Machine Learning in Biometrics

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A bit about us

- Mayank Vatsa, Associate Professor, AR Krishnaswamy Faculty Research Fellow, IIIT Delhi
- Image Analysis and Biometrics Lab - 20+ members including 9 PhD Students - over 75 alumni (at UPenn, Oxford, CMU, MSU, WVU, MSR, IBM, Xerox ...)

A bit about us

- Core Research Areas: Pattern Classification, Machine Learning, Image Processing, Computer Vision and Cognitive Neuroscience
- Application Areas: Biometrics, Forensics, and Medical Image Analysis

Identification

- Automated person identification is a long awaited task in artificial intelligence
- Traditional methods of identification are (i) token-based and (ii) knowledge-based
- Knowledge-based includes something that you know, for instance passwords and pin
- Token-based is something that you possess, for instance ID cards

Identification

- Both are vulnerable to attacks
- Current methods of verification follow these methodologies
- Combined estimate of the identity fraud in welfare disbursements, credit card transactions, cellular phone, and ATM exceed tens of billions of dollar every year

Biometrics for Person Identification

- Biometrics can be used to identify or verify individuals

- There are several biometric modalities such as face, fingerprint, iris, signature, and gait

- India has implemented the biggest biometrics project till date - AADHAAR

Biometrics for Person Identification

- Advantages: difficult to steal, unique, permanence
- Challenges: Depending on the biometric modality, difficult to acquire, high intra-class variations, high inter-class similarities

Twins

Same person

Test of Intra-class Variations

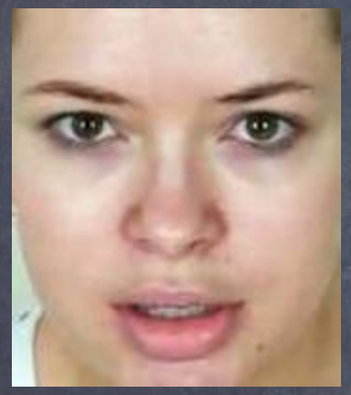
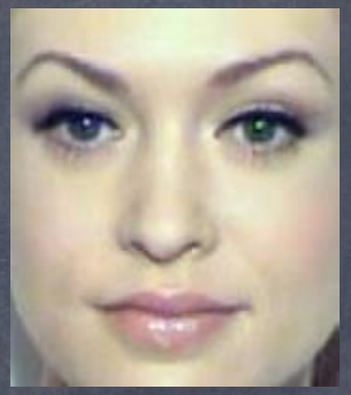
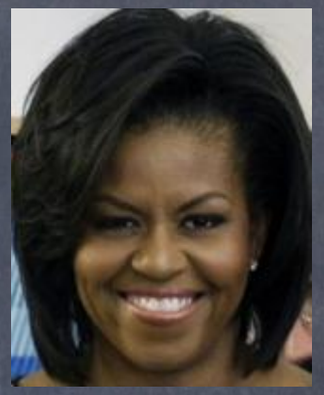
Test of Intra-class Variations

15 images of person A

5 images of similar looking impostors

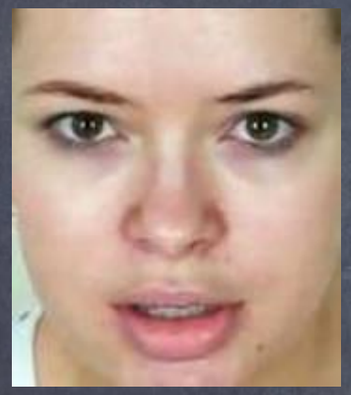
Test of Intra-class Variations

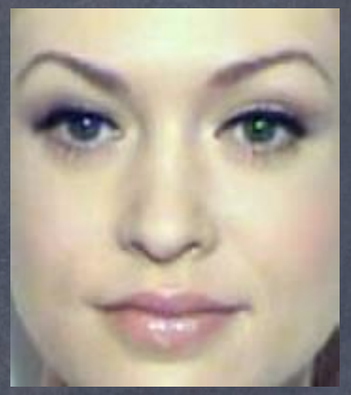
Test of Inter-class Similarities

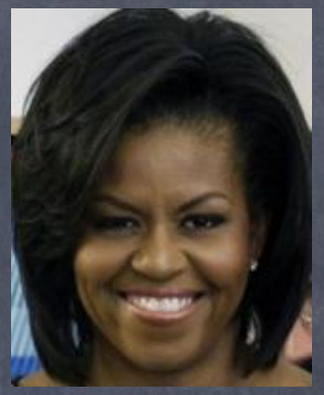







Test of Inter-class Similarities

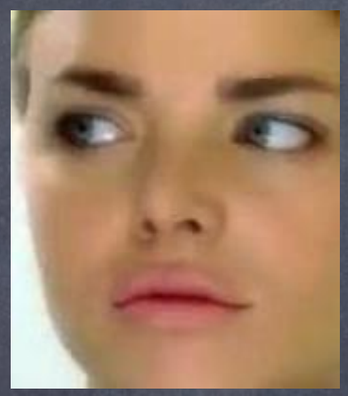
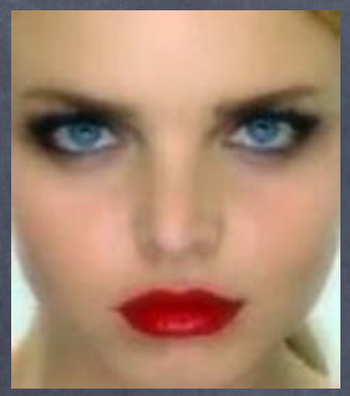




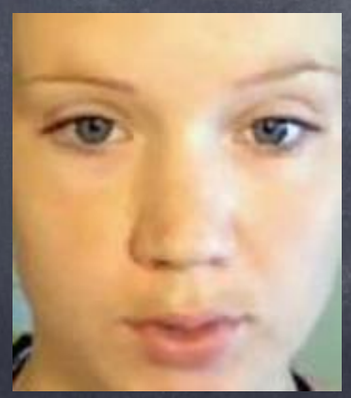


All are Impostors

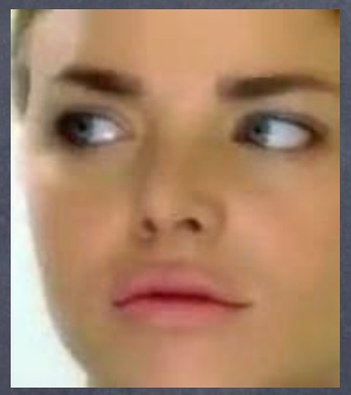
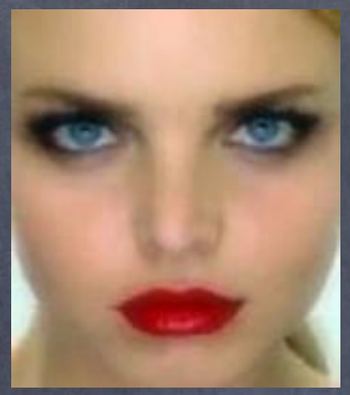
Test of Intra-class Variations



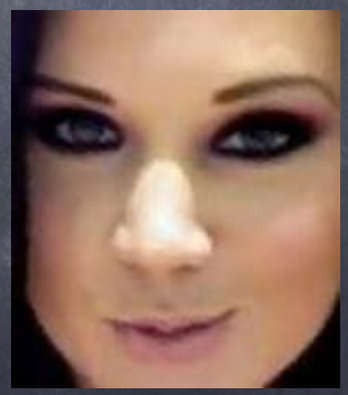




Test of Intra-class Variations

All are genuine



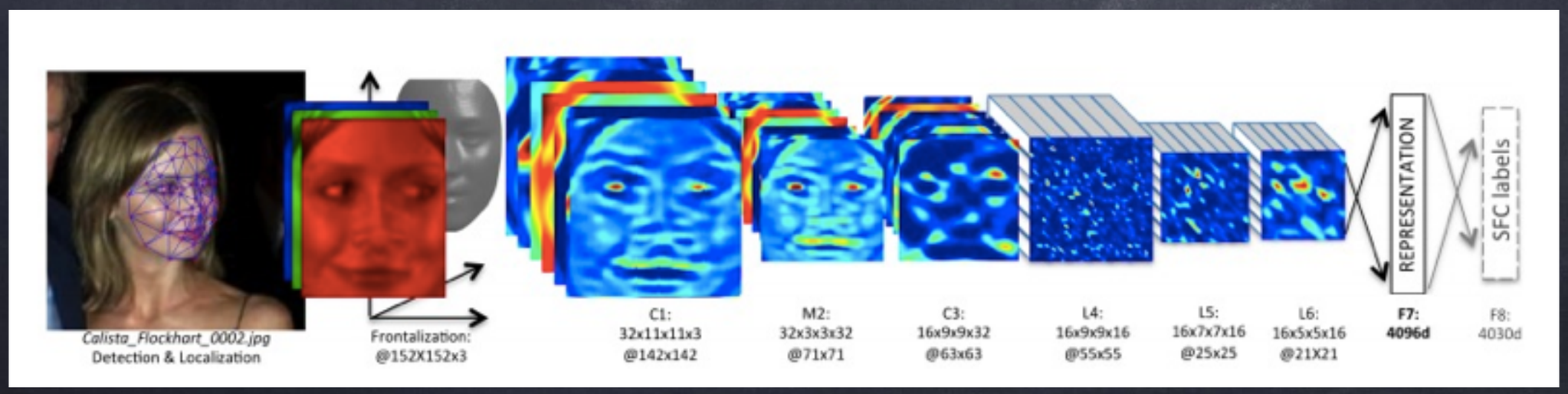



Current Research Agenda

- At IAB lab, we are addressing the problem in multiple ways:
  - face recognition in constrained and unconstrained environments
  - fingerphoto recognition using mobile phones
  - iris recognition at a distance
  - periocular recognition at a distance
  - latent fingerprint recognition

