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# Autoencoder based Domain Adaptation for Speaker Recognition under Insufficient Channel Information

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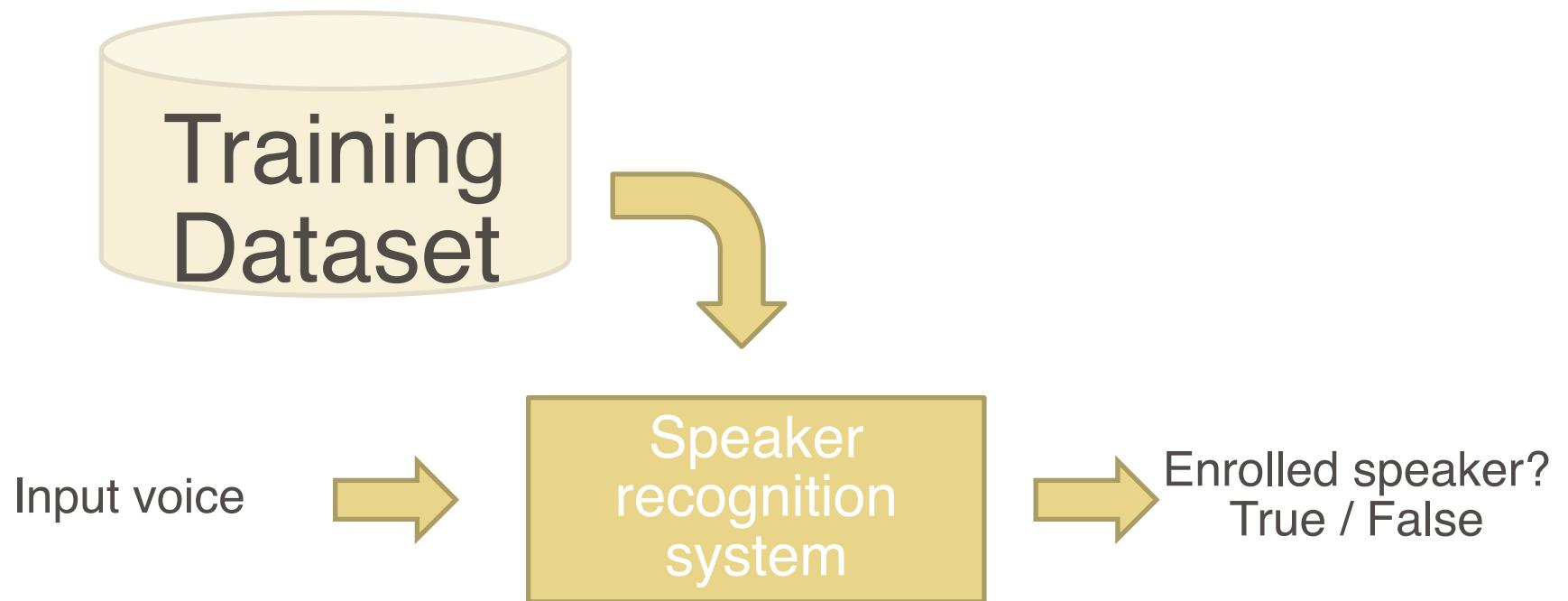
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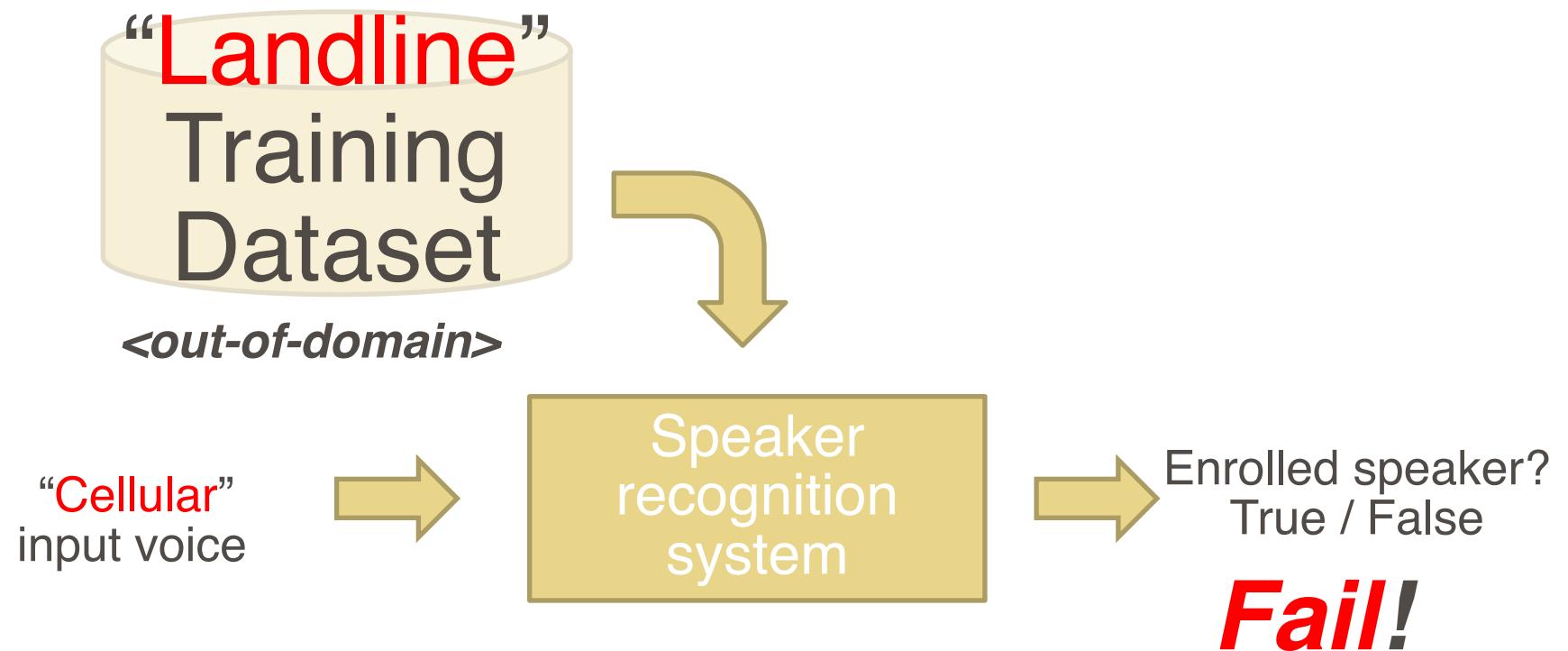
# Introduction

