Few-Shot Learning With Global Class Representations

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Background

▷ Few-Shot Learning (FSL) is inspired by the few-shot learning ability of humans.

▷ We are provided with a set of base classes with sufficient training samples per class, and a set of novel classes with only a few labeled samples (shots) per class. Base class set and novel class set are disjoint.

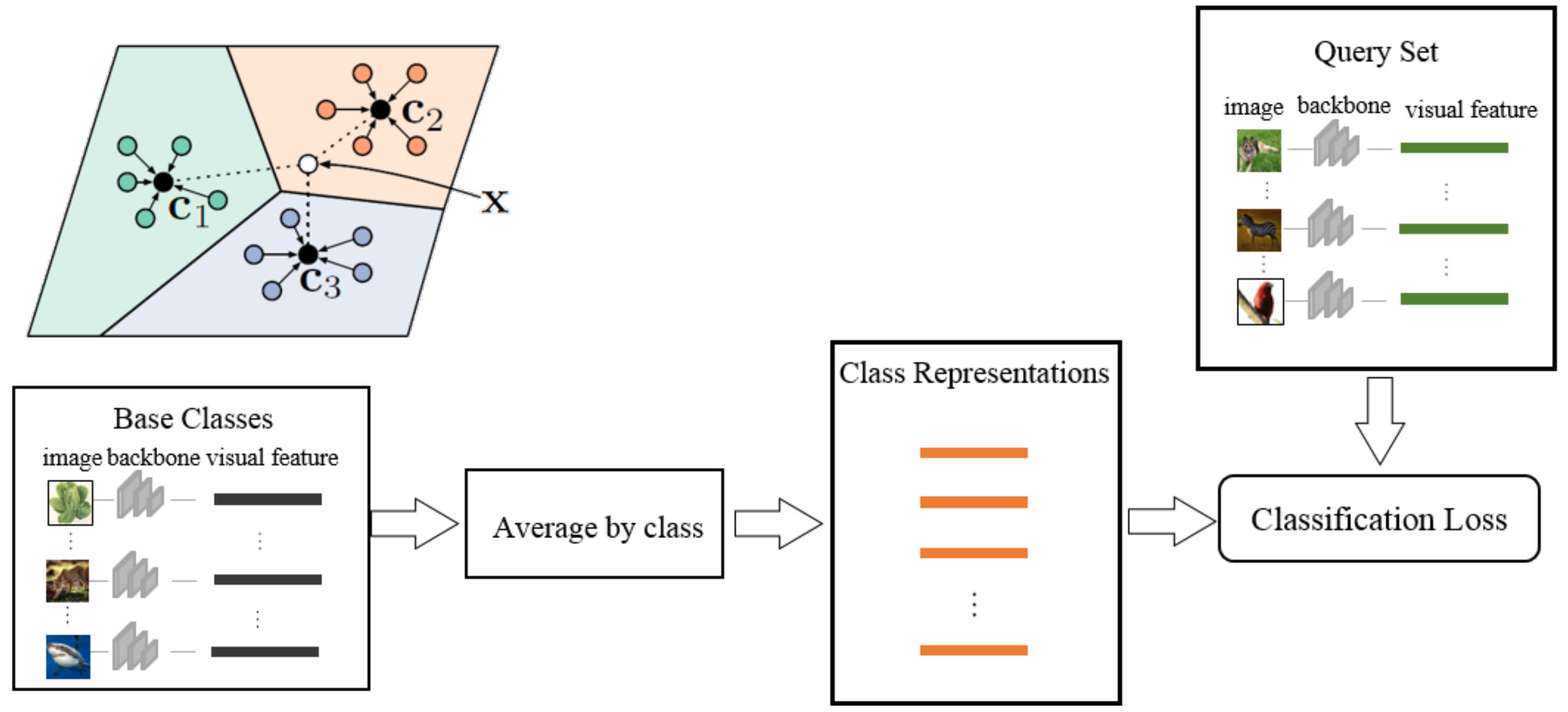
▷ FSL aims to learn a classifier for the novel classes with few shots by transferring knowledge from the based classes.

