Soft biometrics for human identification

Mark S. Nixon

Professor of Computer Vision

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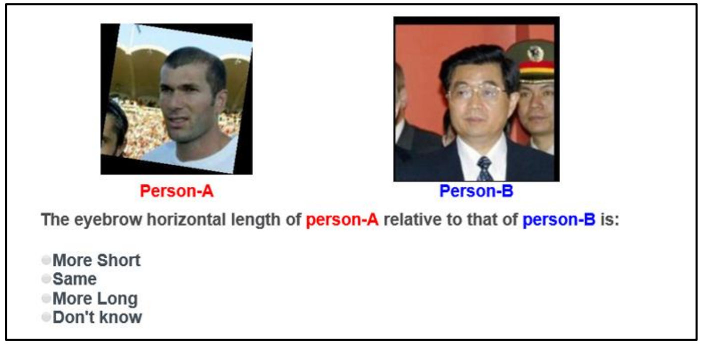

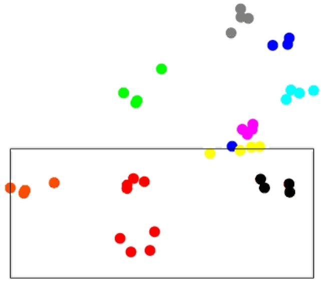

Body Face Clothing Recognition

IEEE/ IAPR Winter School on Biometrics,
Shenzen China 2019

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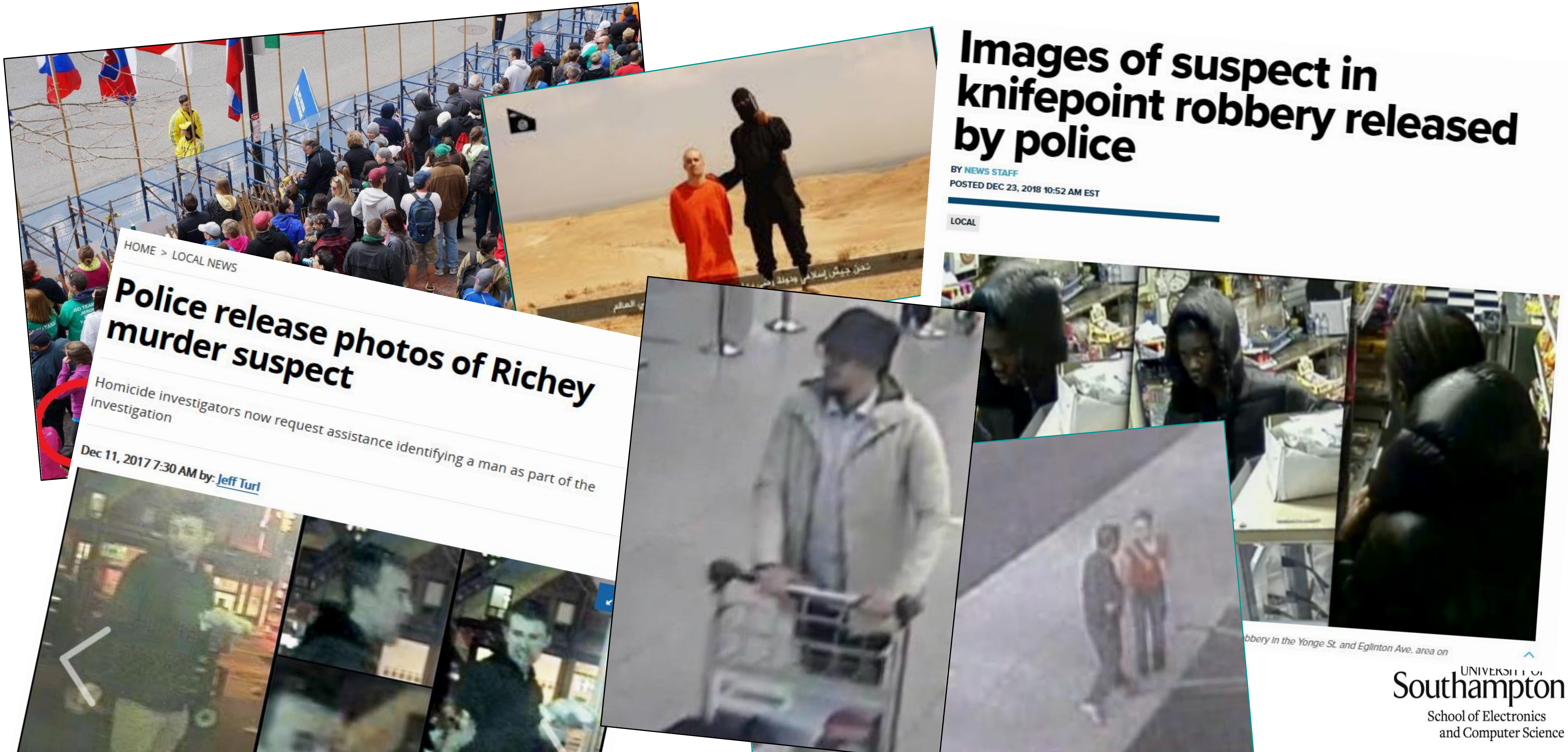
Society needs means of identification



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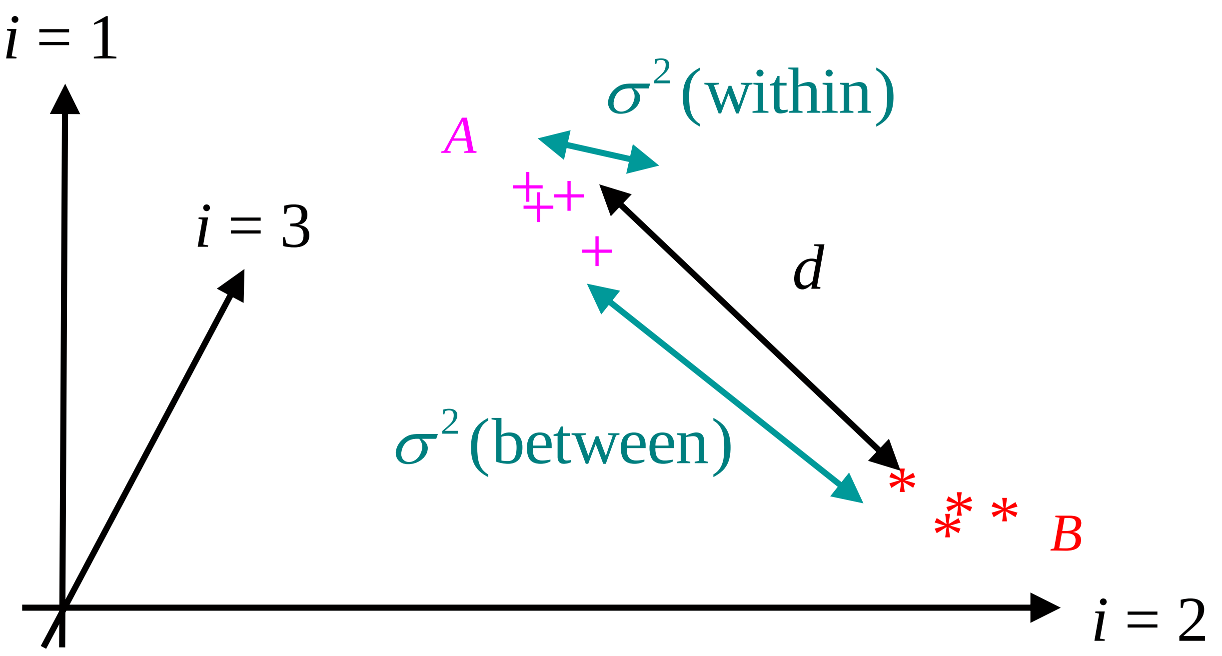
Basis

i) we measure distance *d*:

$$d(A,B)=\sqrt{\sum_{i=1}^{N}\left(x_{iA}-x_{iB}\right)^2};N=\#\text{ measurements};\ A,B=\text{subjects}$$

ii) we want variance within subject << variance between subjects



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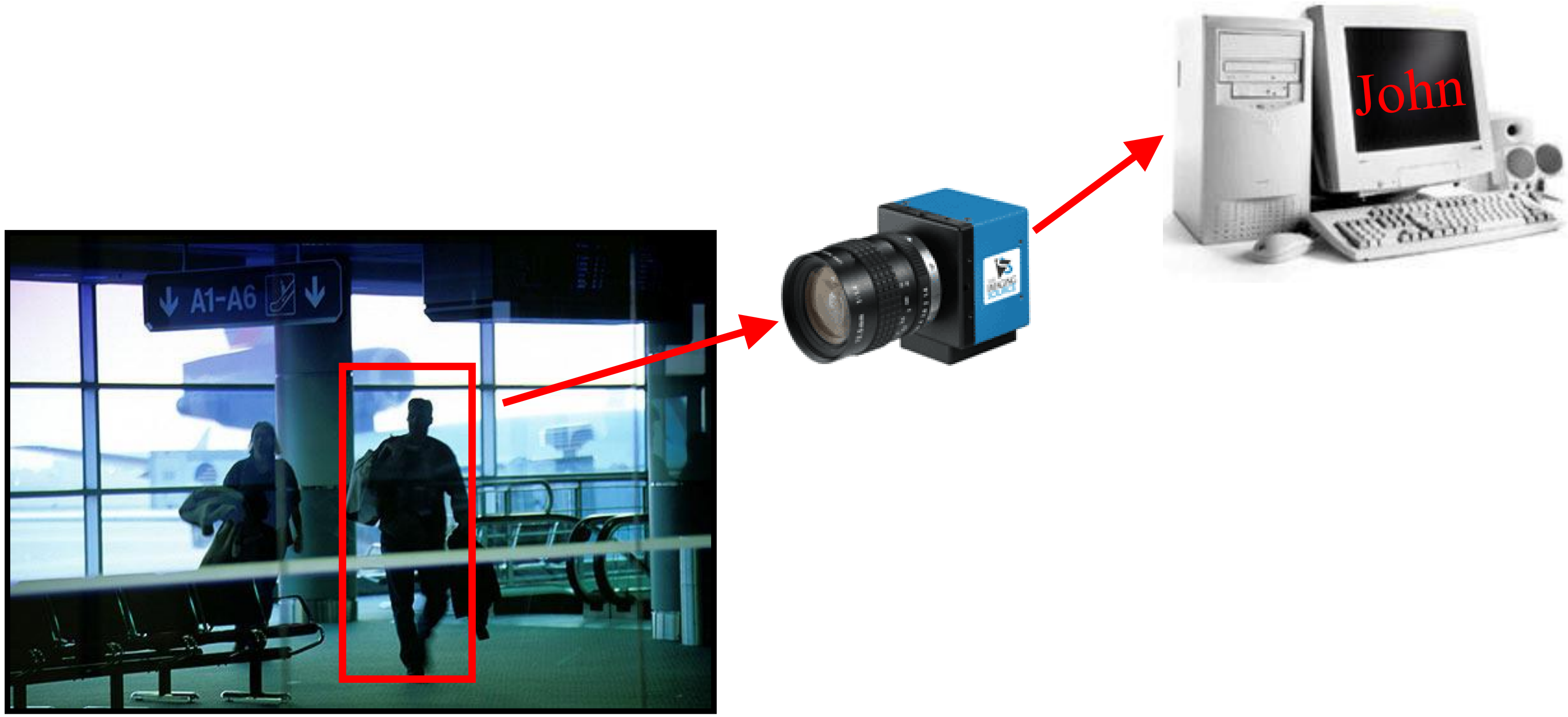
Vision-based biometrics



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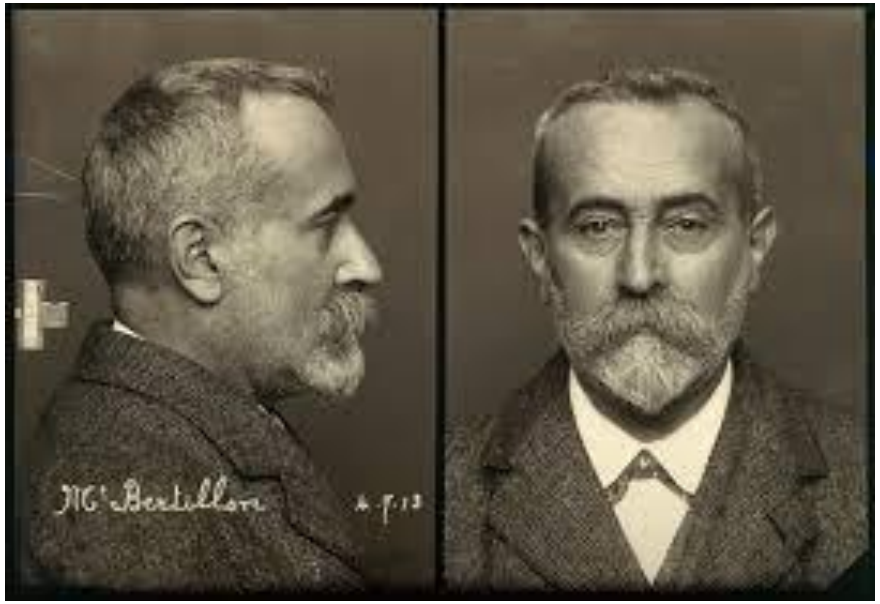
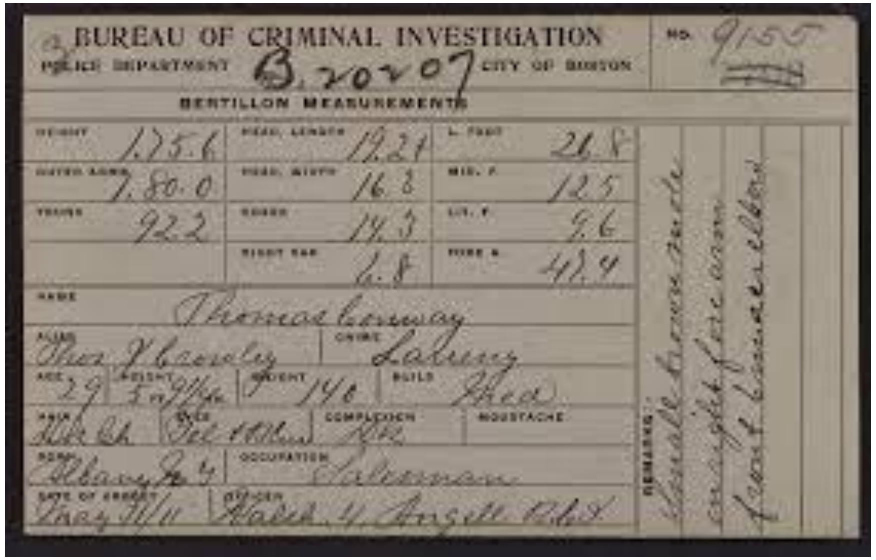
History of soft biometrics: Bertillonage



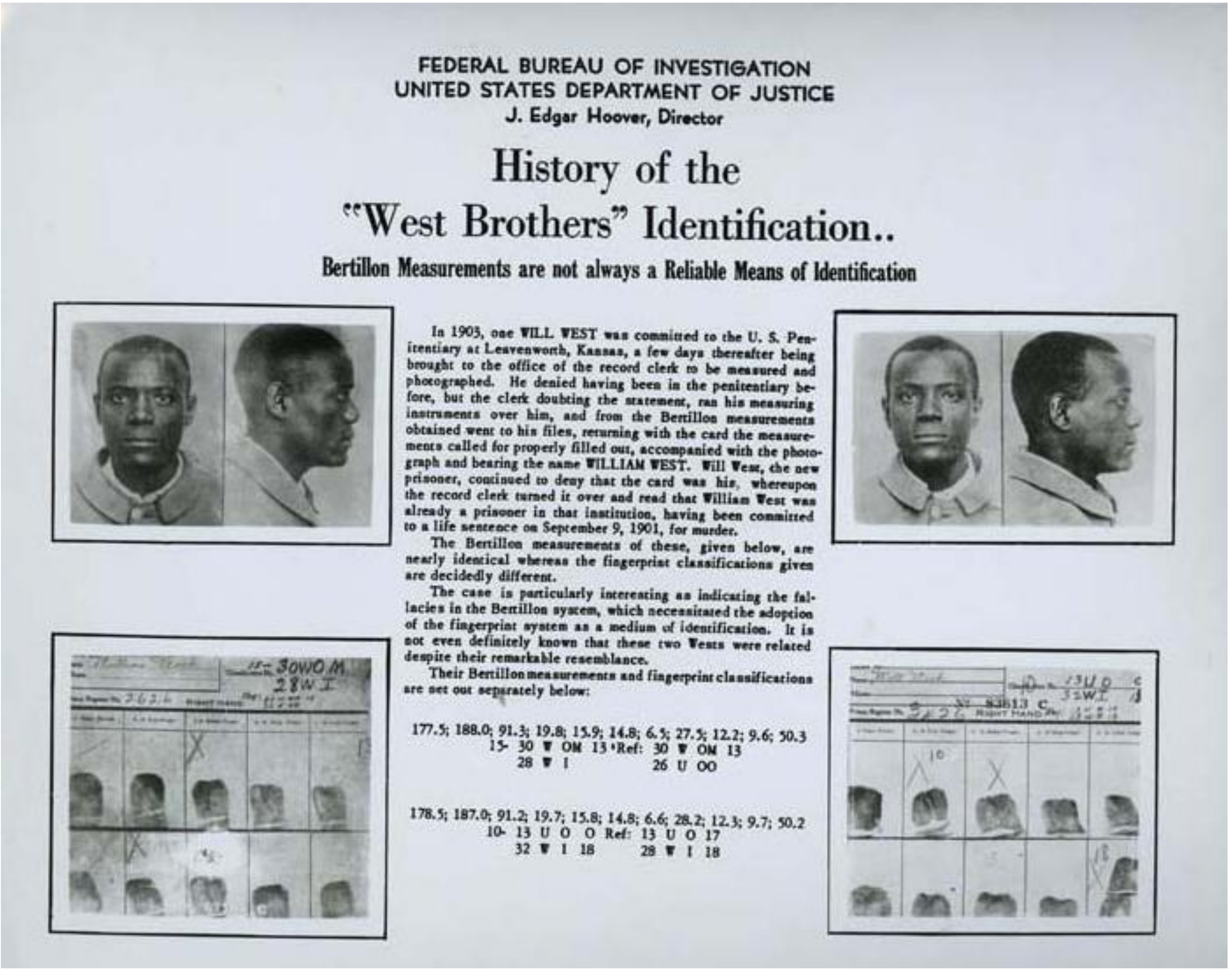


Recycled from
Ross and Nixon
Tutorial on Soft Biometrics
BTAS 2016

A. Bertillon, *Identification of Criminals*

West vs West

- 1903, Will West committed to penitentiary at Leavenworth, Kansas
- Bertillon measurements matched William West, who was committed for murder in 1901
- Led to fingerprints
- Story is true?



FEDERAL BUREAU OF INVESTIGATION
UNITED STATES DEPARTMENT OF JUSTICE
J. Edgar Hoover, Director

History of the
"West Brothers" Identification..

Bertillon Measurements are not always a Reliable Means of Identification

In 1903, one WILL WEST was committed to the U. S. Penitentiary at Leavenworth, Kansas, a few days thereafter being brought to the office of the record clerk to be measured and photographed. He denied having been in the penitentiary before, but the clerk doubting the statement, ran his measuring instruments over him, and from the Bertillon measurements obtained went to his files, returning with the card the measurements called for properly filled out, accompanied with the photograph and bearing the name WILLIAM WEST. Will West, the new prisoner, continued to deny that the card was his, whereupon the record clerk turned it over and read that William West was already a prisoner in that institution, having been committed to a life sentence on September 9, 1901, for murder.

The Bertillon measurements of these, given below, are nearly identical whereas the fingerprint classifications given are decidedly different.

The case is particularly interesting as indicating the fallacies in the Bertillon system, which necessitated the adoption of the fingerprint system as a medium of identification. It is not even definitely known that these two Wests were related despite their remarkable resemblance.

Their Bertillon measurements and fingerprint classifications are set out separately below:

177.5; 188.0; 91.3; 19.8; 15.9; 14.8; 6.5; 27.5; 12.2; 9.6; 50.3
15- 30 W OM 13 Ref: 30 W OM 13
28 W I 26 U OO

178.5; 187.0; 91.2; 19.7; 15.8; 14.8; 6.6; 28.2; 12.3; 9.7; 50.2
10- 13 U O O Ref: 13 U O 17
32 W I 18 28 W I 18

"This image was probably used in a ca. 1960s FBI training session"
www.LawEnforcementMuseum.org

What are ‘soft’ biometrics?

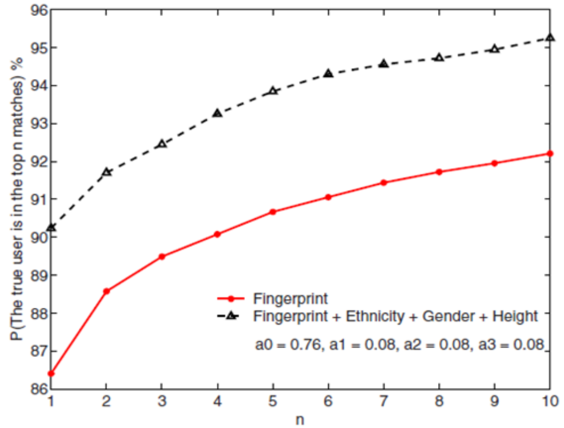
1. Descriptors to aid search. (Wayman *CTST* 1997)
2. Broad descriptors to separate populations. (Wayman *CTST* 1997)
3. Improving accuracy of primary biometrics. (Jain, Dass and Nandakumar *SPIE* 2004)
4. Descriptions to facilitate recognition by bridging human and machine descriptions (Samangooei and Nixon *BTAS* 2008)
5. “Estimation or use of personal characteristics describable by humans that can be used to aid or effect person recognition” (Nixon et al, *PRL* 2015)
6. “These attributes are typically gleaned from primary biometric data, are classifiable in pre-defined human understandable categories, and can be extracted in an automated manner.” (Dantcheva … Ross, *TIFS* 2016)

Soft biometrics for identification

Bertillonage 1890
(body, face, iris, ear, nose…)

Nandakumar and Jain 2004
(augmenting traditional biometrics)

Ethnicity
+ Gender
Height



Face Soft
Attribute
Kumar, Klare, Zhang
Relative Attribute
[Graumann], Reid, Almudhahka
Forensic Tome

Body Soft
Categorical Samangooei
Comparative
Reid, Martinho-Corbishley
Semantic Denman

Other Soft
Tattoos Lee, Di
Clothing Jaha
Makeup Dantcheva
Hair Chan, Proenca

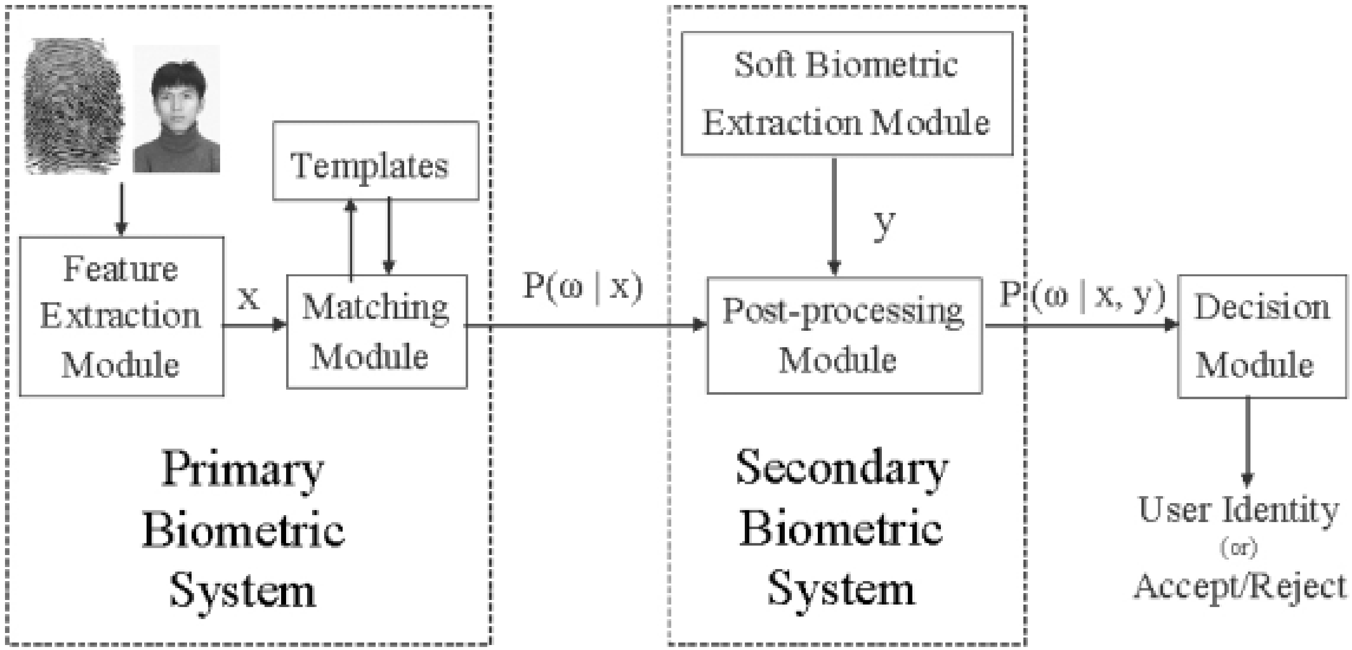
Estimation of Age + Gender + Ethnicity + Weight + Height + …

Advantages of soft biometrics

1. Human understandable description
   rich in semantics, e.g., a face image described as a “young Asian male”
   bridges gap between human and machine descriptions
1. Robustness to image quality
   soft biometric attributes and low quality data
   subject at a distance from the camera
1. Privacy
   lack of distinctiveness implies privacy friendly
   … but we can recognise you anywhere
1. Performance improvement
   use in conjunction with biometric cues such as face, fingerprint and iris
   fusion to improve accuracy. ID invariance to viewpoint, illumination.

First mention of soft biometrics

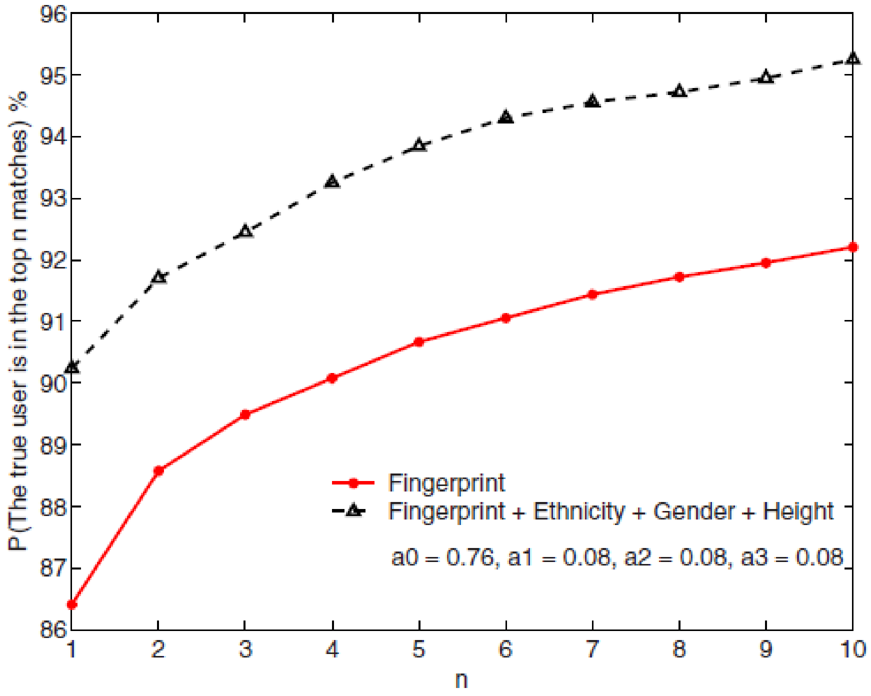
- Integration of Soft Biometric Traits with a Fingerprint Biometric System
- x is the fingerprint, y is the soft biometric

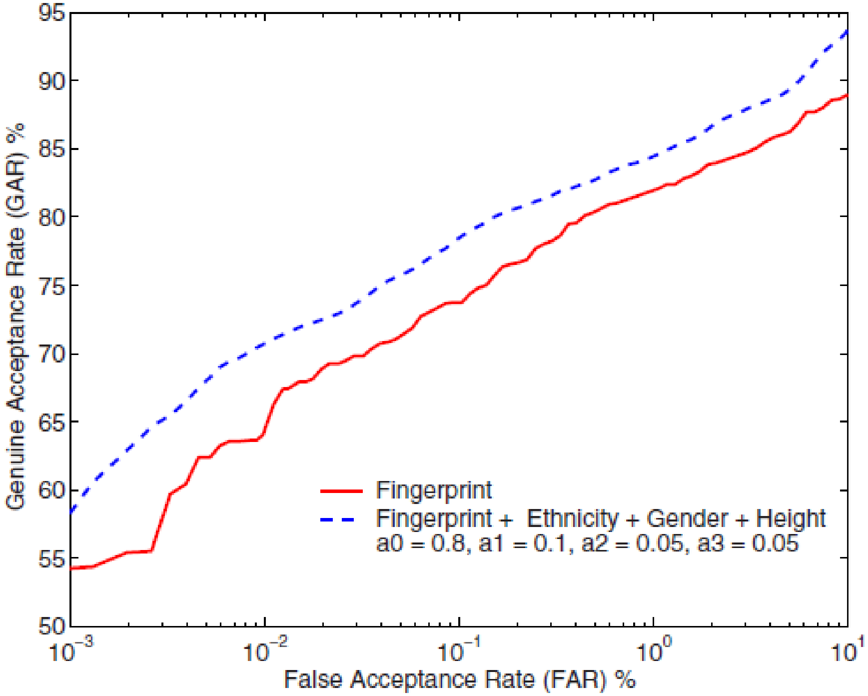


Jain, Dass, and Nandakumar, *ICBA* 2004

Performance

- Recognition performance of a fingerprint system after including soft biometrics
- Identification and verification
- Fingerprint + ethnicity + gender + height

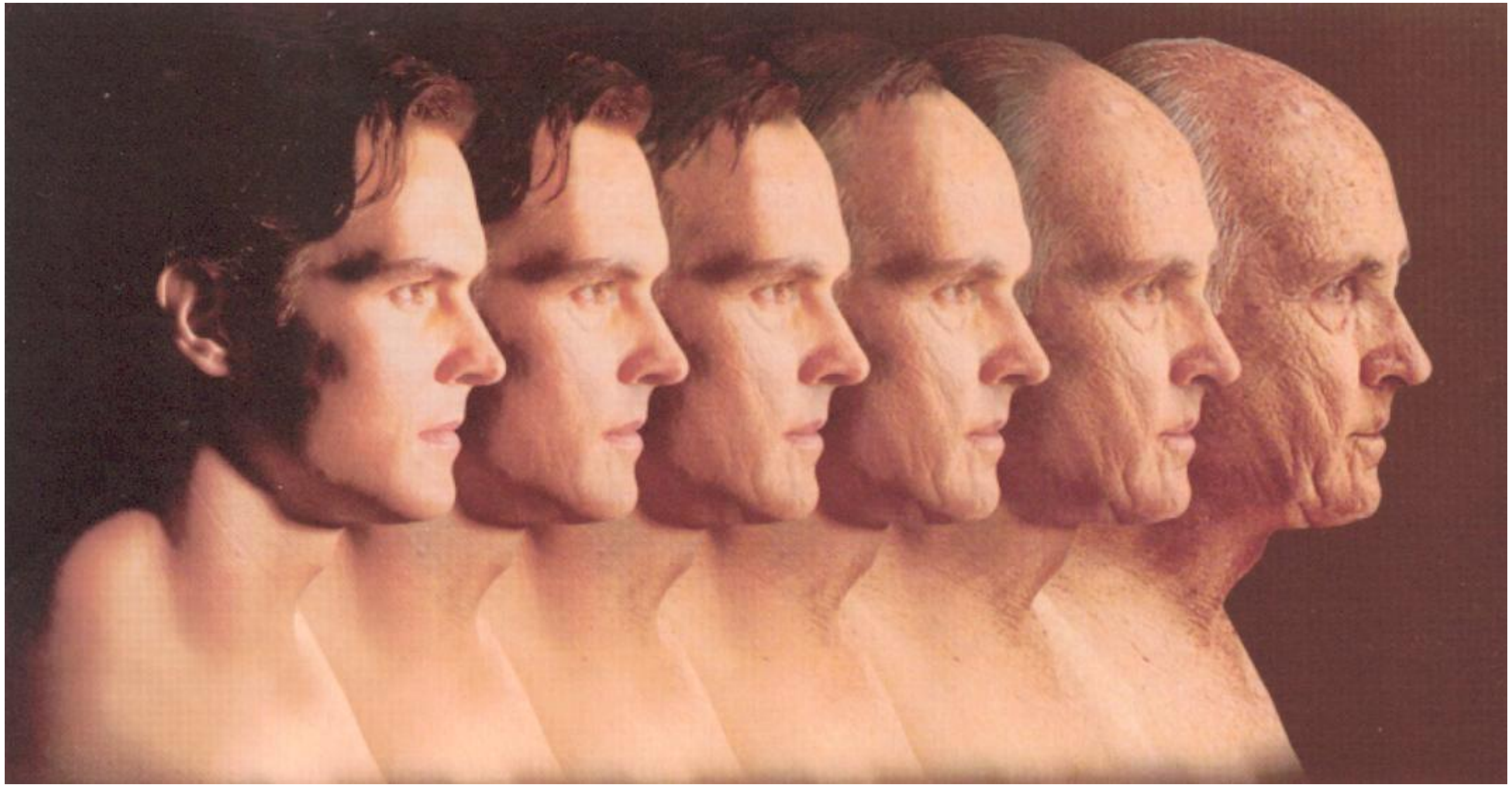




Jain, Dass, and Nandakumar, *ICBA* 2004

Soft Biometrics from Face

Face and Age

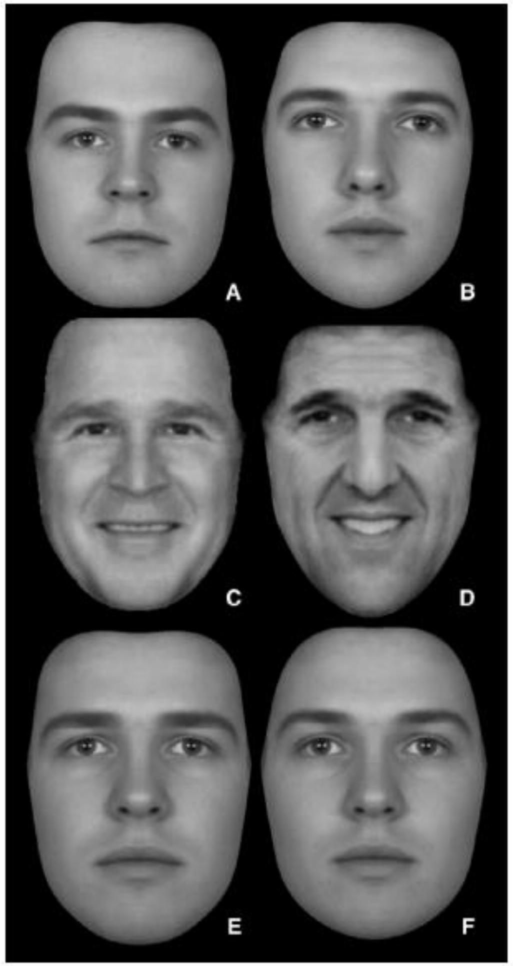


Beautyanalysis.co
m

Face and Kinship

[Lu 2013]
[Guo 2012]
[Fang 2010]
[Shao 2011]

Face and Voting Decisions



- The role of facial shape in voting behavior

- Face and sexual inclination??????

