HYBRID ATTENTION-BASED PROTOTYPICAL NETWORKS FOR FEW-SHOT SOUND CLASSIFICATION

Paper Number: 4769

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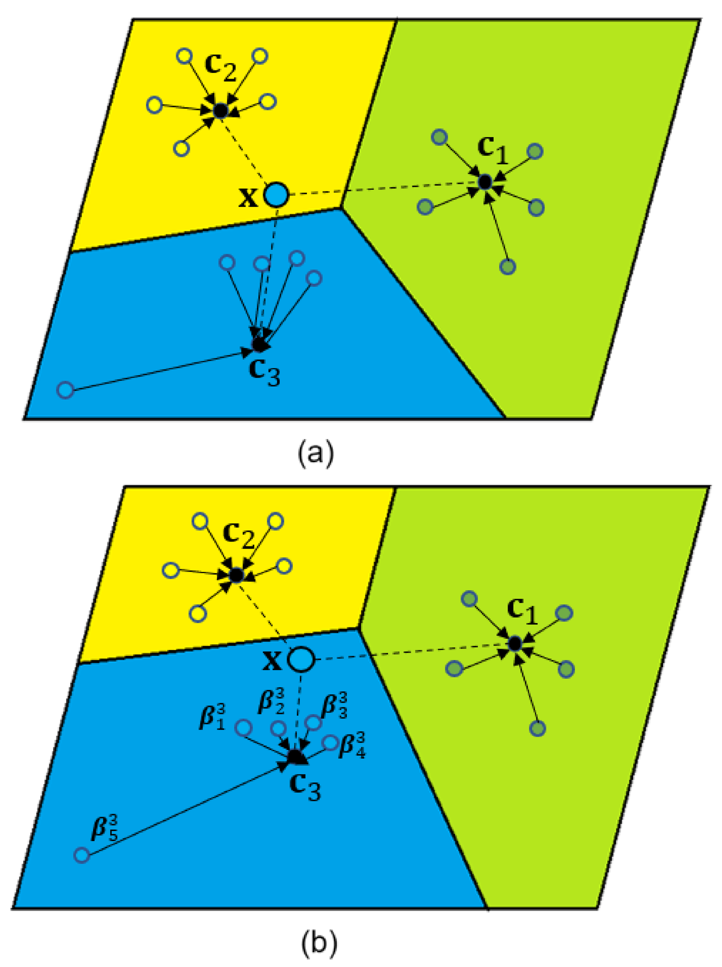
Abstract

