



Generating Pseudo-labels Adaptively for Few-shot Model-Agnostic Meta-Learning

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Motivation

- The classifier of MAML family is highly sensitive to the pseudo query data.
- The feature extractor of MAML family is highly adaptable to the pseudo query data.
- The imbalance of pseudo query data may have negative impact.

Contribution

- This work is the first to incorporate label propagation used in transductive methods to generate pseudo-labels for MAML.
- We propose to use adaptive picking to select instances from the pseudo query set to balance the number of samples for each class.
- We apply our Generative Pseudo-label method to two typical variants of MAML, and improve their performance, demonstrating the applicability of our approach.

Formulation

For all tasks, we compute adapted body parameters :

$$\theta_{body_i}^{TPN} = \theta_{body} - \alpha \nabla_{\theta_{body}} \mathcal{L}_{spt_i}(f_{\theta_{body}, \theta_{head}}).$$

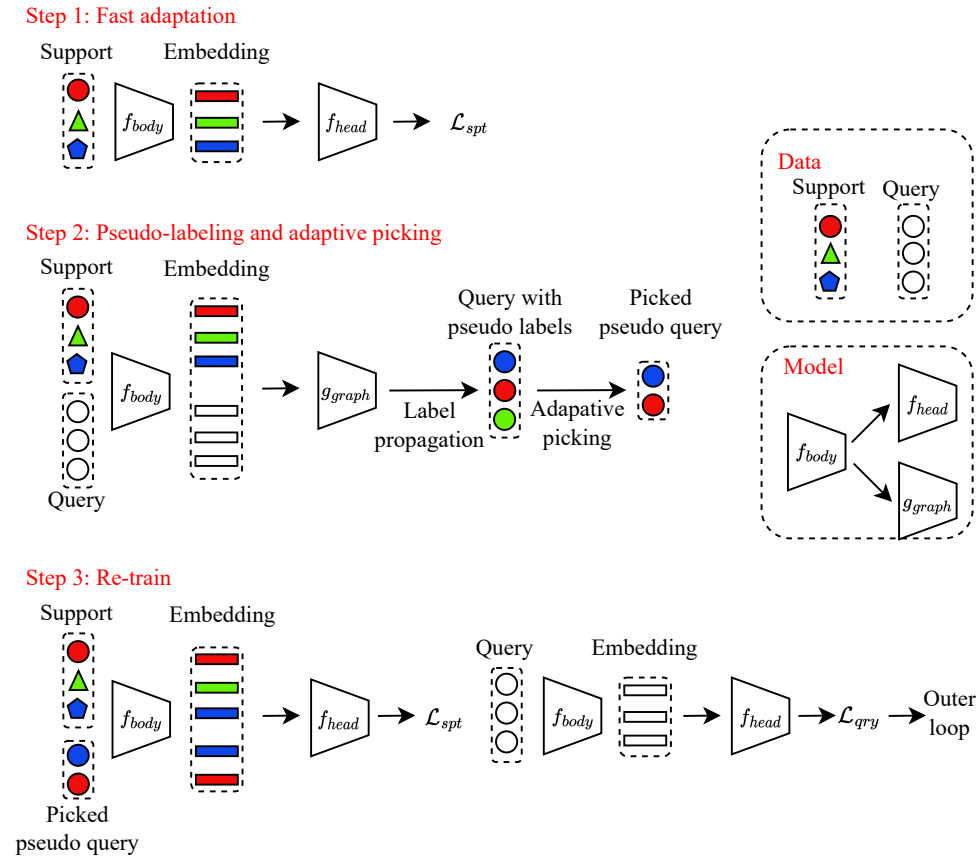
We construct the weighted graph:

$$Graph_i = g_{\theta_{graph}}(f_{\theta_{body_i}^{TPN}}(spt_i, qry_i)).$$

We Re-update parameters with new support set examples:

$$\theta'_{body_i}, \theta'_{head_i} \leftarrow \theta_{body}, \theta_{head} - \beta \nabla_{\theta_{body}, \theta_{head}} \mathcal{L}_{spt'_i} f_{\theta_{body}, \theta_{head}}.$$

Network Architecture



- In phase 1, the few-shot model up-dates its parameters through the support set.
- In phase 2, we adopt the label propagation of TPN to label the query set, which will be filtered by adaptive picking to select the pseudo query data.
- In phase 3, the picked pseudo query data will be added to the support set for re-training, then the loss of the query set is calculated as in MAML.

Experiments

We conduct a comprehensive experimental analysis of our GP-MAML, GP-ANIL, and GP-BOIL.

Method	MiniImageNet		CIFAR-FS		FC100	
	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot
MAML	48.24	61.52	57.57	72.31	36.64	47.26
ANIL	49.61	64.90	58.34	72.34	36.38	47.16
BOIL	49.82	67.60	58.69	75.31	38.80	51.42
MAML(w_{qry})	34.89	50.11	43.71	58.40	25.24	30.51
ANIL(w_{qry})	37.49	48.41	46.23	59.52	25.68	30.97
BOIL(w_{qry})	49.88	68.08	60.91	76.32	39.67	52.02
MAML(w_{AP})	51.37	63.82	62.58	75.08	38.65	48.92
ANIL(w_{AP})	53.00	67.86	63.44	75.12	38.37	48.71
BOIL(w_{AP})	52.42	69.84	63.51	77.76	40.76	52.97
GP-MAML	52.71	68.06	64.03	75.60	38.57	48.50
GP-ANIL	55.92	70.73	65.66	75.08	38.95	51.16
GP-BOIL	55.55	71.36	66.55	78.50	41.80	53.71

Conclusion

- We generated pseudo-labels by using label propagation with adaptive picking, introduced transductive methods to typical inductive methods.
- We address the problem that inductive methods can not fully utilize information of the query set.
- We also proposed a simple yet effective method called adaptive picking to select samples from distinct classes with balanced quantity.

References

- [1] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In Proceedings of the 34th International Conference on Machine Learning, 2017.
- [2] Yanbin Liu, Juho Lee, Minseop Park, Saehoon Kim, Eunho Yang, Sung Ju Hwang, and Yi Yang. Learning to propagate labels: Transductive propagation network for few-shot learning. In 7th International Conference on Learning Representations, 2019.