

Helpful or Harmful: Inter-Task Association in Continual Learning

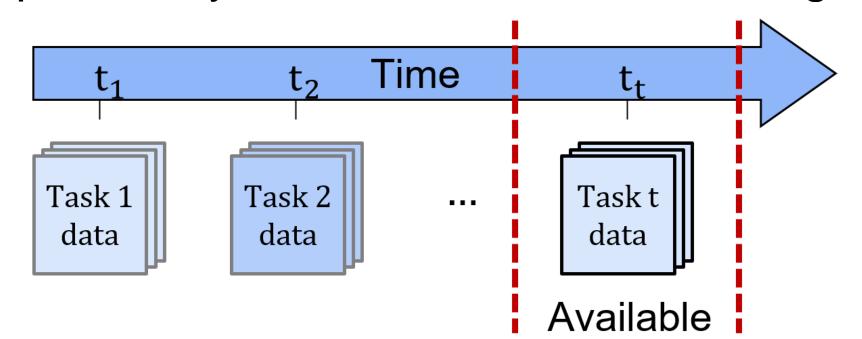
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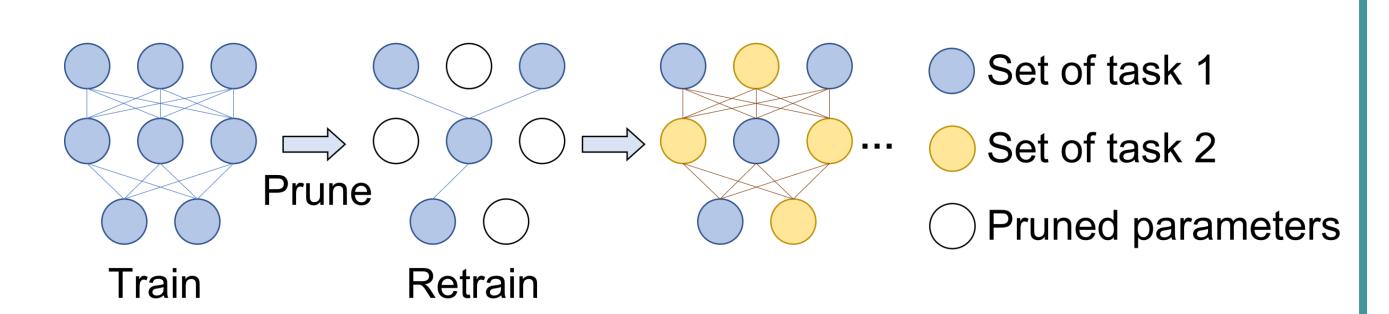
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INTRO & MOTIVATION

- Learning sequentially incoming tasks
- Limit accessibility to the old data
- Forget previously learned tasks when training on new tasks



■ Baseline: structural allocation approach [1]



- Problem: Associate all parameters when inferencing
- Goal: Differentiate helpful and harmful information
- Approach: Reformulate the forgetting problem into a task interference problem

