Lecture 10 Applications/Deep Learning

COMP3204 & COMP6223 Computer Vision

Where is feature extraction used these days?

Book
pp
250-258;
271-279

Department of Electronics and Computer Science

UNIVERSITY OF Southampton
School of Electronics and Computer Science

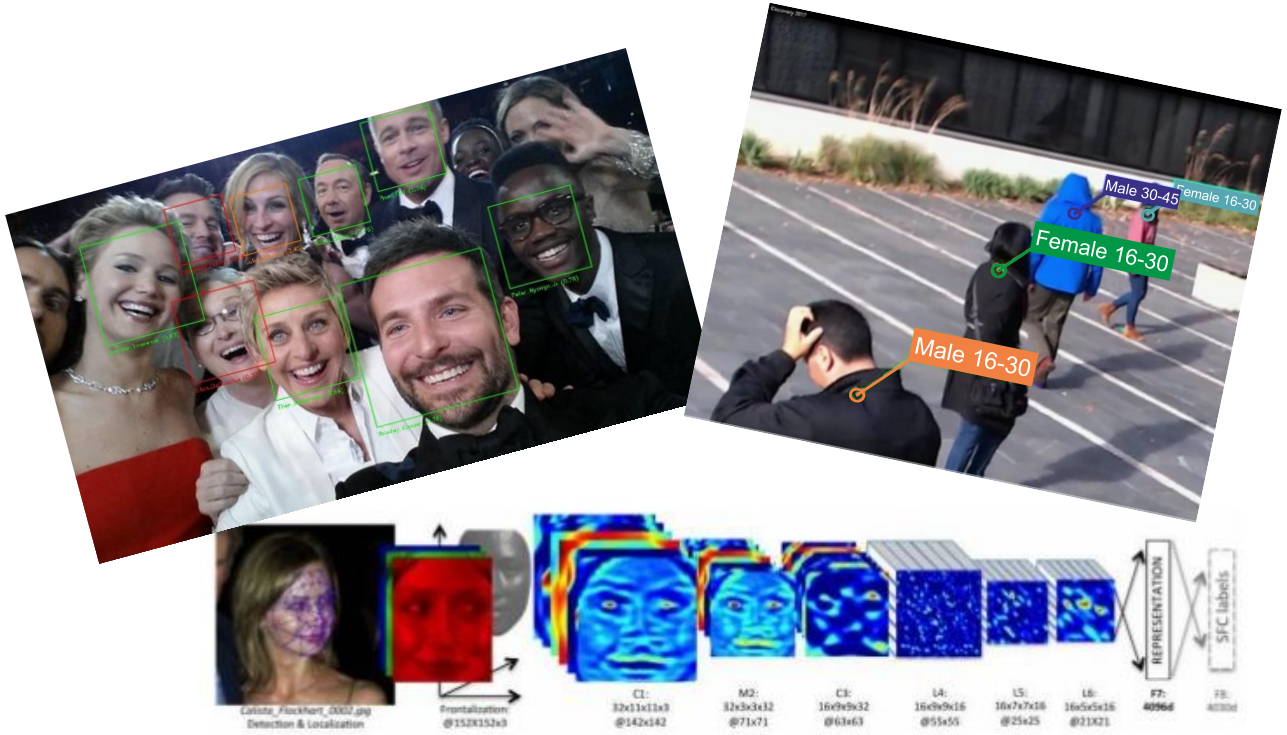
Content

1. Where is computer vision going?
2. Where and how is it used?

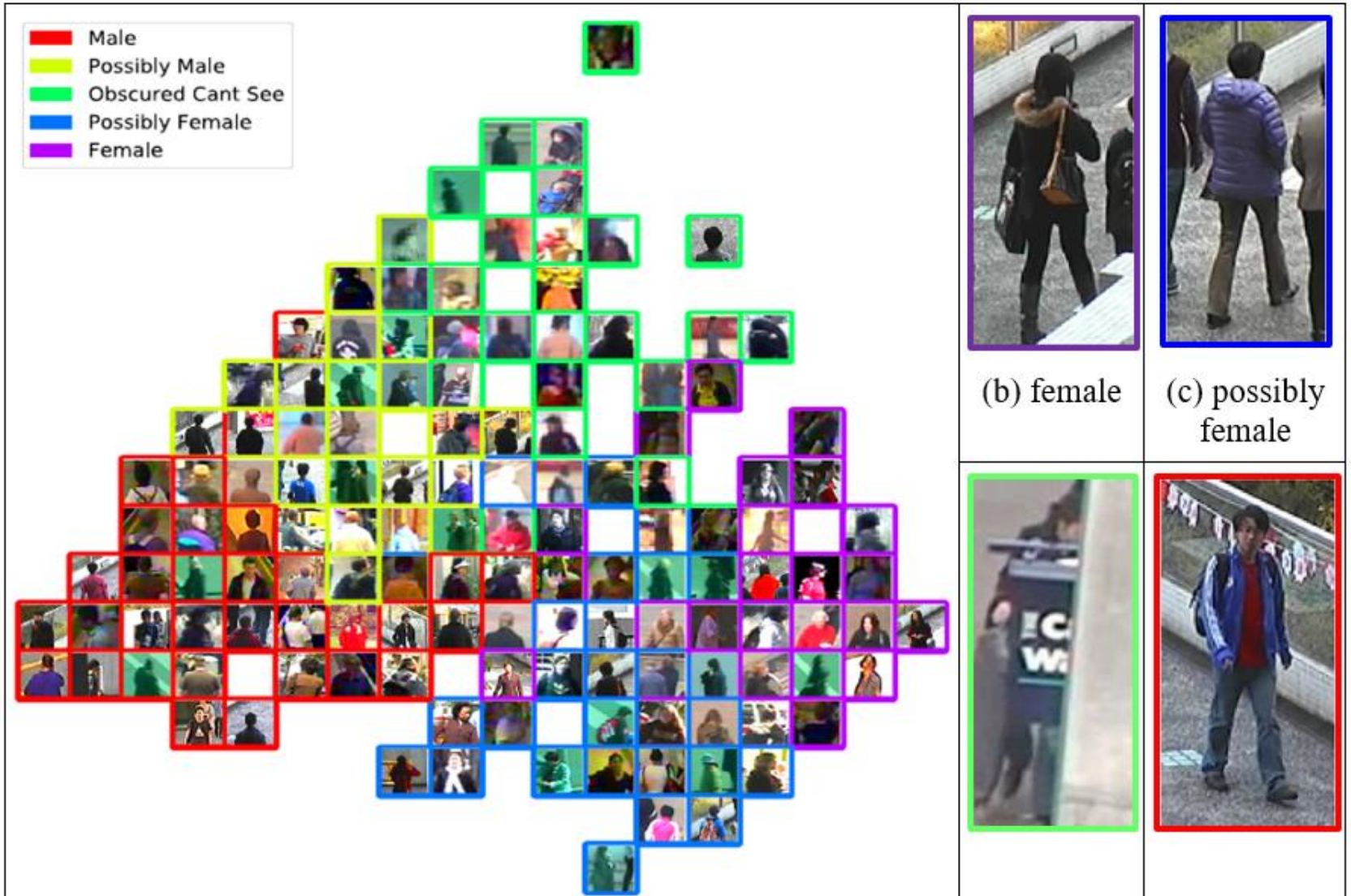
Where is computer vision used?