- Speaker recognition task



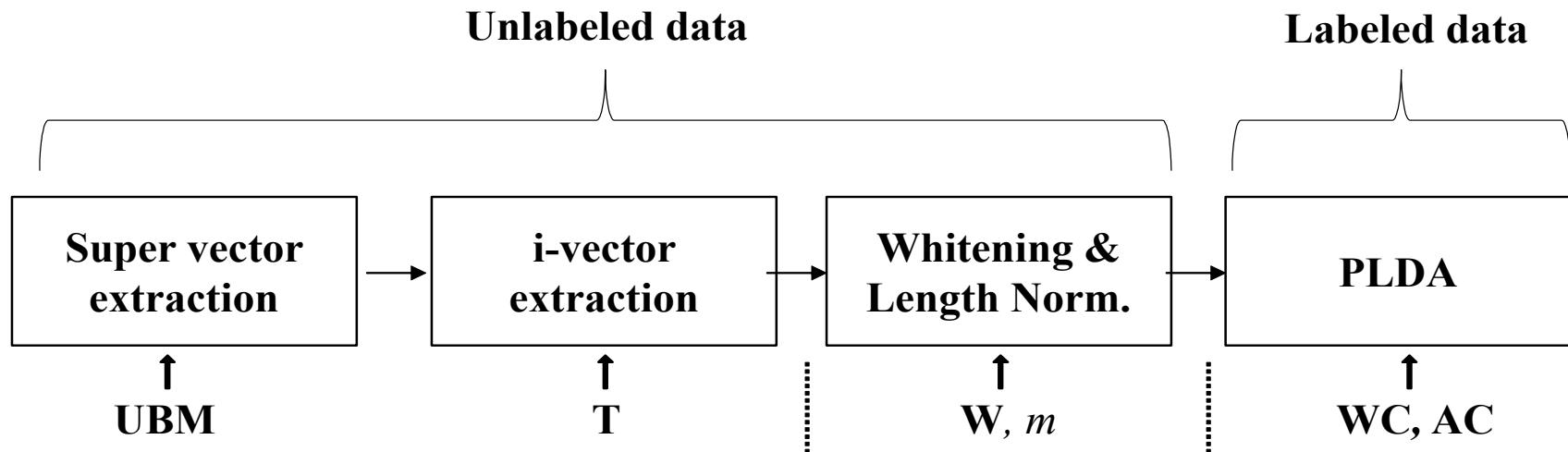
# Introduction

- Channel domain mismatched condition



# Introduction

- Domain adaptation challenge 2013 @ JHU workshop
  - SRE10 (evaluation) collected in 2010 (mostly cellular)
    - \* 7,169 target and 408,950 non-target trials
  - SWB collected from 1992-2000 (mostly landline), mismatched
  - SRE collected from 2004-2008 (mostly cellular), matched
    - \* Suppose we don't have labels on SRE



# Introduction

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System #	Unlabeled data		Labeled data		EER	Domain matched benchmark
	UBM, T	W,m	WC,AC			
0*	SRE	SRE	SRE		2.43	
1	SWB	SRE	SRE		2.33	
2	SWB	SRE	SWB		5.70	
3*	SWB	SWB	SWB		6.92	

Table 2: *SRE10 Test using DAC13 i-vector set.*

# Motivation

- Insufficient Channel Information

	SWB	SRE	SRE-1phn
#spkrs	3114	3790	3787
#calls	33039	36470	25640
Avg. #calls/spkrs	10.6	9.6	6.77
Avg. #phone_num/spkr	3.8	2.8	1

<Statistics in DAC 13 i-vector Dataset>

System #	UBM, T	W,m	WC,AC	EER	
1	<b>SWB</b>	<b>SRE</b>	<b>SRE</b>	2.33	
2	<b>SWB</b>	<b>SRE</b>	<b>SWB</b>	5.70	 better
3	<b>SWB</b>	<b>SRE-1phn</b>	<b>SRE-1phn</b>	9.34	 worse
4	<b>SWB</b>	<b>SRE-1phn</b>	<b>SWB</b>	5.66	

