Person Re-identification

Introduction and Trends

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CCCV 2017 • Tianjin

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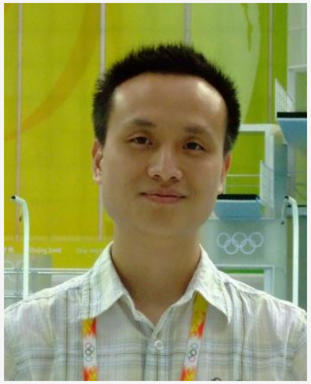

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CONTENT

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PART ONE

Introduction

Background

- Security concerns

2011 riot in London

2013 Boston Marathon bombings

2012 “8.10” serial killer Zhou Kehua

2014 “3.1” Kunming terror attack

Background

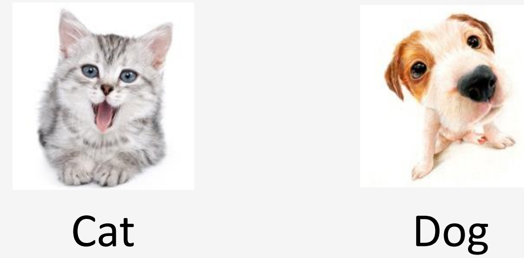
- Surveillance cameras everywhere
- However,
  - Mostly, searching suspects still requires large amount of labors
  - Automatic algorithms are still very poor
  - But the real demand is increasing

Background

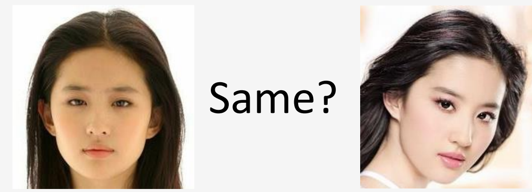
Search suspects in a large amount of videos

Concepts

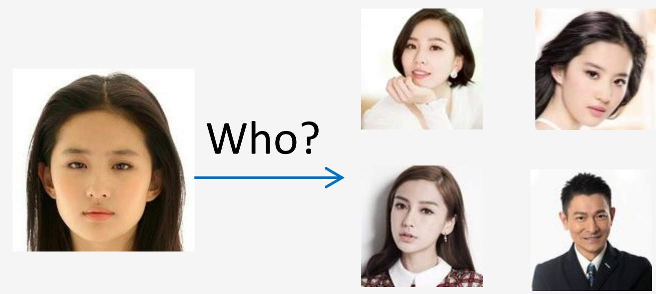
- **Classification:** classes fixed



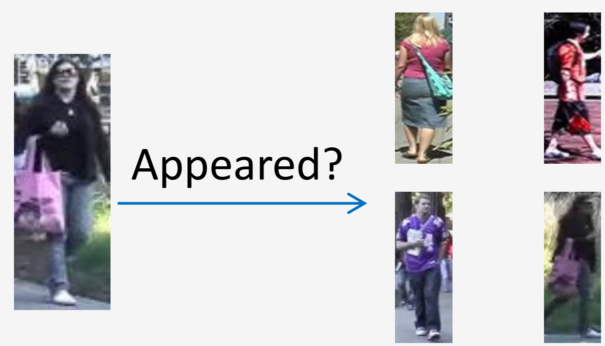
- **Verification:** pairwise



- **Identification:** gallery IDs known

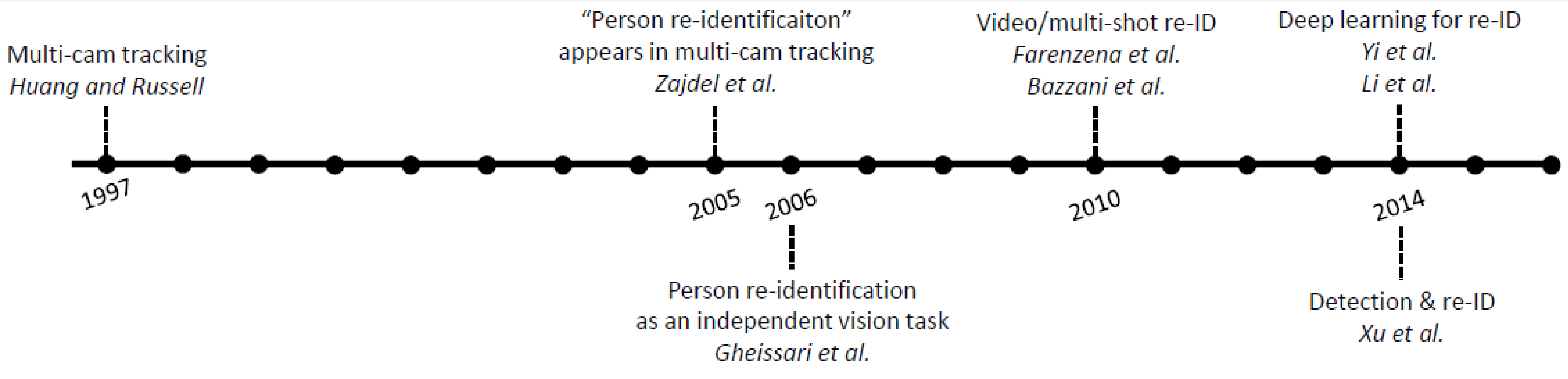


- **Re-identification :** gallery IDs unknown



注：Identification在国家标准中翻译为辨识，因此Re-identification翻译为再辨识为妥

History



From Zheng et al. 2016.

