accounted, decoder network projects features to classifier. For generalization to unseen tasks, parameters in base and these parameters are updated with MAML. Meta-learner provides initial values for these parameters in base and these modules are updated with MAML. accounted, decoder network projects features to classifier. For generalization to unseen tasks, parameters in base in the se parameters in base accounted, decoder network projects features to classifier. For generalization to unseen tasks, parameters in base in the second parameters in base accounted, decoder network projects features to classifier. For generalization to unseen tasks, parameters in base in the second parameters in base accounted, decoder network projects features to classifier. For generalization to unseen tasks, parameters in base accounted, decoder network projects features to classifier. For generalization to unseen tasks, parameters in base accounted, decoder network projects features to classifier. For generalization to unseen tasks, parameters in base accounted, decoder network projects features to classifier. For generalization to unseen tasks, parameters in base accounted to the second parameters are under the second parameters and the second parameters are under the second parameters

ing samples. In our approach, the parameters of the model are explicitly trained such that a small number of gradient steps with a small amount of training data from a new task will produce good generalization performance on that task. In

MAML optimizes for generalization, akin to cross-validation. veloping new methods and analyzing existing ones. We then proposed a model-agnostic meta-learning algorithm, or MAML, that embeds gradient descent into the meta-learner, aiming to find an initial representation such that one or a few gradient steps leads to effective generalization. This meta-learner, by construction, will acquire consistent learn-