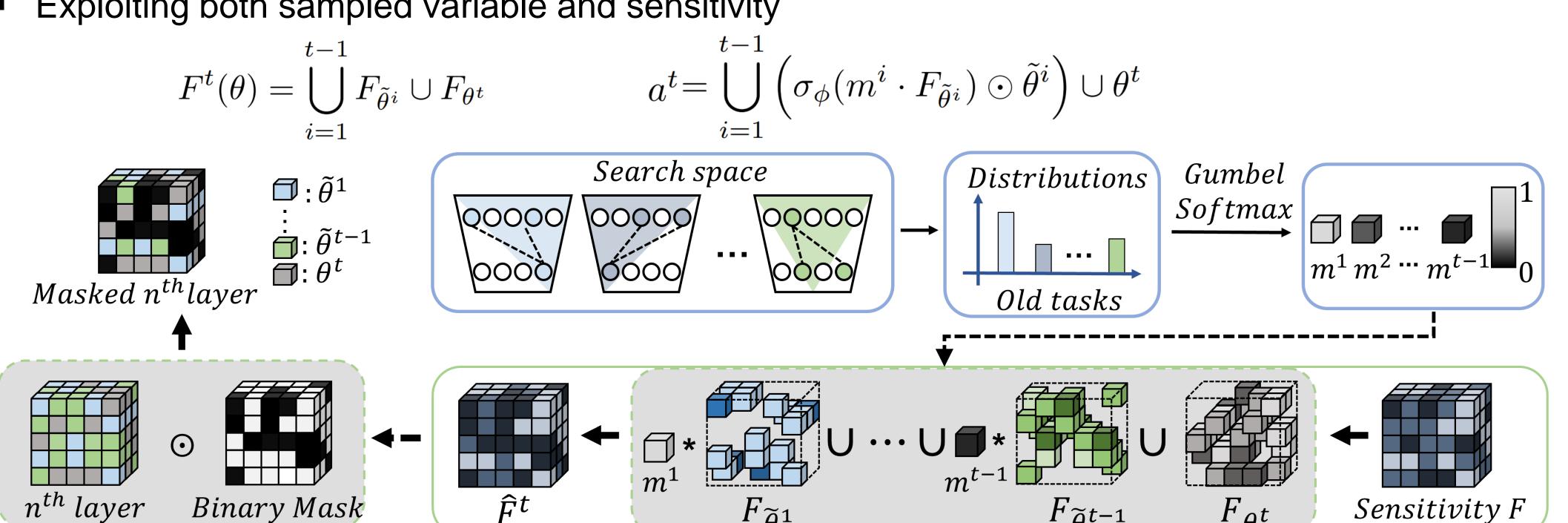
H²: INTER-TASK ASSOCIATION

Selects contributable parameters from older tasks in a coarse-to-fine manner

- Search (Coarse level)
- Find an optimal network structure a^t
- Exploit cooperative disjoint set discovered by gradient based search
- Update the set of parameters θ^{t}

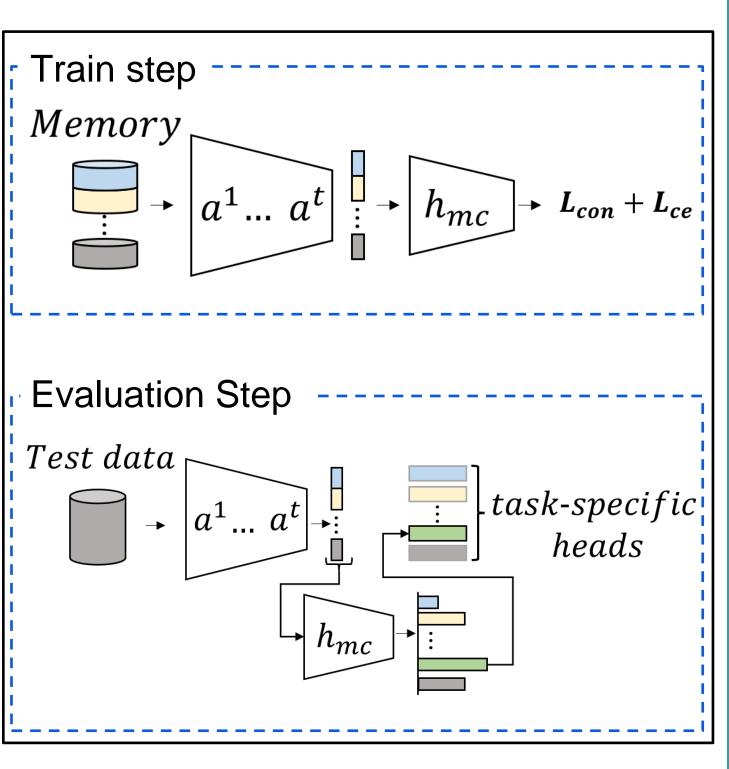
$$\min_{\alpha} \min_{\theta^t} \mathbf{E}_{a^t \sim P_{\alpha}} \left[\mathcal{L}(a^t, \theta^t) \right] \quad a^t = \bigcup_{i=1}^{t-1} \left(m^i \cdot \tilde{\theta}^i \right) \cup \theta^t \quad m^i = \text{GumbelSoftmax}(\alpha^i | \alpha)$$

- Sensitivity measure (Finer level)
 - Further explore useful information from selected old tasks
 - Exploiting both sampled variable and sensitivity



Meta Classifier

- Require when task identity is unknown
- Predict the task label and allocate the corresponding network
- Employ contrastive loss for discrimination between tasks