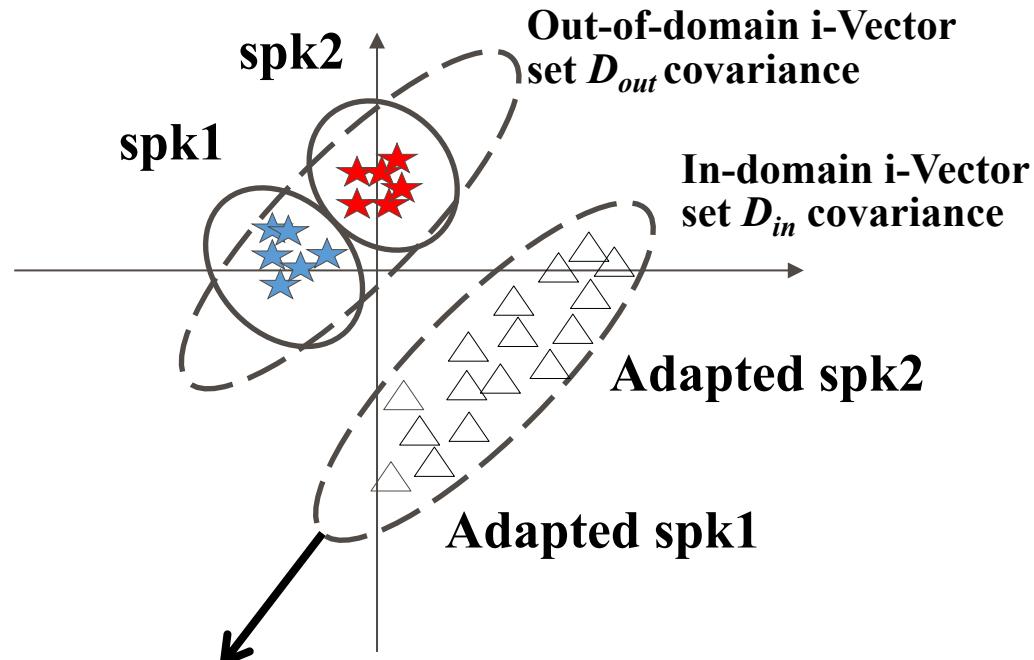
< SRE10 Test using DAC13 i-vector set >

**Performance degraded by Insufficient channel information although it is matched domain dataset**

# Proposed Approach

- Auto-encoder based Domain Adaptation (AEDA)

★ ★ : out-of-domain i-Vector from  $D_{out}$  with label  
△ ▲ : adapted i-Vector from  $D_{out}^t$   
△ : in-domain i-Vector from  $D_{in}$  without label

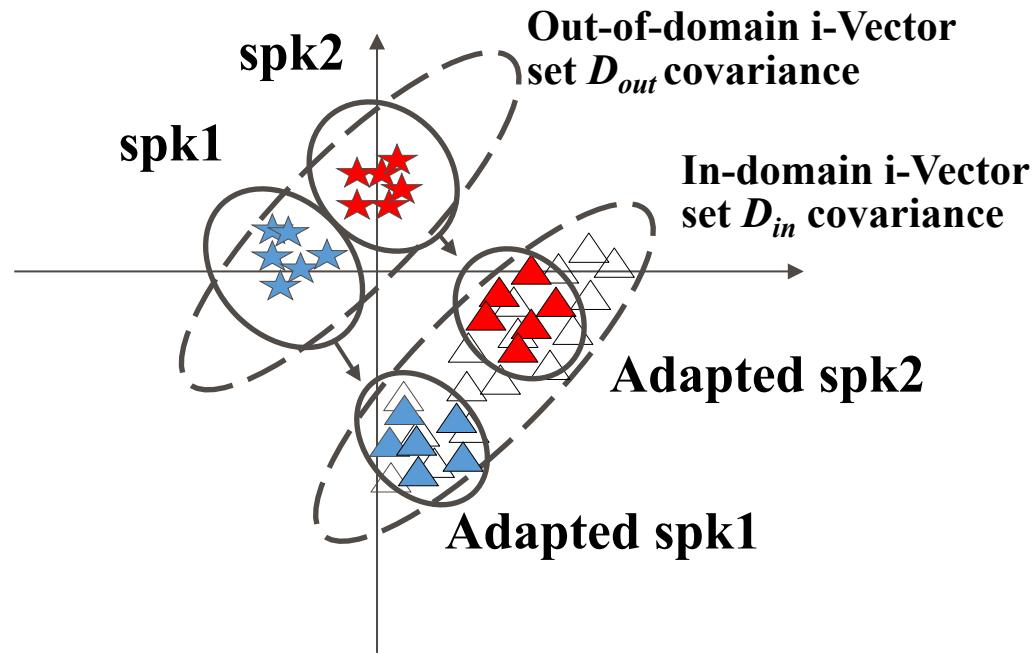


*Useless because of insufficient channel information*

# Proposed Approach

- Auto-encoder based Domain Adaptation (AEDA)

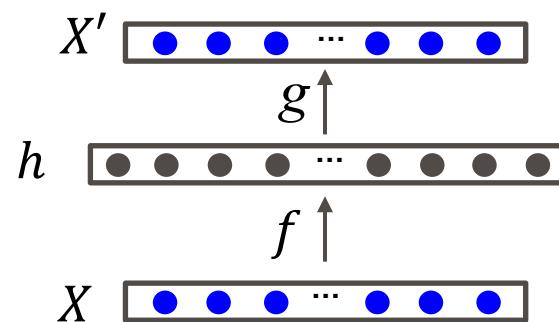
★ ★ : out-of-domain i-Vector from  $D_{out}$  with label  
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*Transferring labeled out-of-domain dataset to in-domain*