[Little 2007][Todorov 2005]

Images: more than meets the eye?

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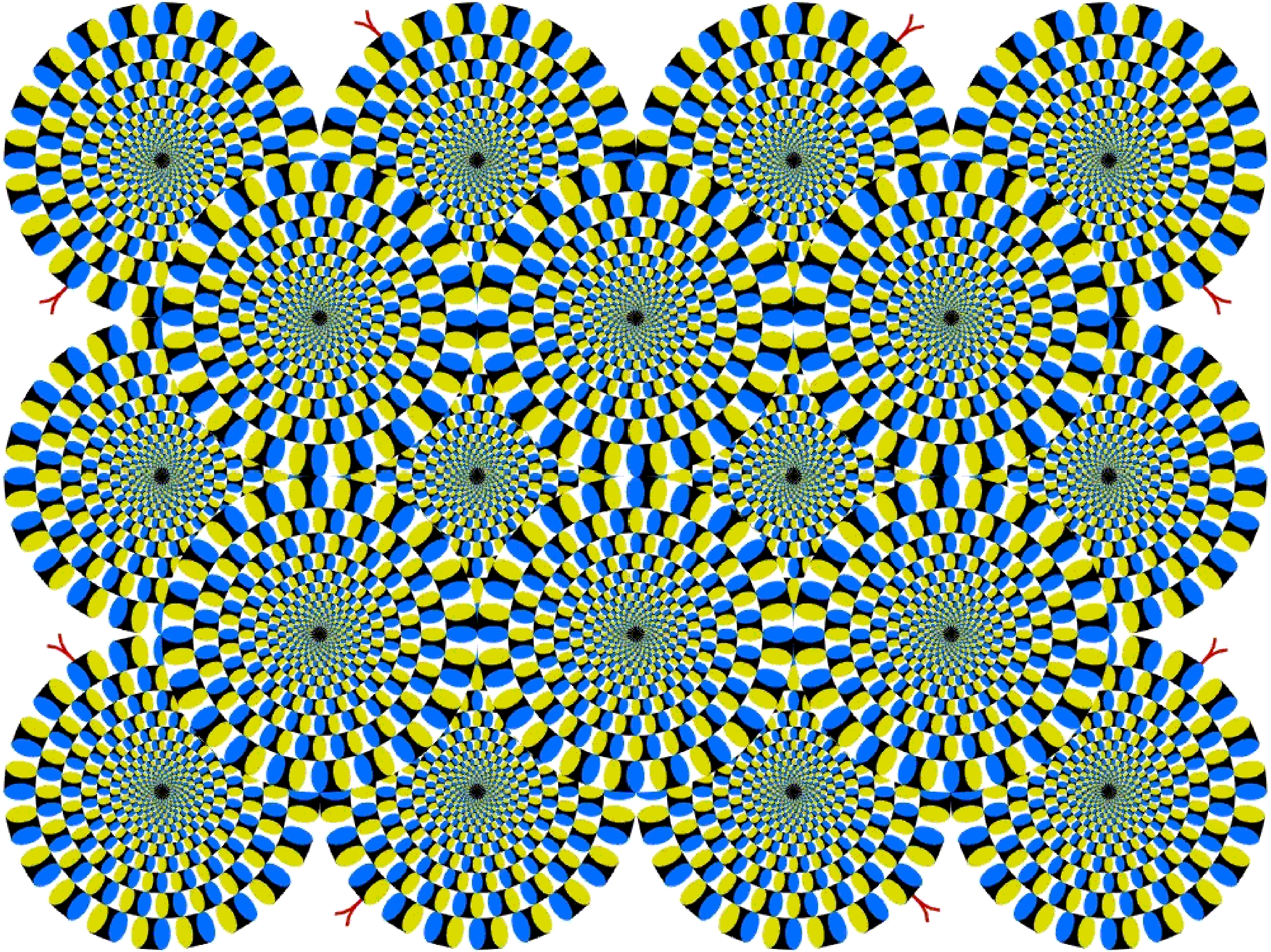
Computer vision and human vision have different abilities

Van Dyck 1635; Trafalgar Square



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Motivation: Murder case in Australia 2014

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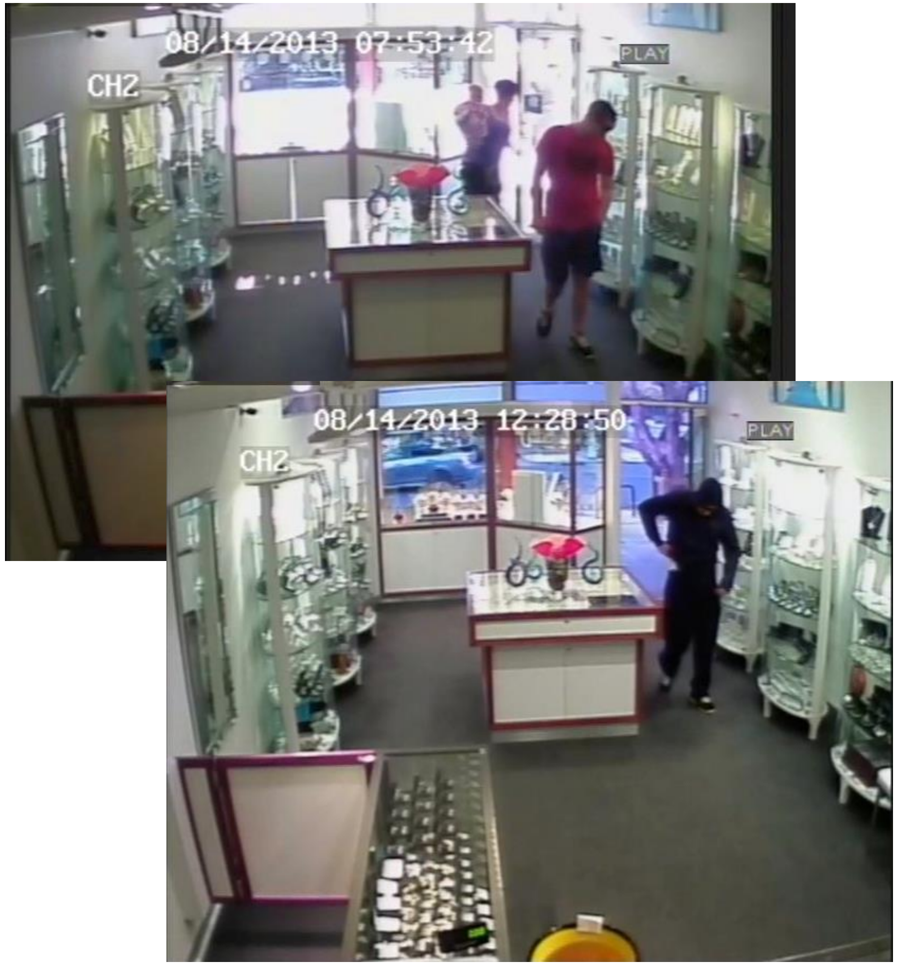


Herald Sun
MELBOURNE 8C-15C

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TRUECRIMESCENE new crimes, cold cases, latest investigations

Murdered jeweller Dermot O'Toole's widow Bridget says her husband would be alive if his killer Gavin Perry wasn't out on parole

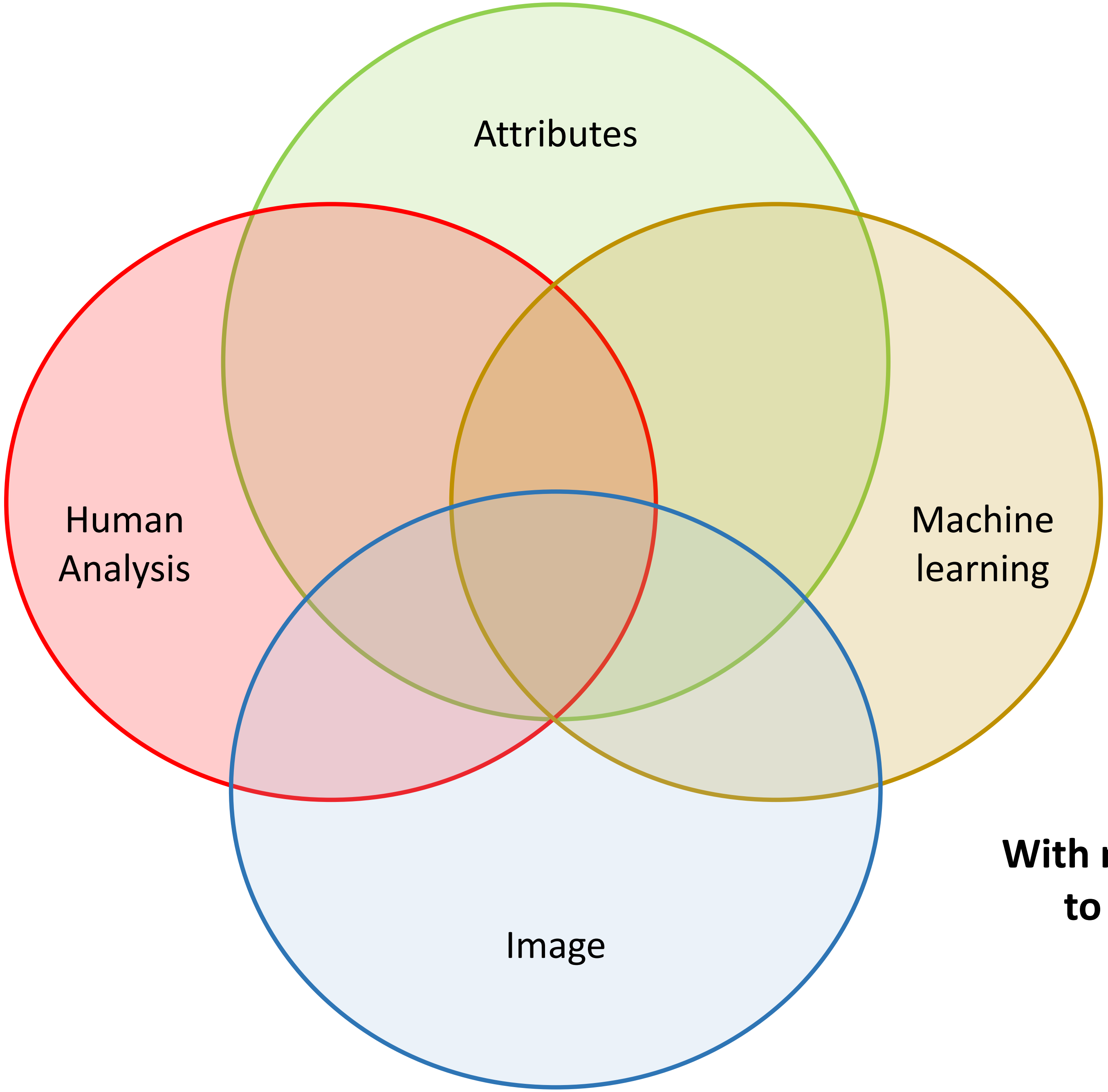
PADRAIC MURPHY HERALD SUN JUNE 24, 2014 2:19PM

SHARE | SAVE THIS STORY

Bridget O'Toole has described the impact of her husband's murder to the

60 Minutes Australia: Eye Catching

Bouchrika, Nixon, Carter, *J. F…* *Science* 2011, and *Eusipco* 20…



With many thanks to Dan MC!

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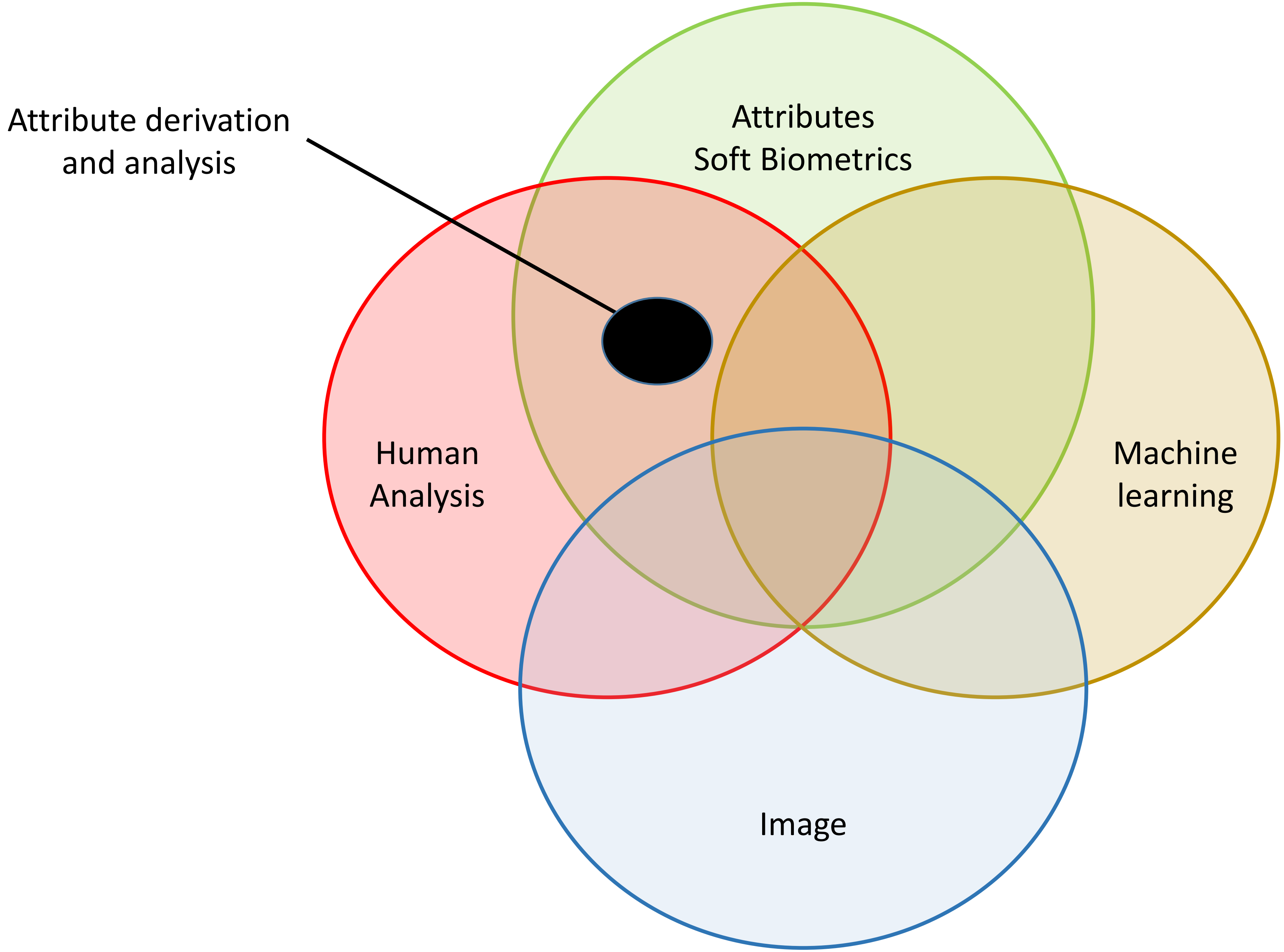
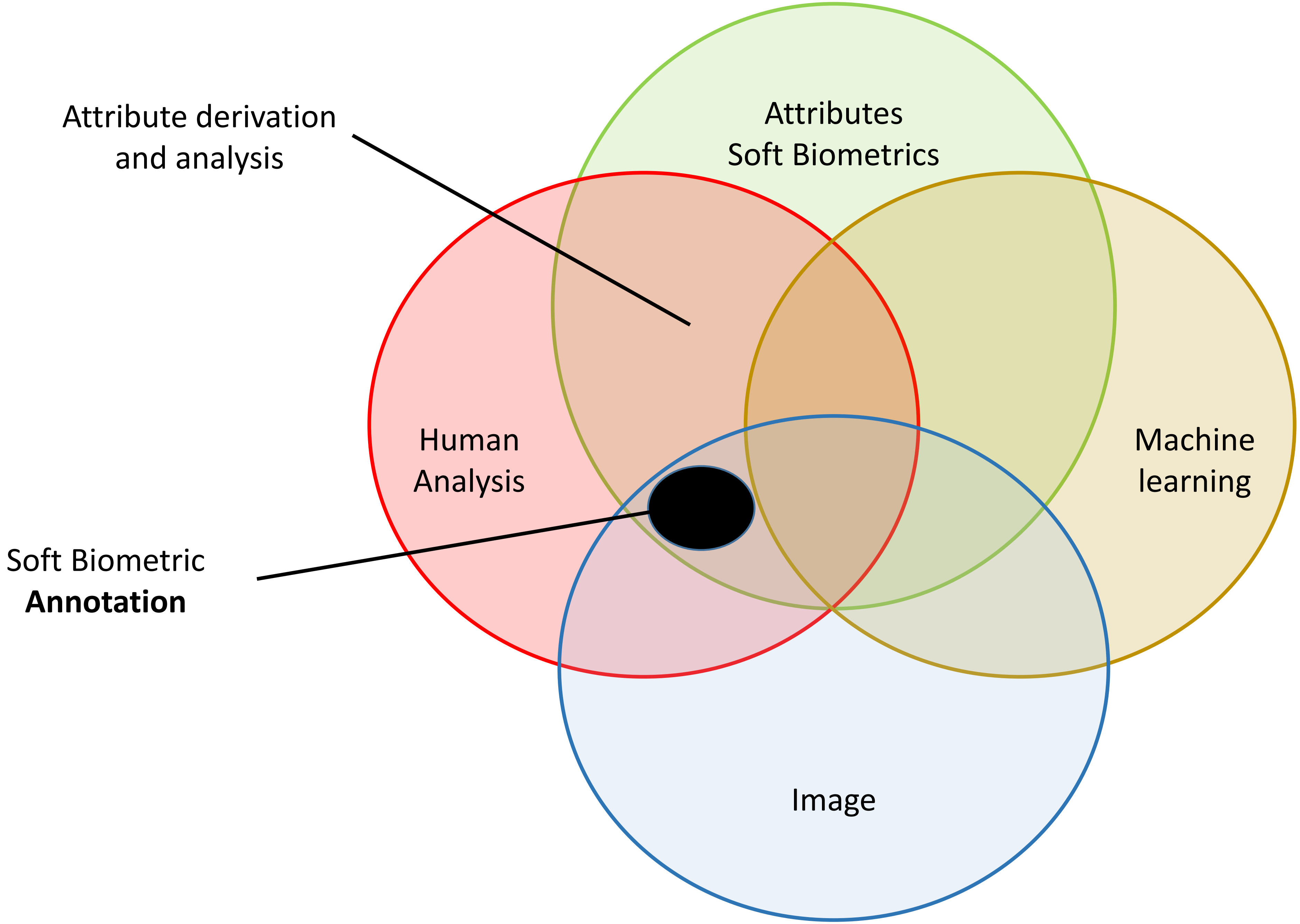
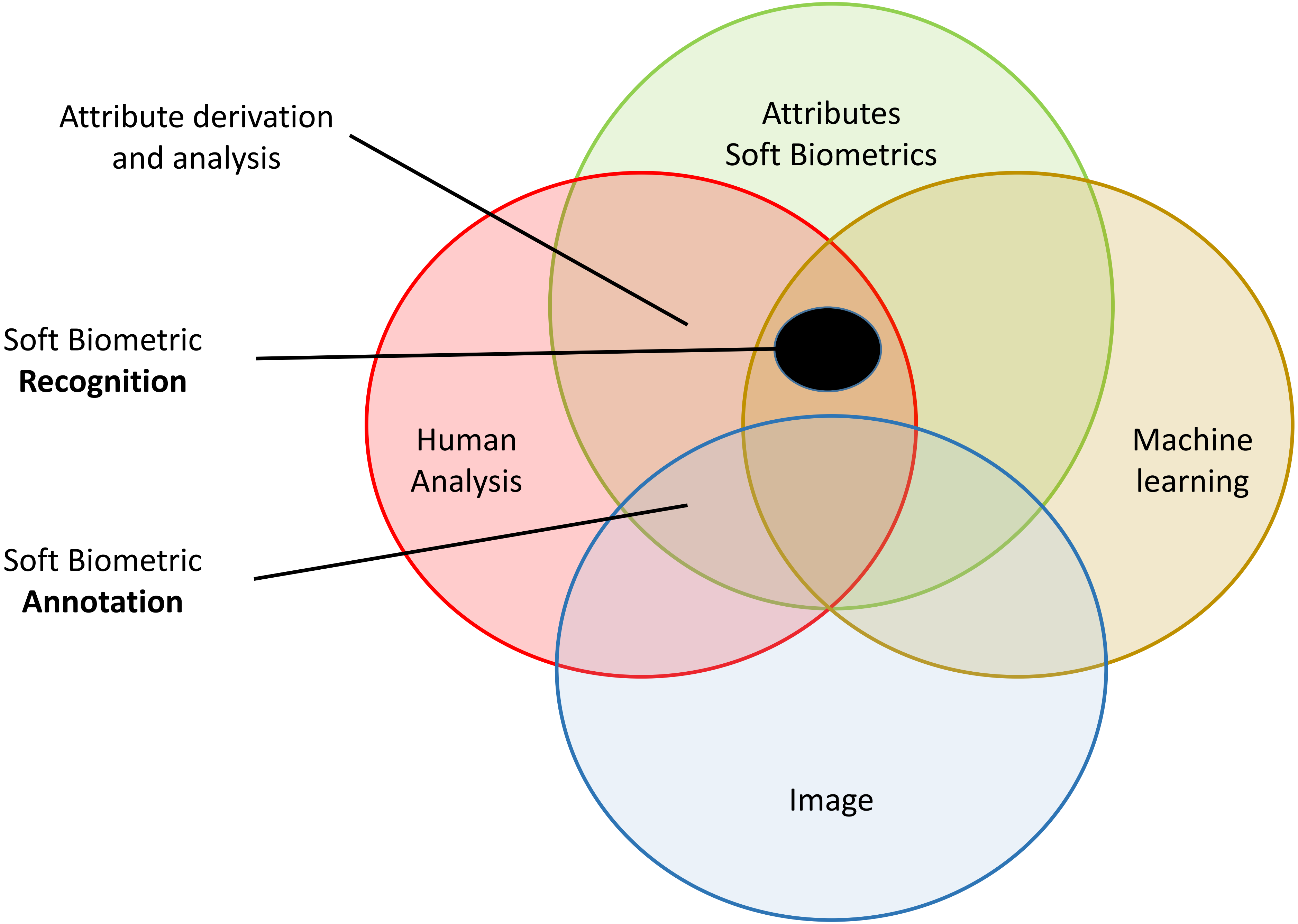



Attribute derivation
and analysis
Attributes
Soft Biometrics
Human
Analysis
Machine
learning
Soft Biometric
Annotation
Image


Attribute derivation and analysis
Soft Biometric **Recognition**
Soft Biometric **Annotation**
Attributes Soft Biometrics
Human Analysis
Machine learning
Image

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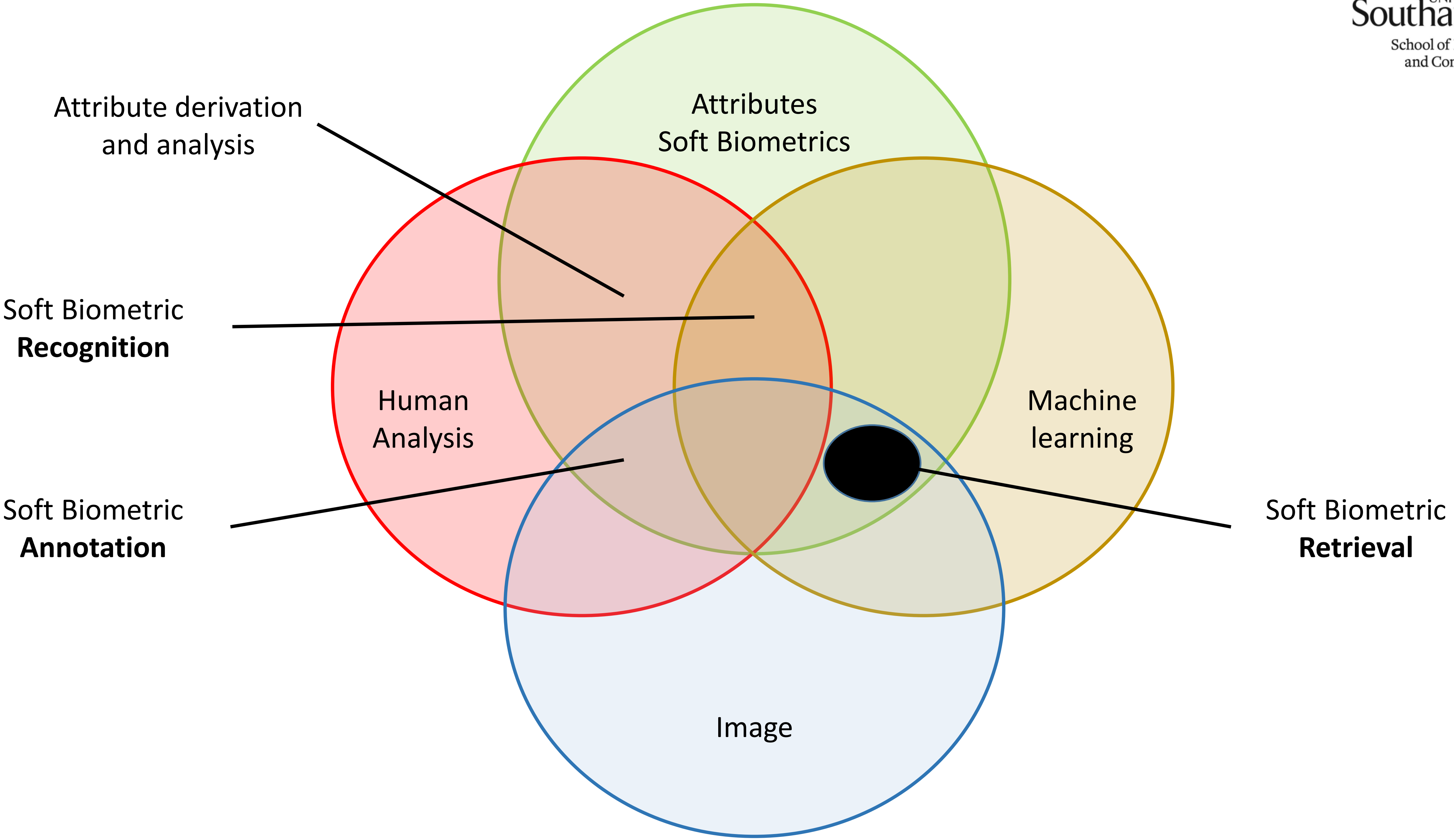

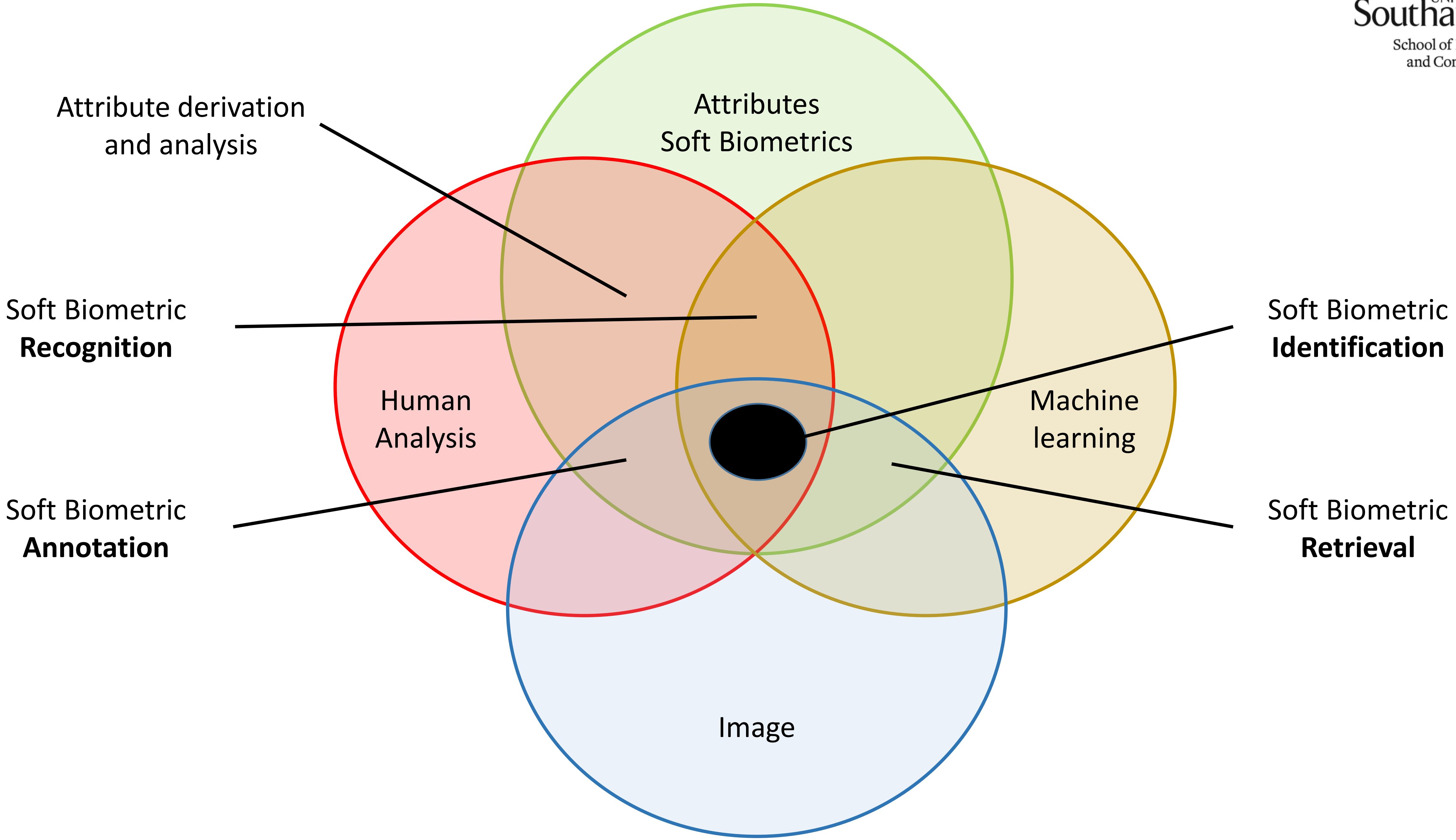

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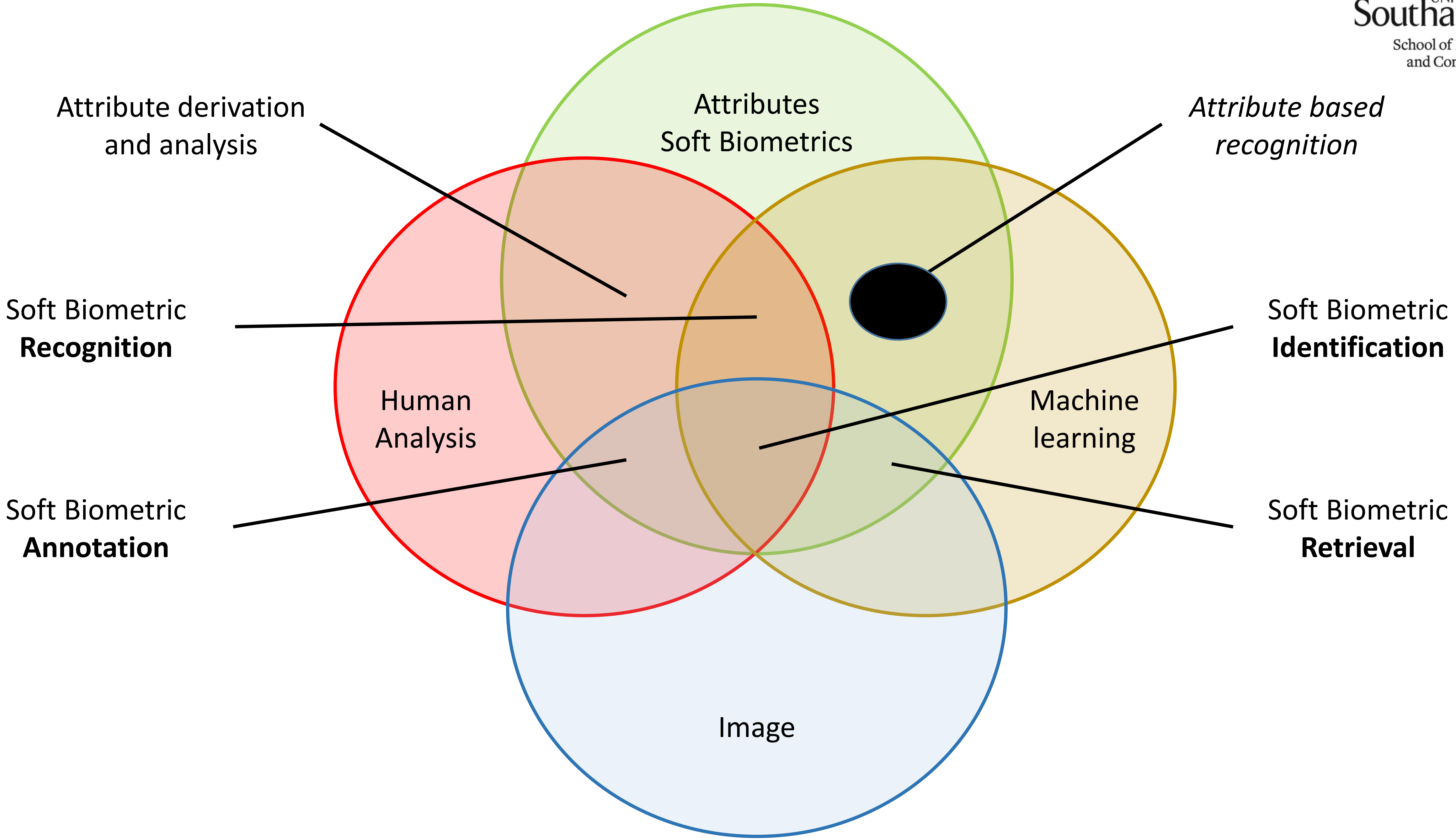
Attribute derivation and analysis
Attributes
Soft Biometrics
Attribute based recognition
Soft Biometric **Recognition**
Soft Biometric **Identification**
Human Analysis
Machine learning
Soft Biometric **Annotation**
Soft Biometric **Retrieval**
Image

