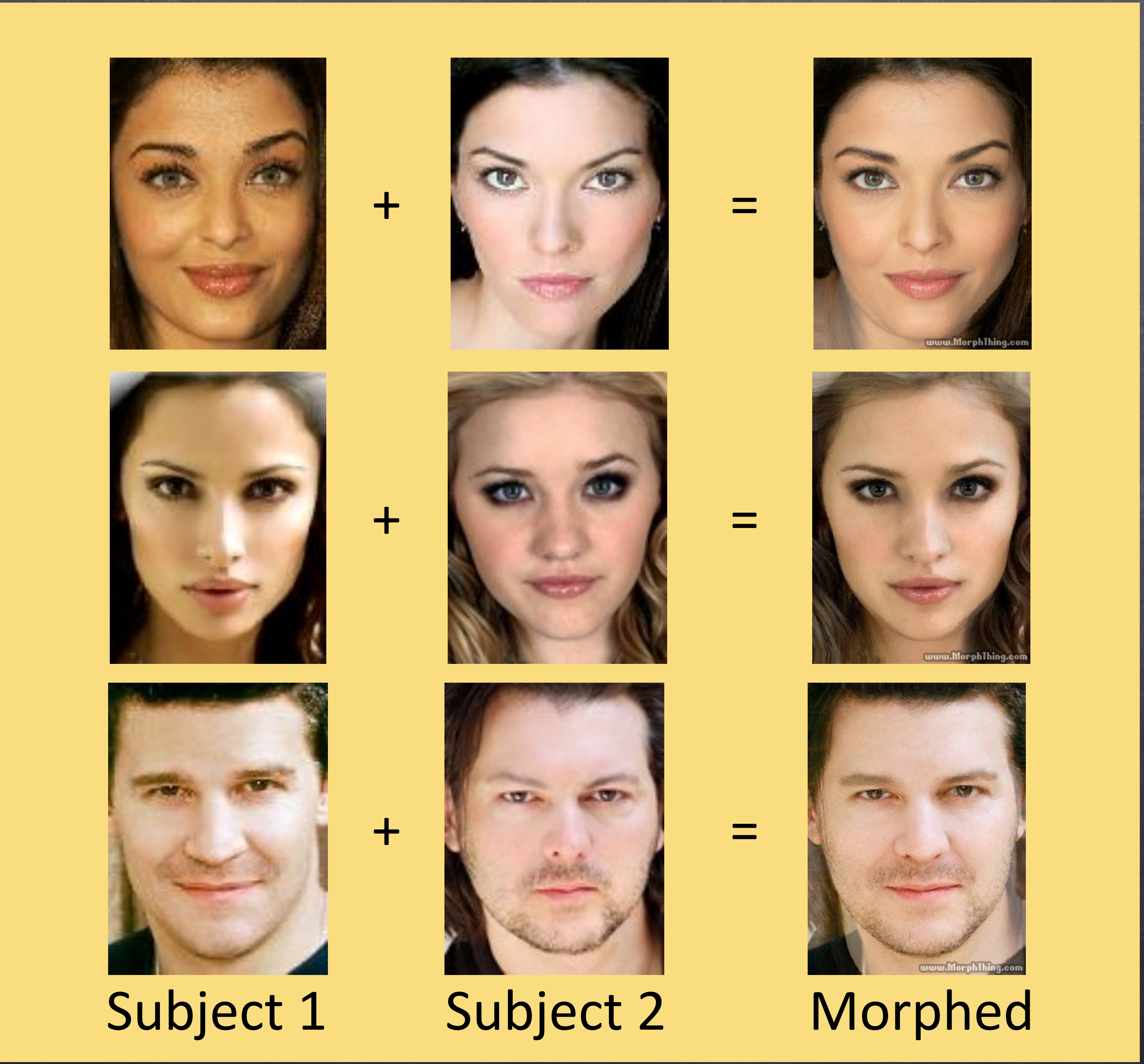



Kushwaha et al. CVPRW - DFW2018, Singh et al. IEEE T-BIOM2019

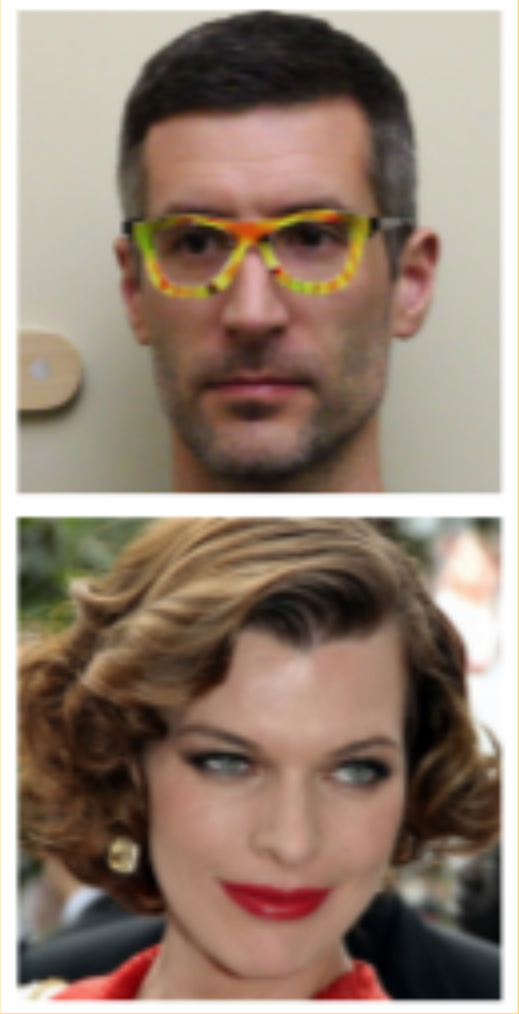
# Digital Adversarial Attacks

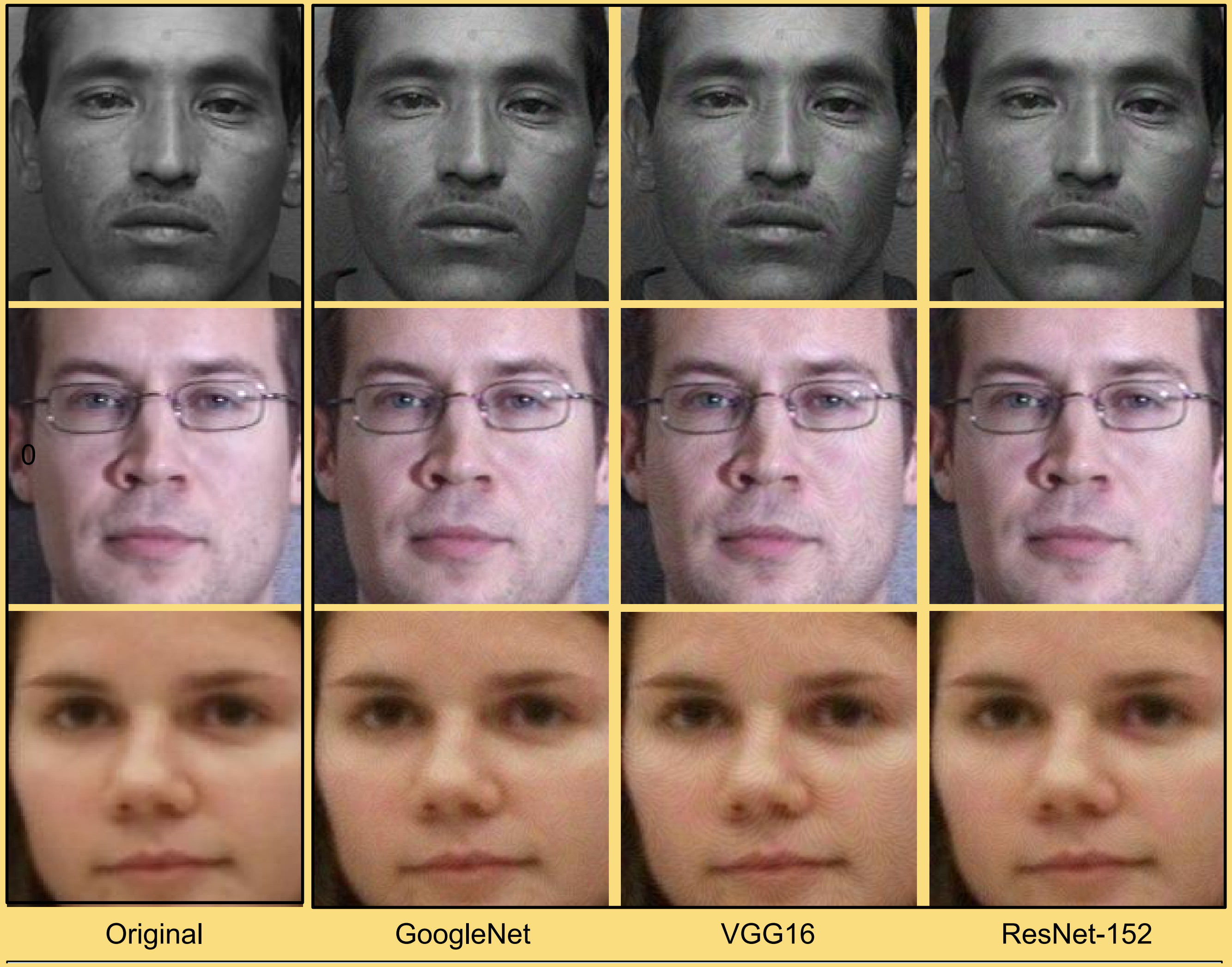
- Digital retouching
- Photoshop effects
- Morphing

Bharati et al. IEEE T-IFS 2016, IJCB2017


+
=
www.MorphThing.com
Subject 1
Subject 2
Morphed

# Digital Adversarial Attacks

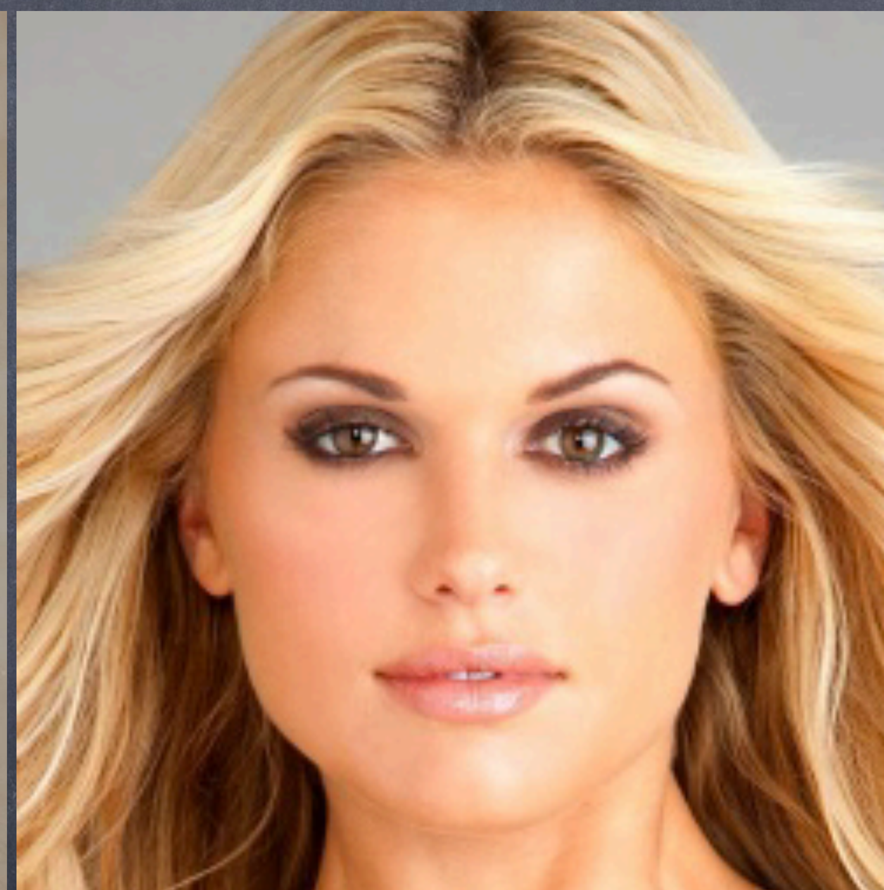





CCS, 2016

Universal Attack, CVPR 2017

# Who are these celebrities?



Non-existing identities

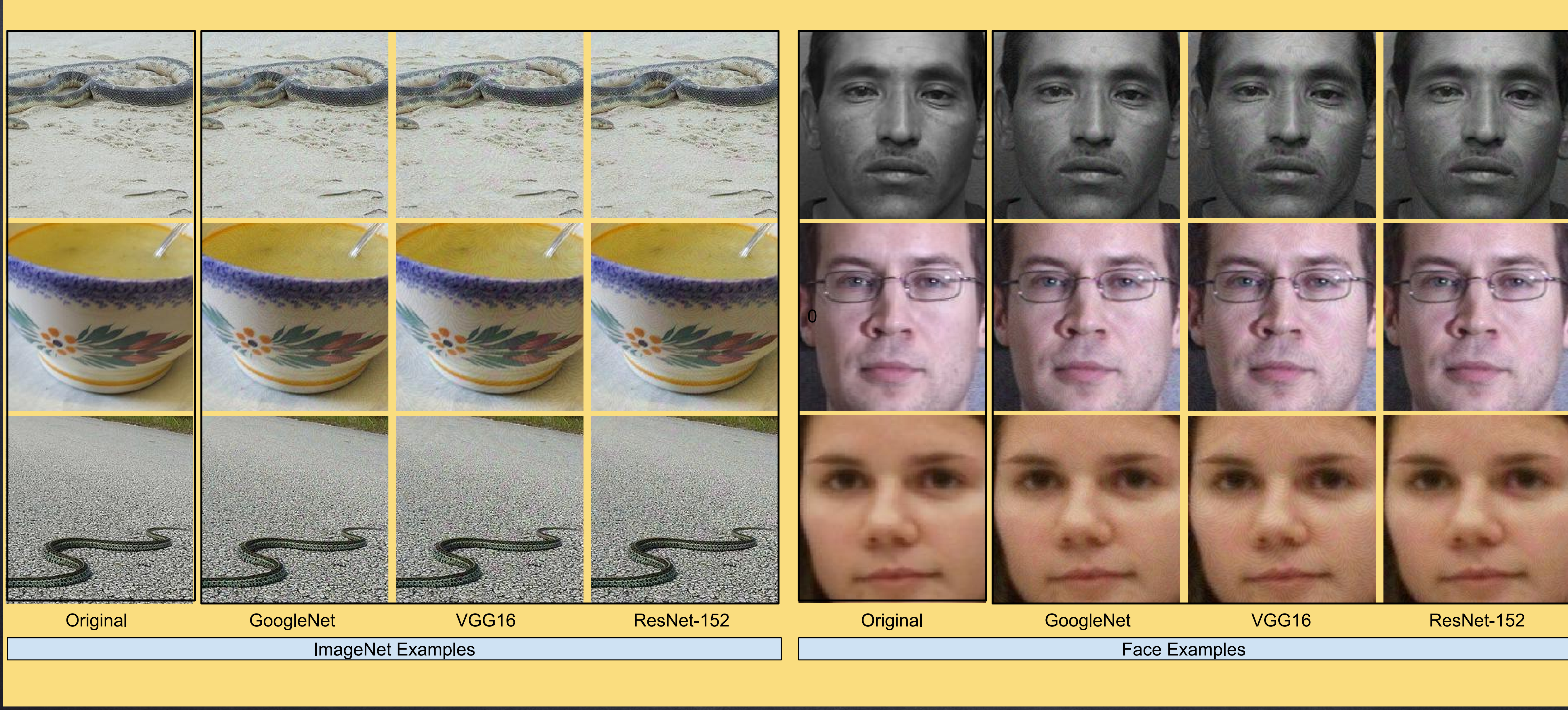
PROGRESSIVE GROWING OF GANS FOR IMPROVED QUALITY, STABILITY, AND VARIATION, ICLR2018

# Adversarial Attacks in Videos

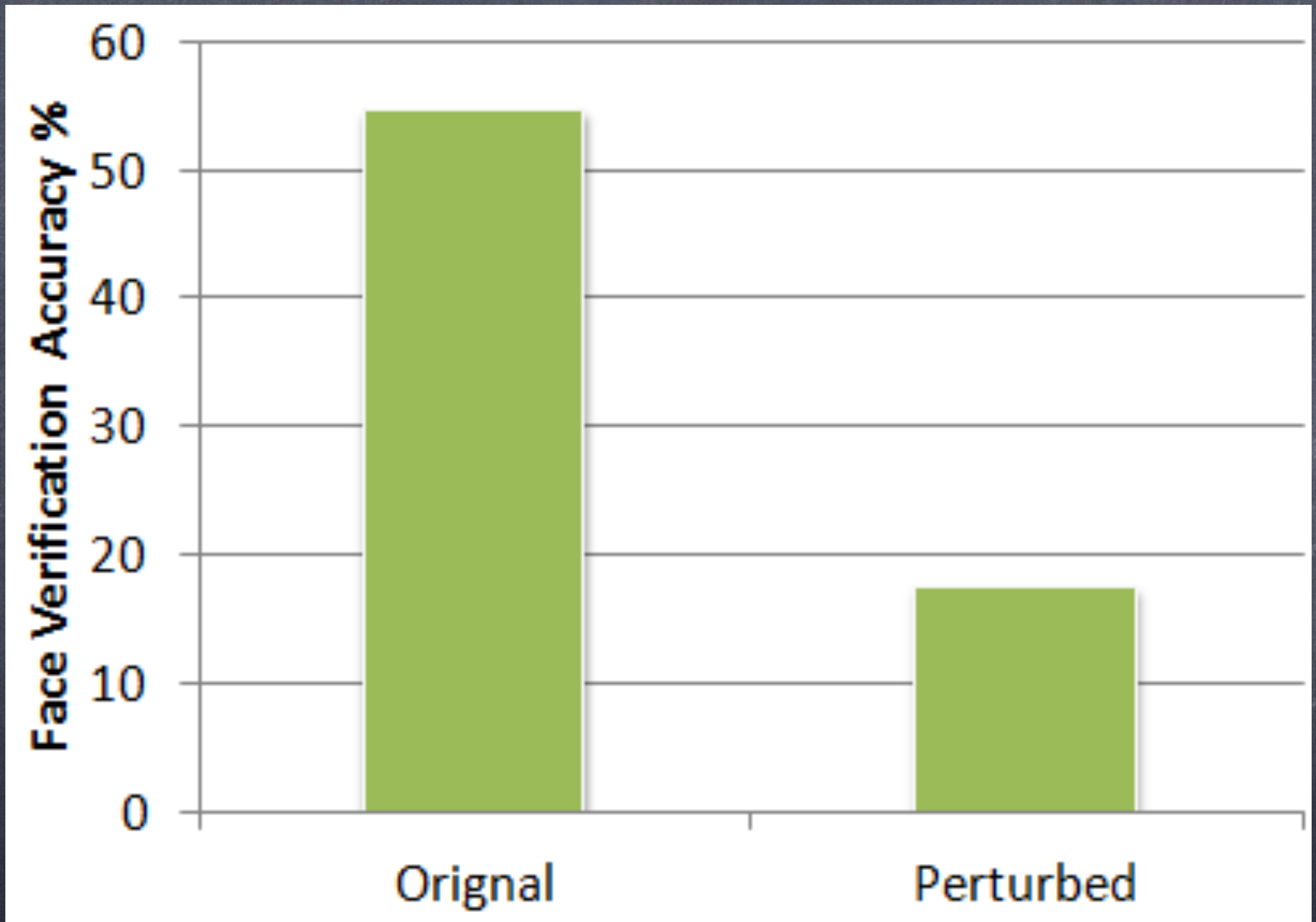
https://www.engadget.com/2017/11/10/counterfeit-ai-machine-learning-forgery/

# Facial Reenactment

# Imperceptible Noise



# Impact on Face Recognition




VGG-Face model

G. Goswami, N. Ratha, A. Agarwal, R. Singh, and M. Vatsa. Unravelling robustness of deep learning based face recognition against adversarial attacks. AAAI, 2018

# Key Takeout (so far)

- So, now we are convinced that deep learning based systems can be attacked
- Keyword is "adversarial perturbation"

# How Adversarial Perturbation Works?

# Adversarial Attacks - Since When?

- In the context of DL, adversarial examples were discovered by
  - C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, and R. Fergus. Intriguing properties of neural networks. arXiv preprint arXiv:1312.6199, 2013.
- In PR, False Accepts and False Rejects have been studied at length with respect to perturbations
- Biometrics systems have studied the biometrics zoo
- Biometrics systems have studied presentation attacks
- Adversarial Machine Learning has been known for a long time (since 2004)

# Numerical Example

1. From: spammer@example.com
Cheap mortgage now!!!

Feature Weights

2. cheap = 1.0
mortgage = 1.5

3. Total score = 2.5> 1.0 (threshold)

**Spam**

# Numerical Example

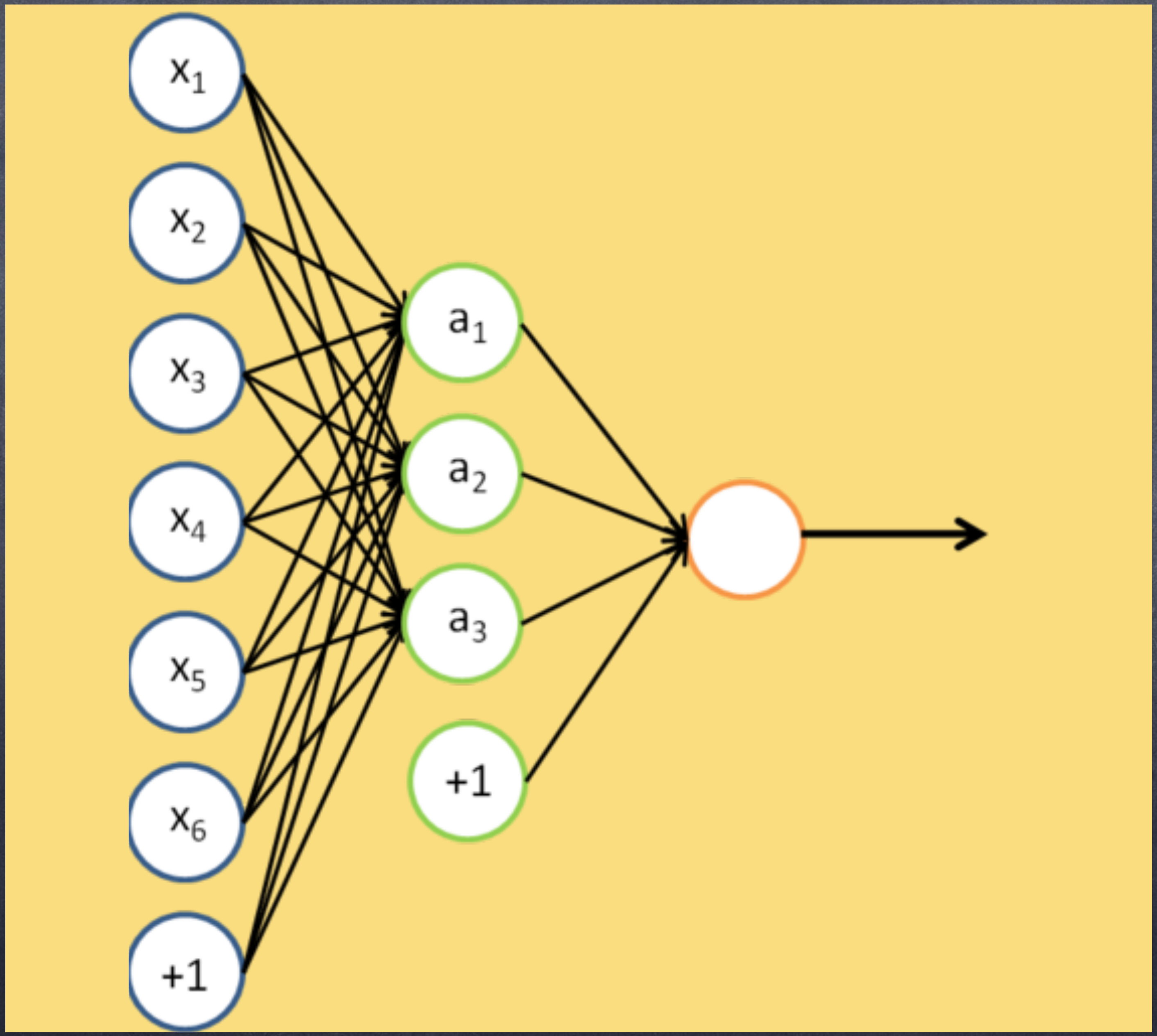
1. From: spammer@example.com
   Cheap mortgage now!!!
   Joy Oregon