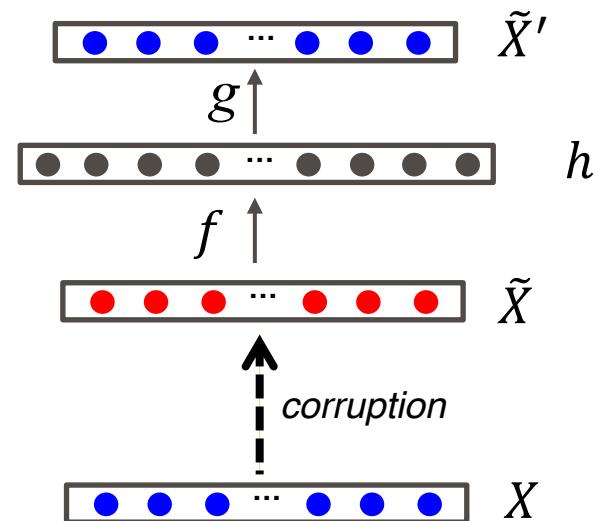
# Proposed Approach

- Autoencoder and Denoising Autoencoder



$$\mathcal{L}(X, X') = ||X - X'||^2$$

<Autoencoder>

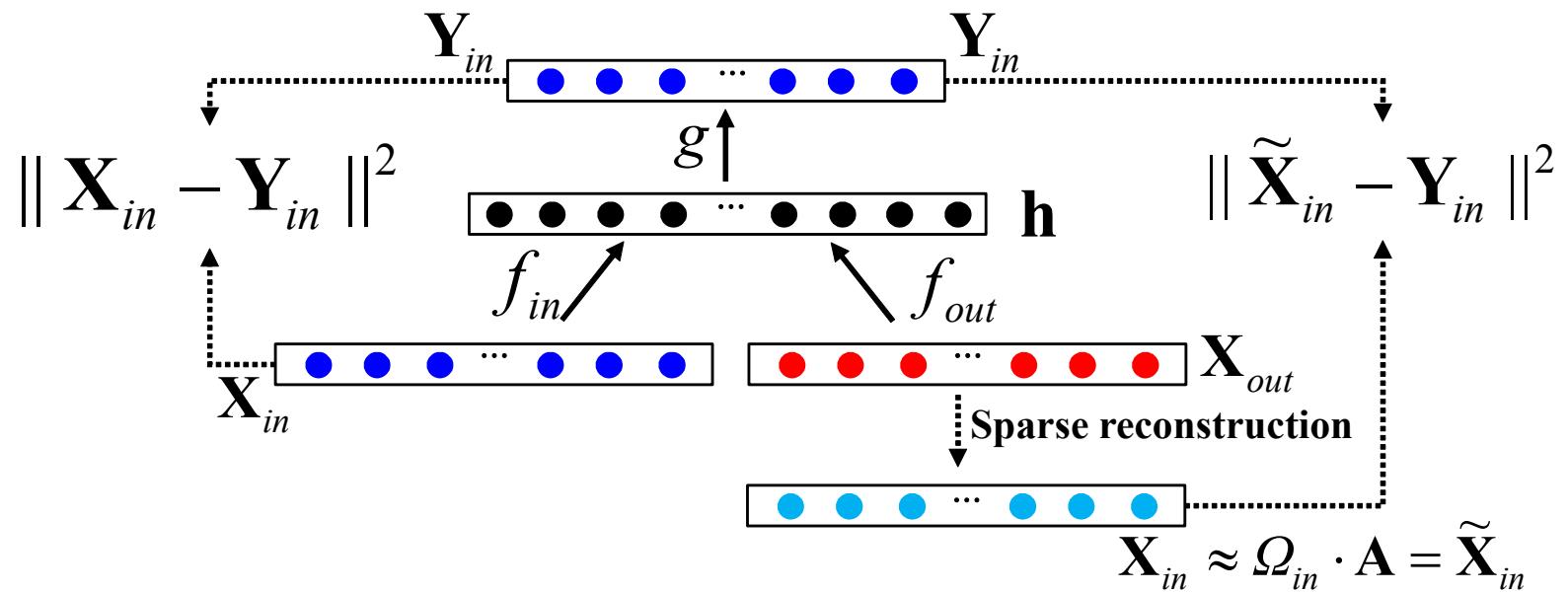


$$\mathcal{L}(X, \tilde{X}') = ||X - \tilde{X}'||^2$$

<Denoising Autoencoder>

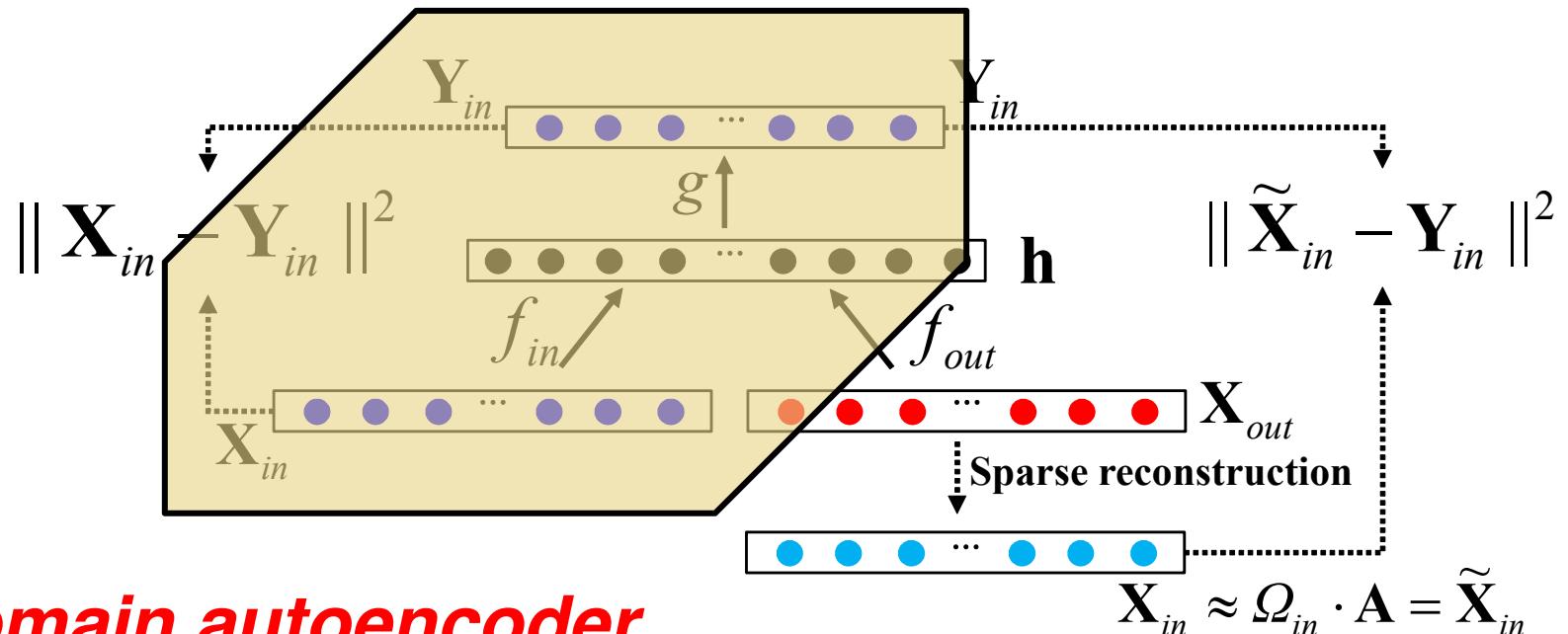
# Proposed Approach

- Auto-encoder based Domain Adaptation (AEDA)