Deep Neural Network

- Facebook's DeepFace Software Can Match Faces With 97.25% Accuracy - Forbes
- Facebook Creates Software That Matches Faces Almost as Well as You Do - MIT Technology Review



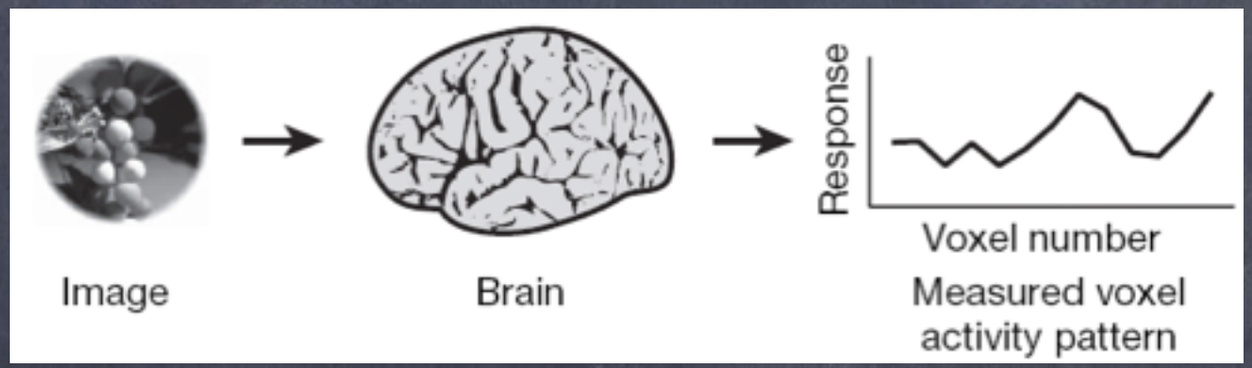
Deep Neural Network

- Recently, Google announced 99.6% accuracy and Baidu announced 99.7% accuracy on LFW database using deep learning architecture

Pick Any Application ...

- If training data is large, there is a deep learning architecture which provides state of the art results

Object Recognition in Human Brain



?

Kay, K.N., Naselaris, T., Prenger, R.J., & Gallant, J.L. (2008). Identifying natural images from human brain activity. Nature, 452, 352-355.

(1) Measure brain activity for an image

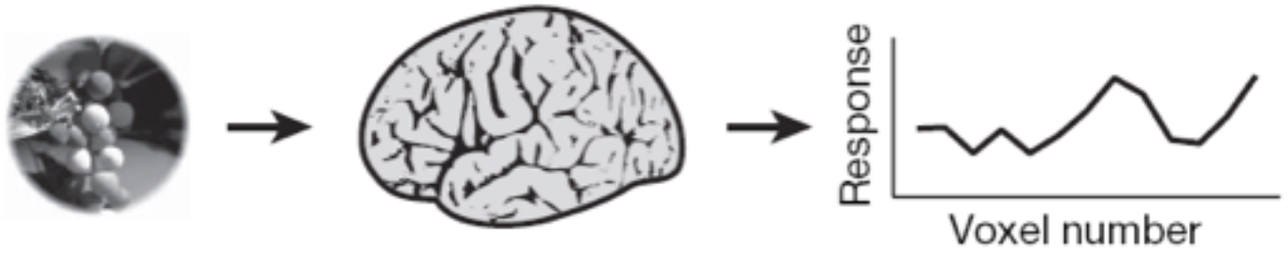
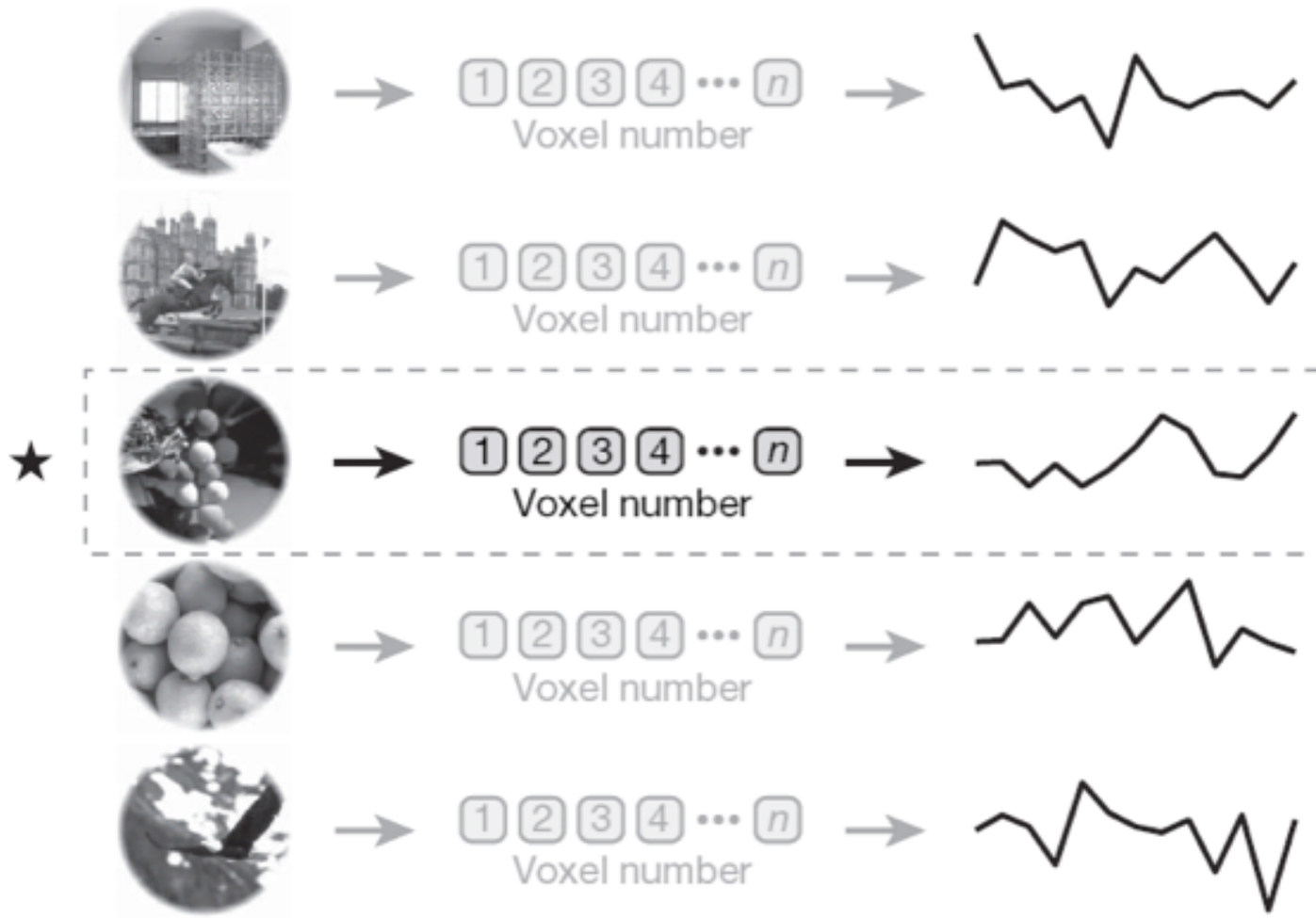


Image | Brain | Measured voxel activity pattern

(2) Predict brain activity for a set of images using receptive-field models

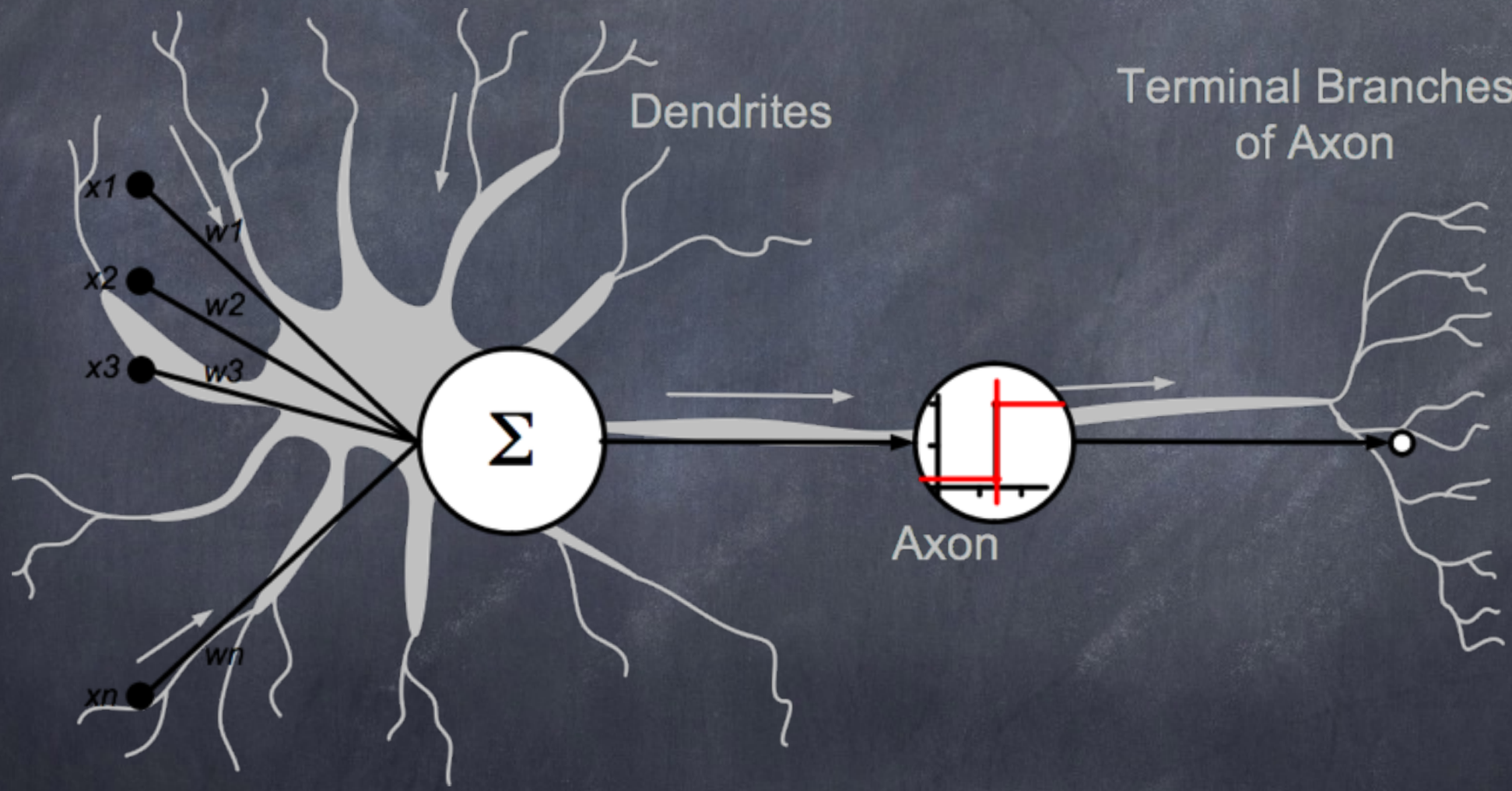


★

Set of images | Receptive-field models for multiple voxels | Predicted voxel activity patterns

