

Improving Meta-Learning Model via Meta-contrastive Loss

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Problems & Ideas

- Problems of meta-learning model in few-shot learning
 - Can we design some meta-regularizations to improve the performance?
Just like some classical machine learning algorithms.
- Ideas:
 - Limited data leads to model conflict.
 - Meta-knowledge should overcome this problem.
 - Using meta-contrastive loss to help align the models.

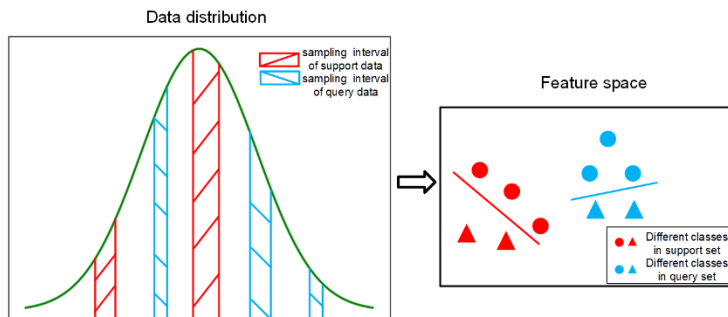


Fig 1. Illustration of model conflict

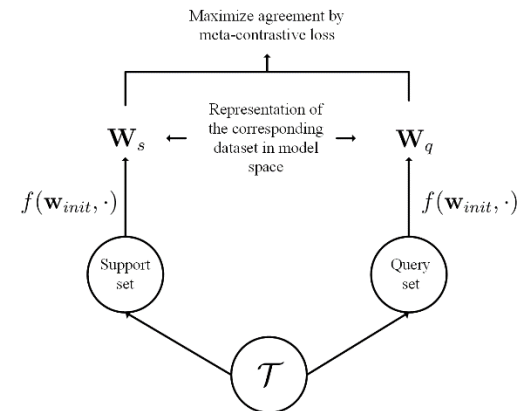


Fig 2. overview of the proposed meta-contrastive loss

Main Contributions

- **Few-shot sine curve regression**

Table 1 Mean square error of few-shot regression. Lower is better.

Methods	5-shot	10-shot
ANIL	0.746 ± 0.044	0.354 ± 0.018
ANIL-ours	0.744 ± 0.044	0.345 ± 0.018

- **Few-shot classification on miniImageNet**

Table 2 Accuracy of 5-way classification on miniImageNet.

Methods	Embedding	miniImageNet 5-shot
ANIL	ConvNet	58.51 ± 0.46
ANIL-ours	ConvNet	60.11 ± 0.46
R2D2	ConvNet	56.79 ± 0.41
R2D2-ours	ConvNet	61.70 ± 0.41
MetaOpt	ConvNet	64.06 ± 0.41
MetaOpt-ours	ConvNet	65.80 ± 0.40
R2D2	ResNet12	58.48 ± 0.43
R2D2-ours	ResNet12	70.04 ± 0.40
MetaOpt	ResNet12	66.64 ± 0.41
MetaOpt-ours	ResNet12	68.49 ± 0.42

- **Few-shot classification on CUB**

Table 4 Accuracy of 5-way classification on CUB2011.

Methods	CUB2011 5-shot
ANIL	71.82 ± 0.49
ANIL-ours	73.91 ± 0.47
R2D2	75.73 ± 0.40
R2D2-ours	77.23 ± 0.38
MetaOpt	74.88 ± 0.42
MetaOpt-ours	75.92 ± 0.41