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SSPP-DAN: Deep Domain Adaptation Network for Face Recognition with Single Sample Per Person

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  - LFW for SSPP

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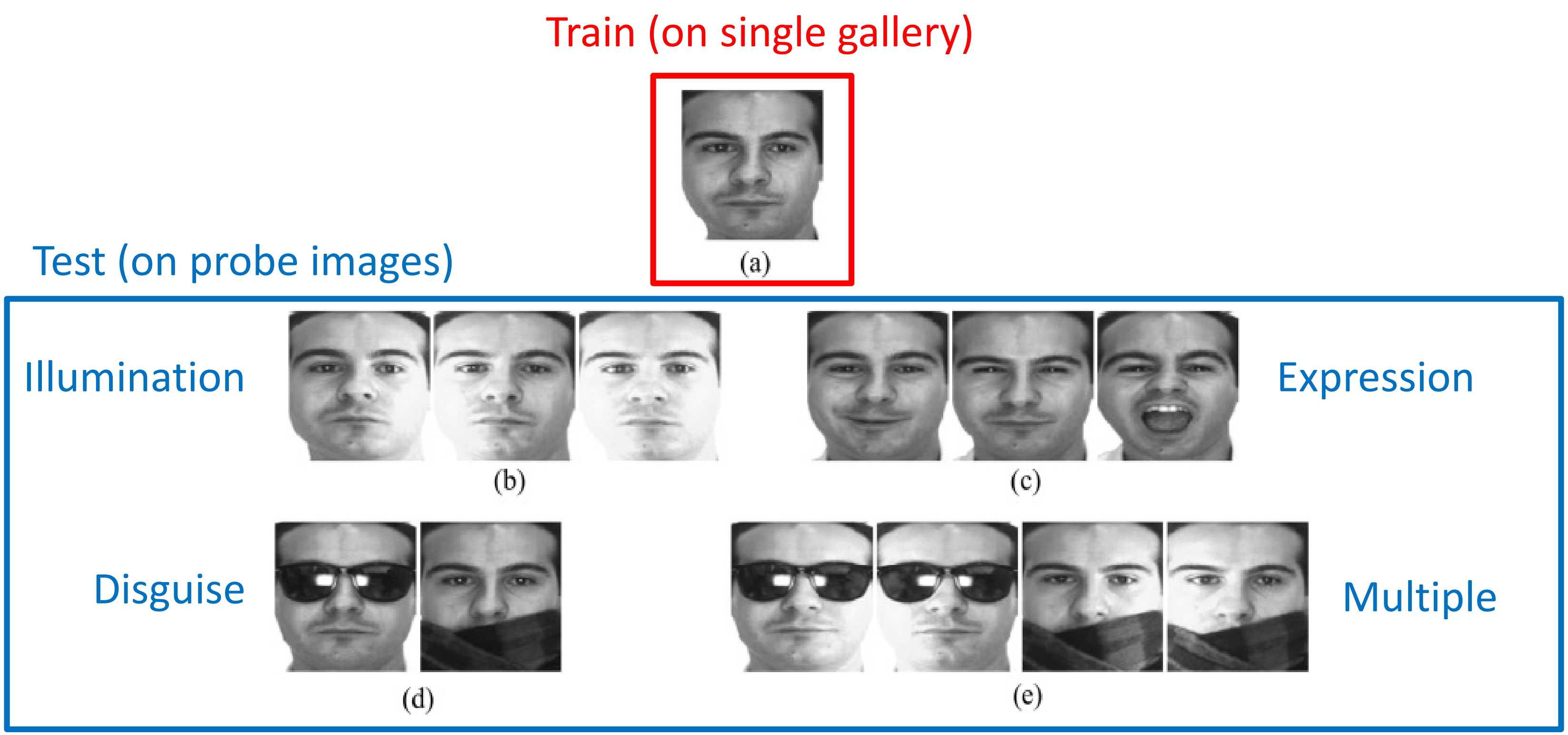
Motivation & Problem Definition

SSPP face recognition

- **Face recognition using Single Sample Per Person (SSPP)**
  - Identify or verify identities using <u>**only one single gallery image**</u>
  - Related to the recently attracted one-shot learning

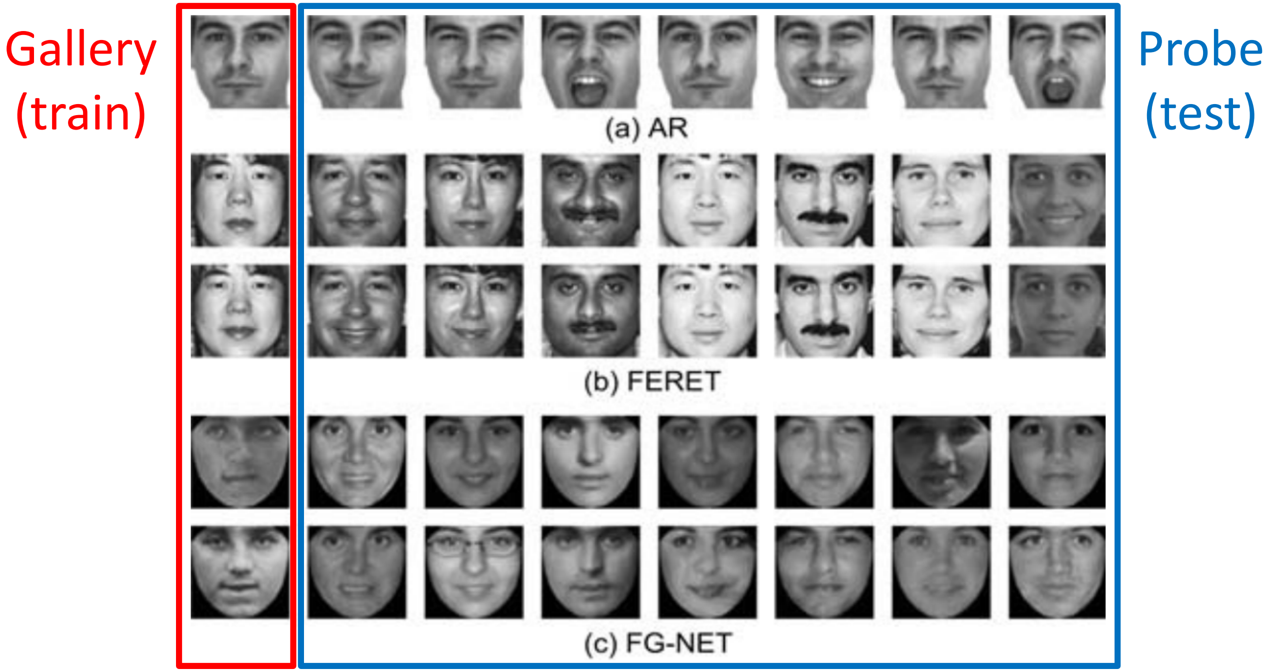


Sample images of the AR database

SSPP face recognition

▪ Limitations of existing SSPP datasets

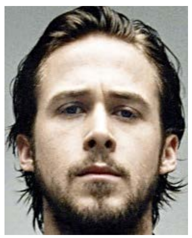
- Lab controlled environment
- Consistent shooting environment



Lu, Jiwen, Yap-Peng Tan, and Gang Wang. "Discriminative multimanifold analysis for face recognition from a single training sample per person." *IEEE transactions on pattern analysis and machine intelligence* 35.1 (2013): 39-51.