Feature Weights

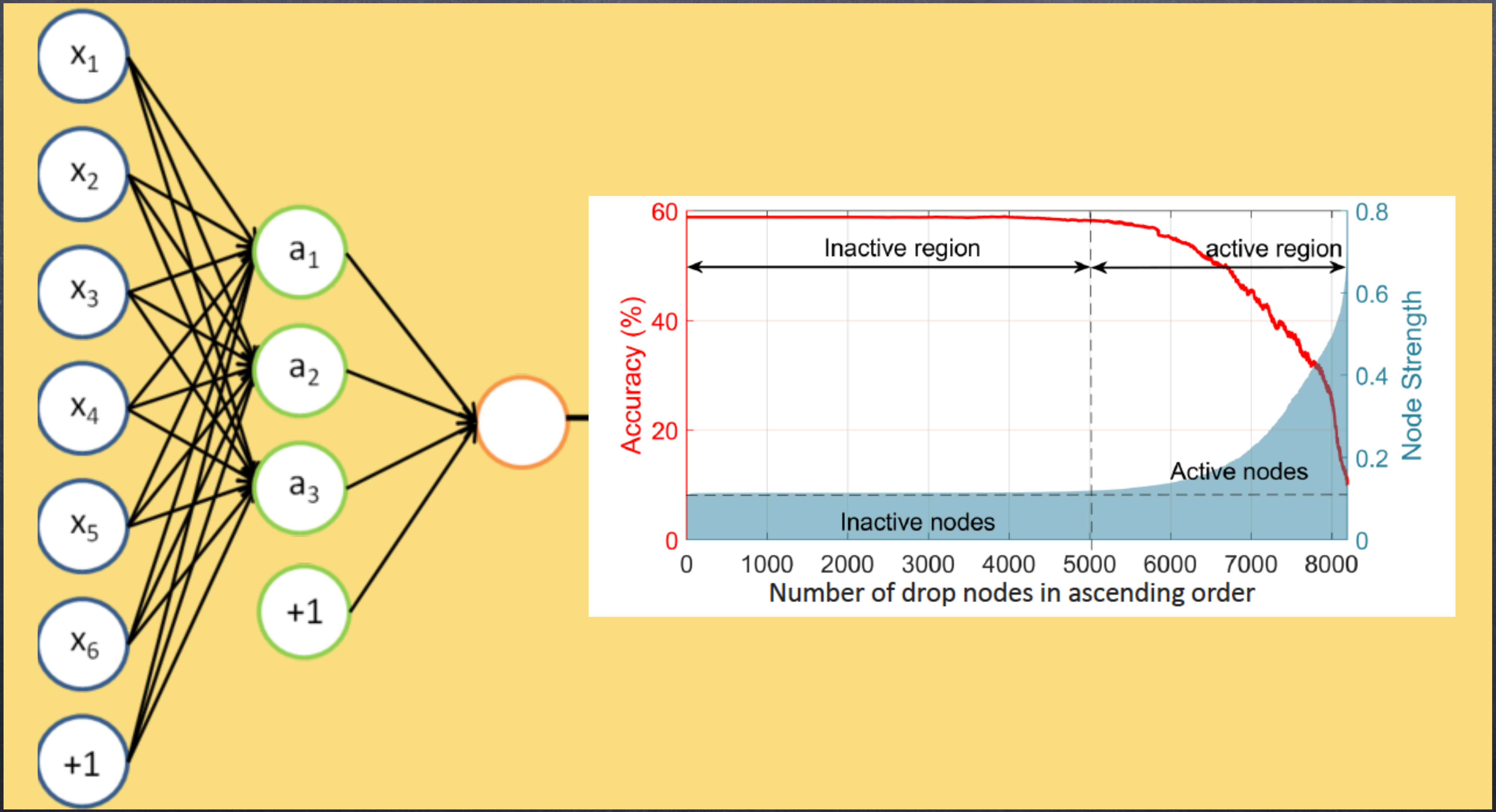
2. cheap = 1.0
   mortgage = 1.5
   Joy= -1.0
   Oregon = -1.0
3. Total score = 0.5< 1.0 (threshold)

OK

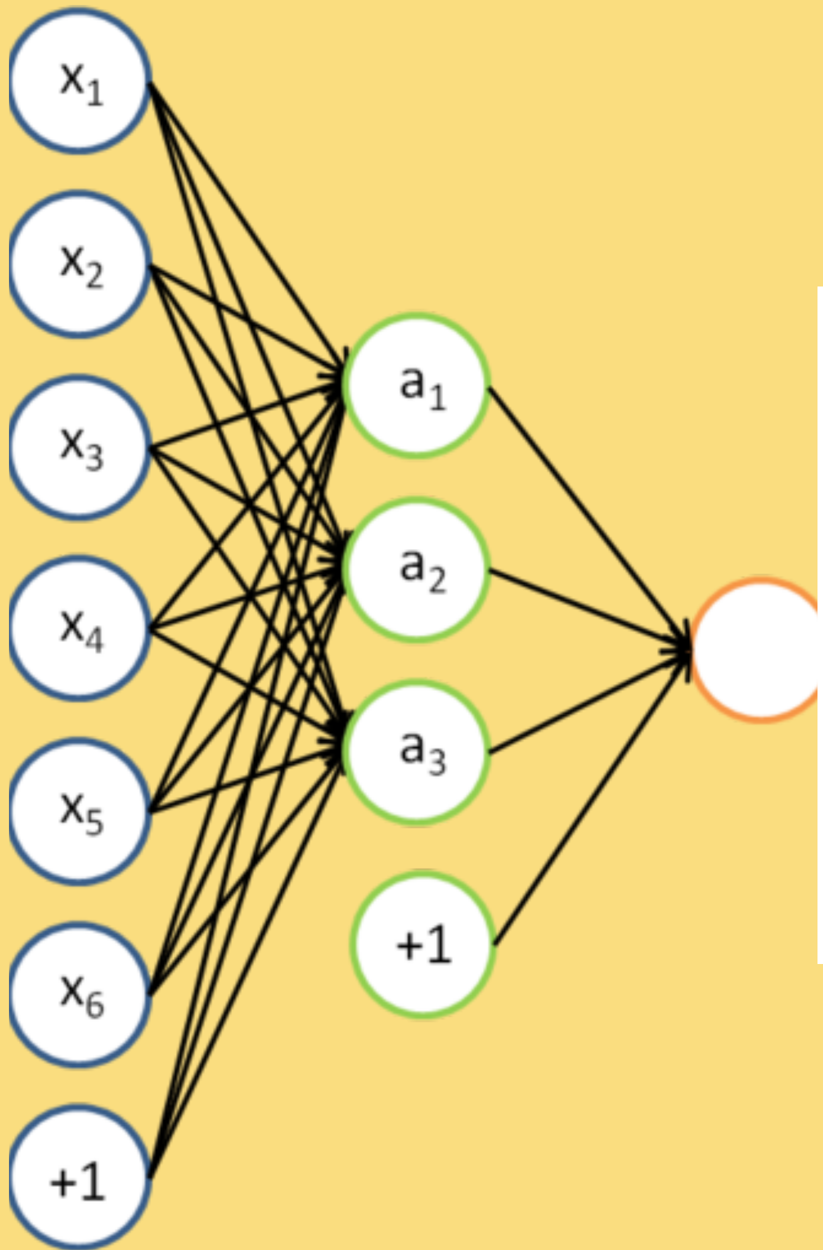
# Let us take a simple Neural Net

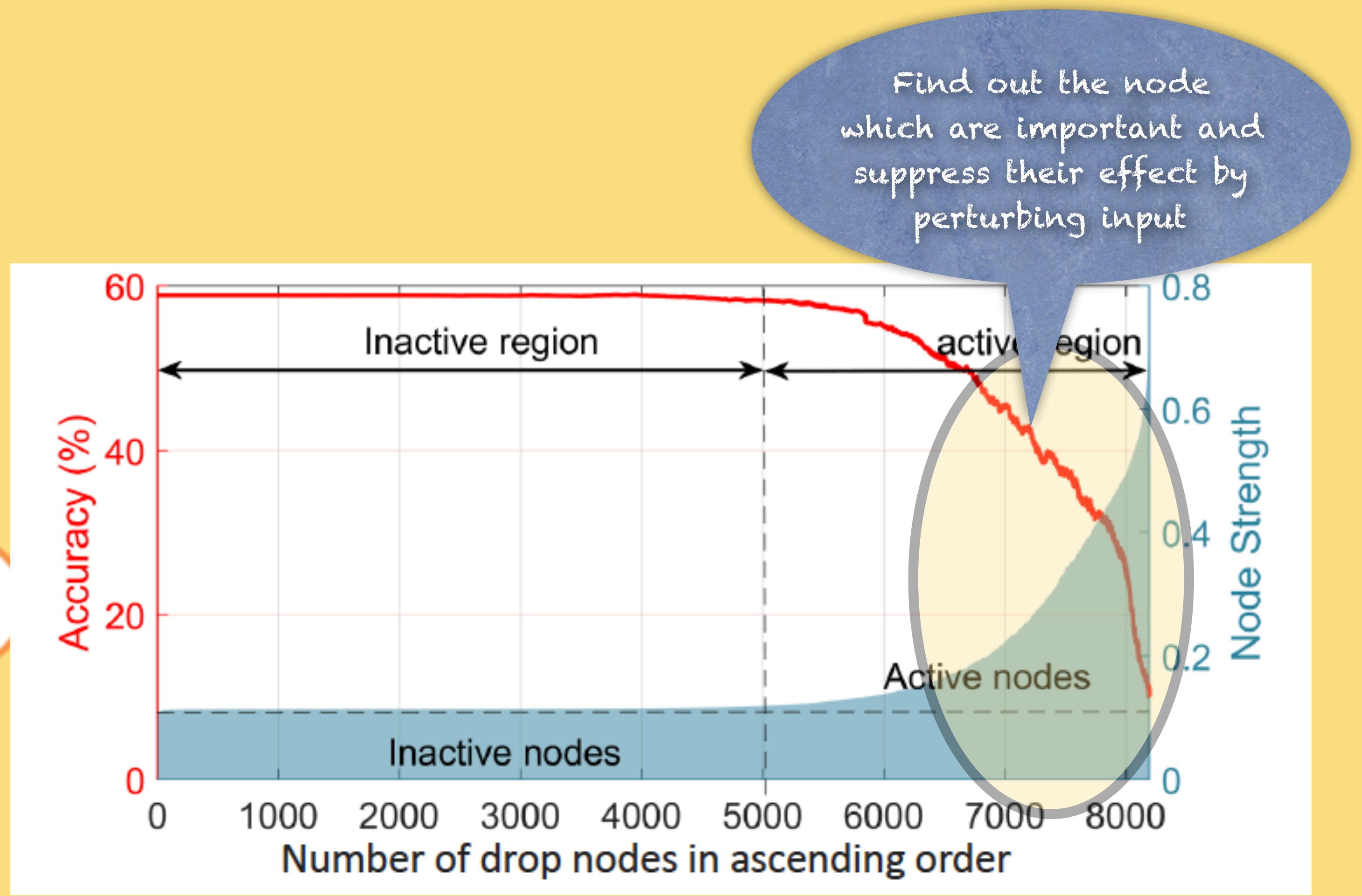


# Let us take a simple Neural Net

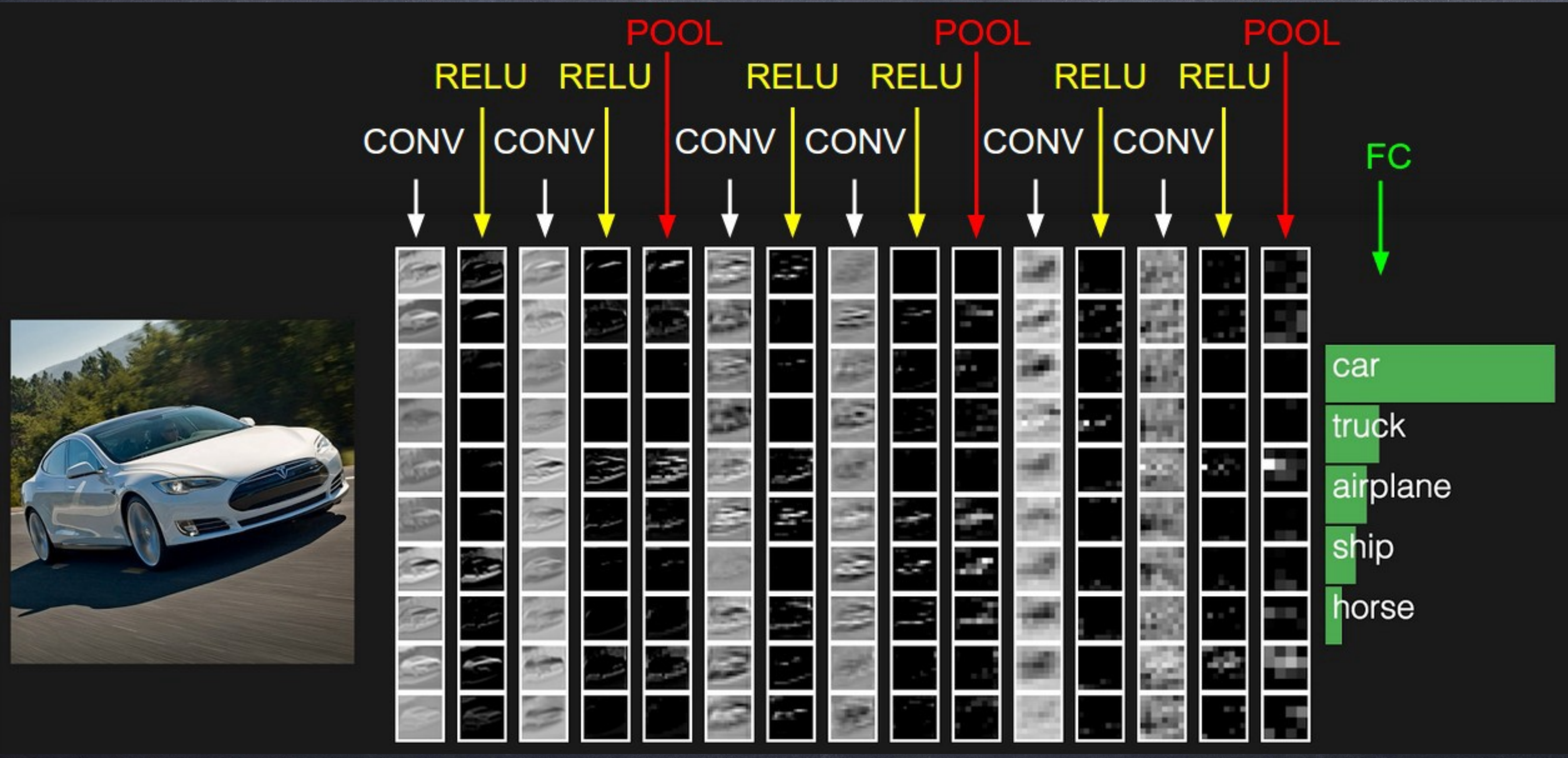


# Let us take a simple Neural Net

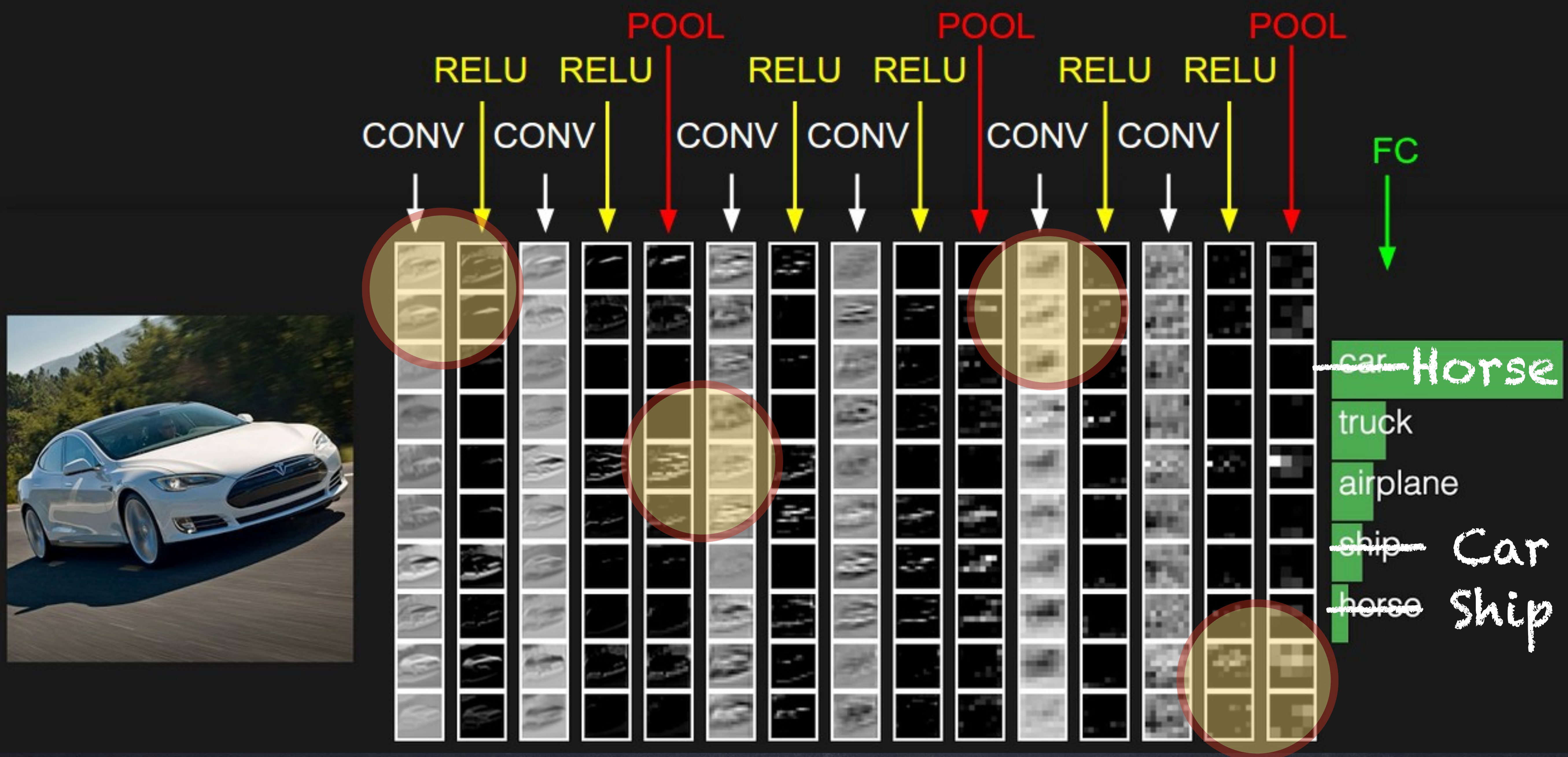


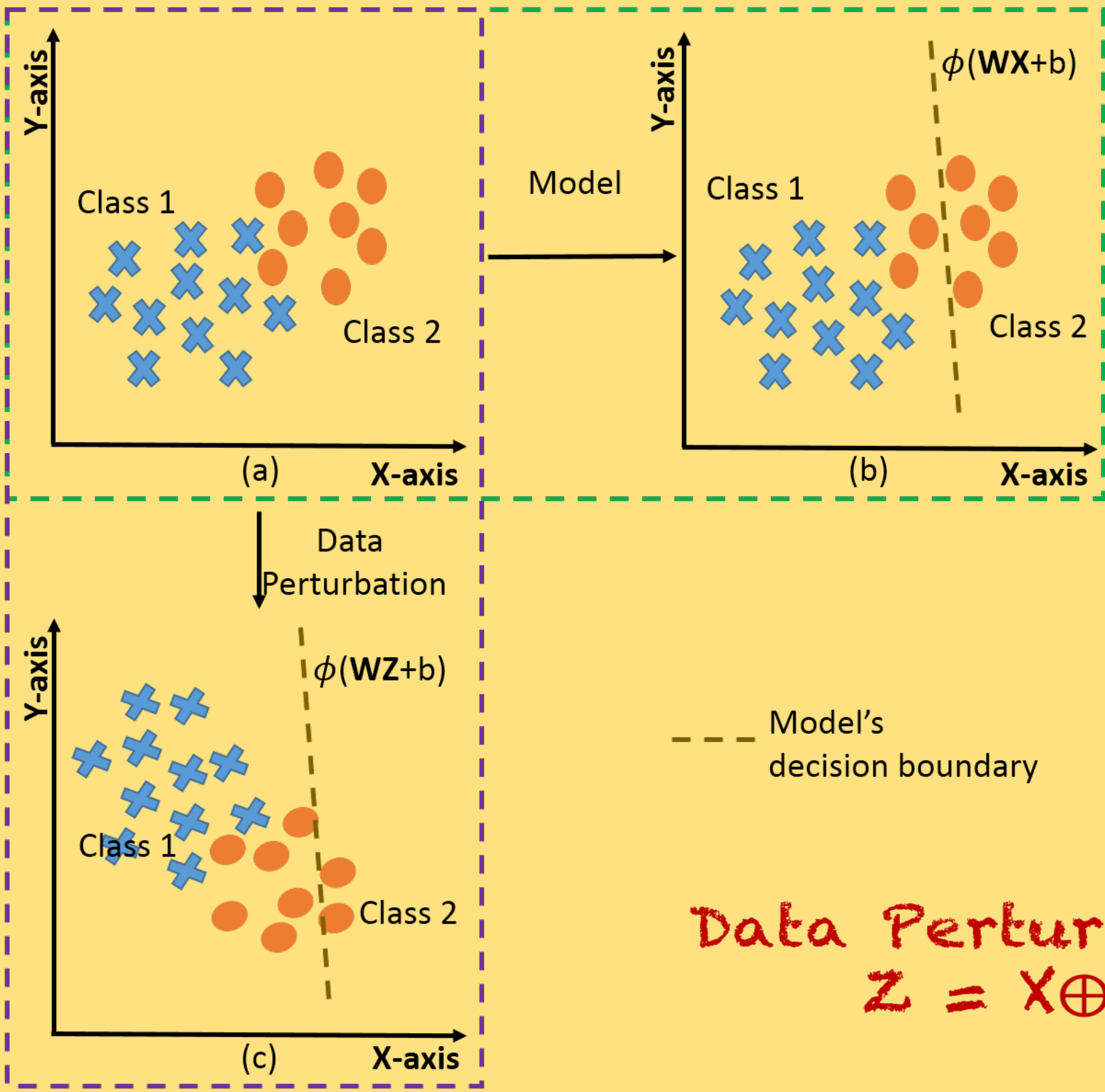
# Extending the example to CNN



# Extending the example to CNN



# Mathematically Adversarial Perturbations



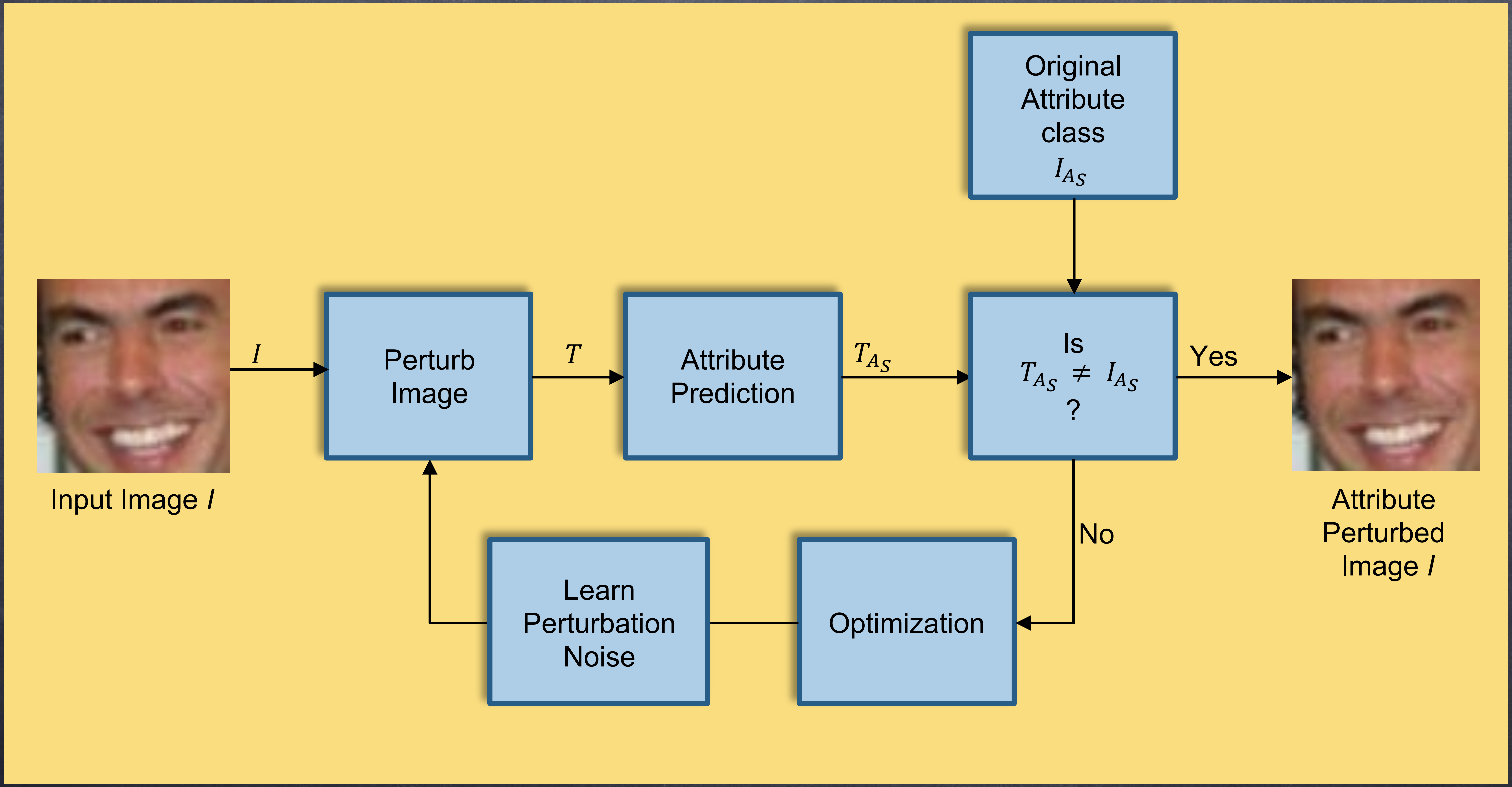

Data Perturbation

$Z = X \oplus N$

# Mathematically

- This can be viewed as an optimization problem, i.e.
- $\min[D(I_o) - D(I_p)] + \min(||I_o - I_p||)$
  - such that $Class(I_o) \neq Class(I_p)$
- First term minimizes the feature distance between original and perturbed information/features
- Second term minimizes the visual difference between original and perturbed images