# Proposed Approach

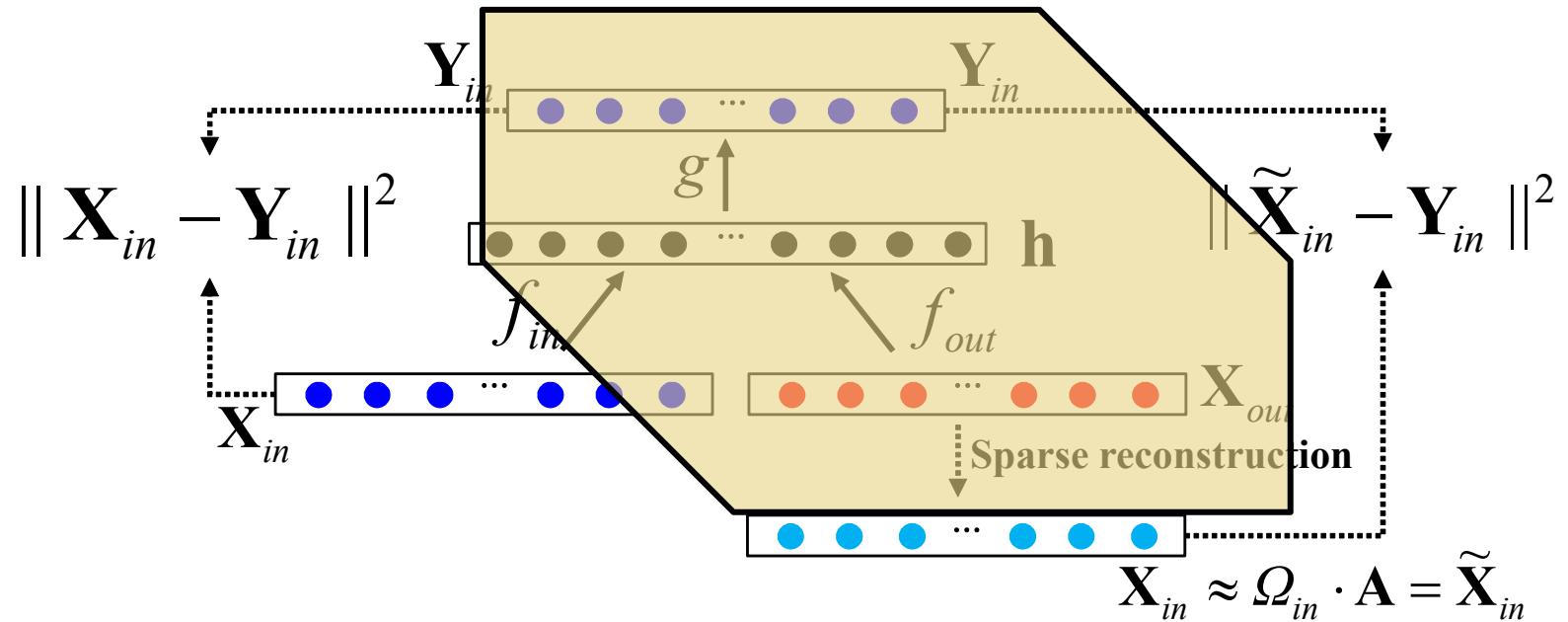
- Auto-encoder based Domain Adaptation (AEDA)



*In-domain autoencoder  
(using unlabeled in-domain dataset)*

# Proposed Approach

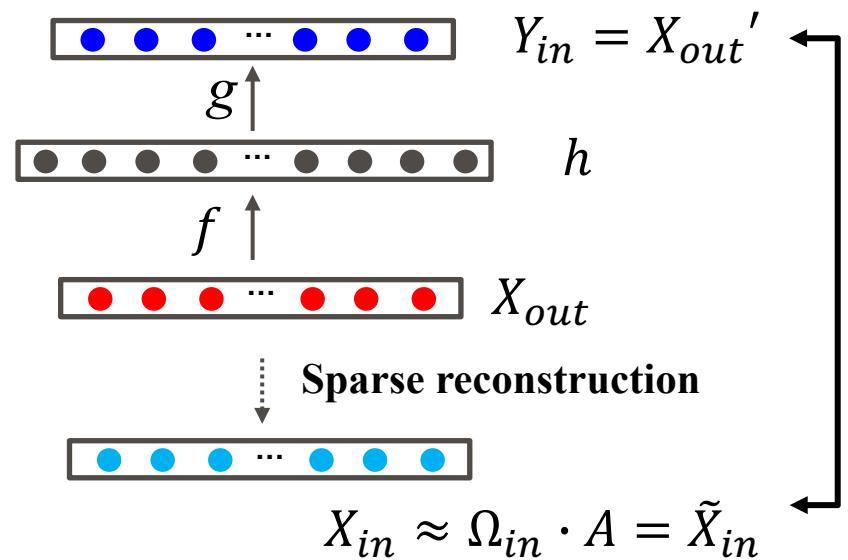
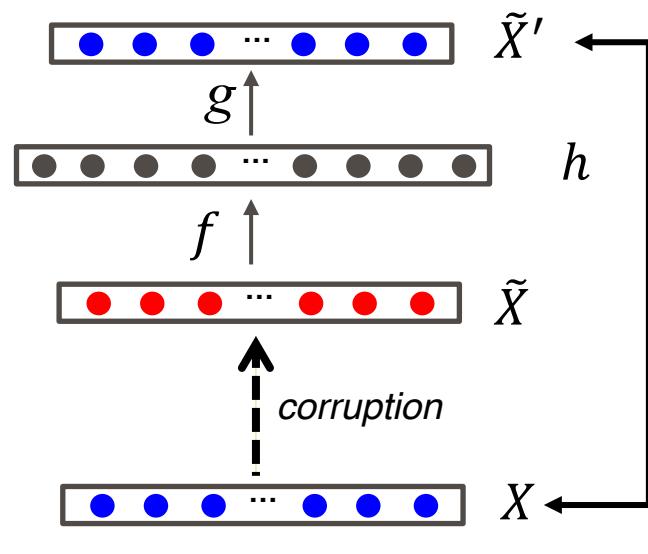
- Auto-encoder based Domain Adaptation (AEDA)