Real-world SSPP Face recognition

Registration
(**Gallery**)



Identification
(**Probe**)

Gallery

A stable image like
clear frontal mugshot
e.g., ID card or e-passport

Probe

Unstable images including
non-trivial variations
e.g., surveillance camera, web images

Variations:
camera sensor, blur,
noise, pose, illumination

Real-world SSPP Face recognition

Registration
(**Gallery**)

Identification
(**Probe**)

Challenges

1. Heterogeneity of the shooting environments

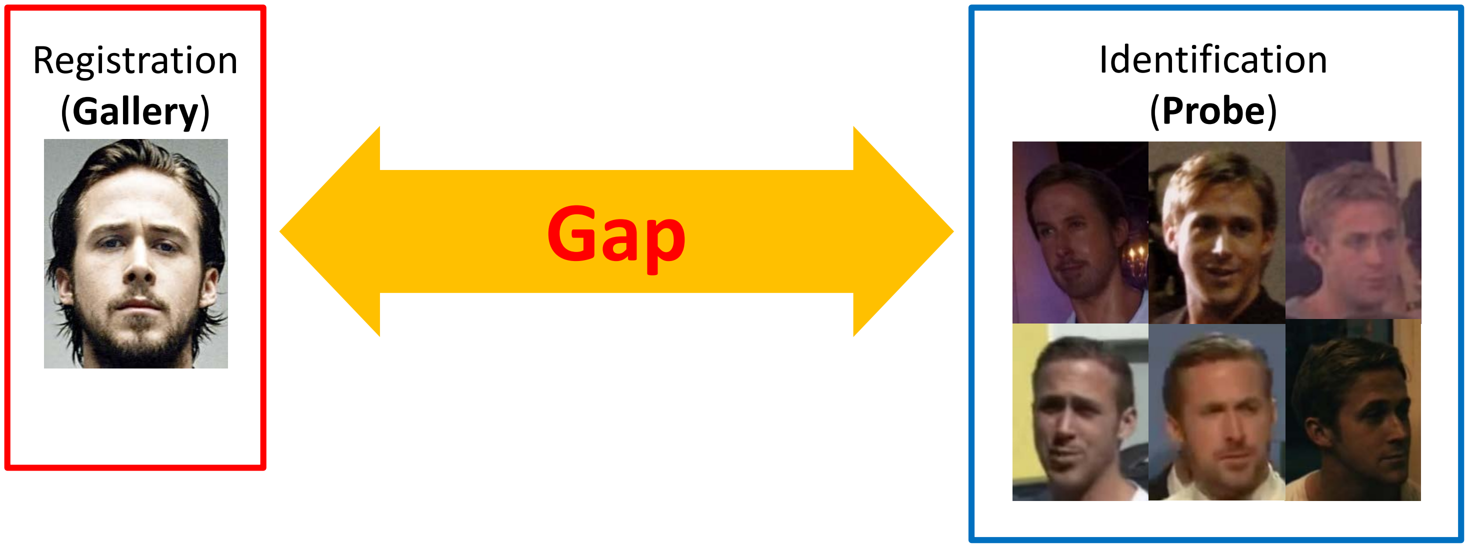
- Gallery: stable environment
- Probe: highly unstable environment

2. Shortage of training samples

- Only one training sample per person is available

Proposed method

Real-world SSPP Face recognition

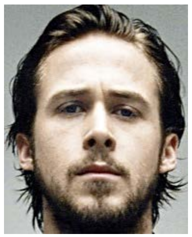


Challenges

1. **Heterogeneity of the shooting environments**
   - Gallery: stable environment
   - Probe: highly unstable environment

Real-world SSPP Face recognition

Registration
(**Gallery**)



Domain Adaptation

Identification
(**Probe**)

Challenges

1. Heterogeneity of the shooting environments

- Gallery: stable environment
- Probe: highly unstable environment

Domain Adaptation (DA)

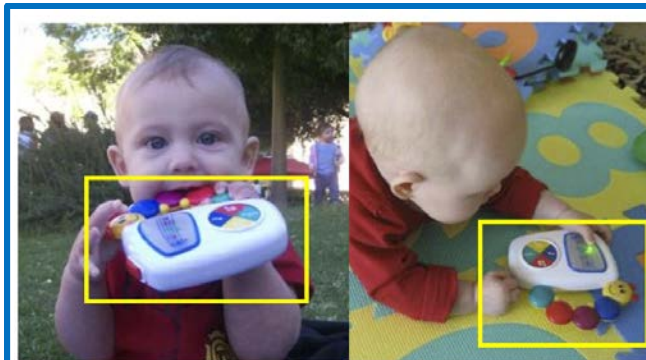
- Adjust a model to a different target domain distribution starting from the source domain knowledge

Source domain

amazon.com

With labels

Target domain



consumer images

Without labels

Domain Adaptation (DA)

- Adjust a model to a different target domain distribution starting from the source domain knowledge

Source domain w/ label

Domain Adaptation (DA)

- Adjust a model to a different <u>target domain distribution</u> starting from the <u>source domain knowledge</u>

Source domain w/ label

Model

Domain Adaptation (DA)

- Adjust a model to a different <u>target domain distribution</u> starting from the <u>source domain knowledge</u>

Source domain w/ label

↓

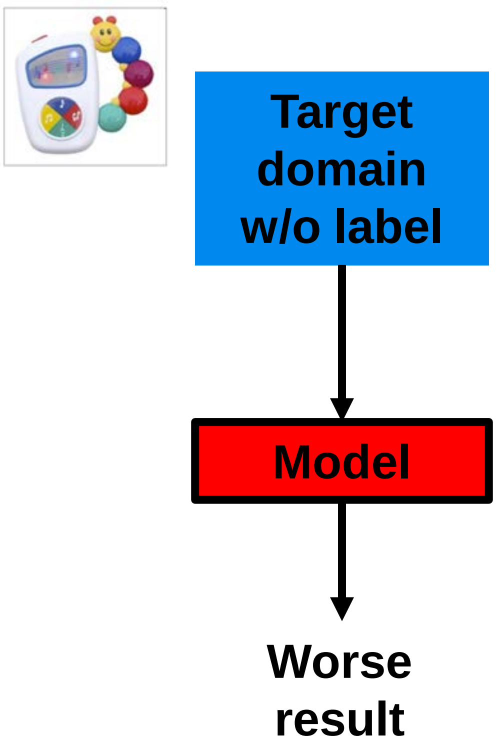
Model

↓

Fine classification

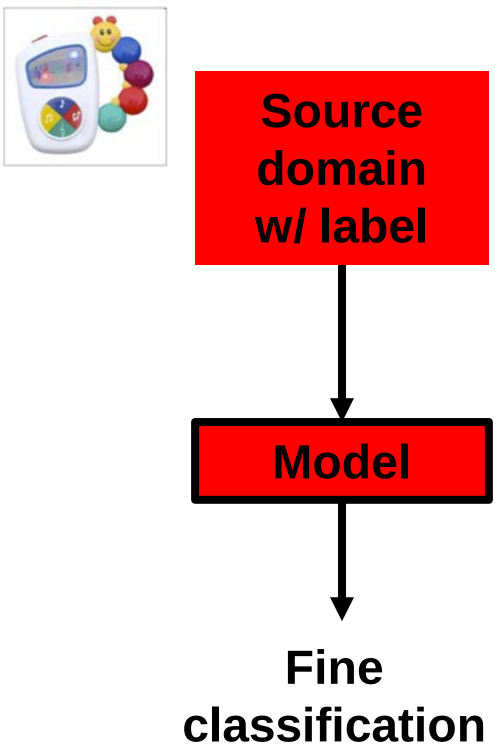
Domain Adaptation (DA)

- Adjust a model to a different target domain distribution starting from the source domain knowledge



Domain Adaptation (DA)

- Adjust a model to a different <u>target domain distribution</u> starting from the <u>source domain knowledge</u>



