Unsupervised Domain Adaptation via Domain Adversarial Training for Speaker Recognition

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Outline

- Introduction
- Proposed Method
- Experimental Setup and Result
- Conclusions



Introduction | Domain Mismatch in Speaker Recognition

- Conventional approaches of speaker recognition usually assume that training and evaluation data share the same probability distributions or the same feature space.

- However, in the real-world application, there is always a mismatch between the training and evaluation datasets, which leads to the **domain mismatch** in speaker recognition.

- **Domain adaptation** is seen as a solution to alleviate the domain mismatch,

Introduction | Previous work

- Domain adaptation for speaker recognition
  - Training dataset ⟶ Source domain
  - Evaluation dataset ⟶ Target domain

- According to the availability of labels in target domain:
  - Supervised domain adaptation
  - Unsupervised domain adaptation
    - Use clustering techniques to estimate speaker label of unlabeled target domain data.
    - Select the unlabeled target and source domain data to estimate a compensation model to compensate the domain mismatch.
    - Learn the domain-invariant space or map the source domain data into target domain space and use the mapped source domain data with its speaker label to train LDA or PLDA.
      - Autoencoder based Domain Adaptation (AEDA): adapt source domain data to target domain.



Introduction | Contribution

- Apply Domain Adversarial Training (DAT) [2] to solve the domain mismatch problem in speaker recognition.
- Project the source domain data and target domain data into the common domain.
- Learn the domain-invariant and speaker-discriminative speech representations.

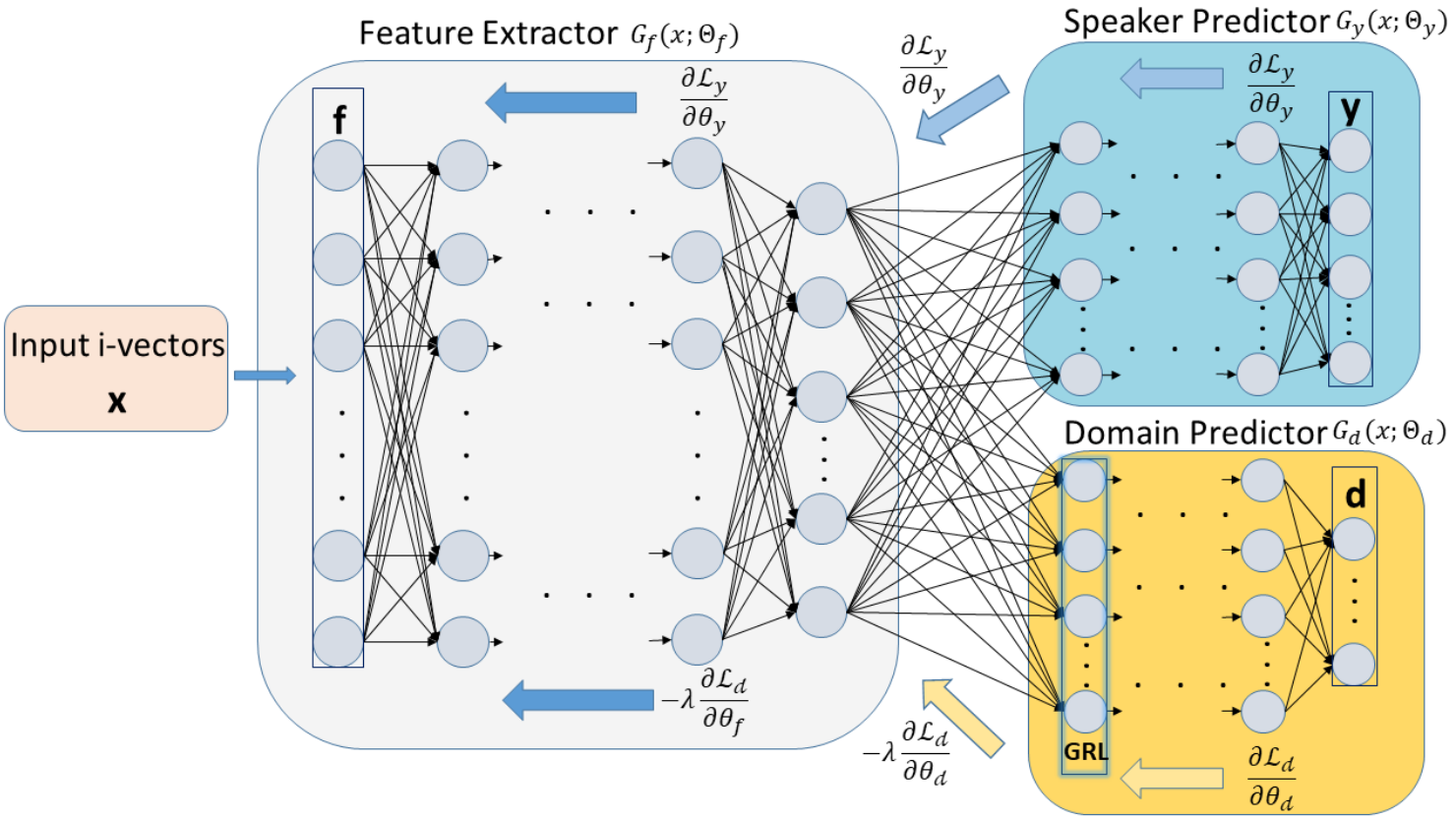
[1] Yaroslav Ganin et al. “Domain-Adversarial Training of Neural Networks”. In: Journal of Machine Learning Research 17.1 (2015), pp. 2096–2030.
[2] Sining Sun et al. “An unsupervised deep domain adaptation approach for robust speech recognition,” Neurocomputing, pp. 79– 87, 2017.