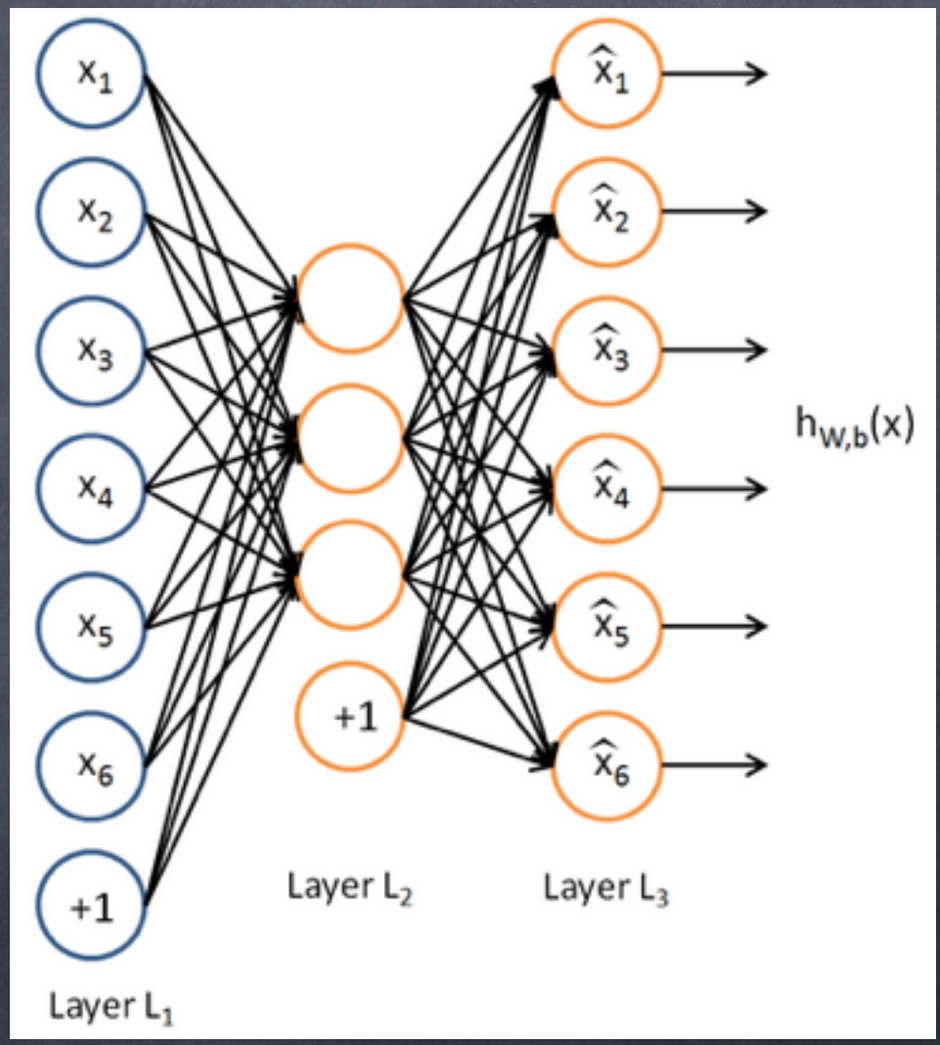
(3) Select the image (★) whose predicted brain activity is most similar to the measured brain activity

From Perceptron to Deep Learning



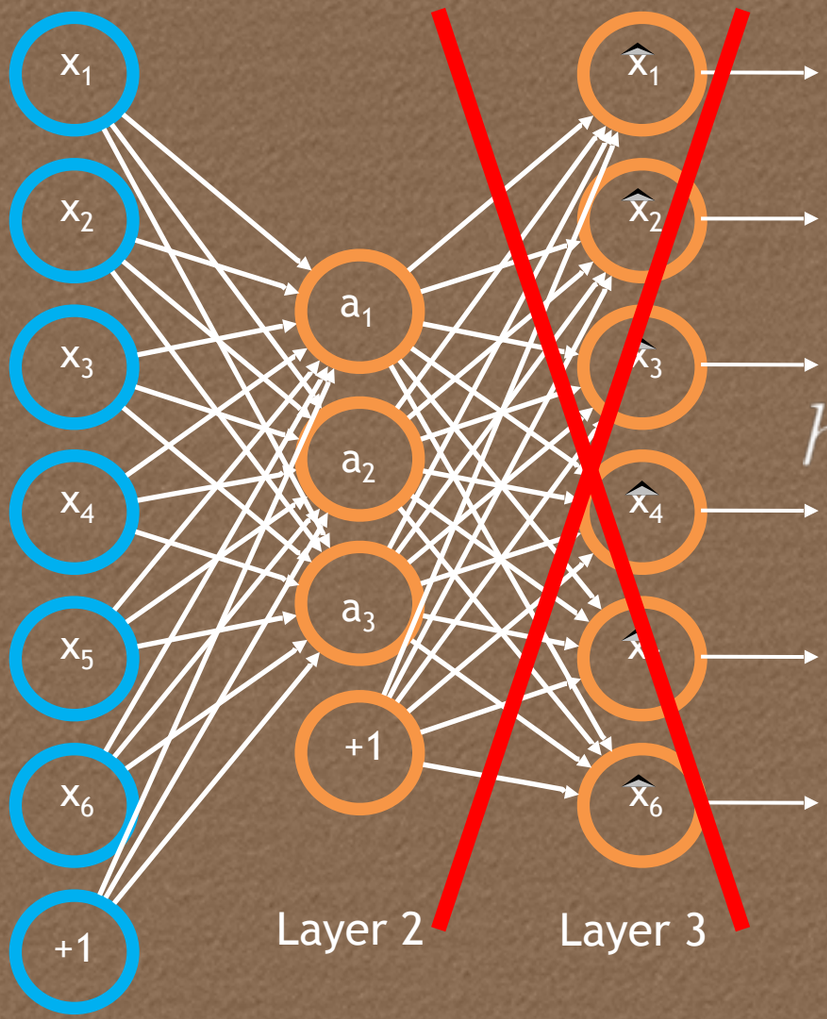
Autoencoders

- Auto-encoders (unsupervised)
- Two parts: encoding and decoding
- Input layer: raw data X
- One hidden layer (encoding): feature learner
- Output layer (decoding): reconstruct $\hat{X}$ such that $||\hat{X}-X||^2$ is minimum