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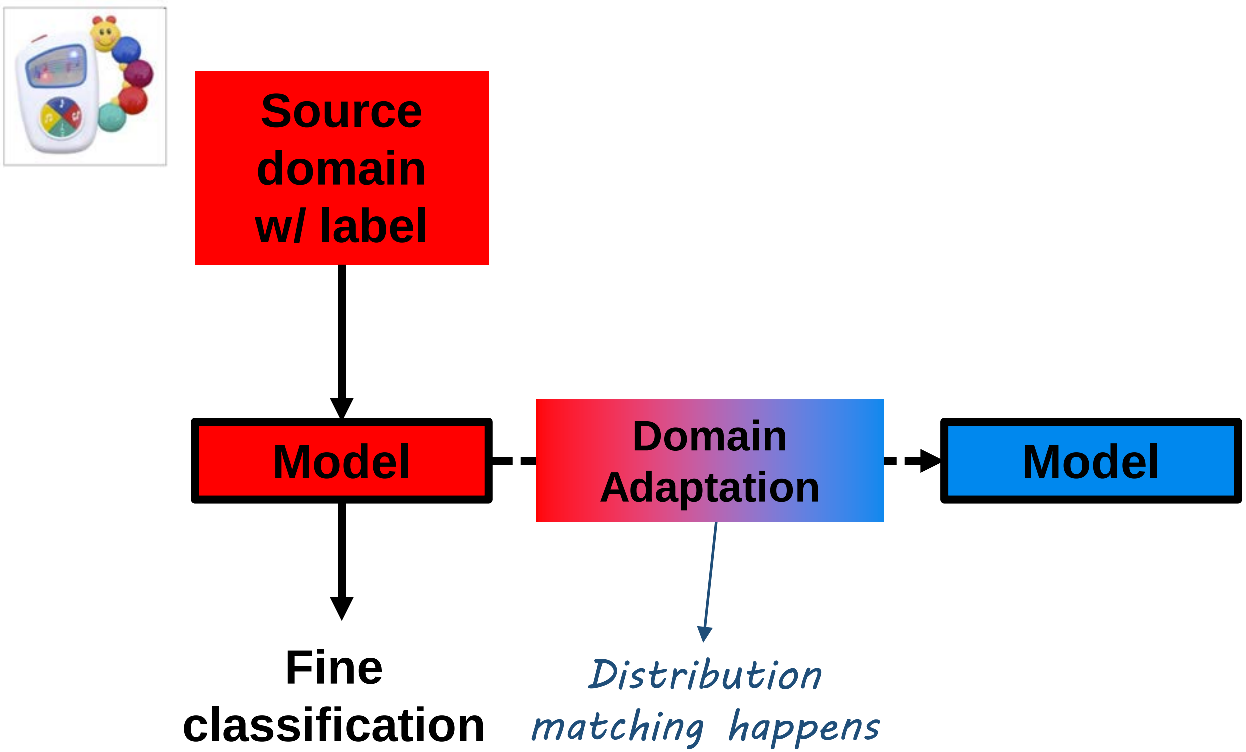
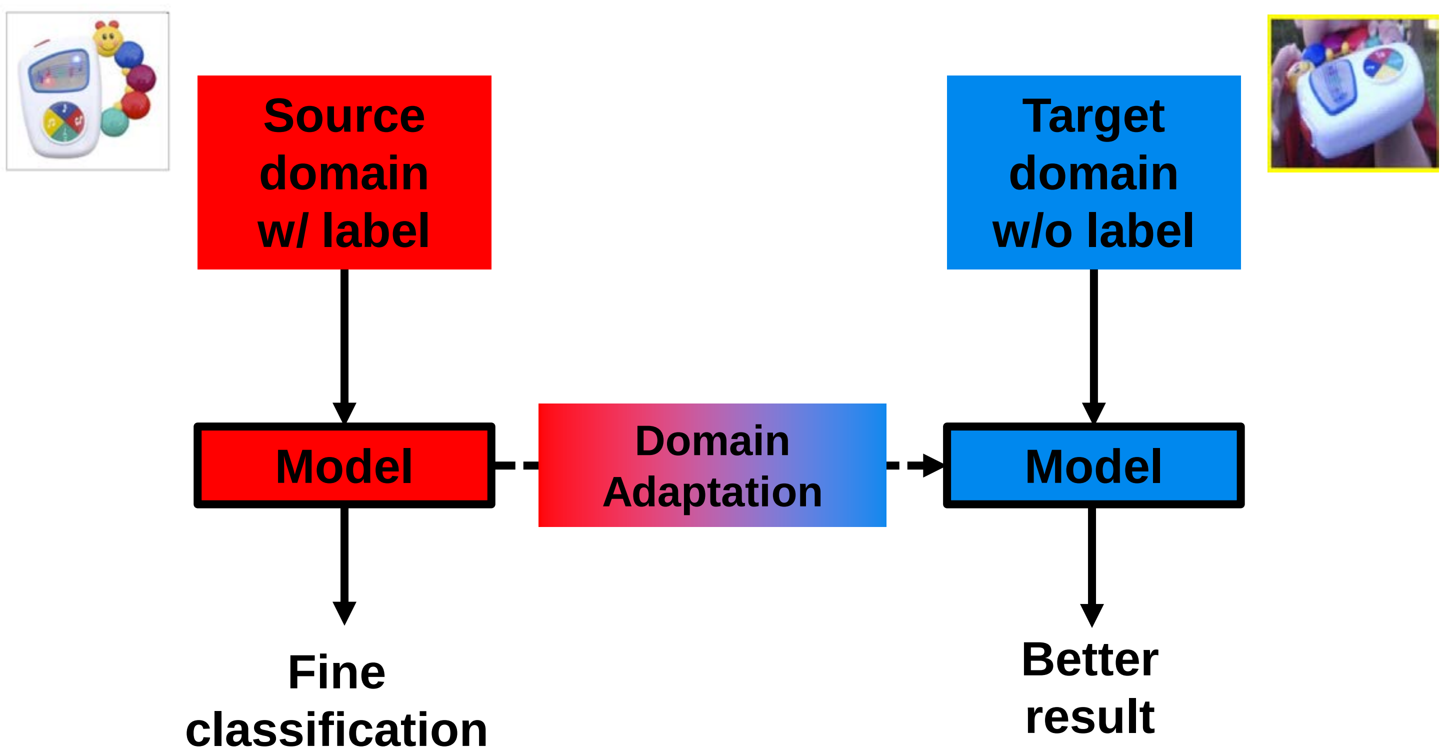