What you see depends on the viewpoint you take

Industry



Academics,
but increasingly everyone



(a) dataset of images classified by gender

(b) female

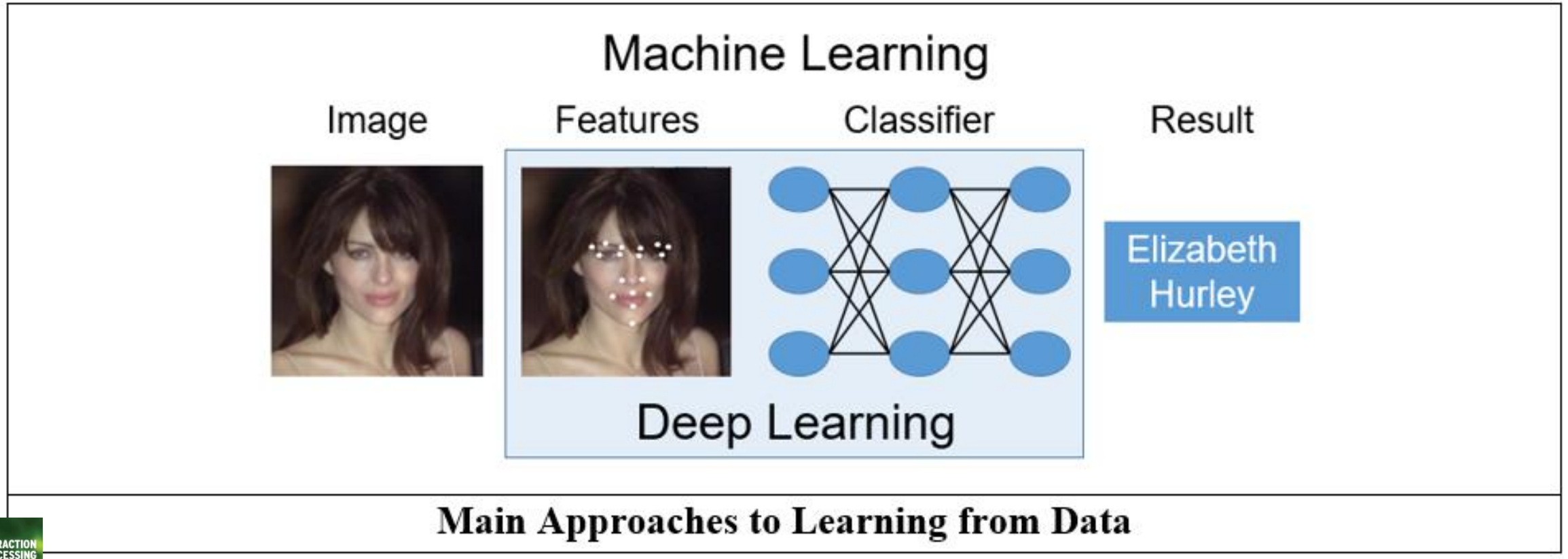
(c) possibly female

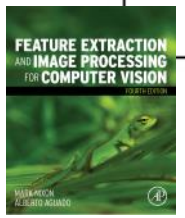
(d) obscured/ can't see

(e) male

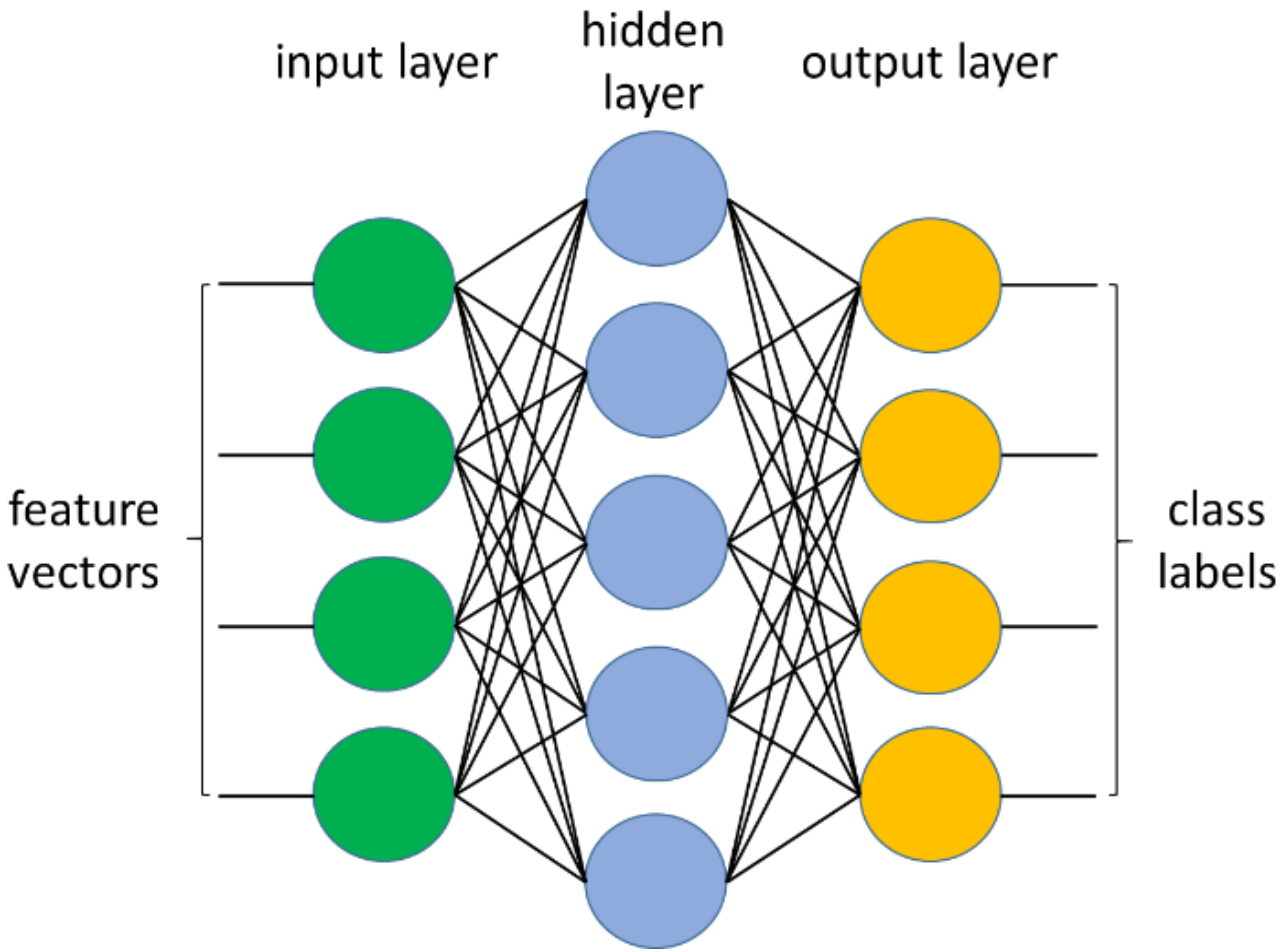
Classifying People by Gender [Martinho-Corbishley18]

On learning


Machine Learning
Image
Features
Classifier
Result
Elizabeth Hurley
Deep Learning
Main Approaches to Learning from Data