*domain transferring  
autoencoder  
(using labeled out-of-domain dataset)*

# Proposed Approach

- Sparse reconstruction



Objective function :  $\min_{\alpha_j} \| \Omega_{in} \alpha_j - \mathbf{y}_j^{in} \|^2 + \gamma | \alpha_j |^2$

$$\mathcal{L}(X, X') = \|X - \tilde{X}'\|^2$$

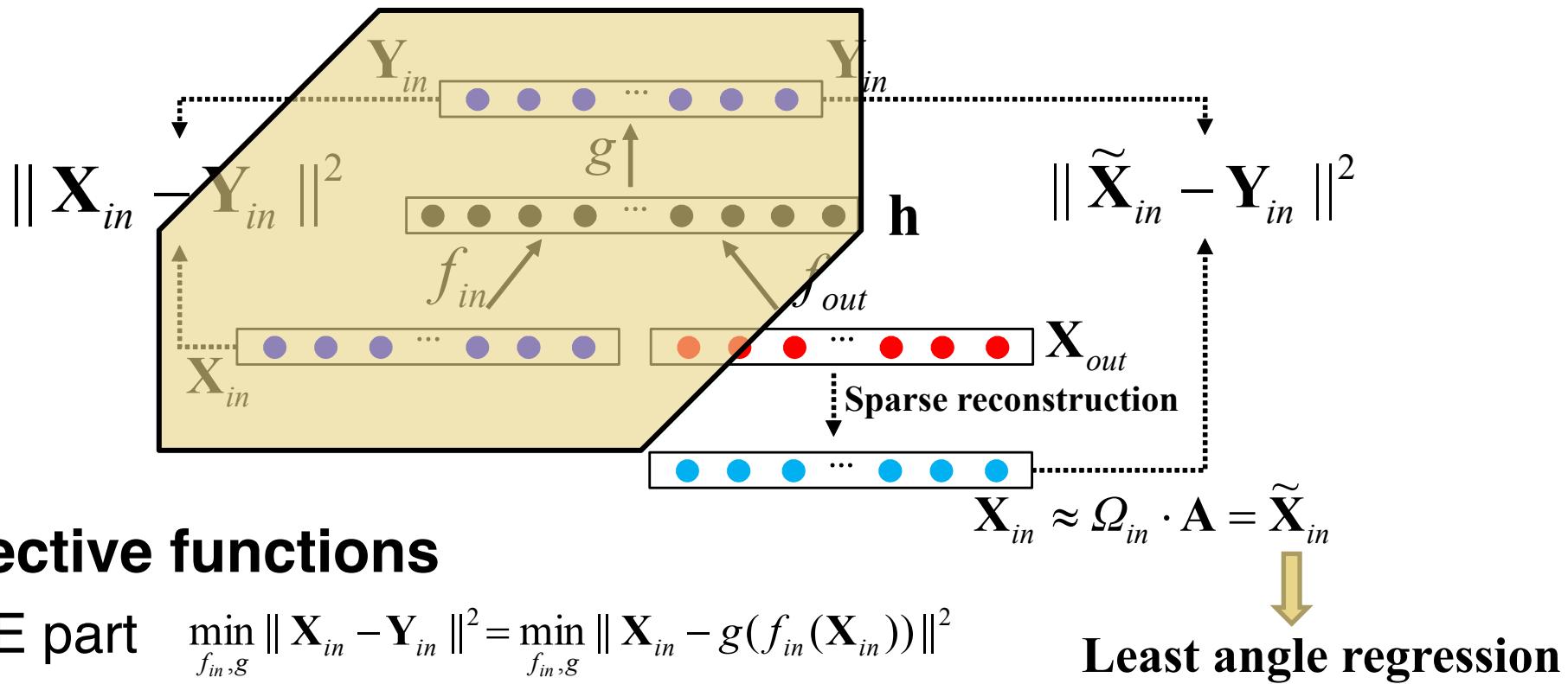
<Denoising Autoencoder>

$$\begin{aligned} \mathcal{L}(X_{in}, Y_{in}) &= \|X_{in} - Y_{in}\|^2 \\ &= \|\tilde{X}_{in} - Y_{in}\|^2 \end{aligned}$$