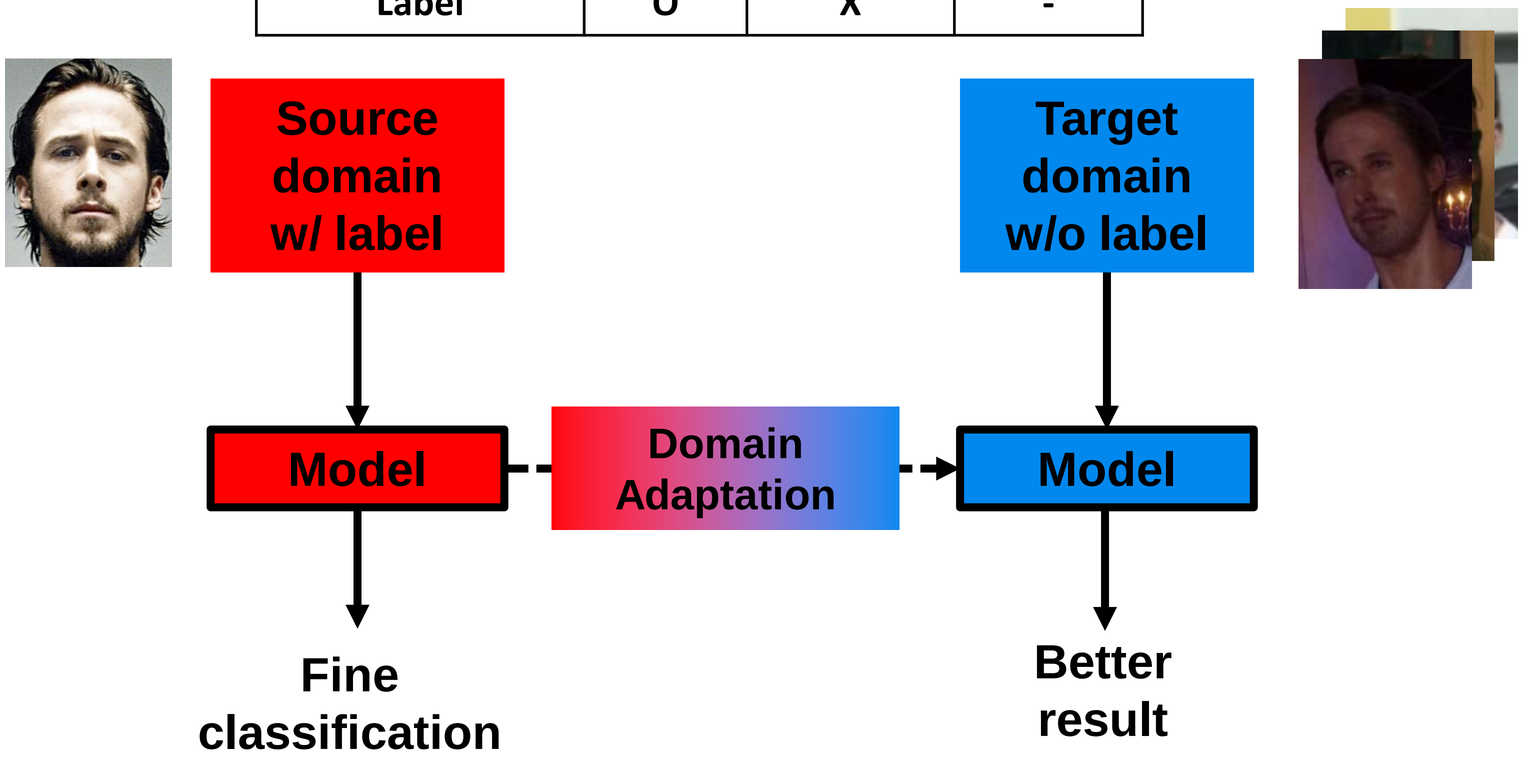
Domain Adaptation (DA)

- Adjust a model to a different target domain distribution starting from the source domain knowledge



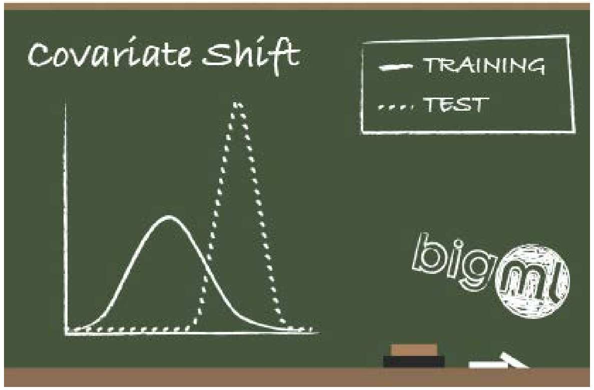
Domain Adaptation (DA)

Purpose	Train		Test
Domain	Source	Target	Target
Image condition	Stable	Unstable	Unstable
Label	O	X	-



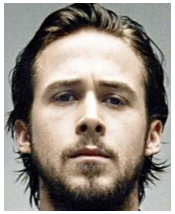
Domain Adaptation (DA)

- Basic assumptions of DA
  - samples are **abundant** in each domain
  - sample distribution of each domain is **related but different**



Lack of samples

Registration
(**Gallery**)



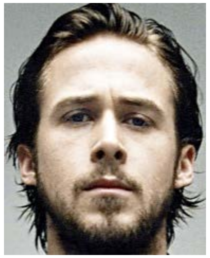
Domain Adaptation

Identification
(**Probe**)

Face synthesis

- Generate virtual samples for lack of samples.

Registration
(**Gallery**)



Synthesized
(from Gallery)

Identification
(**Probe**)

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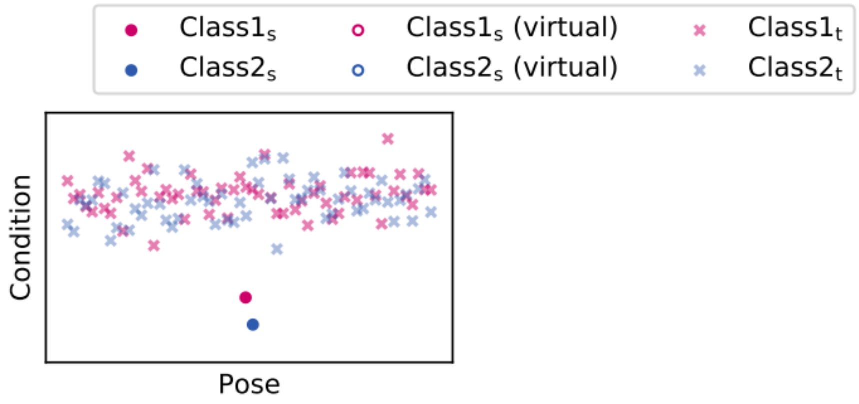
SSPP-DAN