# Example - Attribute Perturbation



# Example - Adversarial Noise of Universal Perturbation

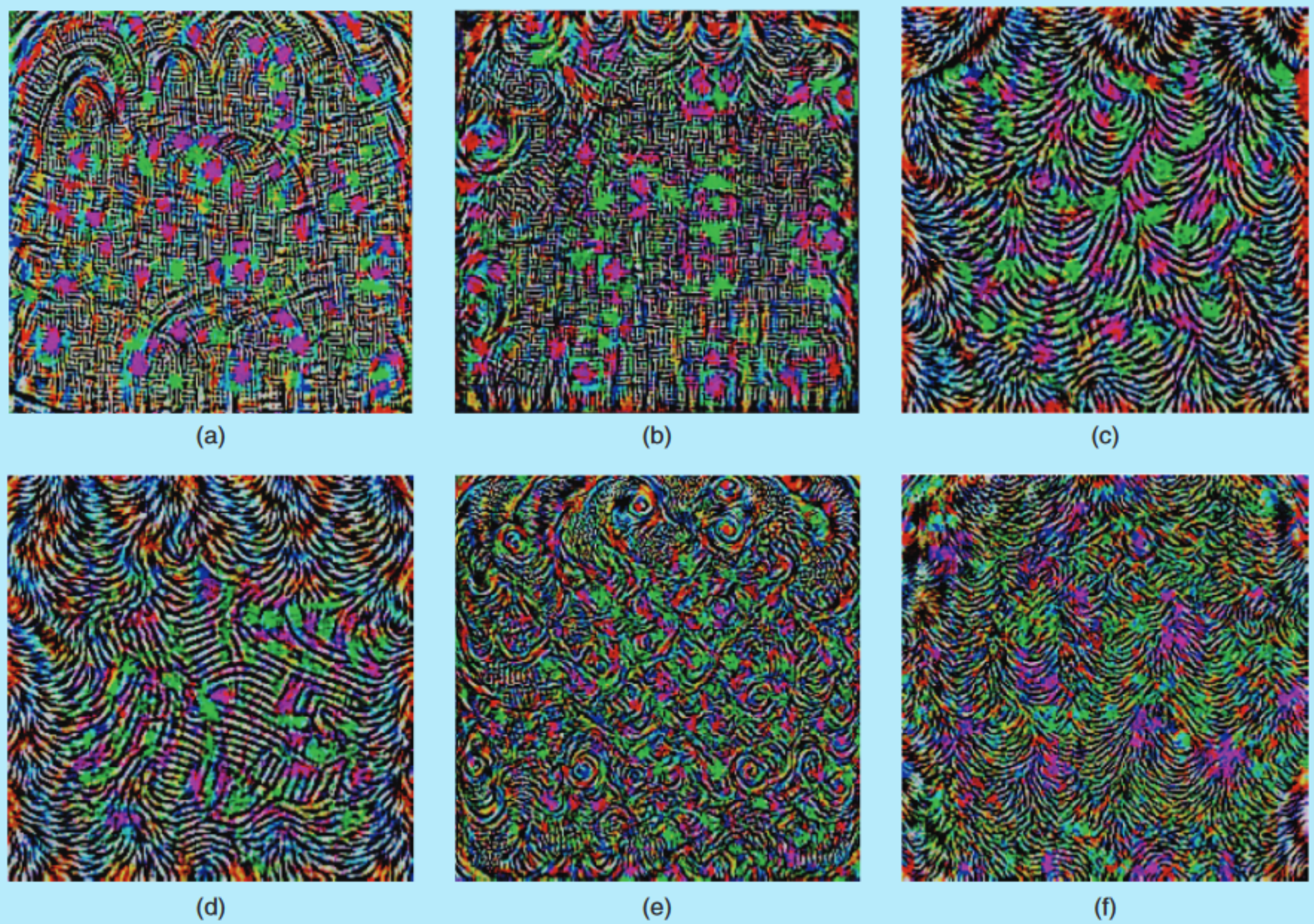
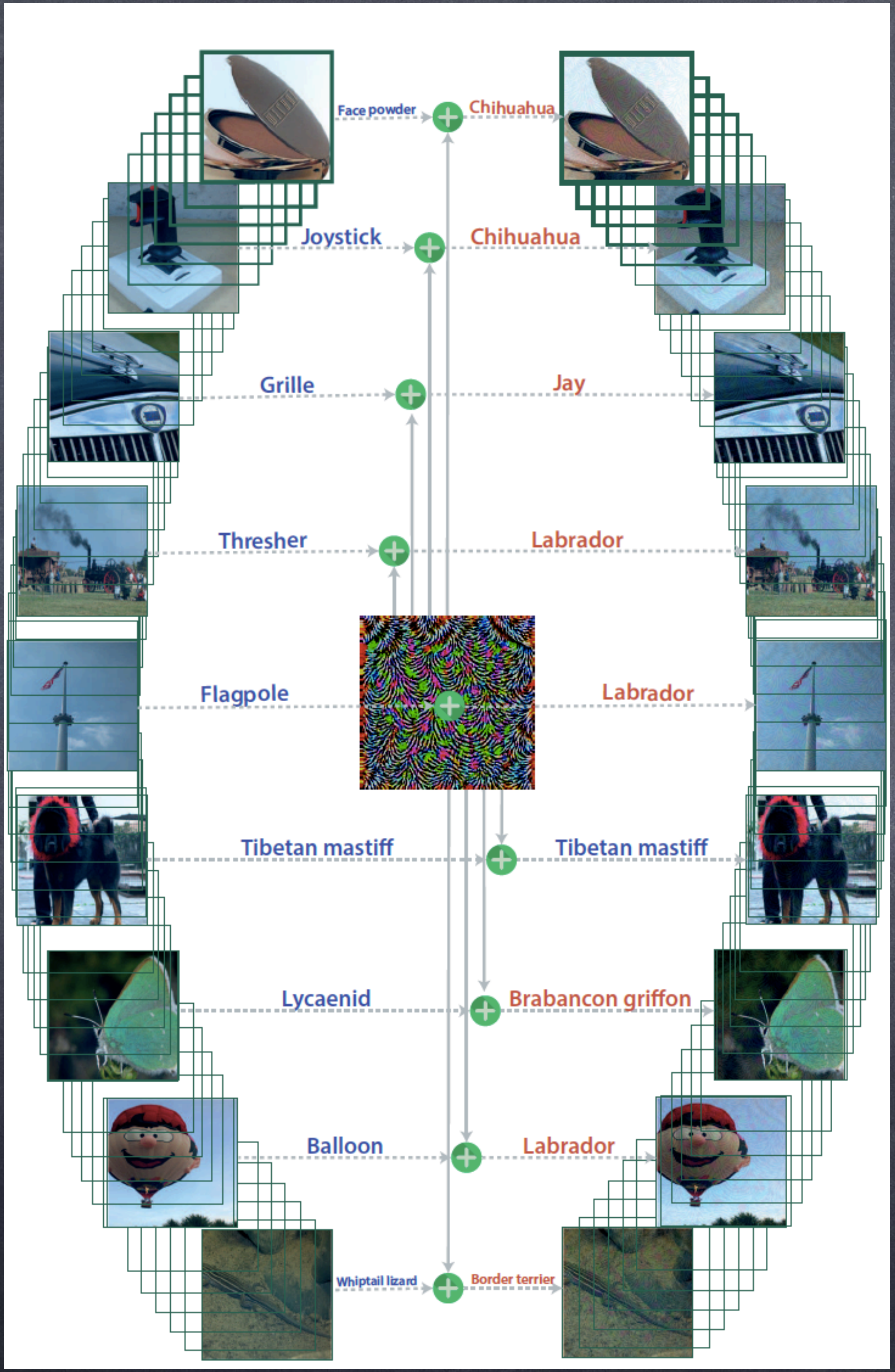


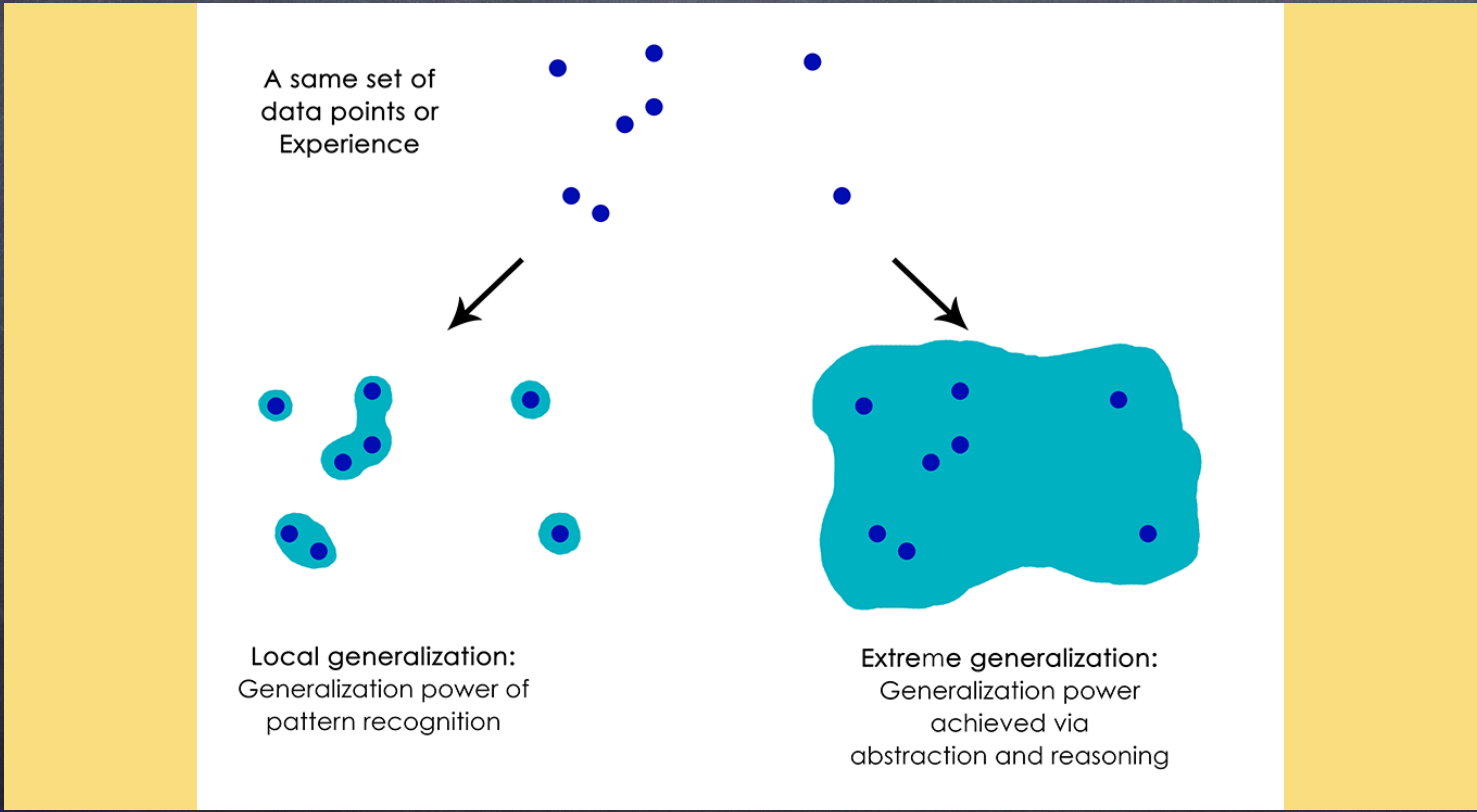

FIGURE 3. Universal perturbations computed for different deep neural network architectures. The pixel values are scaled for visibility. (a) CaffeNet, (b) VGG-F, (c) VGG-16, (d) VGG-19, (e) GoogLeNet, and (f) ResNet-152.

Moosavi-Dezfooli et al.
CVPR2017




Moosavi-Dezfooli et al.
CVPR2017

# Why Adversarial Perturbation Works?



| Adversarial | Authors | Descriptions |
|---|---|---|
| Generation | Szegedy et al., 2013 | L-BFGS: $L(x + \rho, l) + \|\|\rho\|\|^2$ s.t., $x_i + \rho_i \in [b_{min}, b_{max}]$ |
| | Goodfellow, Shlens, and Szegedy, 2015 | FGSM: $x_0 + \varepsilon(\nabla_x L(x_0, l_0))$ |
| | Papernot et al., 2016 | Saliency Map: $l_0$ distance optimization |
| | Moosavi-Dezfooli, Fawzi, and Frossard, 2016 | DeepFool: for each class; $l \neq l_0$; minimize d(l,l0) |
| | Carlini and Wagner, 2017 | C & W: lp distance metric optimization |
| | Moosavi-Dezfooli et al., 2017 | Universal (Image-Agnostic): Distribution based perturbation |
| | Rauber, Brendel, and Bethge, 2017 | Blackbox: Uniform, Gaussian, Salt and Pepper, Gaussian Blur, Contrast |

# Attacks on Faces

- Grid based occlusion (Grid)
- Most significant bit based noise (xMSB)
- Eye region occlusion (ERO)
- Forehead and brow occlusion (FHBO)
- Beard-like occlusion (Beard)
- Universal Perturbation

# Attacks on Faces


Goswami et al. AAAI2018, IJCV2019

# Evaluating Robustness

MEDS

| System | Original | Grids | xMSB | FHBO | ERO | Beard |
|---|---|---|---|---|---|---|
| COTS | 24.1 | 20.9 | 14.5 | 19.0 | 0.0 | 24.8 |
| OpenFace | 66.7 | 49.5 | 43.8 | 47.9 | 16.4 | 48.2 |
| VGG-Face | 78.4 | 50.3 | 45.0 | 25.7 | 10.9 | 47.7 |
| LightCNN | 89.3 | 80.1 | 71.5 | 62.8 | 26.7 | 70.7 |
| L-CSSE | 89.1 | 81.9 | 83.4 | 55.8 | 27.3 | 70.5 |

PaSC

| System | Original | Grids | xMSB | FHBO | ERO | Beard |
|---|---|---|---|---|---|---|
| COTS | 40.3 | 24.3 | 19.1 | 13.0 | 0.0 | 6.2 |
| OpenFace | 39.4 | 10.1 | 10.1 | 14.9 | 6.5 | 22.6 |
| VGG-Face | 54.3 | 3.2 | 1.3 | 15.2 | 8.8 | 24.0 |
| LightCNN | 60.1 | 24.6 | 29.5 | 31.9 | 24.4 | 38.1 |
| L-CSSE | 61.2 | 43.1 | 36.9 | 29.4 | 39.1 | 39.8 |

All values indicate genuine accept rate (%) at 1% false accept rate

# What an Attacker can Cause?

- Confidence reduction - the output confidence score is reduced, thus introducing class ambiguity
- Random mis-classification - an input is modified in order to output any class different than the correct one
- Targeted mis-classification - an input is modified in order to output a specific target class

# Types of Attacks

- White-box
- Grey-box
- Black-box

# White-box Attack

- The attacker has perfect knowledge of the DNN used (architecture, hyper-parameters, weights, etc.), has access to the training data and knowledge about any defense mechanisms employed (e.g. adversarial detection systems).
- Therefore, an attacker has the ability to completely replicate the model under attack

# Grey-box Attack

- In this case the attacker can collect some information about the network's architecture (e.g. she knows a certain model/uses an open-source architecture), she knows the model under attack was trained using a certain dataset or has information about some defense mechanisms
- In any of these cases, the information is neither complete nor certain and provides the attacker an ability to partially simulate the model under attack

# Black-box Attack

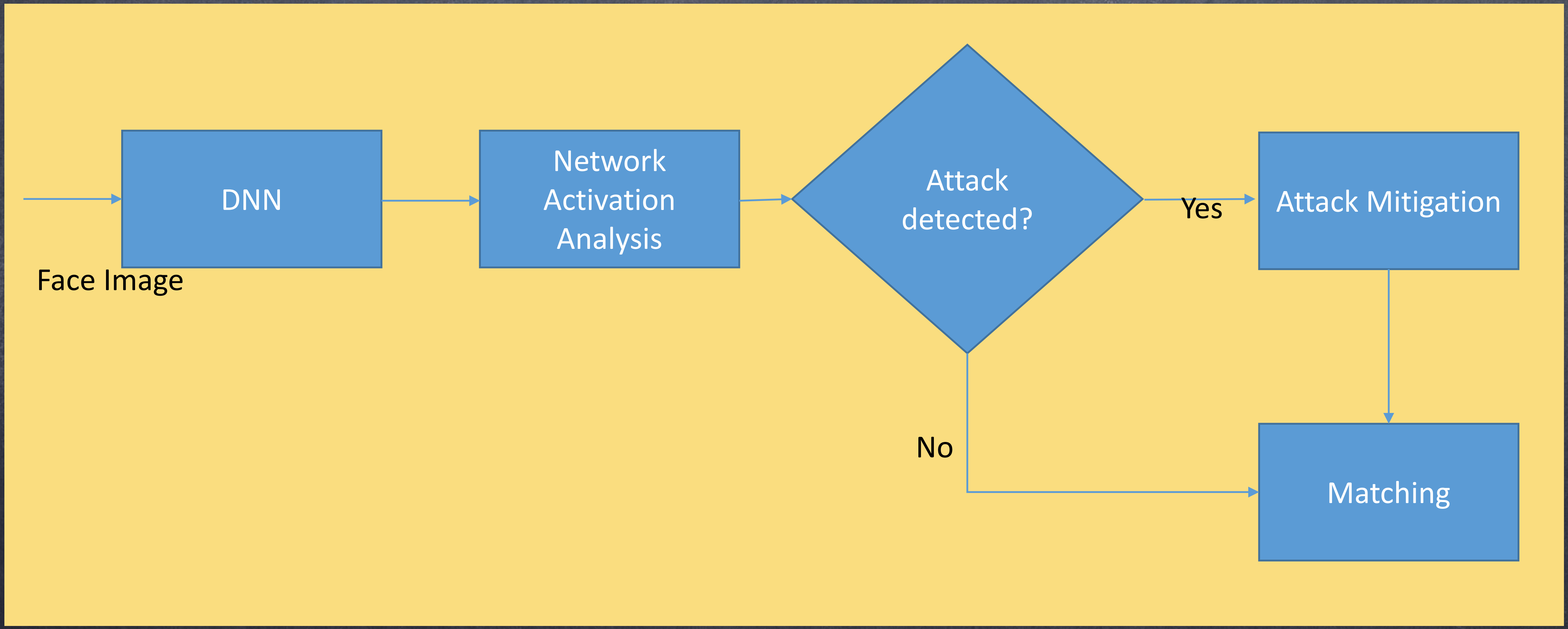
- The attacker has no knowledge about the model under attack, however, she has the ability to use the model (or a proxy of it) as an oracle.
- The attacker can supply limited inputs and collect output information to build attack model

# Catalog of Adversarial Attacks

| Attack | Modify (M) or Generate (G) Input | Optimisation (OP), Sensitivity (SA), Geometric Transformations (GT) Generative Models (GM) | Targeted (TG), Non-Targeted (NTG) | Single-Shot (SS), Iterative (IT) | White-box (WB), Grey-box (GB), Black-box (BB) | Specific (SP), Universal (UN) |
|---|---|---|---|---|---|---|
| L-BFGS [185] | M | OP | TG | IT | WB | SP |
| Deep Fool [135] | M | OP | NTG | IT | WB | SP |
| UAP [132] | M | OP | NTG | IT | WB | UN |
| Carlini [29] | M | OP | TG / NTG | IT | WB | SP |
| CFOA (Madry / PG) [128] | M | OP | TG / NTG | IT | WB | SP |
| STA [90] | M | OP | TG / NTG | IT | WB | SP |
| ZOO [35] | M | OP | TG / NTG | IT | BB | SP |
| IS [137] | M | OP | TG / NTG | IT | BB | SP |
| FGS [70] | M | SA | NTG | SS | WB | SP |
| JSMA [146] | M | SA | TG | IT | WB | SP |
| RSSA [188] | M | SA | NTG | SS / IT | WB | SP |
| BPDA [7] | M | SA | TG | IT | WB | SP |
| Elastic-Net [34] | M | SA | TG | IT | WB | SP |
| BI [109] | M | SA | NTG | IT | WB | SP |
| ILC [109] | M | SA | TG | IT | WB | SP |
| Momentum [47] | M | SA | NTG | IT | WB | SP |
| Substitute [145] | M | SA | TG | SS / IT | BB | SP |
| Rotation Tr. [52] | M | GT | NTG | SS / IT | WB / GB | SP |
| ManiFool [97] | M | GT | TG / NTG | IT | WB | SP |
| Spatial Tr. [198] | M | GT | TG | IT | WB | SP |
| ATN [8] | G | GM | TG / NTG | IT | WB | SP |
| NAE [211] | G | GM | TG | IT | WB | SP |

Akhtar and Mian, 2018

# What to do with Adversarial Perturbations?



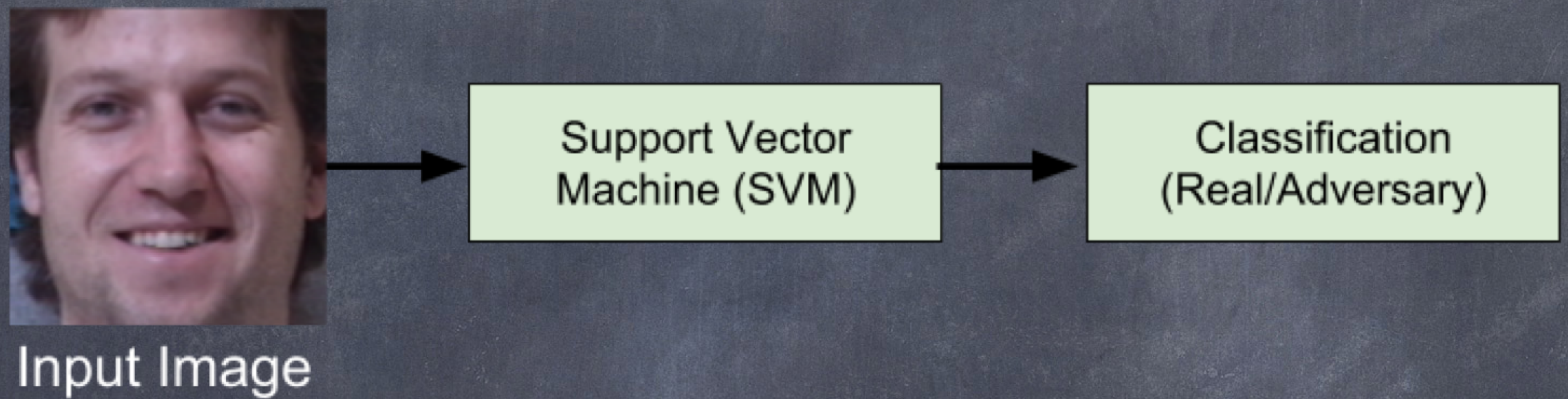
# How to detect adversarial perturbation (attack)?

# What Could be a simplest approach?

# A simple approach

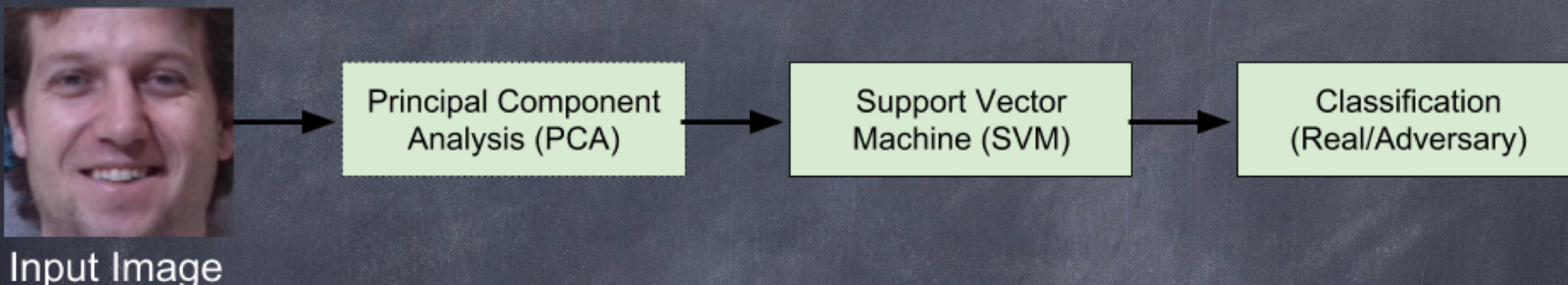
- Treat this problem as 2 class classification problem

# A simple approach



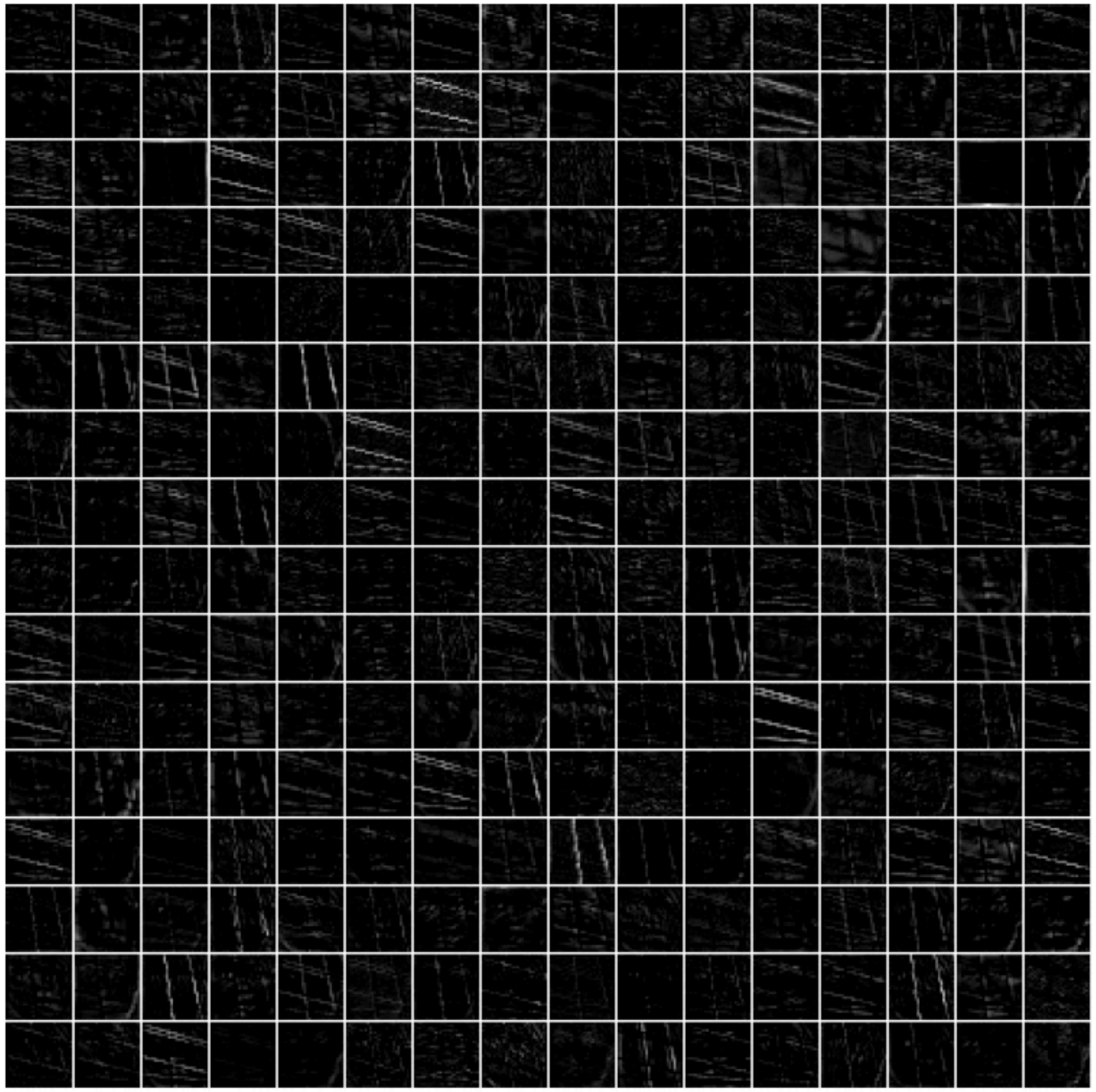

Black-box approach: we do not know about adversary but learn a classifier to identify the difference between real and perturbed samples