Method

DAT in Speaker Recognition

- Domain Adversarial Training (DAT)



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Method

DAT in Speaker Recognition

- Gradient Reversal Layer (GRL)
  - ensures the feature distributions over the two domains are similar so that we can get domain-invariant and speaker-discriminative features.
  - multiplies by a certain **negative** hyper parameter during the backpropagation, used to trade off two losses.
- Loss Function

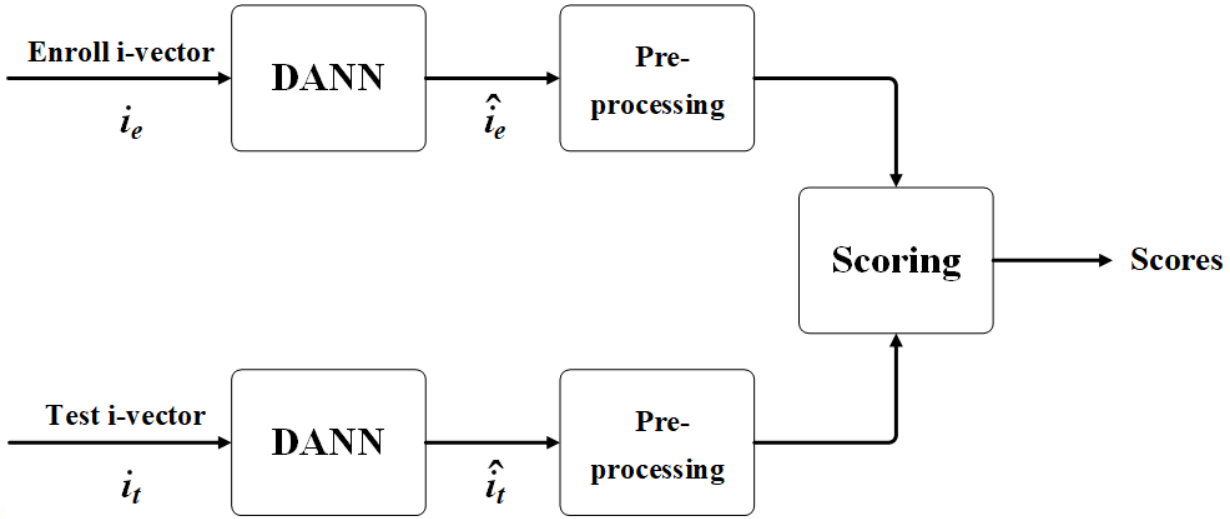
$$E(\Theta_f, \Theta_y, \Theta_d) = \sum_{\substack{i=1,\dots N \\ \mathbf{d}_i=[1,0]}} L_y(G_y(G_f(\mathbf{x}_i;\Theta_f);\Theta_y), \mathbf{y}_i) - \lambda \sum_{i=1,\dots N} L_d(G_d(G_f(\mathbf{x}_i;\Theta_f);\Theta_d), \mathbf{d}_i)$$