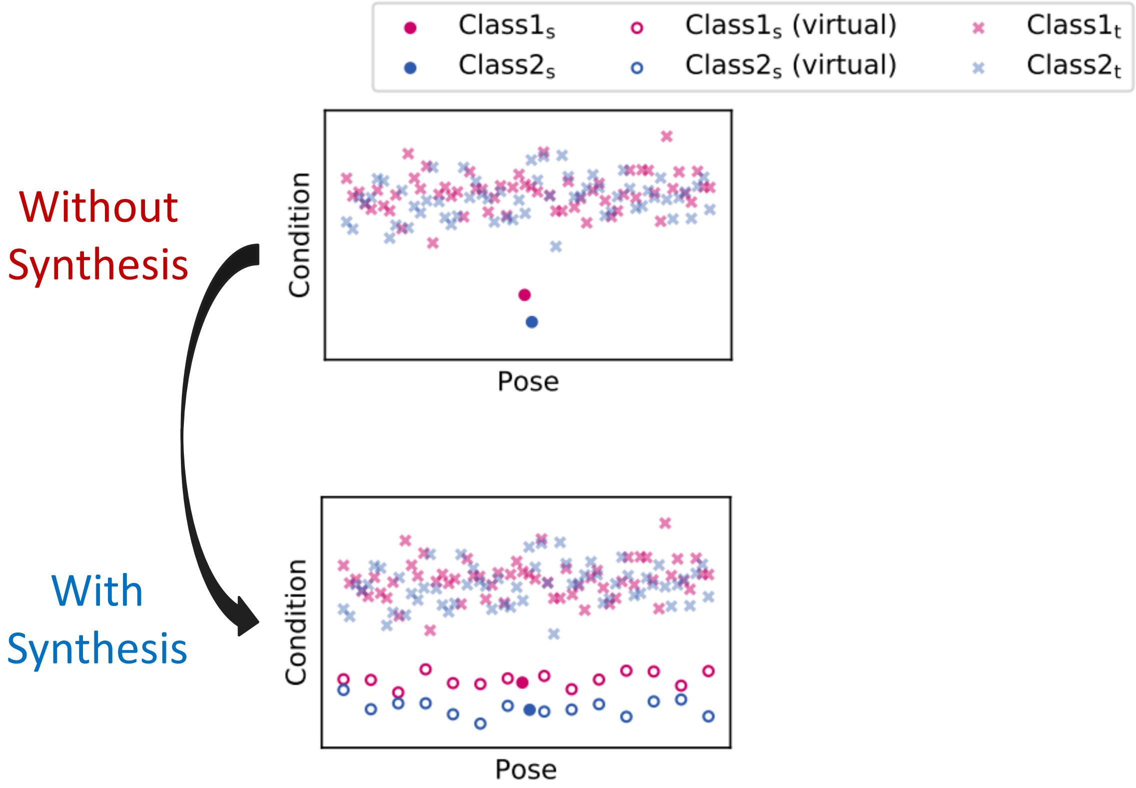
- Image synthesis

Without Synthesis



SSPP-DAN

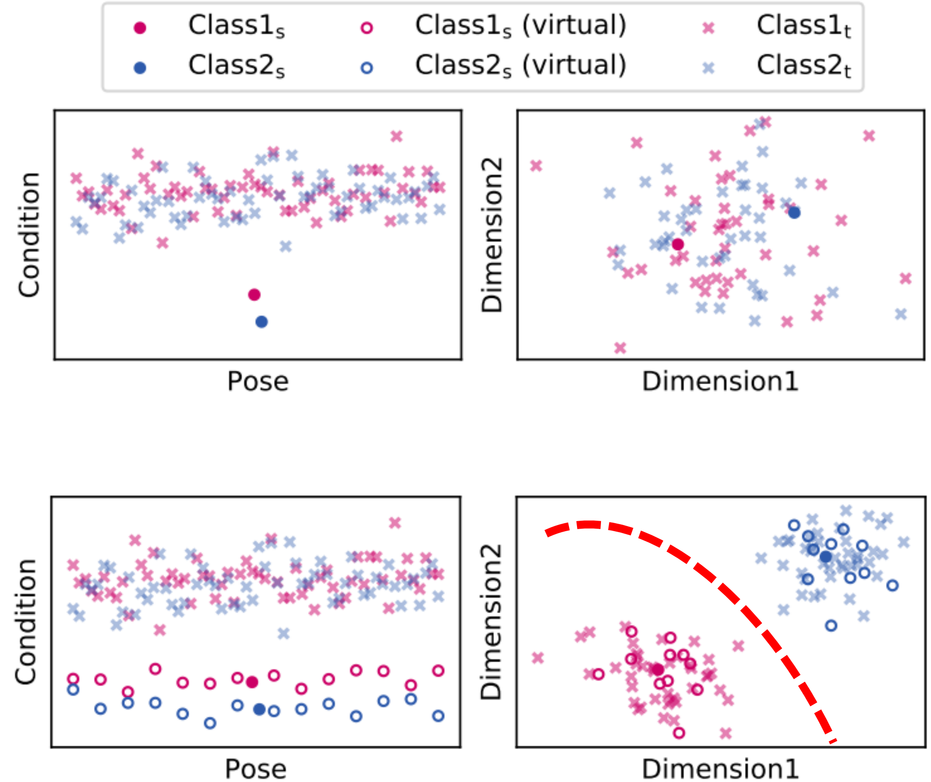
- Image synthesis
  >> **distribution of samples**



SSPP-DAN

- Image synthesis
  >> **distribution of samples** >> **Success of DA**

Without Synthesis

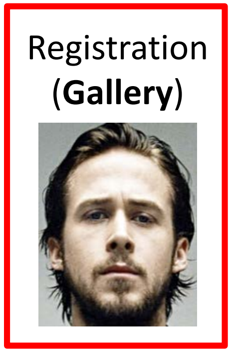


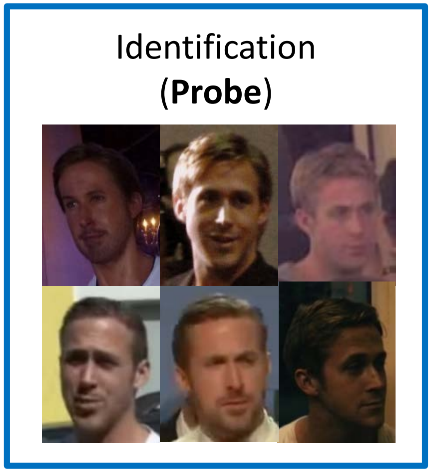
DA fails

With Synthesis

DA succeeds

Real-world SSPP Face recognition

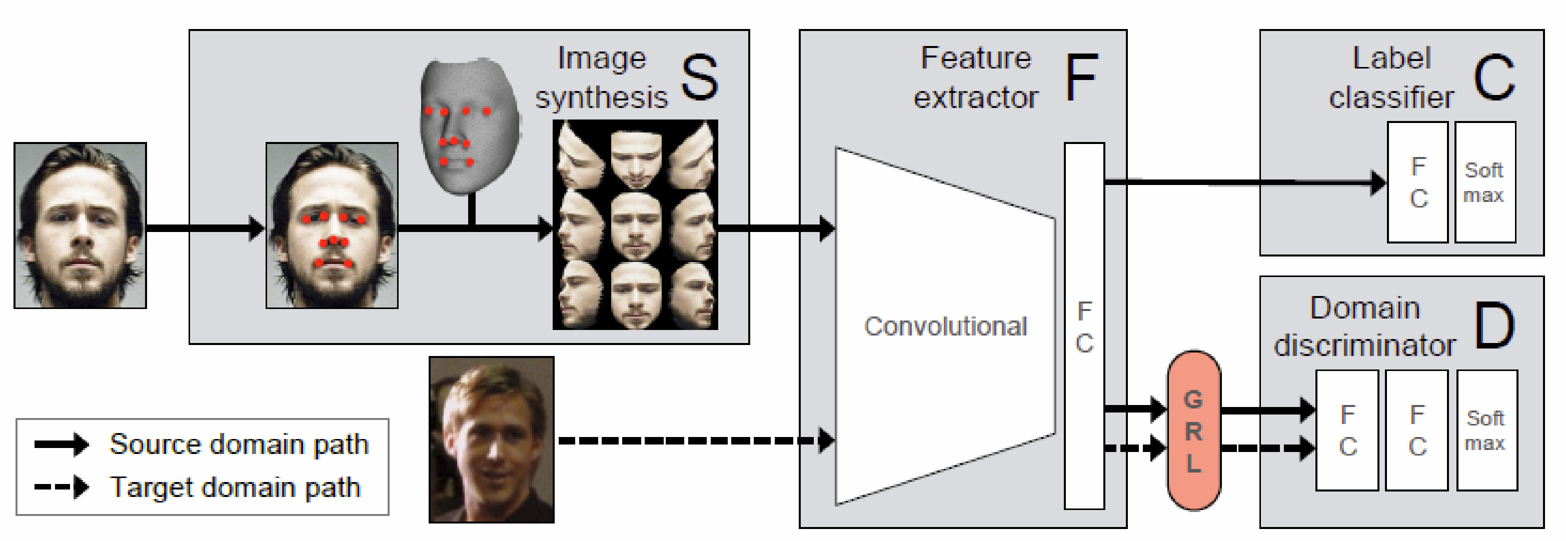




Challenges

1. **Heterogeneity of the shooting environments**
   - Gallery: stable environment
   - Probe: highly unstable environment
2. **Shortage of training samples**
   - Only one training sample per person is available

SSPP-DAN: Domain Adaptation Network for Single Sample Per Person



1. **Domain adaptation network**
   - From stable face domain (source) to unstable face domain (target)
2. **Face synthesis**
   - Generate virtual samples