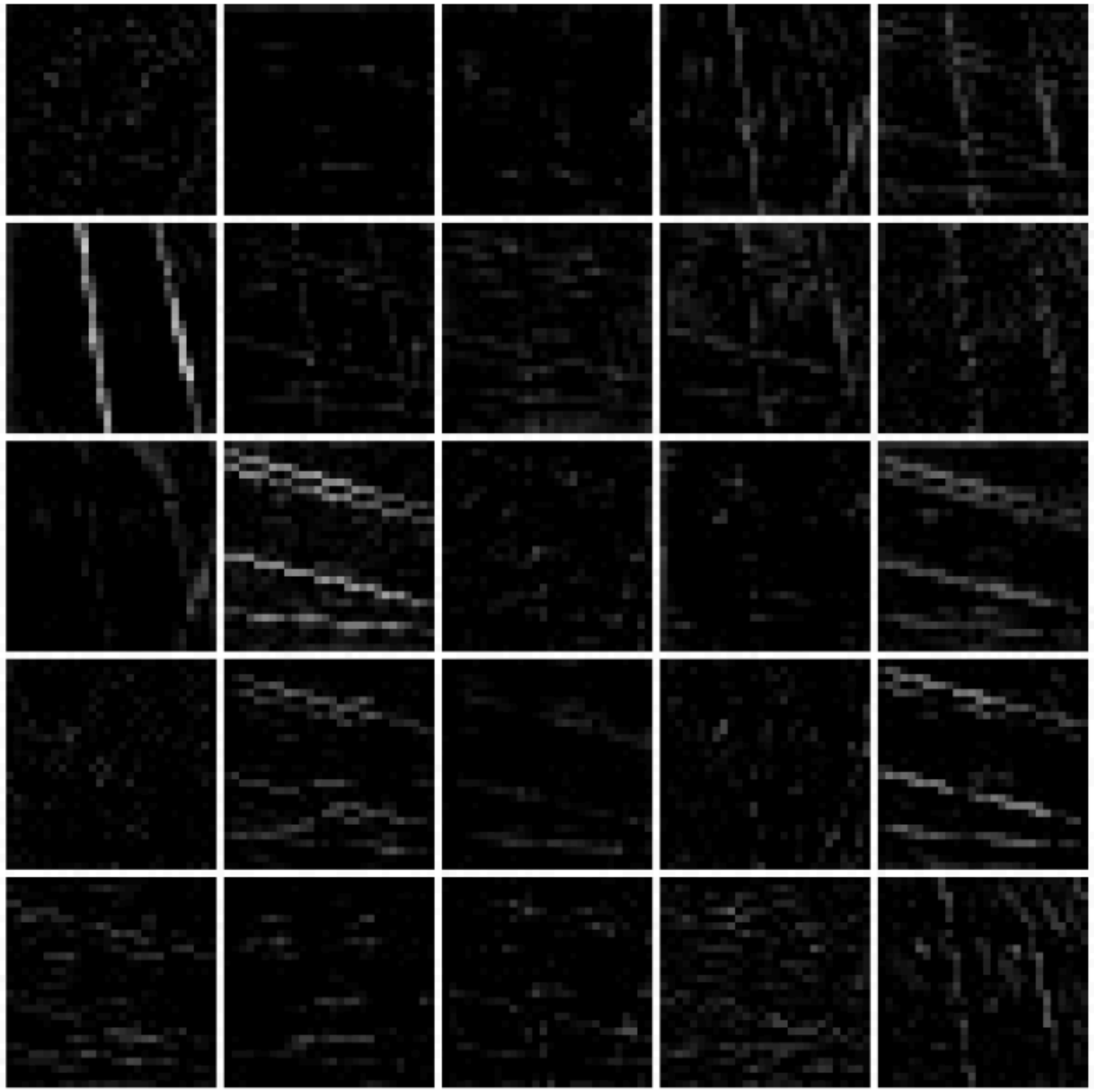
# A slightly modified version



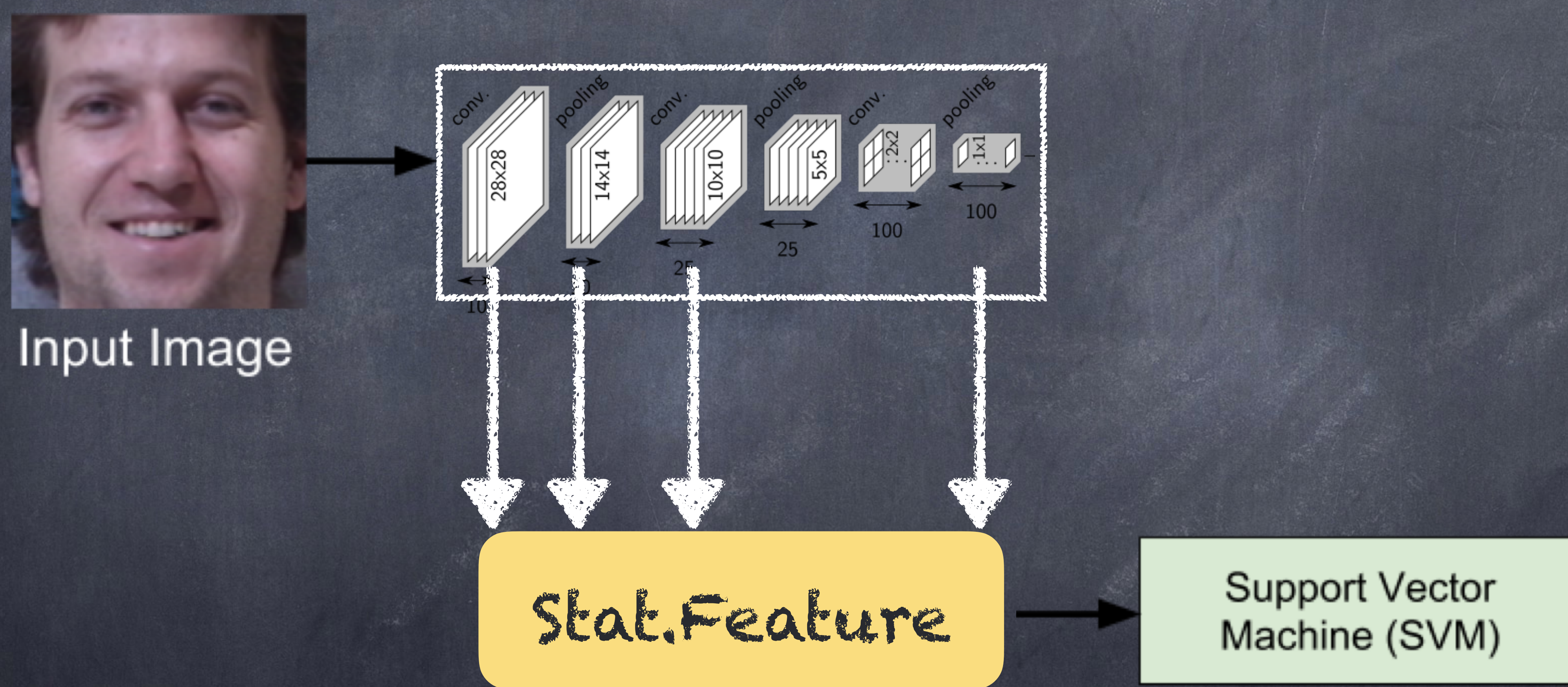

Black-box approach: we do not know about adversary but learn a classifier to identify the difference between real and perturbed samples

# Look at network activation



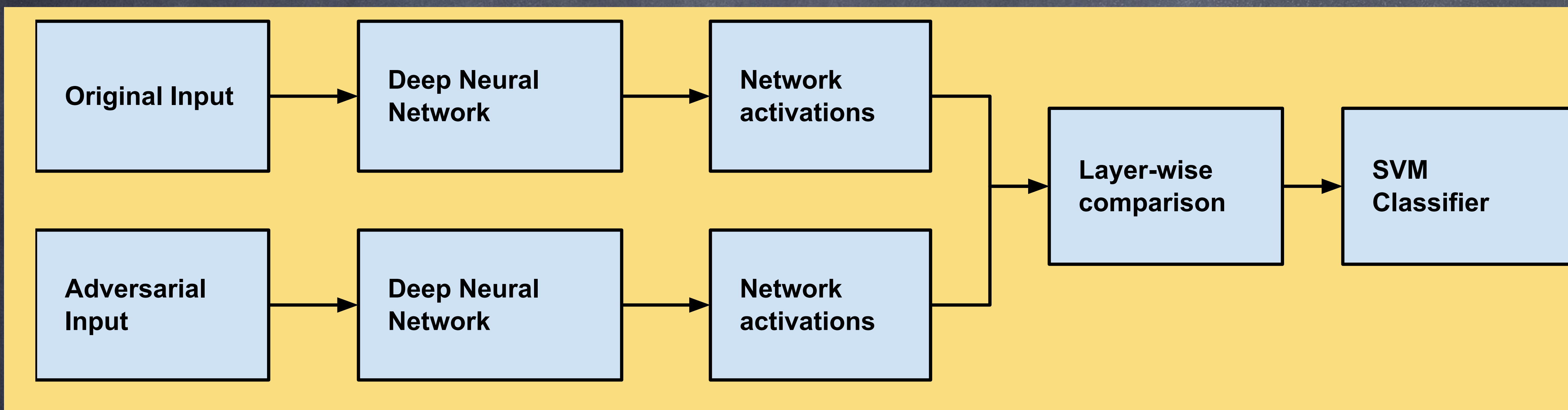


# CNN based White-box Approach

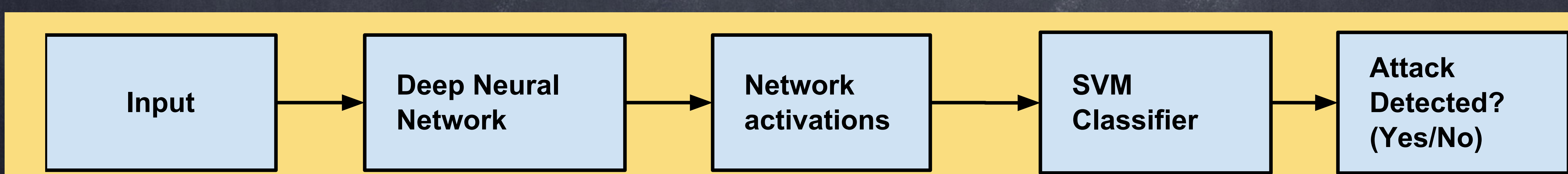



Li&Li, ICCV2017

# Adversarial Perturbation Detection




White-box Training




Testing

Goswami et al AAAI2018

# Adversarial Perturbation Detection ...

- Each layer in a deep neural network essentially learns a function or representation of the input data
- The features obtained for a distorted and undistorted image are measurably different from one another
- Internal representations computed at each layer are different for distorted images as compared to undistorted images
- To detect distortions, the pattern of the intermediate representations for undistorted images are compared with distorted images at each layer

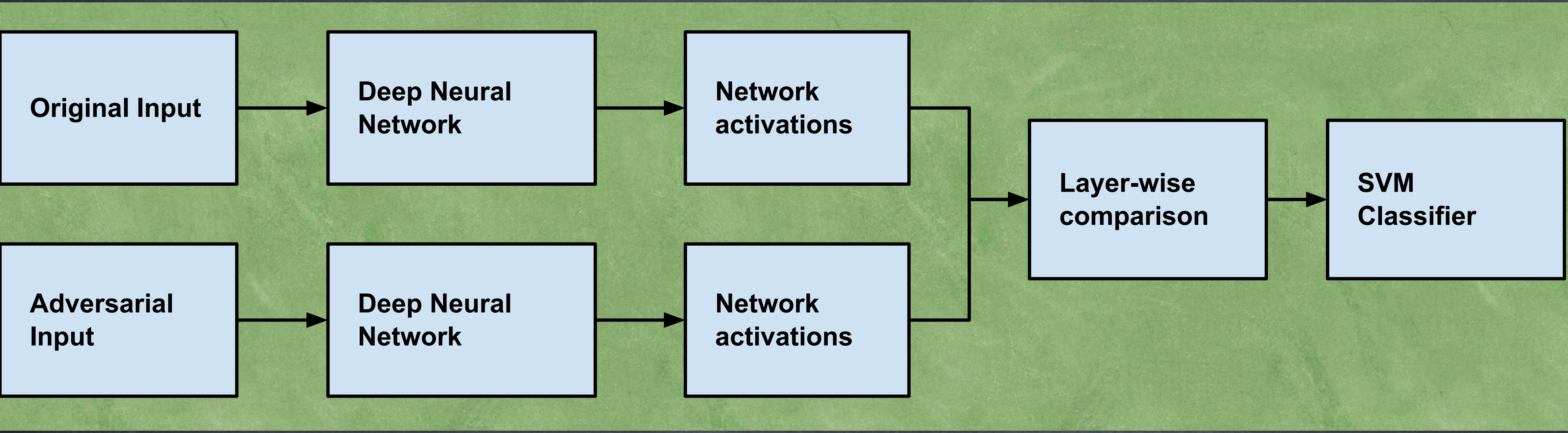
# Adversarial Perturbation Detection ...

$$\mu_i = \frac{1}{N_{train}} \sum_{j=1}^{N_{train}} \phi_i(I_j)$$

$$\psi_i(I, \mu) = \sum_{z}^{\lambda_i} \frac{|\phi_i(I)_z - \mu_{iz}|}{|\phi_i(I)_z| + |\mu_{iz}|}$$

- Intermediate representations computed for an arbitrary image I can be compared with the layer-wise means

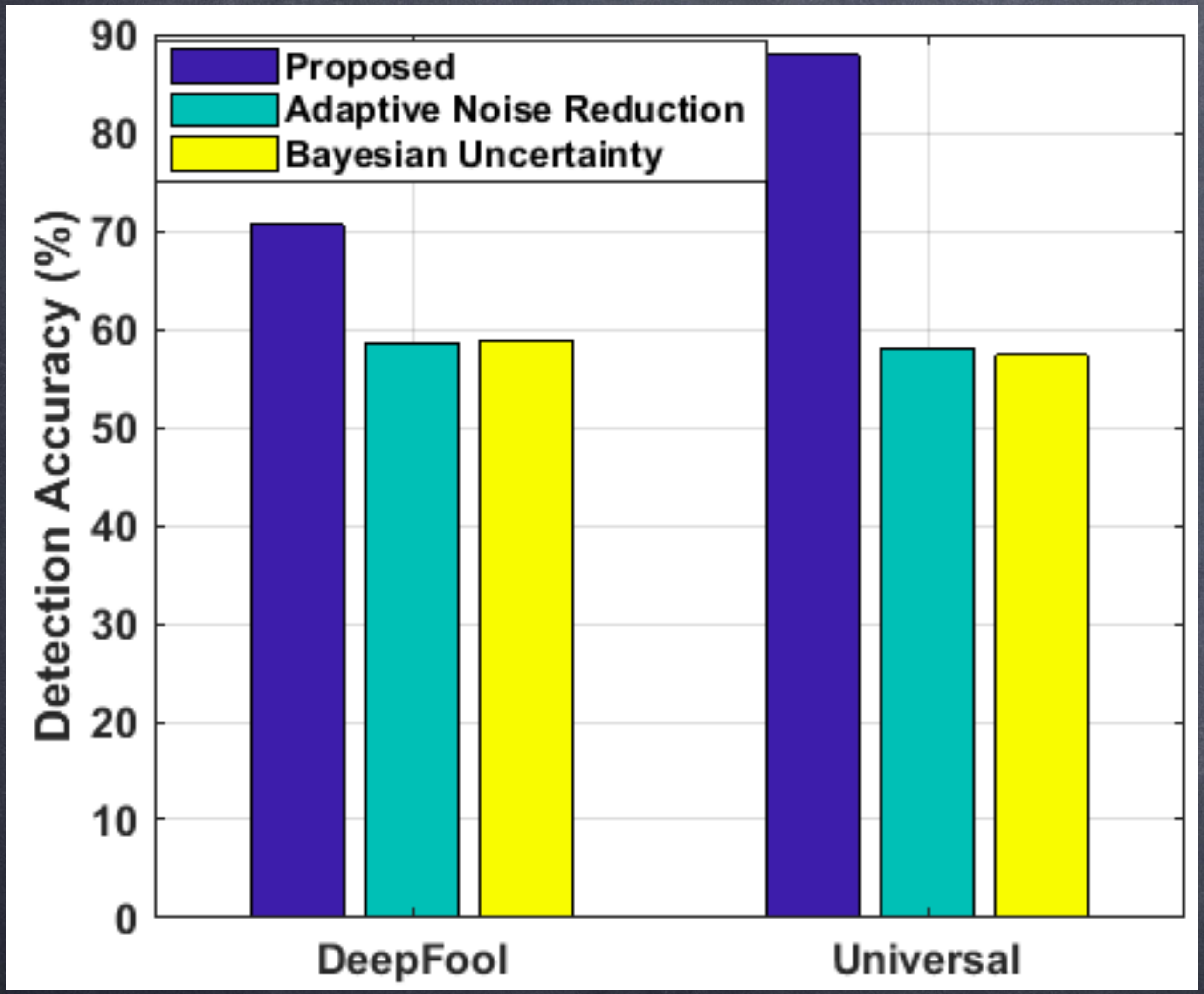
# Adversarial Perturbation Detection



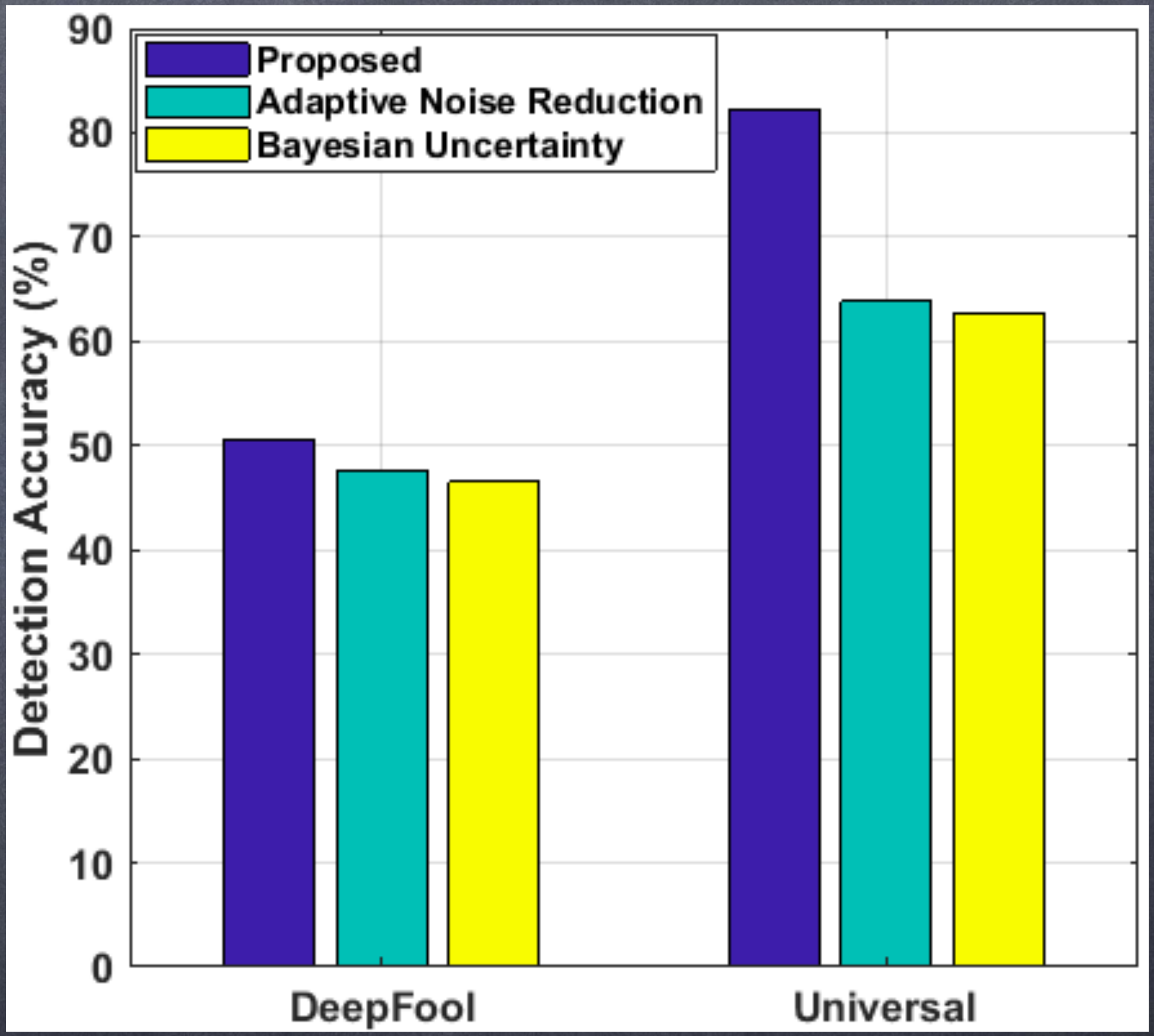

White-box Training


Testing

# Detection Results




PaSC database



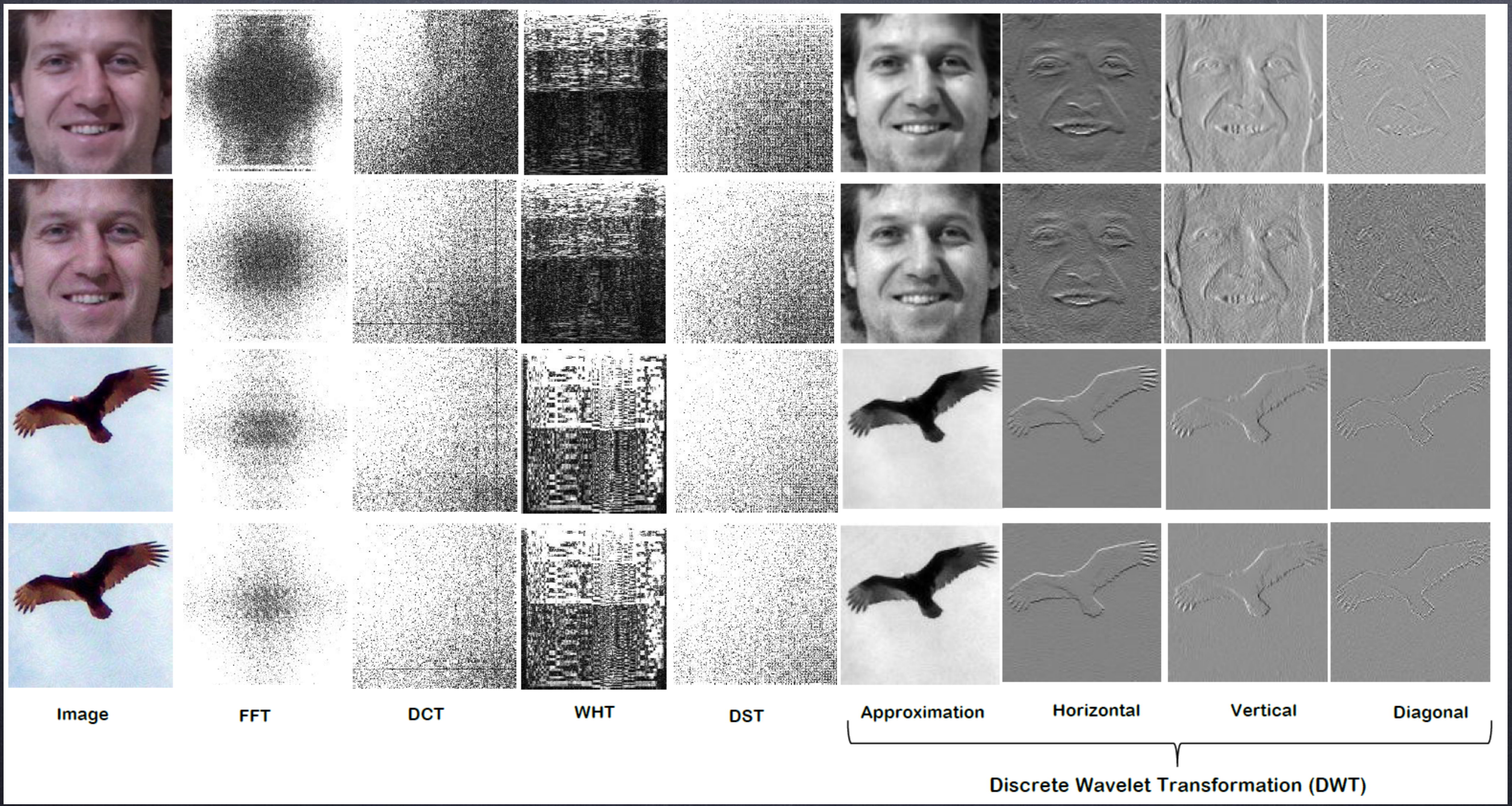

MEDS database

Goswami et al., Unravelling Robustness of Deep Learning based Face Recognition Against Adversarial Attacks, AAAI 2018 (Extended version in IJCV2019)

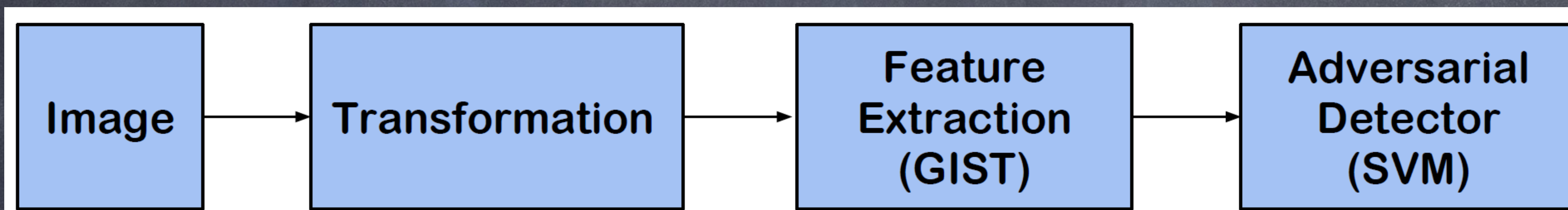
# Other Methods

| | Authors | Descriptions |
|---|---|---|
| Detection | Grosse et al., 2017 | Statistical test for adversarial and original data distribution |
| | Gong, Wang, and Ku; Metzen et al., 2017 | Neural network based classification |
| | Feinman et al., 2017 | Randomized network using Dropout at both training and testing |
| | Lu, Issaranon, and Forsyth, 2017 | Quantize ReLU output for discrete code + RBF SVM |
| | Das et al., 2017 | JPEG compression to reduce the effect of adversary |
| | Li & Li, 2017 | CNN maps + PCA statistics + Cascade SVM |