Difference with Multi-camera Tracking

- Multi-camera tracking
  - Usually online
  - Need to track all persons in all cameras
  - In a local area
  - In a short duration

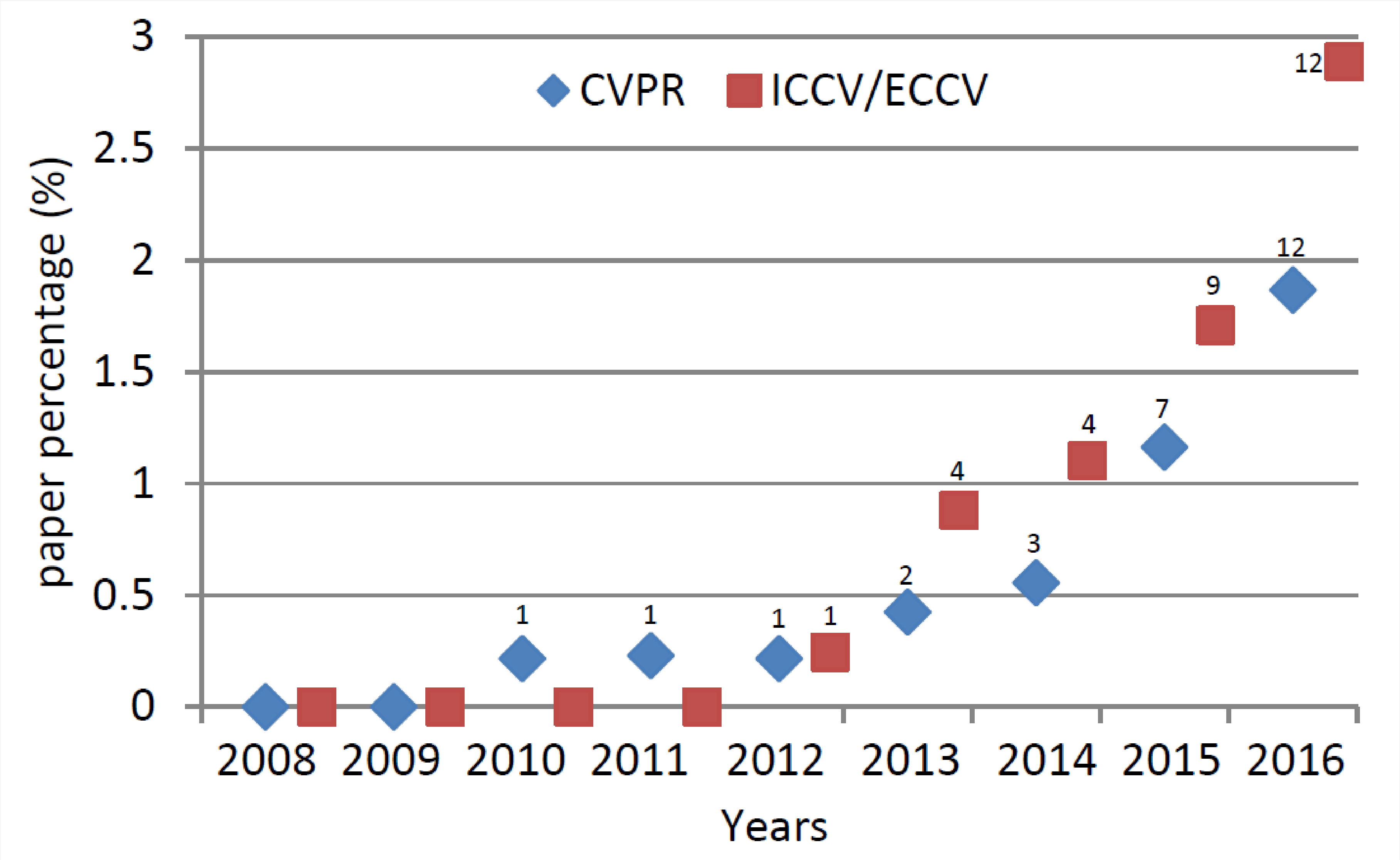
Multi vs. multi

- Person Re-identification
  - Usually offline, for retrieval
  - Re-identify one specific person
  - Across broad areas
  - With a possible long time

One vs. multi

Oriented from multi-camera tracking,
but is a particular independent task now.

Popularity



From Zheng et al. 2016.

Pipeline

Preprocess

- Pedestrian detection
- Single-camera Tracking

Representation

- Hand-crafted features
- Feature learning

Matching

- Traditional Distances
- Metric learning
- Re-ranking

Challenges

- Viewpoint changes
- Pose changes
- Illumination variations
- Occlusions
- Low resolutions
- Limited labeled data
- Generalization ability

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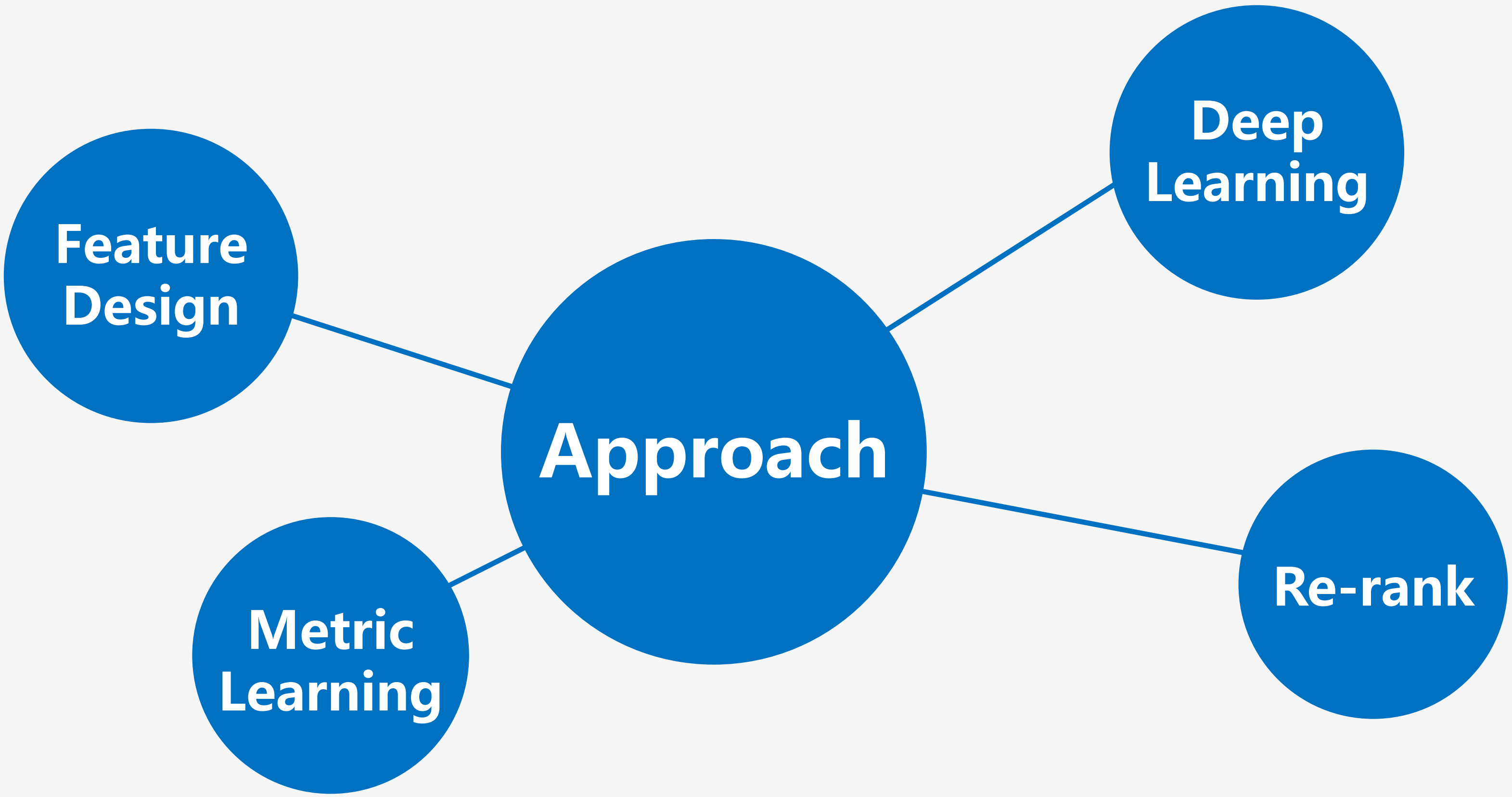
PART TWO

