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

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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.

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.
  \[ c_k = \frac{1}{N_k} \sum_{x \in S} f_k(x), \quad k \in \{1, \ldots, K\} \]
  \[ P(y=k|x) = \frac{\exp(-d(f_k(x), c_k))}{\sum_{k'} \exp(-d(f_k(x), c_{k'}))} \]
- Feature-level Attention
  - Wang et al. 2021
- Instance-level Attention
  - Snell et al. 2017

Model Architecture

Results and Discussion
- ESC-50
  - Training sets:
    - Prototypical Networks: 64,401.13\% ± 71.18\% ± 1.23\%
    - Prototypical (Ours): 64,401.13\% ± 71.18\% ± 1.23\%
  - Test sets:
    - Prototypical Networks: 71.08\% ± 7.08\% ± 1.13\%
    - Prototypical (Ours): 71.08\% ± 7.08\% ± 1.13\%
- NoiseESC-50
  - Training sets:
    - Prototypical Networks: 61.55\% ± 5.56\% ± 1.12\%
    - Prototypical (Ours): 61.55\% ± 5.56\% ± 1.12\%
  - Test sets:
    - Prototypical Networks: 61.55\% ± 5.56\% ± 1.12\%
    - Prototypical (Ours): 61.55\% ± 5.56\% ± 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 noiseESC-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.

Experimental Setup
- Datasets
  - ESC-50: 2000 5-second-long audio recordings organized into 50 balanced classes.
  - noiseESC-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 downsampld 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.

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

- Instance-level Attention

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