# Let us look at Transformations



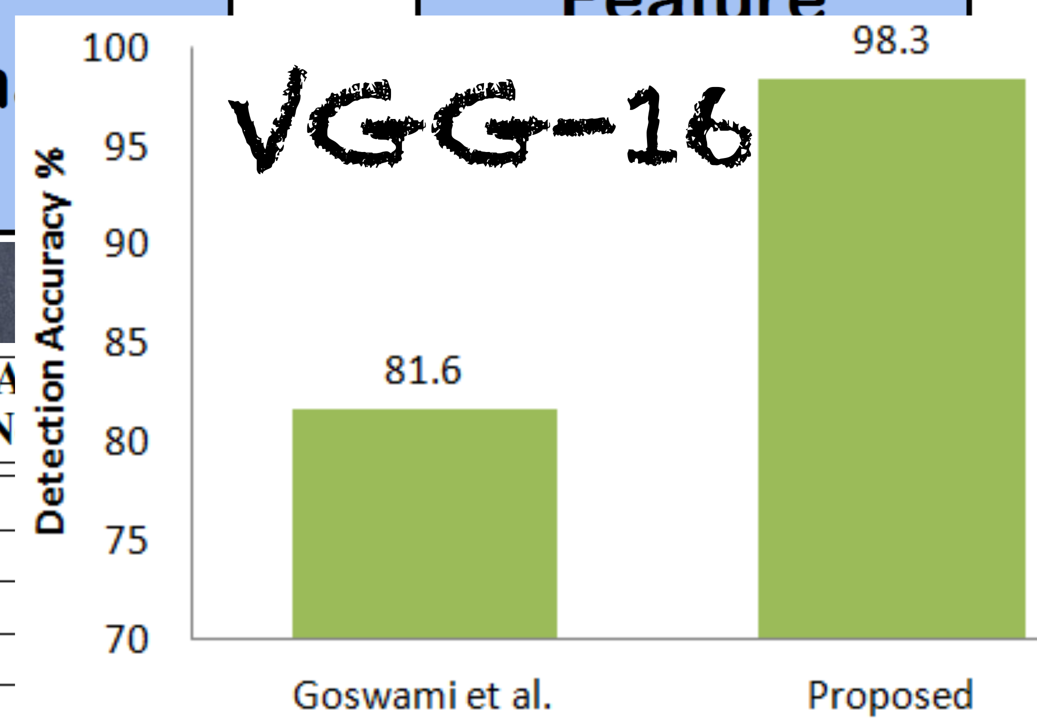
# Non-Deep Learning Approach




| Database | DNN Model | Attack | Adaptive Noise [31] | Bayesian Uncertainty [14] | GIST Features + SVM Classification (Proposed) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Image | DCT | FFT | DWT | DST | WHT |
| MEDS | VGG-16 | Universal | 80.2 | 80.3 | 96.4 | 57.4 | 96.3 | 98.3 | 94.3 | 78.5 |
| | | F3 | 79.6 | 79.9 | 96.5 | 61.6 | 96.9 | 98.3 | 96.5 | 88.0 |
| | GoogLeNet | Universal | 79.2 | 79.9 | 92.6 | 60.5 | 97.1 | 99.4 | 97.0 | 85.3 |
| | | F3 | 77.0 | 77.3 | 93.1 | 60.3 | 97.8 | 97.2 | 93.1 | 83.4 |
| | CaffeNet | Universal | 78.9 | 78.4 | 94.01 | 59.0 | 92.9 | 98.2 | 95.1 | 82.3 |
| | | F3 | 78.8 | 78.5 | 99.2 | 67.5 | 97.6 | 99.8 | 99.2 | 88.6 |
| Multi-PIE | VGG-16 | Universal | 75.5 | 74.7 | 99.9 | 57.7 | 100.0 | 100.0 | 99.6 | 93.0 |
| | | F3 | 76.0 | 75.0 | 99.9 | 61.8 | 100.0 | 99.9 | 99.9 | 98.9 |
| | GoogLeNet | Universal | 69.4 | 69.8 | 99.9 | 61.8 | 100.0 | 99.9 | 100.0 | 98.9 |
| | | F3 | 70.2 | 70.5 | 99.9 | 59.8 | 100.0 | 99.9 | 99.9 | 99.0 |
| | CaffeNet | Universal | 71.1 | 70.3 | 100.0 | 58.2 | 100.0 | 99.9 | 99.9 | 97.4 |
| | | F3 | 70.2 | 69.6 | 99.9 | 67.1 | 100.0 | 100.0 | 100.0 | 99.0 |

Agrawal et al. 2018

# Non-Deep Learning Approach


| Database | DNN Model | Attack | A… N… | [illegible] | [illegible] | [illegible] | …FT | DWT | DST | WHT |
|---|---|---|---|---|---|---|---|---|---|---|
| MEDS | VGG-16 | Universal | [illegible] | [illegible] | [illegible] | [illegible] | …6.3 | 98.3 | 94.3 | 78.5 |
| | | F3 | [illegible] | [illegible] | [illegible] | [illegible] | …6.9 | 98.3 | 96.5 | 88.0 |
| | GoogLeNet | Universal | [illegible] | [illegible] | [illegible] | [illegible] | …7.1 | 99.4 | 97.0 | 85.3 |
| | | F3 | [illegible] | [illegible] | [illegible] | [illegible] | …7.8 | 97.2 | 93.1 | 83.4 |
| | CaffeNet | Universal | [illegible] | [illegible] | [illegible] | [illegible] | …2.9 | 98.2 | 95.1 | 82.3 |
| | | F3 | 78.8 | 78.5 | 99.2 | 67.5 | 97.6 | 99.8 | 99.2 | 88.6 |
| Multi-PIE | VGG-16 | Universal | 75.5 | 74.7 | 99.9 | 57.7 | 100.0 | 100.0 | 99.6 | 93.0 |
| | | F3 | 76.0 | 75.0 | 99.9 | 61.8 | 100.0 | 99.9 | 99.9 | 98.9 |
| | GoogLeNet | Universal | 69.4 | 69.8 | 99.9 | 61.8 | 100.0 | 99.9 | 100.0 | 98.9 |
| | | F3 | 70.2 | 70.5 | 99.9 | 59.8 | 100.0 | 99.9 | 99.9 | 99.0 |
| | CaffeNet | Universal | 71.1 | 70.3 | 100.0 | 58.2 | 100.0 | 99.9 | 99.9 | 97.4 |
| | | F3 | 70.2 | 69.6 | 99.9 | 67.1 | 100.0 | 100.0 | 100.0 | 99.0 |

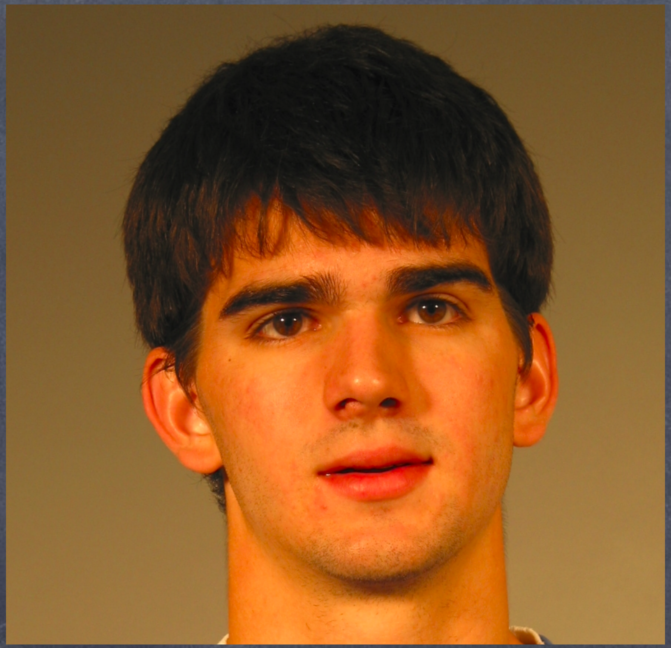
…VM Classification (Proposed)

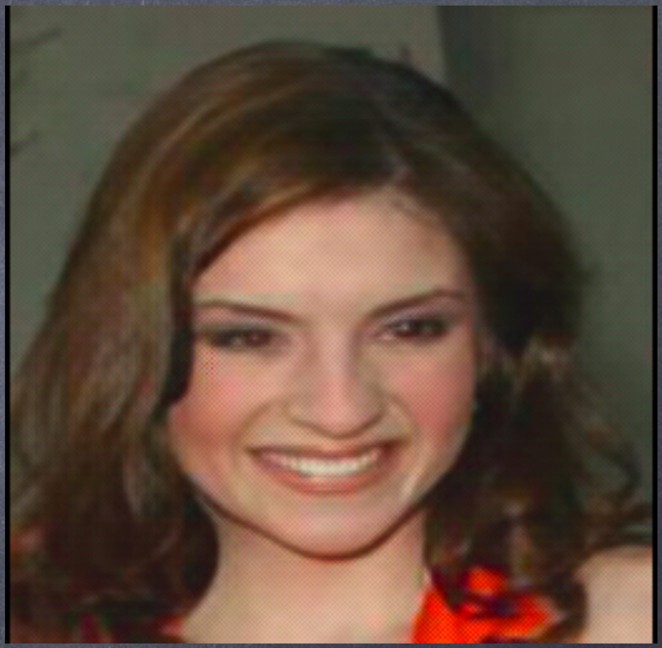
Agrawal et al. 2018

# Detecting GANs Generated (and Retouched) Images

- GANs generated images

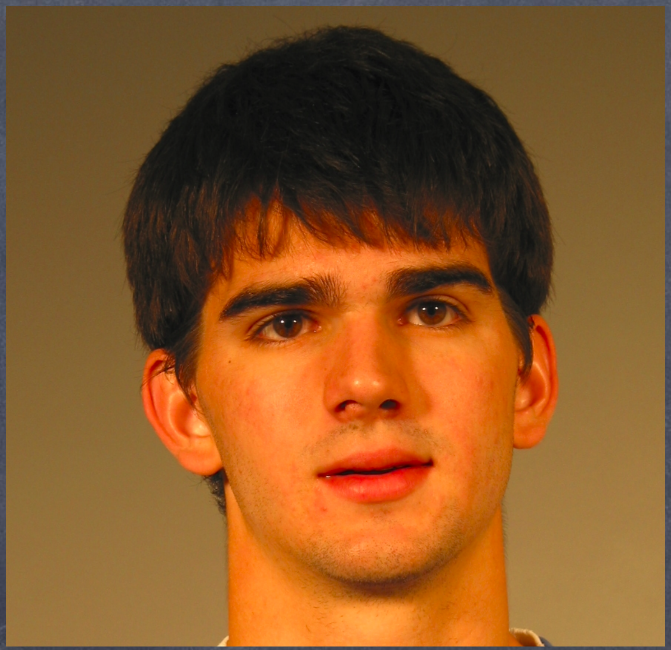
# Which one of these images is/are original?



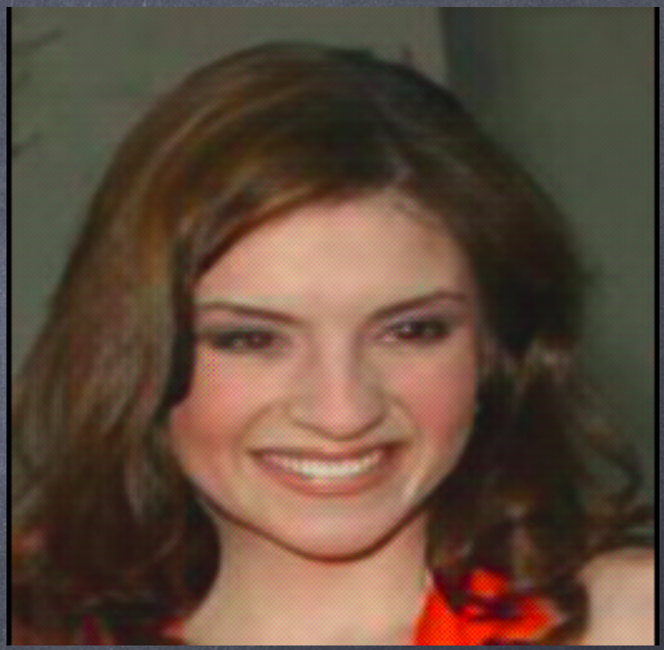


# Which one of these images is/are original?

Retouched

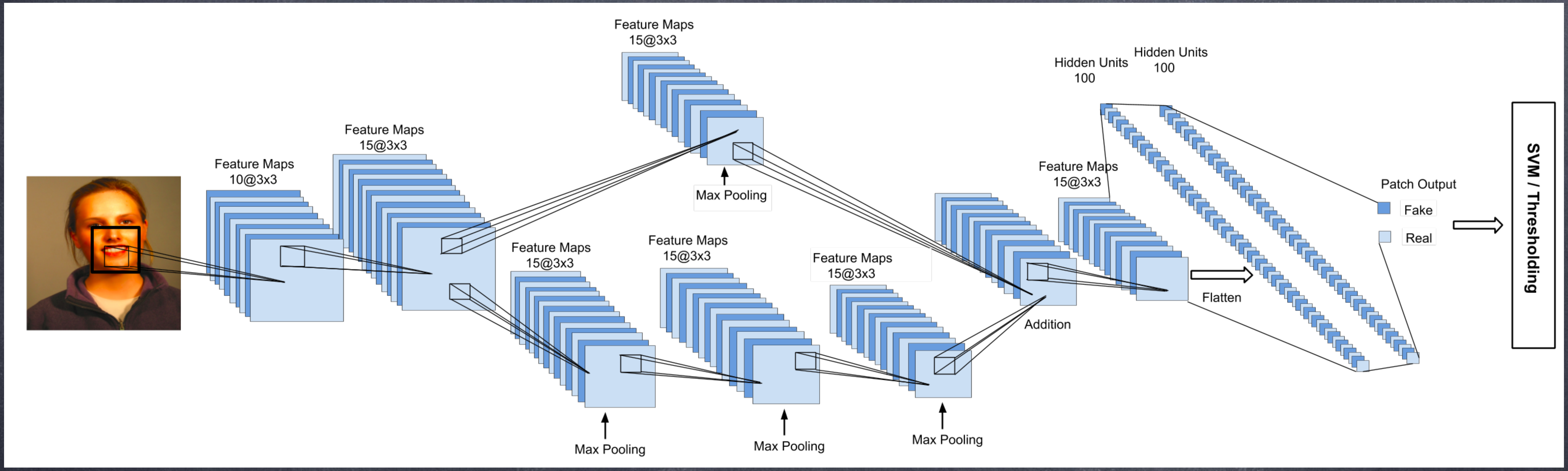


Original



Generated

# Proposed Pipeline




Input Image

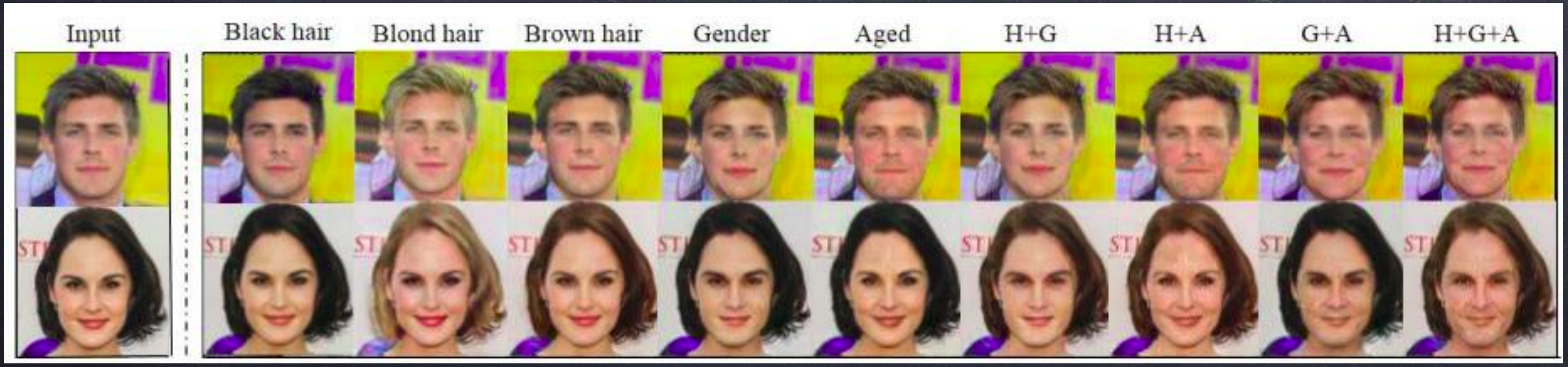
Deep CNN Model

Decision

Jain et al. - On Detecting Synthetic Alterations using GANs and Retouching, BTAS2018

# Databases

Retouching Output
IIITD-ND Database




StarGAN Output

# Results (Retouching)

## ND-IIITD dataset

| Algorithm | Accuracy |
|---|---|
| Kee et al. [1] | 48.8% |
| Aparna et al. [2] | 87.1% |
| Proposed (Thresholding) - (64,64,3) | 99.4% |
| Proposed (SVM) - (64,64,3) | 99.7% |
| Proposed (Thresholding) - (128,128,3) | 99.5% |
| Proposed (SVM) - (128,128,3) | 99.7% |

[1] E. Kee and H. Farid, “A perceptual metric for photo retouching,” PNAS, vol. 108, no. 50, pp. 19 907–19 912, 2011.
[2] A. Bharati, R. Singh, M. Vatsa, and K. W. Bowyer, “Detecting facial retouching using supervised deep learning,” IEEE TIFS, vol. 11, no. 9, pp. 1903–1913, 2016.

# Results (Synthetic images from GANs)

- To ensure that the network wasn't learning compression differences, images were converted to PNG compressed format.
- Images were compressed to detect them in compressed form like they undergo while being circulated.

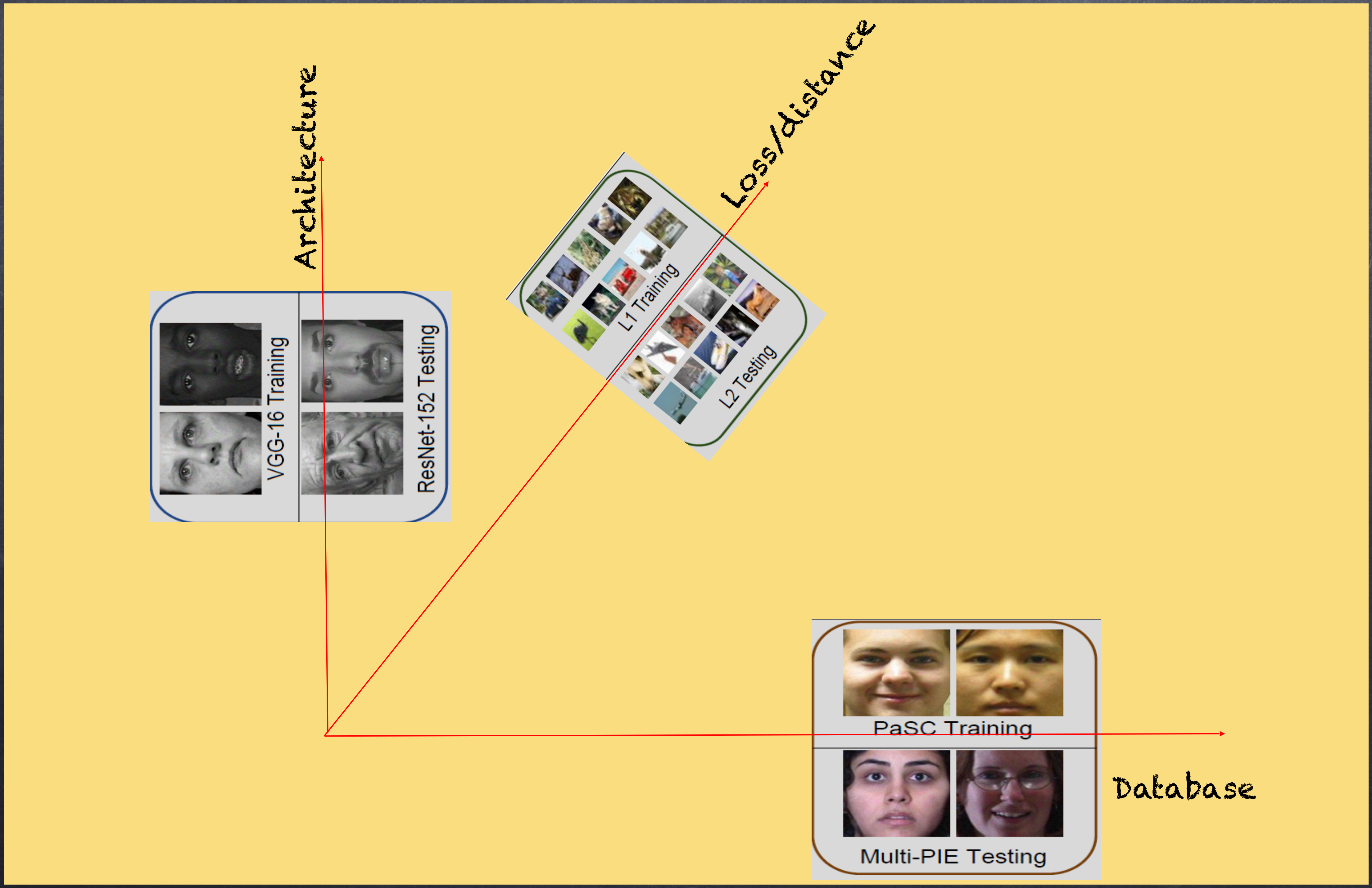
| Algorithm | Accuracy |
|---|---|
| Bharati et al. [1] | 91.83% |
| Proposed (Thresholding) | 99.83% |
| Proposed (SVM) | 99.73% |

| Compression | Accuracy (SVM) | Accuracy (Thresholding) |
|---|---|---|
| JPG Images | 96.33% | 88.89% |
| PNG Images | 99.73% | 99.83% |

A. Bharati, R. Singh, M. Vatsa, and K. W. Bowyer, "Detecting facial retouching using supervised deep learning," IEEE TIFS, vol. 11, no. 9, pp. 1903–1913, 2016.

# Some Extensions: Effective Perturbation Detection

Image Agnostic, Model Agnostic, Database Agnostic



# Detection: Key Takeout

- Detection is an important step to check if the systems are attacked or not
- Solution may lie in non-DL domain

# How to mitigate the effect of attacks?

# A Simple Approach

# A Simple Approach

- White-box approach: retrain the model with original and perturbed samples
- What is the problem with this approach?