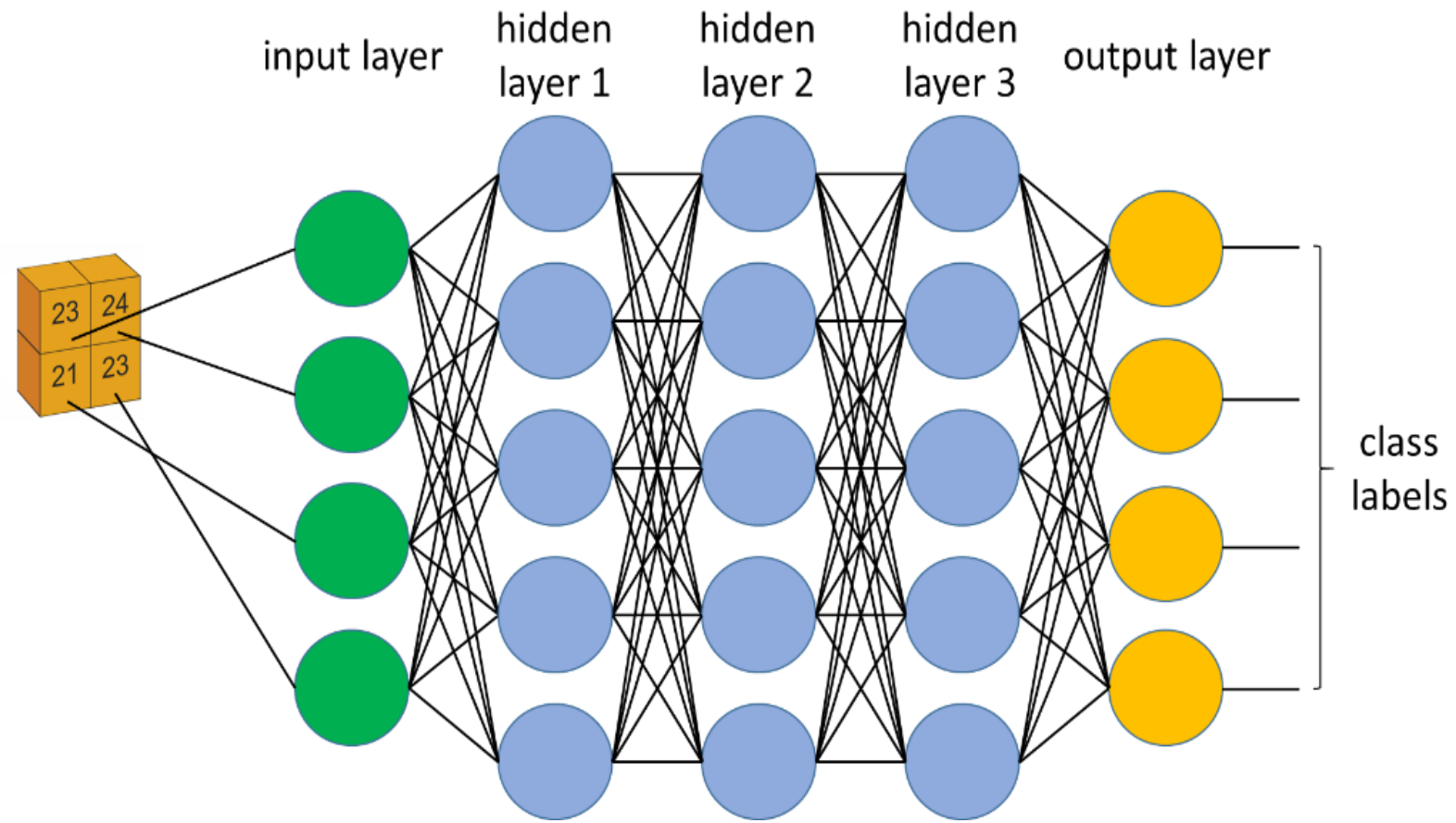

FEATURE EXTRACTION
AND IMAGE PROCESSING
FOR COMPUTER VISION

80’s

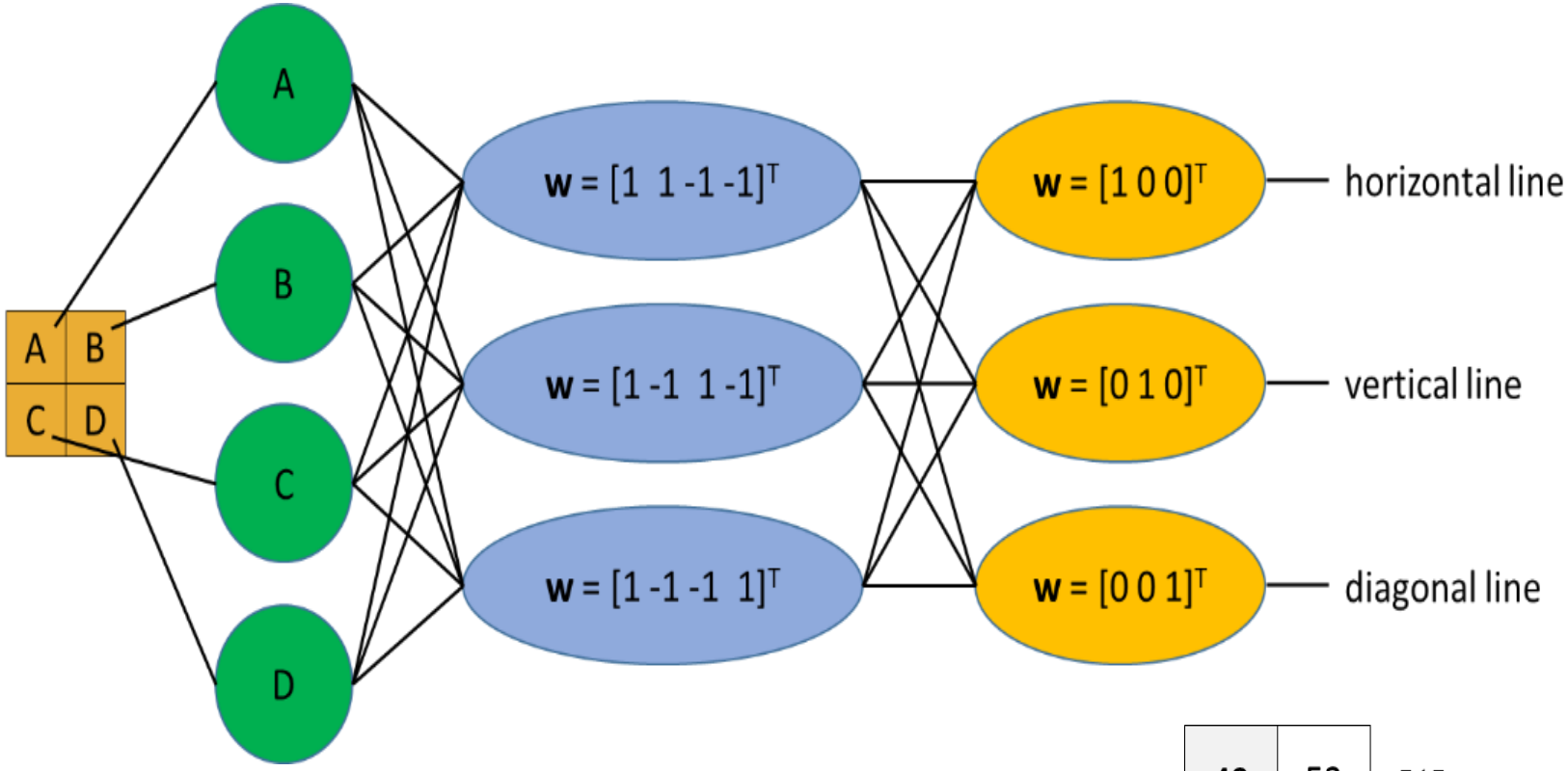

input layer
hidden layer
output layer
feature vectors
class labels

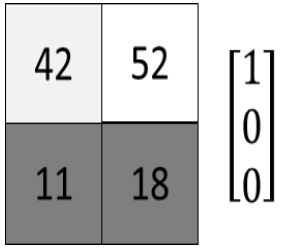

FEATURE EXTRACTION
AND IMAGE PROCESSING
FOR COMPUTER VISION

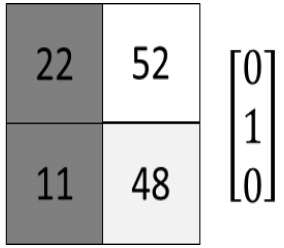
Basis of a Deep Neural Network

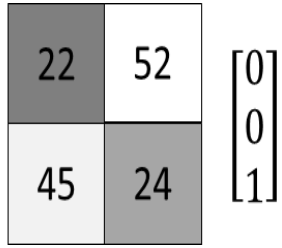


Trained Example Neural Network

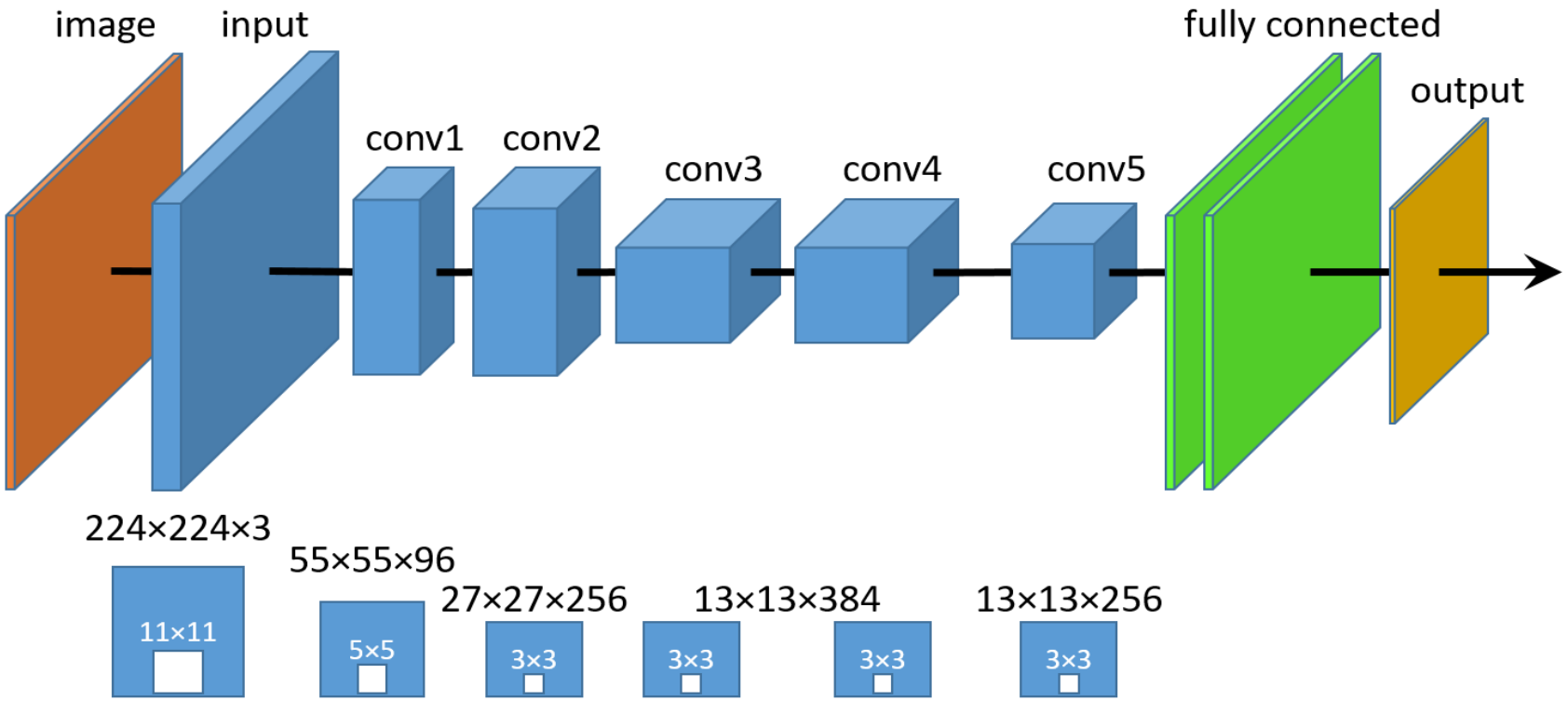




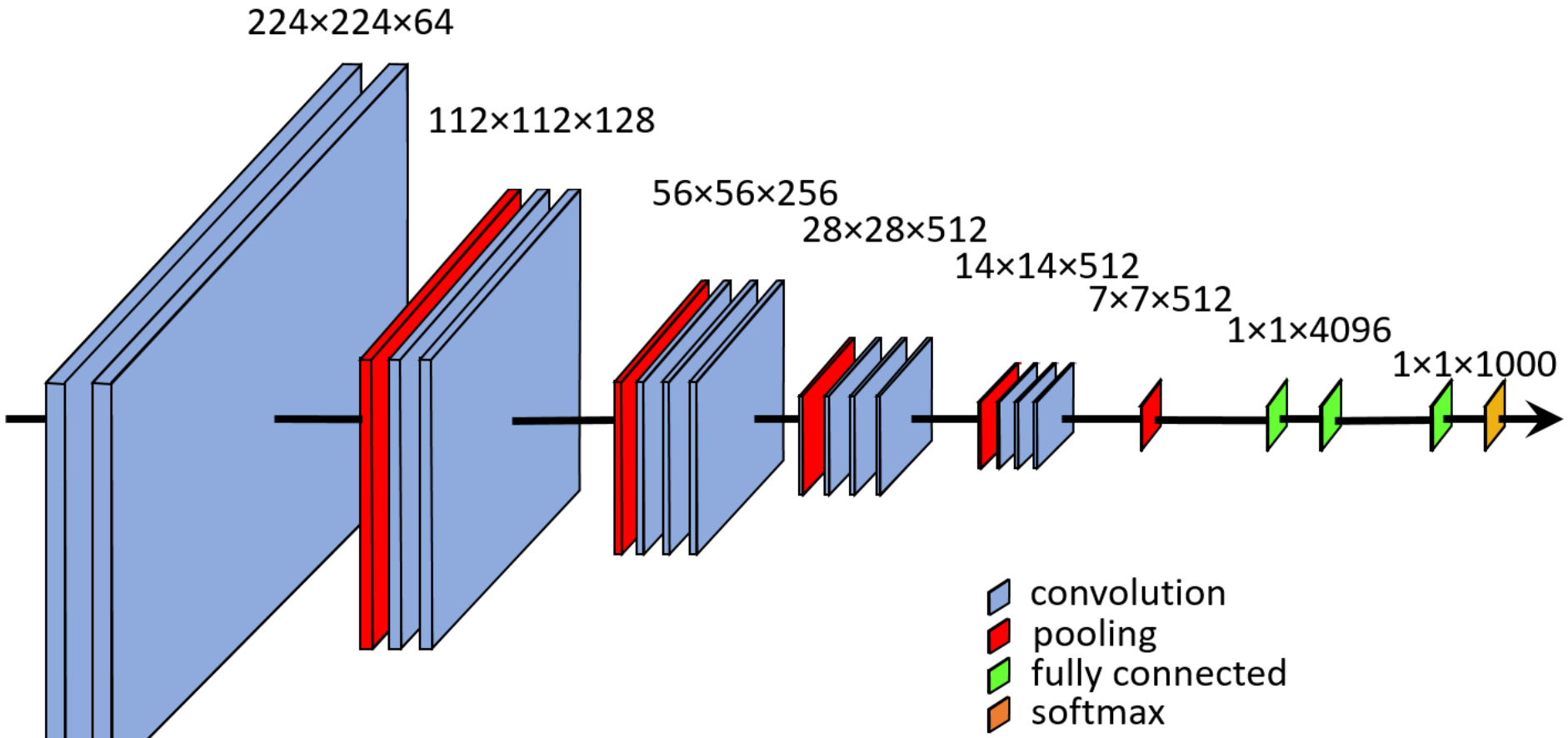




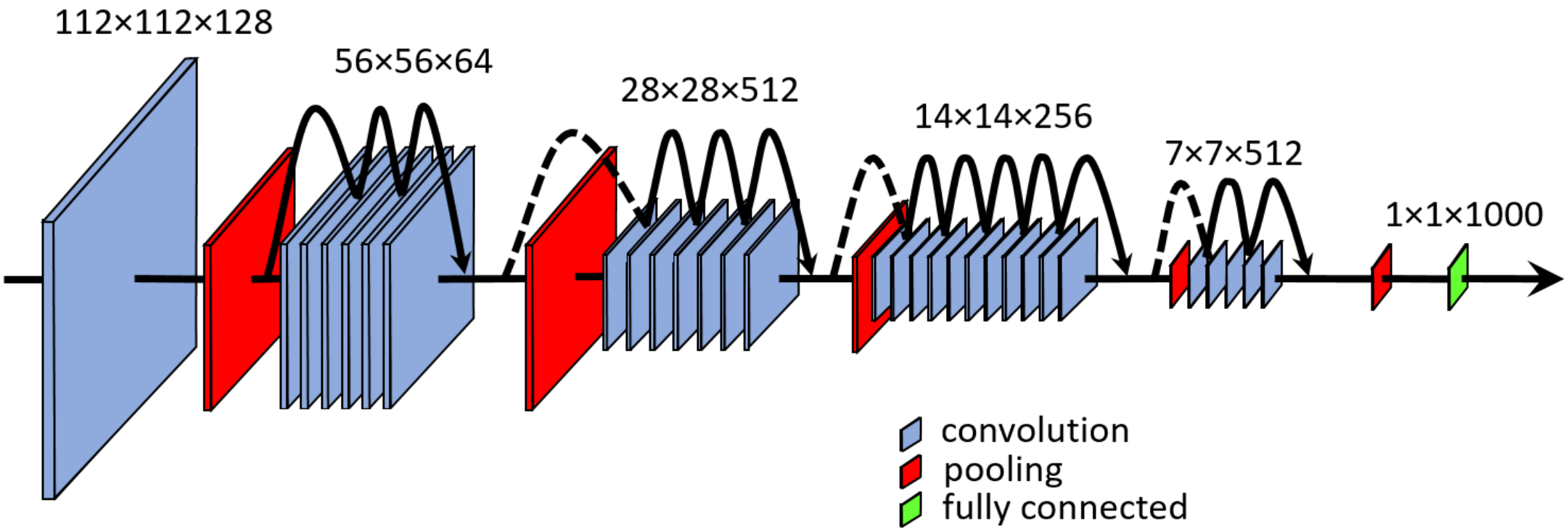
Alexnet architecture