Related Work

▷ Prototypical Network [1]

▷ Learning class prototype/representation for each class with a few samples

▷ Only using base class data for training → overfitting to base classes



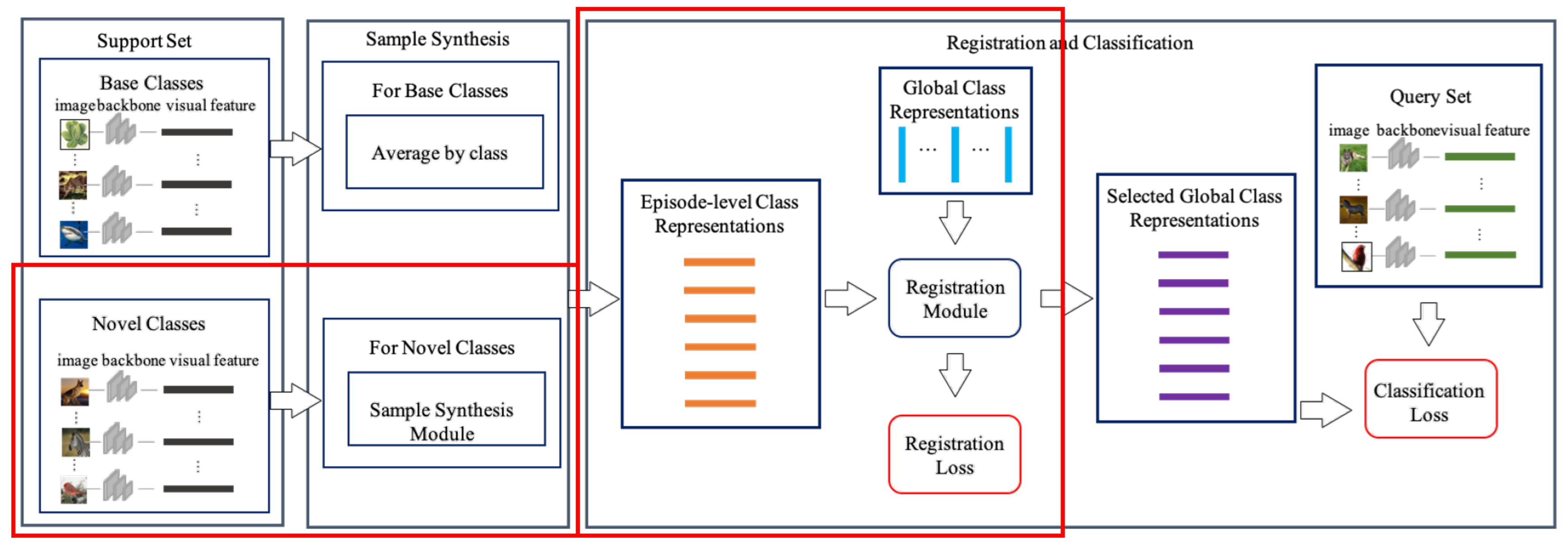
Motivation

▷ Our idea: learn global representations for each base or novel class.

▷ By involving the novel class data in the model training, we can ensure that the learned FSL model is suited for the novel classes.

▷ Since the representation is learned jointly using both base and novel class training samples, it is called a global representation.

Global Class Representation Learning



▷ First, we propose a sample synthesis method to synthesize episodic representation for each class in the support set.

▷ Second, the registration module is leveraged to select global representation according to their episodic representation, and the selected global representations are then used to classify query images.

▷ The classification loss of query images and registration loss are used to jointly optimize the global representations, the registration module, and the feature extractor.

Experimental Results

Model	5 way Acc.	
	1 shot	5 shot
Meta-LSTM [2]	43.44 ± 0.77	60.60 ± 0.71
Matching Networks [3]	43.56 ± 0.84	55.31 ± 0.73
Model-Agnostic Meta-Learning [4]	48.70 ± 1.84	63.11 ± 0.92
Prototypical Networks [1]	49.42 ± 0.78	68.20 ± 0.66
Direct Loss Minimization [5]	50.28 ± 0.80	63.70 ± 0.70
Relation Networks [6]	50.44 ± 0.82	65.32 ± 0.70
MetaGAN [7]	52.71 ± 0.64	68.63 ± 0.67
Memory Matching Networks [8]	53.37 ± 0.48	66.97 ± 0.35
Ours	53.21 ± 0.40	72.34 ± 0.32

Table 1 Comparative Results on the MiniImageNet dataset

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