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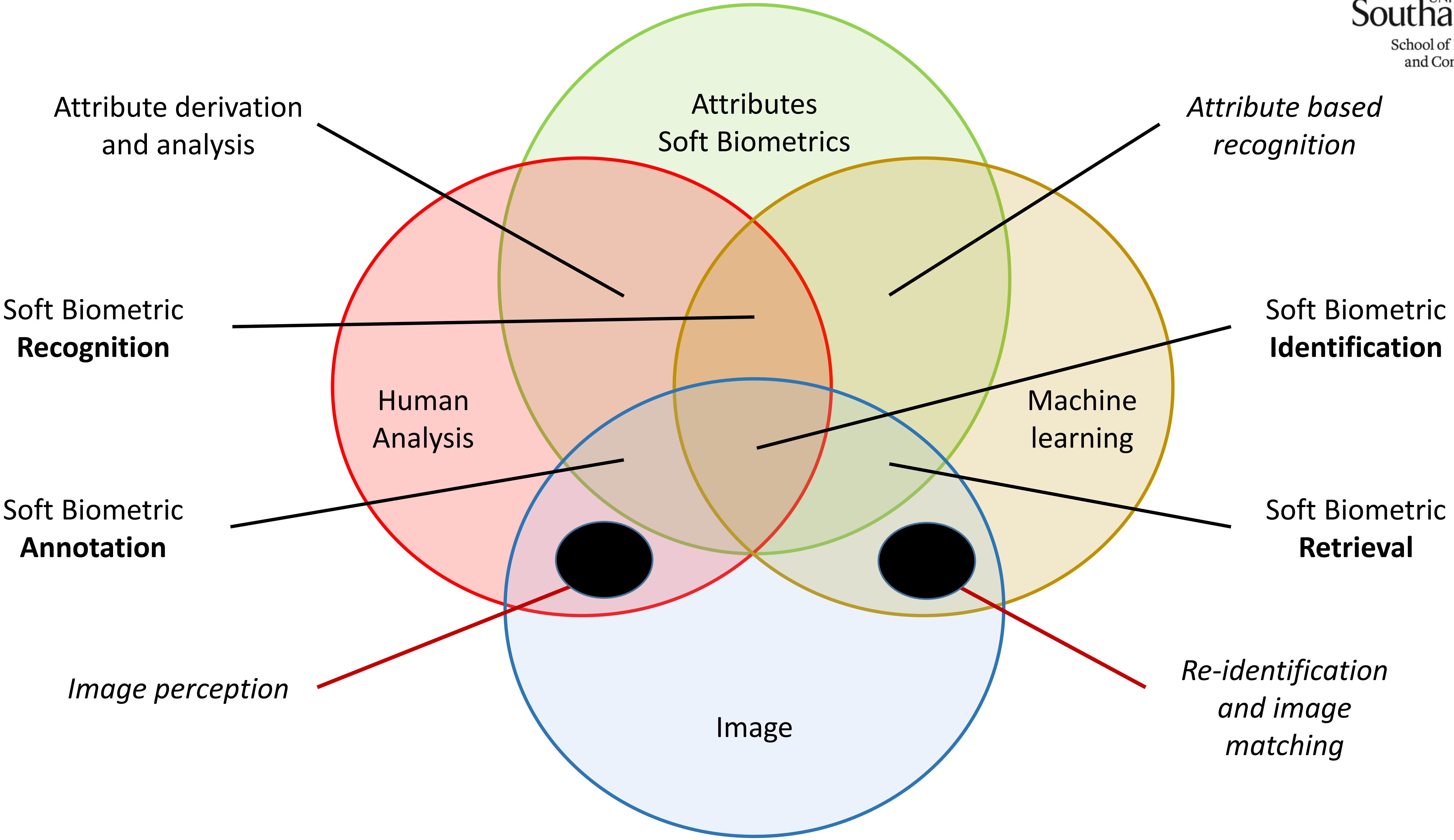
and Computer Science



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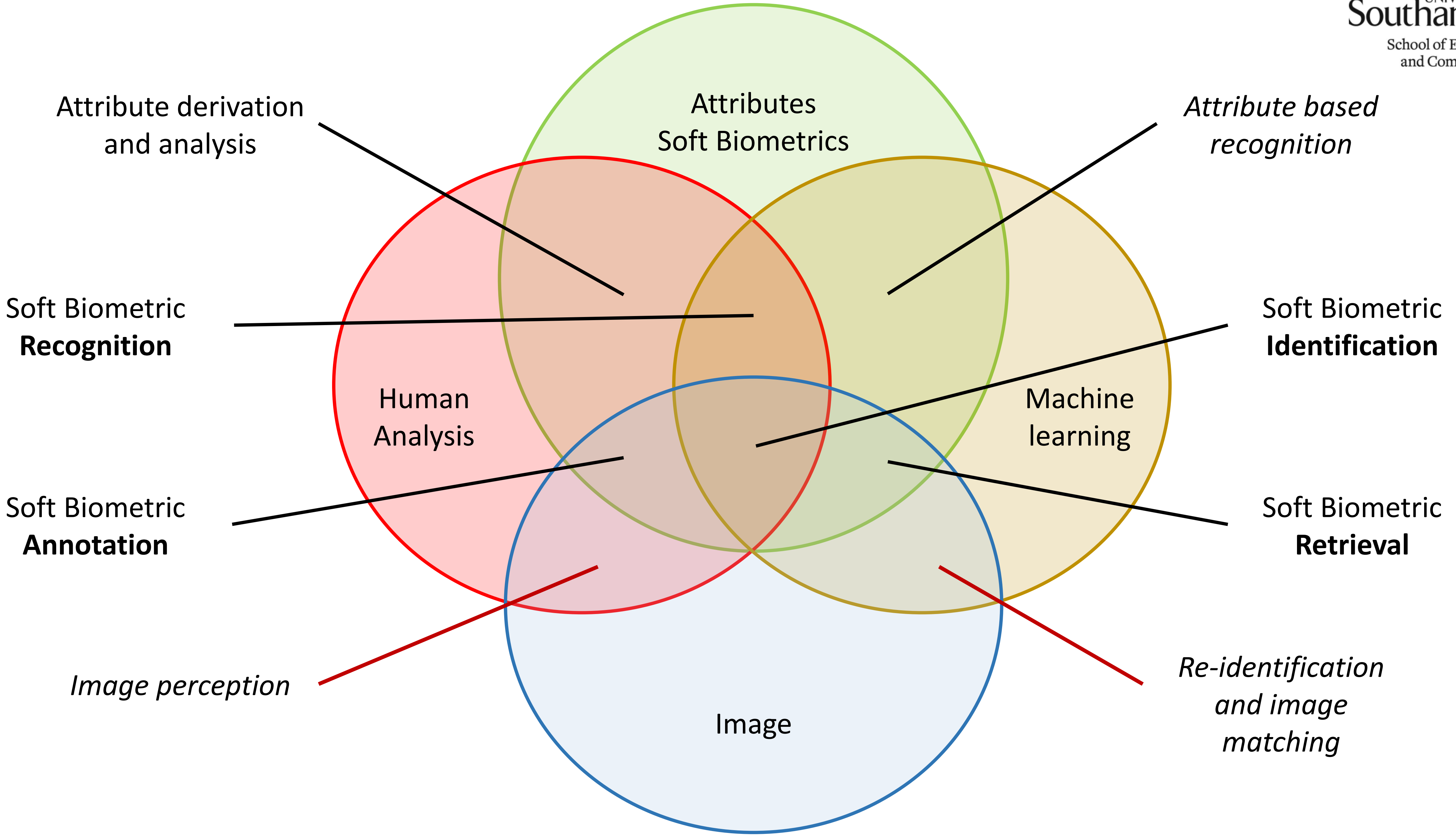
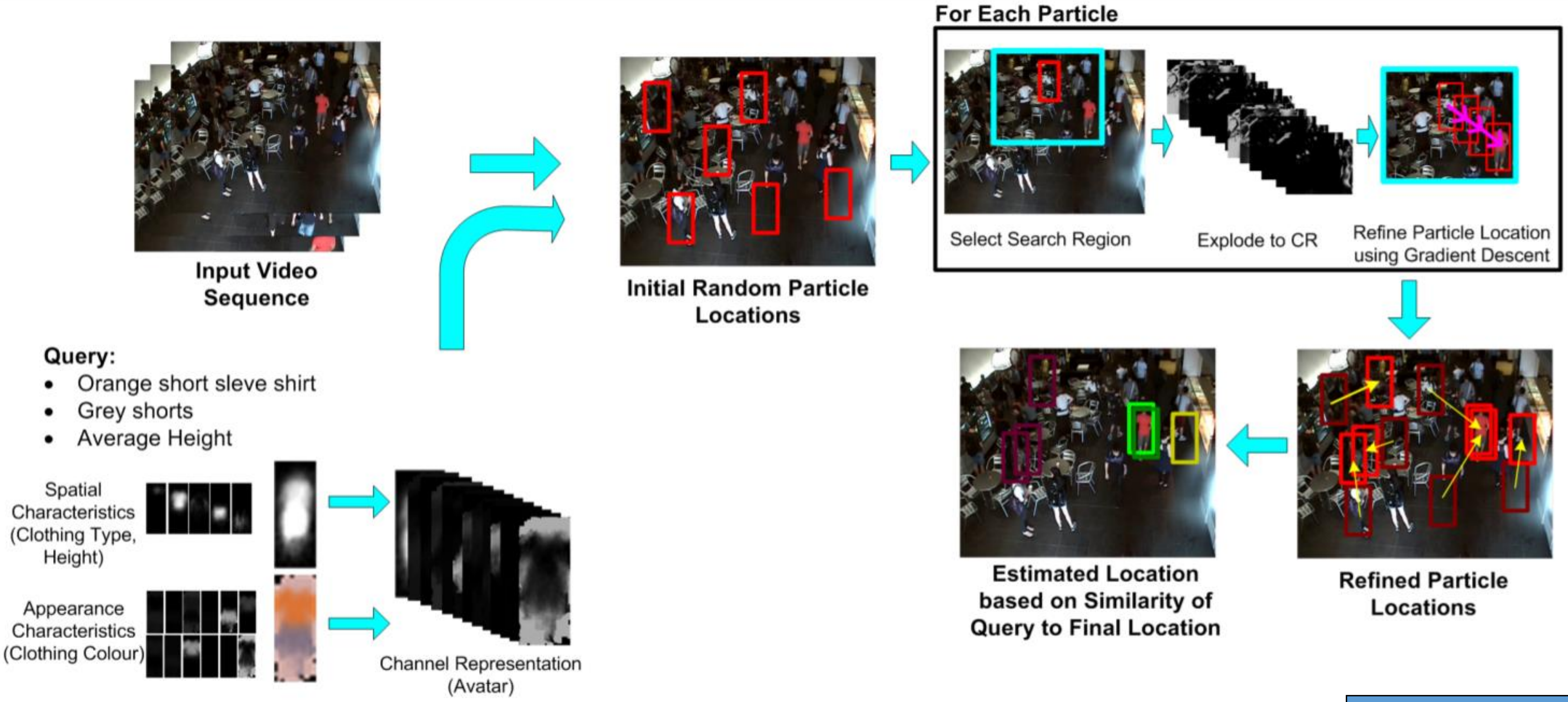


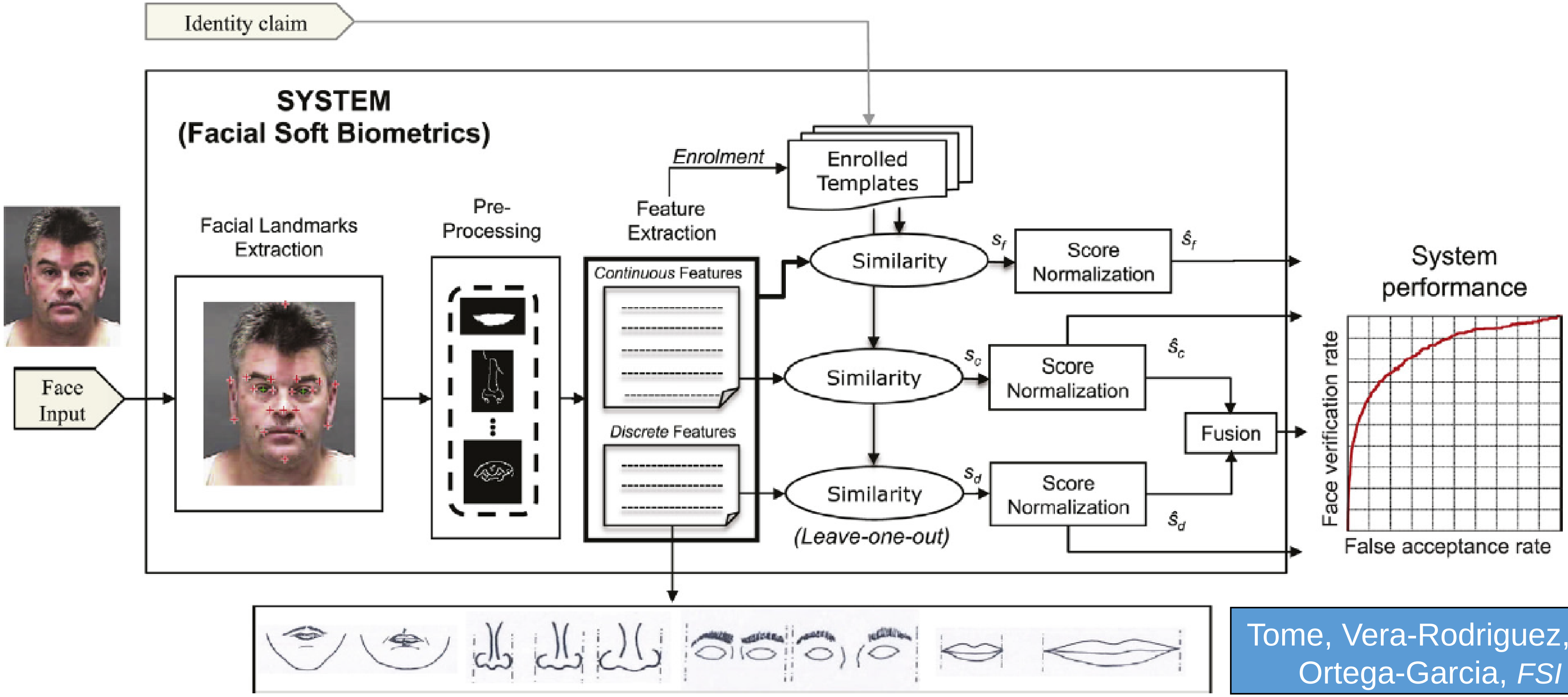
Halstead’s approach



Halstead, Denman, Fookes, *PRL 2016*

Facial soft biometric features for forensic face recognition

“a functional feature-based approach useful for real forensic caseworks, based on the shape, orientation and size of facial traits”



Tome, Vera-Rodriguez, Fierrez, Ortega-Garcia, *FSI 2015*

Descriptions and attributes for identification

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

What can you recognise?

64×97

128×194

256×386

Gender estimation on PETA

- Gender?

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

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

Google: “suspect description form”

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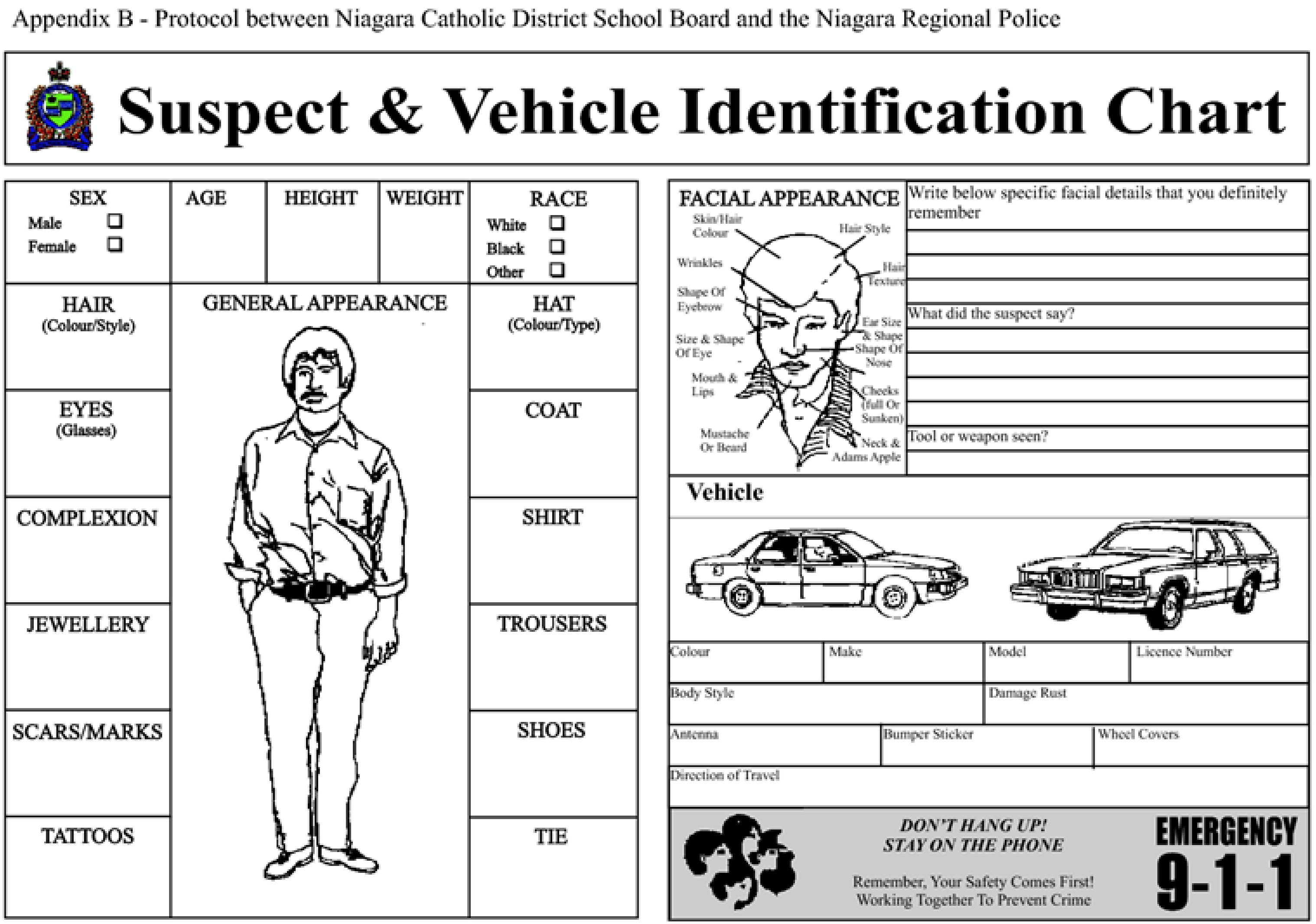
Appendix B - Protocol between Niagara Catholic District School Board and the Niagara Regional Police

Suspect & Vehicle Identification Chart

SEX: Male ☐ Female ☐ | AGE | HEIGHT | WEIGHT | RACE: White ☐ Black ☐ Other ☐

HAIR (Colour/Style)
EYES (Glasses)
COMPLEXION
JEWELLERY
SCARS/MARKS
TATTOOS

GENERAL APPEARANCE

HAT (Colour/Type)
COAT
SHIRT
TROUSERS
SHOES
TIE

FACIAL APPEARANCE
Skin/Hair Colour
Hair Style
Wrinkles
Hair Texture
Shape Of Eyebrow
Ear Size & Shape
Size & Shape Of Eye
Shape Of Nose
Mouth & Lips
Cheeks (full Or Sunken)
Mustache Or Beard
Neck & Adams Apple

Write below specific facial details that you definitely remember

What did the suspect say?

Tool or weapon seen?

Vehicle

Colour | Make | Model | Licence Number
Body Style | Damage Rust
Antenna | Bumper Sticker | Wheel Covers
Direction of Travel

DON'T HANG UP!
STAY ON THE PHONE
Remember, Your Safety Comes First!
Working Together To Prevent Crime

EMERGENCY 9-1-1

OK, eyewitnesses are fallible

Traits and terms

Global Features

- Features mentioned most often in witness statements
- Sex and age quite simple
- Ethnicity
  - Notoriously unstable
  - There could be anywhere between 3 and 100 ethnic groups
  - 3 "main" subgroups plus 2 extra to match UK Police force groupings

So we thought!!

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

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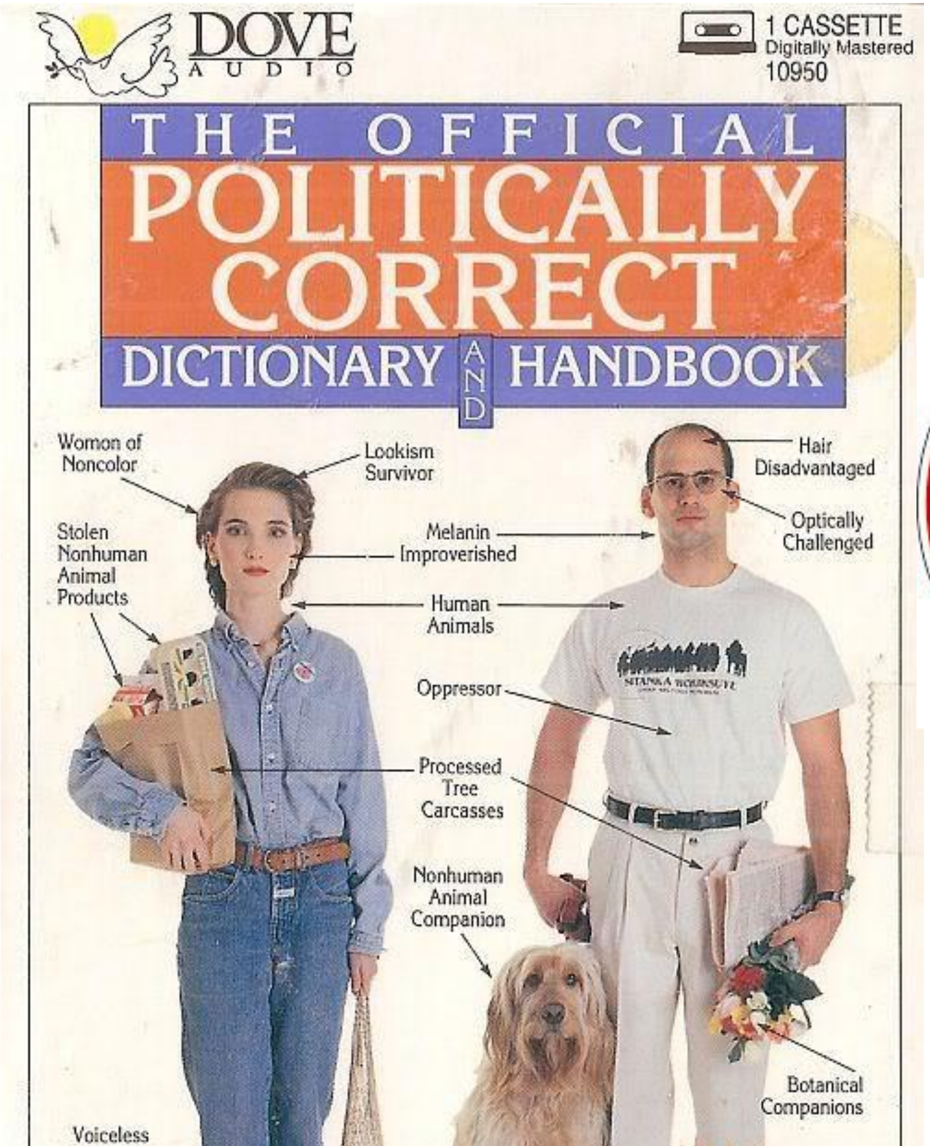
Phrasing questions

- No ‘political correctness’
- Note, or avoid, homonyms and polysemes
- Eschew completely argot and colloquialism

    E.g. nose: hooter, snitch, conk (UK), schnozzle (US?)

….. and avoid words like eschew



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

A bit of psychology

Need to gather labels from humans

- *Memory issues:* view a subject as many times as needed
- *Defaulting:* explicitly asked to fill out every feature
- *Value Judgments:* categorical qualitative values.
- *Observer variables:* collect description of annotators
- *Other race effect* is very difficult to handle

Labelling via CrowdFlower

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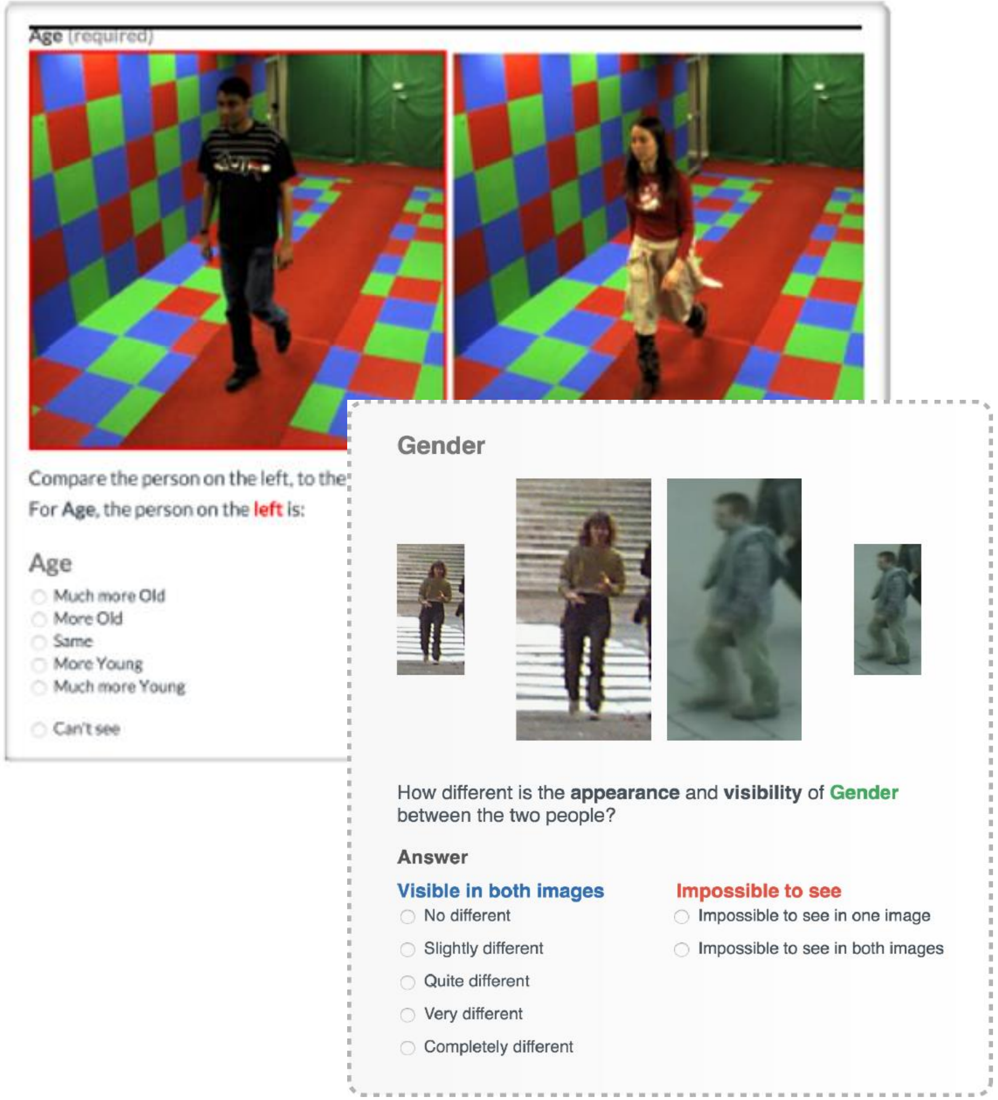


- Professional labelling environment
- Can evaluate labellers (continuously)
- Ensure wide population of labellers
- Not expensive
- Others available (Amazon Mechanical Turk not available in UK)

https://www.crowdflower.co

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

Databases

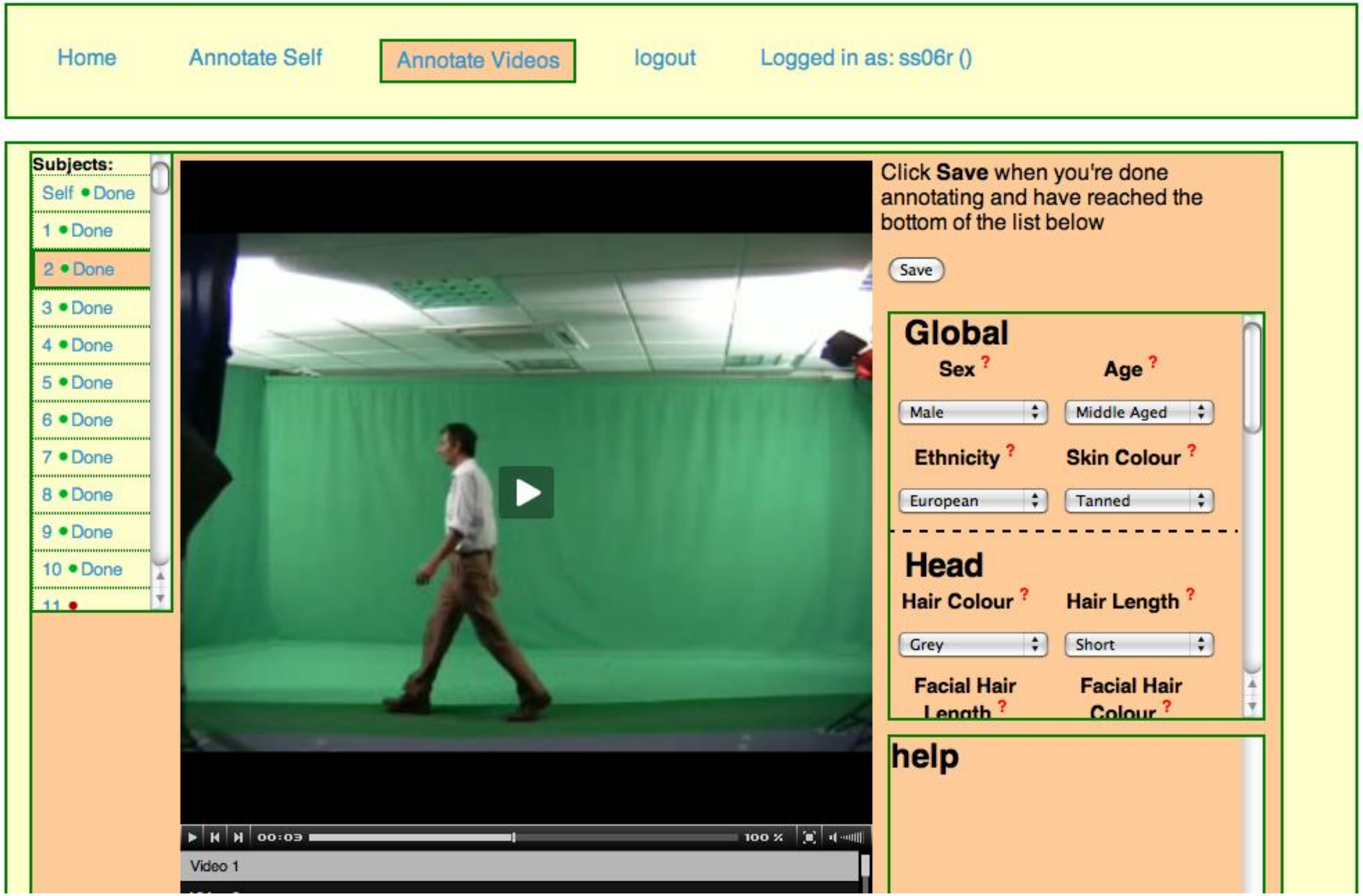
Laboratory

- Southampton Gait Database
- Southampton 3D Gait and Face

'Real' World

- PEdesTrian Attribute (PETA)
- LFW
- Clothing Attribute Dataset

Adding semantic labels



Samangooei and Nixon, *IEEE BTAS* 2008

Human body descriptions: recognition capability

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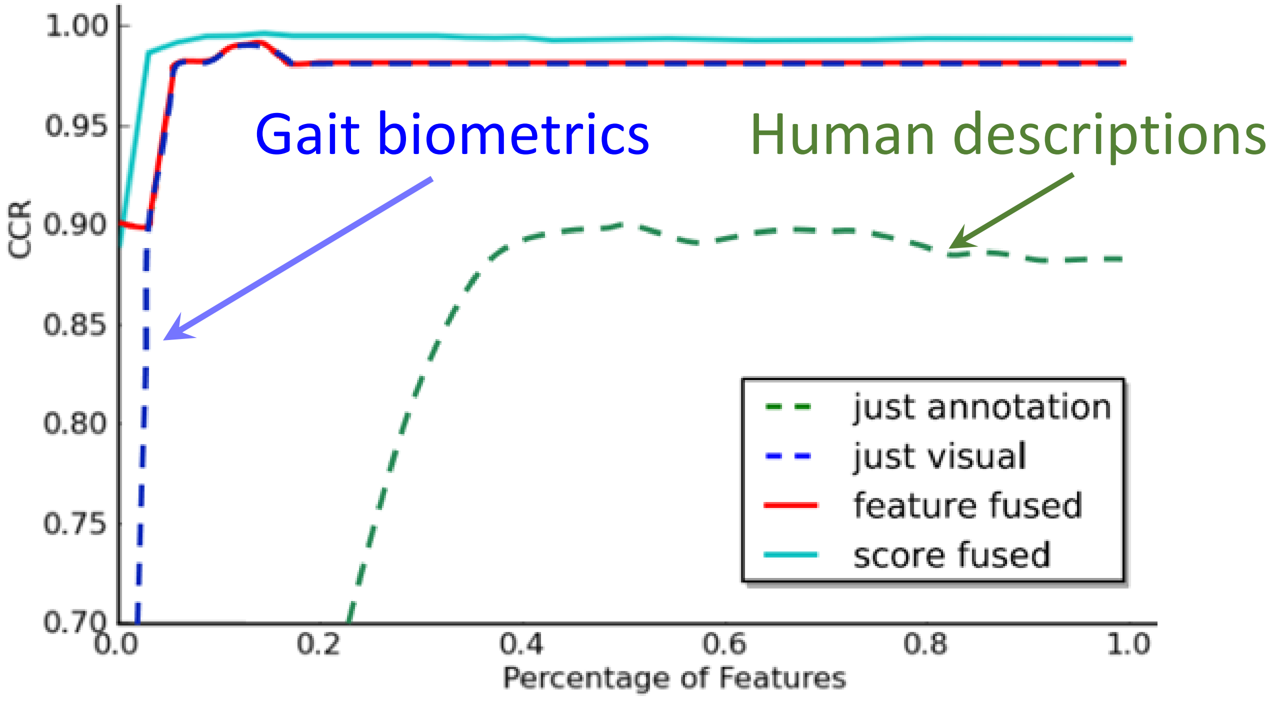
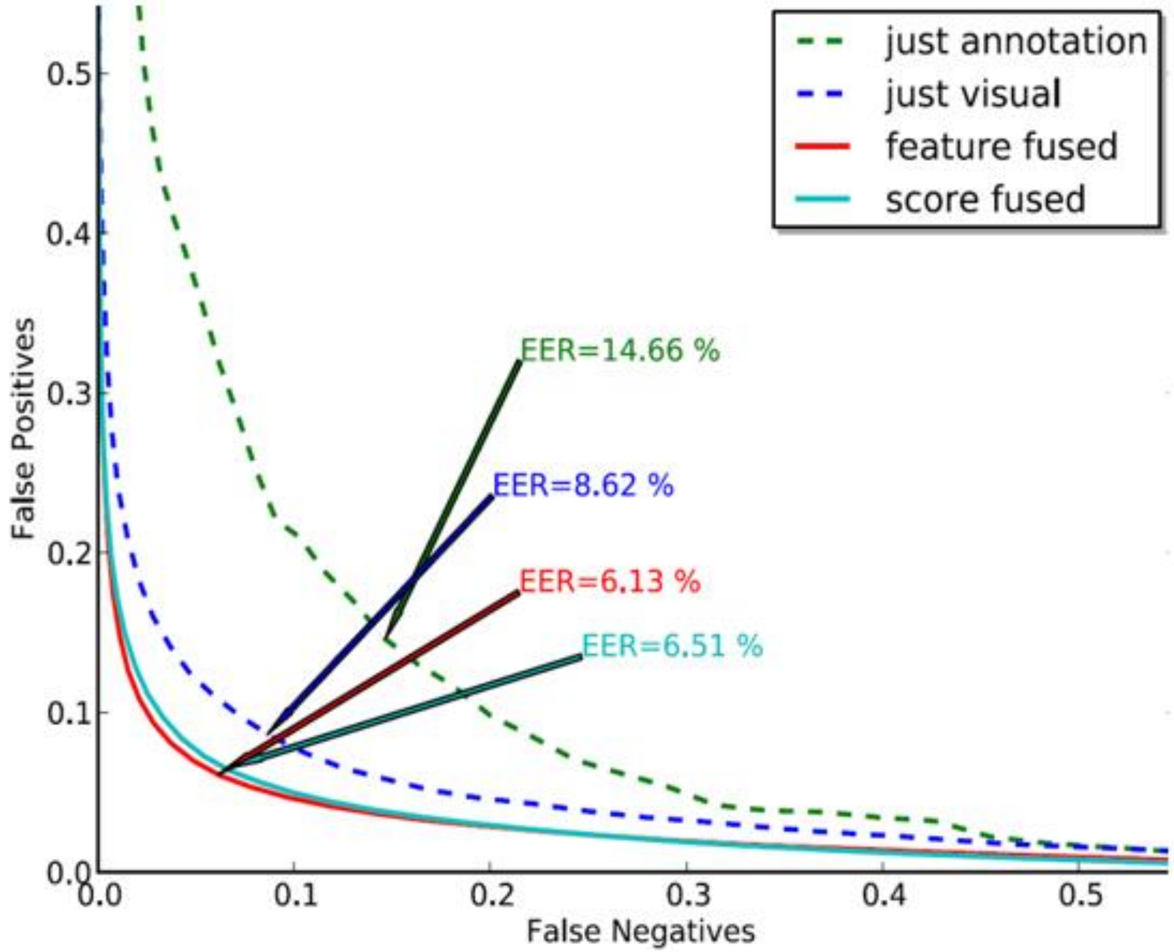