$$= \sum_{\substack{i=1,\dots N \\ \mathbf{d}_i=[1,0]}} L_y^i(\Theta_f, \Theta_y) - \lambda \sum_{i=1,\dots N} L_d^i(\Theta_f, \Theta_d)$$



Method | i-vector Scoring

- Domain Adversarial Neural Network (DANN): we call the model trained by DAT method as DANN
  - Input: enroll data i-vector (i_e) and test i-vector (i_t)
  - Extract new vectors $\widehat{i_e}$, $\widehat{i_t}$ from the hidden layer of the feature extractor sub-network from DANN
  - Domain-invariant and speaker-discriminative speech representations



Experimental Setup and Result

- Dataset:
  - 2013 domain adaptation challenge dataset (DAC 13) i-vector Dataset
    - Source domain data: SWB
    - Target domain data: SRE, SRE-1phn
    - Test data: SRE10 telephone data

	SWB	SRE	SRE-1phn
#spks	3114	3790	3787
#calls	33039	36470	25640
#calls/spkrs	10.6	9.6	6.77
#phone_num/spkr	3.8	2.8	1.0

i-vector Statistic in DAC 13 i-vector Dataset



Experimental Setup and Result

- Baseline Experiments:
  - System1: domain match
  - System2: domain mismatch
  - System3: domain match & insufficient channel information
  - System4: domain mismatch

System#	Pre-processing	PLDA	EER%	DCF10	DCF08
1	SRE	SRE	2.33	0.402	0.235
2	SRE	SWB	5.65	0.632	0.427
3	SRE-1phn	SRE-1phn	9.35	0.724	0.520
4	SRE-1phn	SWB	5.66	0.633	0.427



Experimental Setup and Result

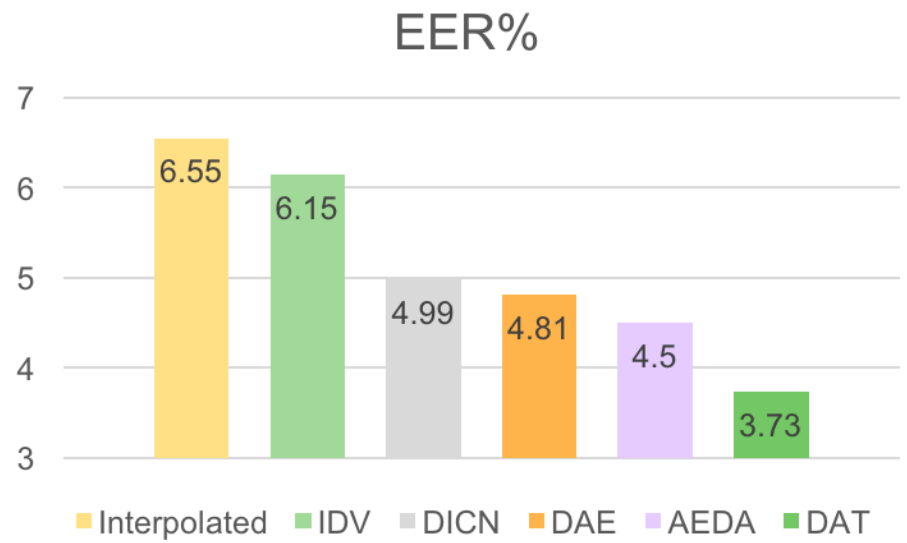
- DAT method Experiments:
  - Training data of DANN:
    - SWB i-vectors with speaker labels (used to train the whole network)
    - SRE-1phn i-vectors without speaker label (used to train the feature extractor and domain classifier)
  - Baseline systems:
    - System 4: PLDA ⟶ SWB (Source domain data)