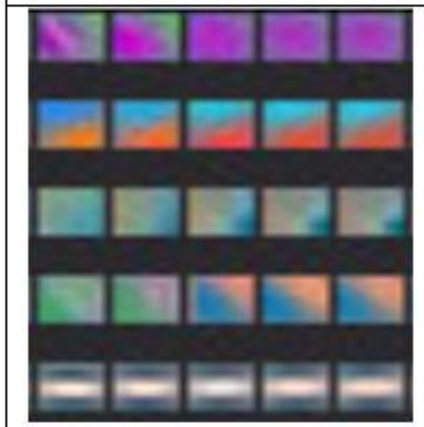
VGG architecture



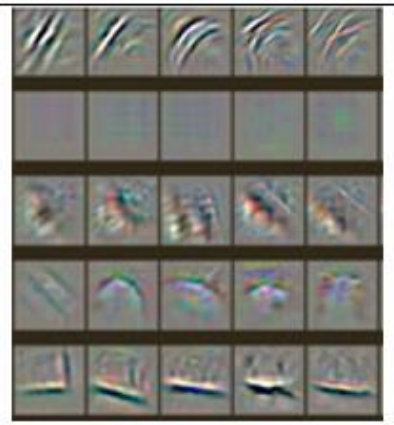
Resnet architecture



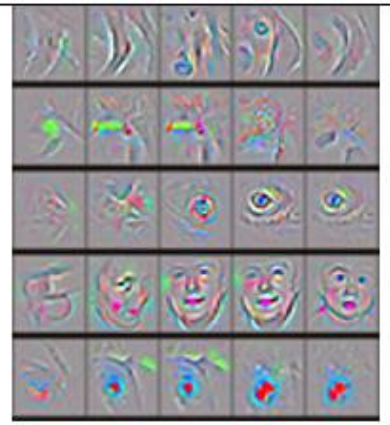
(a) part of a database of face images



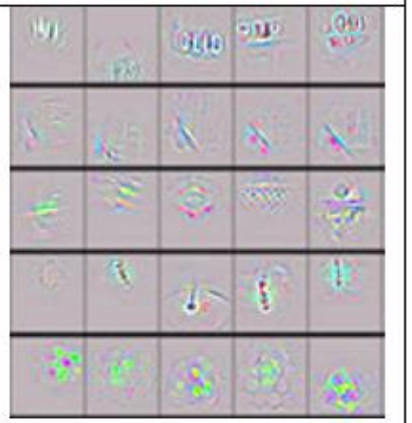
(b) level 1 features



(c) level 2 features



(d) level 3 features



(e) level 4 features

Features at Different Levels in Deep Learning

(a) full image

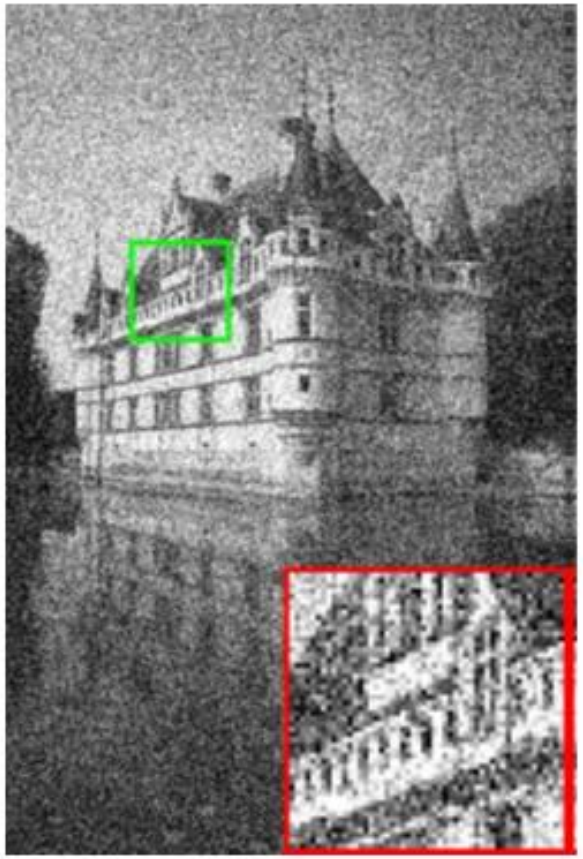
(b) ground truth

(c) by interpolation

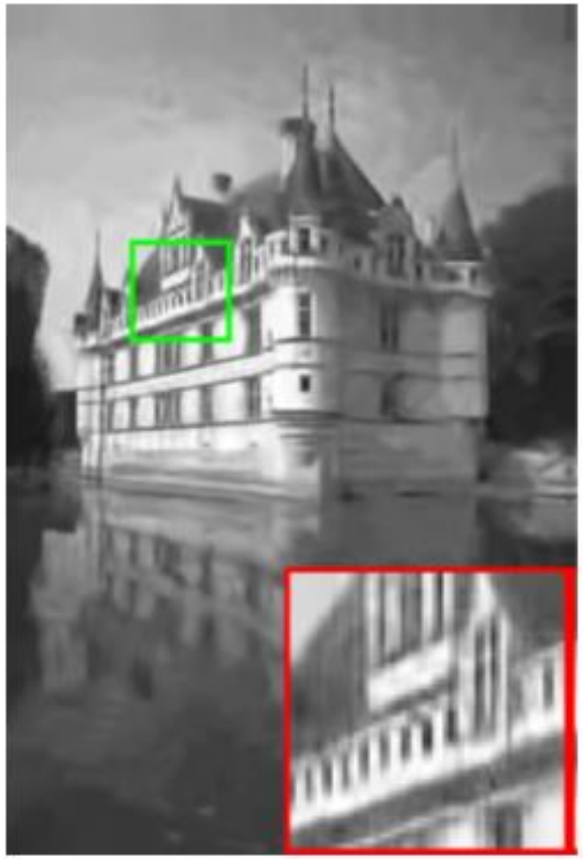
(d) by DRNN

(e) by LFSR

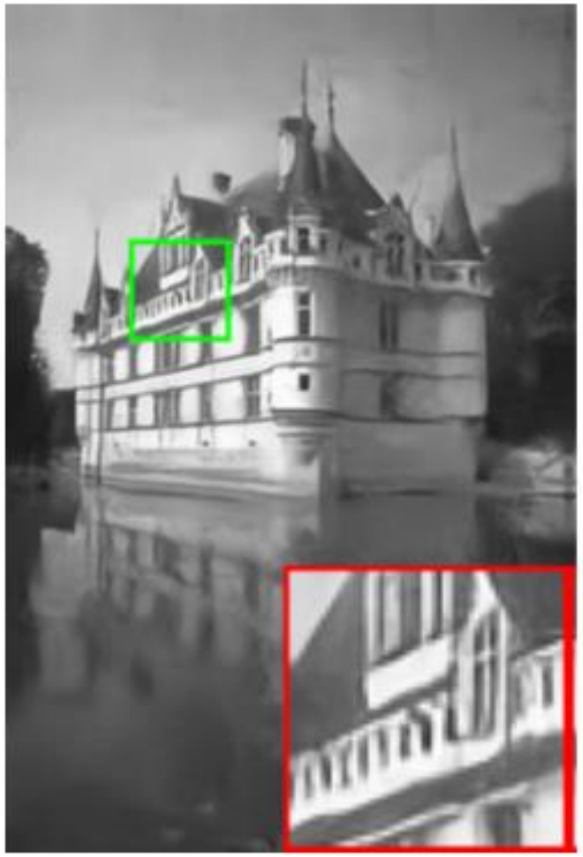
Lightfield Image Resizing [Gul18]