Approach

Approach



Main research directions in person re-identification

Feature Design

Colors

RGB, HSV, YCbCr, Lab, Color names

Textures

Gabor, LBP, SILTP, Schmid, BiCov

Hybrid

ELF, LOMO, GOG

Structure

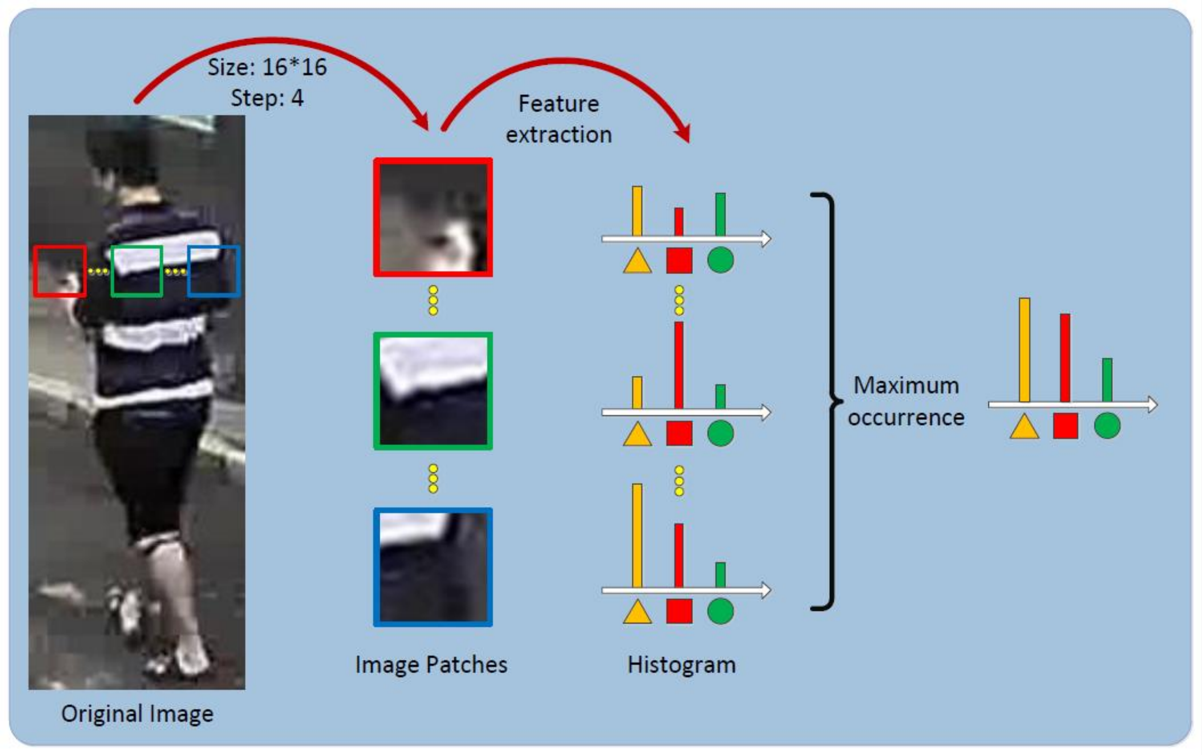
Pictorial, SDALF, Saliency

Attribute

Age, gender, bag

Feature Design

- Typical feature: LOMO
  - Viewpoint changes: local maximal occurence
  - Illumination variations: retinex and SILTP