<*Out-of-domain transferring autoencoder*>

# Proposed Approach

- Structure of Autoencoder which sharing hidden layer  $h$



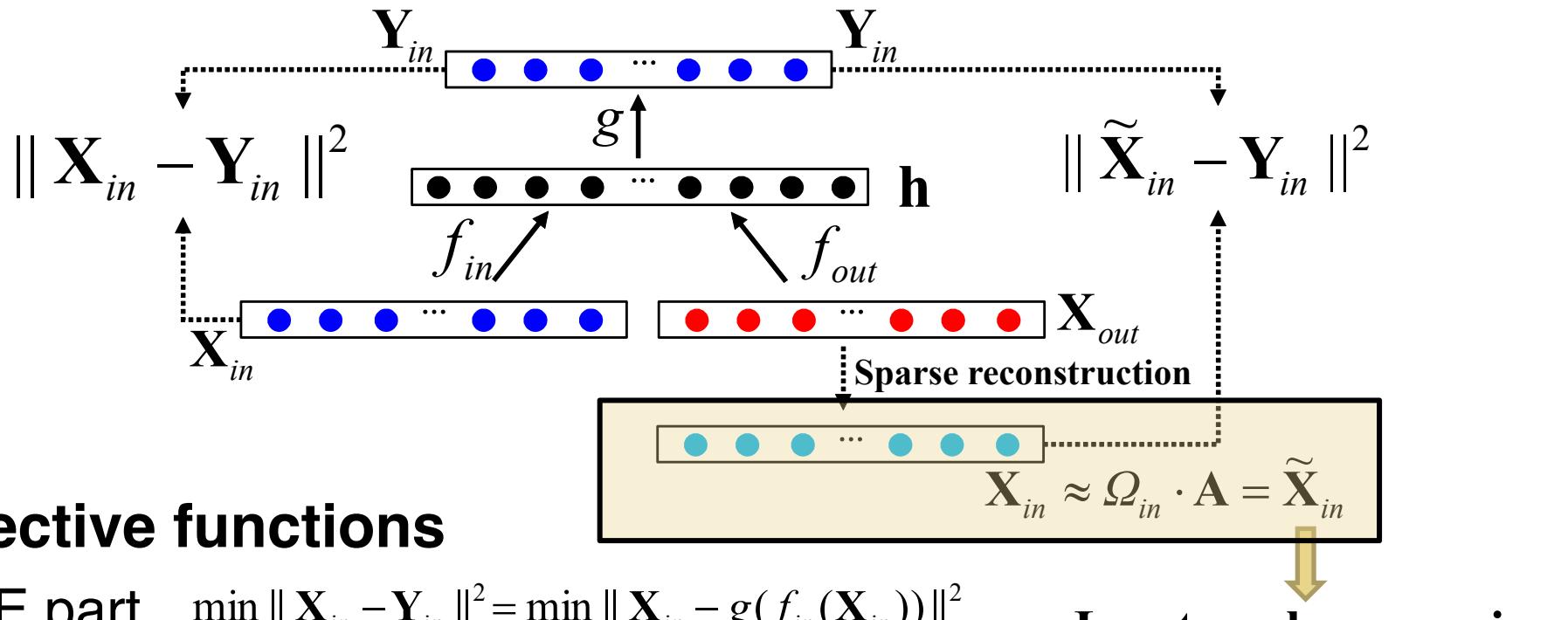
- Objective functions

– AE part  $\min_{f_{in}, g} \|\mathbf{X}_{in} - \mathbf{Y}_{in}\|^2 = \min_{f_{in}, g} \|\mathbf{X}_{in} - g(f_{in}(\mathbf{X}_{in}))\|^2$

Least angle regression

# Proposed Approach

- Structure of Autoencoder which sharing hidden layer  $h$



- Objectives functions

– AE part  $\min_{f_{in}, g} \|X_{in} - Y_{in}\|^2 = \min_{f_{in}, g} \|X_{in} - g(f_{in}(X_{in}))\|^2$

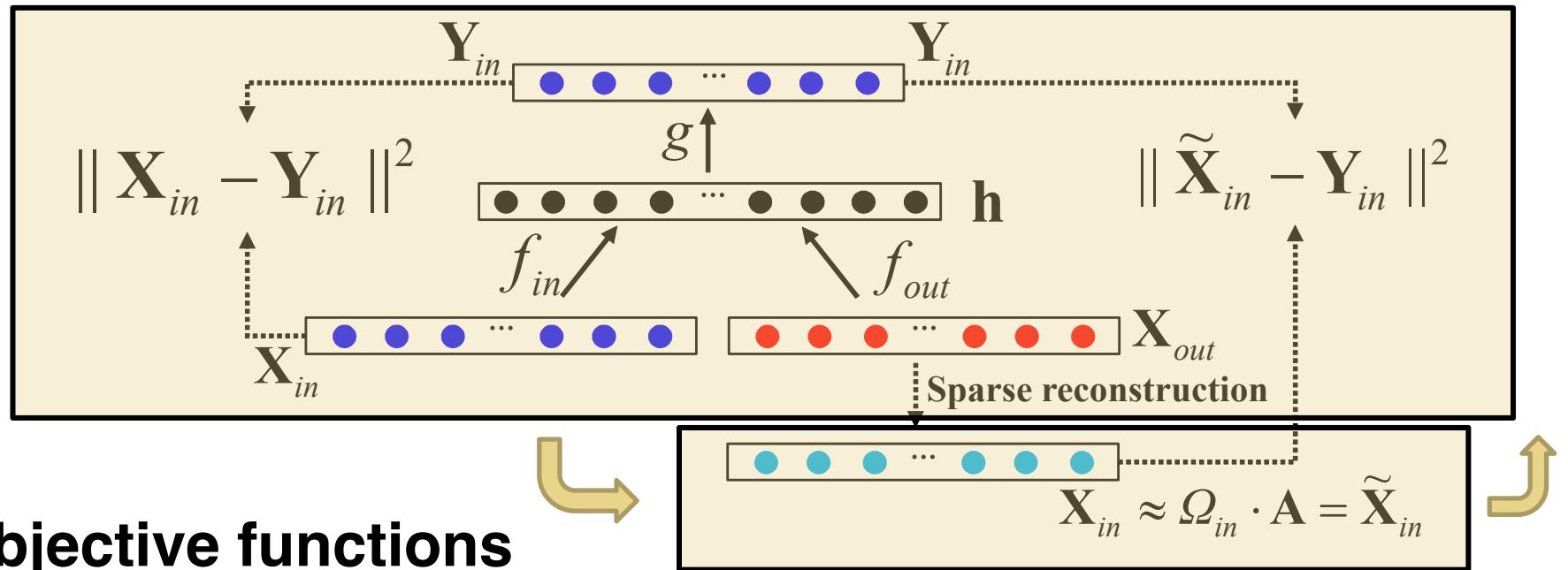
Least angle regression

- Least angle regression for sparse reconstruction

$$\min_{\alpha_j} \|\Omega_{in} \alpha_j - y_j^{in}\|^2 + \gamma |\alpha_j|^2$$

# Proposed Approach

- Structure of Autoencoder which sharing hidden layer  $h$



- Objectives functions

– AE part  $\min_{f_{in}, g} \|\mathbf{X}_{in} - \mathbf{Y}_{in}\|^2 = \min_{f_{in}, g} \|\mathbf{X}_{in} - g(f_{in}(\mathbf{X}_{in}))\|^2$

