Continual Learning For On-Device Environmental Sound Classification

Spotlight presentation at DCASE 2022

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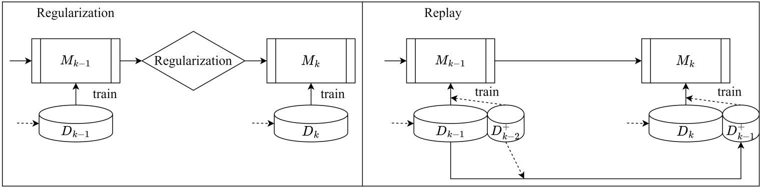
The Problem

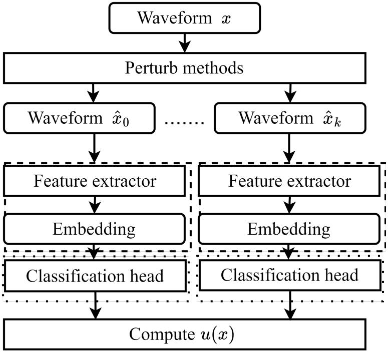
- Learning unseen classes is a major problem for on-device environmental sound classification.
- We utilise the continual learning paradigm to help address this problem.
- Our continual learning based method selects historical data for training by measuring per-sample classification uncertainty.
- Experimental results on the DCASE 2019 Task 1 and ESC-50 dataset show that our method outperforms baseline continual learning methods on accuracy and computational efficiency.

Approaches

- Continual learning (CL) aims to continuously learn new knowledge over time while retaining and reusing previously learned knowledge.
- Existing CL methods can be generally divided into two categories:
  - regularization-based methods
  - replay-based methods/ rehearsal-based



Uncertainty



(a) Perturb per waveform

- The ***Uncertainty*** memory update algorithm selects a sample based on its uncertainty
- Specifically, the first step groups the tasks $\tau_k = (x, c)$ in the training buffer $\hat{D}_{k-1}$ into subsets of unique classes D_c
- The second step estimates the uncertainty of each sample x in D_c
- Finally the samples to replay are selected based on this score.

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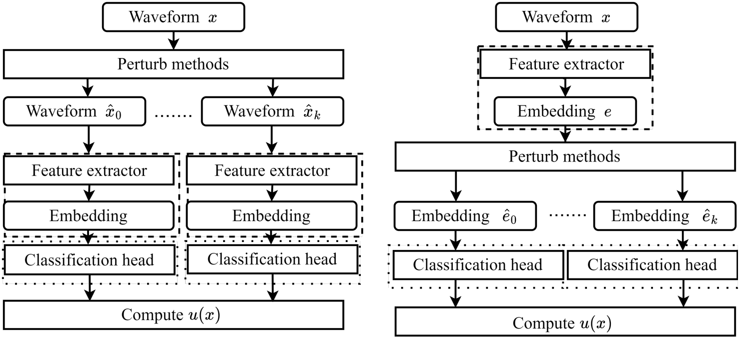
Uncertainty++



(a) Perturb per waveform **(b) Perturb per embedding**

$$\hat{e} = e + U(-\frac{\lambda}{2}, \frac{\lambda}{2}) * std(e)$$

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The Results

Method	DCASE 2019 Task 1		ESC-50	
	ACC ↑	BWT ↑	ACC ↑	BWT ↑
Finetune	0.205	-0.276	0.181	-0.307
Random	0.473	-0.115	0.225	-0.231
Reservoir	0.568	-0.096	0.430	-0.121
Prototype	0.559	-0.089	0.482	**-0.104**
Uncertainty	0.578	**-0.079**	0.477	-0.111
Uncertainty++	**0.581**	**-0.079**	**0.500**	-0.121

- Uncertainty++ method achieves better performance than the five baselines including existing MUA methods.
- Even with only two perturbation methods, our proposed method still outperforms other two baselines.

Method	K	DCASE 2019 Task 1		ESC-50	
		ACC ↑	BWT ↑	ACC ↑	BWT ↑
Uncertainty-Shift	2	0.557	-0.101	0.461	**-0.111**
	4	0.575	-0.103	0.476	-0.118
	6	0.567	-0.079	0.477	-0.118
Uncertainty-Noise	2	0.560	-0.100	0.465	-0.118
	4	0.535	-0.104	0.473	-0.118
	6	0.578	-0.079	0.458	-0.120
Uncertainty++	2	0.571	-0.102	**0.500**	-0.121
	4	0.548	-0.103	0.481	-0.114
	6	**0.581**	**-0.079**	0.484	-0.119

Method	K	Average Time (s) ↓
Uncertainty-Shift	2	1221.7
	4	2205.1
	6	2926.1
Uncertainty-Noise	2	246.2
	4	390.8
	6	506.3
Uncertainty++	**2**	**44.0**
	4	48.5
	6	55.1

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