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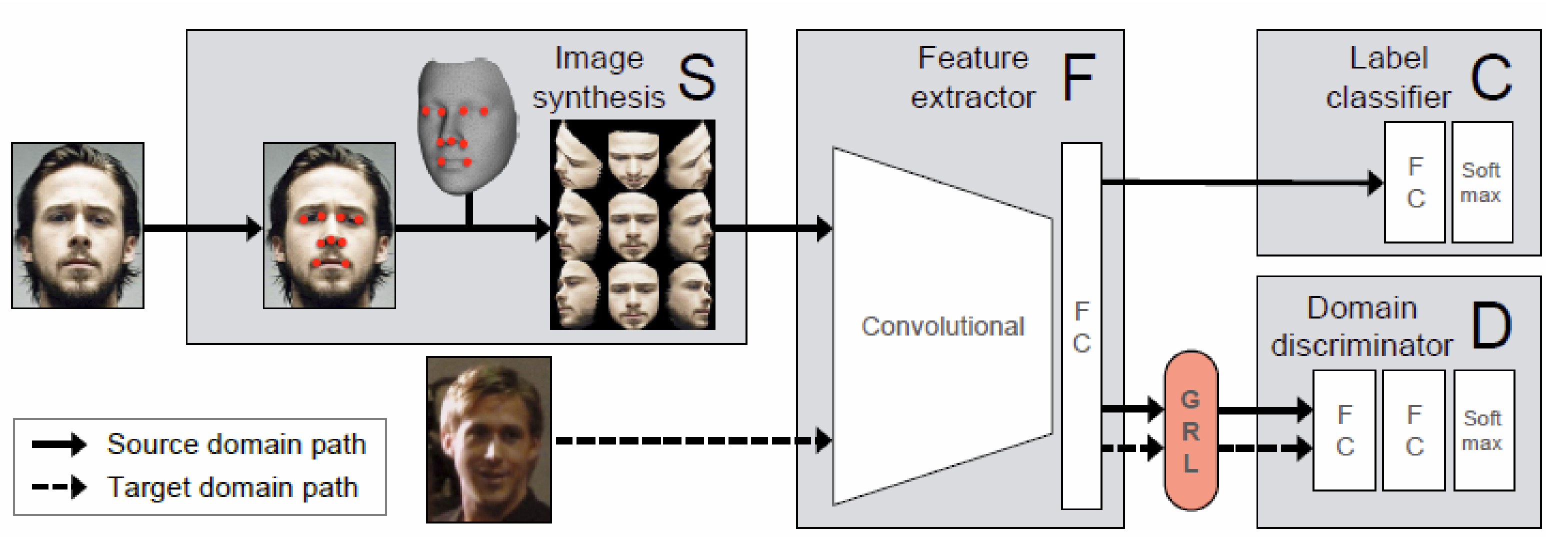
SSPP-DAN



1. **Domain adaptation network**
   with domain-adversarial training

- Feature learning
- Domain adaptation
- Classifier learning

Jointly

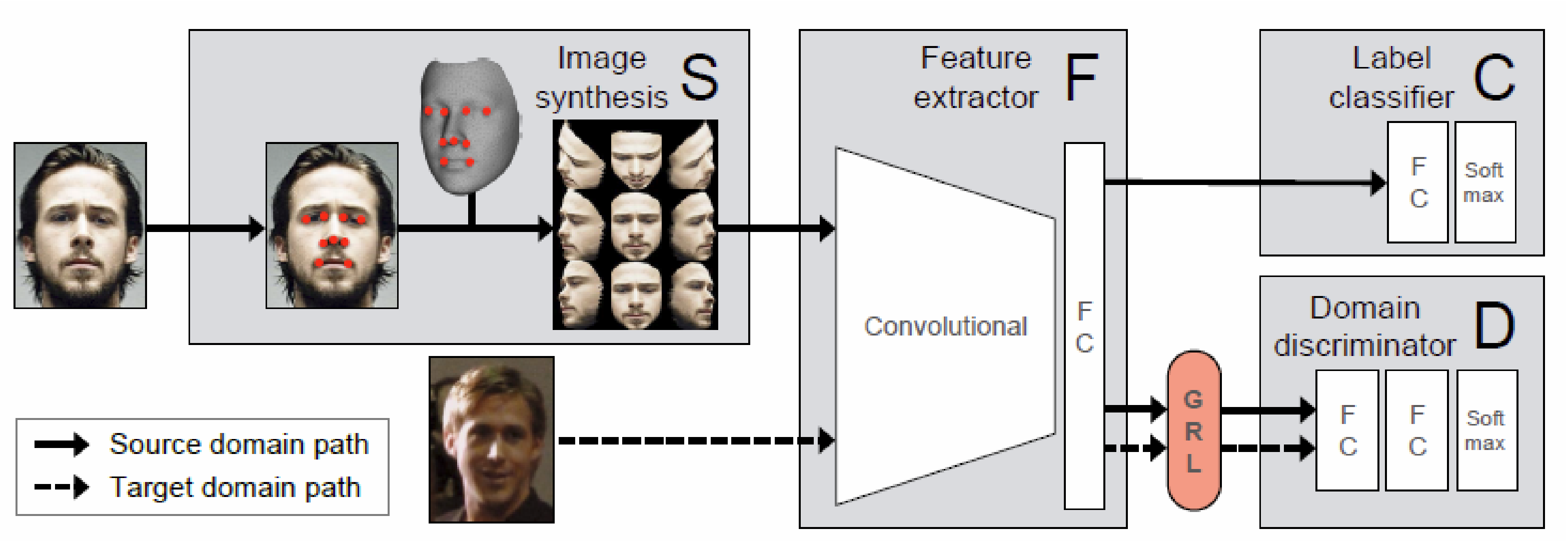
$$L_C = \sum_{i \in S} L_C^i \qquad \text{when update } \theta_C$$

$$L_D = \sum_{i \in S \cup T} L_D^i \qquad \text{when update } \theta_D$$

$$L_F = \sum_{i \in S} L_C^i - \lambda \sum_{i \in S \cup T} L_D^i \qquad \text{when update } \theta_F$$

Ganin, Yaroslav, and Victor Lempitsky. "Unsupervised domain adaptation by backpropagation." International Conference on Machine Learning. 2015.

SSPP-DAN

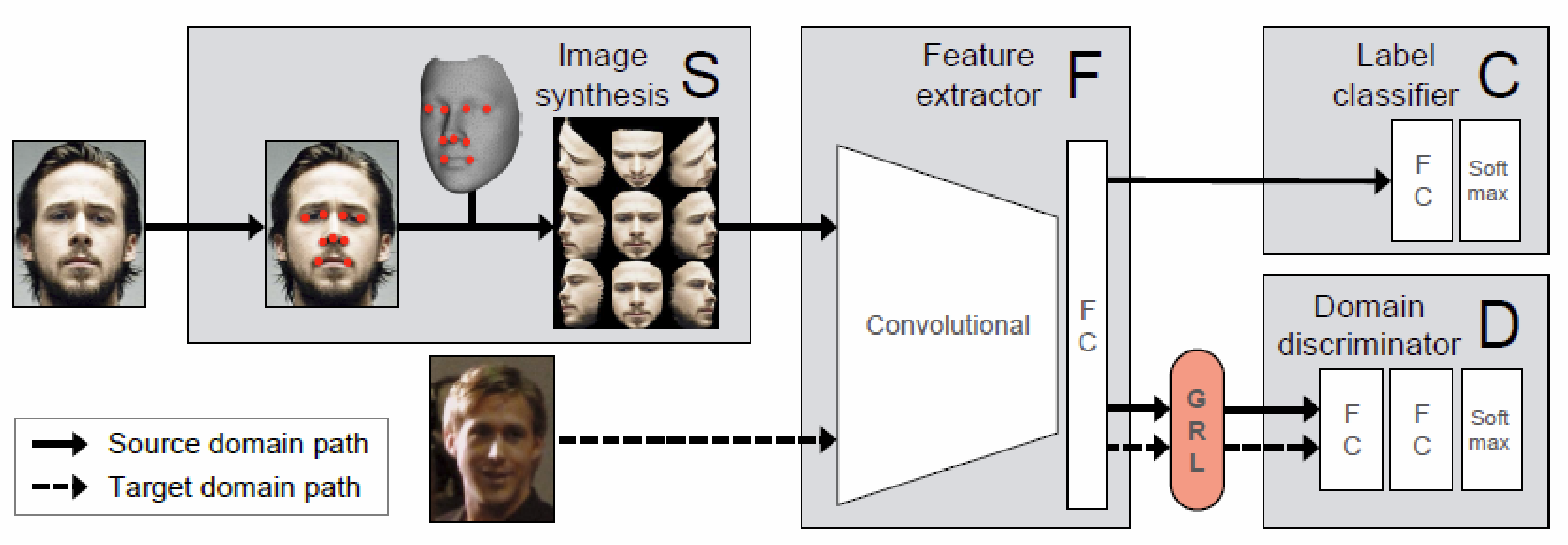


2. **Face synthesis**
   - Generate virtual samples

1) Landmark detection
   - Supervised descent method
2) 2D → 3D mapping
3) Pose estimation
4) Image synthesis
   - (yaw: -80°~+80°, pitch: -10°~40°)

