



## A-CRNN: A Domain Adaptation Model for Sound Event Detection Wei Wei, Hongning Zhu, Emmanouil Benetos, and Ye Wang ICASSP 2020

## Problem to Address





#### Domain adaptation for sound event detection

## Overview





- Sound event detection
  - Start time
  - End time
  - Label



## Overview





- Sound event detection
  - Start time
  - End time
  - Label
- Domain Adaptation
  - Mismatch between datasets

# Domain Adaptation





- Source domain
  - Labeled data



# Domain Adaptation





- Source domain
  - Labeled data
- Target domain
  - Unlabeled data



# Related Work



- CRNN
  - Convolutional recurrent neural network (Adavanne et al., 2017)
  - State-of-the-art sound event detection system



# Related Work



- Adversarial-based domain adaptation models
  - Introducing domain discriminators to perform adversarial training
  - (Ganin et al., 2015)







- Motivation
  - Most of the datasets are recorded in Europe
  - No existing dataset for sound event detection focuses on the domain adaptation problem





- Motivation
  - Most of the datasets are recorded in Europe
  - No existing dataset for sound event detection focuses on the domain adaptation problem
- Basic information
  - 3 to 5 minutes each
  - 9 hours in total
  - Collected around university campus in Singapore





- Event classes
  - car
  - children
  - large vehicle
  - people speaking
  - people walking
- Same as the DCASE dataset
  - Task 3 of DCASE 2017 challenge





- Recording equipment high quality
  - Roland CS-10EM



• Zoom H5







- Recording equipment poor quality
  - iPhone XS







- Recording equipment annotation
  - Action camera







- Post-processing
  - Alignment









- Domain adaptation
  - Mismatch of event characteristics and acoustic environment





- Domain adaptation
  - Mismatch of event characteristics and acoustic environment
  - Mismatch of recording conditions





- Domain adaptation
  - Mismatch of event characteristics and acoustic environment
  - Mismatch of recording conditions
  - Mismatch of background noise



- An unsupervised adversarial-based domain adaptation model
- Based on a domain adaptation model for acoustic scene classification <sup>[1]</sup>
- Three steps
  - Pre-training
  - Adversarial training
  - Testing

[1] Shayan Gharib, Konstantinos Drossos, Emre Cakir, Dmitriy Serdyuk, and Tuomas Virtanen, "Unsupervised adversarial domain adaptation for acoustic scene classification," in Proceedings of the Detection and Classification of Acoustic Scenes and Events 2018 Workshop (DCASE2018), November 2018, pp. 138–142.





- Pre-training step
  - Train a model for the source domain



$$\min_{M_s,C} L_s = -\frac{1}{N_s} \sum_{n=1}^{N_s} \sum_{k=1}^K \mathbb{1}_{[k=Y_s^n]} \log C(M_s(X_s^n))$$





- Adversarial training step
  - Adapt the mapping to fit the target domain







Adversarial training step







- Testing step
  - Test the model on the target domain







- Detailed architecture
  - CNN mappings (both source and target mapping)

Input	log Mel-band energies
	128 filters of shape 3 x 3, ReLU, 1 x 5 max pooling
Convolutional layers	128 filters of shape 3 x 3, ReLU, 1 x 2 max pooling
	128 filters of shape 3 x 3, ReLU, 1 x 2 max pooling





- Detailed architecture
  - RNN classifier

Dequirrant la vara	32 units, GRU, tanh		
Recurrent layers	32 units, GRU, tanh		
	16 units, time distributed, ReLU		
Fully connected layers	5 units, time distributed, Sigmoid		





- Detailed architecture
  - RNN discriminator

Recurrent layers	32 units, GRU, tanh
	32 units, GRU, tanh
	32 units, GRU, tanh
Fully connected layers	64 units, time distributed, ReLU
	64 units, time distributed, ReLU
	16 units, time distributed, ReLU
	2 units, time distributed, Softmax





- Evaluation metrics <sup>[2]</sup>
  - F-score
  - Error rate



[2] Annamaria Mesaros, Toni Heittola, and Tuomas Virtanen, "Metrics for polyphonic sound event detection," Applied Sciences, vol. 6, no. 6, pp. 162, 2016.







- Experiment results
  - Improvement on both source and target domains

 Table 1: Results (Source: SG-high; Target: SG-low)

Model	Source domain		Target domain	
	<b>F-score</b>	<b>Error rate</b>	<b>F-score</b>	Error rate
CRNN	0.583	0.620	0.442	0.743
A-CRNN	0.590	0.609	0.480	0.688





- Experiment results
  - Slight drop on source domain
  - Clear improvement on the target domain

Table 2: Results	(Source: SG-high)	Target: DCASE)

 Table 3: Results (Source: DCASE; Target: SG-high)

Model	lel Source domain Target de		t domain	Model	Source domain		Target domain		
	<b>F-score</b>	Error rate	<b>F-score</b>	Error rate		<b>F-score</b>	Error rate	<b>F-score</b>	Error rate
CRNN A-CRNN	0.470 0.427	0.793 0.869	0.256 0.458	0.947 0.826	CRNN A-CRNN	0.528 0.514	0.705 0.716	0.163 0.301	1.072 0.960





- Experiment results
  - Smaller improvement

 Table 4: Results (Source: DCASE; Target: SG-low)

Model	Source domain		Targe	t domain
	<b>F-score</b>	Error rate	<b>F-score</b>	Error rate
CRNN	0.528	0.705	0.223	1.097
A-CRNN	0.511	0.757	0.295	0.936





- Experiment results
  - Class-wise F-score

Class name	DCASE	to SG-high	<b>DCASE to SG-low</b>		
	CRNN	A-CRNN	CRNN	A-CRNN	
car	0.256	0.473	0.357	0.479	
children	0.072	0.005	0.235	0.005	
large vehicle	0.119	0.004	0.109	0.024	
people speaking	0.297	0.056	0.334	0.149	
people walking	0.081	0.096	0.082	0.104	

# Future Work





• Other non-adapted model architectures

# Future Work





- Other non-adapted model architectures
- Improve performance for certain classes

# Future Work





- Other non-adapted model architectures
- Improve performance for certain classes
- Other domain shift aspects
- Semi-supervised domain adaptation model

## Conclusions





- Problem addressed
  - Domain adaptation for sound event detection
- Solution
  - SG dataset
  - Domain adaptation model: A-CRNN





# Thank you