

Algorithm 1 CMTA

Initialize: replay buffer D with \emptyset
Initialize: initial hidden state h_0 with zero tensor
Initialize: policy π with ϕ , Q-function Q , task encoder g , k experts f^1, \dots, f^k , $lstm$, fully connected layer \mathcal{W}
Input: state s_t for each environment, one-hot task id z_τ

- 1: **for** episode $m = 1, 2, \dots$ **do**
- 2: **for** time-step $t = 1, 2, \dots$ **do**
- 3: **for** each task τ_i **do**
- 4: $z_{enc}^j = f^j(s_t), \forall j \in 1, \dots, k$
- 5: $z_{task} = g(z_\tau)$
- 6: $h_t = lstm(s_t; h_{t-1})$
- 7: $\alpha_1, \dots, \alpha_k = softmax(\mathcal{W}(h_t; z_{task}))$
- 8: $z_{enc} = \sum_{j=1}^k \alpha_j \cdot z_{enc}^j$
- 9: $z = z_{task} || z_{enc}$
- 10: sample action $a_t \sim \pi(\cdot | z_{task}; z_{enc})$
- 11: Perform action a_t , get reward r_t and next state s_{t+1} .
- 12: $D = D \cup \{s_t, a_t, r_t, s_{t+1}, h_t, z_\tau\}$
- 13: **end for**
- 14: randomly sample batch from D
- 15: compute $L_{contrastive}$ by Eq 3
- 16: compute L_{actor} and L_{critic} by Eq9 and Eq10
- 17: update k experts with $L_{contrastive}$
- 18: update π_ϕ with L_{actor}
- 19: update all components except π_ϕ with L_{critic}
- 20: **end for**
- 21: **end for**

423 **B Libraries**

424 We use the following open-source libraries: MetaWorld², MTEnv³, MTRL⁴.

²<https://github.com/rlworkgroup/metaworld>, commit-id:af8417bfc82a3e249b4b02156518d775f29eb289

³<https://github.com/facebookresearch/mtenv>

⁴<https://github.com/facebookresearch/mtrl>

425 C Additional Experiment Results

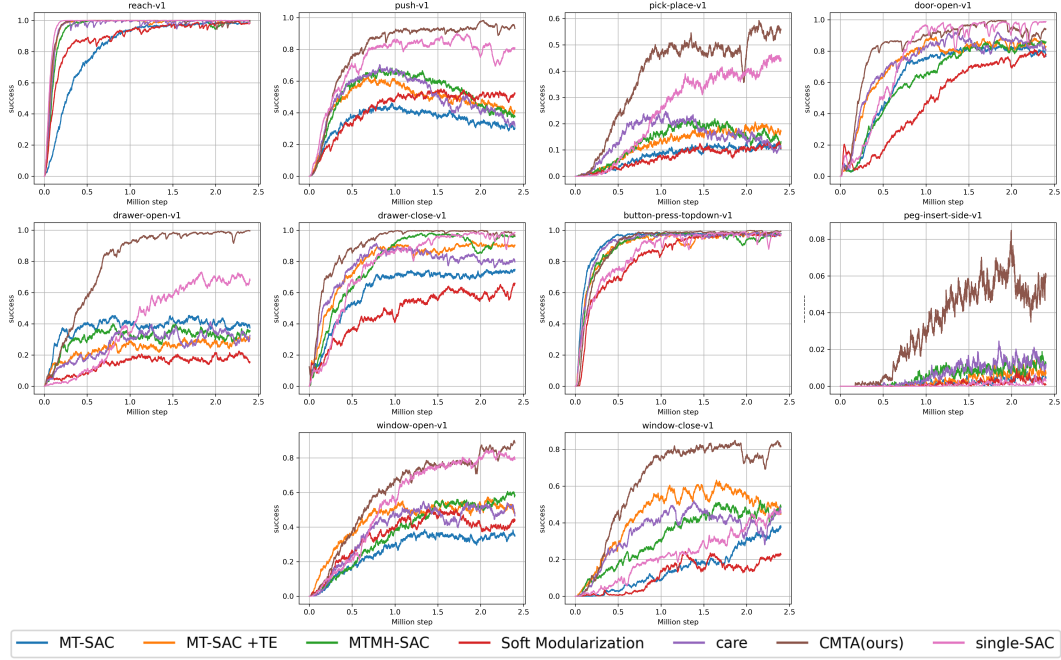


Figure 6: Training curves of different methods on each task of MT10-Mixed, each curve is averaged over 8 seeds. Our approach consistently outperforms baselines in all tasks, whether on asymptotic performance or sample efficiency.

426 D Hyperparameter Details.

Table 3: Hyperparameter values that are common across all the methods

Hyperparameter	Hyperparameter values
batch size	$128 \times \text{number of tasks}$
network architecture	feedforward network
actor/critic size	three fully connected layers with 512 units
non-linearity	ReLU
policy initialization	standard Gaussian
temperature	learned and distangled with tasks
exploration parameters	run a uniform exploration policy 1500 steps
num of samples / num of train steps per iteration	1 env step / 1 training step
evaluation frequency	3000 steps
replay buffer size	5000000
policy learning rate	$3e-4$
Q function learning rate	$3e-4$
optimizer	Adam
policy learning rate	$3e-4$
beta for Adam optimizer for policy	(0.9, 0.999)
Q function learning rate	$3e-4$
beta for Adam optimizer for Q function	(0.9, 0.999)
discount	0.99
Episode length (horizon)	150
reward scale	1

Table 4: Hyperparameter values of task encoder

Hyperparameter	Hyperparameter values
task encoder train from scratch	embedding layer with dim 64 + FC 128 + FC 64 + FC 64
pretrained	pre-trained embedding layer with dim 512 + FC 128 + FC 64 + FC 64

Table 5: Hyperparameter values of Soft Modularization

Hyperparameter	Hyperparameter values
task encoder type	train from scratch
routing network size	4 layers and 4 modules per layer with dim 64

Table 6: Hyperparameter values of CARE

Hyperparameter	Hyperparameter values
task encoder type	pre-trained embedding layer
encoder size	FC 64 + FC 64
number of encoders	6

Table 7: Hyperparameter values of CMTA

Hyperparameter	Hyperparameter values
task encoder type	train from scratch
encoder size	FC 64 + FC 64
number of encoders	6
β	2500