S. Liao et al., "Person Re-identification by Local Maximal Occurrence Representation and Metric Learning," In CVPR 2015.

Metric Learning

Traditional Methods

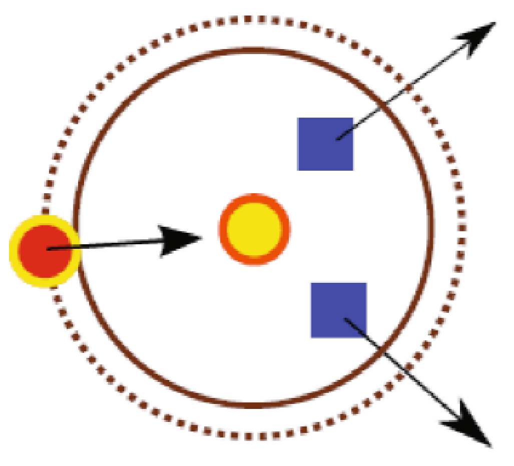
ITML, LMNN, LDML

Optimization Methods

PRDC, MLAPG

Fast Methods

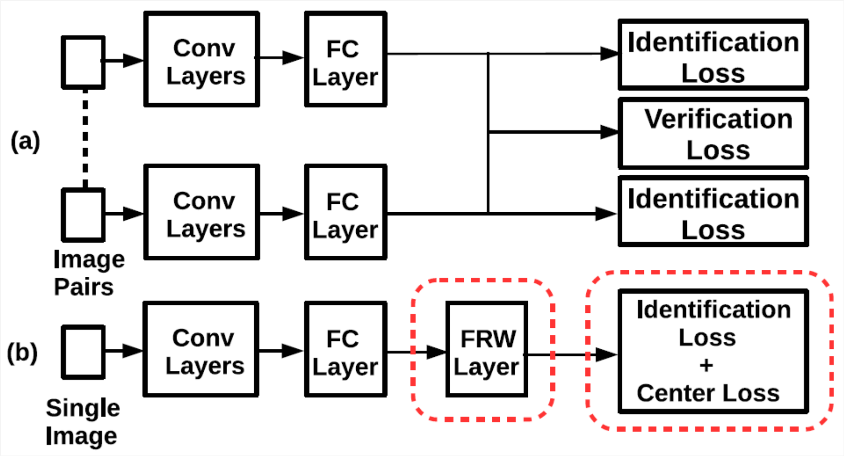
KISSME, XQDA, LSSL

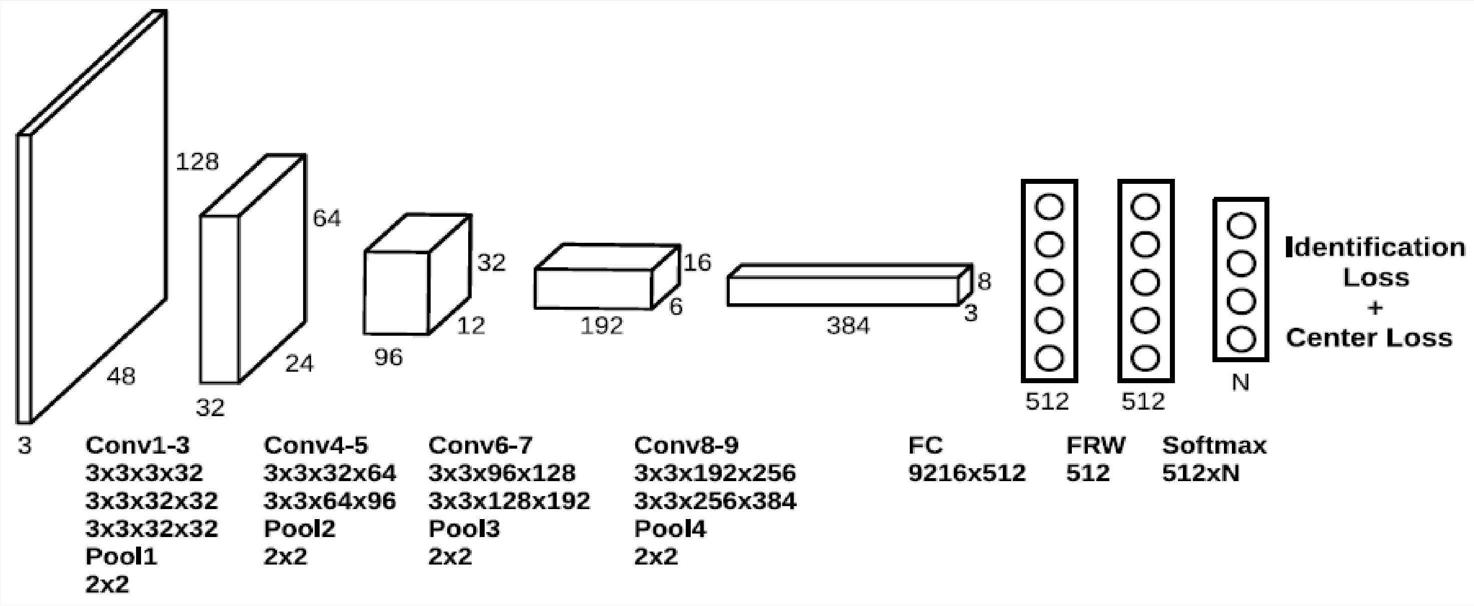


$$D^2_{\mathbf{M}}(\mathbf{x}, \mathbf{z}) = \|\mathbf{x} - \mathbf{z}\|^2_{\mathbf{M}} = (\mathbf{x} - \mathbf{z})^T \mathbf{M} (\mathbf{x} - \mathbf{z})$$

Deep Learning

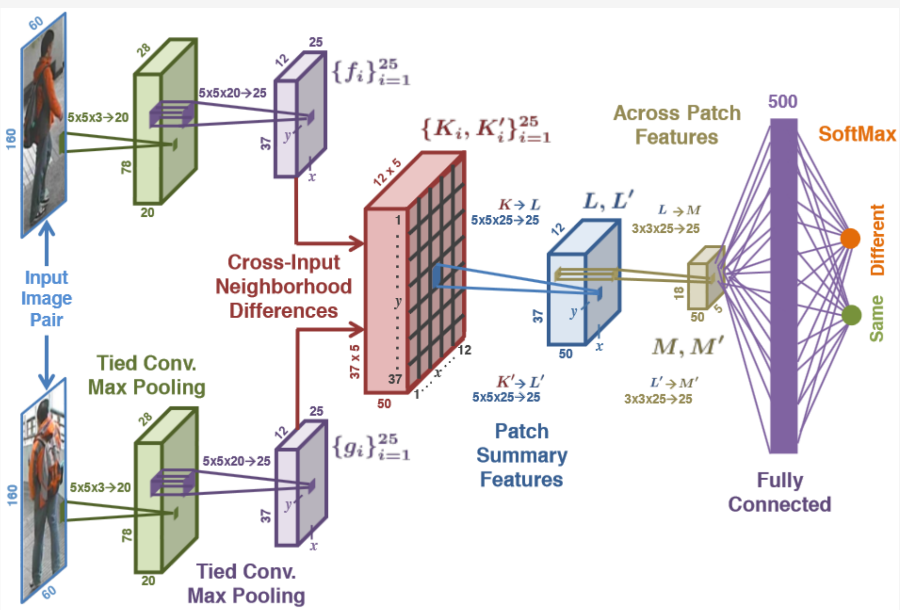
- Deep metric learning
  - Cosine similarity
  - Contrastive loss
  - Triplet loss
  - Center loss