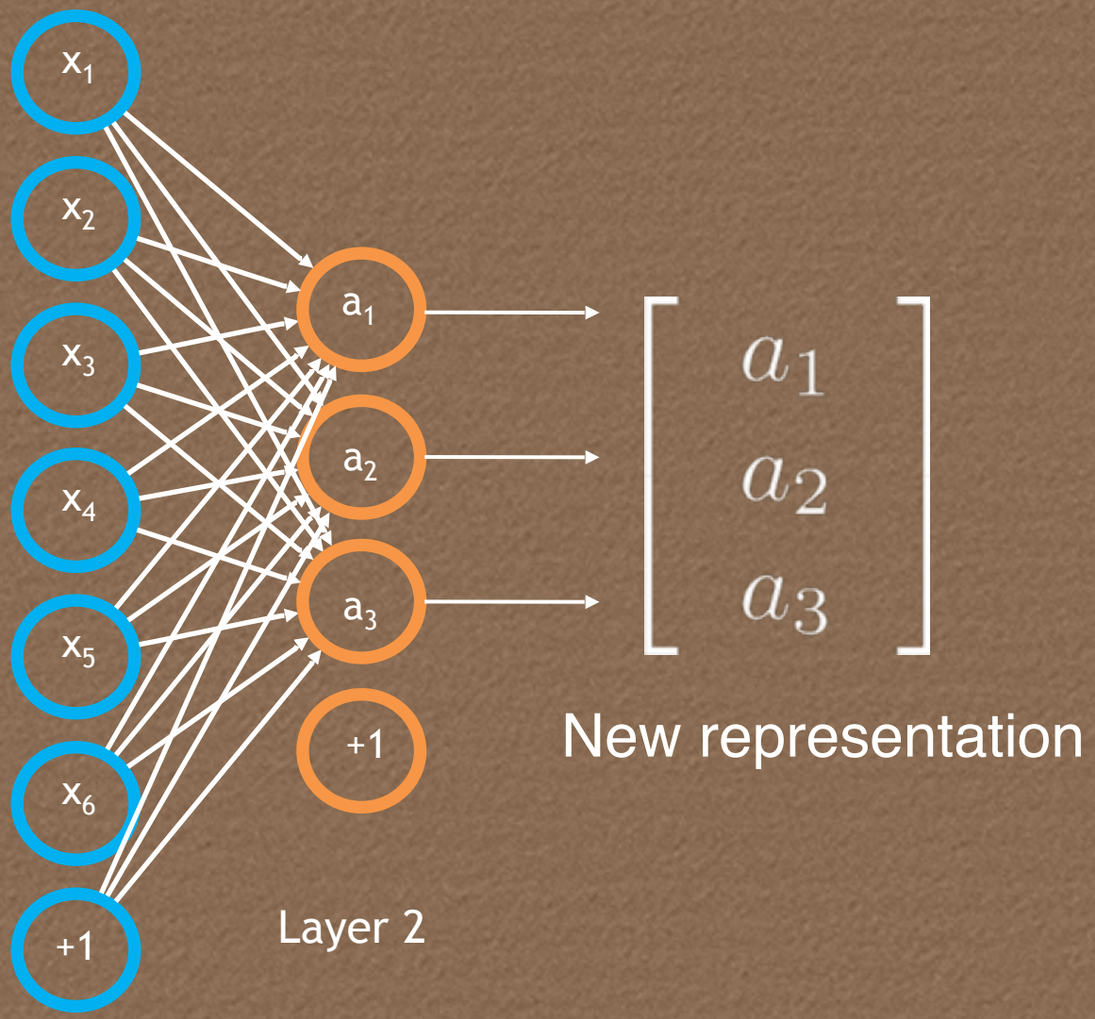


Credit: A. Ng

Autoencoders

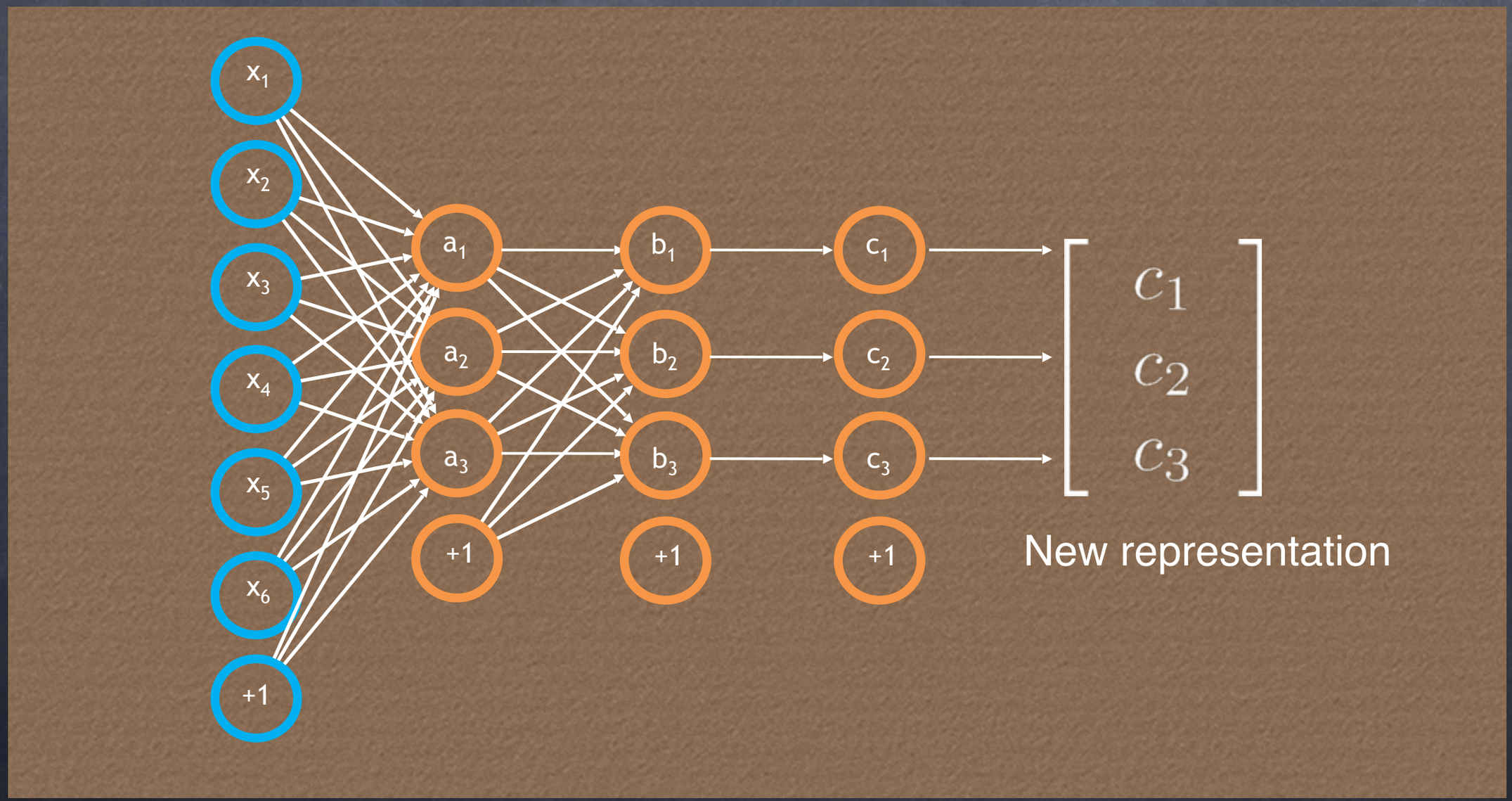


$h_\theta(x)$



Credit: A. Ng

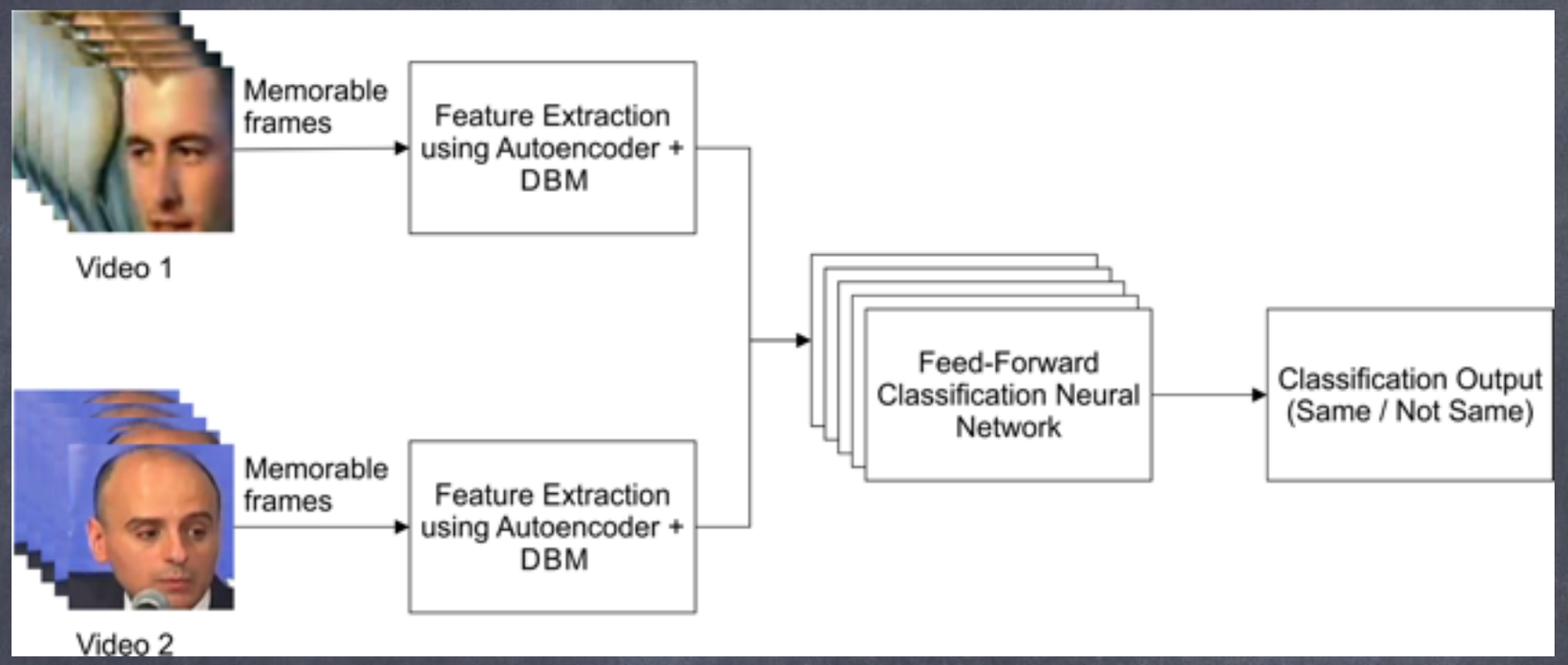
Stacked Denoising Autoencoder

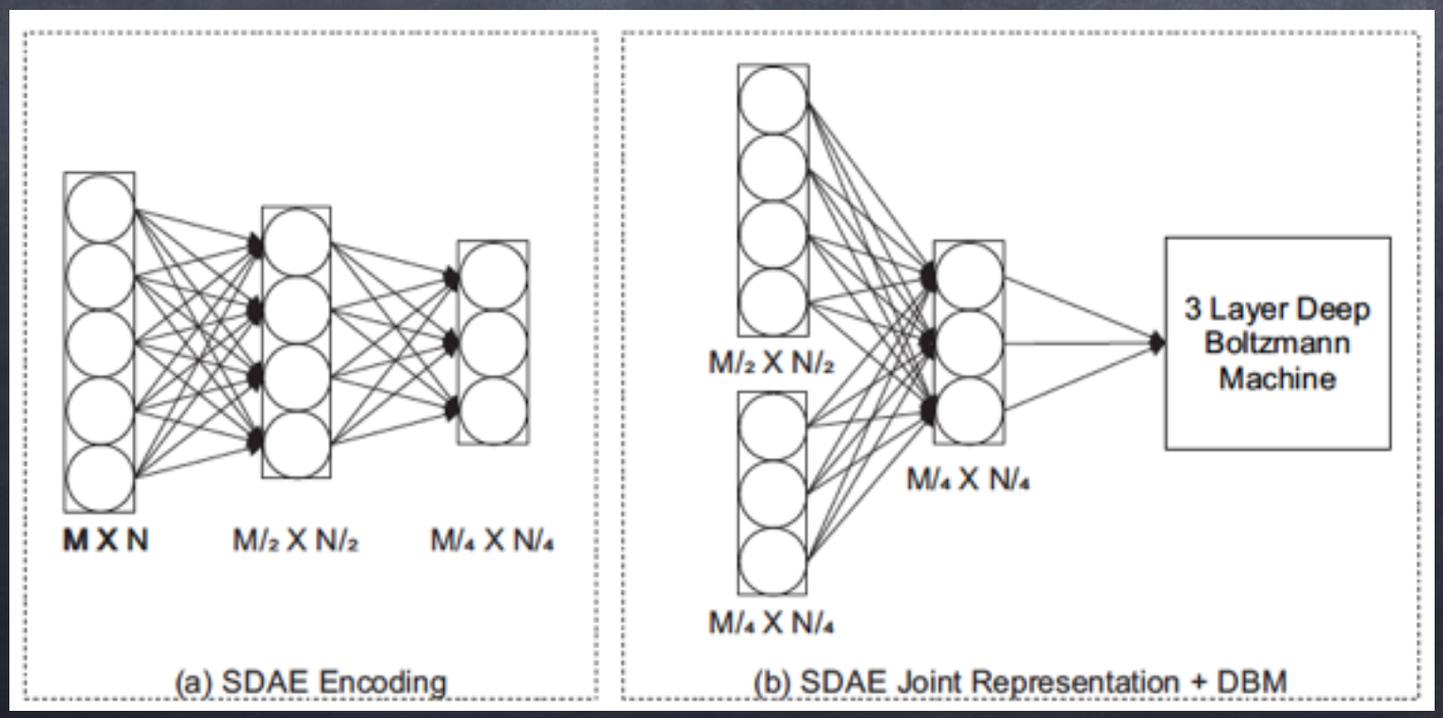


Greedy layer by layer training

Credit: A. Ng

Video Face Recognition using SDAE and DBM



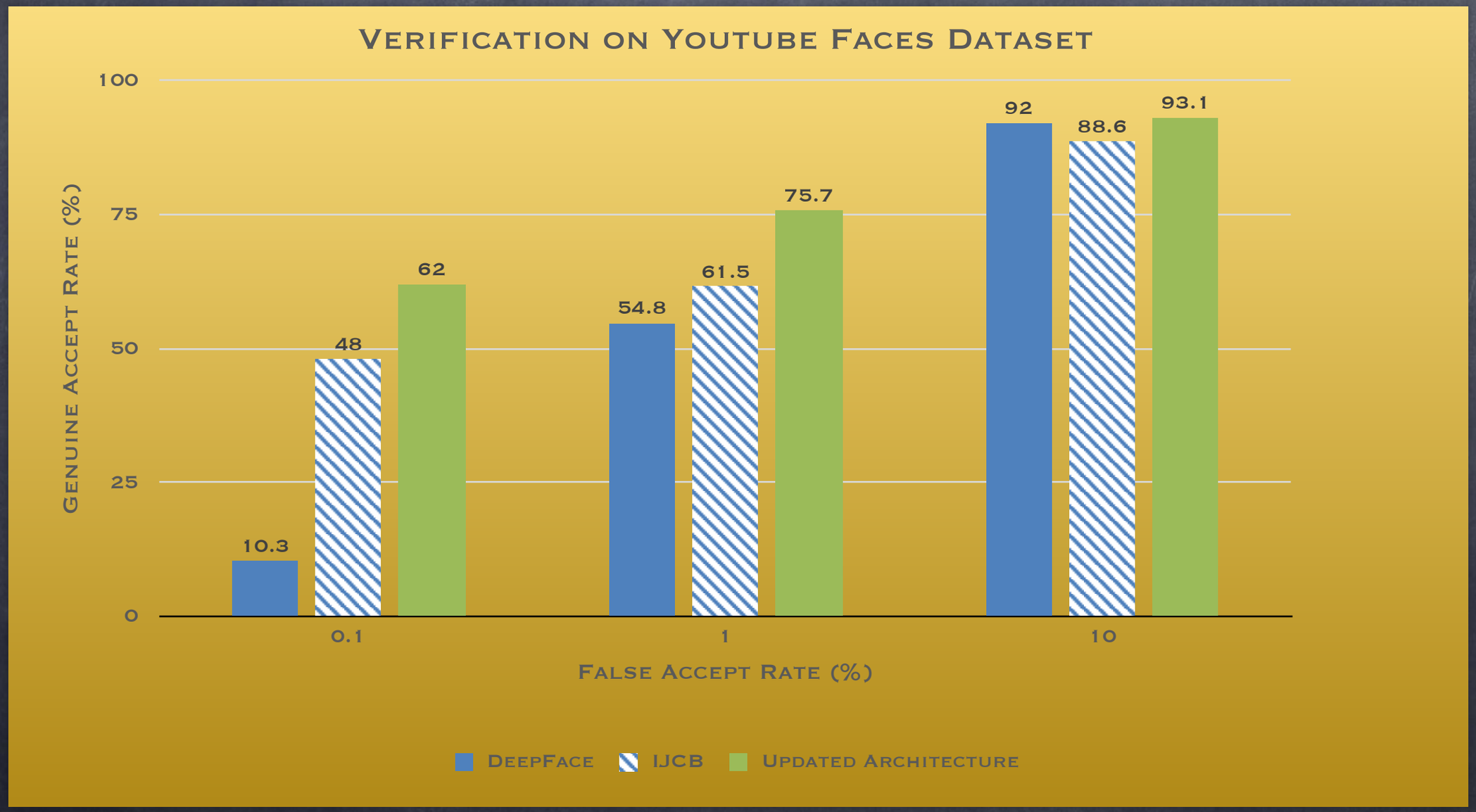


Goswami et al. 2014

Video Face Recognition using SDAE and DBM

