Few-Shot Learning Based on Metric Learning Using Class Augmentation

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Introduction

Few-shot learning is a machine learning problem in which new classes are learned from only a few samples. We propose a few-shot learning approach based on metric learning in which the number of classes in the training data for performing metric learning is increased. We augmented the number of classes by synthesizing samples of imaginary classes from original training data at a feature level. The approach is evaluated using miniImageNet, and the effectiveness is demonstrated.

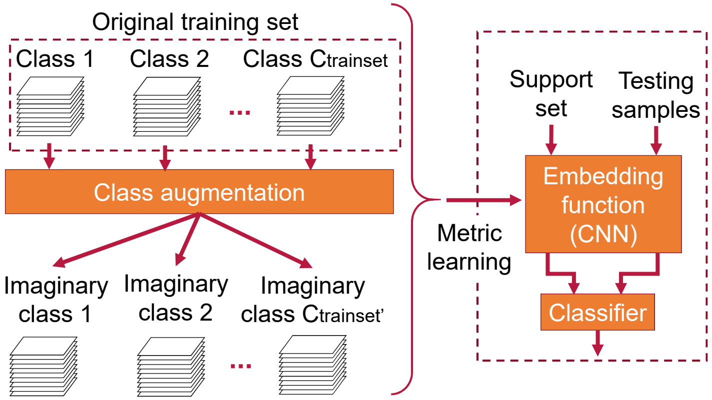
Problem Definition

- *N*-way *K*-shot learning: the few-shot learning from *N* classes data with *K* labeled samples in each class
- Three datasets are used for learning and testing.
  - Training set: dataset for learning prior knowledge
  - Support set: samples for learning *N* classes
  - Testing set: dataset for testing the few-shot learning results

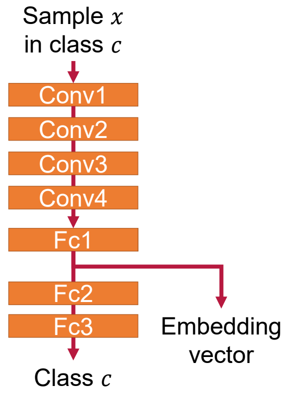
  The classes for the support set and testing set are shared.

Proposed Method

- The number of classes in the training set is expanded and the class-augmented training data set is used in metric learning.
- By combining samples in the original training set class c_1 and class $c_2 (\neq c_1)$, we generate a new samples in an imaginary class that does not exist in the original training set.
- The data augmentation approach used in previous works expands the number of support set. In contrast, our method expands the number of classes in the training set.
- In contrast to the mixup, we assign a new class label different from the original class to the generated samples.



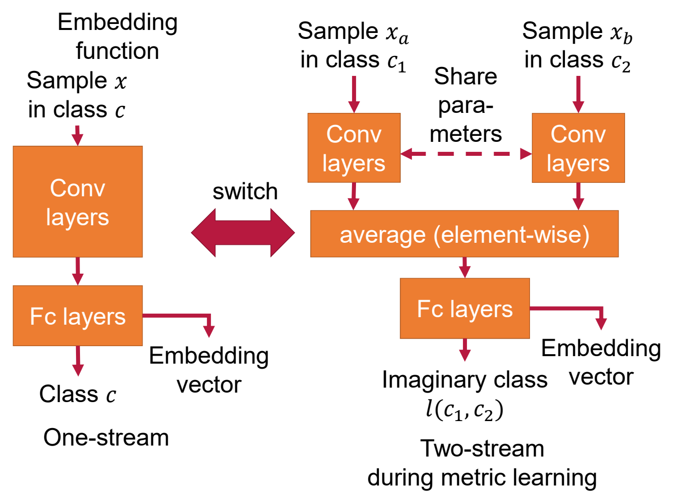
- A CNN is used as an embedding function for few-shot learning.
- The CNN is trained on the class-augmented training set to perform metric learning.
- Support set and testing samples are mapped into the embedding space using the trained CNN and the class of the testing sample is identified with a classifier.
- The nearest neighbor method or a multi-class SVM is used as the classifier.



Embedding function

Synthesis Method

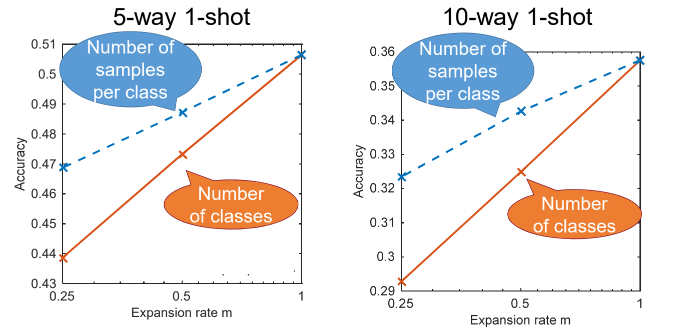
- An imaginary sample x_{ab} of the imaginary class $l(c_a, c_b)$ is synthesized by combining the original training set samples x_a in class c_1 and x_b in class c_2 in a feature map during CNN training.
- During CNN training, the stream in the CNN is changed to a two-stream configuration. Samples x_a and x_b are combined by taking the element-wise average in the feature maps. The CNN is trained by the inputting samples x_a and x_b with the imaginary class label $l(c_a, c_b)$.
- When all training is complete, the average layer is removed, and the CNN reverts to the one-stream architecture



Results on miniImageNet

1. Preliminary Experiment

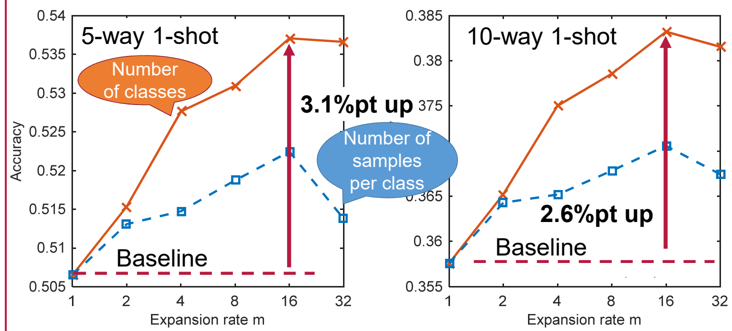
- Accuracy of few-shot learning when the number of classes used in metric learning is decreased and when the number of samples per class is decreased by the same rate instead of reducing the number of classes



- <u>The number of classes has a greater impact on the accuracy</u> of few-shot learning than the number of samples per class.

2. Main Experiment

- Accuracy of few-shot learning when the number of training set classes is increased by *m* times the original number of classes



- The accuracy of few-shot learning increases as the number of classes used in metric learning increases until *m* = 16.
- By increasing the number of classes by 16 times, <u>the accuracy increases by 3.1% points</u> for 5-way 1-shot learning.

Conclusion

We proposed a few-shot learning approach that increased number of classes for the training data to perform metric learning. Although the proposed method is relatively simple, the method demonstrated good performance.