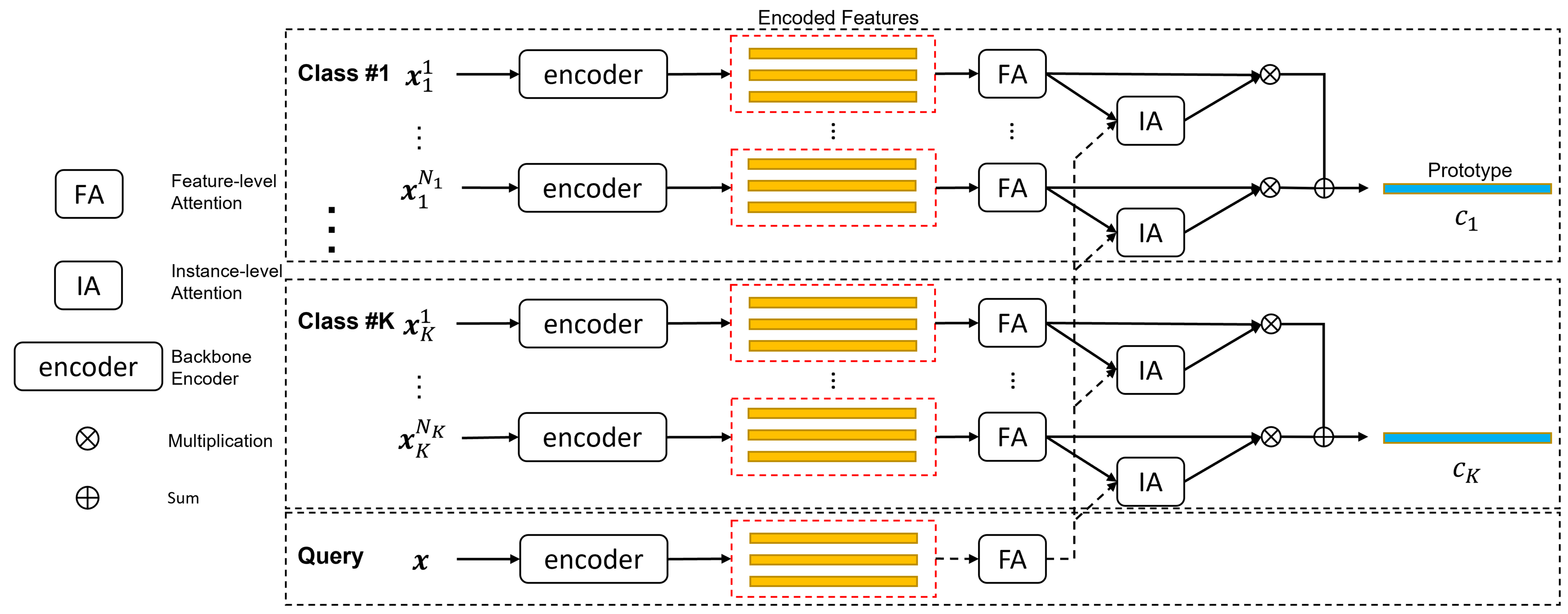
In recent years, prototypical networks have been widely used in many few-shot learning scenarios. However, as a metric-based learning method, their performance often degrades in the presence of bad or noisy embedded features, and outliers in support instances. In this paper, we introduce a hybrid attention module and combine it with prototypical networks for few-shot sound classification. This hybrid attention module consists of two blocks: a feature-level attention block, and an instance-level attention block. These two attention mechanisms can highlight key embedded features and emphasize crucial support instances respectively. The performance of our model was evaluated using the ESC-50 dataset and the noiseESC-50 dataset. The model was trained in a 10-way 5-shot scenario and tested in four few-shot cases, namely 5-way 1-shot, 5-way 5-shot, 10-way 1-shot, and 10-way 5-shot. The results demonstrate that by adding the hybrid attention module, our model outperforms the baseline prototypical networks in all four scenarios.

Motivations

- In audio classification tasks, attention is often used to emphasize certain temporal, channel, or spectral features.
- Prototypical networks, as a metric-based embedding learning, often suffers from bad feature vectors and outliers in the support instances.



Model Architecture

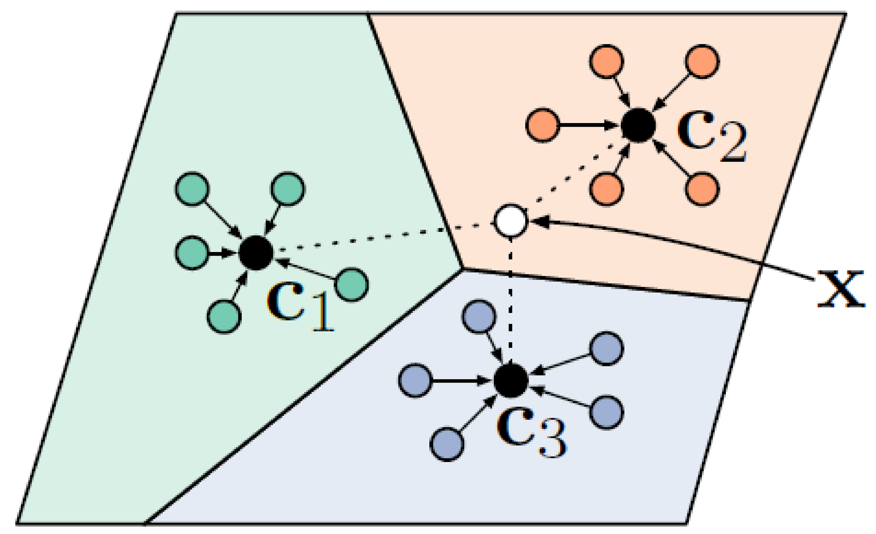


Related Work

- Prototypical Networks
  - The key idea is the computation of prototypes to represent each class by averaging the encoded feature vectors of support samples in each class.
  - The query sample is classified to the class of which the prototype is the nearest.