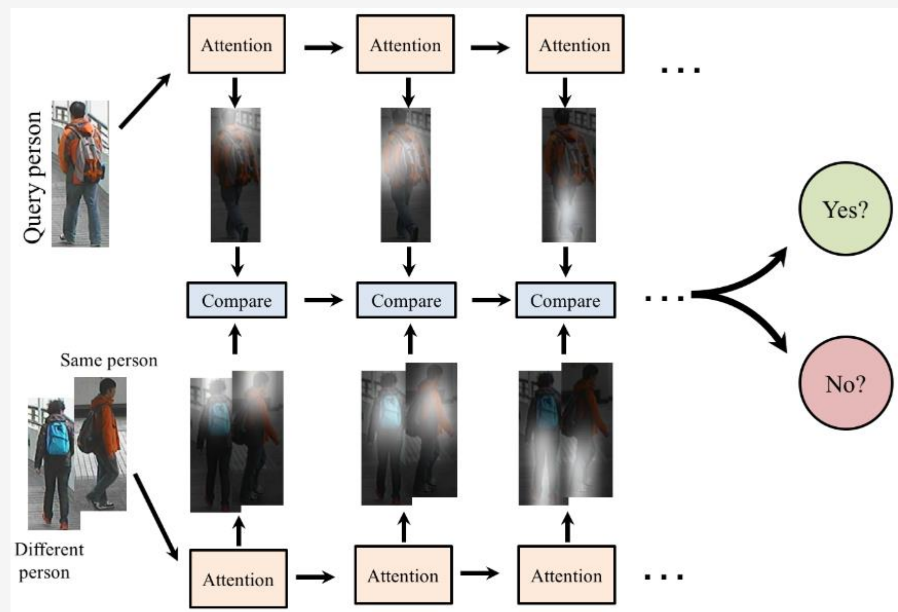




Deep Learning

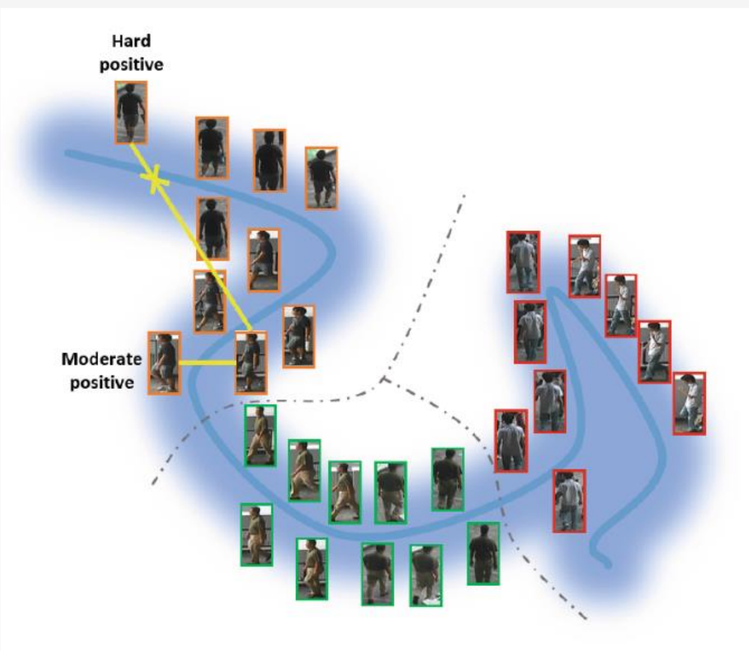
- Deep structures
  - Siamese CNN
  - Cross-input neighborhood, patch summary
  - Gating CNN
  - Contextual LSTM
  - Attention network





Deep Learning

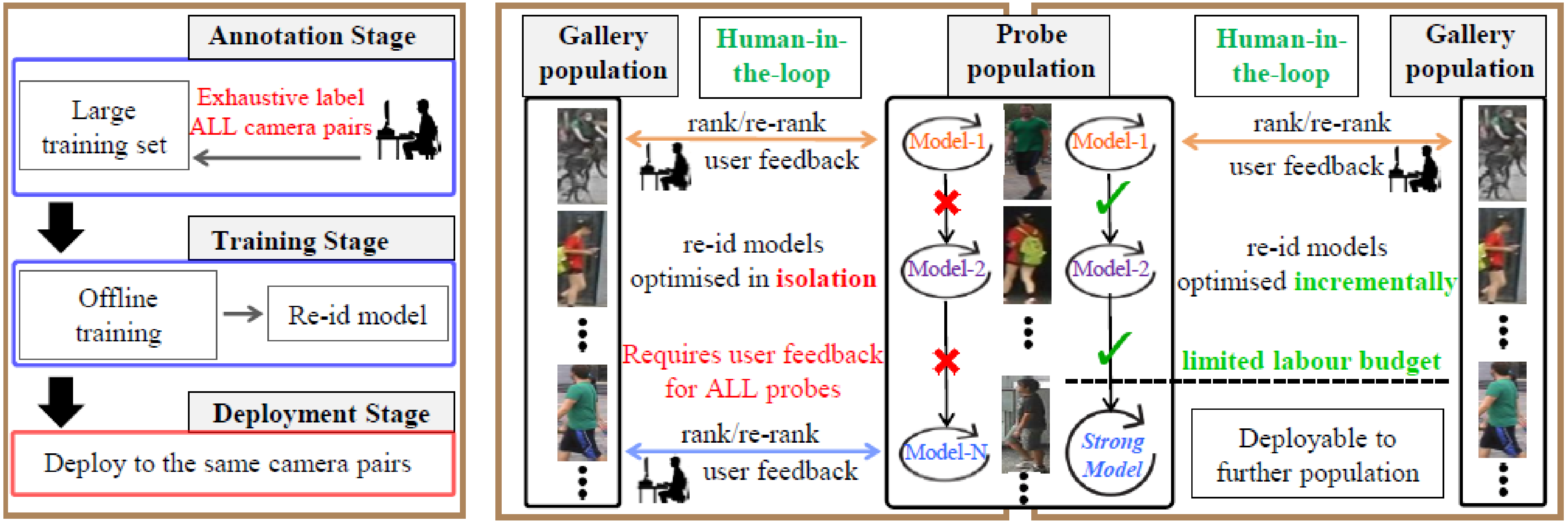
- Sample mining
  - Hard negative mining
  - Moderate positive sample mining