- YouTube Faces:
  - 1,595 subjects
  - 3,425 videos
- PaSC (Video):
  - 265 subjects
  - 2,802 videos (handheld and high quality), 280 videos for training

Video Face Recognition using SDAE and DBM



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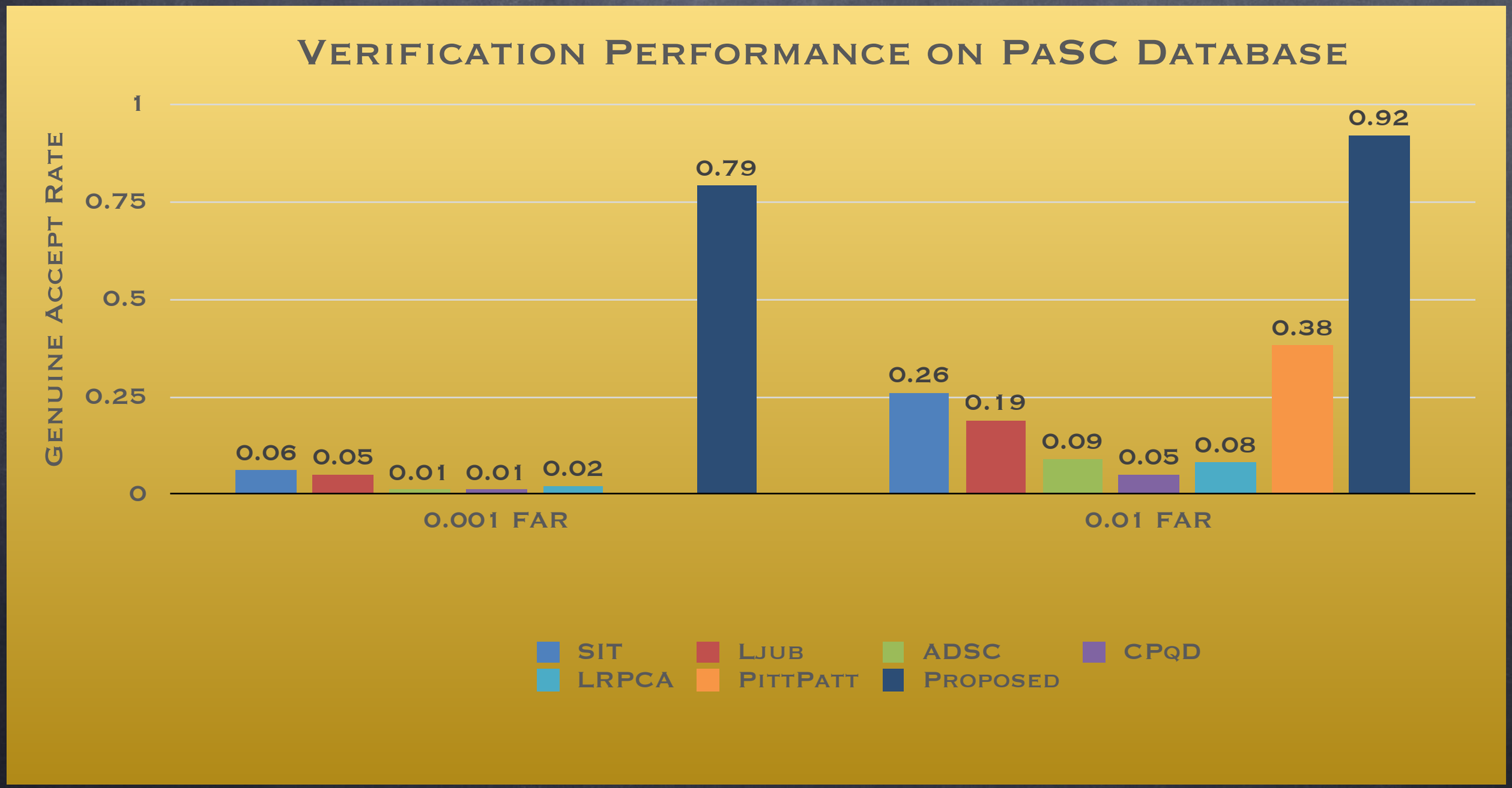


Newborn Face Recognition using SDAE and OSS

Bharadwaj et al. 2016

Newborns and Infants

4 hrs

4 months

8 months

Why we need identity system for newborns?