(a) image with added noise



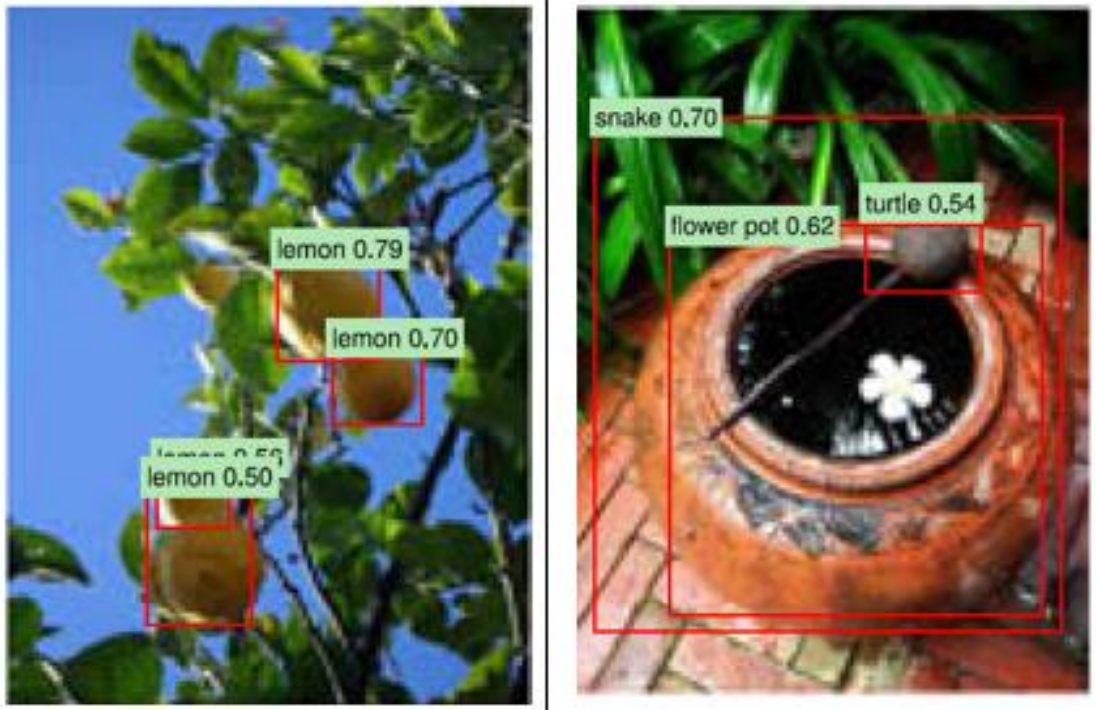
(b) denoising by transform domain



(c) denoising by modified VGG

Image Denoising [Zhang17]

(a) some of the top activations



(b) semantic segmentation

Object Extraction by Region-Based Convolutional Networks [Girshick16]

Motivation: Murder case in Australia 2014

Bouchrika, Nixon, Carter, *J. Forensic Science* 2011, and *Eusipco* 2010

Automating eye witness statements

Eyewitness statement

"24 year old male average height wearing shirt"

Image of crime

Generate description

Subject	Gender	Age	Height	Nose W	Top
?	M	24	171	2.4	Shirt

Database of images

Generate descriptions

Subject	Gender	Age	Height	Nose W	Top
123456	M	25	172	2.3	Shirt
123457	F	36	156	2.2	Blouse
123458	M	58	182	1.2	T shirt

Database of descriptions

Gender estimation on PETA

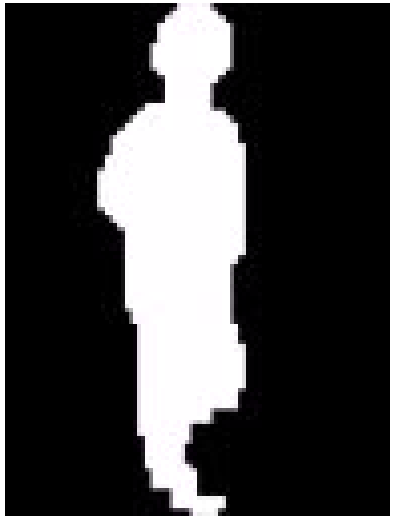
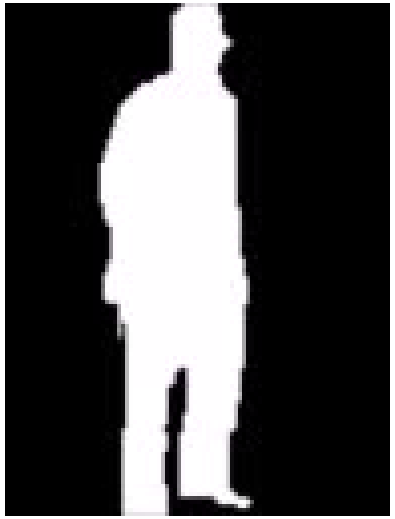
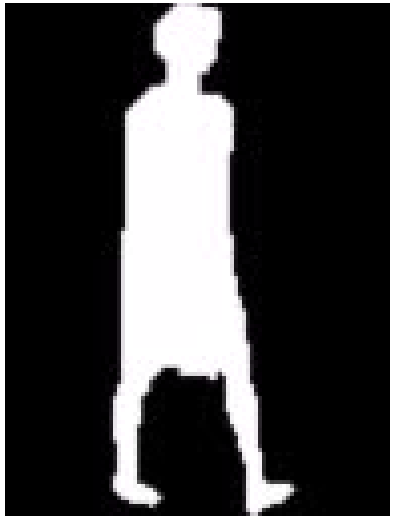
- Gender?

Subject	1	2	3
PETA image			
PETA label	A B	A B	A. Male B. Female

Martinho-Corbishley, Nixon and Carter, *Proc. BTAS 2016*

Gait-based Age Estimation using a Whole-generation Gait Database

- How old is he/she?

Subject	1	2	3
Gait			
Age	A. 4 years old B. 14 years old C. 24 years old	A. 62 years old B. 72 years old C. 82 years old	A. 24 years old B. 34 years old C. 44 years old

Makihara, Okumura, Iwama, and Yagi, *Proc. IJCB 2011*

Traits and terms

Body Features

- Based on whole body description stability analysis by MacLeod et al.
  - Features showing consistency by different viewers looking at the same subjects
- Mostly comprised of 5 point qualitative measures