$$\mathbf{c}_k = \frac{1}{N_k}\sum_{i=1}^{N_k} f_\theta(\mathbf{x}_i^k), \quad k \in \{1, \ldots, K\}$$

$$P_\theta(y=k|\mathbf{x}) = \frac{\exp(-d(f_\theta(\mathbf{x}), \mathbf{c}_k))}{\sum_{k'} \exp(-d(f_\theta(\mathbf{x}), \mathbf{c}_{k'}))}$$

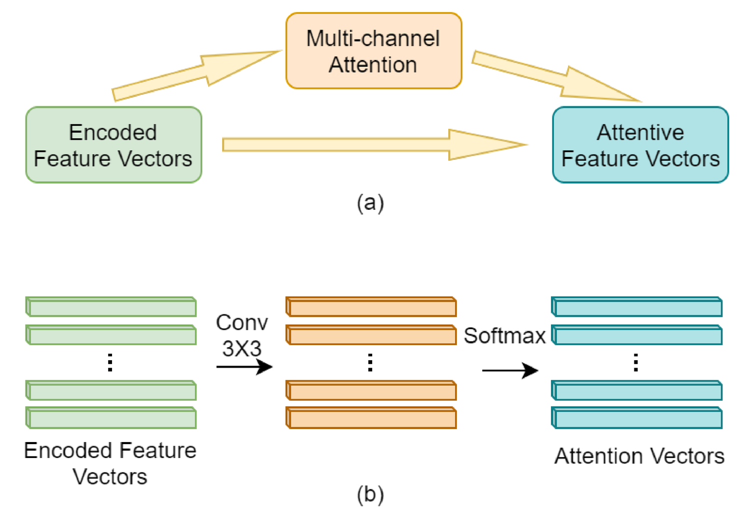


(a) Few-shot

Snell et al. 2017

Model Details

- Backbone Network
  - It contains 3 blocks consisting of a 3x3 convolutional layer, batch normalization, ReLU activation, and a max pooling layer consecutively.
  - Max pooling layer kernel sizes: 8x2, 8x2, and 2x1. Convolutional layer channel numbers: 128, 256, and 384.
- Feature-level Attention



Wang et al. 2021

- Instance-level Attention

$$\mathbf{c}_k = \sum_{i=1}^{N_k} \beta_i^k f_\theta(\mathbf{x}_i^k)$$

$$\beta_i^k = \frac{e_i^k}{\sum_{n=1}^{N_k} e_n^k}$$

$$e_i^k = sum\{\sigma(f_\phi(f_\theta(\mathbf{x}_i^k)) \circ f_\phi(f_\theta(\mathbf{x})))\}$$

Experimental Setup

- Datasets
  - ESC-50: 2000 5-second-long audio recordings organized into 50 balanced classes.
  - *noise*ESC-50: created in Chou et al. 2019 by mixing clean ESC-50 samples with random acoustic scenes from DCASE2016 dataset as additive background noise.
- Data Preparation
  - We randomly selected 35 classes for 10-way 5-shot training, 5 classes for 5-way 5-shot validation, and the remaining 10 classes for testing.
  - All audio clips were downsampled from 44.1kHz to 16kHz, and log mel-spectrograms with 128 mel bins were extracted.
  - The input features were z-score normalized using the mean and standard deviation of the training set before being fed into the model.

Results and Discussion

- ESC-50

Model	5-way 1-shot	5-way 5-shot	10-way 1-shot	10-way 5-shot
Prototypical Networks	64.40±1.38%	83.83±0.92%	47.83±1.10%	71.00±1.04%
Proto-FA (Ours)	**71.18±1.23%**	89.60±1.08%	**57.08±1.43%**	78.48±1.51%
Proto-HA (Ours)	–	**90.35±0.83%**	–	**80.08±1.31%**

- *noise*ESC-50

Model	5-way 1-shot	5-way 5-shot	10-way 1-shot	10-way 5-shot
Prototypical Networks	61.53±0.40%	81.03±0.57%	45.90±0.28%	64.98±0.52%
Proto-FA (Ours)	**71.35±0.90%**	88.00±0.63%	**56.55±1.22%**	78.55±0.75%
Proto-HA (Ours)	–	**88.78±0.45%**	–	**79.08±1.12%**

- Discussion
  - The feature-level attention module is capable of making data samples more distinguishable.
  - Instance-level attention module is able to focus on crucial support samples for both clean and noisy scenarios.
  - However, with *noise*ESC-50, when all the support and query samples are degraded, the advantage of instance-level attention module might not be as big as with clean data.