- Baby abduction and swapping - both unintentional and intentional

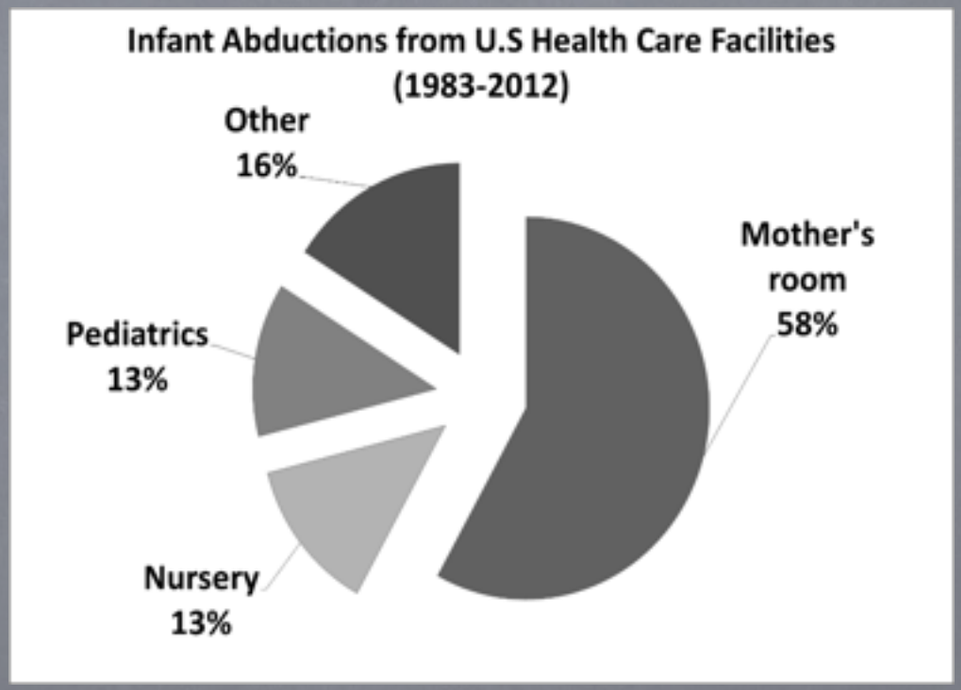
Why we need identity system for newborns?

- Gwalior, April 2016: 'Baby farm' busted at Gwalior hospital
- Karimgunj (Assam), Dec 2015: Couple alleges newborn swapped
- Kurukshetra, Sep 2015: Get newborn clicked with family to avoid swapping controversies: NCSC member
- Chandigarh, July 2015: Newborn's death: Parents accuse hospital of changing their child with somebody else's

Why we need identity system for newborns?

In USA, National Center for Missing and Exploited Children has reported 300 infant abductions since 1983. Of these cases, 44% were from hospitals or other health care facilities, with more than half from the mother's hospital room

34 newborns in a neonatal intensive care unit at any given day, there is 50% chance of incorrect identification



Current systems are inadequate

- The American Academy of Pediatrics (AAP) and the American College of Obstetricians and Gynecologists (ACOG) stated that
  - "...individual hospitals may want to continue the practice of footprinting or fingerprinting, but universal use of this practice is no longer recommended."

Biometrics for newborns

Approach	Modality	Manual / Automatic	No. of subjects	Comments
Fields et al. (1960)	Ear	M	206	Adequate discriminability of ear to establish identity
Shepard et al. (1966)	Footprint	M	51	Low recognition due to incorrect capture practices in hospitals
Pela et al. (1975)	Footprint	M	1917	Ridge information not sufficient for manual recognition
Weingertner et al. (2008)	Palmprint	M	106	Poor performance by experts using high resolution capture device
Bharadwaj et al.(2010)	Face	A	34	Low verification accuracy
Lemes et al. (2011)	Palmprint	A	20	Special capture equipment and collection process
Tiwari et al. (2011)	Ear	A	210	Capture, segmentation and orientation correction a challenge
Jain et al. (2014)	Fingerprint	A	20 & 70	Fusion of commercial fingerprint SDKs
Jain et al. (2016)	Fingerprint	A	66	1270 ppi sensor, Image enhancement and commercial system matching
This research (2016)	Face	A	450	Learning based encoding and distance metric scheme

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Newborns: Unintentionally non-cooperative users

Other Challenges

- Large foreheads
- Lanugo
- Twins

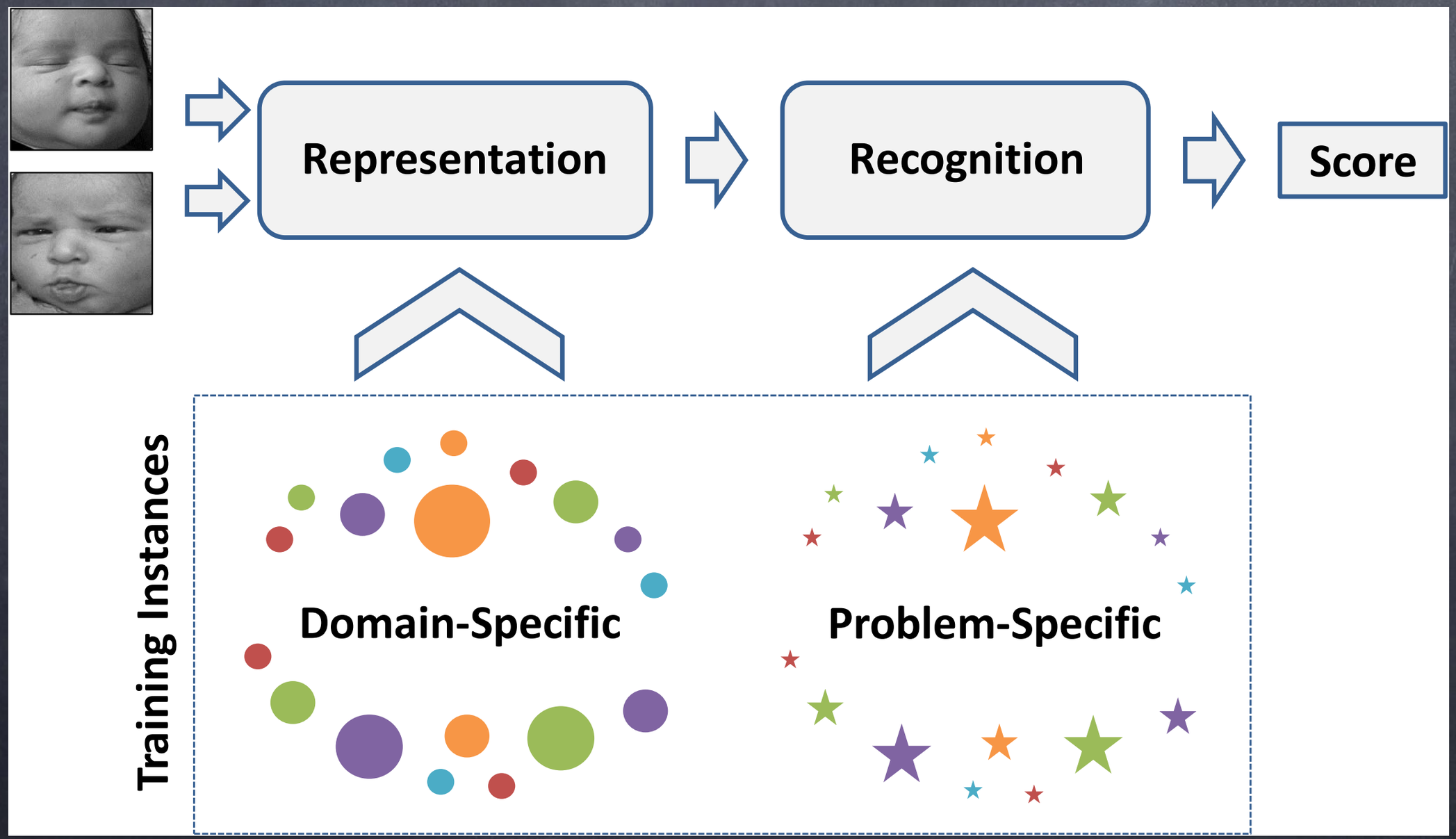
(a)

(b)