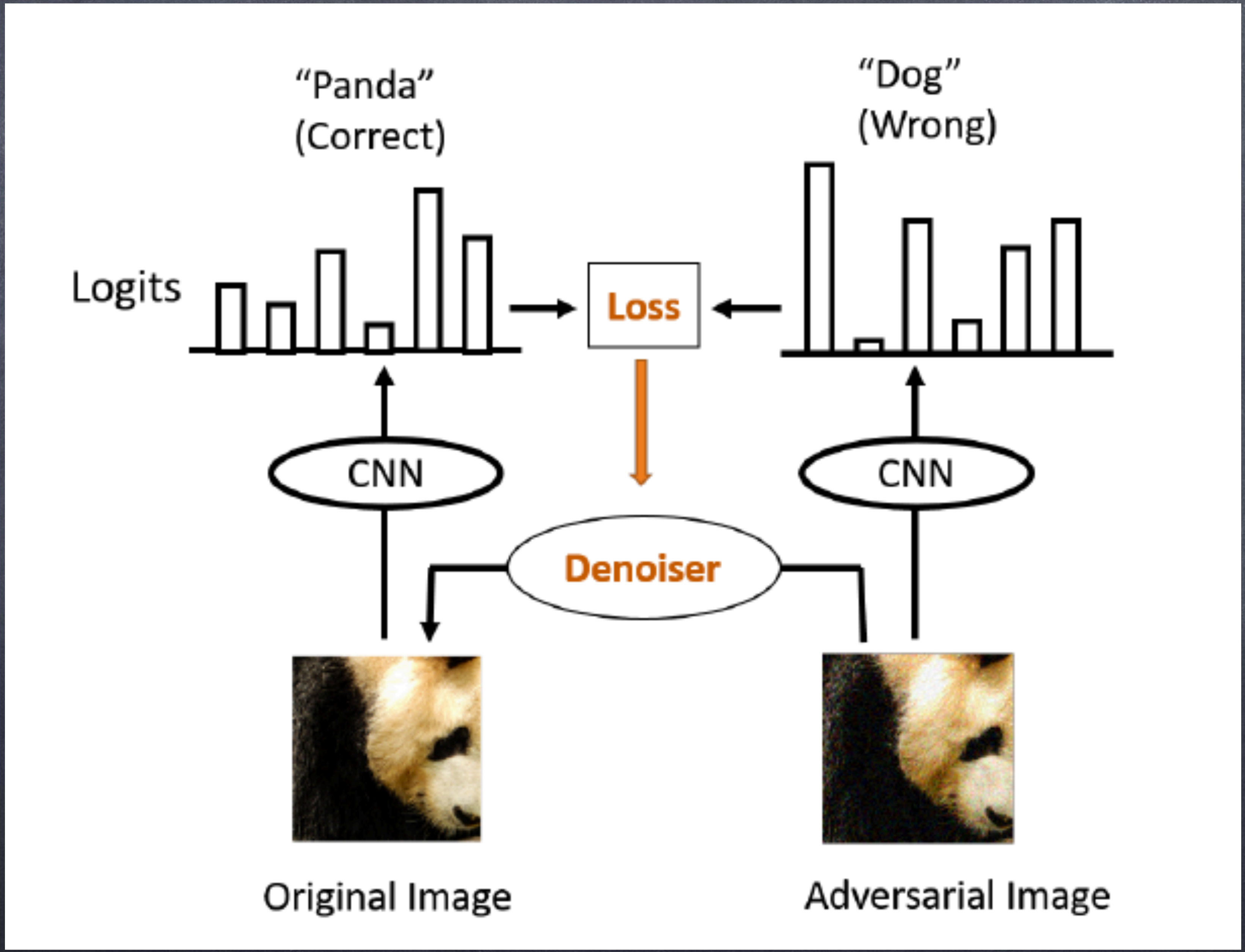
# A Simple Approach

- White-box approach: retrain the model with original and perturbed samples
- What is the problem with this approach?
- A new attack is proposed and we have to start the training process again :)

# Another simple approach

- Transform an input image:
- e.g. apply Gaussian blur and then proceed with classification
- Pixel Deflection (CVPR2018)

# Image Denoiser

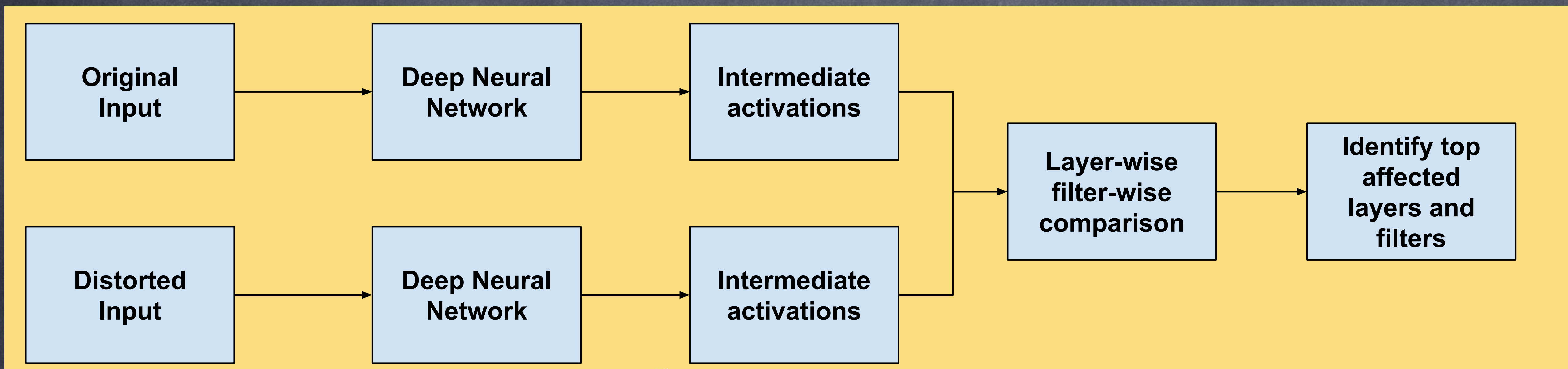



Liao et al, CVPR2018

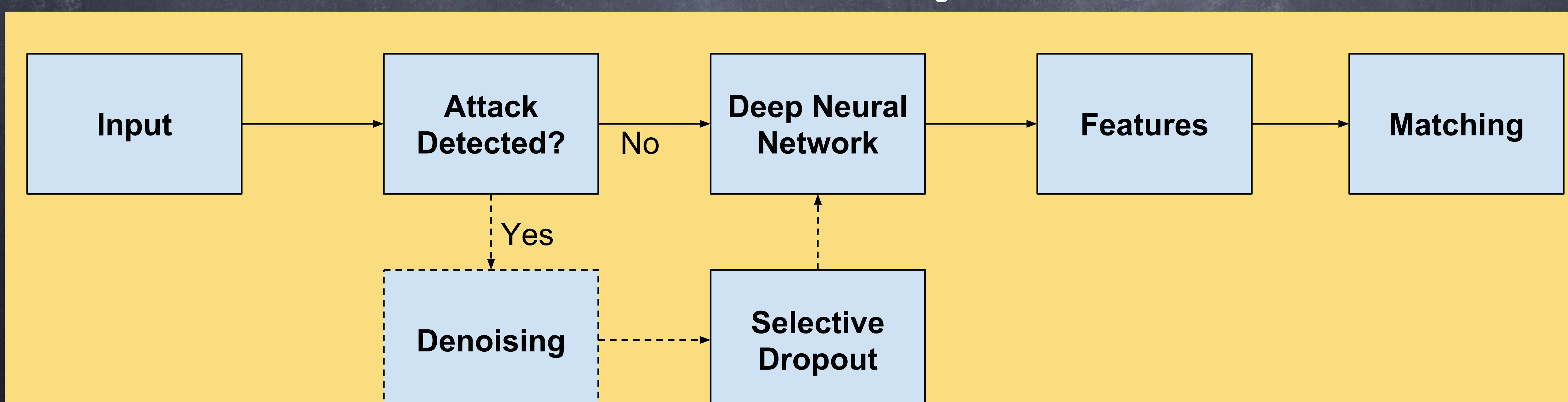
# Modified Approach

- Defense-GAN (ICLR2018)
- Train a WGAN trained on legitimate (un-perturbed) training samples to "denoise" adversarial examples
- Prior to feeding a test image x to the classifier, it is projected onto the range of the generator by minimizing the reconstruction error $||G(z) - x||$
- The resulting reconstruction $G(z)$ is then given to the classifier for classification task
- Since the generator was trained to model the unperturbed training data distribution, this added step "removes" any potential adversarial noise.

# Adversarial Perturbation Mitigation




Training




Testing

Goswami et al. IJCV2019

# Results of Adversary Mitigation

| Algorithm | Original | Distorted | Corrected |
|---|---|---|---|
| LightCNN | 60.5 | 25.9 | 36.2 |
| | 89.3 | 41.6 | 61.3 |
| VGG-Face | 54.3 | 14.6 | 24.8 |
| | 78.4 | 30.5 | 40.6 |

Mitigation Results on face database

# Catalog of Defense Approaches

- Reactive vs proactive
- Detection vs transformation vs training vs architecture vs generative

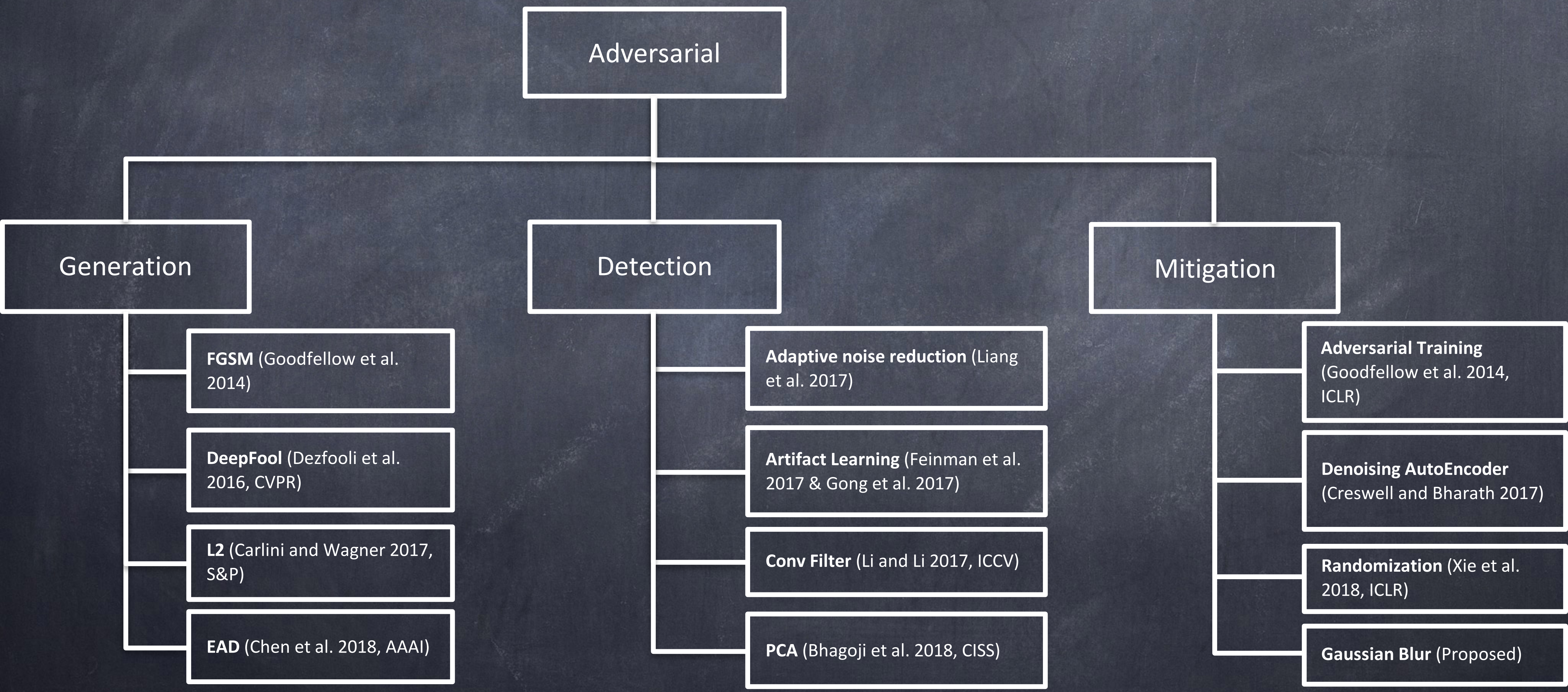
| Defence | Type | Method |
|---|---|---|
| Statistical Detection [75] | Reactive | Detection |
| Binary Classification [67] | Reactive | Detection |
| In-Layer Detection [130] | Reactive | Detection |
| Detecting from Artifacts [59] | Reactive | Detection |
| SafetyNet [124] | Reactive | Detection |
| Saliency Data Detector [207] | Reactive | Detection |
| Linear Transformations Detector [16] | Reactive | Detection |
| Key-based Networks [210] | Reactive | Detection |
| Ensemble Detectors [1] | Reactive | Detection |
| Generative Detector [116] | Reactive | Detection |
| Convolutional Statistics Detector [118] | Reactive | Detection |
| Feature Squeezing [203] | Reactive | Detection |
| PixelDefend [177] | Reactive | Detection |
| MagNet [129] | Reactive | Detection |
| VAE Detector [62] | Reactive | Detection |
| Bit-Depth [78] | Reactive | Input Transformation |
| Basis Transformations [168] | Reactive | Input Transformation |
| Randomised Transformations [201] | Reactive | Input Transformation |
| Thermometer Encoding [24] | Reactive | Input Transformation |
| Blind Pre-Processing [153] | Reactive | Input Transformation |
| Data Discretisation [32] | Reactive | Input Transformation |
| Adaptive Noise [119] | Reactive | Input Transformation |
| FGSM Training [70] | Proactive | Training |
| Gradient Training [175] | Proactive | Training |
| Gradient Regularisation [127] | Proactive | Training |
| Structured Gradient Regularisation [158] | Proactive | Training |
| Robust Training [169] | Proactive | Robust Training |
| Strong Adversary Training [90] | Proactive | Robust Training |
| CFOA Training [128] | Proactive | Robust Training |
| Ensemble Training [188] | Proactive | Robust Training |
| Stochastic Pruning [44] | Proactive | Robust Training |
| Distillation [86] | Proactive | Architecture |
| Parseval Networks [37] | Proactive | Architecture |
| Deep Contractive Networks [77] | Proactive | Architecture |
| Biological Networks [139] | Proactive | Architecture |
| DeepCloak [60] | Proactive | Architecture |
| Fortified Networks [111] | Proactive | Architecture |
| Rotation-Equivariant Networks [48] | Proactive | Architecture |
| HyperNetworks [180] | Proactive | Architecture |
| Bidirectional Networks [151] | Proactive | Architecture |
| DAM [108] | Proactive | Architecture |
| Certified Defences [152] | Proactive | Certified |
| Formal Tools [98, 51, 92, 161] | Proactive | Certified |
| Distributional Robustness [176] | Proactive | Certified |
| Convex Outer Polytope [102] | Proactive | Certified |
| Lischitz Margin [191] | Proactive | Certified |
| Defence Gan [165] | Proactive | Generative |
| FB-GAN [9] | Proactive | Genearative |

# Toolboxes: SmartBox

- Lack of a benchmark platform to standardize research efforts in attack, detection and mitigation
- SmartBox: Benchmarking Adversarial Detection and Mitigation Algorithms for Face Recognition

Goel et al. Benchmarking Adversarial Detection and Mitigation Algorithms for Face Recognition, IEEE BTAS, 2018

# SmartBox


Adversarial
Generation
Detection
Mitigation
**FGSM** (Goodfellow et al. 2014)
**DeepFool** (Dezfooli et al. 2016, CVPR)
**L2** (Carlini and Wagner 2017, S&P)
**EAD** (Chen et al. 2018, AAAI)
**Adaptive noise reduction** (Liang et al. 2017)
**Artifact Learning** (Feinman et al. 2017 & Gong et al. 2017)
**Conv Filter** (Li and Li 2017, ICCV)
**PCA** (Bhagoji et al. 2018, CISS)
**Adversarial Training** (Goodfellow et al. 2014, ICLR)
**Denoising AutoEncoder** (Creswell and Bharath 2017)
**Randomization** (Xie et al. 2018, ICLR)
**Gaussian Blur** (Proposed)

# Other Toolboxes

- CleverHans
- Foolbox
- Adversarial Robustness Toolbox

# Databases used to benchmark

- PaSC, MultiPIE, CelebA
- MNIST, F-MNIST
- CIFAR-10, CIFAR-100
- ImageNET
- SVHN

| Defence | Datasets | Models |
|---|---|---|
| Statistical Detection [75] | MNIST, DREBIN, MicroRNA | DT, SVM, 2 layers-CNN |
| Binary Classification [67] | MNIST, CIFAR-10, SVHN | AlexNet |
| In-Layer Detection [130] | CIFAR-10, 10-class ImageNet | ResNet |
| Detecting from Artifacts [59] | MNIST, CIFAR-10, SVHN | LeNet, 12-layer CNN |
| SafetyNet [124] | CIFAR-10, ImageNet-1000 | ResNet, VGG19 |
| Saliency Data Detector [207] | MNIST, CIFAR-10, ImageNet | AlexNet, AlexNet, VGG19 |
| Linear Transformations Detector [16] | MNIST, HAR | SVM |
| Key-based Networks [210] | MNIST | 2/3-layers CNN |
| Ensemble Detectors [1] | MNIST, CIFAR-10 | 3-layers CNN |
| Generative Detector [116] | CIFAR-10, CIFAR-100 | 6-layers CNN |
| Convolutional Statistics Detector [118] | ImageNet | VGG-16 |
| Feature Squeezing [203] | MNIST, CIFAR-10, ImageNet | 7-layers CNN, DenseNet MobileNet |
| PixelDefend [177] | ImageNet | ResNet, VGG |
| MagNet [129] | MNIST, CIFAR-10 | 4/9-layers CNN |
| VAE Detector [62] | MNIST, SVNH, COIL-100 | - |
| Bit-Depth [78] | ImageNet | ResNet, DenseNet, Inception-v4 |
| Basis Transformations [168] | ImageNet | Inception-v3, Inception-v4 |
| Randomised Transformations [201] | ImageNet | Inception-v3, ResNet |
| Thermometer Encoding [24] | MNIST, CIFAR-10, CIFAR-100, SVHN | 30-layers CNN, Wide ResNet |
| Blind Pre-Processing [153] | MNIST, CIFAR-10, SVHN | LeNet, ResNet-50, ResNet-18 |
| Data Discretisation [32] | MNIST, CIFAR-10, ImageNET | InceptionResnet-V2 |
| Adaptive Noise [119] | MNIST, ImageNet | - |
| FGSM Training [70] | MNIST | Maxout |
| Gradient Training [175] | CIFAR-10, SVHN | ResNet-18 |
| Gradient Regularisation [127] | MNIST, CIFAR-10 | Maxout |
| Structured Gradient Regularisation [158] | MNIST, CIFAR-10 | 9-layers CNN |
| Robust Training [169] | MNIST, CIFAR-10 | 2-layers CNN, VGG |
| Strong Adversary Training [90] | MNIST, CIFAR-10 | MxNet |
| CFOA Training [128] | MNIST, CIFAR-10 | 2/4/6-layers CNN, Wide ResNet |
| Ensemble Training [188] | ImageNet | ResNet, InceptionResNet-v2 |
| Stochastic Pruning [44] | CIFAR-10 | Resnet-20 |
| Distillation [86] | MNIST, CIFAR-10 | 4-layers CNN |
| Parseval Networks [37] | MNIST, CIFAR-10, CIFAR-100, SVHN | ResNet, Wide Resnet |
| Deep Contractive Networks [77] | MNIST | LeNet, AlexNet |
| Biological Networks [139] | MNIST | 3-layers CNN |
| DeepCloak [60] | CIFAR-10 | ResNet-164 |
| Fortified Networks [111] | MNIST | 2-layers CNN |
| Rotation-Equivariant Networks [48] | CIFAR-10, ImageNet | ResNet |
| HyperNetworks [180] | ImageNet | ResNet |
| Bidirectional Networks [151] | MNIST, CIFAR-10 | 3-layers CNN |
| DAM [108] | MNIST | DAM |
| Certified Defences [152] | MNIST | 2-layers FC |
| Formal Tools [98, 51, 92, 161] | - | - |
| Distributional Robustness [176] | MNIST | 3-layers CNN |
| Convex Outer Polytope [102] | MNIST, F-MNIST | 2-layers CNN |
| Lischitz Margin [191] | SVHN | Wide ResNet |
| Defence Gan [165] | MNIST, F-MNIST | Defene-GAN |
| FB-GAN [9] | MNIST, F-MNIST | 8-layers CNN |

# Cat and Mouse Game

# Cat and Mouse Game

- On the Robustness of the CVPR 2018 White-Box Adversarial Example Defenses
- “we evaluate the two white-box defenses that appeared at CVPR 2018 and find they are ineffective: when applying existing techniques, we can reduce the accuracy of the defended models to 0%.”

Athalye and Carlini, 2018

# Key Takeout

- Defense mechanism has to be model, database, and attack agnostic
- It will be always be a game between an adversary and a defender

# Is adversarial perturbation always bad?

# Two Approaches

- Privacy Preserving Adversarial Perturbation
- Data Fine-tuning

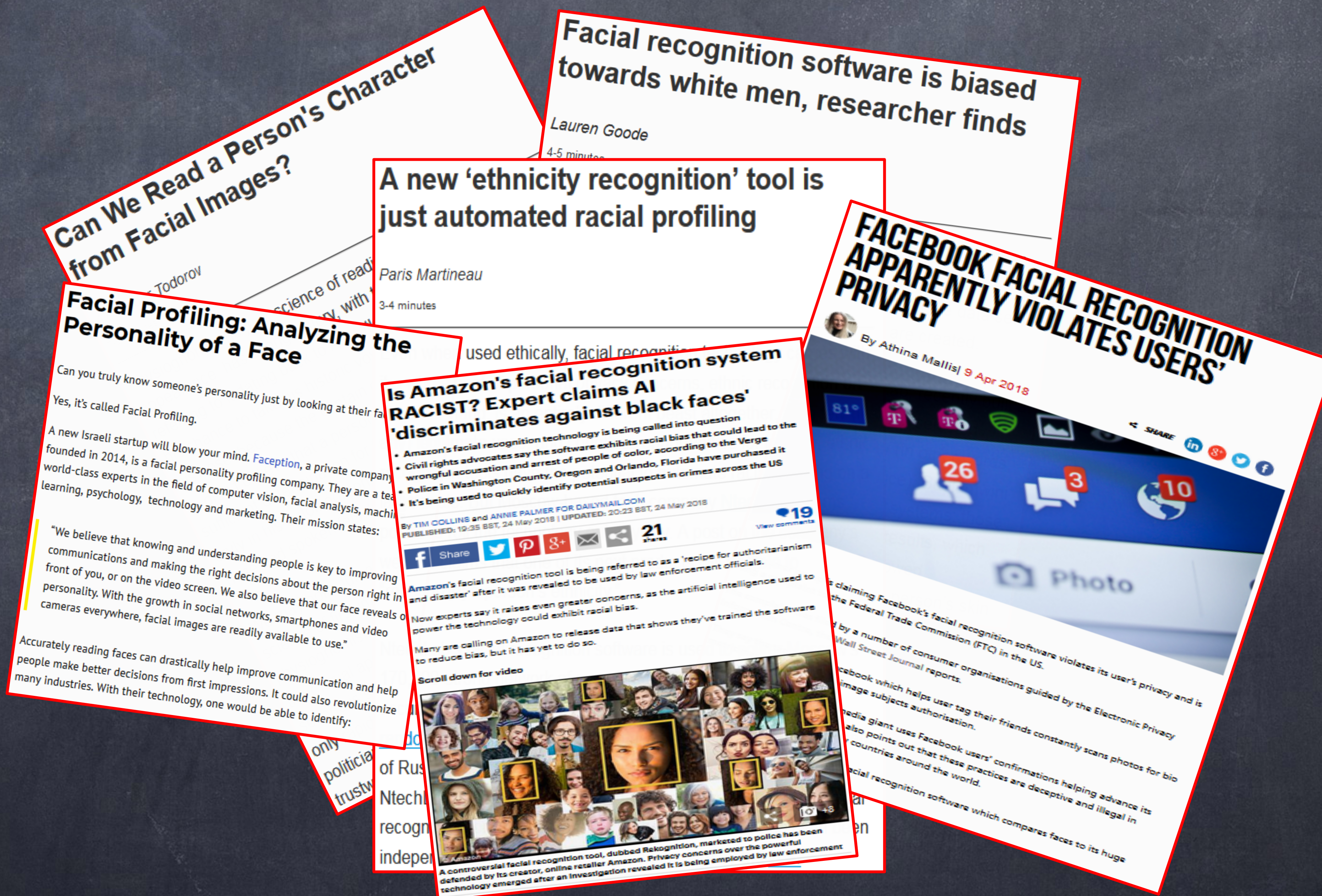
# Privacy Preserving Adversarial Perturbation

Chabbra et al. IJCAI2018

# Adversarial Perturbations – The Positive Side

- While attackers have used adversarial perturbations to "fool" biometrics/face recognition systems, it can be used for assisting in privacy-preserving aspect …

# Face Analysis – In the News



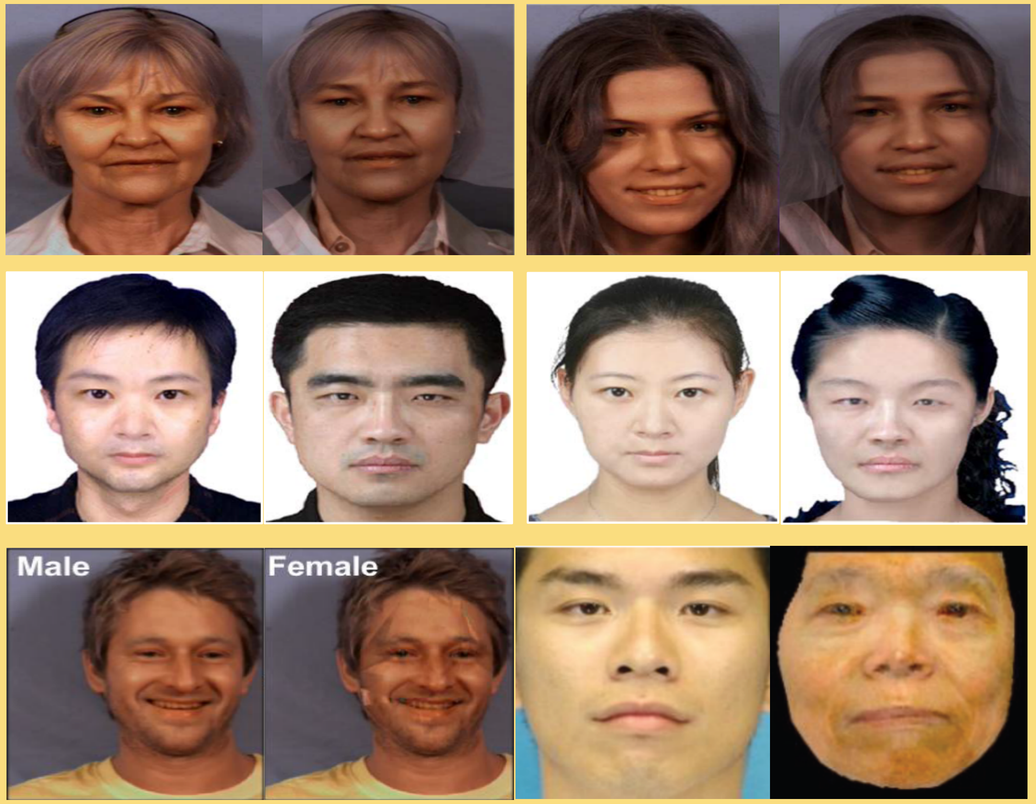
# Right to Privacy

- Automated face analysis pose threat to the privacy of an individual
  - Wang and Kosinksi predicted the sexual orientation from face images
  - Facial attributes such as age, gender, and race can be predicted from one's profile or social media images
  - Profiling of a person using his face image in ID card
  - Identity theft using cross database matching


Yilun Wang and Michal Kosinski. Deep neural networks are more accurate than humans at detecting sexual orientation from facial images. PsyArXiv preprint arXiv: 10.17605/OSF.IO/HV28A, 2017.