e.g. very fat, fat, average, thin, very thin

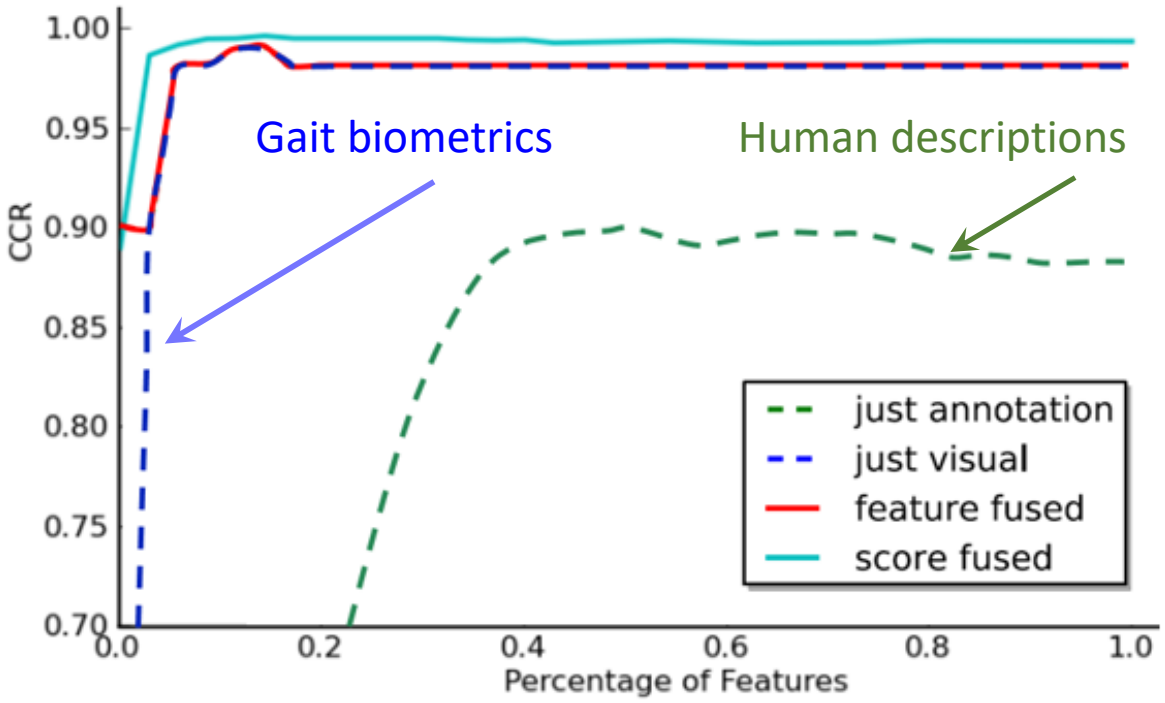
This changed

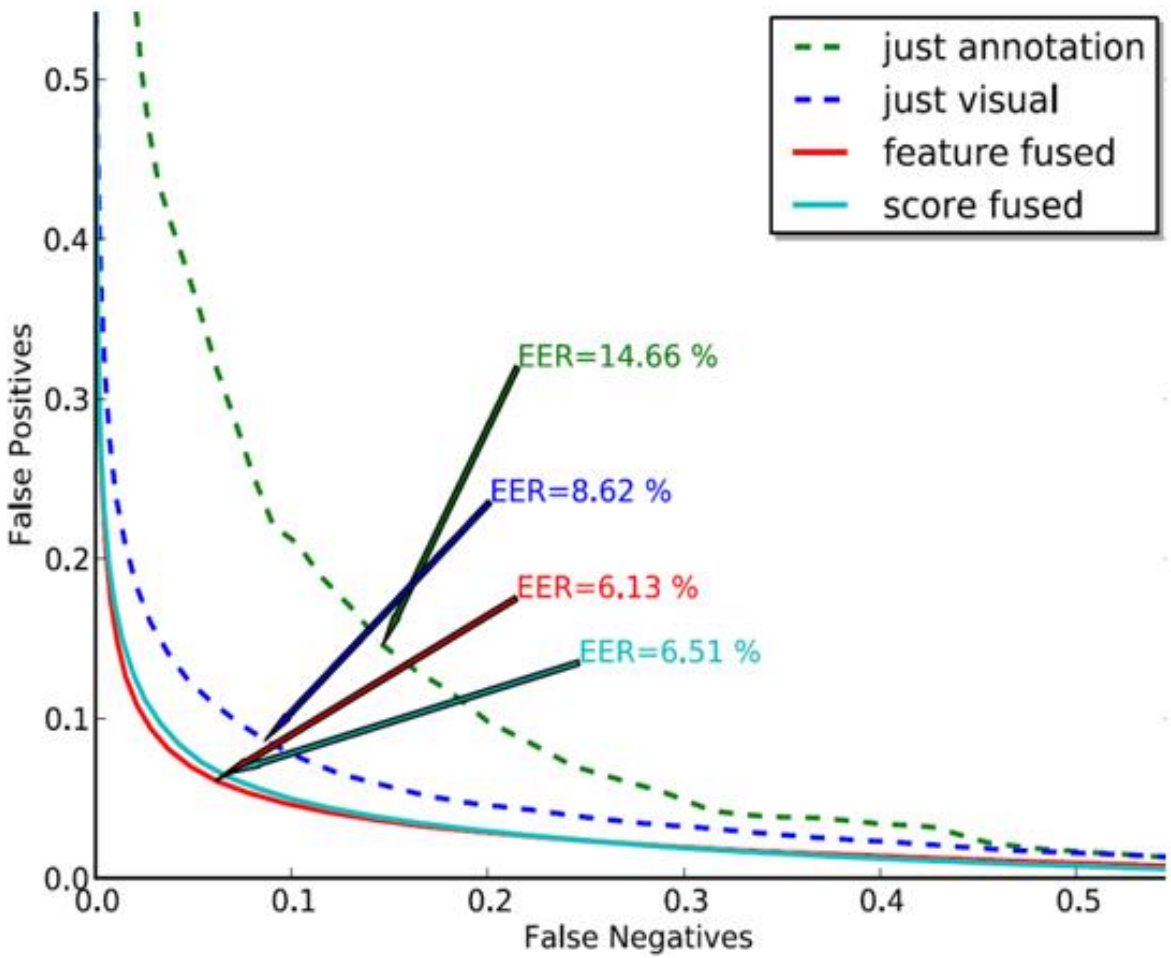
- Most likely candidate for fusion with gait

Samangooei, Guo and Nixon, *IEEE BTAS* 2008

- Global
  - Sex
  - Ethnicity
  - Skin Colour
  - Age
- Body Shape
  - Figure
  - Weight
  - Muscle Build
  - Height
  - Proportions
  - Shoulder Shape
  - Chest Size
  - Hip size
  - Leg/Arm Length
  - Leg/Arm Thickness
- Head
  - Hair Colour
  - Hair Length
  - Facial Hair Colour/Length
  - Neck Length/Thickness

