Table 1: Accuracy results on miniImageNet dataset.

Task		Transfer Learning	Prototypical	Reptile	Reptile MTL	MAML	MAML MTL
5-ways	1 Shot	37.44	49.42	49.16	**51.04**	48.70	**50.99**
	5 Shots	53.28	68.20	65.99	**69.58**	63.11	**67.88**
	100 Shots	90.23	61.13	83.75	**96.56**	82.53	**92.44**
20-ways	1 Shot	15.06	21.54	20.29	**22.27**	20.50	**22.34**
	5 Shots	27.33	34.68	31.46	**36.45**	31.50	**35.95**
	100 Shots	73.56	56.76	68.59	**74.00**	68.55	**74.87**
35-ways	1 Shot	10.49	10.67	9.85	**13.60**	9.61	**14.11**
	5 Shots	20.04	17.53	16.46	**21.59**	16.01	**21.85**
	100 Shots	61.72	38.13	51.09	**68.10**	50.21	**66.34**

model parameters in a direction that the distribution of tasks have agreement with the single specific task of training over the whole classes.

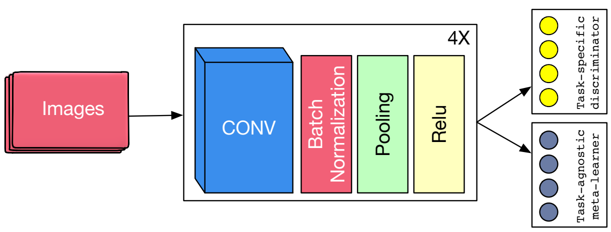

Figure 1: Meta-transfer learning model setup for miniImageNet dataset

Algorithm 1 Meta-Transfer Learning Algorithm

Initialize model parameters, θ
for `iteration = 1,2,...` **do**
  Sample a batch of tasks $\tau_i \sim$ p(τ)
  for all τ_i **do**
    Split the examples of the task into k sub-batches
    $\theta_i = \theta - \alpha_{inner} \nabla L_{\tau_i}(f_\theta)$ for k steps
  $\theta_{metalearner} = \theta - \alpha_{outer} \sum_i \nabla L_{\tau_i}(f_{\theta_i})$ (MAML)
  $\theta_{metalearner} = \theta + \alpha_{outer} \sum_i (\theta_i - \theta)$ (Reptile)
  $\theta_{discriminator} = \theta - \alpha_d \nabla L_{(x,y)}$
  $\theta = \beta\, \theta_{metalearner} + (1 - \beta)\, \theta_{discriminator}$
return θ

Performance Evaluations

The proposed model is evaluated on *miniImageNet* (**?**) dataset, split into 64 training classes and 36 test classes as unseen tasks. The architecture of the model is shown in Figure 1 and the results are demonstrated in Table 1. The base model for transfer learning is trained on all 64 training classes.

Note that for many-classes (35-ways) tasks, the transfer learning baseline outperforms previous meta-learning algorithms, while in few-classes problems, the result is reversed: meta-learning beats transfer learning. Our proposed method, MTL, outperforms both these algorithms in all scenarios by improving the weaknesses of few-shot learning algorithms in generalizing to many-shot and many-classes problems.

Conclusion and Future Work

A single model that is adaptable to unseen tasks is a crucial component in artificial intelligence. In this work, we presented a method to extend the capability of few-shot learning algorithms to many-shot and many-classes learning problems, by integrating them with transfer learning model. The next step is to use this approach on a larger dataset and deeper model, to see whether meta-learning is still outperforming transfer learning or not.

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