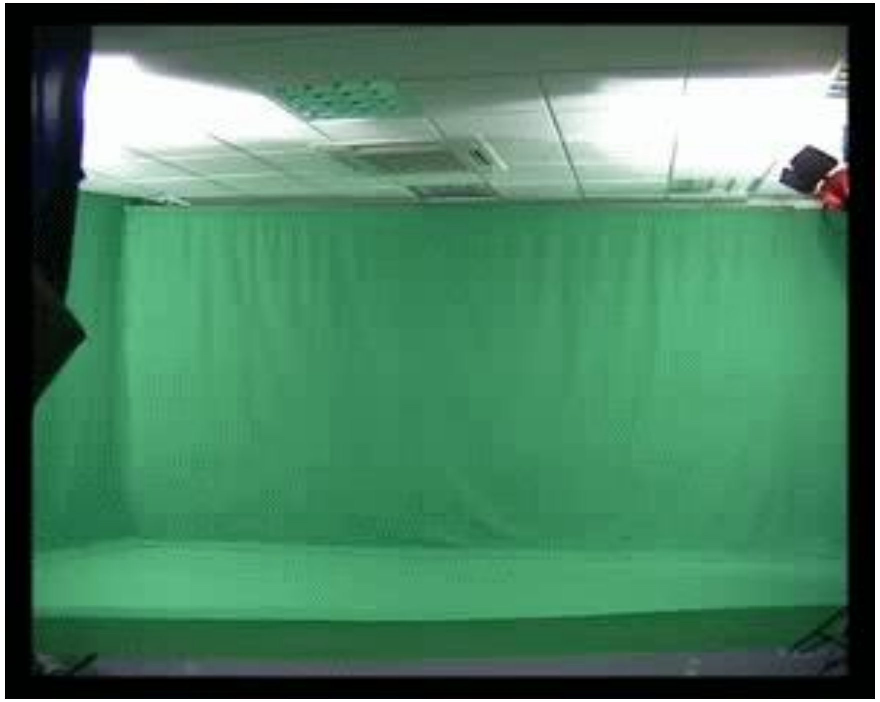


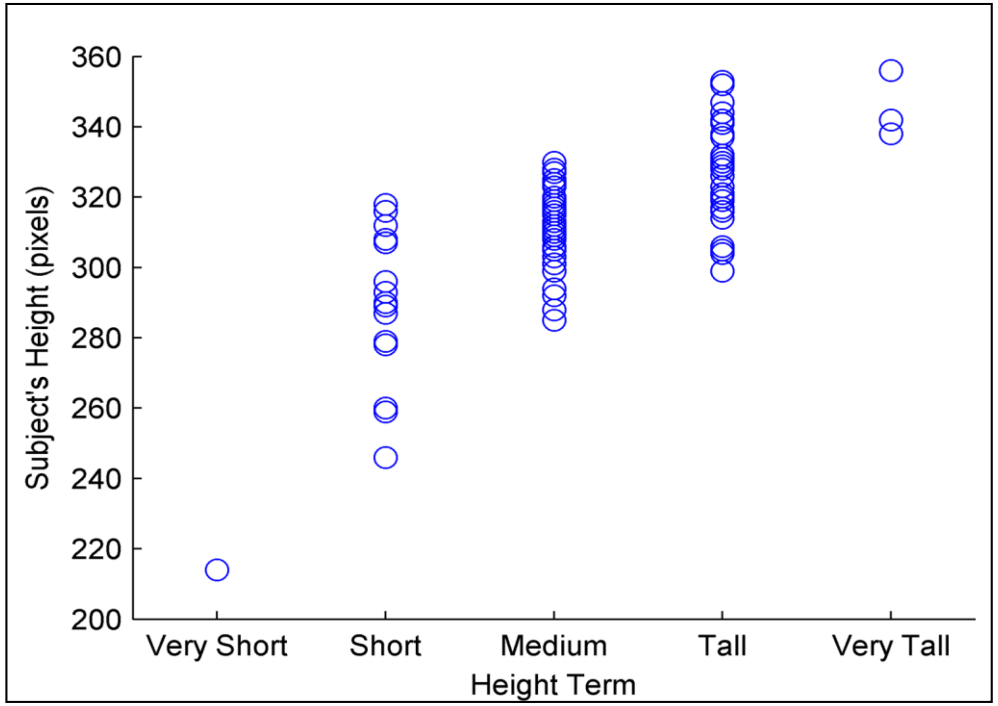
First result

Samangooei and Nixon, *IEEE BTAS* 2008

Problems with absolute descriptors

Subjective = unreliable; Categorical = lacks detail





Reid and Nixon, IEEE *IJCB 2011; TPAMI* 2015

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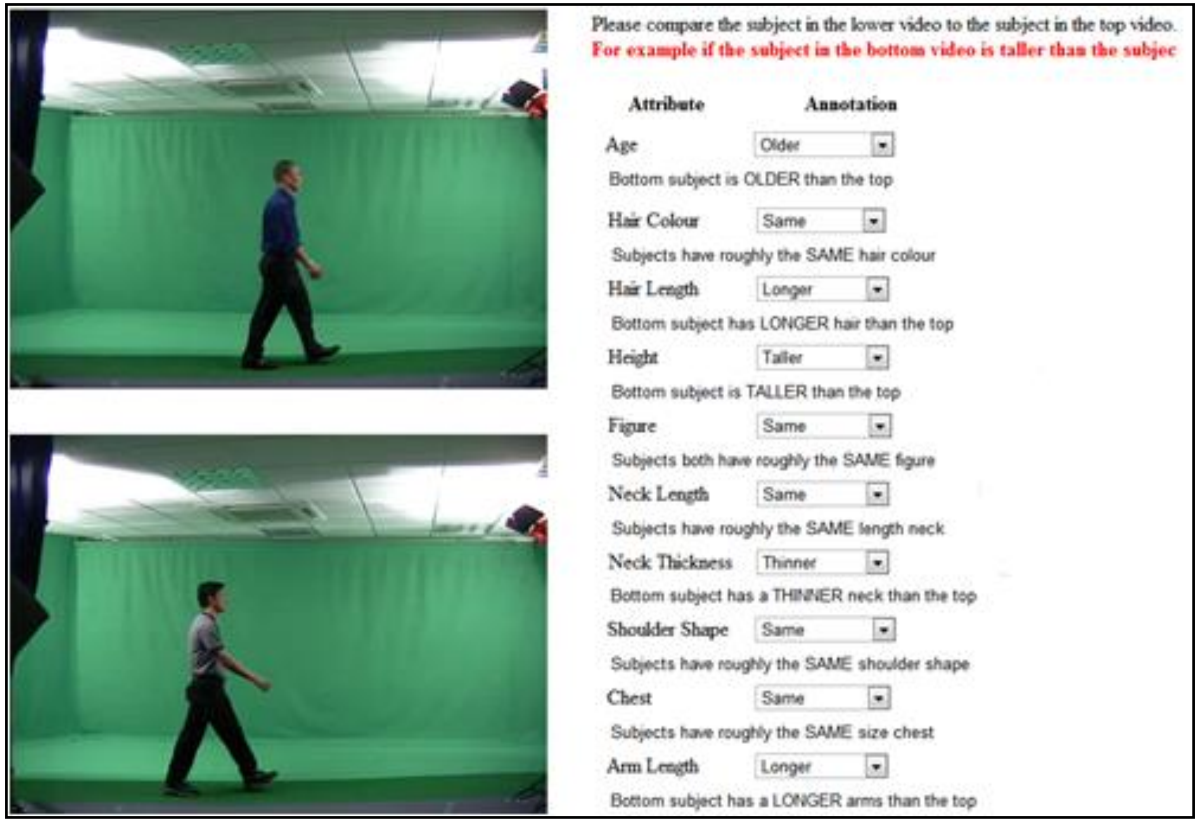
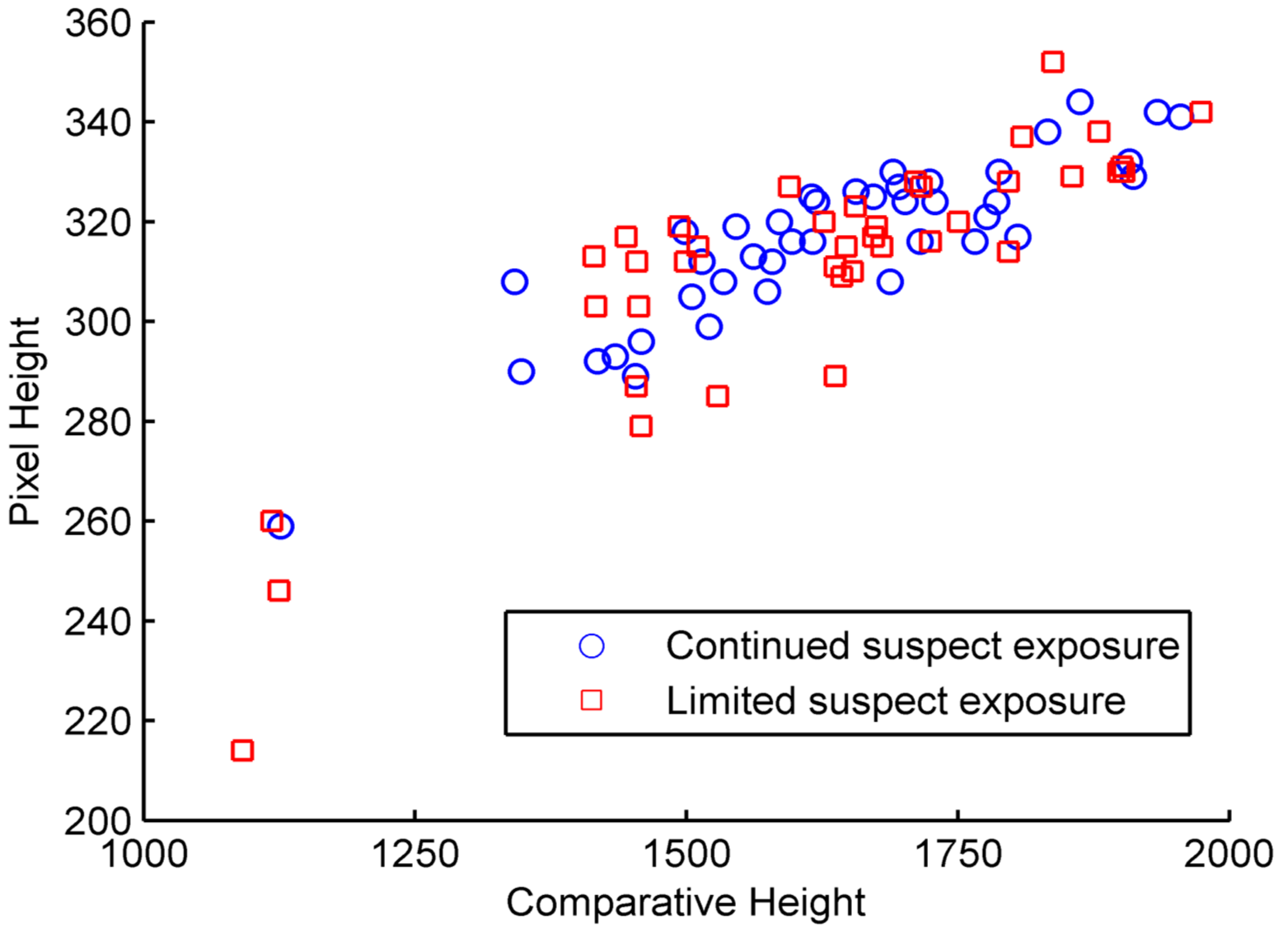
Comparative human descriptions

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



Reid and Nixon, IEEE *IJCB 2011; TPAMI* 2015

Height correlation (with time)



Reid and Nixon, *IEEE ICDP* 2011

Context: relative attributes

(a) Smiling (b) ? (c) Not smiling

(d) Natural (e) ? (f) Manmade

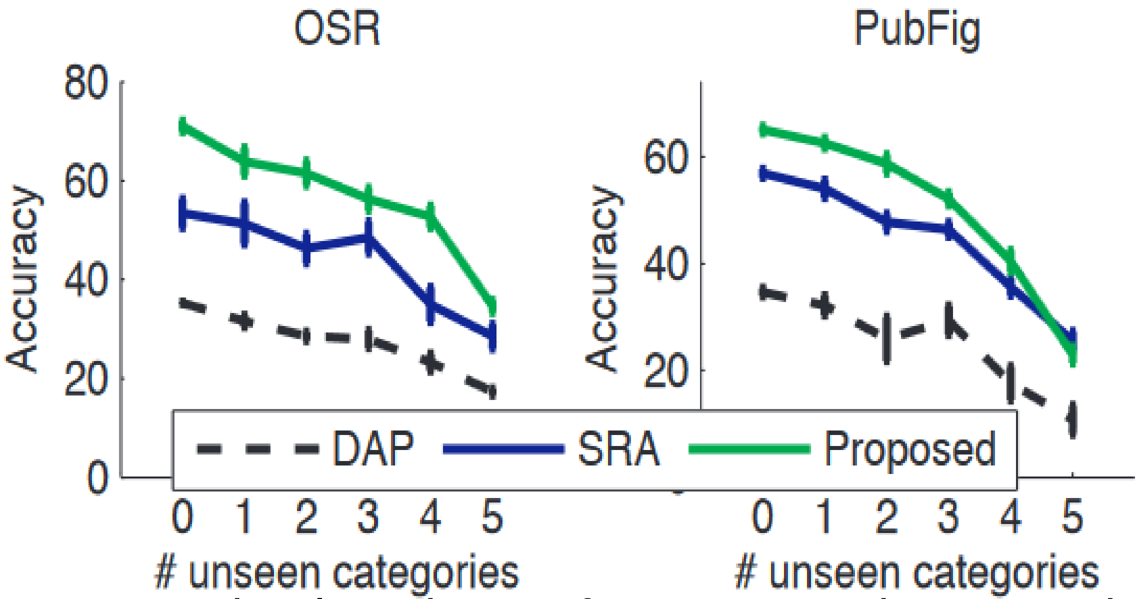
Used ranking SVM

PubFig	ACHJ MS V Z	
Masculine-looking	1 1 1 1 0 0 1 1	$S \prec M \prec Z \prec V \prec J \prec A \prec H \prec C$
White	0 1 1 1 1 1 1 1	$A \prec C \prec H \prec Z \prec J \prec S \prec M \prec V$
Young	0 0 0 0 1 1 0 1	$V \prec H \prec C \prec J \prec A \prec S \prec Z \prec M$
Smiling	1 1 1 0 1 1 0 1	$J \prec V \prec H \prec A \sim C \prec S \sim Z \prec M$
Chubby	1 0 0 0 0 0 0 0	$V \prec J \prec H \prec C \prec Z \prec M \prec S \prec A$
Visible-forehead	1 1 1 0 1 1 1 0	$J \prec Z \prec M \prec S \prec A \sim C \sim H \sim V$
Bushy-eyebrows	0 1 0 1 0 0 0 0	$M \prec S \prec Z \prec V \prec H \prec A \prec C \prec J$
Narrow-eyes	0 1 1 0 0 0 1 1	$M \prec J \prec S \prec A \prec H \prec C \prec V \prec Z$
Pointy-nose	0 0 1 0 0 0 0 1	$A \prec C \prec J \sim M \sim V \prec S \prec Z \prec H$
Big-lips	1 0 0 0 1 1 0 0	$H \prec J \prec V \prec Z \prec C \prec M \prec A \prec S$
Round-face	1 0 0 0 1 1 0 0	$H \prec V \prec J \prec C \prec Z \prec A \prec S \prec M$

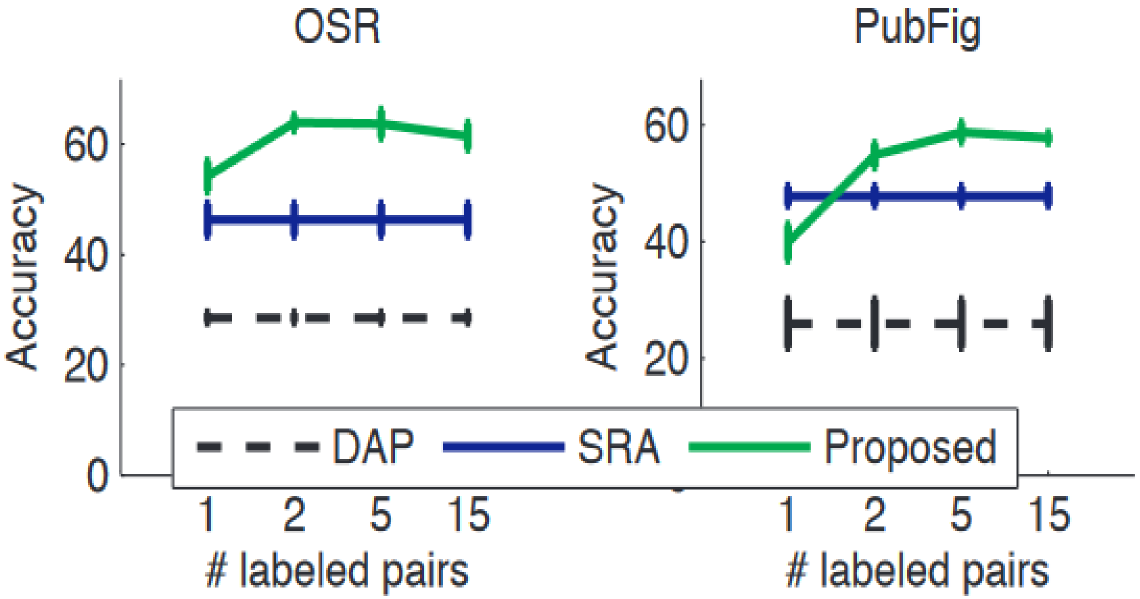
Subset of attributes and Alex Rodriguez (A), Clive Owen (C), Hugh Laurie (H), Jared Leto (J), Miley Cyrus (M), Scarlett Johansson (S), Viggo Mortensen (V) and Zac Efron (Z)

Parikh and Grauman, *IEEE ICCV* 2011

Context: relative attributes



Zero-shot learning performance as the proportion of unseen categories increases. Total number of classes N remains constant at 8



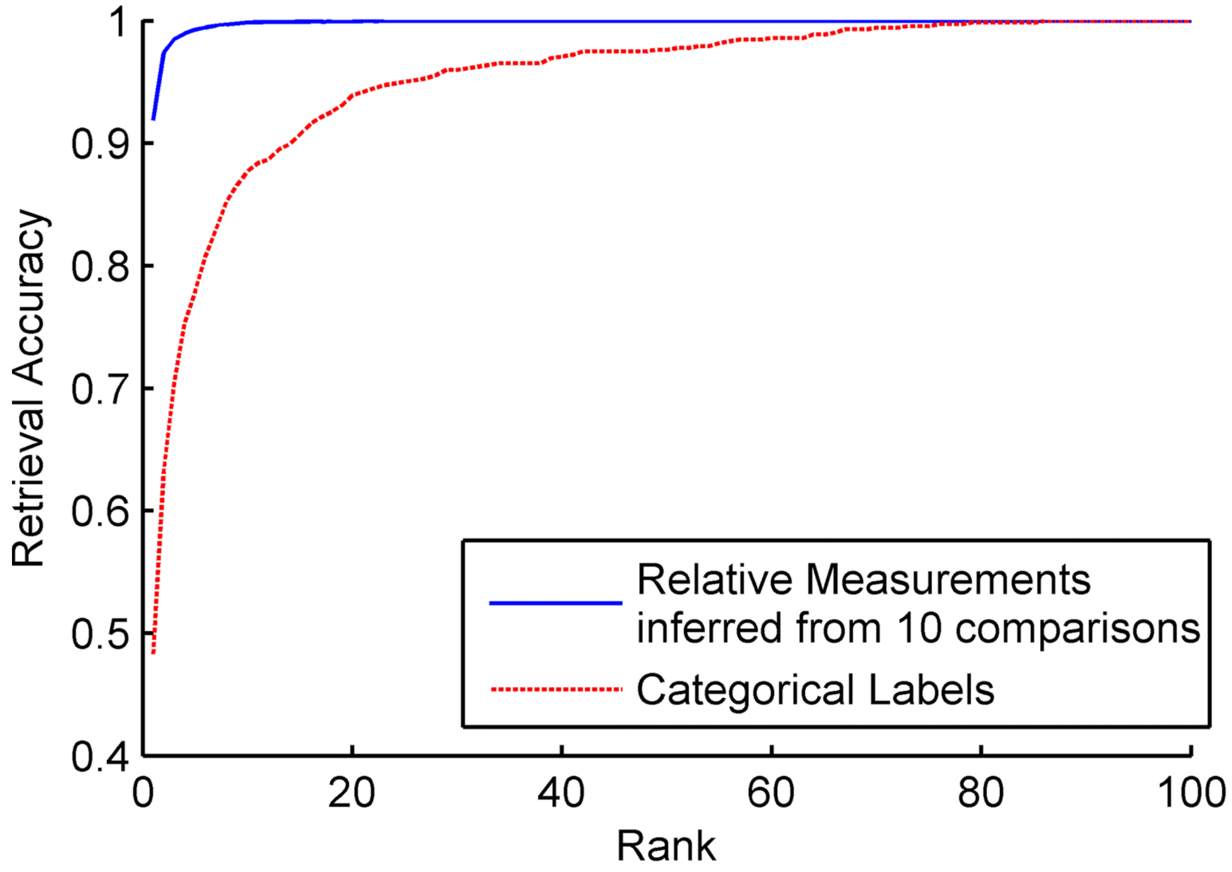
Zero-shot learning performance as more pairs of seen categories are related (i.e. labeled) during training

DAP Direct Attribute Prediction

SRA score-based relative attributes

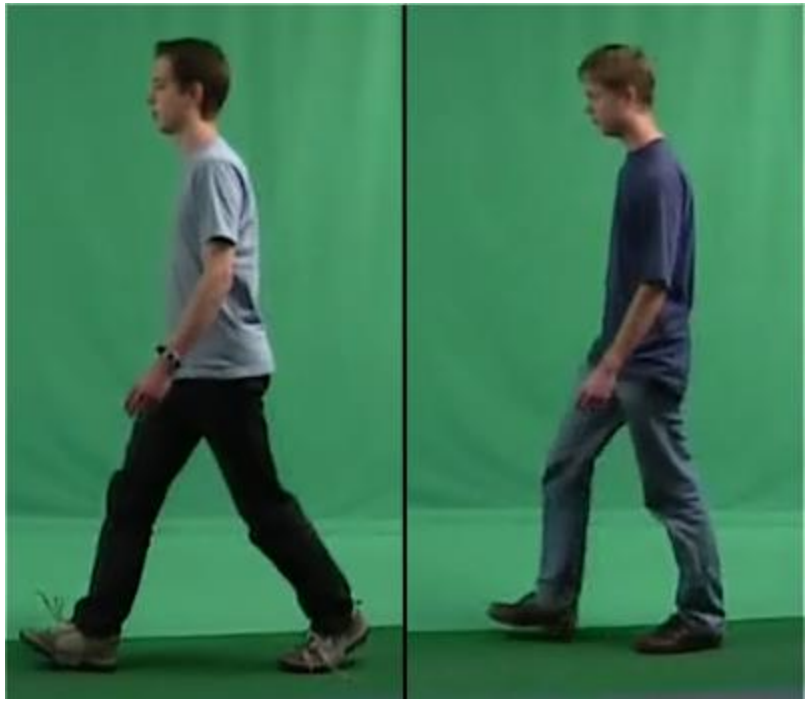
Parikh and Grauman, *IEEE ICCV* 2011

Recognition



Reid and Nixon, *IEEE ICDP* 2011

Recognition/ retrieval



Incorrect with 10 comparisons

Correct with 1 comparison

Reid and Nixon, *IEEE TPAMI* 2015

Ranking comparative descriptions

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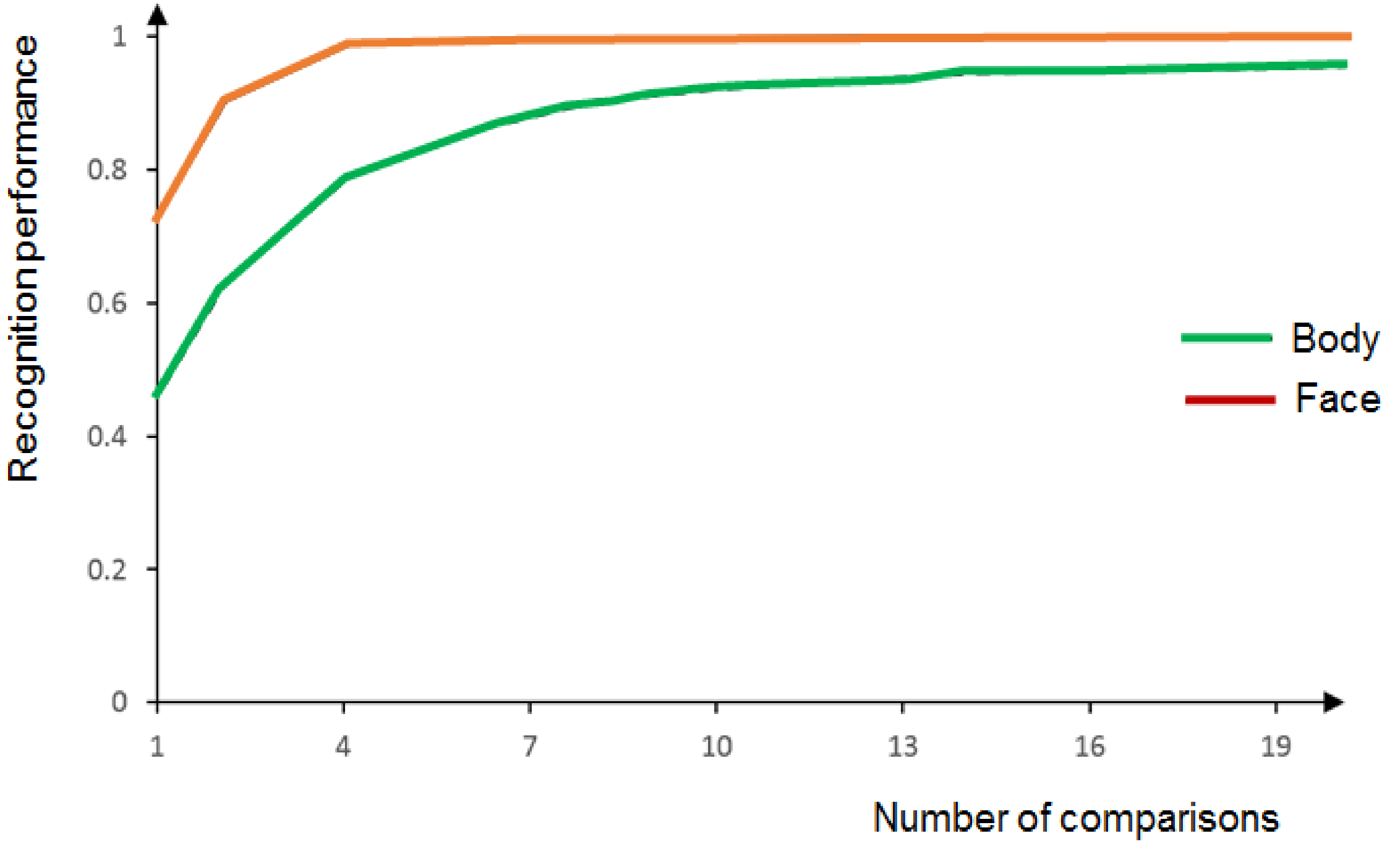
- Use ELO rating system from chess to infer relative descriptions
- Turn comparative labels into a ranked list
- Comparative › categorical
- Alternatives?
- Parameters?