Domain Adaptation

- Data Feed
  - Source (with label): frontal images + synthesized images
  - Target (without label): surveillance camera images



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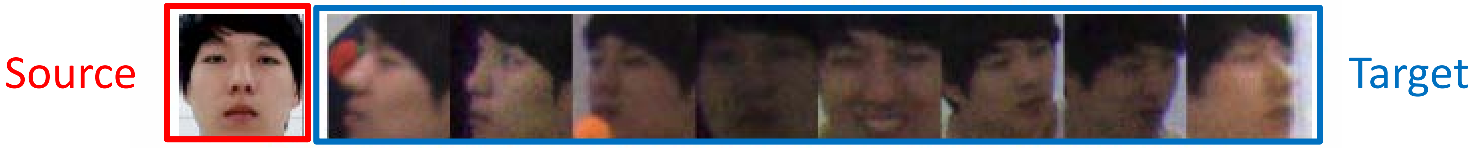
Experiments

Heterogeneous dataset

(a) Shooting condition for the source (left) and target (center and right)



(b) Face regions from the source (leftmost) and target (the others)

Table 1: Dataset specification

Domain	Source	Target
Set	webcam	surveillance
Subjects	30	30
Samples	30	15,900
Pose	frontal	various
Condition	stable	unstable (blur, noise, illumination)

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Heterogeneous dataset

Table 2: Recognition rates (%) for different models and different training sets of the EK-LFH

	Model	Training set	Accuracy
Lower bound	Source only	S	39.22
		$S + S_v$	37.15
	DAN	$S + T$	31.11
	SSPP-DAN	$S + S_v + T$	**58.53**
Upper bound	Train on target	T_l	88.31

S: Labeled webcam T: Unlabeled surveillance
S_v: Virtual set from S T_l: Labeled surveillance

only using face synthesis

only using domain adaptation

Heterogeneous dataset

Table 2: Recognition rates (%) for different models and different training sets of the EK-LFH

Model	Training set	Accuracy
Source only	S	39.22
	S + S_v	37.15
DAN	S + T	31.11
SSPP-DAN	S + S_v + T	**58.53**
Semi DAN	S + T + T_l	67.28
Semi SSPP-DAN	S + S_v + T + T_l	**72.08**
Train on target	T_l	88.31

S: Labeled webcam T: Unlabeled surveillance
S_v: Virtual set from S T_l: Labeled surveillance

Semi: 3 samples per person from target domain are revealed

Labeled Faces in the Wild (LFW)

- Dataset summary
  - Rearranged LFW-A for SSPP face recognition
  - Gallery: 50 images for 50 people
  - Generic set: 108 subjects

Labeled Faces in the Wild (LFW)

Source

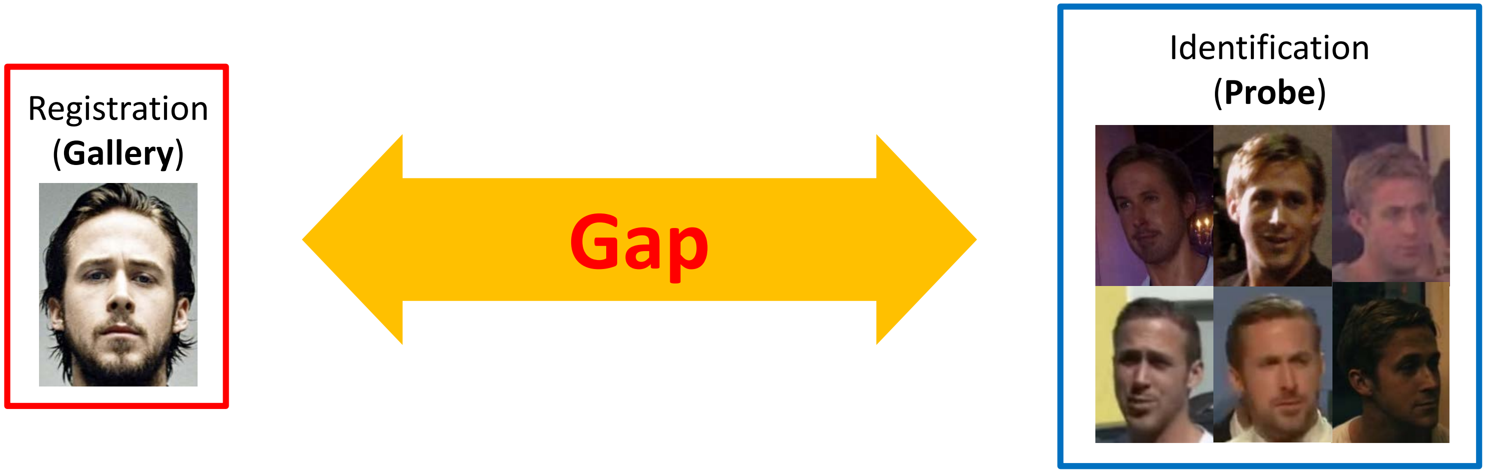
Target

- LFW for SSPP protocol
  - Gallery: 50 images for 50 people
  - Generic set: 108 subjects

Method	Accuracy	Method	Accuracy
DMMA [1]	17.8	RPR [20]	33.1
AGL [6]	19.2	DeepID [21]	70.7
SRC [4]	20.4	JCR-ACF [19]	86.0
ESRC [7]	27.3	VGG-Face [8]	96.43
LGR [22]	30.4	**Ours**	**97.91**

Deep learning

Summary

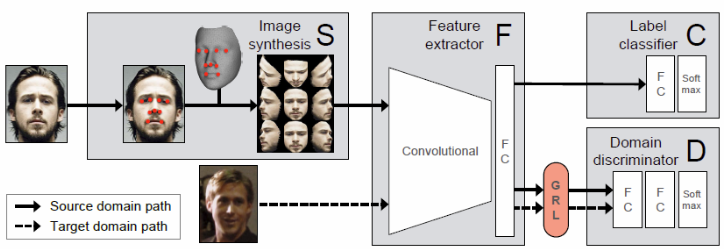


1. **Heterogeneity of the shooting environments**

2. **Shortage of training samples**

Summary

Registration
(**Gallery**)



Identification
(**Probe**)