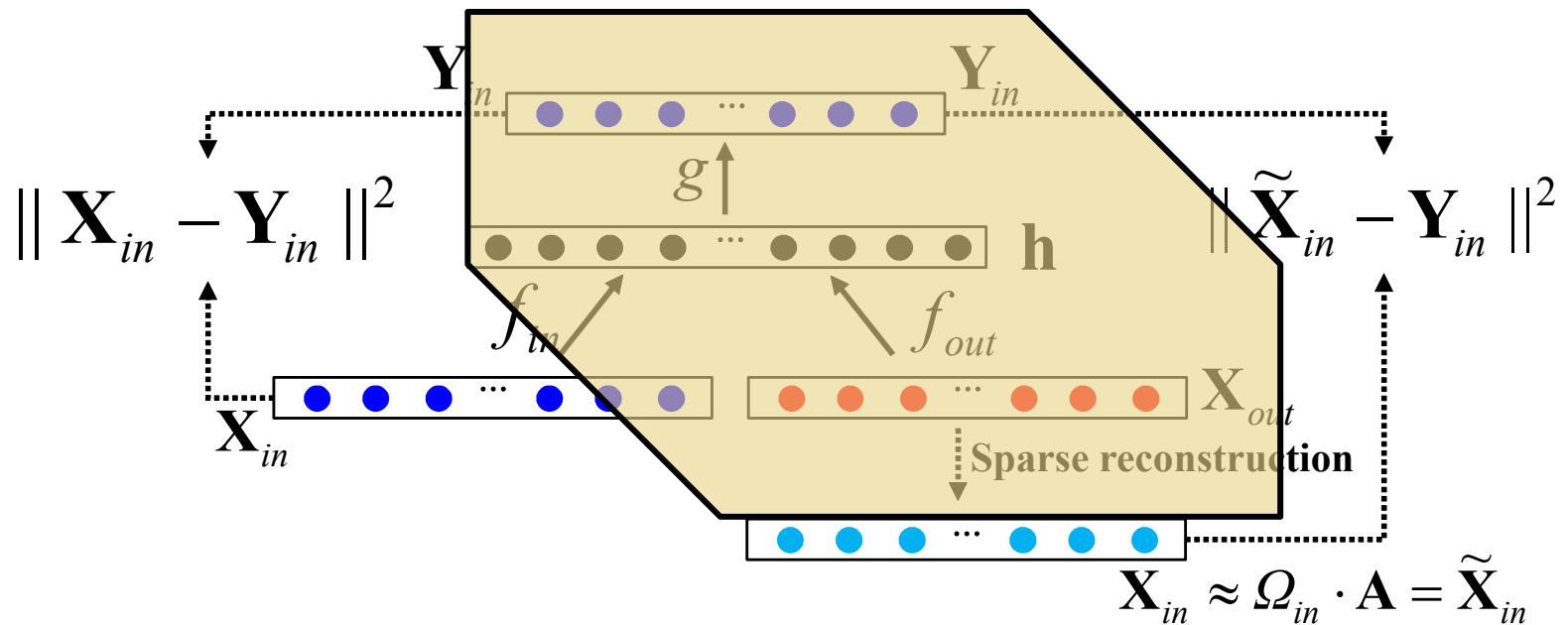
– DAE part  $\min_{f_{out}, g} \|\mathbf{X}_{in} - \mathbf{Y}_{in}\|^2 = \min_{f_{out}, g} \|\mathbf{X}_{in} - g(f_{out}(\mathbf{X}_{out}))\|^2$

– AEDA  $\min_{f_{in}, f_{out}, g} \|\mathbf{X}_{in} - g(f_{in}(\mathbf{X}_{in}))\|^2 + \|\tilde{\mathbf{X}}_{in} - g(f_{out}(\mathbf{X}_{out}))\|^2$

Training network  $\min_{\alpha_j} \|\Omega_{in} \alpha_j - \mathbf{y}_j^{in}\|^2 + \gamma |\alpha_j|^2$  Sparse reconstruction

# Proposed Approach

- Structure of Autoencoder which sharing hidden layer  $h$



- **AEDA**
  - 600 dim i-vector with 1000 hidden node with learning rate 0.005
- **Sparse reconstruction**
  - Least Angle Regression(LARS)
  - Sparsity 0.01
  - Random 1500 spk i-vector for in-domain dictionary  $\Omega_{in}$
- **Performance**
  - Using PLDA with 400 eigenvoice after 400 dim LDA transform
  - EER, DCF10, DCF08

# Experimental result

- Auto-encoder based Domain Adaptation (AEDA)

#	Adaptation & Compensation	WC, AC	EER	DCF10	DCF08
3	-	SRE-1phn	9.34	0.721	0.520
4	-	SWB	5.66	0.633	0.426
5	Interpolated [13]	SWB + SRE-1phn	6.55	0.652	0.454
6	IDV [15]	IDV-SWB	6.15	0.676	0.476
7	DICN [16]	DICN-SWB	4.99	0.623	0.416
8	DAE [23]	DAE-SWB	4.81	0.610	0.398
<b>9</b>	<b>AEDA</b>	<b>AEDA-SWB</b>	<b>4.50</b>	<b>0.589</b>	<b>0.362</b>

*<SRE10 evaluation result with DAC 13 Dataset  
when Unlabeled In-Domain Dataset is Available >*

# Conclusion

- Only small subset of unlabeled in-domain dataset is used for domain adaptation
- Insufficient channel information dataset is effectively used for transferring knowledge of in-domain
- Domain transferring autoencoder part of AEDA can be trained using sparse reconstruction without actual pair of in-domain and out-of-domain

# Q & A

- Thanks!
- Domain related paper :  
**Suwon Shon, Seongkyu Mun and Hanseok Ko,**  
**“Recursive whitening transformation for speaker recognition on Language Mismatched Condition”**  
**@ 4.9 *Evaluation of Speaker and language identification systems session, Wednesday 10:00~12:00***