Reid and Nixon, *IEEE IJCB 2011*

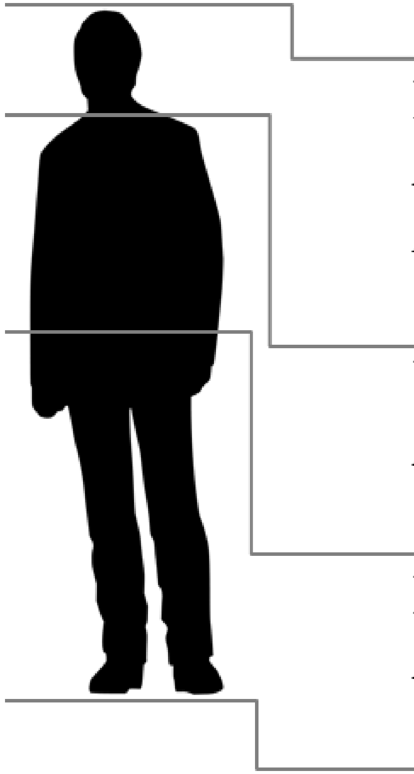
‘Give us the tools to finish the job’

Components

- Data
- Labels (categorical or comparative)
- Ranking algorithm (for comparative labels)
- Feature selection (e.g. SFSS, entropy)
- Computer vision (feature extraction, colour mapping,)
- Classifier (e.g. kNN, SVM, DBN)
- CNNs

http://ww2today.com

Labelling the body, face and clothing



All: gender, age, ethnicity, skin colour

General

Body: figure, weight

Face: length, width, fleshiness

Clothing: tattoos, attachment(s), overall style category

Head/ Face

Body: skin colour, hair colour/ length, neck length/ thickness

Face: parts of skin, hair, forehead, eyes, ears, nose, lips, chin

Clothing: hat, face/ head coverage

Upper Body

Body: arm length/ thickness, chest,

Clothing: neckline, clothing category, sleeve length

Lower Body

Body: leg length/ shape/ thickness, hips' width

Clothing: clothing category/ length, belt, shoes, heel

Body

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

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

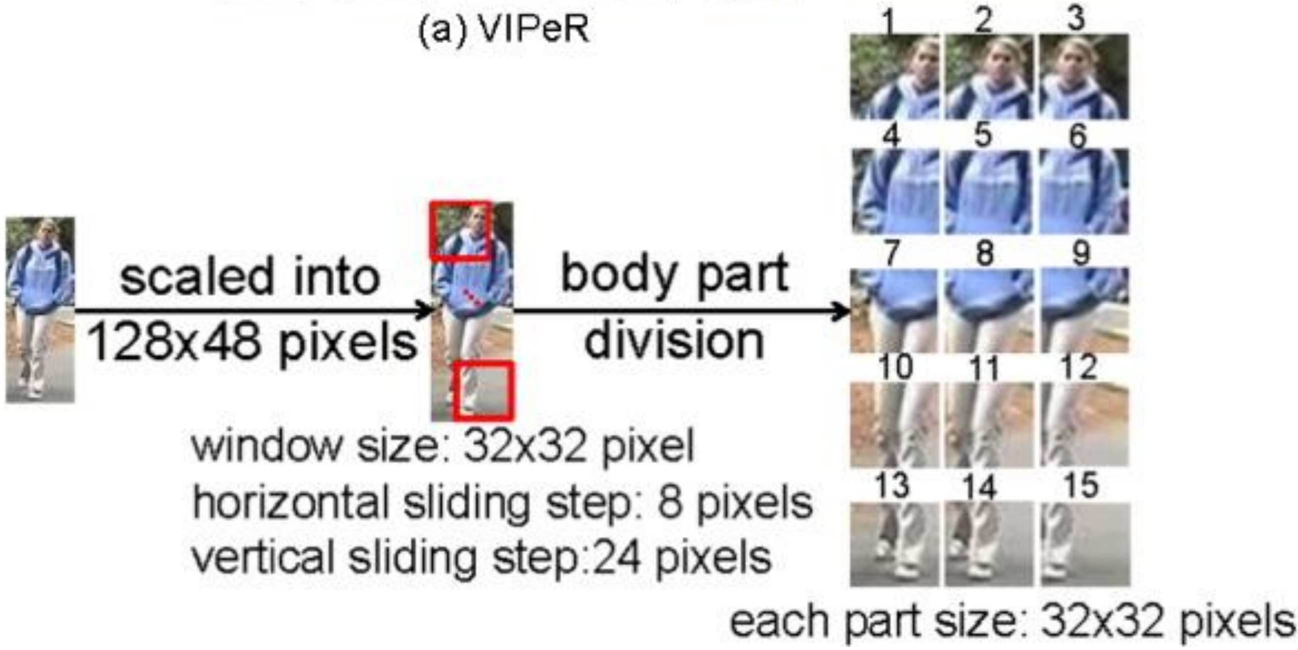
Database of descriptions

Generate descriptions

Context: attribute estimation

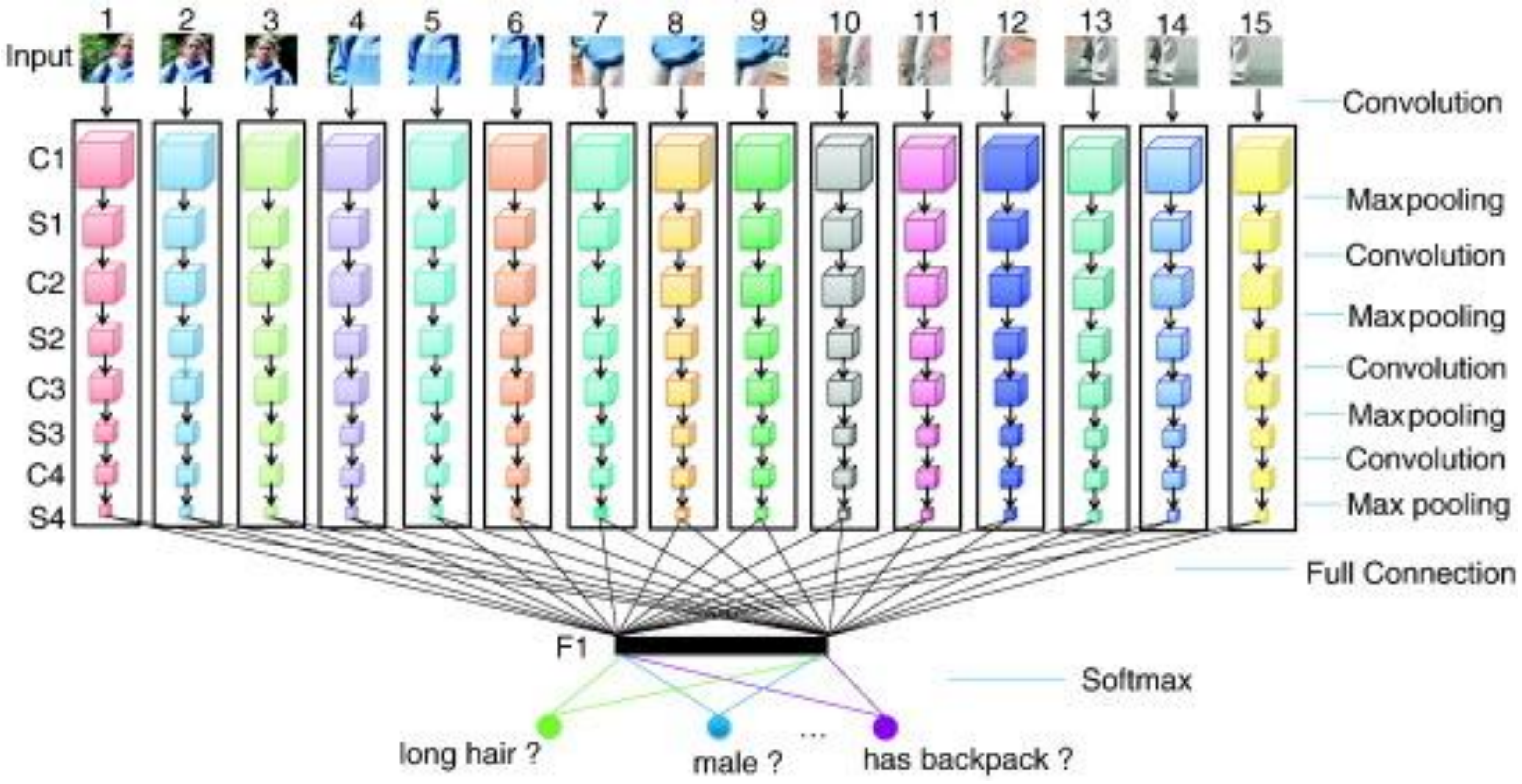
- Pedestrian attribute estimation (gender, clothing)
- Pre-segment pedestrian image
- Use multi label CNN
- Applied to VIPeR , GRID and PETA
- Increased average attribute estimation
- Can be used for re-identification

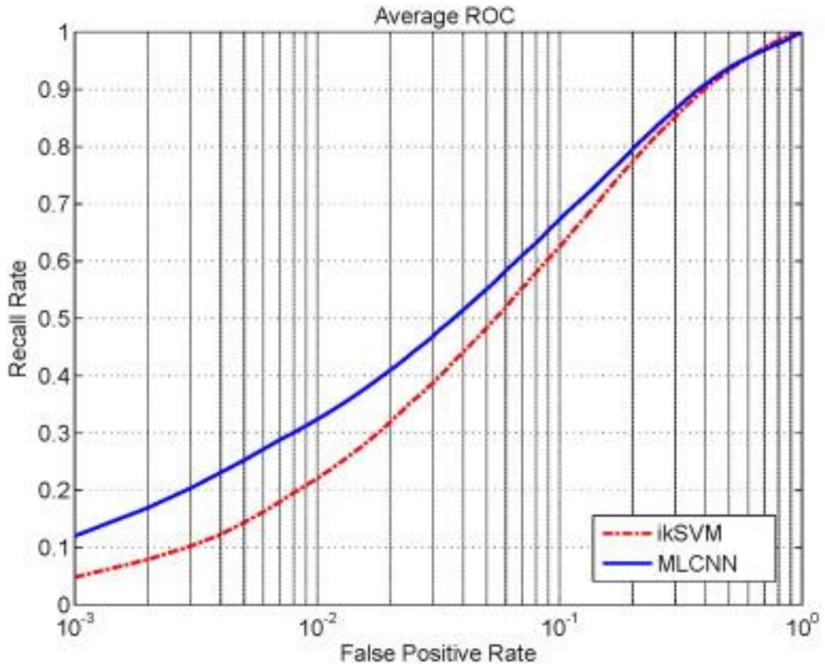
(a) VIPeR



Zhu, Liao, …, Li, *Proc ICB* 2015, *IVC* 2016

Context: attribute estimation



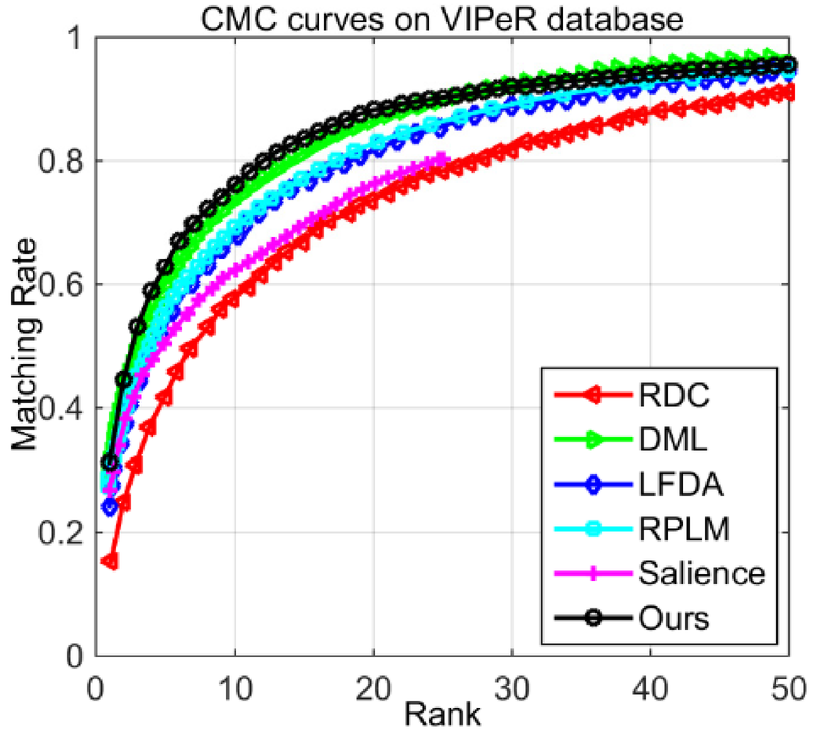


Analysis on PETA

Zhu, Liao, …, Li, *IVC* 2016

Context: attribute estimation

attribute	accuracy rate (%)		recall rate (%) @ FPR=10%		AUC(%)	
	ikSVM	MLCNN	ikSVM	MLCNN	ikSVM	MLCNN
accessoryHat	92.04	96.05	81.37	86.06	91.27	92.62
accessoryMuffler	94.84	97.17	90.68	88.42	95.09	94.47
accessoryNothing	78.87	86.11	35.37	52.57	81.79	86.09
carryingBackpack	76.39	84.30	46.19	58.40	84.52	85.19
carryingMessengerBag	74.51	79.58	50.22	58.30	78.44	82.01
carryingNothing	75.84	80.14	49.36	55.15	81.60	83.08
carryingOther	76.18	80.91	38.57	46.90	74.11	77.68
carryingPlasticBags	86.86	93.45	70.57	67.30	87.69	86.01
footwearBlack	74.29	75.97	50.37	57.24	81.42	84.07

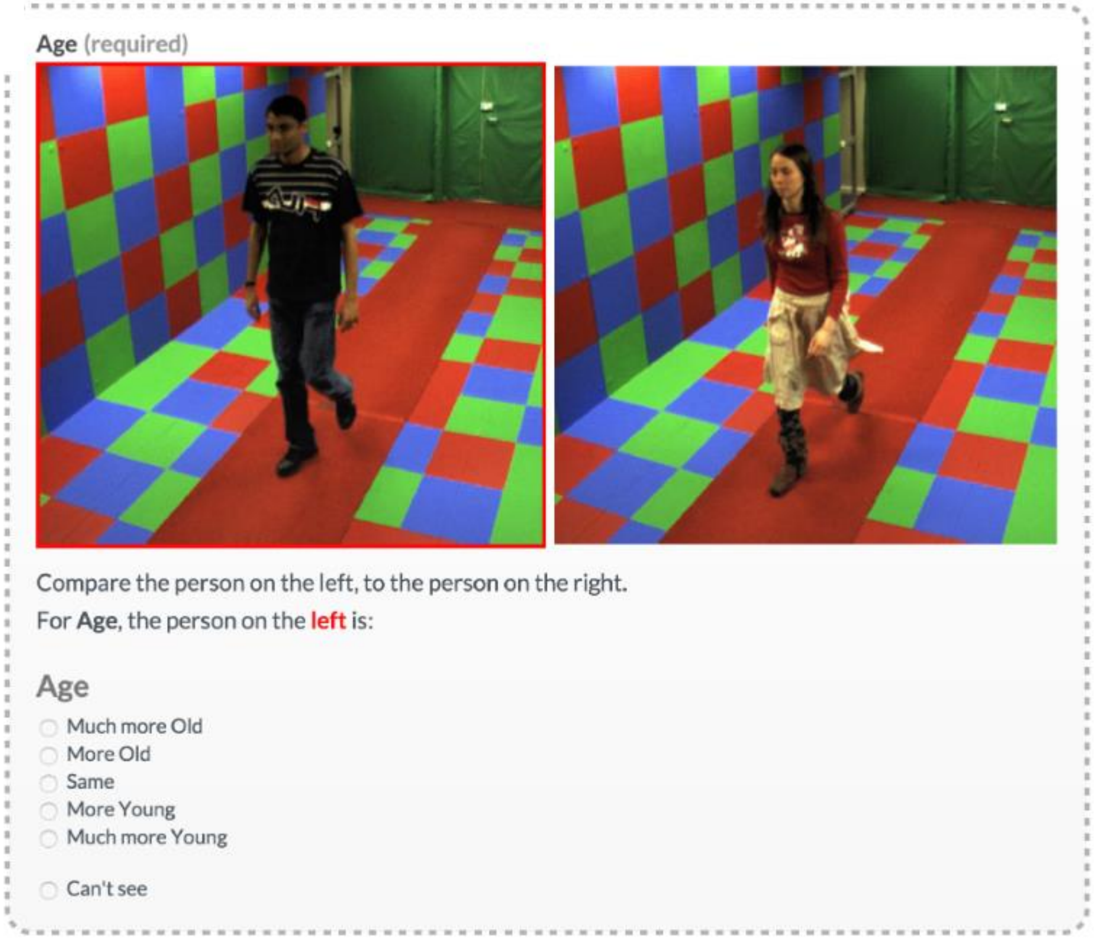


Analysis on ViPER

Zhu, Liao, …, Li, *Proc ICB* 2015, *IVC* 2016

Crowdsourcing body labels

Soft traits	Response labels (5-p 5
Gender	Much more Feminine
Age	Much more Old
Height	Much more Tall
Weight	Much more Heavy
Figure	Much more Fat
Chest size	Much more Big
Arm thickness	Much more Thick
Leg thickness	Much more Thick
Skin colour	Much more Dark
Hair colour	Much more Dark
Hair length	Much more Long
Muscle build	Much more Muscle



Martinho-Corbishley, Nixon and Carter, *IET Biometrics* 2015

Distributions of body labels

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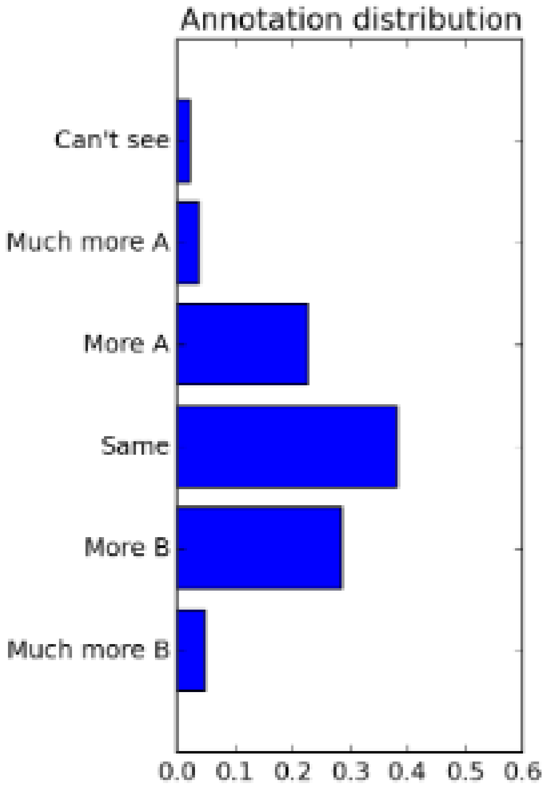
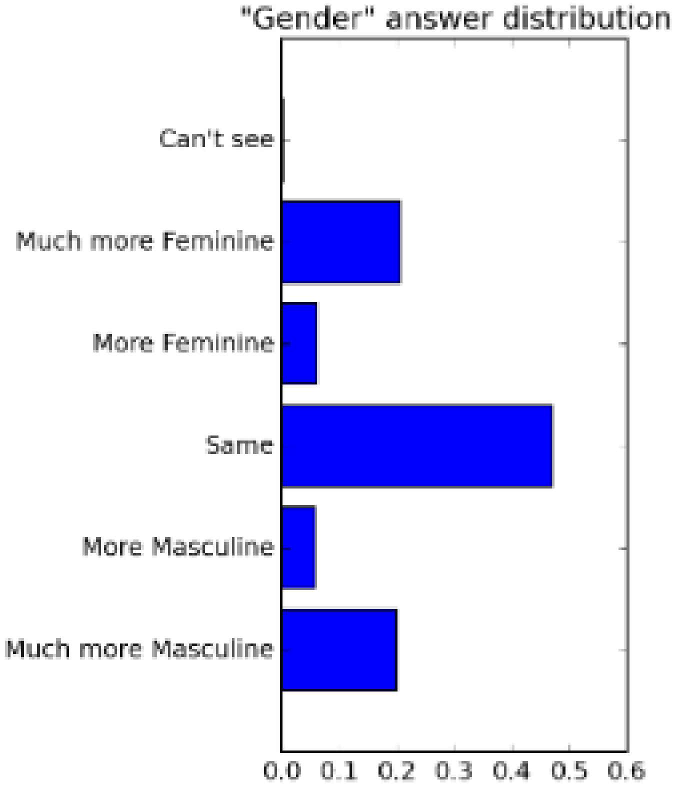
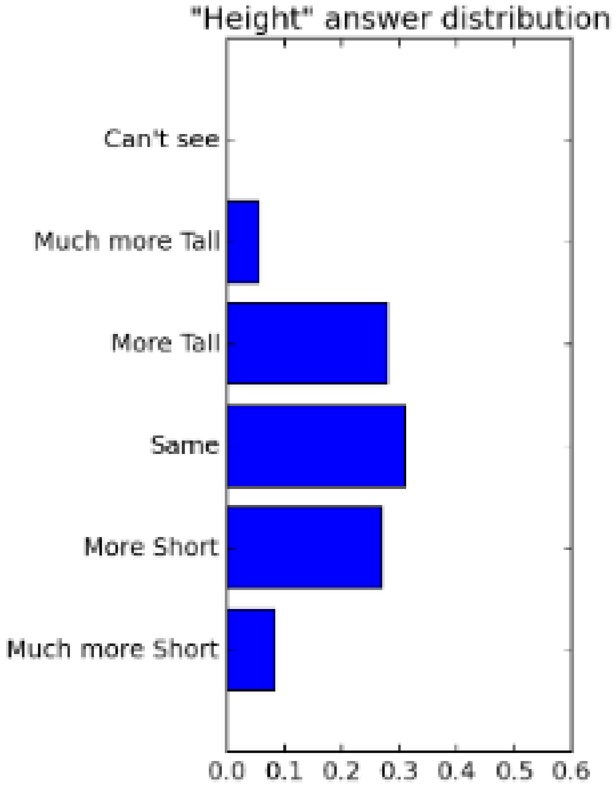


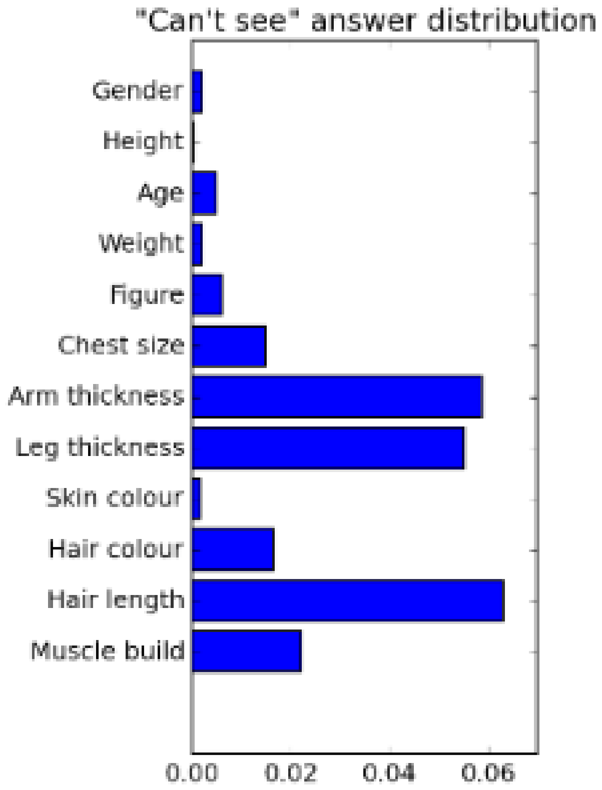
All



Gender



Height



Uncertainty

Martinho-Corbishley, Nixon and Carter, *IET Biometrics* 2015

Recognition by crowdsourced body labels

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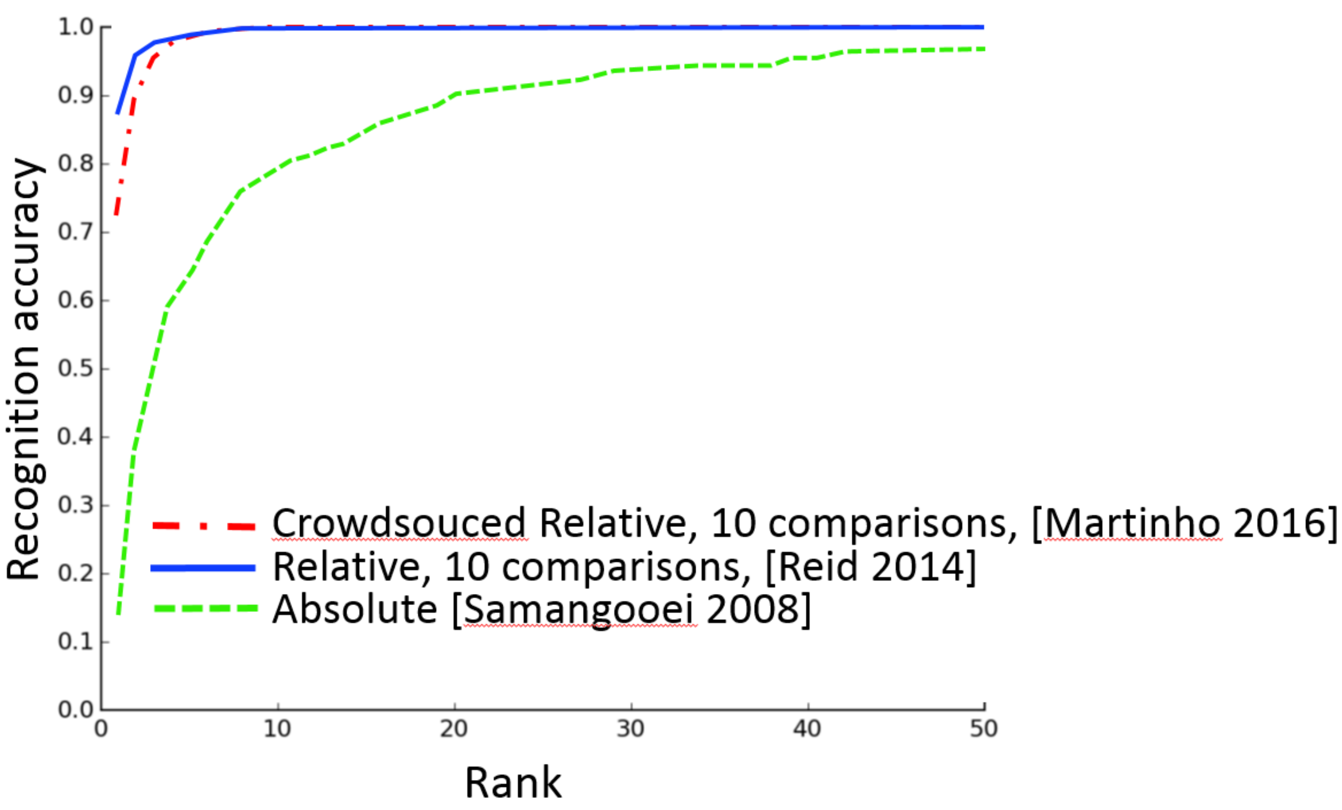
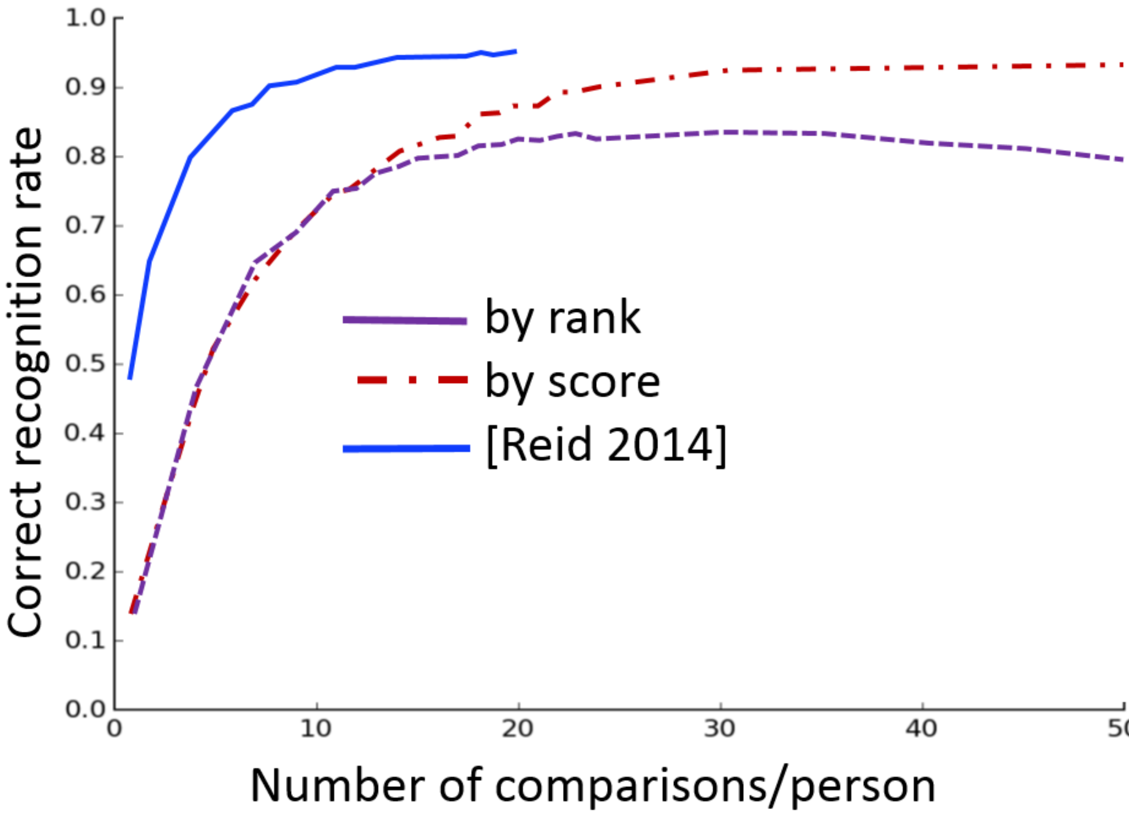


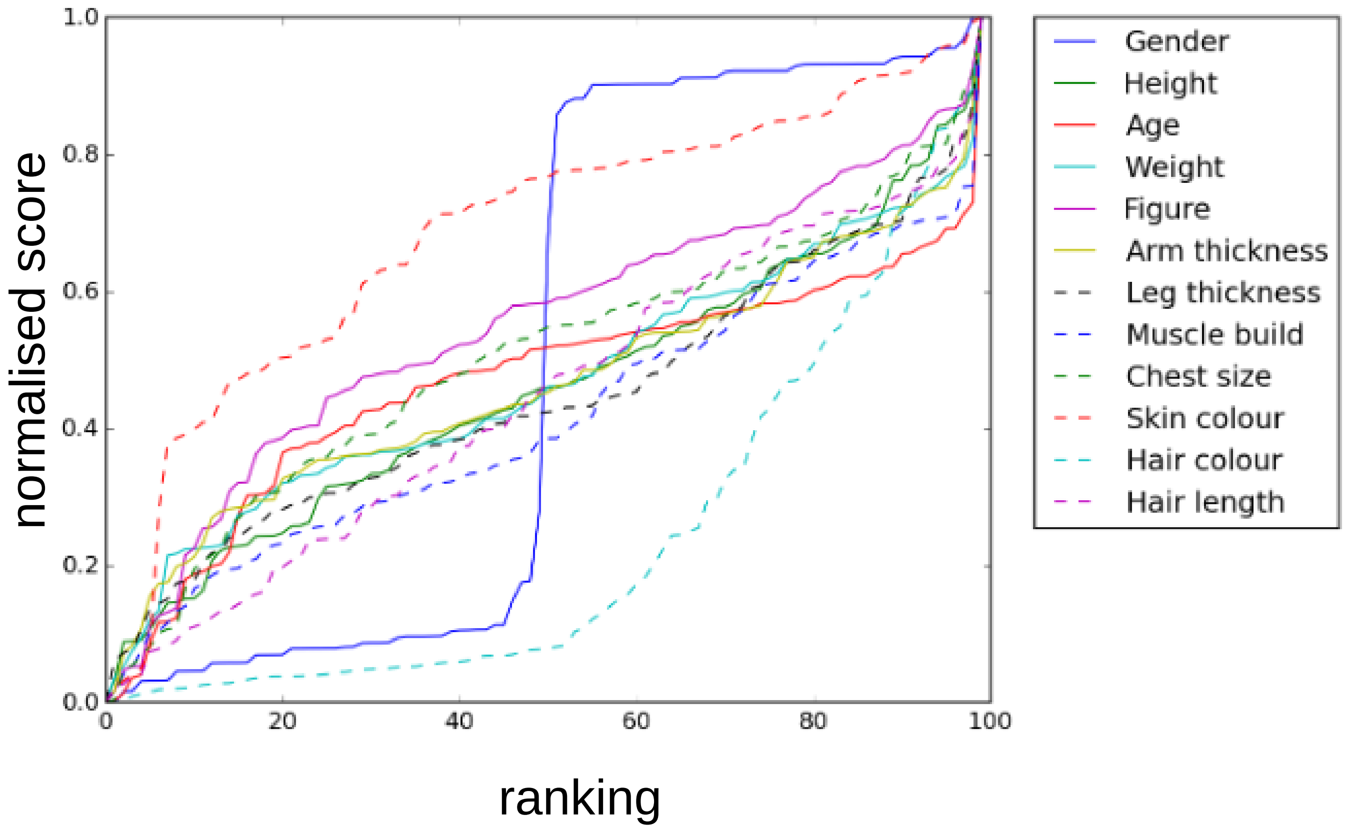


Lower recognition accuracy (expected)

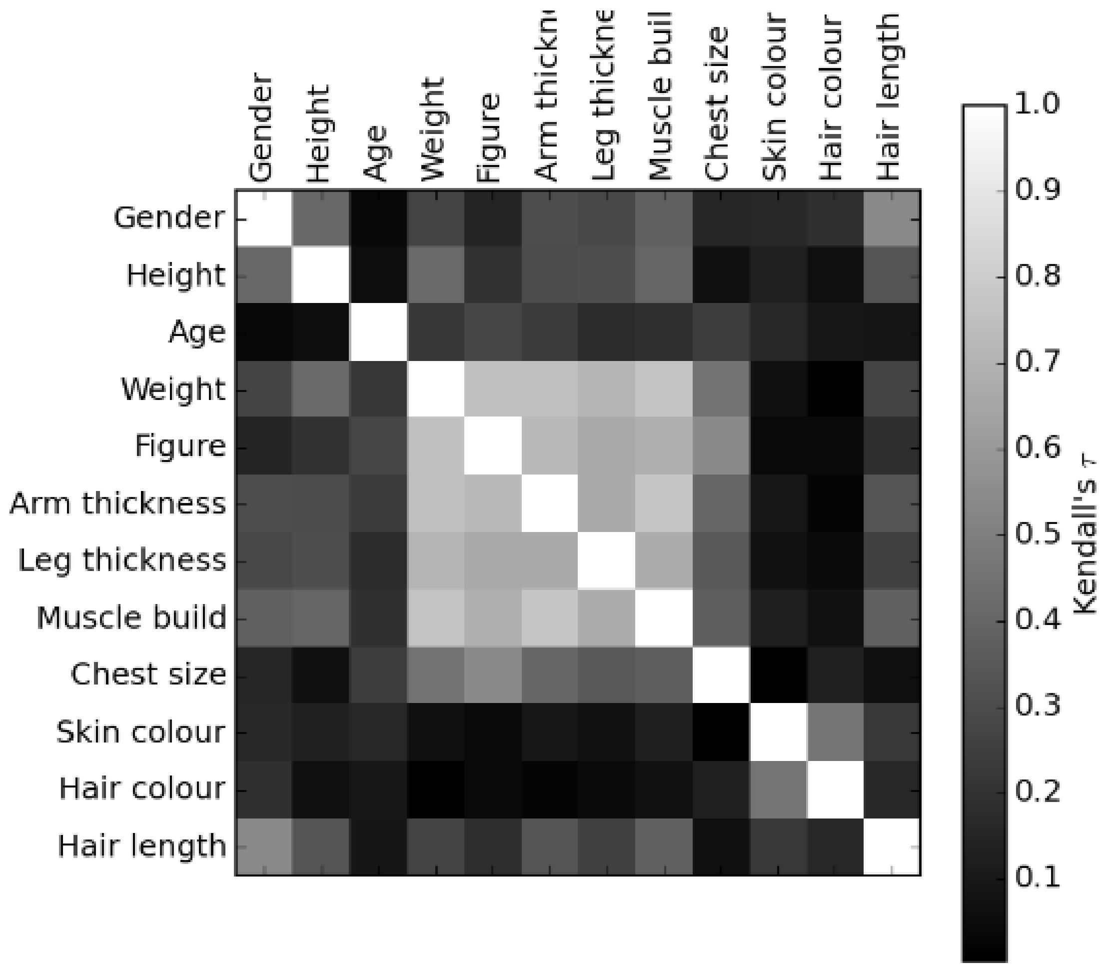
More labels and comparisons increase accuracy (expected)