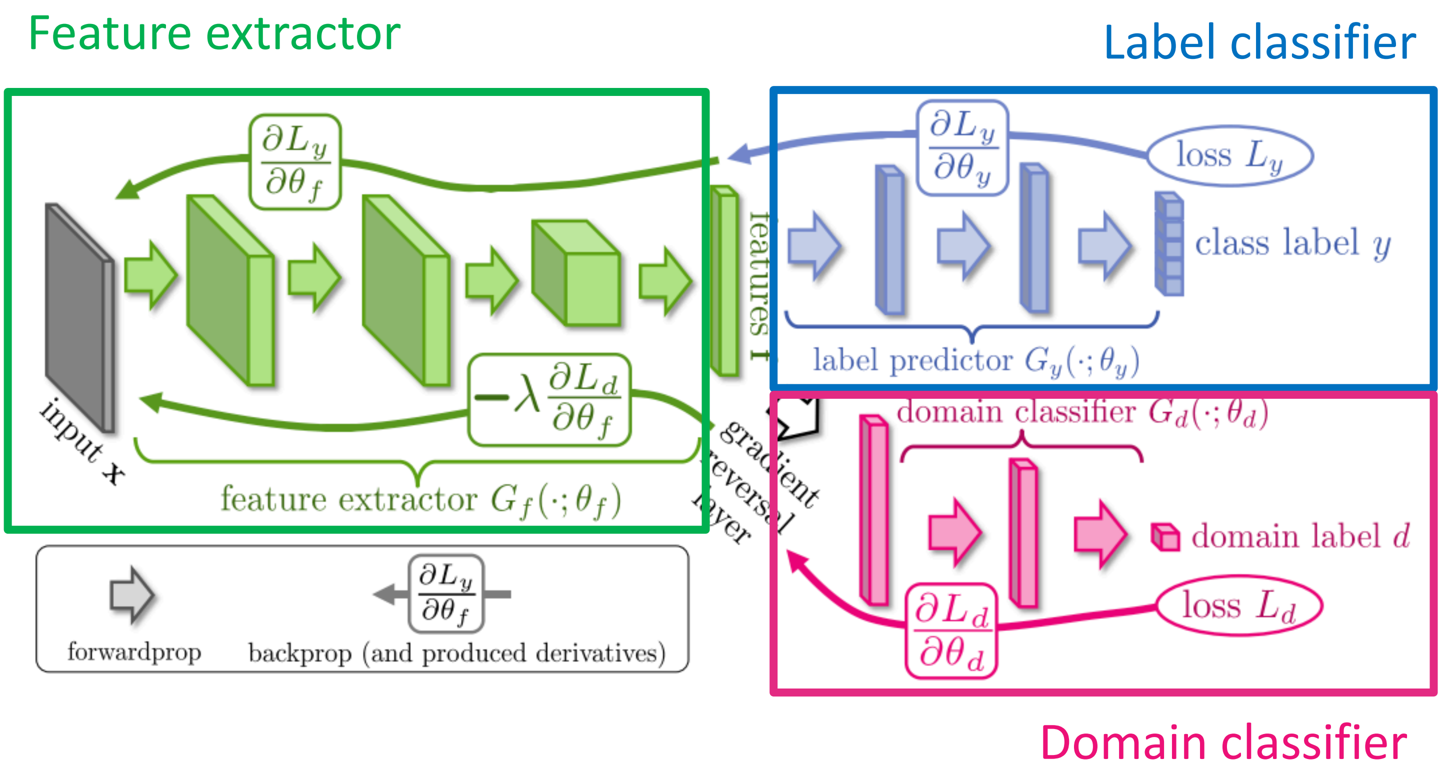
1. **Heterogeneity of the shooting environments**
   - ➢ **Domain adaptation network**
2. **Shortage of training samples**
   - ➢ **Face synthesis**

Questions?

Appendix

Domain Adaptation (DA)

- Domain Adversarial Network
  (Ganin, Yaroslav, and Victor Lempitsky. "Unsupervised domain adaptation by backpropagation." *ICML 2015.)*
  - Unified framework using adversarial training



Domain Adaptation (DA)

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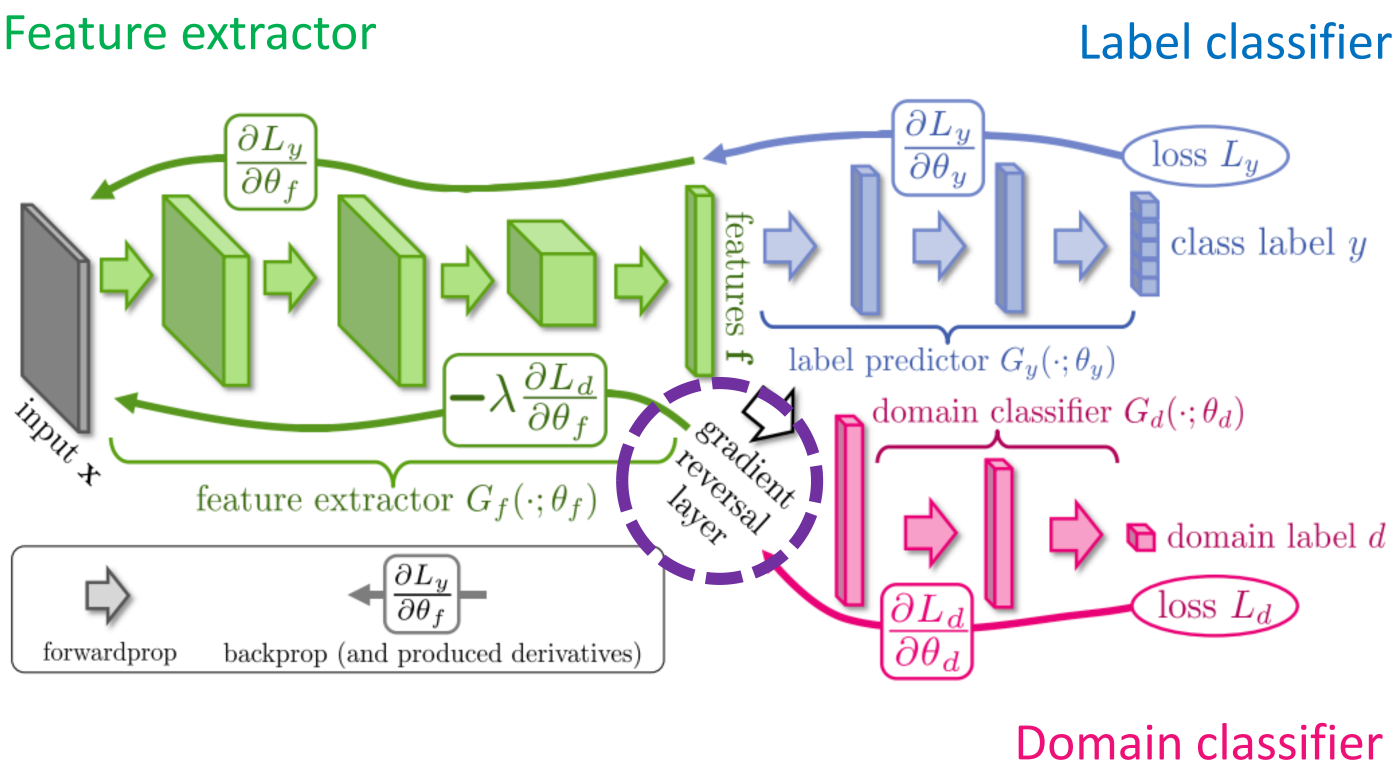

Domain Adaptation

- Adversarial Training
  - F is trained to fool D so that D cannot determine domain of data.
  - Gradient Reversal Layer (GRL)
    - forward: identity operation $R_\lambda(\mathbf{x}) = \mathbf{x}$
    - backward: multiply by $-\lambda$ $\dfrac{dR_\lambda}{d\mathbf{x}} = -\lambda\mathbf{I}$

- Loss for training

$$L_C = \sum_{i \in S} L_C^i \qquad \text{when update } \theta_C$$

$$L_D = \sum_{i \in S \cup T} L_D^i \qquad \text{when update } \theta_D$$

$$L_F = \sum_{i \in S} L_C^i - \lambda \sum_{i \in S \cup T} L_D^i \qquad \text{when update } \theta_F$$

L_C^i and L_D^i: loss of C and D, and
$\theta_D, \theta_F, \theta_C$: parameters of D, F, C

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