H. Shi et al., "Embedding Deep Metric for Person Re-identi cation: A Study Against Large Variations," In ECCV 2016.

Re-ranking

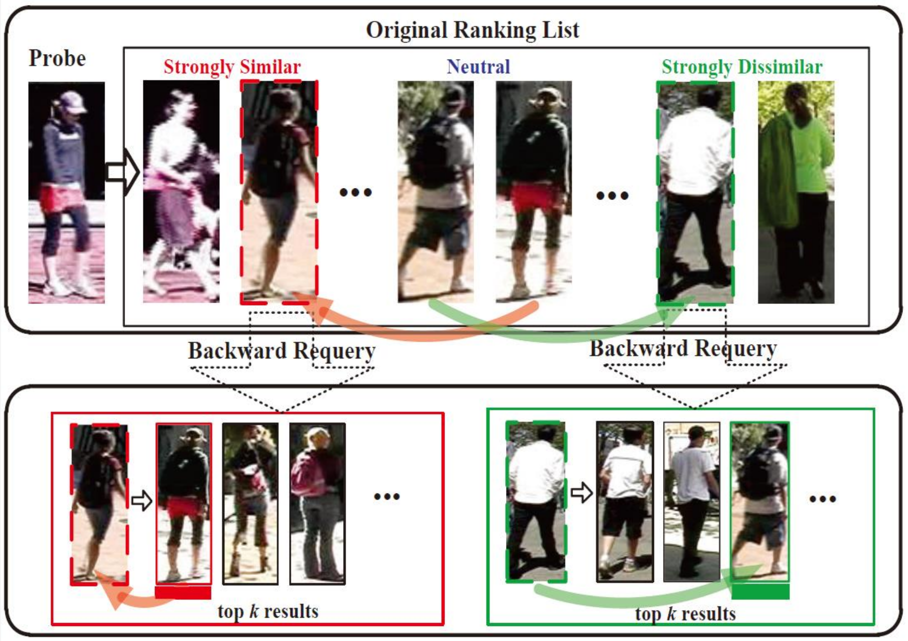
- User feedback based methods (human in the loop)
  - POP
  - HVIL



(a) Train-once-and-deploy re-id models (b) POP: Post rank optimisation [15] (c) HVIL: Human Verification Incremental Learning

Re-ranking

- Context based methods
  - DCIA
  - Bidirectional ranking
  - DSAR



Rank →	1	5	10	25	50
Euc. Dist.+ DCIA	16.29	33.38	47.46	58.86	72.78
DDC [10]	19	-	52	69	80
KISSME+SB [2]	19.3	50.7	63.3	78.2	90.6
KISSME+CCRR [17]	22	49	69	87	95
RIRO [37] (1 Iteration)	28	30	34	51	64
PRRS [4]	33.29	-	78.35	-	97.53
KISSME+ DCIA	38.87	67.96	82.01	93.62	98.36
IRT [1] (1 Iteration)	43	45	46	53	61
LADF+ DCIA	44.67	71.54	83.56	93.82	98.52
POP [23] (1 Iteration)	59.05	60.95	63.10	72.20	-
KCCA+ DCIA	**63.92**	**78.48**	**87.50**	**96.36**	**99.05**

DCIA on VIPeR

Garcia et al., "Person Re-Identification Ranking Optimization by Discriminant Context Information Analysis," In ICCV 2015.

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PART THREE

Evaluation and Benchmark

Evaluation

- Closed-set scenario
  - Probe: query images to be re-identified
  - Gallery: a set of images from surveillance videos to re-identify probe images
  - Performance measure: Cumulative Matching Characteristic (CMC) curves

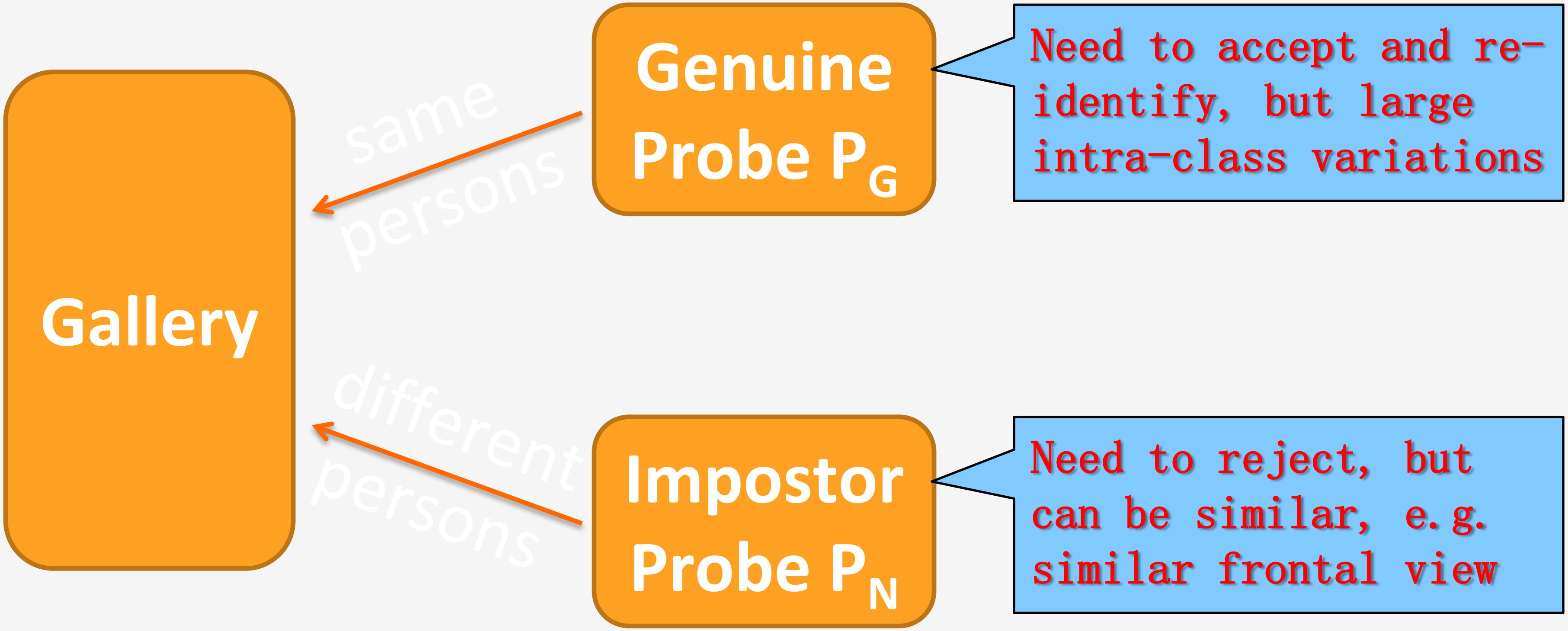
Constraint: each probe image must have the same person appearing in the gallery