Martinho-Corbishley, Nixon and Carter, *IEEE ISBA 2016*

Trait performance

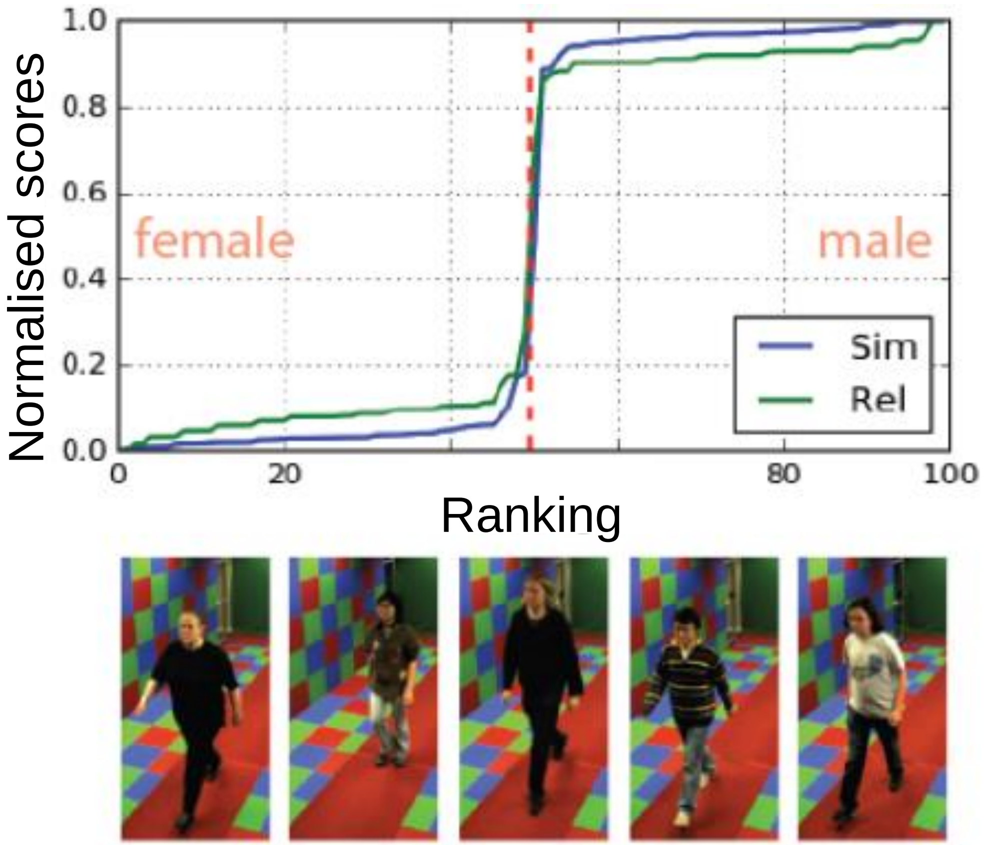


Normalised relative scores vs ranks

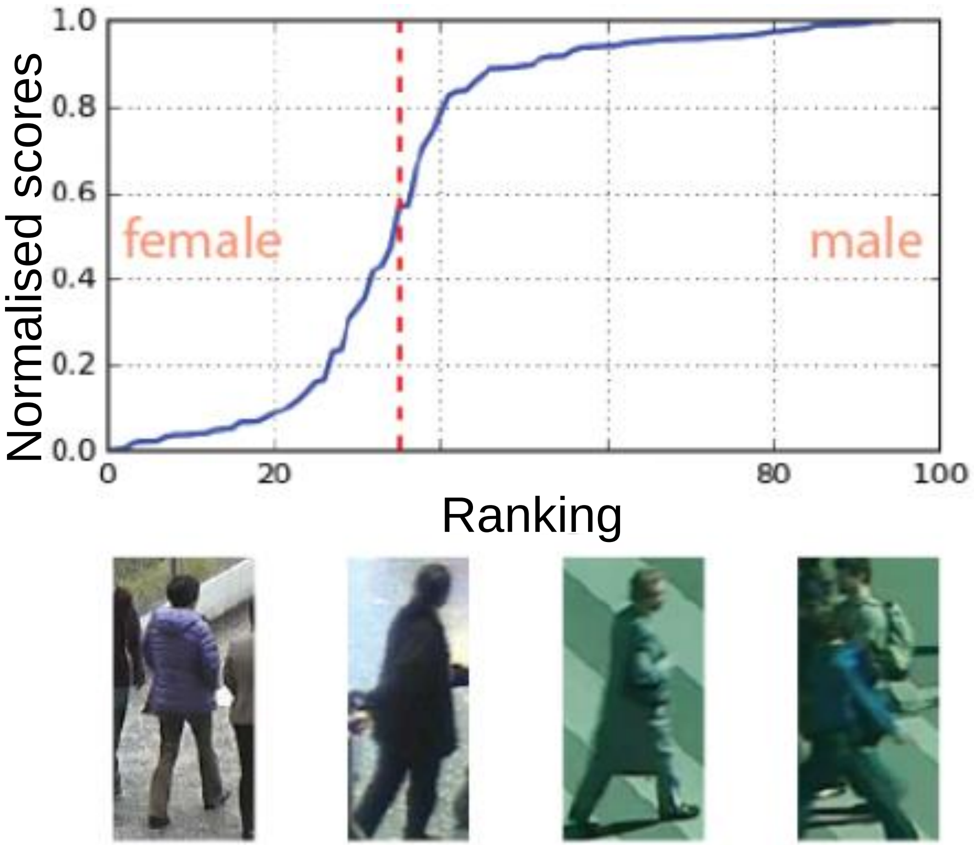


Kentall’s τ correlation

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

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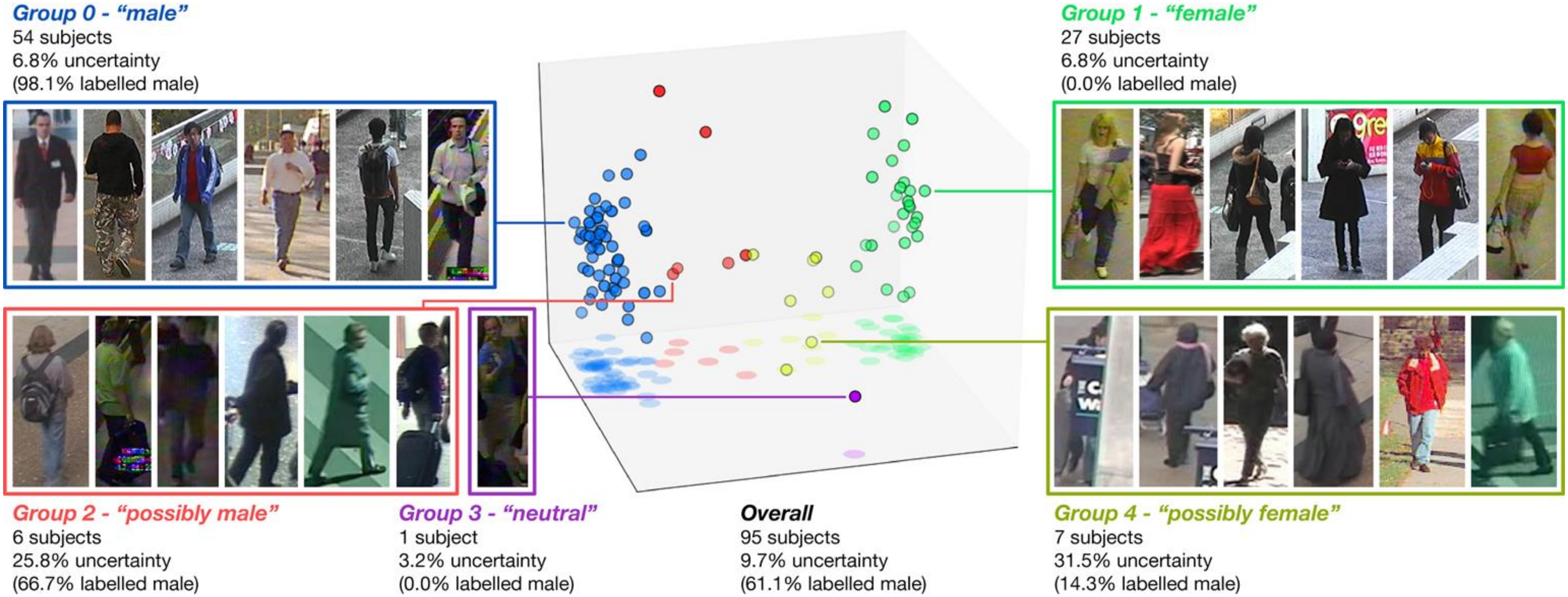
Analysing gender on PETA



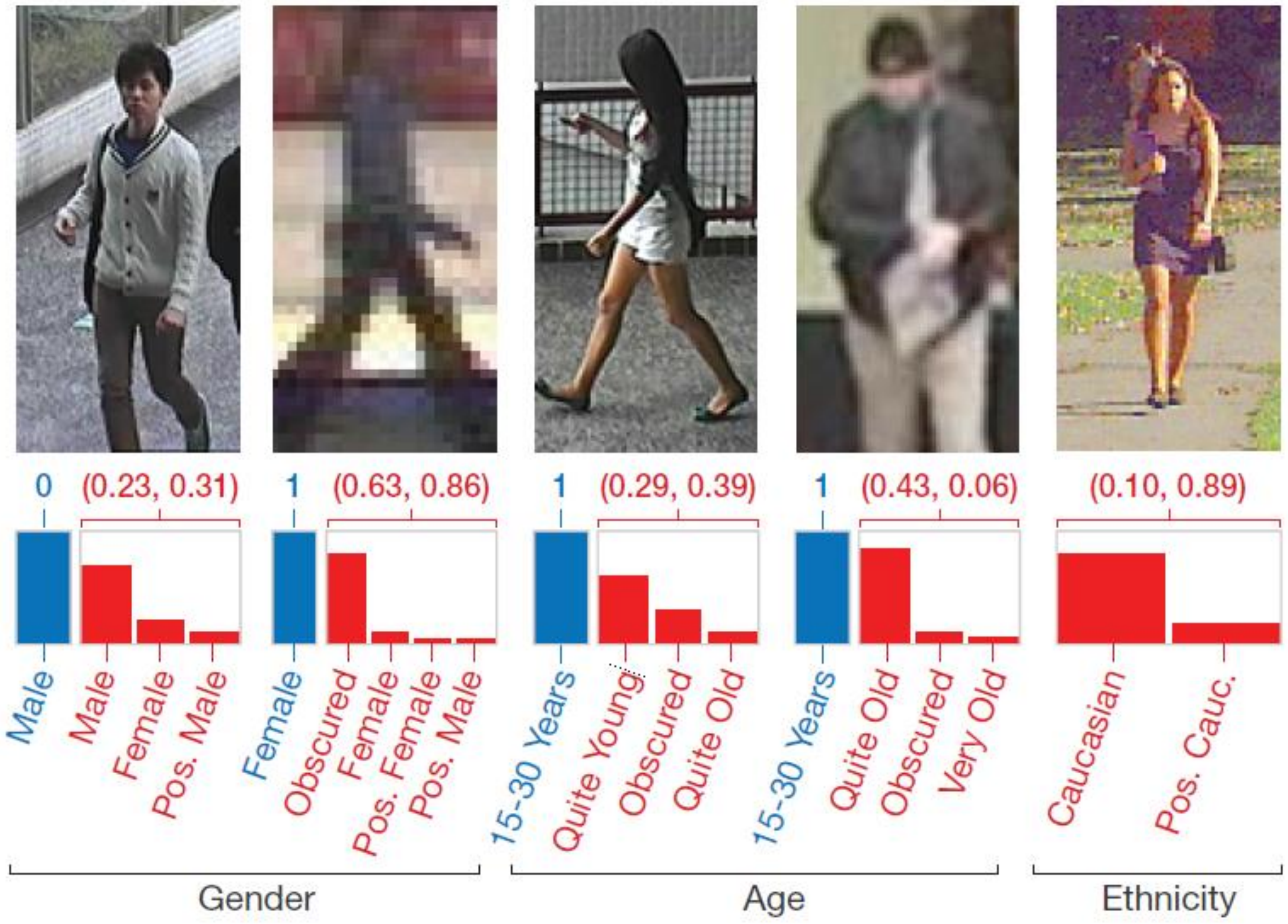
Martinho-Corbishley, Nixon and Carter, *BTAS* 2016

Superfine labels

Most ‘fine’ are actually coarse

Our comparative attributes are superfine

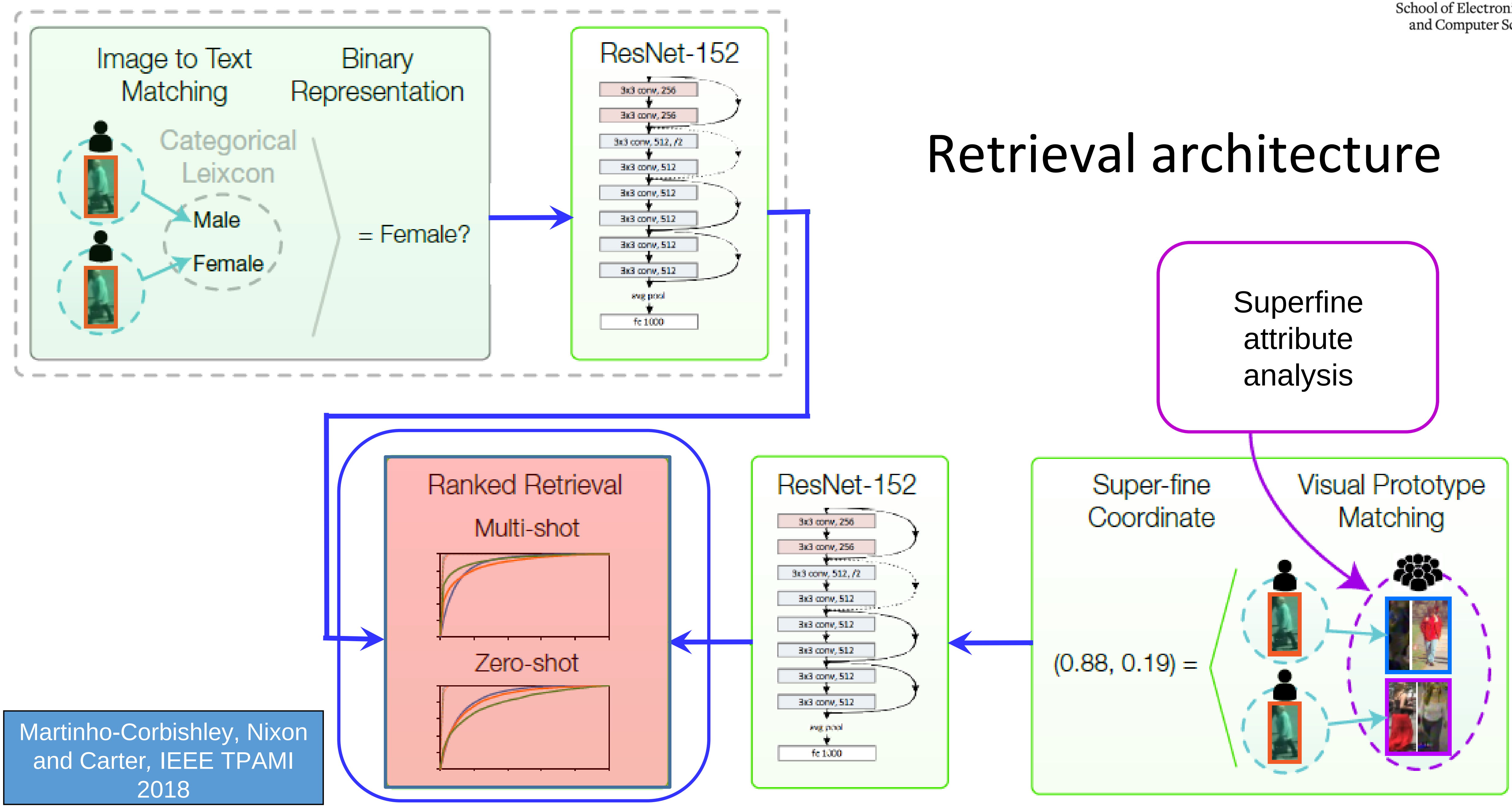
Comparison/ ranking gives many advantages



Martinho-Corbishley, Nixon and Carter, IEEE TPAMI 2018

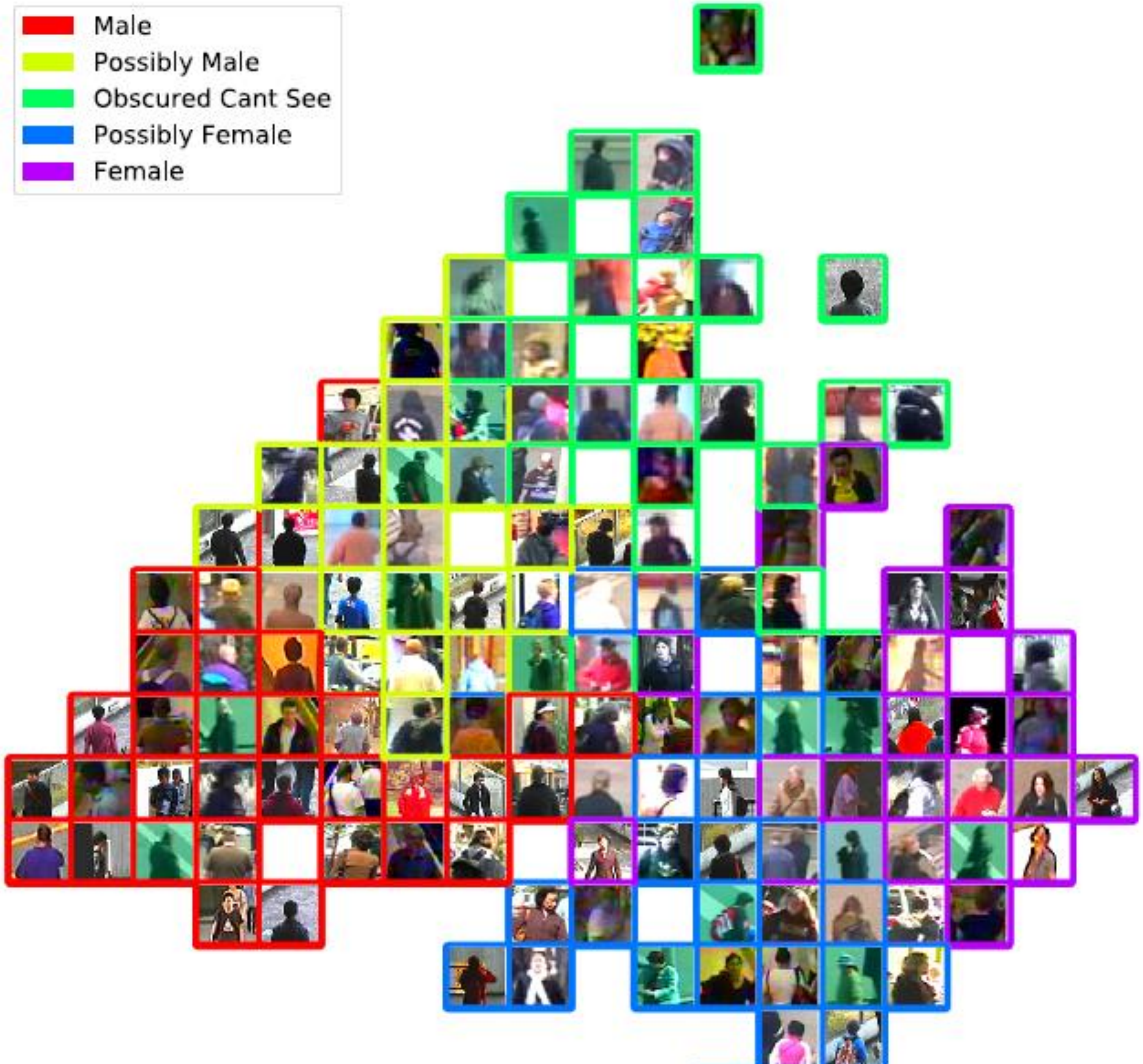
Conventional attribute-based analysis

Retrieval architecture



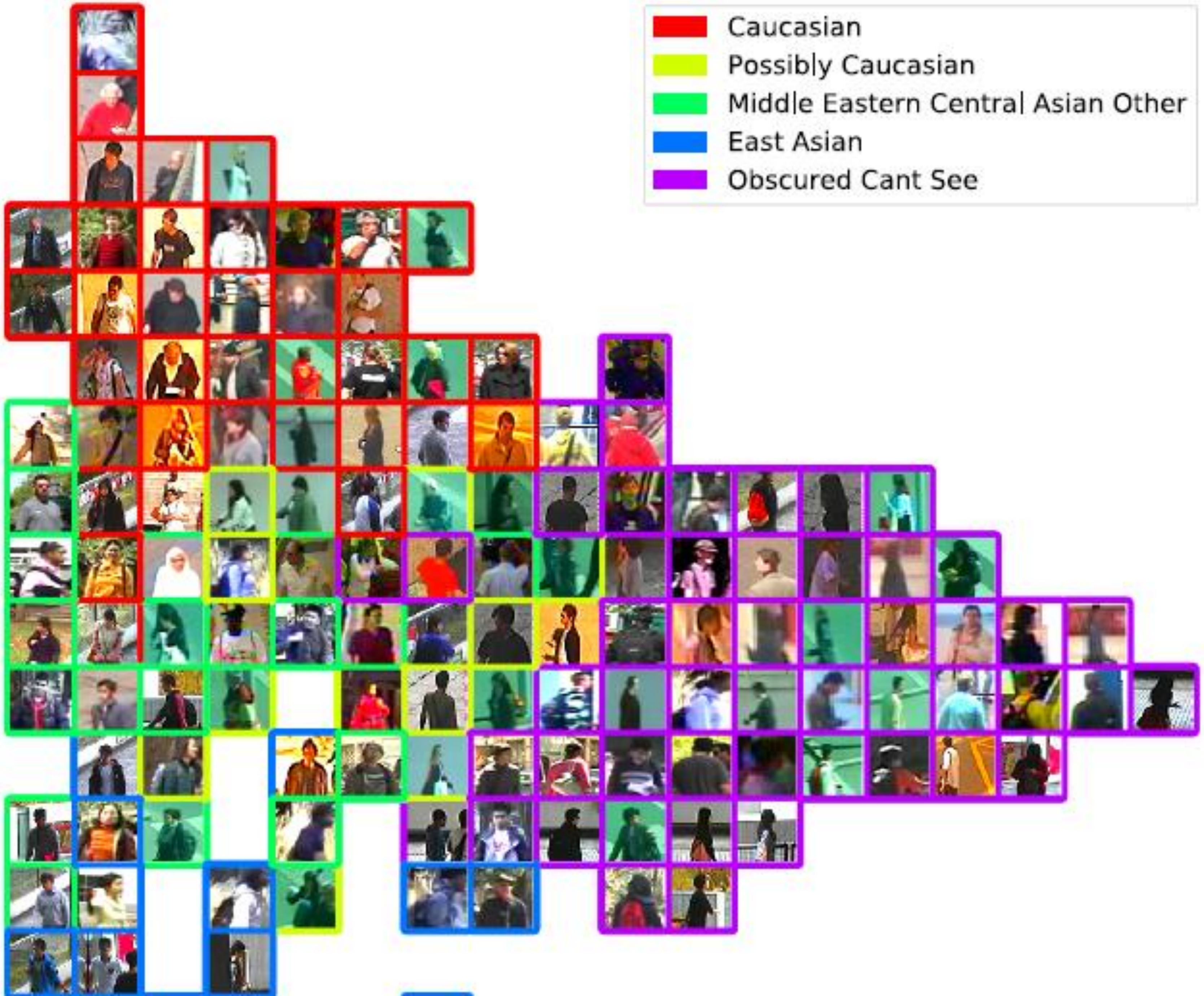
Martinho-Corbishley, Nixon and Carter, IEEE TPAMI 2018

Gender



Martinho-Corbishley, Nixon and Carter, IEEE TPAMI 2018

Ethnicity



Martinho-Corbishley, Nixon and Carter, IEEE TPAMI 2018

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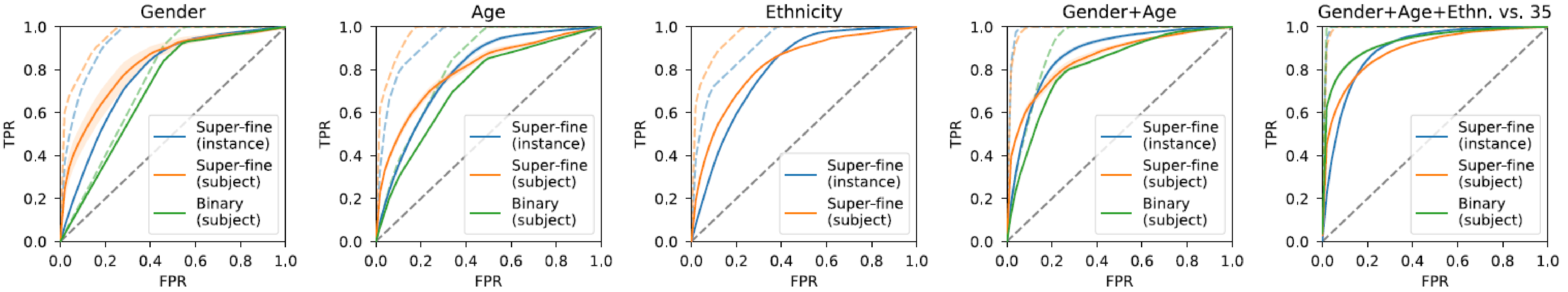
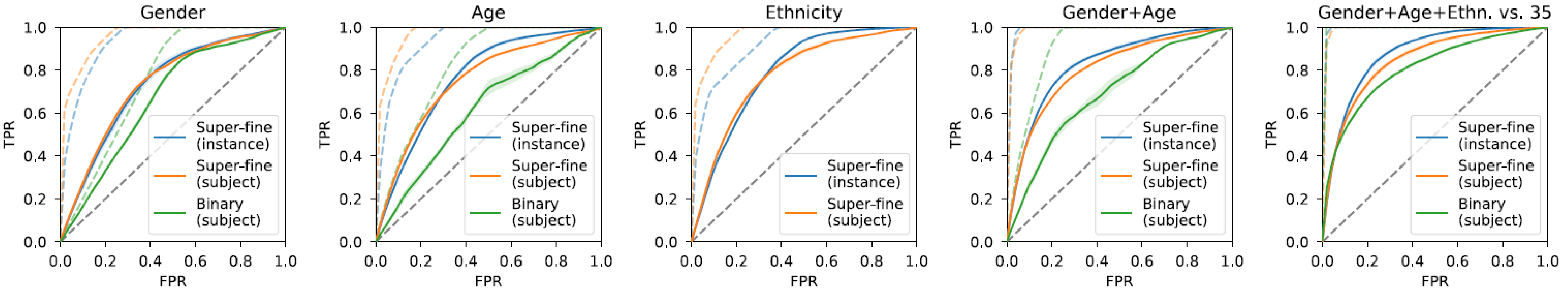
Overall



(a) Multi-shot scenario (instance-level set-split criteria).



(b) Zero-shot scenario (subject-level set-split criteria).

Martinho-Corbishley, Nixon and Carter, IEEE TPAMI 2018

Face

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

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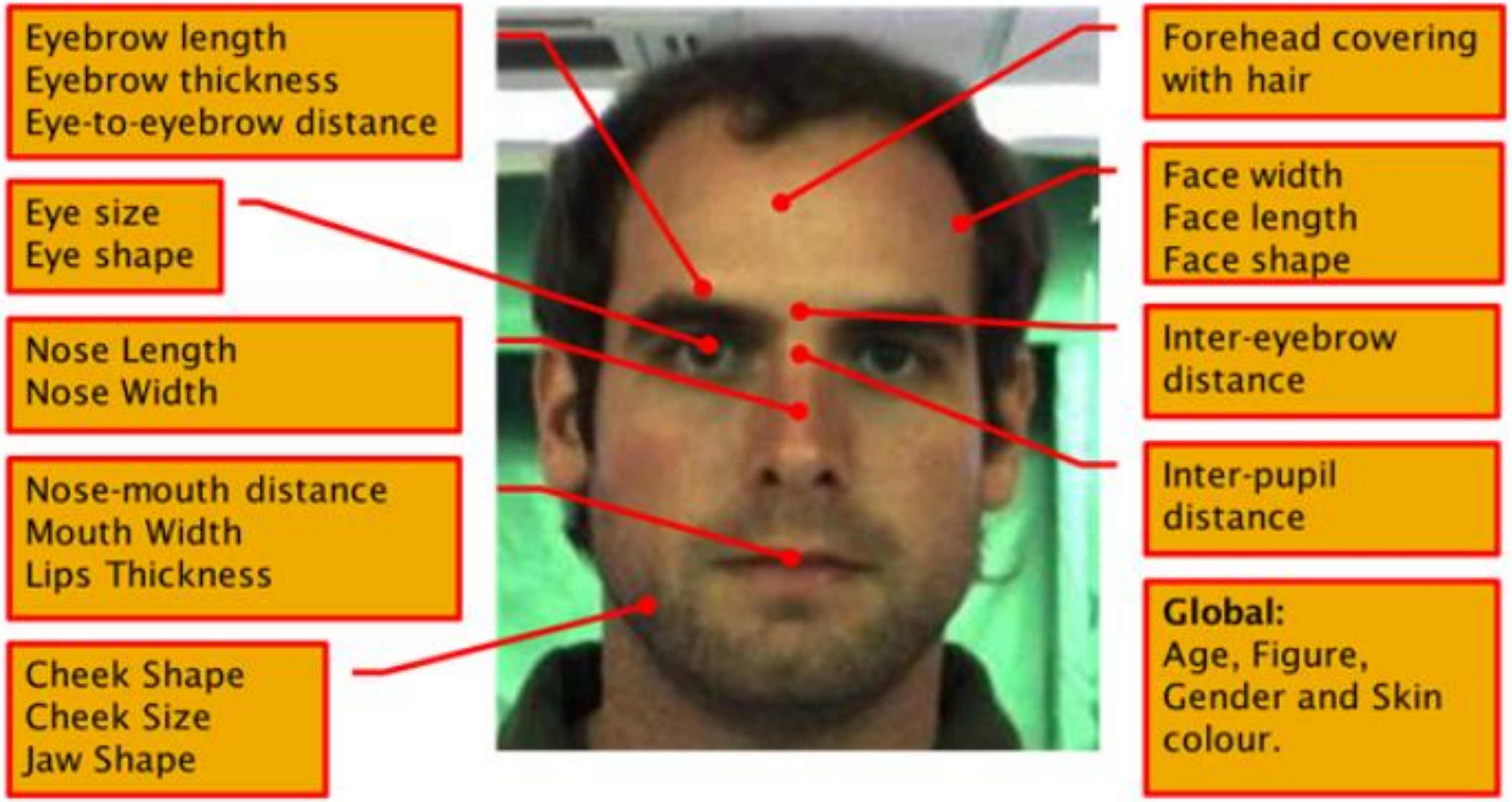
Analysing gender (??!!)

- Gender?

Subject	1	2	3
			
Gender			A. Male B. Female

Recognition by face attributes

Categorical labels
(gender, age +...)
Comparative labels



Reid and Nixon, *IEEE ICB 2013*

Almudhahka, Nixon and Hare, *IEEE ISBA 2016*

Recognition by face via comparative attributes on LFW

	Collected	Inferred	Total
Traits comparisons	241560	132879504	133121064
Subjects' comparisons	10065	5536646	5546711
Average number of comparisons per subject	4.98	1371.1	N/A
Number of annotators	9901		

Almudhahka, Nixon and Hare, *IEEE BTAS 2016*

Compression of 5 point scale: recognition by comparative face labels

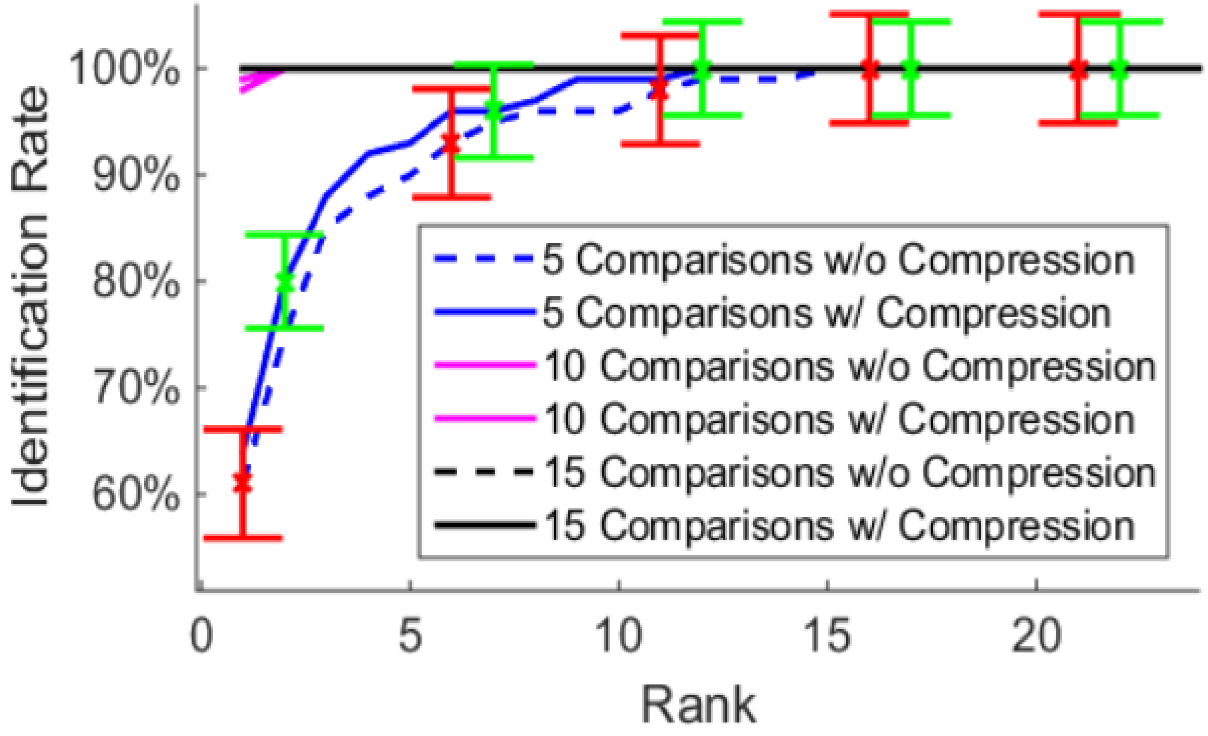
Label compression improves recognition

Data is Southampton tunnel

New system just 3:

bigger, same, smaller

Had we previously added categorical to comparative?