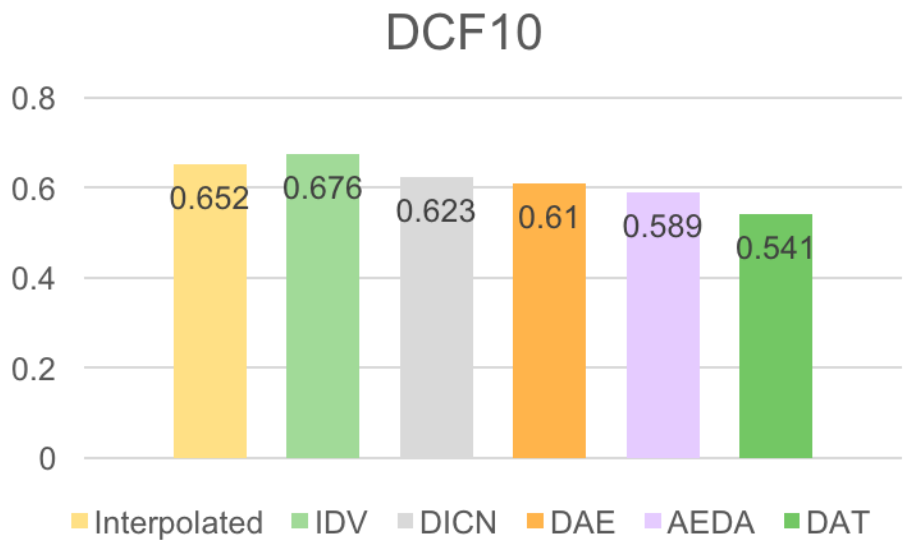
System#	Adaptation Methods	EER%	DCF10	DCF08
4	-	5.66	0.633	0.427
5	**DAT**	**3.73**	**0.541**	**0.335**



Experimental Setup and Result

- DAT vs. state-of-the-art unsupervised domain adaptation methods





Interpolated
IDV: Inter-dataset variability compensation
DICN: Dataset-Invariant Covariance Normalization
DAE: Denoising Autoencoder
AEDA: Autoencoder based Domain Adaptation



Conclusions

- We have proposed to perform domain adversarial training for speaker recognition.
- DAT overcomes the domain mismatch problem by projecting the source domain and target domain data into the same subspace.
- By DAT approach, we can obtain domain-invariant and speaker-discriminative speech representations.
- In future work, we will explore the effectiveness of DAT on NIST SRE 16 database and compare the difference between DAT and the generative adversarial network.



Reference

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- [4] Daniel Garcia-Romero et al. “Unsupervised domain adaptation for i-vector speaker recognition”. In: Proceedings of Odyssey: The Speaker and Language Recognition Workshop. 2014.
- [5] Ahilan Kanagasundaram et al. “Improving out-domain PLDA speaker verification using unsupervised inter-dataset variability compensation approach”. In: ICASSP. 2015.
- [6] Md Hafizur Rahman et al. “Dataset-Invariant Covariance Normalization for Out-domain PLDA Speaker Verification”. In: INTERSPEECH. 2015, pp. 1017–1021.
- [7] Oleg Kudashev et al. “A speaker recognition system for the sitw challenge,” in INTERSPEECH, 2016, pp. 833–837.



Thank you!




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