# Literature

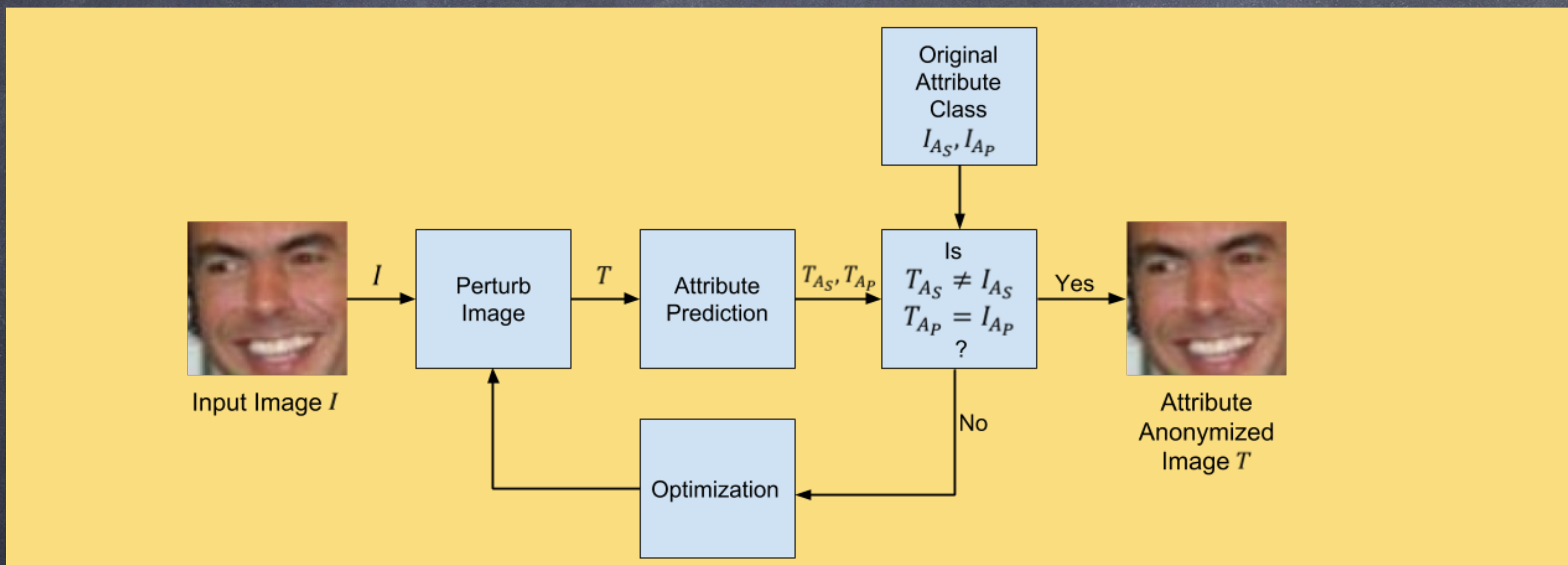
| Author | Method | No. of Attributes | Dataset | Controlling Attributes |
|---|---|---|---|---|
| Othman and Ross, 2014 | Face Morphing and fusion | One | MUCT | No |
| Mirjalili and Ross, 2017 | Delaunay Triangulation and fusion | One | MUCT, LFW | No |
| Mirjalili *et al.*, 2017 | Fusion using Convolutional Autoencoder | One | MUCT, LFW, Celeb-A, AR-Face | No |
| Rozsa et al., 2016, 2017 | Fast Flipping Attribute | Multiple | CelebA | No |
| Chhabra et al., 2018 | Adversarial Perturbation | Multiple | CelebA, MUCT, LFW | Yes |



# Three Key Factors

- While anonymizing facial attributes, there should be no visual difference between original and anonymized images
- Selectively anonymizing few and retaining some attributes require a "control" mechanism
- In face recognition applications, identity should be preserved while anonymizing attributes.

# Overview of the Proposed Approach




I -> input image

T-> perturbed image ($T = I + \omega$)

$I_{AS}$ -> Attributes to be suppressed

$I_{AP}$ -> Attributes to be preserved

# Loss Function

## Attributes only

$$\min \ \underbrace{\left[D\left(\boldsymbol{I}_{\boldsymbol{A_P}}, \boldsymbol{T}_{\boldsymbol{A_P}}\right) - D\left(\boldsymbol{I}_{\boldsymbol{A_S}}, \boldsymbol{T}_{\boldsymbol{A_S}}\right)\right]}_{\text{Attribute Anonymization}} + \underbrace{||\boldsymbol{I} - \boldsymbol{T}||_2^2}_{\text{Visual Appearance}}$$

$$\text{such that} \quad \boldsymbol{T}_{\boldsymbol{A_S}} \neq \boldsymbol{I}_{\boldsymbol{A_S}}, \boldsymbol{T}_{\boldsymbol{A_P}} = \boldsymbol{I}_{\boldsymbol{A_P}}$$

## Attributes + Identity

$$\min \ \left\{f(\boldsymbol{T}) + ||\boldsymbol{I} - \boldsymbol{T}||_2^2 + D(\boldsymbol{Id_I}, \boldsymbol{Id_T})\right\}$$

Chhabra et al. IJCAI 2018

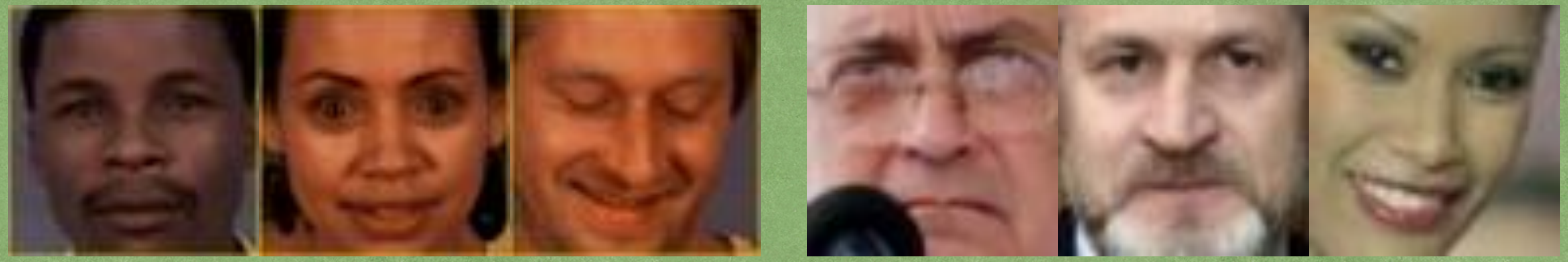
# Experiments

| Experiment | Dataset | # Attributes Anonymized | Attributes Anonymized | |
|---|---|---|---|---|
| | | | Suppressed | Preserved |
| Single Attribute | MUCT, CelebA, LFWCrop | 1 | Gender | - |
| Multiple Attributes | CelebA | 3, 5 | Gender, Attractive, Smiling | Heavy makeup, High cheekbones |
| Identity Preservation | MUCT, LFWcrop | 1+1 | Gender | Identity |

# Single Attribute

MUCT dataset

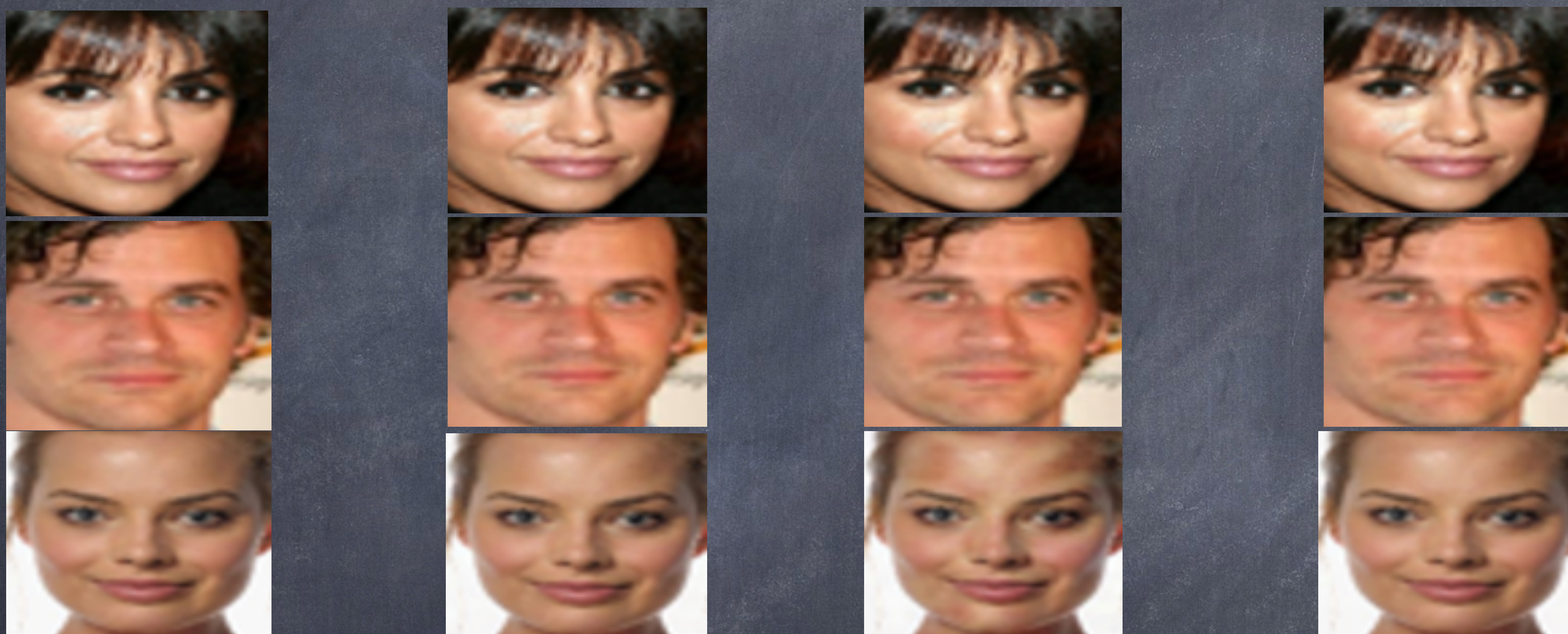
LFWcrop dataset



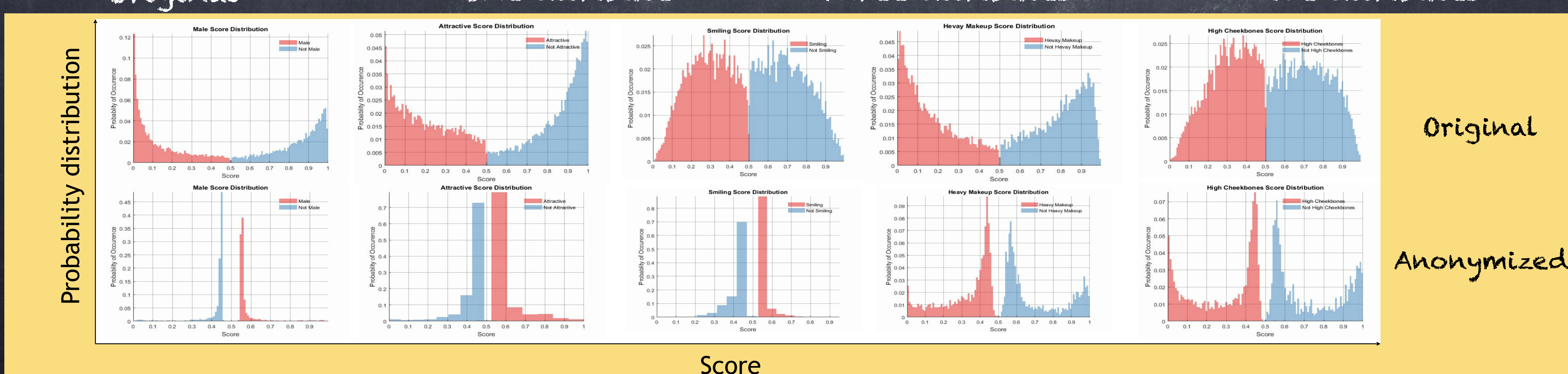
Original Images

Gender Attribute Anonymized Images

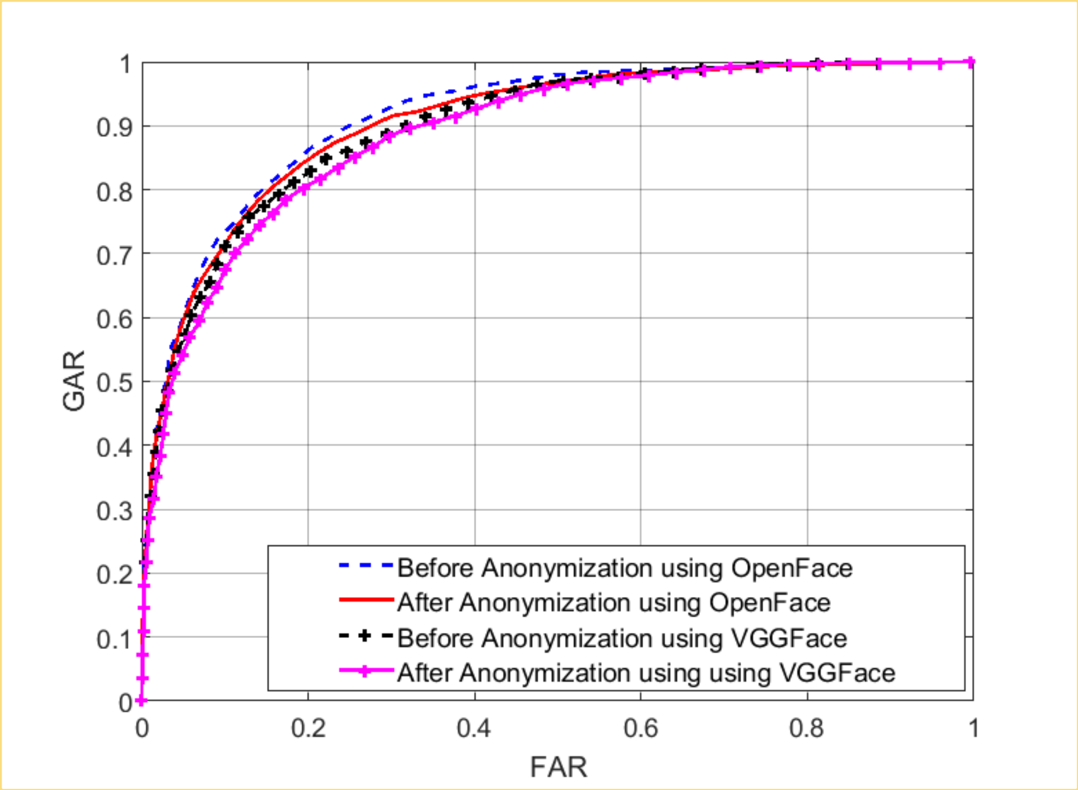
# Attribute Suppression and Preservation



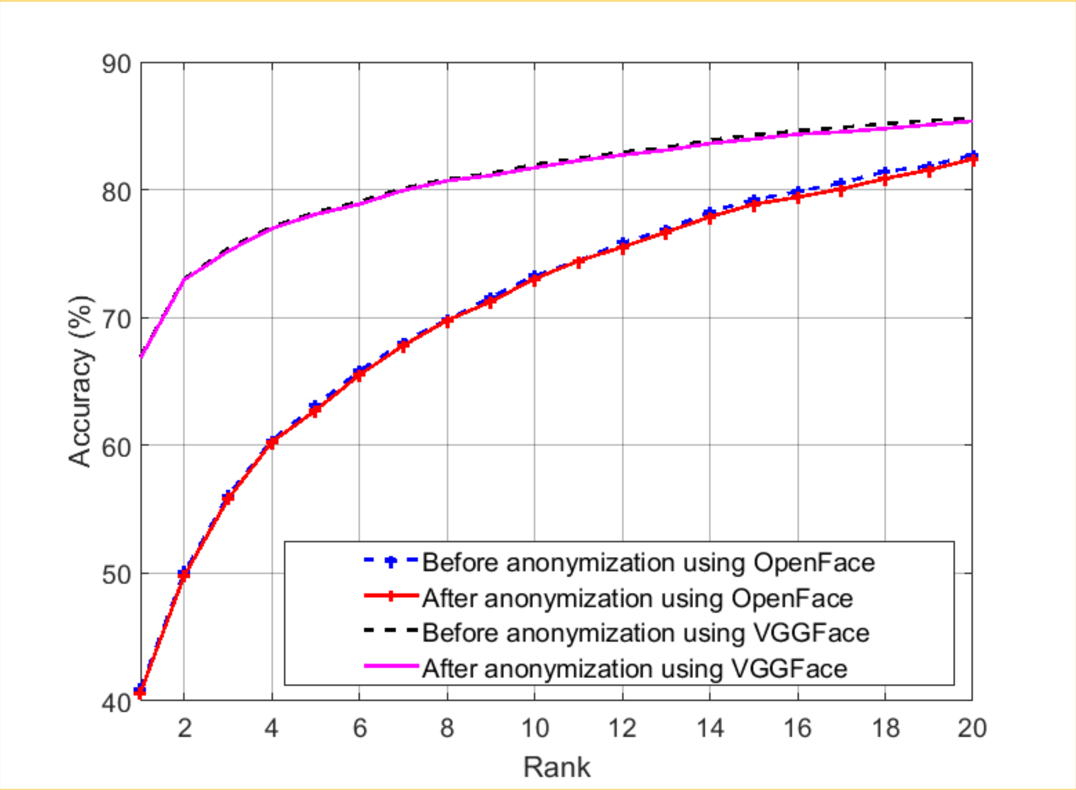
Original One attribute Three attributes Five attributes



# Attribute Suppression with Identity Preservation




ROC curves on the LFWcrop dataset




CMC curve on the MUCT dataset

# Key Takeouts

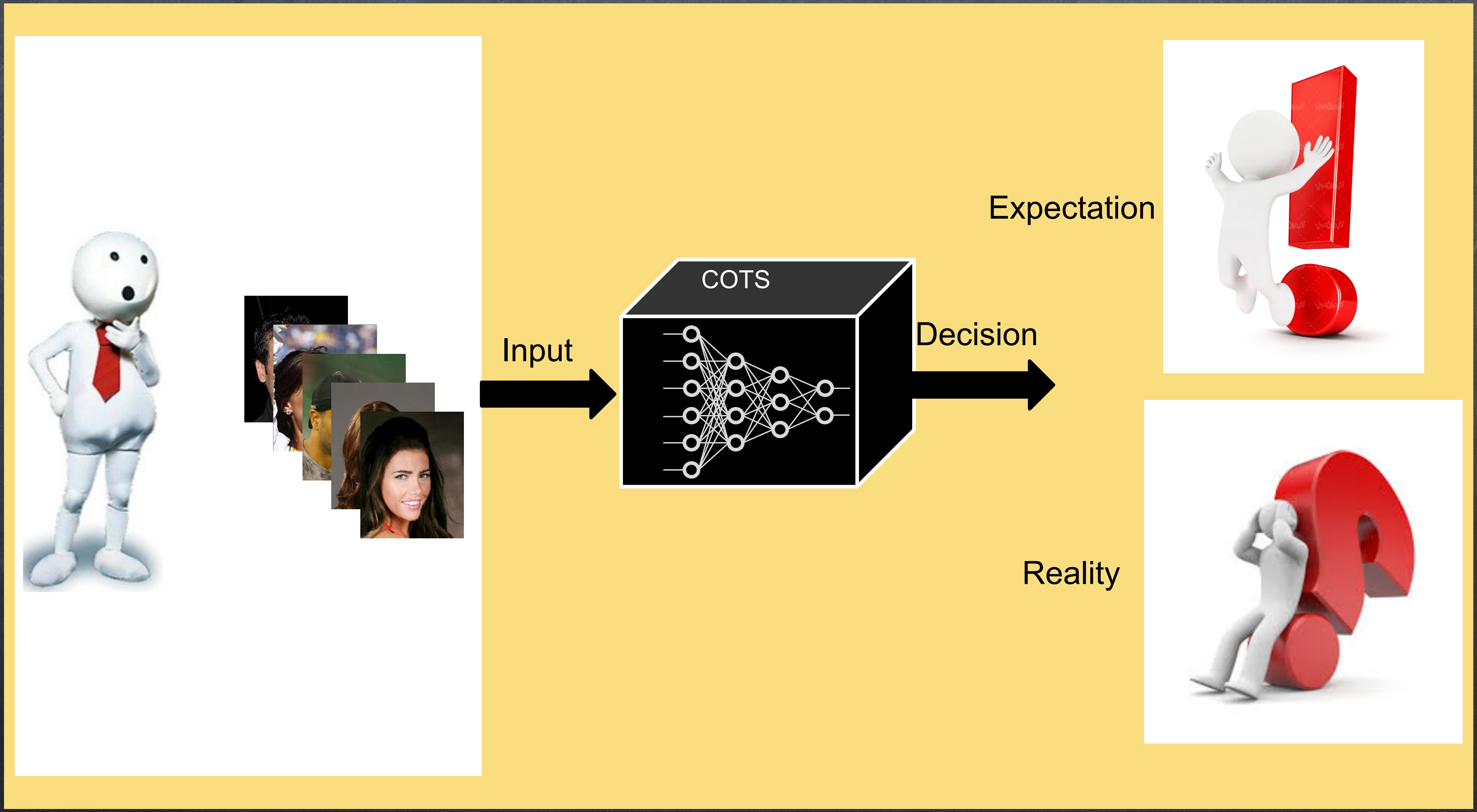
- Adversarial perturbations can be used positively for privacy preserving applications

# Data Fine-Tuning

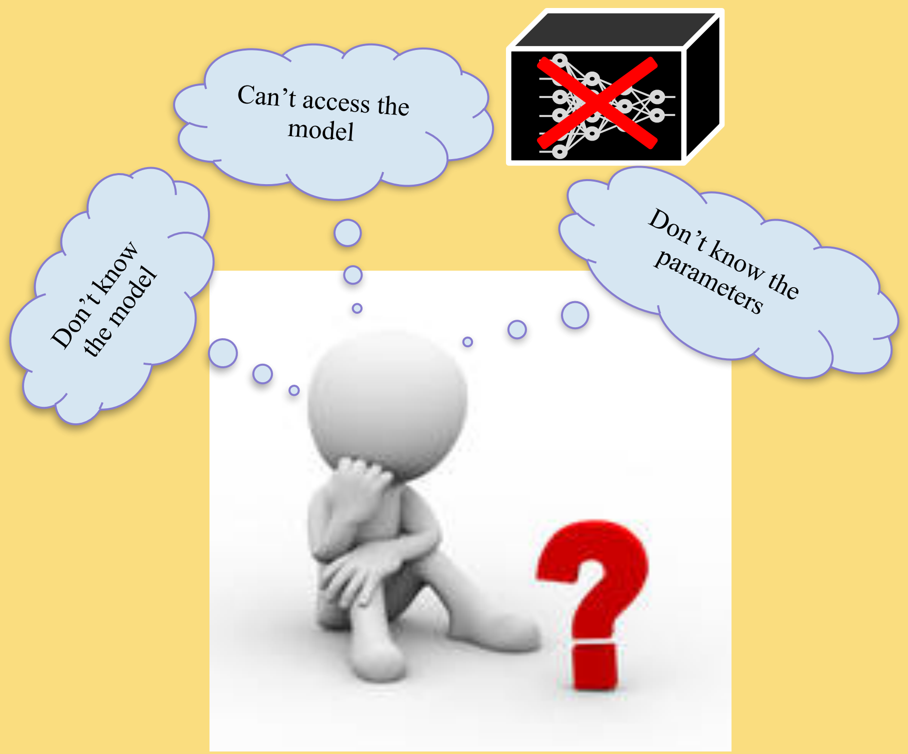
- In DL, traditionally, we perform model fine-tuning, if we have access to the model

Chabbra et al. AAAI2019

# In Real World Applications



# In Real World Applications




✓ Dataset

✗ Model Access

✗ Model Hyperparameters

Output of Model ✓

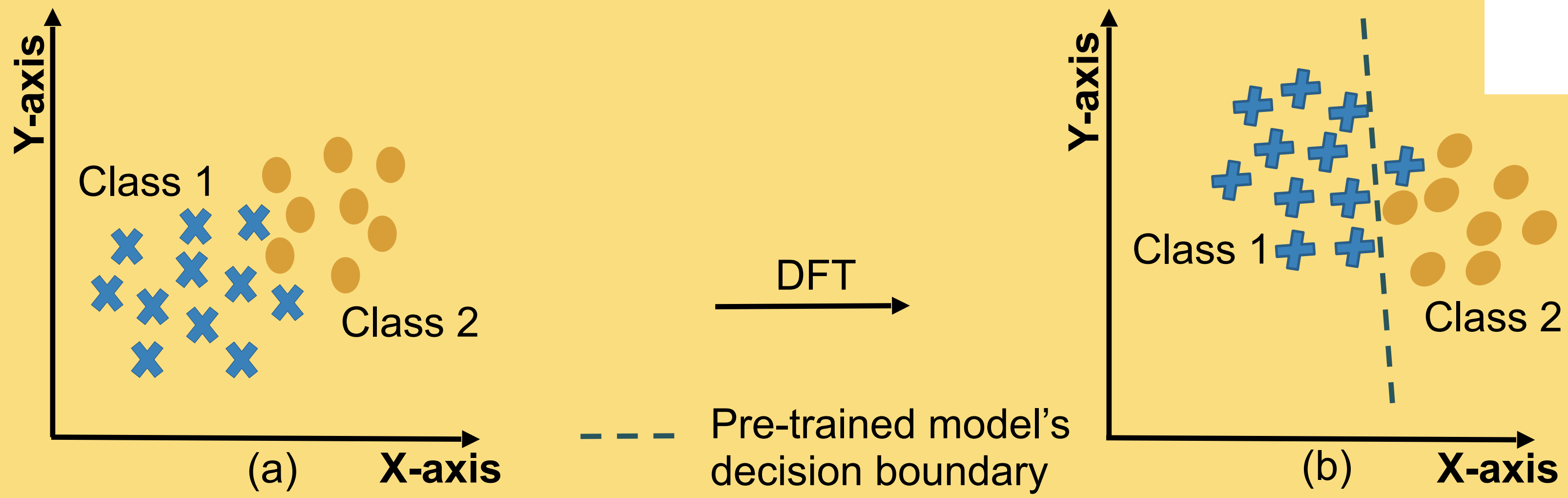
Model Training ✗

Can we enhance the performance of a black-box system?