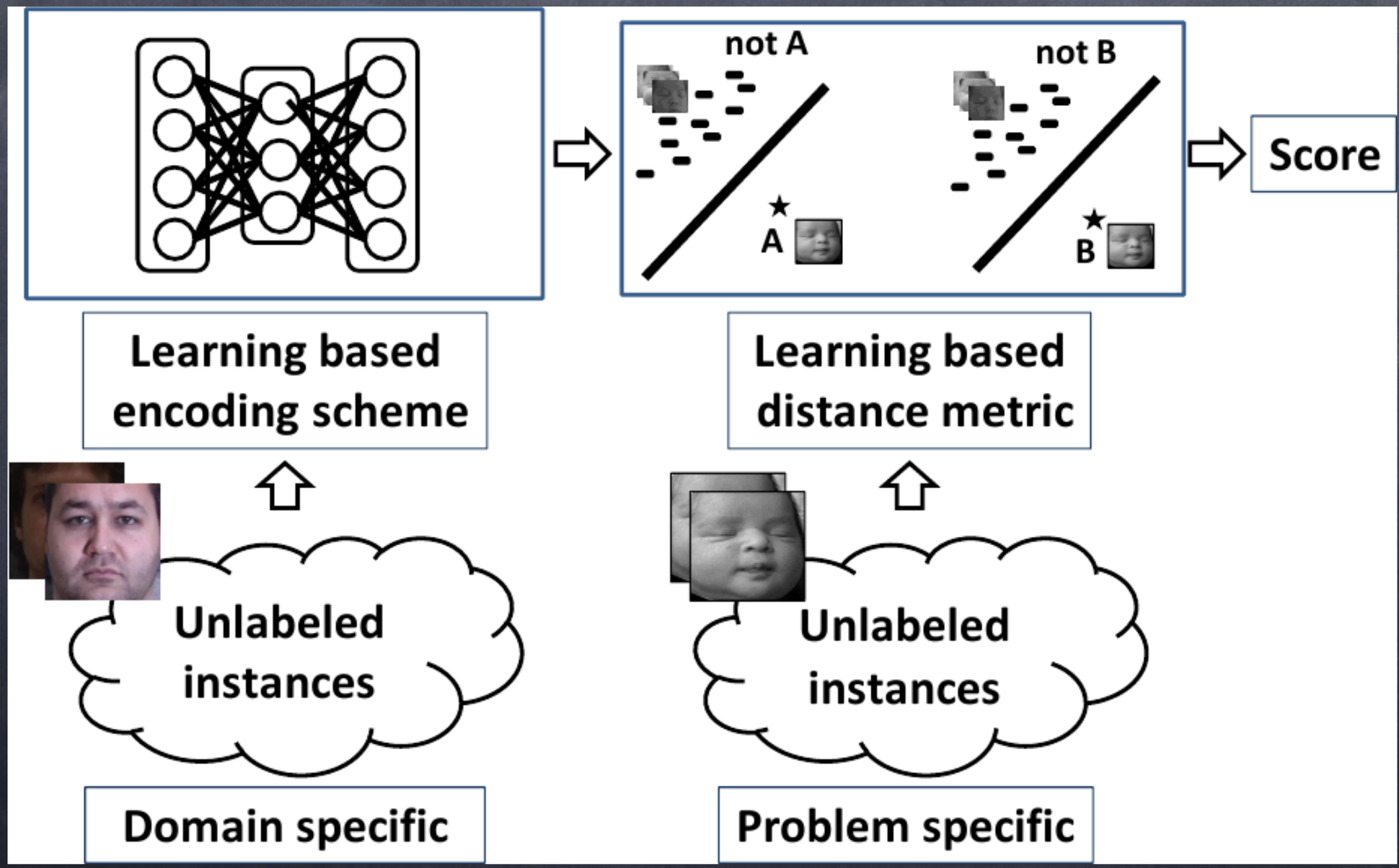
Why regular face recognition is not sufficient?

- The craniofacial characteristics of an infant face are not proportionally equivalent to a miniature adult face

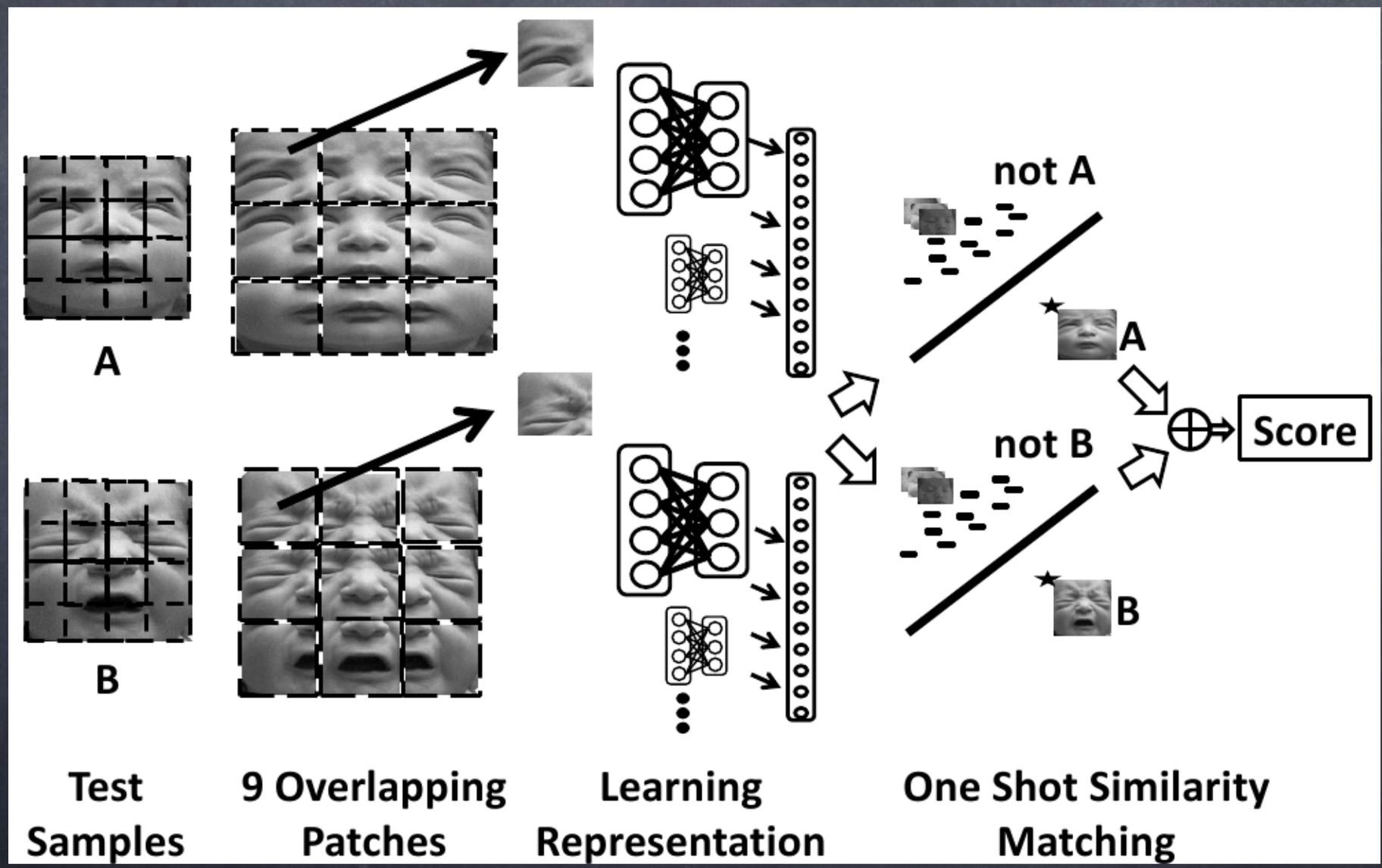
The proposed approach (meta-view)



The proposed approach (macro-view)



The proposed approach (micro-view)