Almudhahka, Nixon and Hare, *IEEE ISBA 2016*

Crossing the semantic gap: estimating relative face attributes

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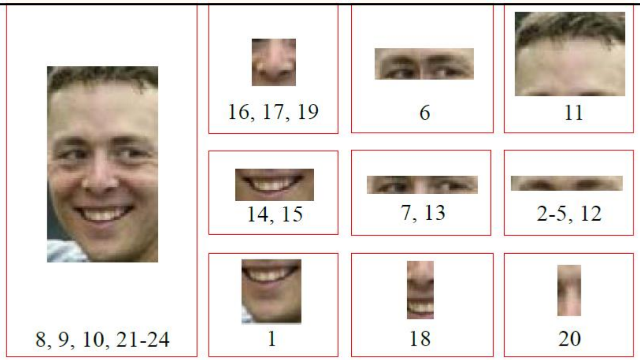
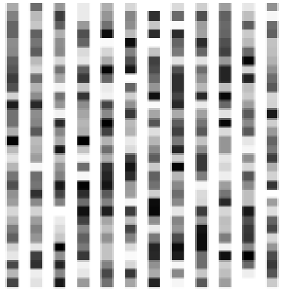


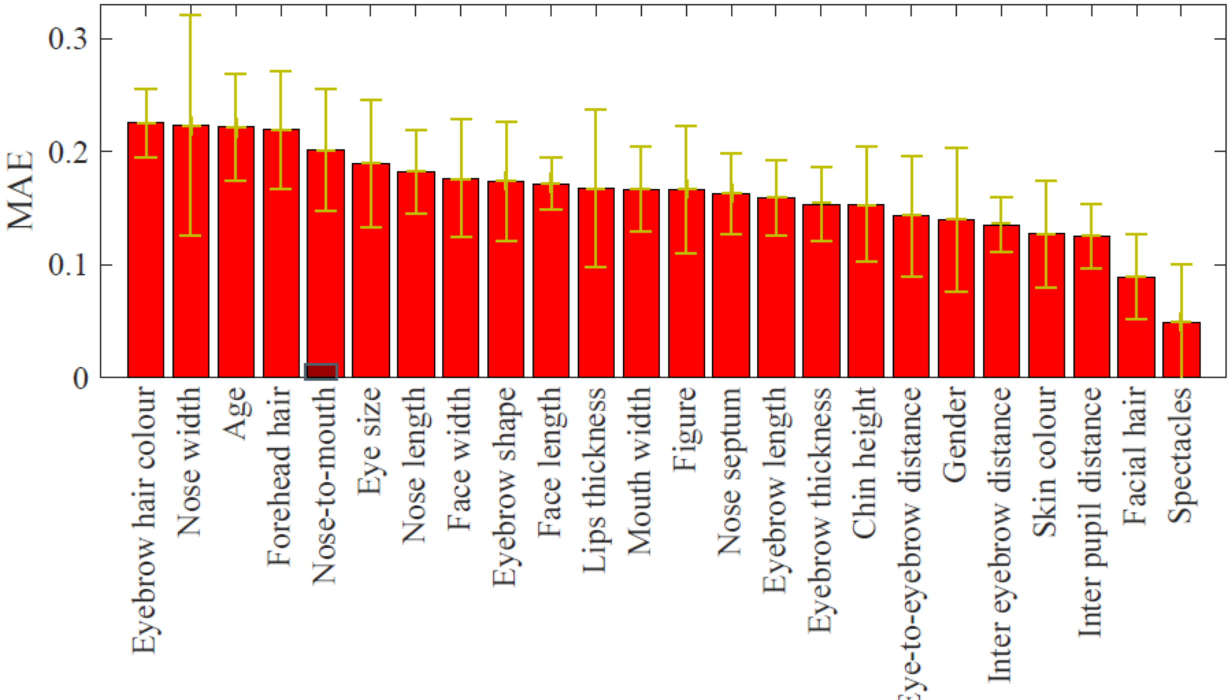


Face alignment

Constrained Local Models/ AAMs

Segmented face parts

Features HOG/GIST/ULBP



Estimation of comparative labels

Almudhahka, Nixon and Hare, *IEEE TIFS 2017*

Estimating face attributes

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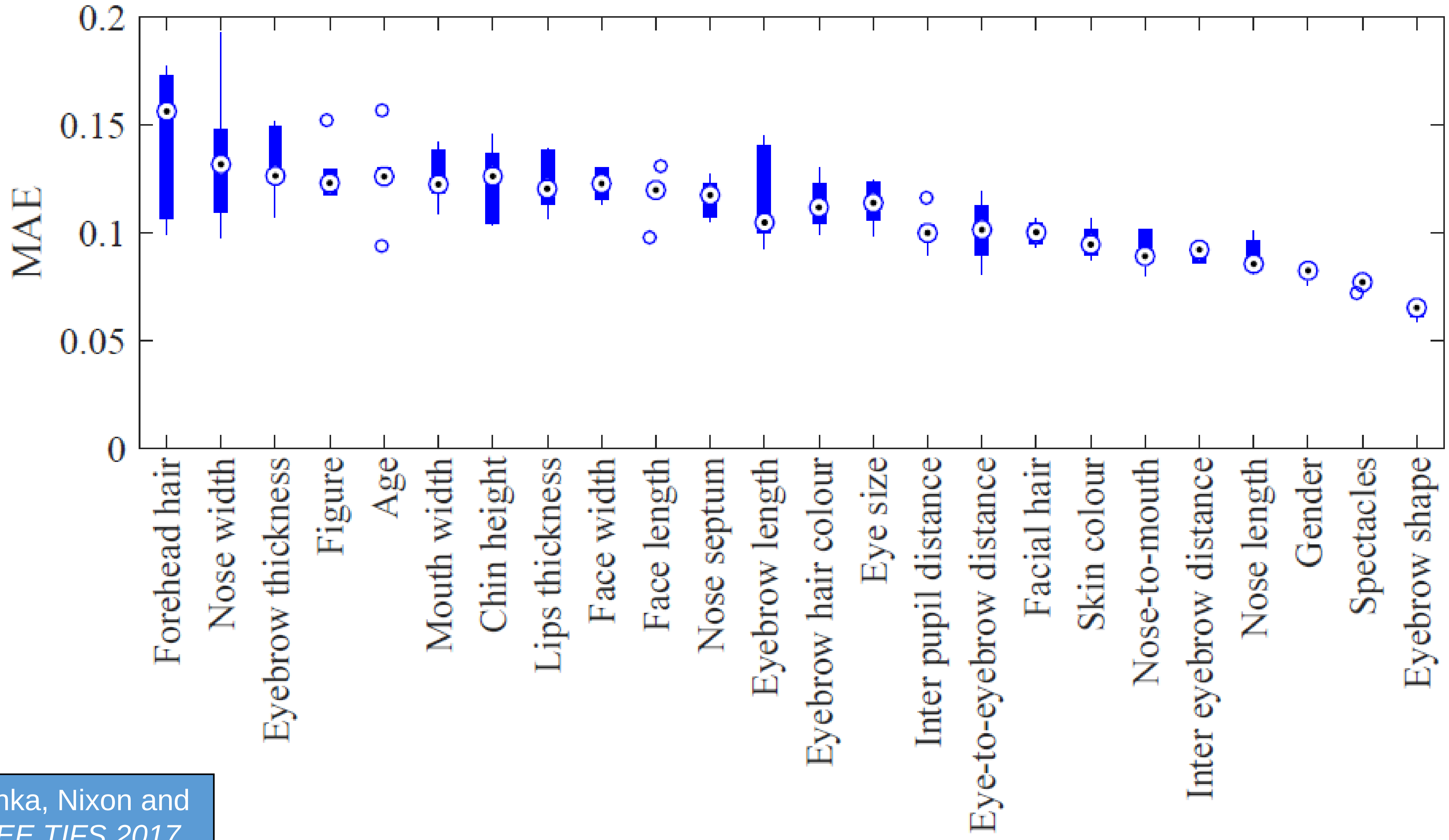

Almudhahka, Nixon and Hare, *IEEE TIFS 2017*

Ranking subjects (images) by estimated face attributes

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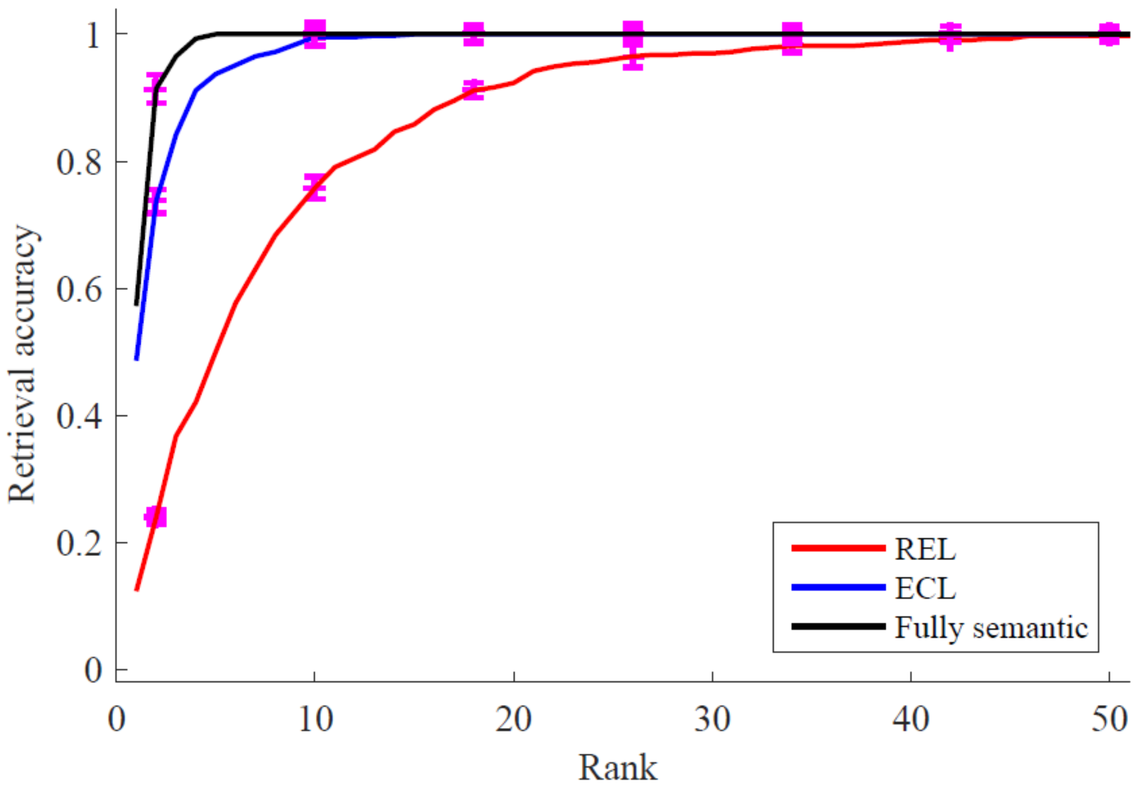
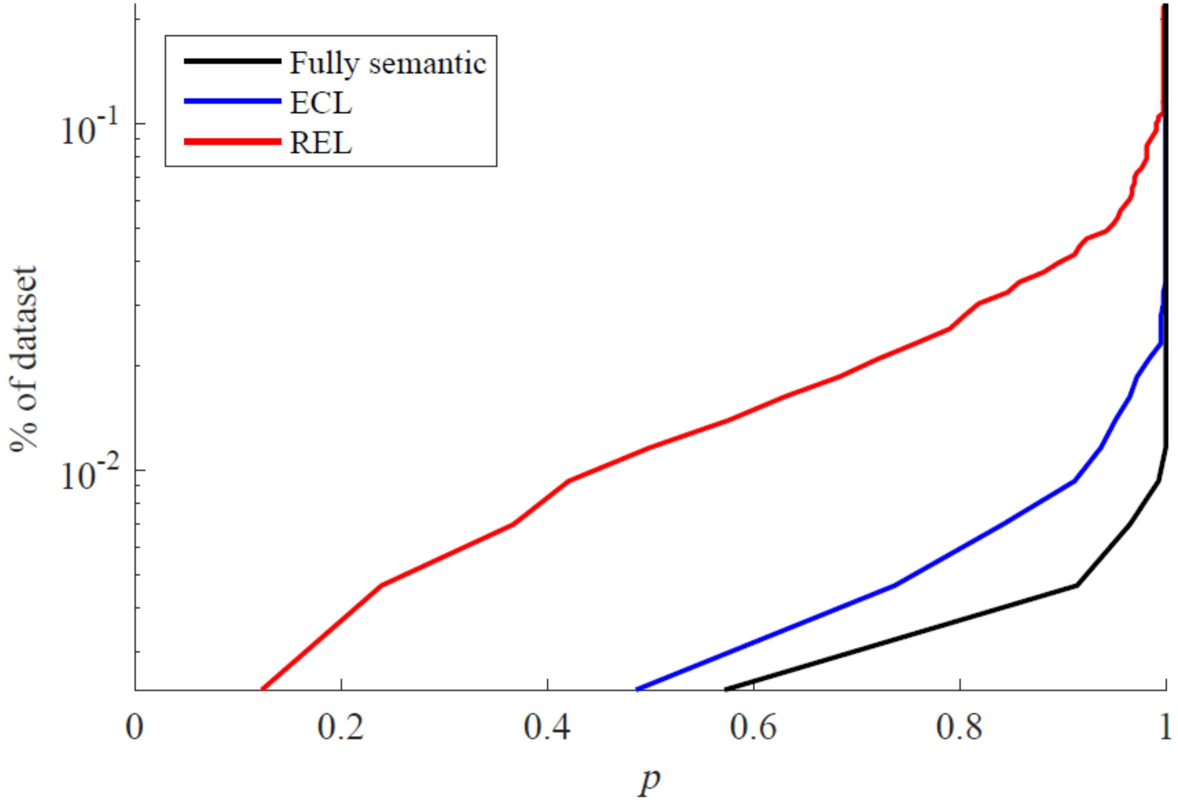
(a) Age (b) Gender

Almudhahka, Nixon and Hare, *IEEE TIFS 2017*

Recognition on LFW



Retrieval performance



Compression of 430 subject LFW-MS4 dataset

Almudhahka, Nixon and Hare, *IEEE TIFS 2017*

Clothing

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

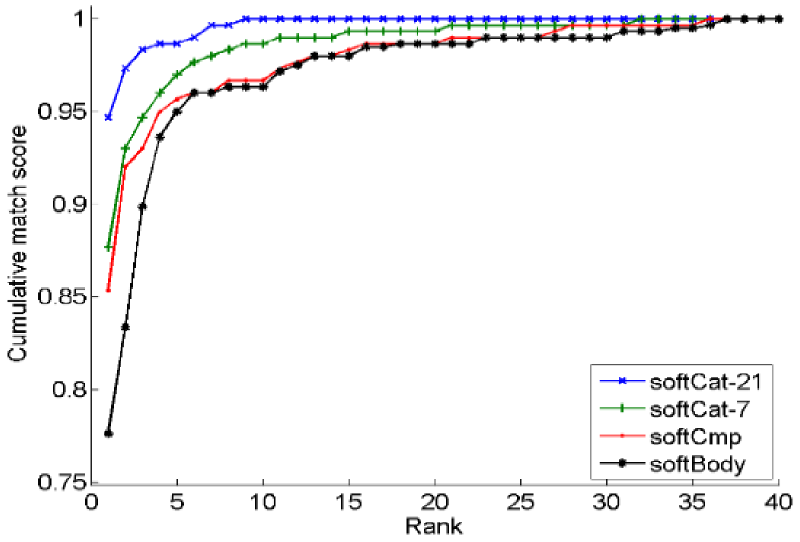
Generate descriptions

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

Subject recognition, by clothing

- Clothing generally unique
- Shakespeare
  - *“Know'st me not by my clothes?”*
  - (Cymbeline Act 4 Scene 2)
- Short term biometric
- Has strong invariance
- Links with computer vision and automatic clothing analysis/ re-identification



Jaha and Nixon, *IEEE IJCB 2014*

Clothing alone and in addition to body descriptions

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By clothing alone 100% accuracy achieved at rank:

tradCat-21: 29 tradCat-7: 37 tradCmp: 63

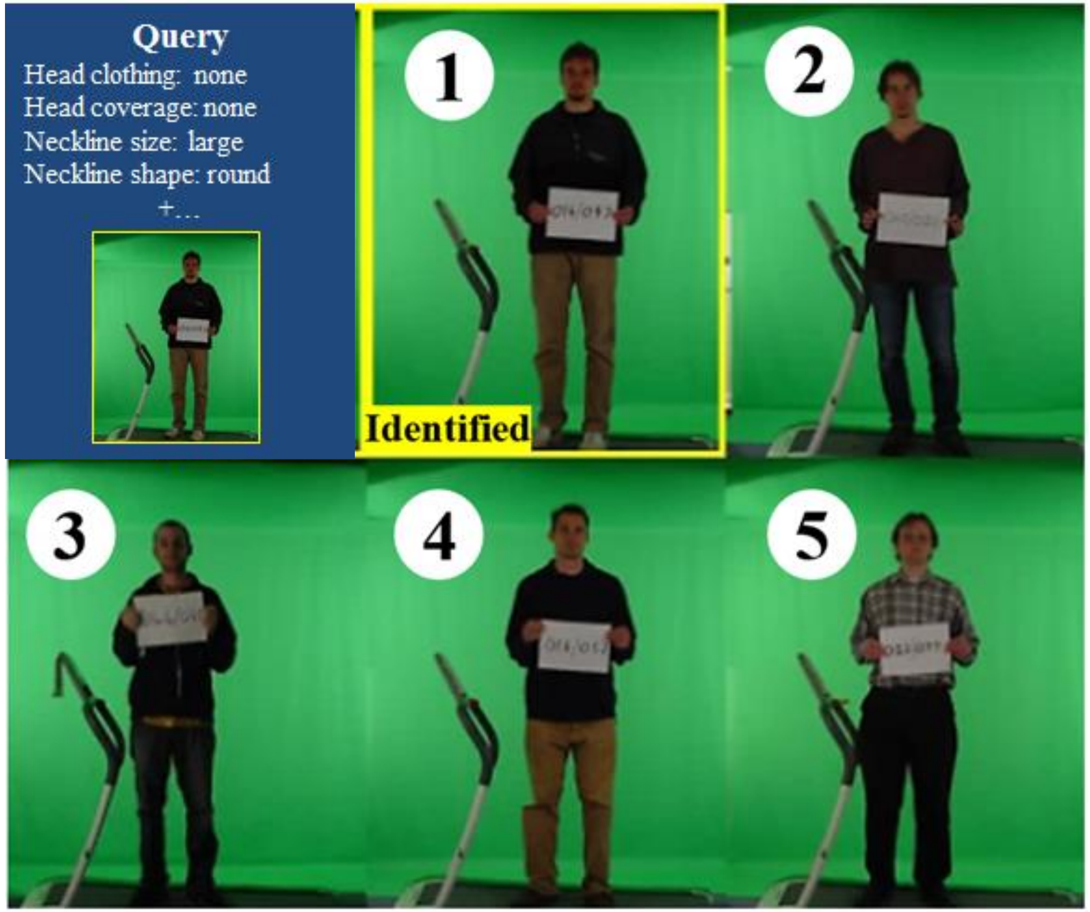
As expected, less power than body

Adding clothing to body allows much greater power

Approach	Top rank	AVG sum match scores up to rank		100% accuracy achieved at rank	EER	AUC	d'
	=1	=10	=128				
softBody	0.78	0.92	0.991	37	0.087	0.028	2.785
softCat-21	**0.95**	**0.99**	**0.999**	**9**	**0.050**	**0.014**	2.634
softCat-7	0.88	0.96	0.996	32	0.063	0.018	2.814
softCmp	0.85	0.94	0.994	36	0.080	0.026	**2.827**

Jaha and Nixon, *IEEE IJCB 2014*

Recognition by clothing

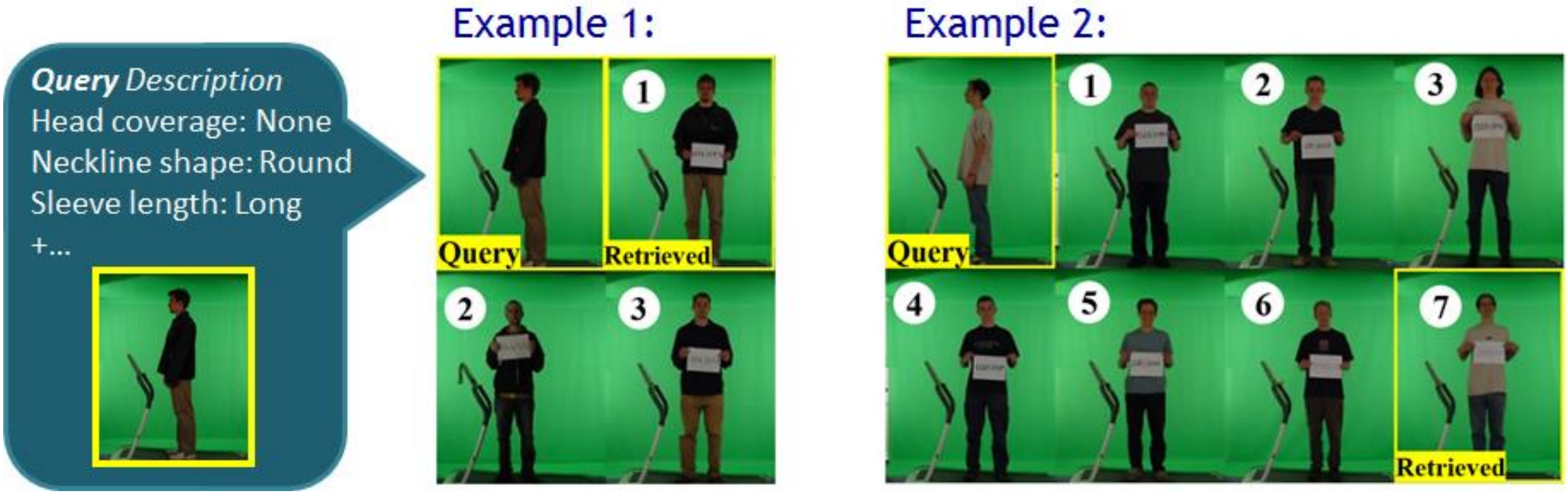


Good match

Poor matches

Jaha and Nixon, *IEEE IJCB 2014*

Viewpoint invariant recognition, by clothing



Clothing has ability to handle 90 degree change

Jaha and Nixon, *IEEE ICB 2015*

Automated clothing: grabcut person/ clothing initialisation

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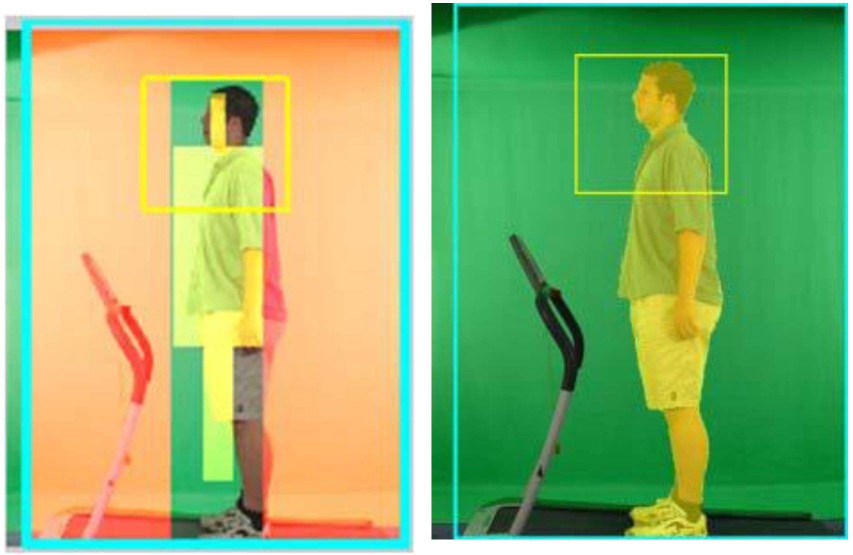
- Color models used to initialize the Grabcut person extractor
- Color models arranged to highlight foreground/ background
- Result highlighted for (later) subject segmentation



Jaha and Nixon, *IEEE TIFS 2016*

Automated clothing labelling on CAT

Jaha and Nixon, *IEEE TIFS 2016*

Fusion (or what if one is hidden…)

Image of crime

Generate description

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

Eyewitness statement
"24 year old male average height wearing 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

Fusion for recognition – traditional soft

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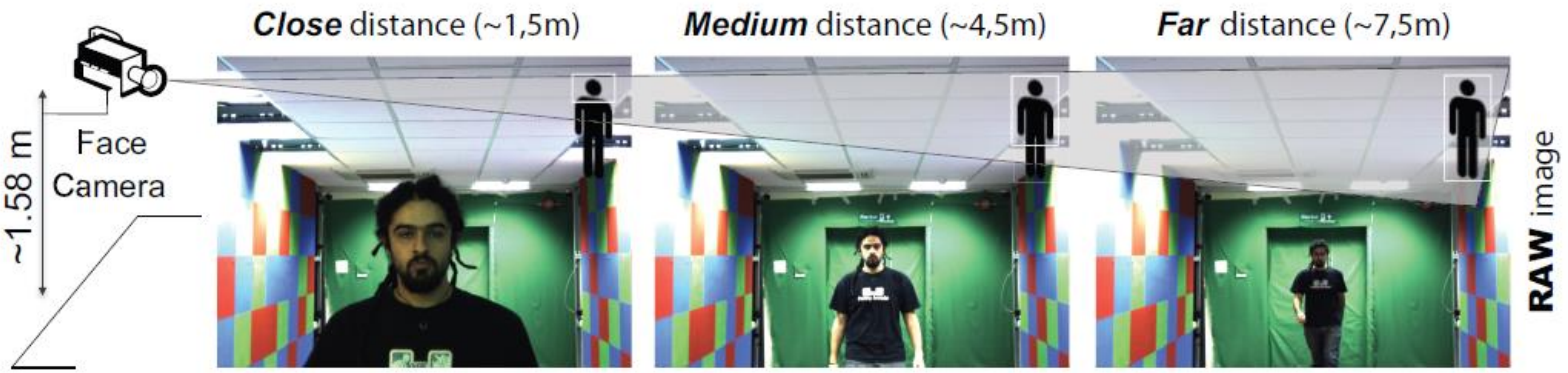

Tome, Fierrez, Vera-Rodriguez and Nixon, *IEEE TIFS* 2014

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Fusion for recognition - data

(a) Laboratory -- close

(b) Subject extraction

(c) Outdoor background

(d) Synthetic -- close

(a) 2m

(b) 4.5m

(c) 7m

Guo, Nixon and Carter ICPR 2018

Fusion for recognition -body

TABLE I BODY ATTRIBUTES AND CORRESPONDING COMPARATIVE LABELS

Body traits	Labels
Gender	More feminine, Same, More masculine
Age	Older, Same, Younger
Height	Taller, Same, Shorter
Weight	Fatter, Same, Thinner
Shoulder shape	More square, Same, Rounder
Hair colour	Lighter, Same, Darker
Hair length	Shorter, Same, Longer
Neck length	Shorter, Same, Longer
Humpback	More straight, Same, More curved
Arm length	Longer, Same, Shorter

Guo, Nixon and Carter ICPR 2018

Fusion for recognition -face

TABLE II FACE ATTRIBUTES AND CORRESPONDING COMPARATIVE LABELS

Face traits	**Labels**
Eyebrow shape	More straight, Same, More curved
Nose shape	More flatter, Same, More protruding
Forehead	Straighter hairline, Same, More receded hairline
Eyes	Smaller, Same, Larger
Ears	More hidden, Same, More evident
Skin colour	Lighter, Same, Darker
Face size	Shorter, Same, Longer
Face	More bony, Same, Fleshier
Lips	Thinner, Same, Thicker
Chin and jaw	More angular, Same, Rounder

Guo, Nixon and Carter ICPR 2018

Fusion for recognition -clothing

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TABLE III CLOTHING ATTRIBUTES AND CORRESPONDING CATEGORICAL LABELS

Clothing traits	Labels
Upper body clothing category	Jumper, T-shirt, Shirt, Blouse, Sweater, Coat, Hoodie, Other
Lower body clothing category	Trouser, Skirt, Dress
Any attached object category	None, Bag, Gloves, Hat, Scarf, Necktie, Other
Clothing style	Well-dressed, Business, Sporty, Fashionable, Casual, Other
The majority colour of upper body	Grey, Black, White, Jeans blue, Others
The majority colour of lower body	Grey, Black, White, Jeans blue, Others
Face coverage	Yes, No
head coverage	Yes, No
Presence of belt	Yes, No, Unsure
Wear glasses	Yes, No

Fusion for recognition –single mode

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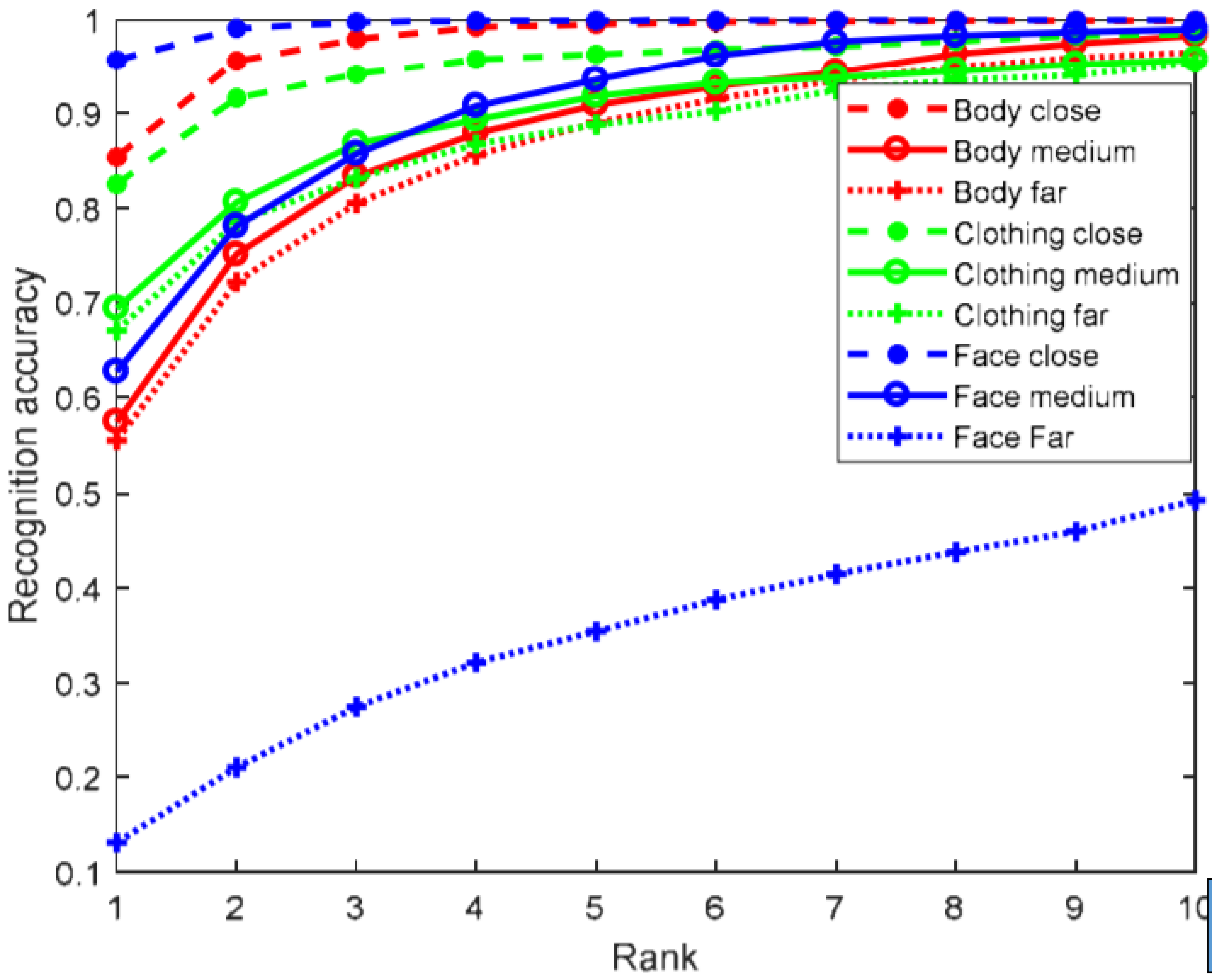

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Fusion for recognition – modalities and distance