# Data Fine-tuning

- Data Fine-tuning (DFT)

$$\Phi(\boldsymbol{WX} + b) \xrightarrow{\text{DFT}} \Phi(\boldsymbol{WZ} + b)$$



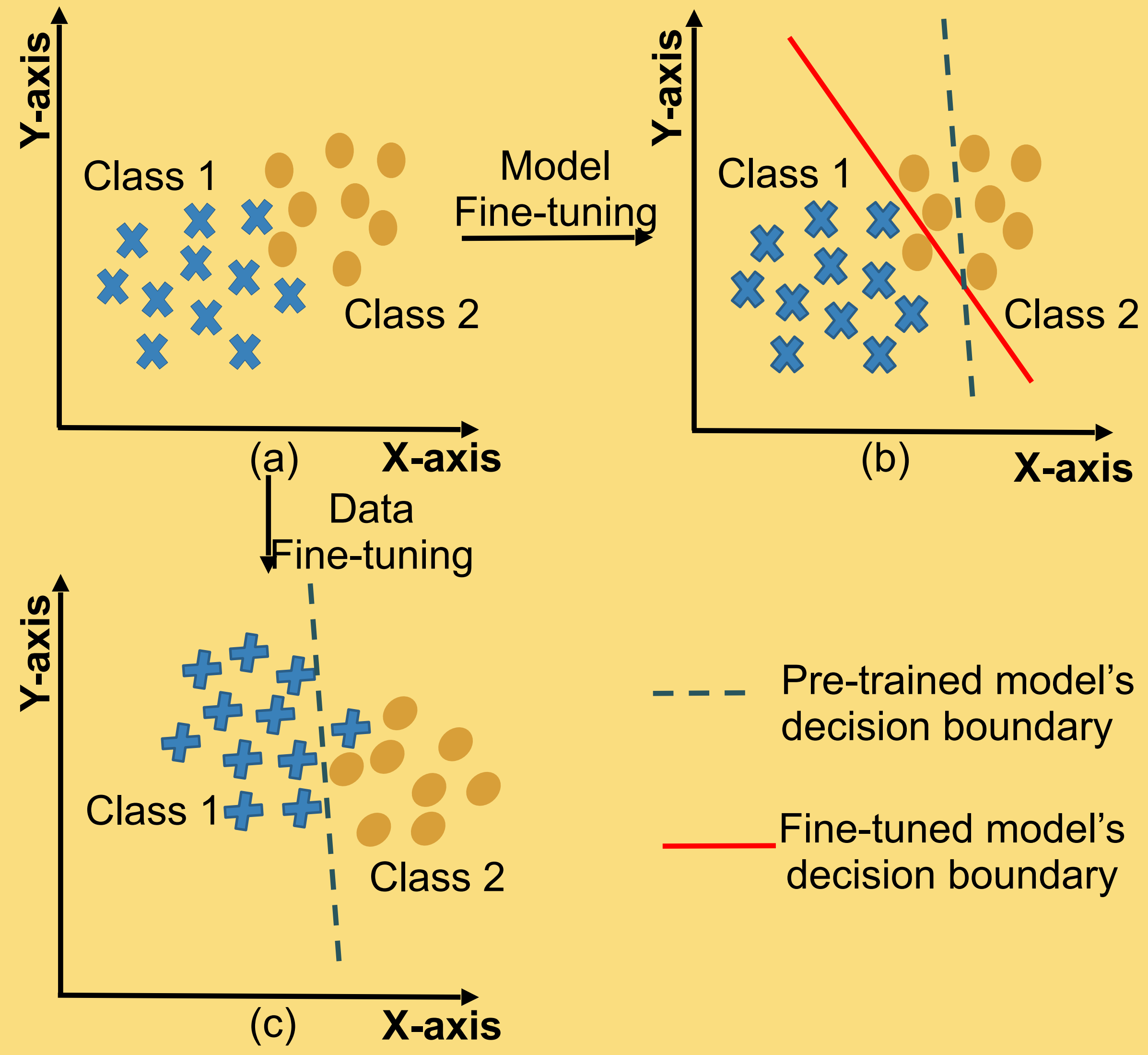
# Model Fine-tuning vs Data Fine-tuning

## Model Fine-tuning

$$\Phi(\boldsymbol{W}\boldsymbol{X} + b) \xrightarrow{\text{MFT}} \Phi(\boldsymbol{W}'\boldsymbol{X} + b')$$

## Data Fine-tuning

$$\Phi(\boldsymbol{W}\boldsymbol{X} + b) \xrightarrow{\text{DFT}} \Phi(\boldsymbol{W}\boldsymbol{Z} + b)$$



# Data Fine-tuning

- Learn a single perturbation for a given dataset
- The visual appearance of the image should be preserved after performing data fine-tuning

# Optimization

$\boldsymbol{X}$ → Original Training Set

$\boldsymbol{Z}$ → Perturbed Training Set

$\boldsymbol{y}$ → True Labels

$\boldsymbol{N}$ → Perturbation

$\boldsymbol{m}$ → Number of Images

$\boldsymbol{A}$ → Set of Attributes

$$\left.\boldsymbol{Z_k} = \frac{1}{2}\left(tanh\left(\boldsymbol{X_k} + \boldsymbol{N}\right) + 1\right)\right\}$$

Transform image in range of 0 to 1

Output scores

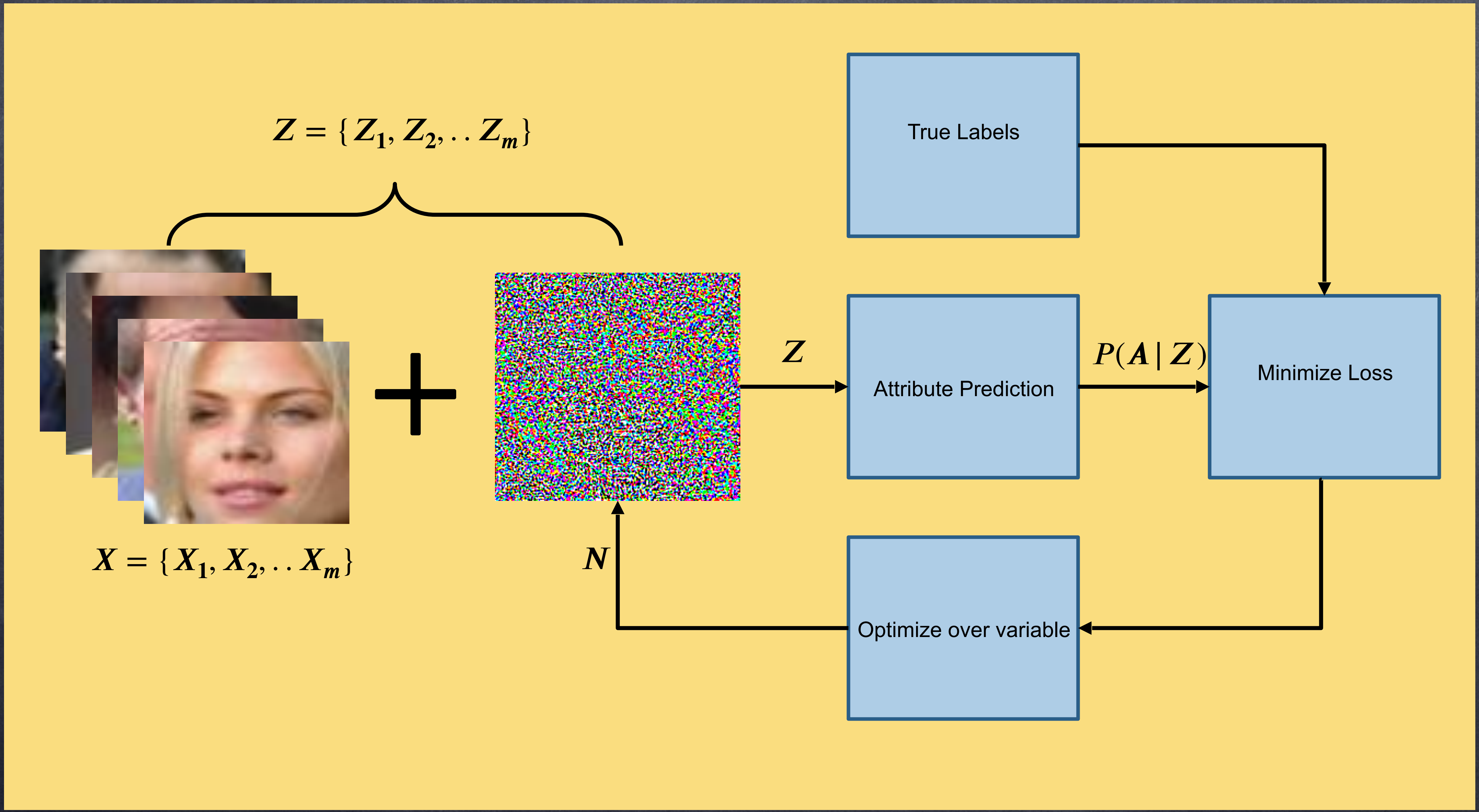
Model Input

$$P(\boldsymbol{A_i} \mid \boldsymbol{Z_k}) = \boldsymbol{\Phi}_{A_i}(\boldsymbol{Z_k}, \boldsymbol{W}, b)$$

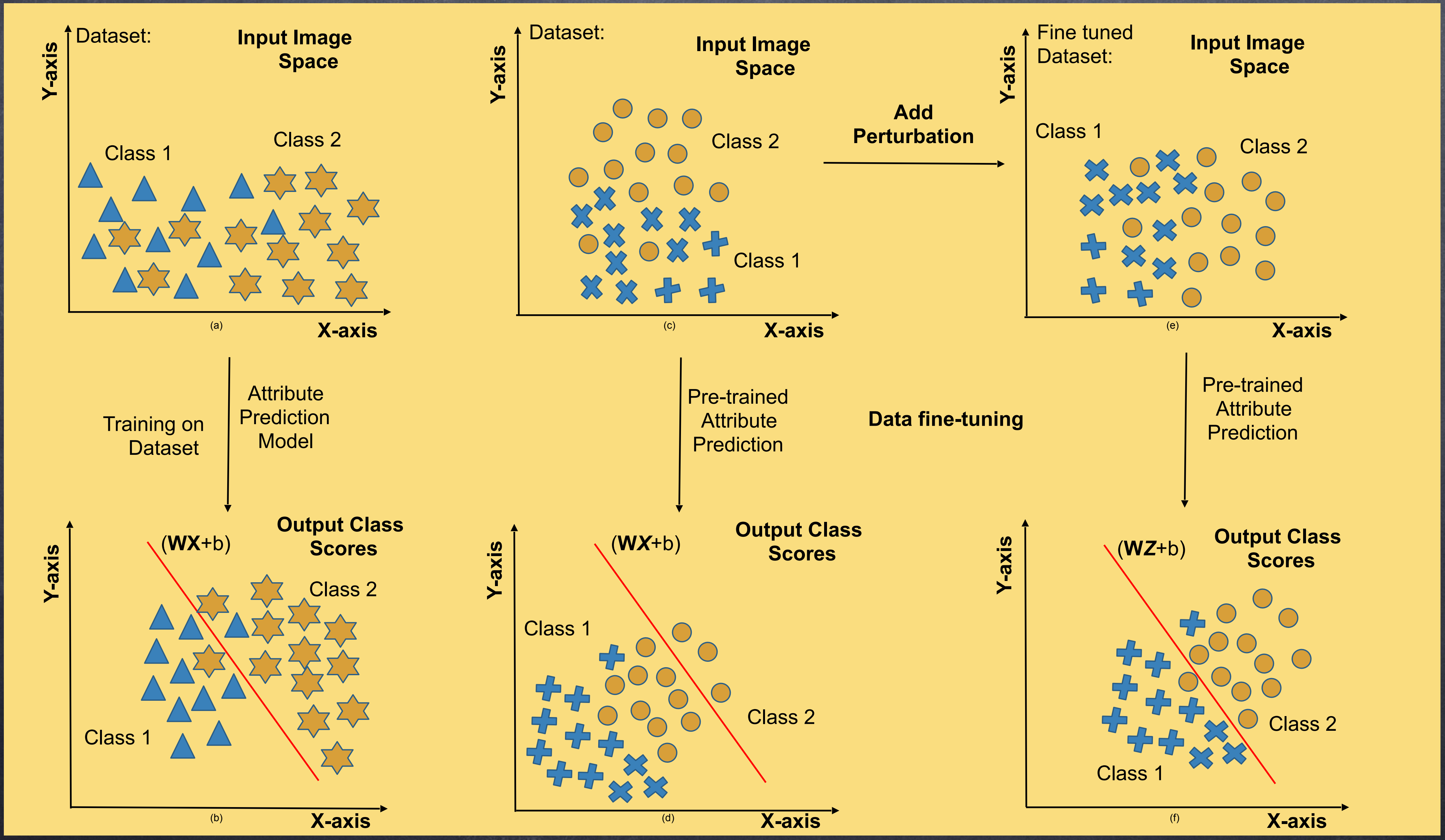
Enforces the outputs scores towards true labels

$$\min_{\boldsymbol{N}} \quad \frac{1}{m}\sum_{k=1}^{m} \max(0, 1 - \boldsymbol{y}_{i,k}^{T} P(\boldsymbol{A_i} \mid \boldsymbol{Z_k}))$$

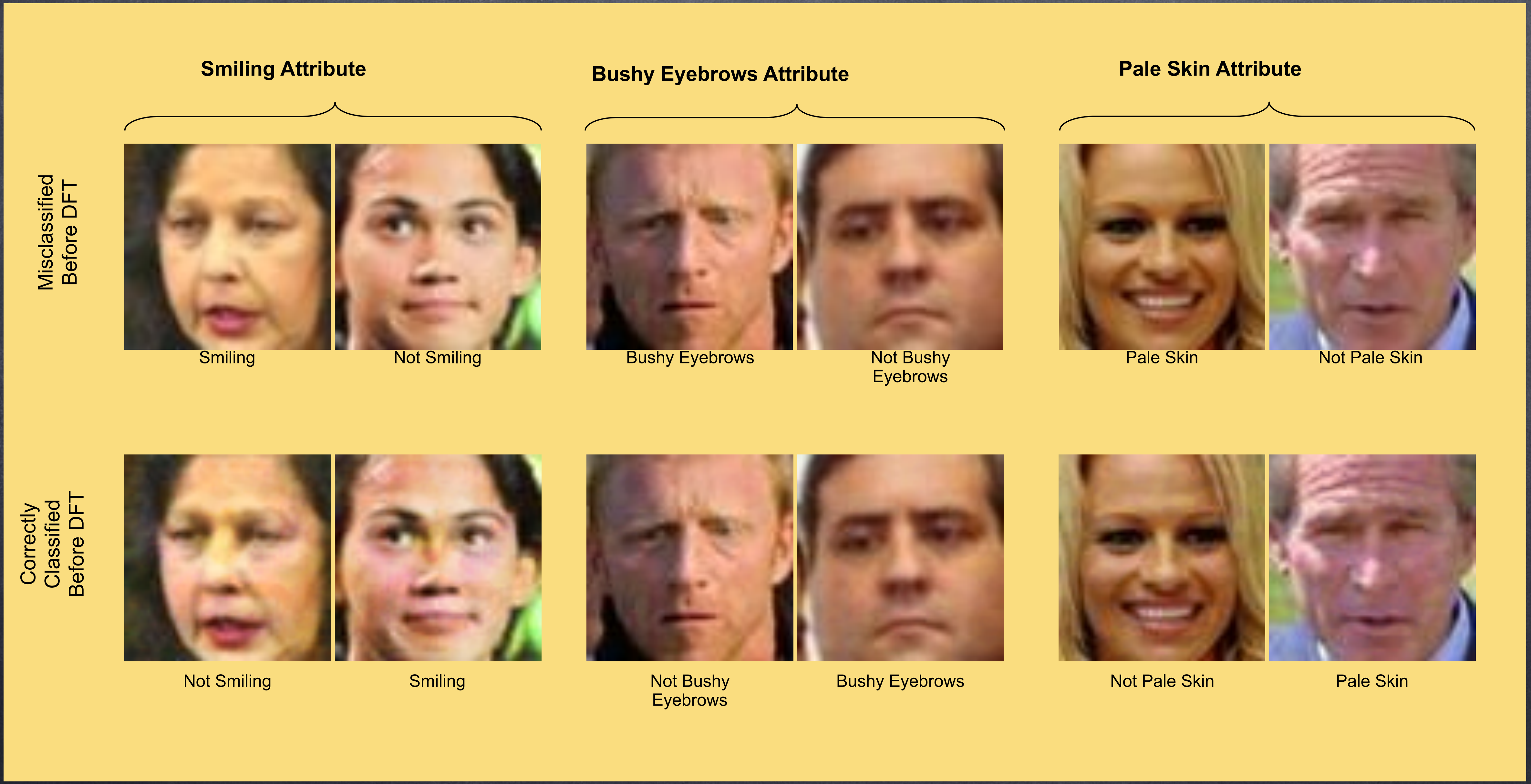
# Illustration of Data Fine-tuning for Attribute Prediction



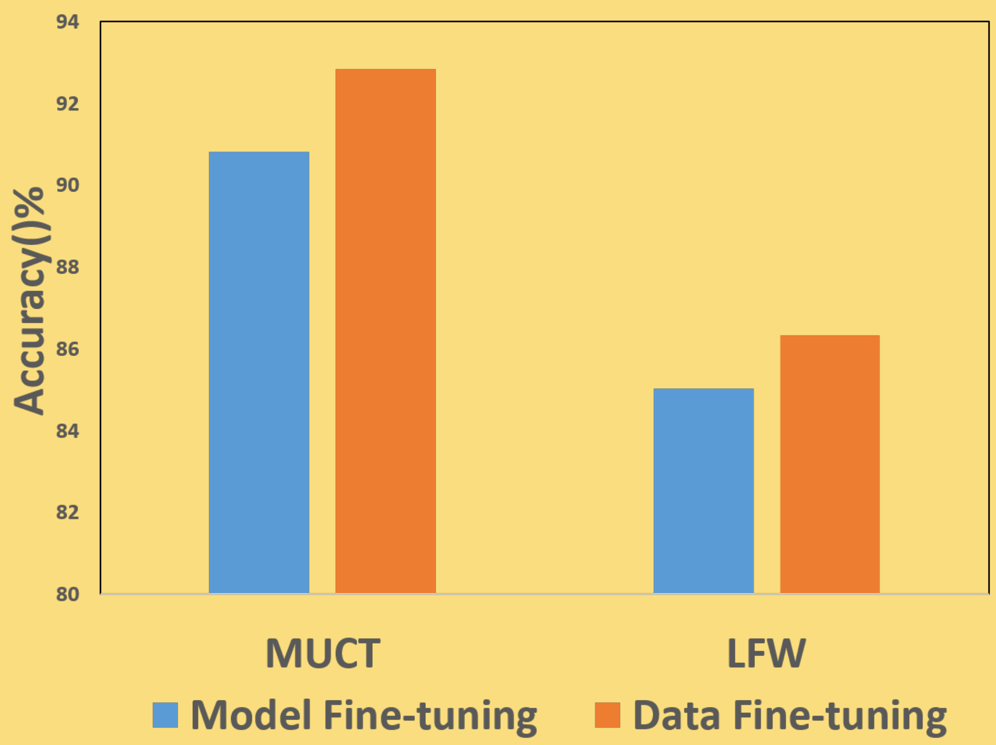
# Illustration of Data Fine-tuning for Attribute Prediction



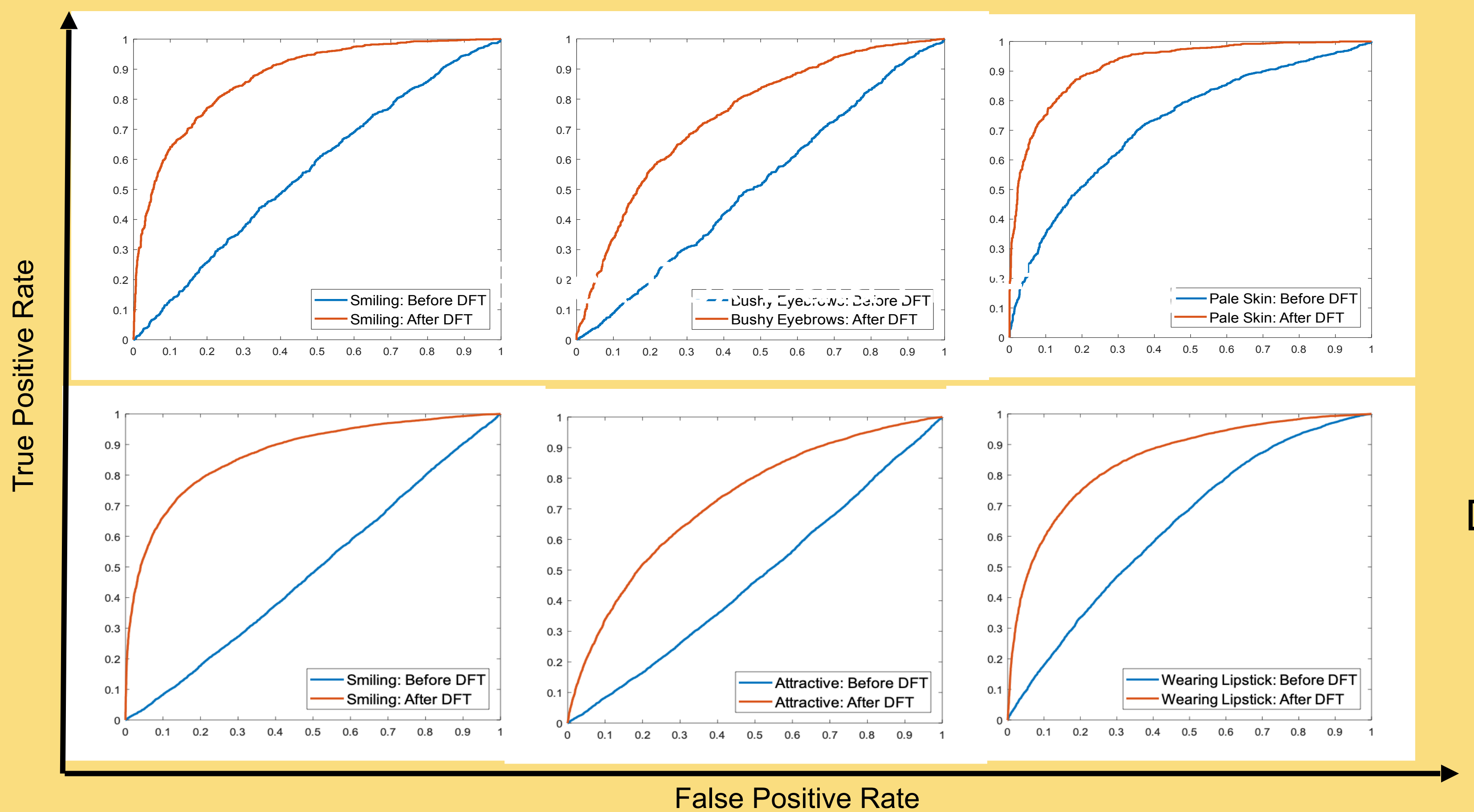
# Visual Results



# Model Fine-tuning vs Data Fine-tuning

# Black Box Data Fine-tuning




Dataset: LFW
Model: CelebA

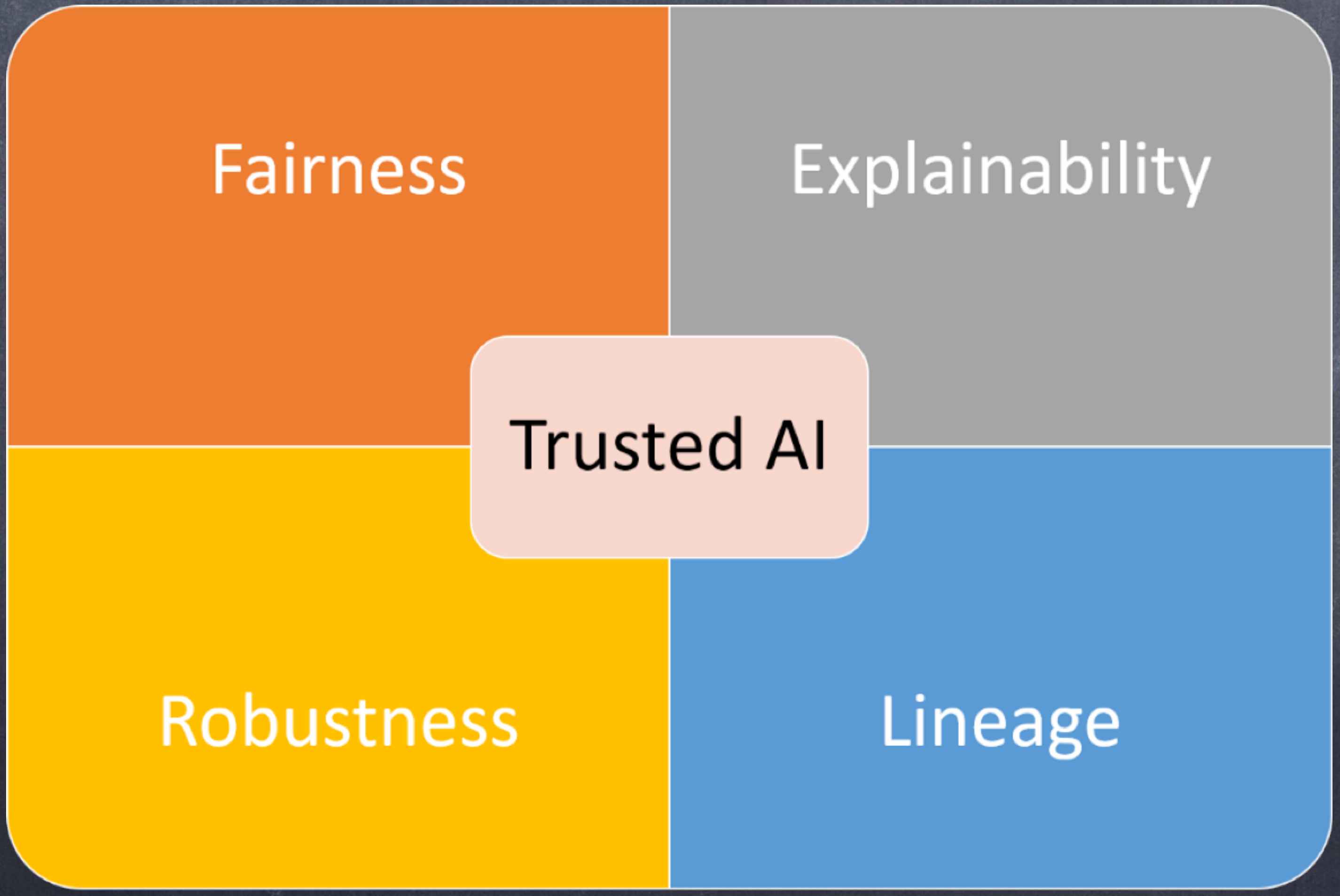
Dataset: CelebA
Model: LFW

# Key Takeout

- Data fine-tuning is an attractive alternative to model fine-tuning, specifically, when model is unknown or black-box

# Trusted AI

- Robustness is an important topic for building Trusted-AI systems but there are three other important topics




https://towardsdatascience.com/towards-ai-transparency-four-pillars-required-to-build-trust-in-artificial-intelligence-systems-d1c45a1bdd59

# Research Questions

- How to detect attacks?
  - Current strategy: Detect individual attacks
  - Generalized digital perturbation detection algorithm
  - Generalized digital and physical attack detection algorithm

# Research Questions

- How to mitigate attacks?
  - Current strategy: Attack-wise mitigation algorithm
  - Generalized mitigation strategy - agnostic to model, attack and database

# Research Questions

- Attribute anonymization:
  - Can we design algorithms that allow selecting attributes for anonymization
  - Design anonymization algorithms that are independent of prediction algorithm and image characteristics

# Research Questions

- Can we perform data fine-tuning + model fine-tuning for performance enhancement?
- Identify other applications of perturbations

# Acknowledgments

Puspita Majumdar, Gaurav Goswami, Askhay Agarwal, Saheb Chhabra, Akhil Goel, Anirudh Singh, Anubhav Jain and collaborators Dr. Richa Singha and Dr. Nalini Ratha

www.iab-rubric.org