Human descriptions: recognition capability



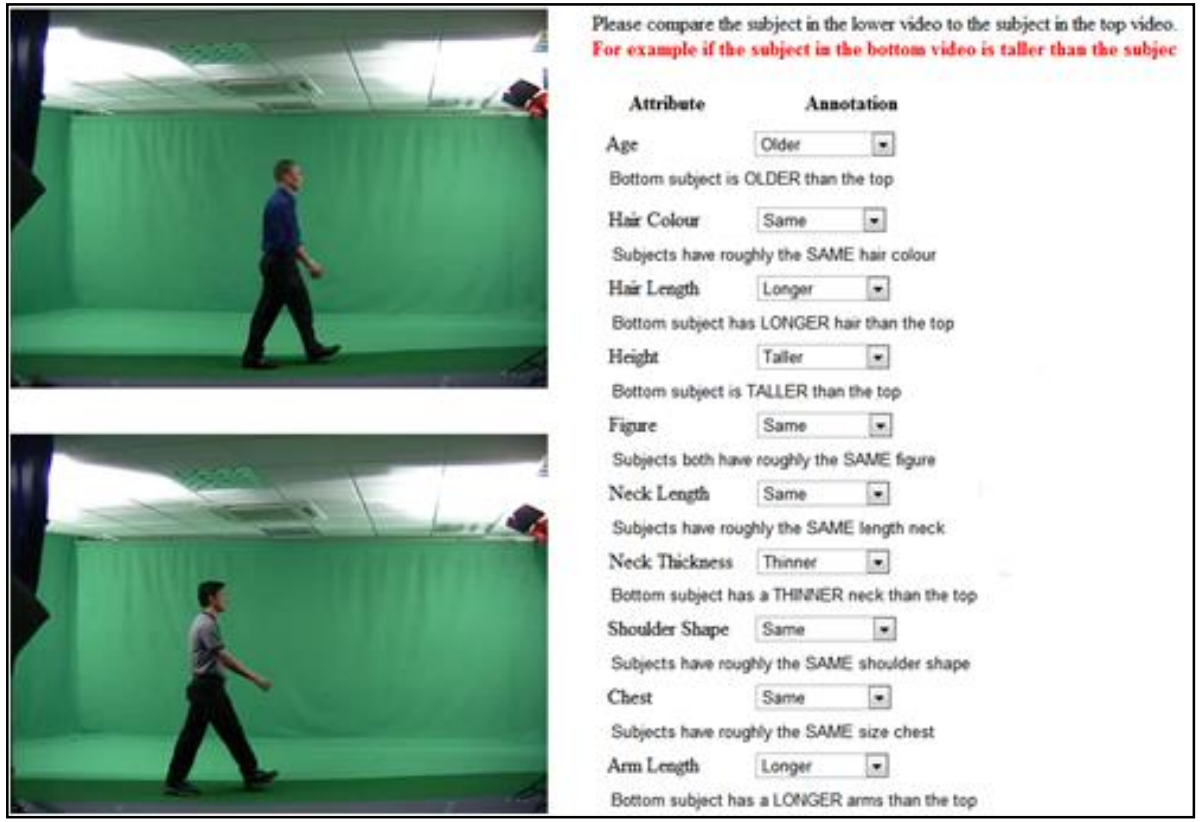


First result

Samangooei and Nixon, *IEEE BTAS* 2008

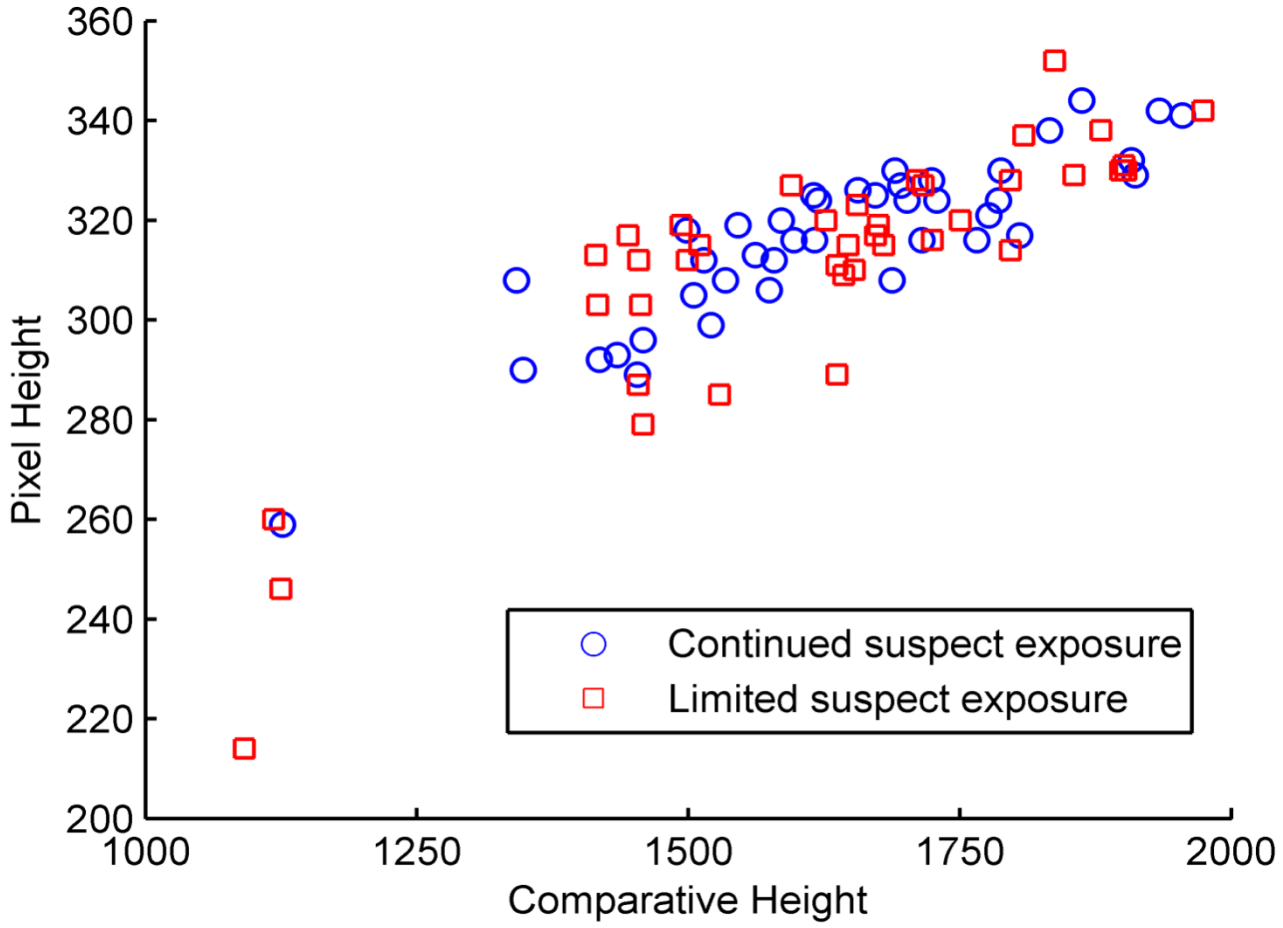
Comparative human descriptions

- Compare one subject's attribute with another's
- Infer continuous relative measurements



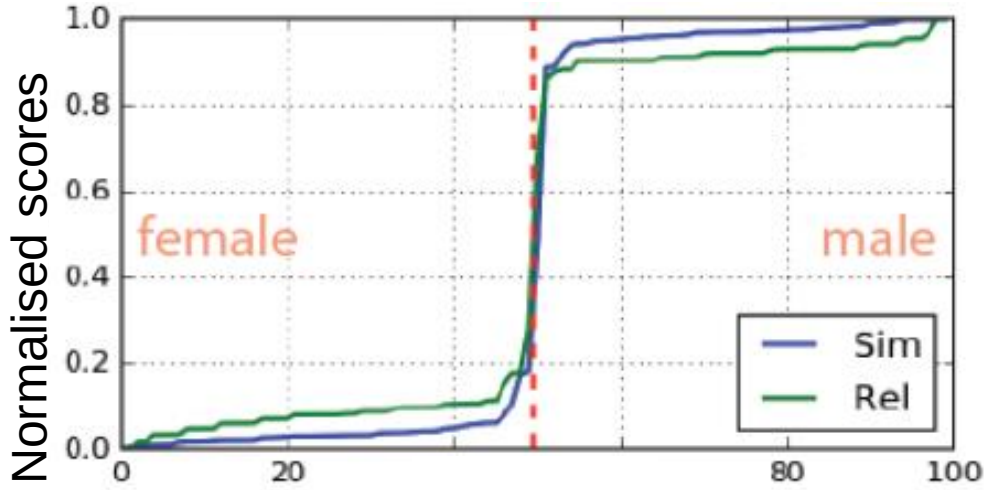
Reid and Nixon, *IEEE ICDP* 2011, TPAMI 2014

Height correlation (with time)

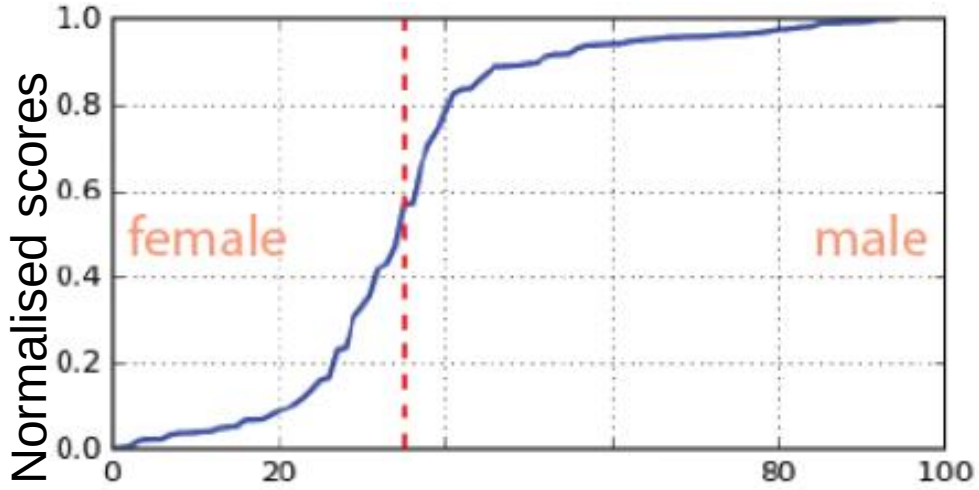


Reid and Nixon, *IEEE ICDP* 2011, TPAMI 2014

Pairwise similarity comparisons on PETA



Relative	0.18	0.28	0.68	0.86	0.88
Similarity	0.17	0.18	0.47	0.89	0.89



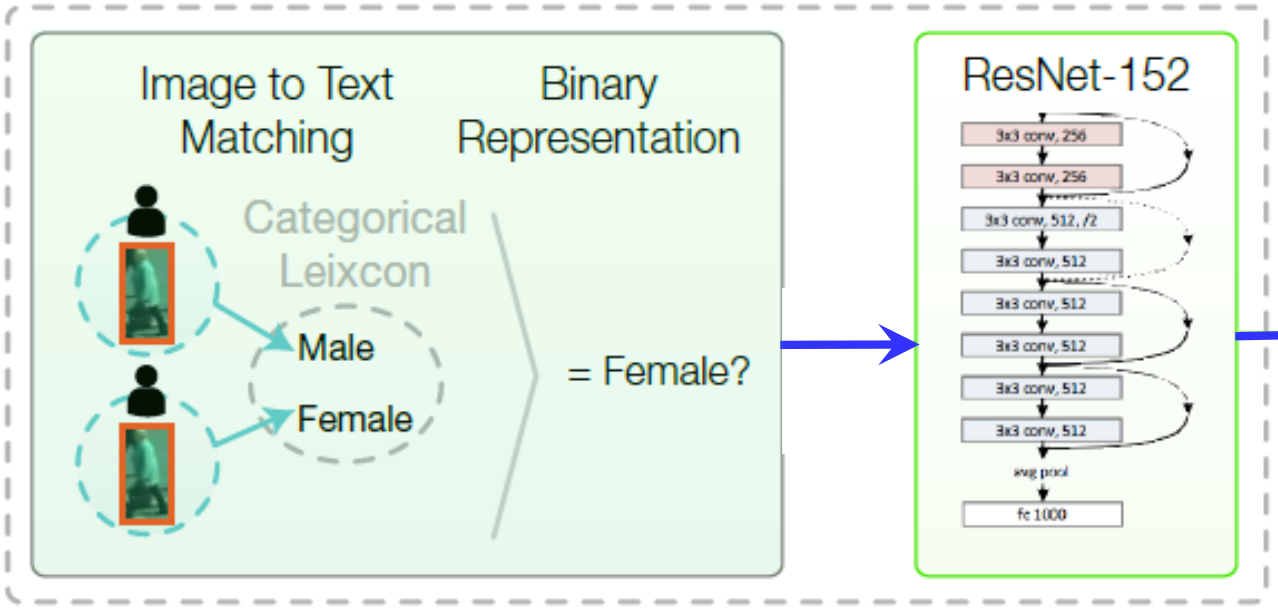
Binary	male	female	female	female
Similarity	0.47	0.57	0.83	0.95

Gender distribution not binary

Can measure confidence

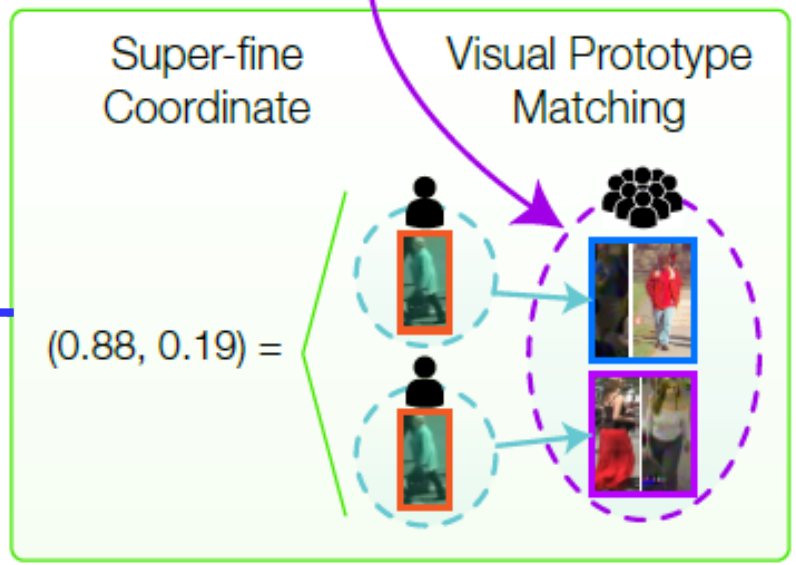
Martinho-Corbishley, Nixon and Carter, *BTAS* 2016