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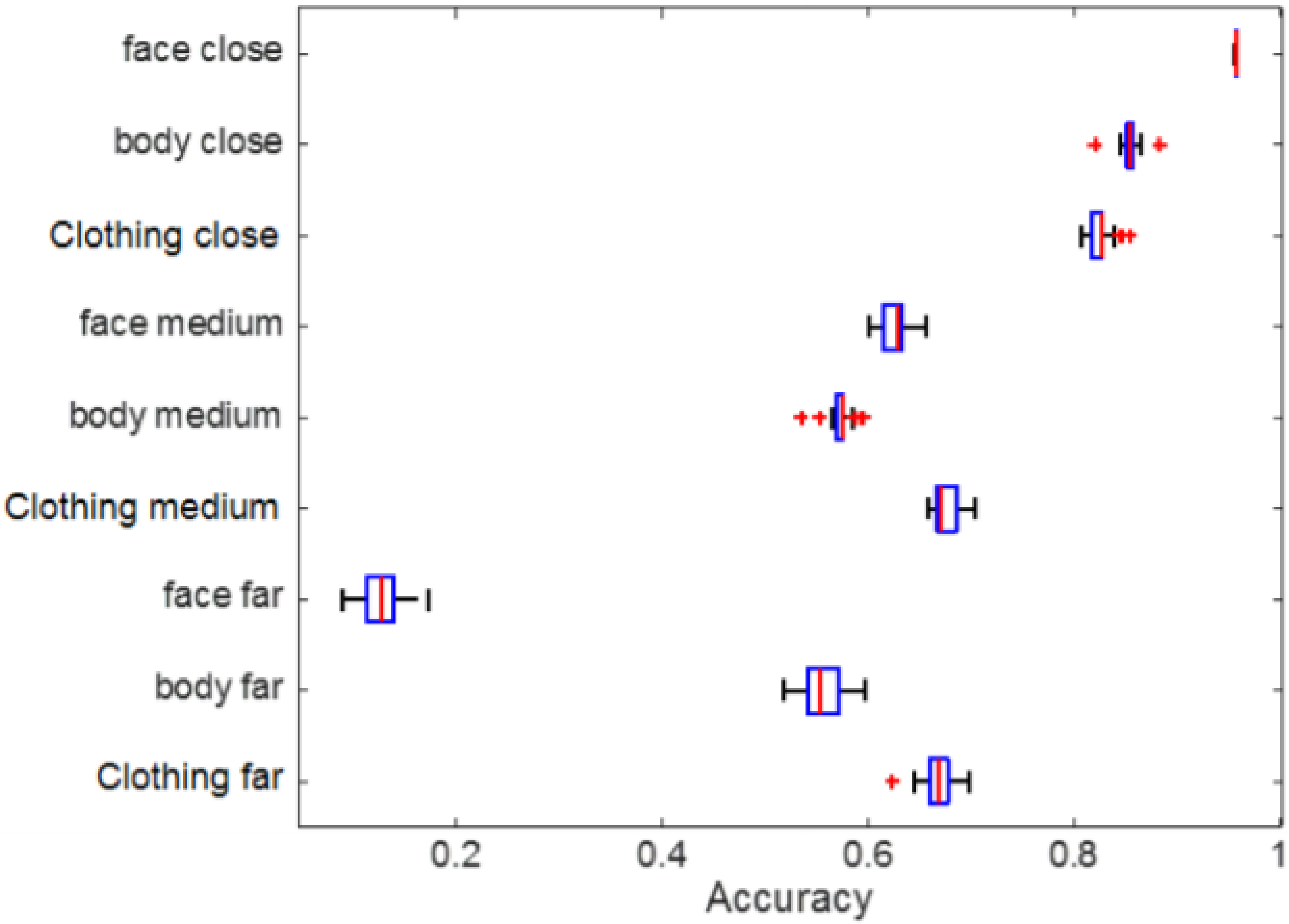

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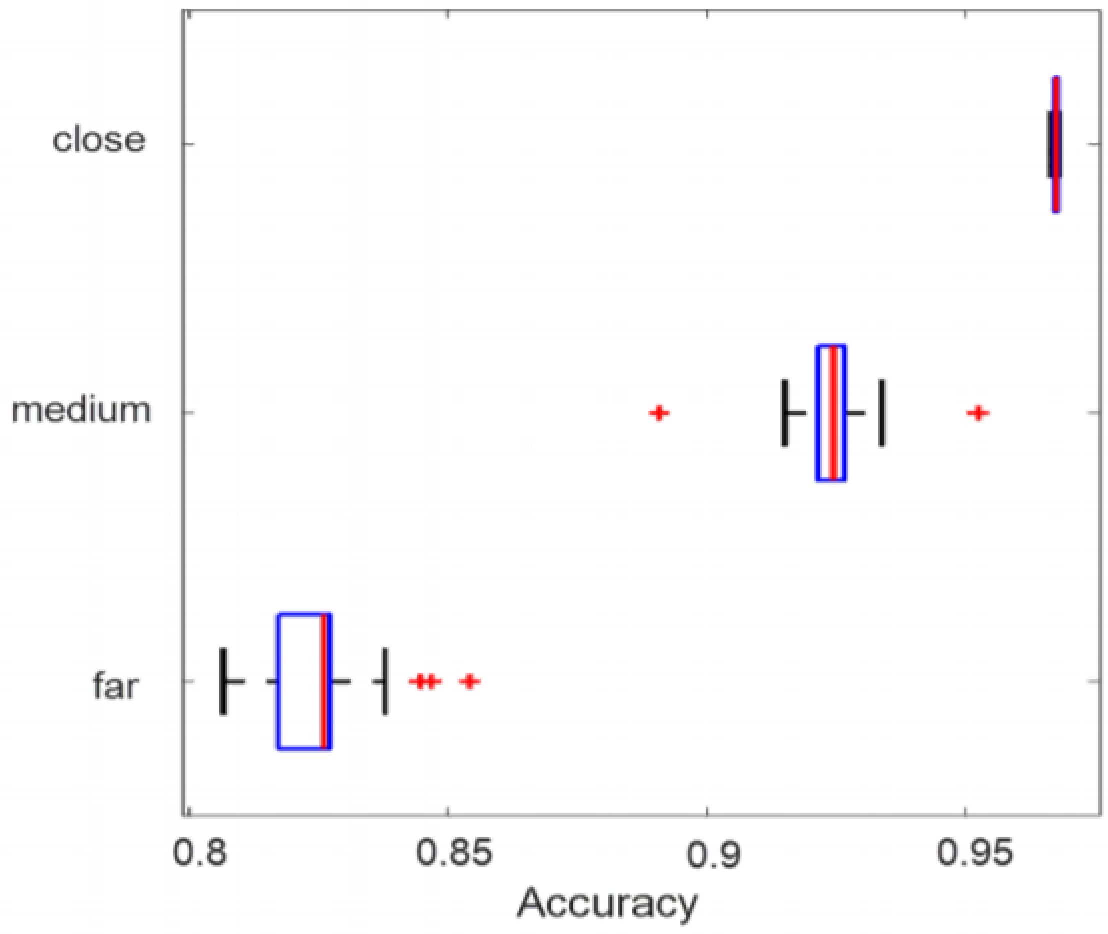
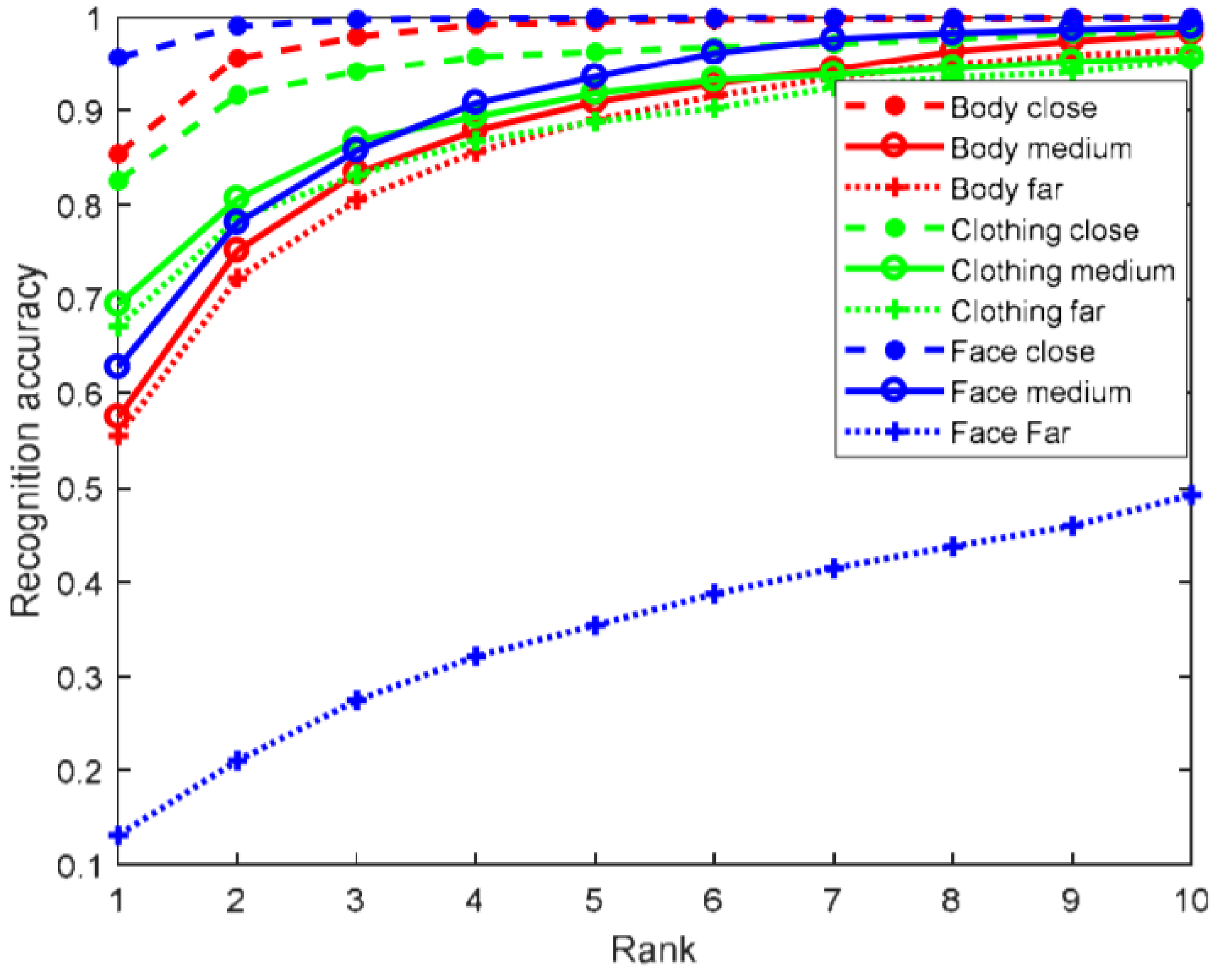
Fusion for recognition – fusion at 3 distances



Fusion



Single (for comparison)

Fusion for recognition – fusion methods

	Close		Medium		Far	
	Accuracy	*EER*	*Accuracy*	*EER*	*Accuracy*	*EER*
Bayesian theory [7]	96.3%	3.84%	84.6%	4.15%	78.1%	4.26%
Log likelihood ratio [9]	96.1%	3.91%	87.7%	4.02%	76.5%	4.29%
Logistic regression [12]	96.4%	3.86%	82.3%	4.23%	75.5%	4.33%
Nonlinear weight ranks [15]	96.9%	3.85%	86.2%	4.11%	79.3%	4.24%
PAV based [16]	97.0%	3.83%	86.0%	4.09%	79.1%	4.24%
Rank-score fusion	97.3%	3.77%	92.5%	3.88%	82.6%	4.17%.

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AVSS 2018
15th IEEE International Conference on Advanced Video and Signal-based Surveillance
27-30 November 2018, Auckland, New Zealand

Semantic Person Retrieval in Surveillance Using Soft Biometrics

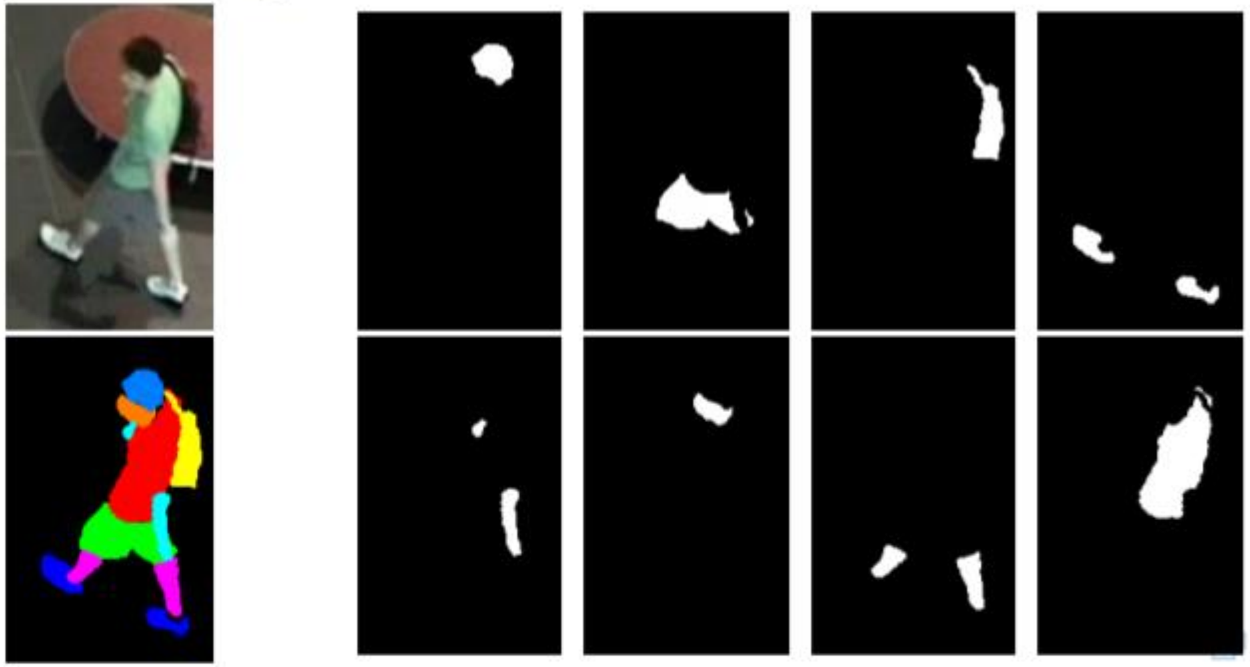
Michael Halstead, Simon Denman, Clinton Fookes, YingLi Tian, Mark Nixon

November 27th, 2018

Task 1

Data:

- Separated into training (520 images) and evaluation (196 images) sets.
- Subjects were captured across two locations on a university campus, using ten cameras.
- Each "image" has an RGB image, a soft biometric query, and in the training set a semantic mask is included.



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Task 1

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- Leg and torso type as either long or short.
- Gender.
- Luggage (carrying or not).
- Pose (front, back, 45^o, or 90^o).

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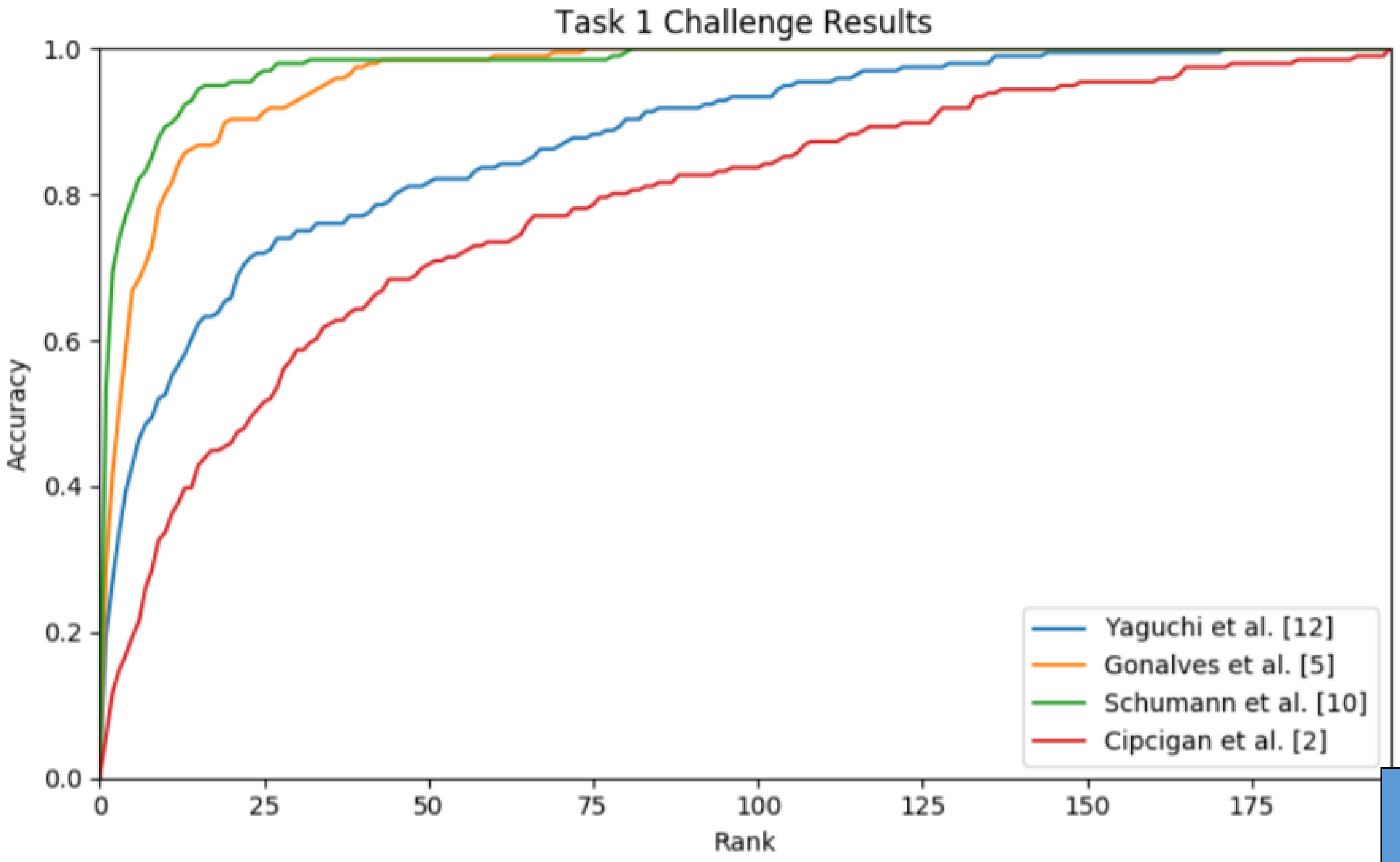
Task 1 Performance

- Unsurprisingly all techniques based around deep learning.
- Cipcigan et. al:
  - Used semantic segmentation to locate body parts;
  - Hand selected features and classifiers used on appropriate regions;
  - Only technique to not be solely deep learning.
- Gonalves et. al, Schumann et. al, and Yaguchi et. al:
  - Similar pipeline;
  - Trained DCNN (four for Schumman) adapted to attribute prediction.

The results of Task 1 - CMC curve and rank performance.



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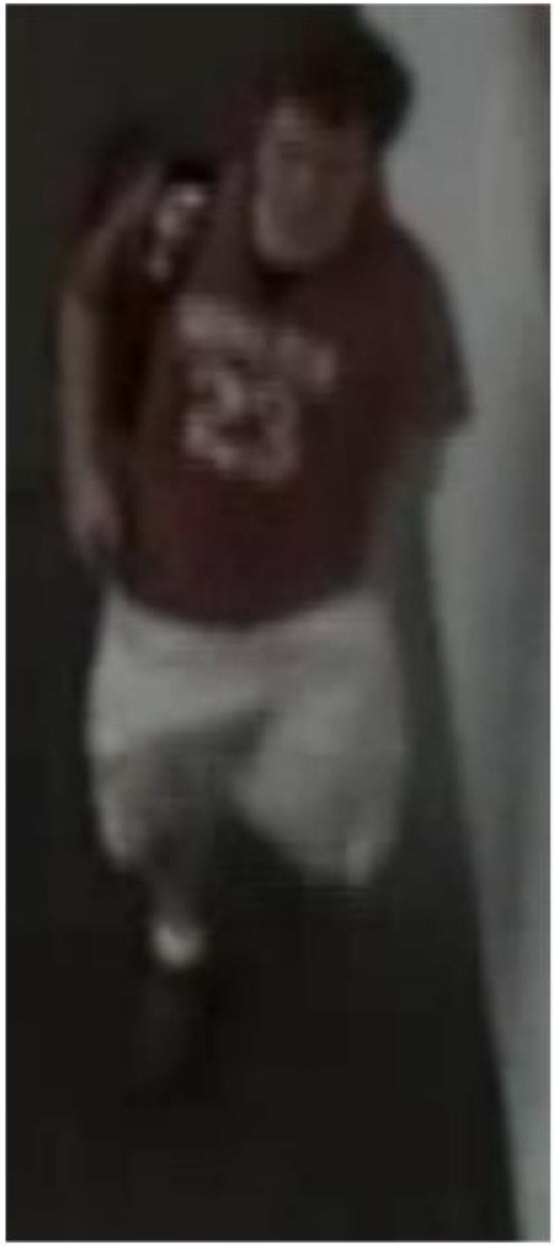
Task 1 Performance: Difficult Subjects



- Subject 111, average rank 66.
- Query: Male, short sleeved brown and white shirt, grey shorts, with luggage.
- Poor lighting conditions.
- Ambiguity in clothing colour.

Task 2

How is this different from Task 1?

- More inline with a surveillance situation.
- The query is used to search a video for the desired subject.
- Multiple potential pedestrians in a scene.
- Varying levels of crowd density, crowd flow, occlusions, and illumination.

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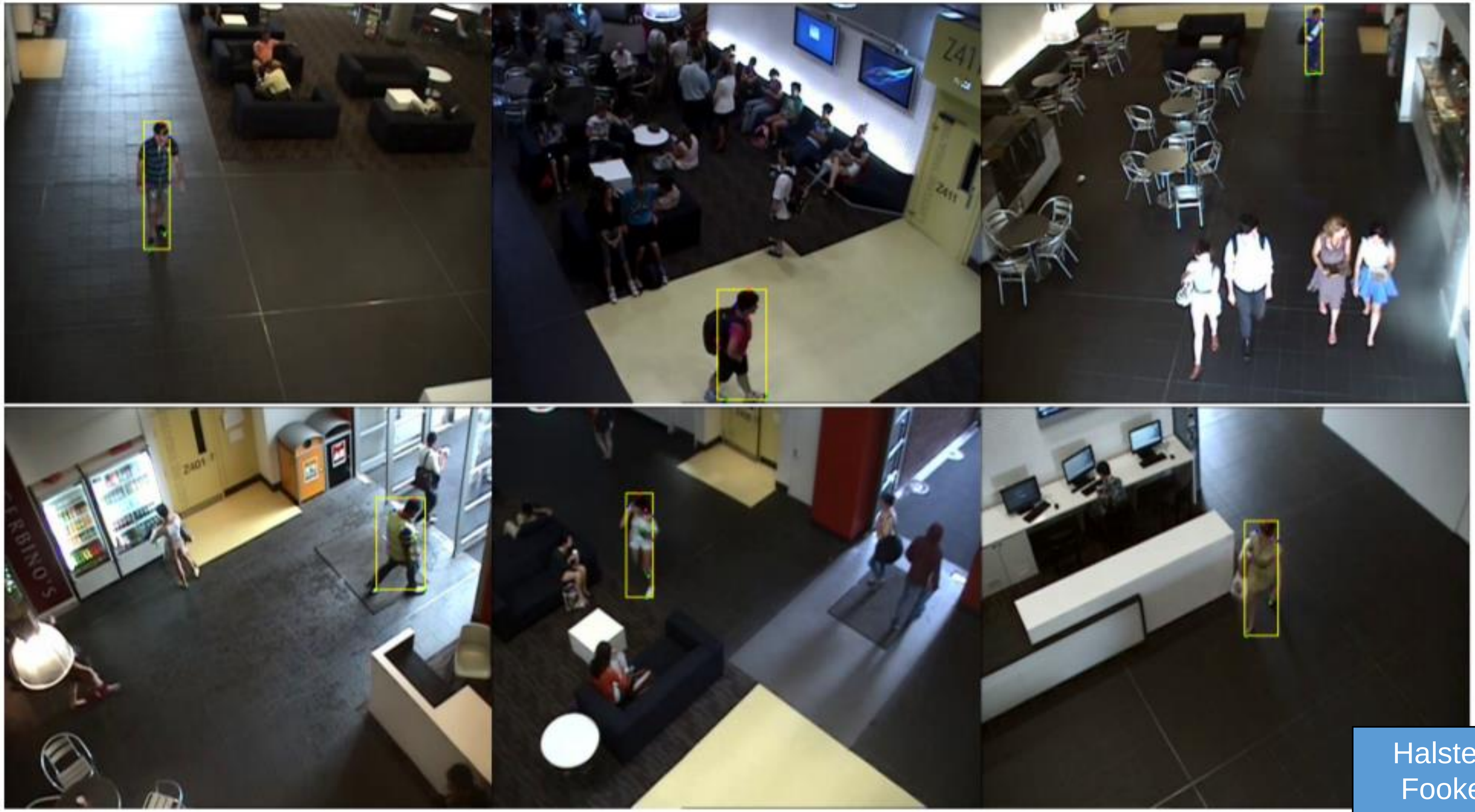
Task 2



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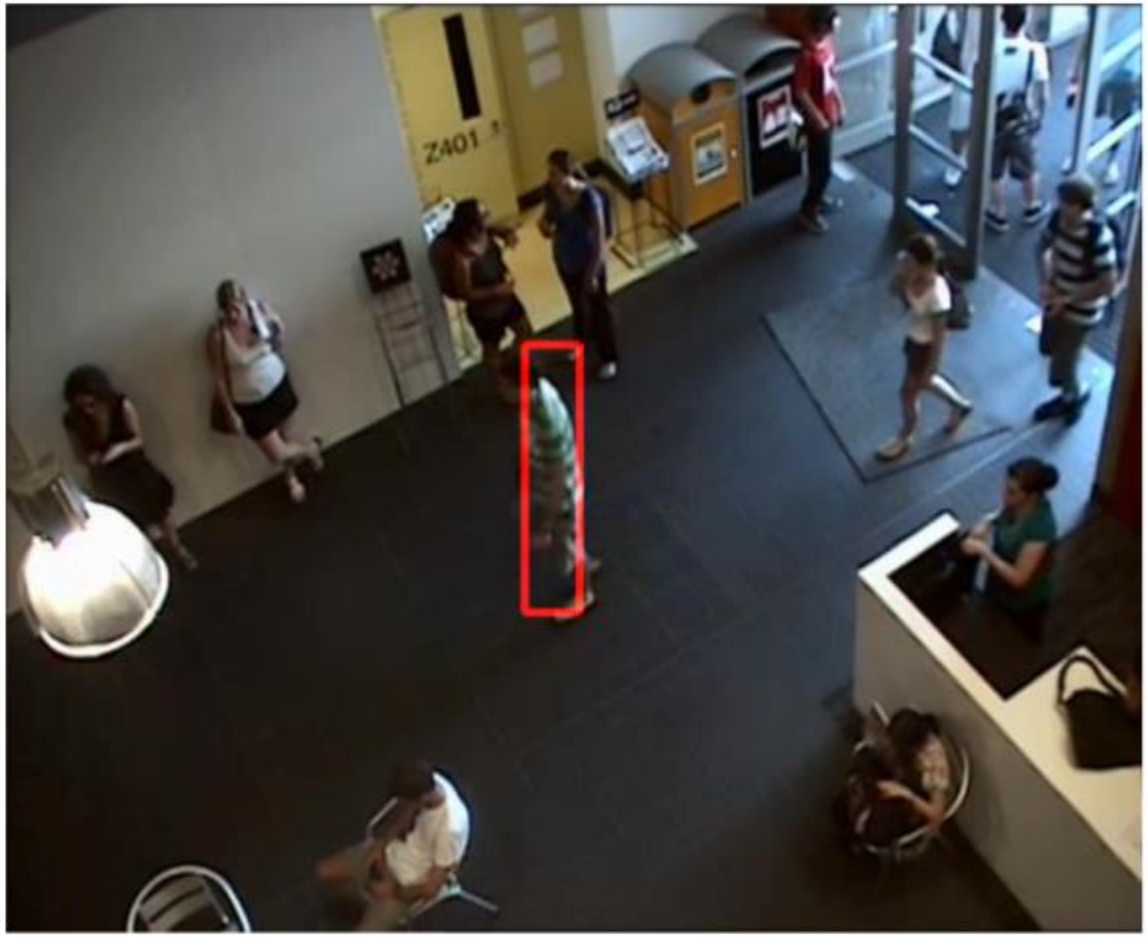
Task 2 Performance

Results based on Intersection over Union.

Approach	Average IoU	% w IoU > 0.4
Yaguchi [12]	**0.511**	0.669
Galiyawala [4]	0.363	0.522
Schumann [10]	0.503	**0.759**
Baseline [1]	0.290	0.493

Task 2 Performance

- Sequence 27 (Hard).
- High level of crowding.
- Illumination issues.
- Subjects with similar appearance (striped shirt).



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Conclusions (and where does this take us?)

- Yes, we can recognise people by the way they walk
- ….. and by human descriptions
- Challenging technology
- Needs new techniques and new insight
- Can generalise to forensics
- Human descriptions need wider investigation (covariates, antispoofing) as to performance advantages
- Motivate need for new insight as to automated identification vs. human identification
- and they are great fun. ……………………..questions?

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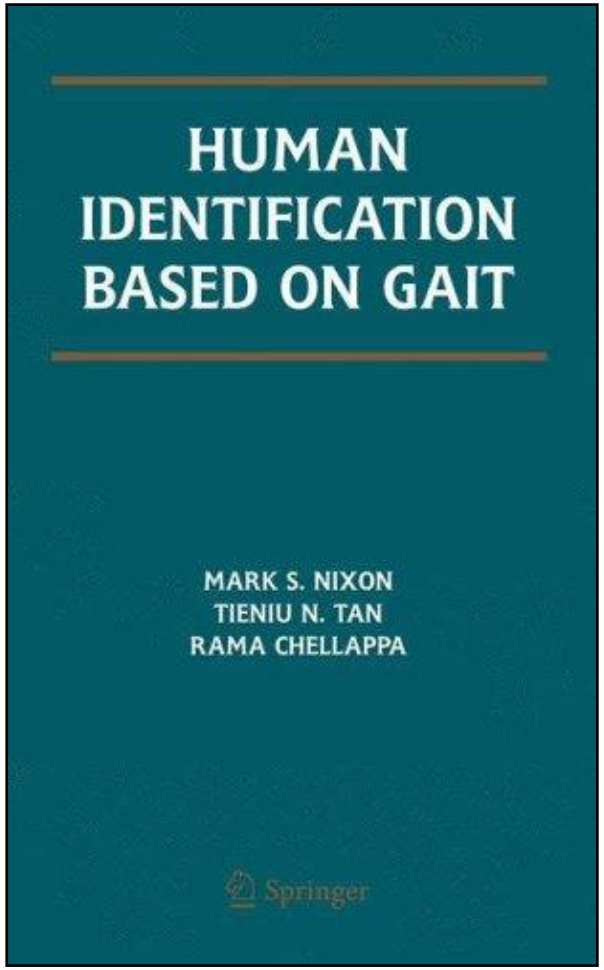
And thanks to ….

Dr John Carter, Dr Sasan Mahmoodi, Dr Jon Hare

Dr Hani Muammar, Dr Adrian Evans, Prof. Xiaoguang Jia, Prof Yan Chen, Prof Steve Gunn, Dr Colin Davies, Dr Mark Jones, Dr Alberto Aguado, Dr David Cunado, Dr Jason Nash, Prof Ping Huang, Dr David Benn, Dr Liang Ng, Dr Mark Toller, Dr John Manslow, Dr Mike Grant, Dr Jamie Shutler, Dr Karl Sharman, Prof Andrew Tatem, Layla Gordon, Dr Richard French, Dr Vijay Laxmi, Dr James Hayfron-Acquah, Dr Chew-Yean Yam, Dr Yalin Zheng, Dr Jeff Foster, Dr Jang Hee Yoo, Dr Nick Spencer, Dr Stuart Prismall, Wan Mohd.-Isa, Dr Peter Myerscough, Dr Richard Evans, Dr Stuart Mowbray, Dr Rob Boston, Dr Ahmad Al-Mazeed, Dr Peter Gething, Dr Dave Wagg, Dr Alex Bazin, Dr Mike Jewell, Dr Lee Middleton, Dr Galina Veres, Dr Imed Bouchrika, Dr Xin Liu, Dr Cem Direkoglu, Hidayah Rahmalan, Dr Banafshe Arbab-Zavar, **Dr Baofeng Guo**, **Dr Sina Samangooei**, Dr Michaela Goffredo , Dr Daniel Thorpe, Dr Richard Seely, Dr John Bustard, Dr Alastair Cummings, Dr Muayed Al-Huseiny, Dr Mina Ibrahim, Dr Darko Matovski, Dr Gunawan Ariyanto, Dr Sung-Uk Jung, Dr Richard Lowe, **Dr Dan Reid**, Dr George Cushen, Dr Ben Waller, Dr Nick Udell, Dr Anas Abuzaina, Dr Thamer Alathari, Dr Musab Sahrim, Dr Ah Reum Oh, Dr Tim Matthews, **Dr Emad Jaha**, Dr Peter Forrest, Dr Jaime Lomeli, **Dr. Dan Martinho-Corbishley**, **Dr Bingchen Guo**, Dr Jung Sun, **Dr Nawaf Almudhahka**, **Tom Ladyman,** Di Meng**, Moneera Alamnakani**

Sponsors: EPSRC, Home Office, MoD (GD), DARPA, ARL, EU

More information ……



MICHIGAN STATE

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Thank you!!
> 21 (!!)
Male
White (?)
(was) 6’
Slim
Grey(ish) hair
Random hairstyle

... and some papers

Surveys on soft biometrics

- D Reid, MS Nixon, A Ross, On Soft Biometrics for Surveillance, *Handbook of Stats,* 2013
- MS Nixon, PL Correia, K Nasrollahi, TB Moeslund, A Hadid, M Tistarelli, On soft biometrics, *Pattern Recognition Letters*, **68**(2), 2015

Recent (soft) papers

- P Tome, J Fierrez, R Vera-Rodriguez, MS Nixon, Soft biometrics and their application in person recognition at a distance, *IEEE TIFS,* **9**(3), 2014
- D Reid, MS Nixon, Soft biometrics; human identification using comparative descriptions, *IEEE TPAMI,* **36**(6), 2014
- ES Jaha, MS Nixon, From Clothing to Identity; Manual and Automatic Soft Biometrics, *IEEE TIFS,* **11**(10), 2016
- N Almudhahka, MS Nixon, J Hare, Semantic Face Signatures: Recognizing and Retrieving Faces By Verbal Descriptions, *IEEE TIFS,* **13**(3), 2017
- D Martinho-Corbishley, MS Nixon, JN Carter, Analysing comparative soft biometrics from crowdsourced annotations, *IEEE TPAMI,* 2018
- B Guo, MS Nixon, JN Carter, A Joint Density Based Rank-Score Fusion for Soft Biometric Recognition at a Distance, *ICPR* 2018