Evaluation

- Open-set scenario

Open-set Person Re-identification

- Task: determine the same person of the probe in the gallery, or reject the probe
- Two subsets of probes



Open-set Person Re-identification

- Performance measures:
  - Detection and Identification Rate (DIR): percentage of images in P_G that correctly accepted and re-identified
  - False Accept Rate (FAR): percentage of images in P_N that falsely accepted

Closed-set Benchmark Datasets

Dataset	#Cameras	#Persons	#Images	#Views
VIPeR	2	632	1,264	2
ETHZ	1	146	8,555	1
i-LIDS	5	119	476	2
QMUL GRID	8	250	1,275	2
PRID2011	2	200	1,134	2
CUHK01	2	971	3,884	2
CUHK02	5 pairs	1,816	7,264	2
CUHK03	6	1,360	13,164	2
CAMPUS-Human	3	74	1,889	3
Market-1501	6	1,501	32,668	-
MARS	6	1,261	1,191,003	-
DUKE	8	1,404	36,411	-

Open-set Benchmark Datasets

Dataset	#Cameras	#Persons	#Images	#Views
Open-world	6	28	4,096	-
OPeRID	6	200	7,413	5

Closed-set Benchmark Results

Method	Rank 1	Rank 5	Rank 10
XQDA	46.3	78.9	88.6
MLAPG	51.2		
DNS	54.7	84.8	94.8
LSSCDL	51.2		
Siamese LSTM	57.3	80.1	88.3
IDLA	45.0	76.0	83.5
Gated S-CNN	61.8	80.9	88.3
EDM	52.0		
Joint Learning	52.2		
CAN	63.1	82.9	88.2
CNN Embedding	66.1	90.1	95.5
Deep Transfer	84.1		
Center Loss	82.1	96.2	98.2

Benchmark on CUHK03 (detected)

Open-set Benchmark Results

- On OPeRID

	FAR=1%		FAR=10%	
	Rank=1	Rank=10	Rank=1	Rank=10
IDENTITY	0.84	0.91	7.36	9.21
MAHAL [13]	1.89	1.99	10.50	11.97
KISSME [13]	1.82	1.92	9.99	11.46
LMNN [29]	0.41	0.41	3.97	4.58
ITML [6]	1.18	1.21	8.39	9.27
LADF [19]	1.53	1.74	9.11	10.82
RRDA	**3.99**	**4.35**	**14.51**	**16.72**

Very poor!

S. Liao et al., "Open-set Person Re-identification," In arXiv 2014.

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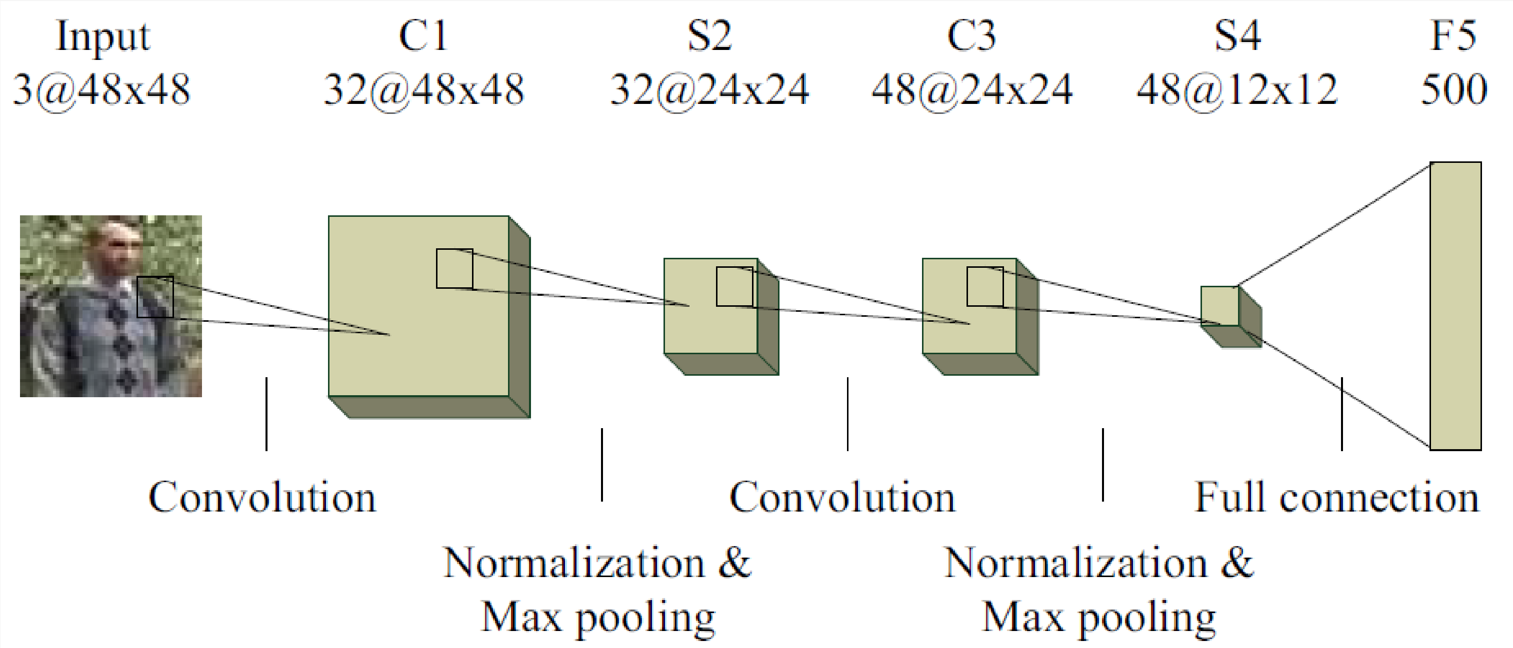
PART FOUR