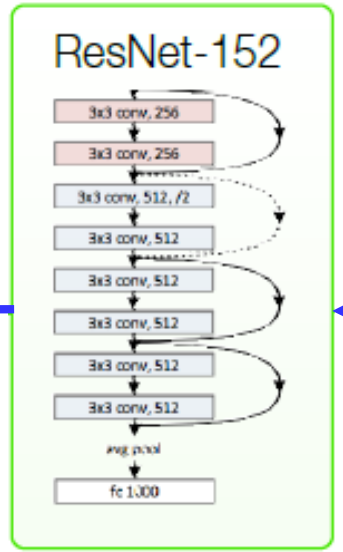
Conventional attribute-based analysis

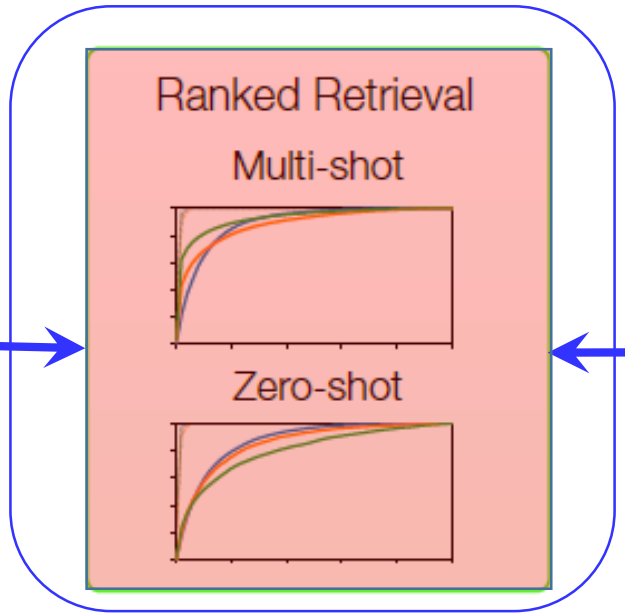


Retrieval architecture

Superfine attribute analysis

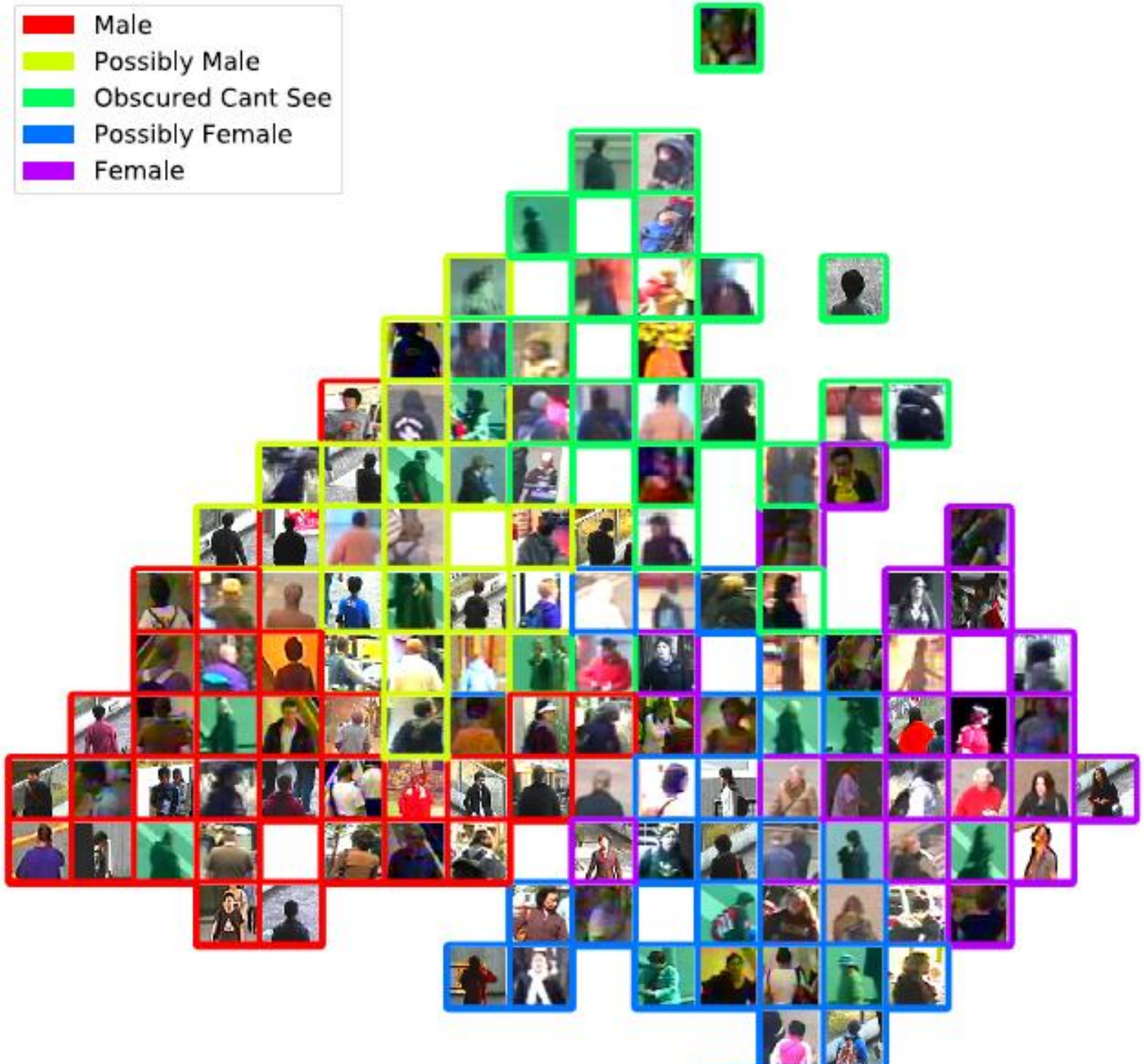






Martinho-Corbishley, Nixon and Carter, IEEE TPAMI 2019

Gender



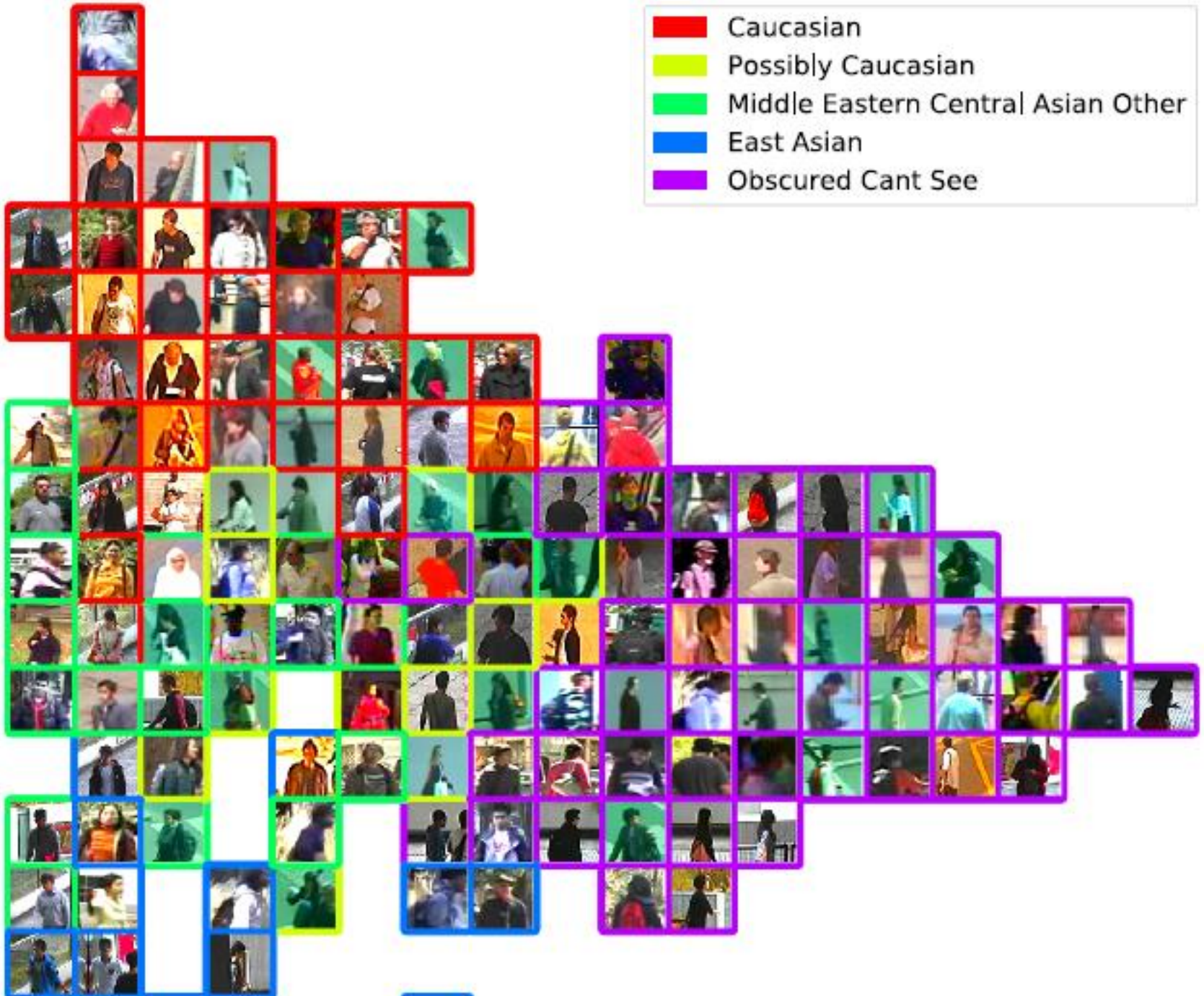
Martinho-Corbishley, Nixon and Carter, IEEE TPAMI 2019

Analysing gender (??!!)

- Gender?

Subject	1	2	3
			
Gender			A. Male B. Female

Ethnicity



Martinho-Corbishley, Nixon and Carter, IEEE TPAMI 2019

Takeaway time

1 – computer vision works and has a great future

2 – big difference between hand crafted and deep learning

3 – some parts are the same (group operators/ templates)

4 – what will happen in the future?

Jon Hare will happen in the future!

Beyond that, I can only speculate. Enjoy!