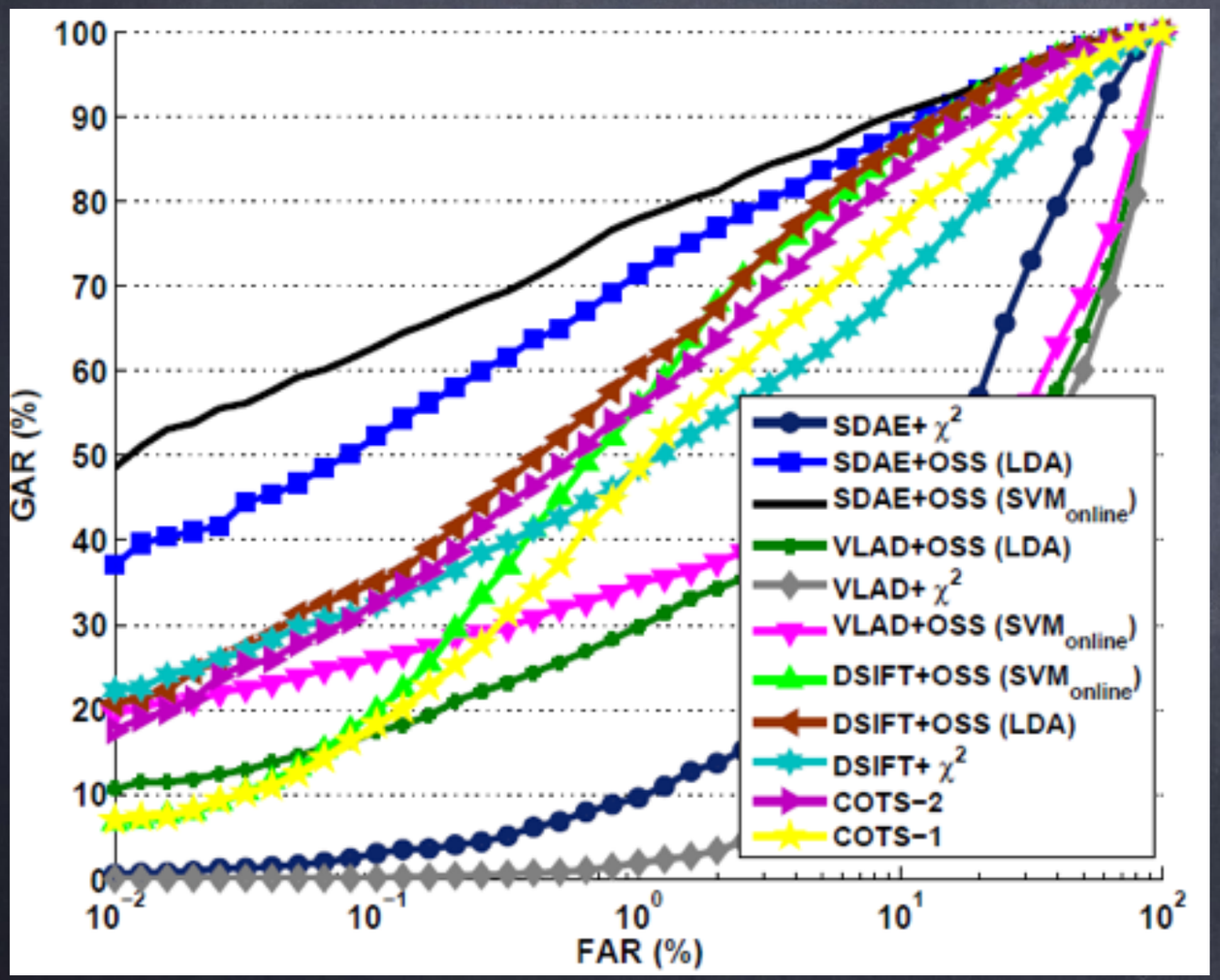
Newborn face database

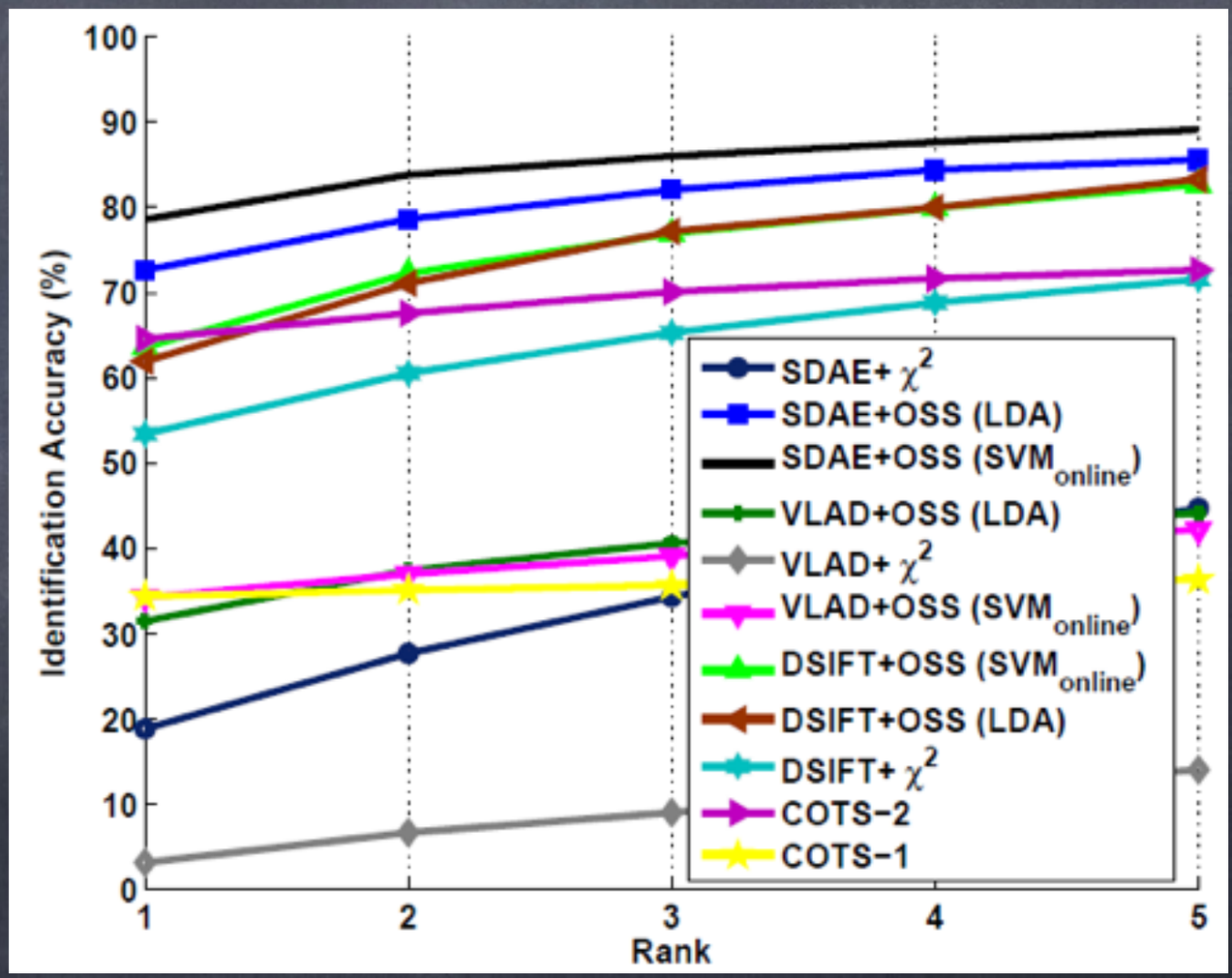
- 450 newborns
  - 96 babies with multiple sessions
- 1200+ images
- various hospitals
- 4 years

Experimental protocol

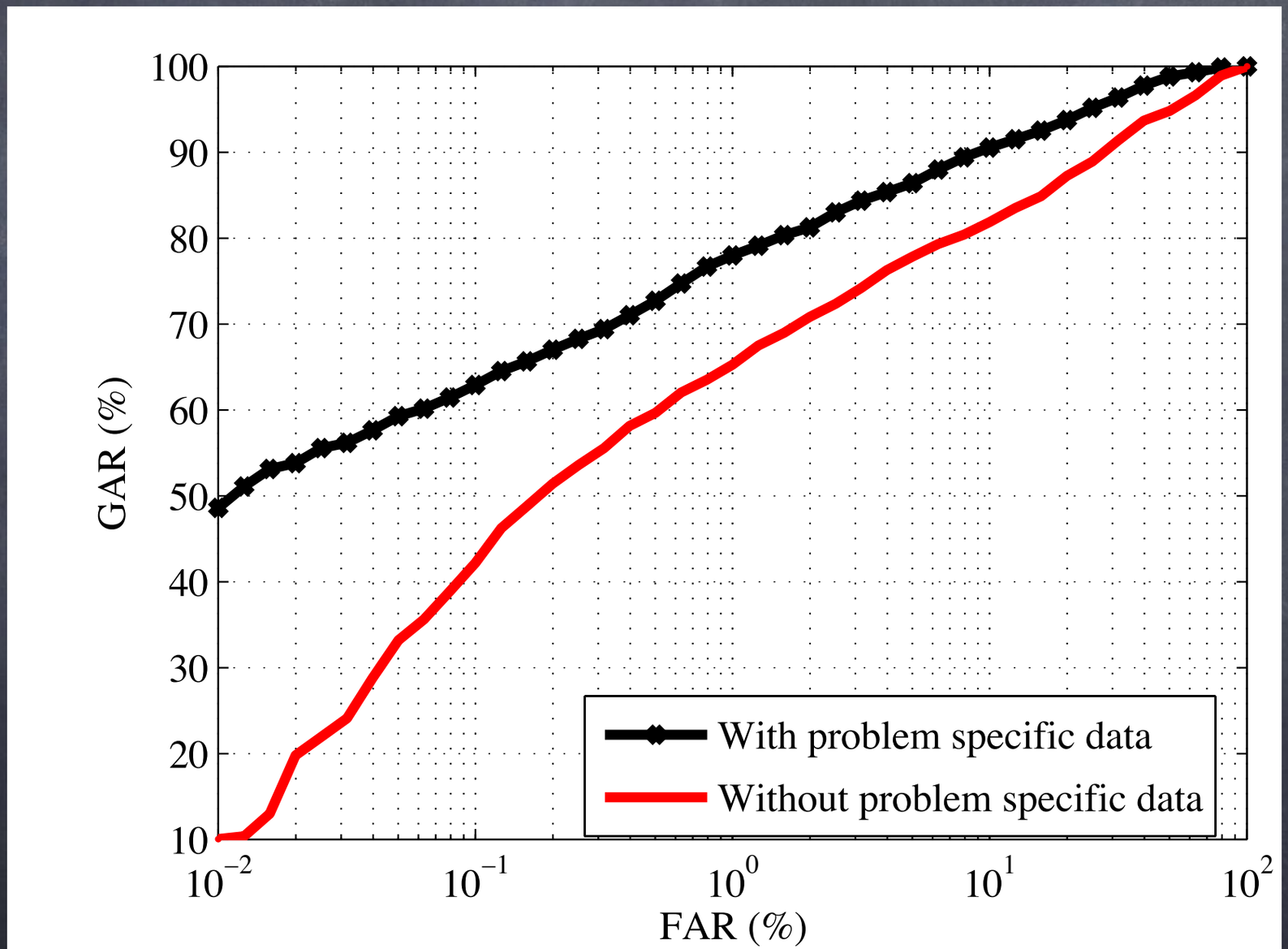
- 50,000+ face images to learn "face" representation (domain specific information)
- Images from 10 newborns (multi-session) + 358 single sample newborns are used as problem specific training (≈400 images)
- 5 times random sub-sampling based cross-validation

Results


GAR (%)
FAR (%)
SDAE+ χ^2
SDAE+OSS (LDA)
SDAE+OSS (SVM$_{online}$)
VLAD+OSS (LDA)
VLAD+ χ^2
VLAD+OSS (SVM$_{online}$)
DSIFT+OSS (SVM$_{online}$)
DSIFT+OSS (LDA)
DSIFT+ χ^2
COTS-2
COTS-1


Identification Accuracy (%)
Rank
SDAE+ χ^2
SDAE+OSS (LDA)
SDAE+OSS (SVM$_{online}$)
VLAD+OSS (LDA)
VLAD+ χ^2
VLAD+OSS (SVM$_{online}$)
DSIFT+OSS (SVM$_{online}$)
DSIFT+OSS (LDA)
DSIFT+ χ^2
COTS-2
COTS-1

Results


100
90
80
70
60
50
40
30
20
10
GAR (%)
10^{-2}
10^{-1}
10^{0}
10^{1}
10^{2}
FAR (%)
With problem specific data
Without problem specific data

Next Step

- Can we derive inspiration from how human brain performs face recognition to arrive at an efficient algorithm?

- Combines Deep Learning and Domain Adaptation

Contributors

iab-rubric.org