Future Directions

Future Directions

1

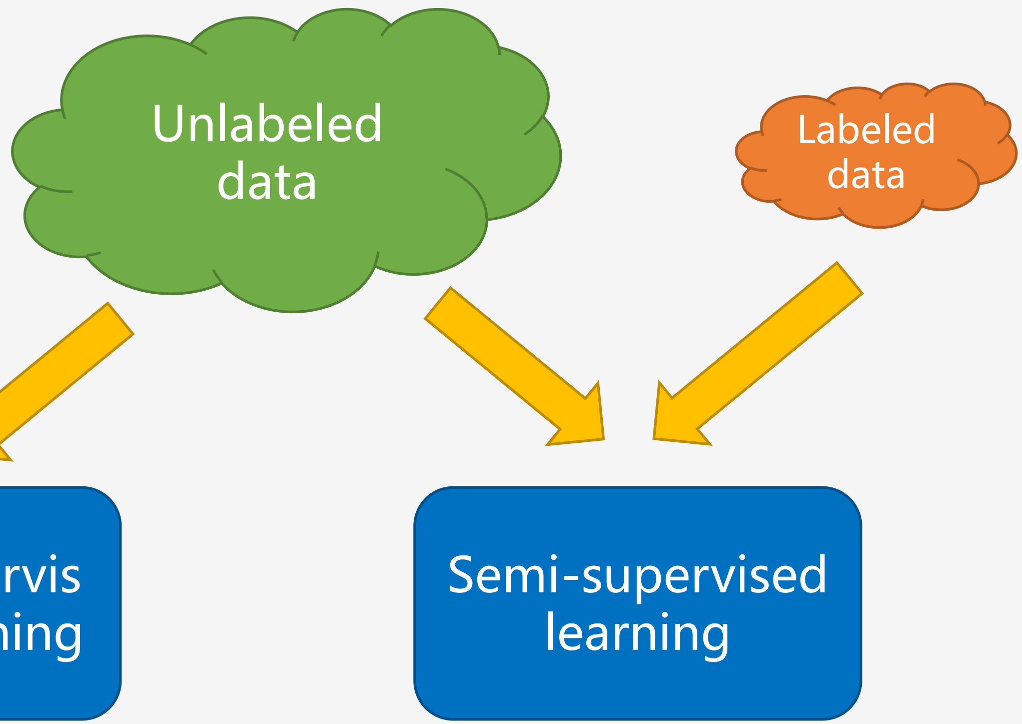
With the help of large datasets, deep learning methods have achieved much better performance, and are becoming important for person re-identification.



Future Directions

2

Due to limited labeled data and large diversity in practical scenarios, semi-supervised learning or unsupervised learning will be potentially useful for practical applications in exploring large amount of unlabeled data.



Future Directions

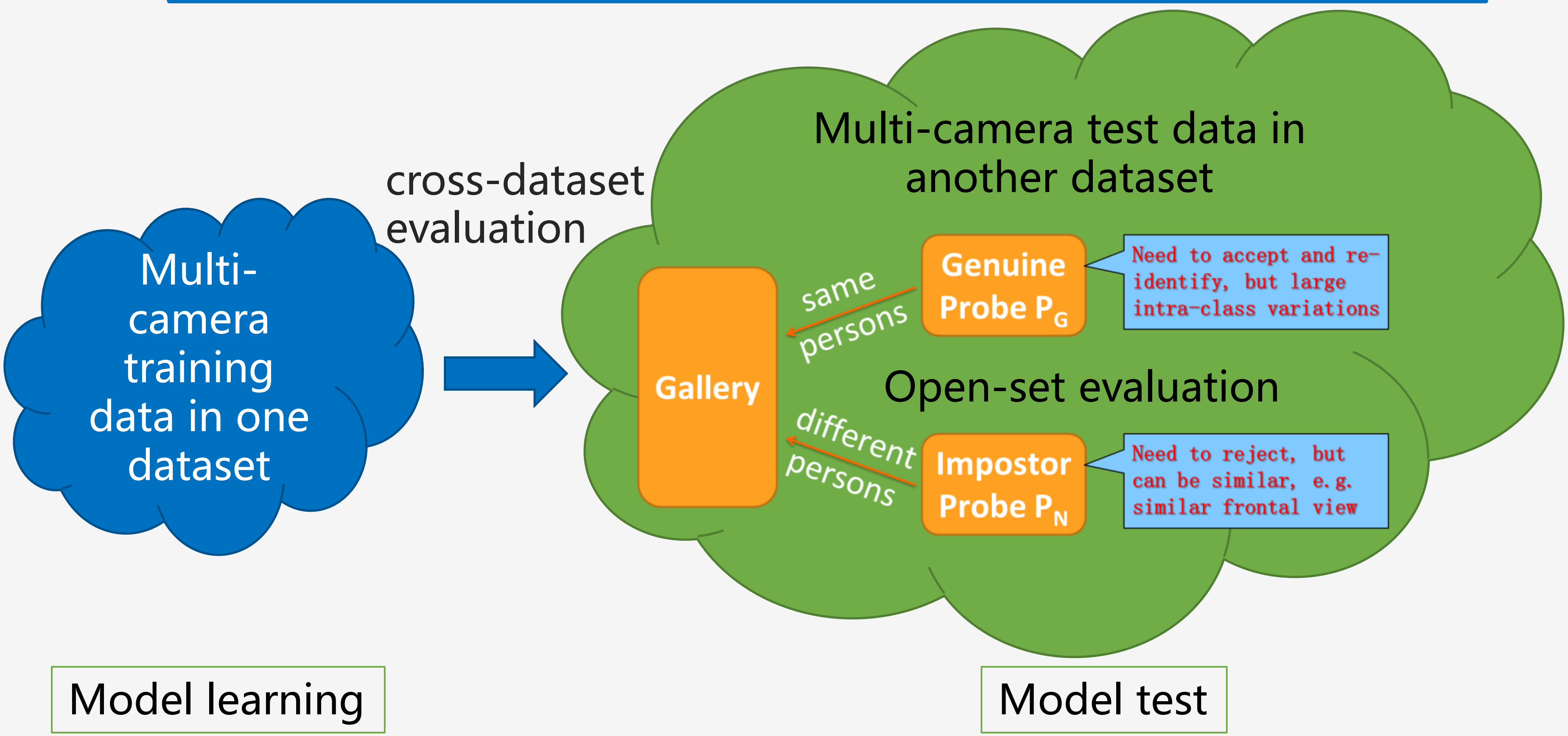
3

Performance of cross-dataset evaluation is still very poor. Re-ranking methods may be very useful in improving the performance.

Future Directions

4

For evaluation, open-set person re-identification and cross-dataset evaluation will be preferred in evaluating practical performance.



Thanks!

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http://www.cbsr.ia.ac.cn/users/scliao/