RESULTS: TASK- AND CLASS- INCREMENTALLEARNING SCEARIOS

Stanford Cars

Stanford Cars

Flowers

Wikiart

Sketch

Wikiart

|Avg| Avg

Sketch

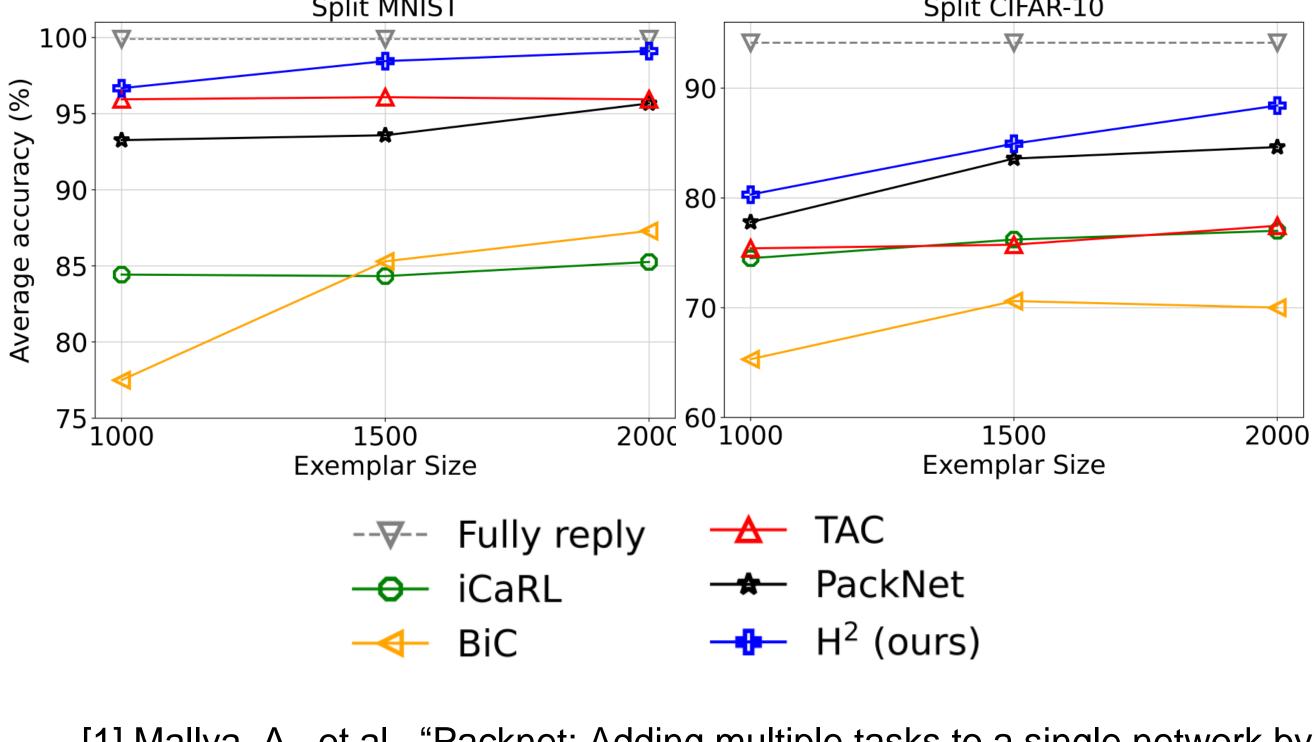
Task-incremental: ImageNet and Find-grained datasets

CUBS

ImageNet

Method	Acc	Param	Acc	Param	Acc	Param	Acc	Param	Acc	Param	Acc	Param	Acc	Param
EWC-On	54.5	23.4	64.1	23.4	52.1	23.4	78.7	23.4	51.4	23.4	30.7	23.4	55.3	23.4
LwF	64.5	23.4	51.7	23.4	43.9	23.4	72.9	23.4	42.7	23.4	45.5	23.4	53.6	23.4
PackNet	75.7	12.5	80.4	15.6	86.1	18.0	93.0	19.7	69.4	21.0	76.7	22.0	80.2	18.1
Piggyback	76.1	23.4	81.5	20.5	89.6	19.7	94.7	22.3	71.3	16.3	79.9	18.0	82.2	20.0
$\overline{\mathrm{H}^2 \; \mathrm{(Ours)}}$	75.7	12.5	84.1	14.5	90.6	15.9	94.9	15.2	75.1	9.4	76.2	4.1	82.8	11.9

■ Class-incremental: Split MNIST and Split CIFAR-10

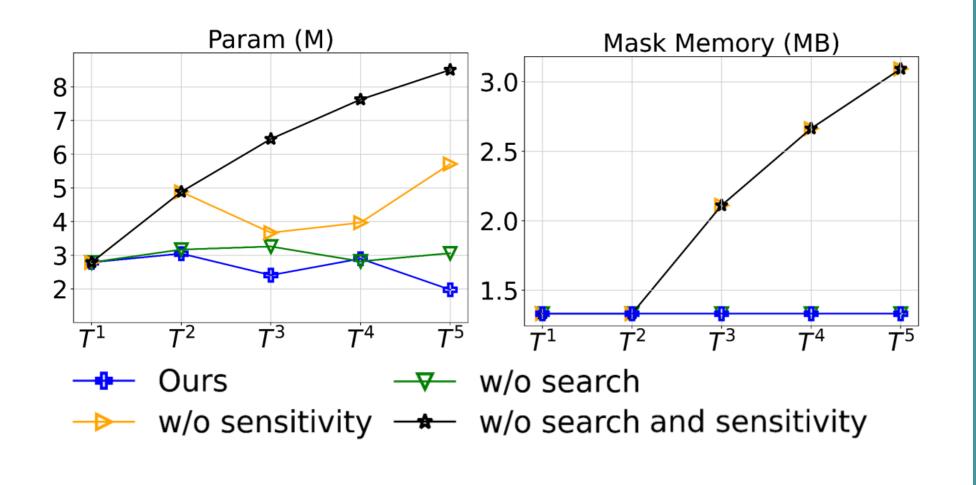


[1] Mallya, A., et al., "Packnet: Adding multiple tasks to a single network by iterative pruning.", CVPR (2018).

RESULTS: ABLATIONS

ResNet-18 (Split CIFAR-10)

	Class-incremental						
Method	T^1	T^2	T^3	T^4	T^5		
Ours	98.8	91.2	87.4	86.1	80.3		
w/o search	98.8	89.5	84.9	84.5	79.6		
w/o sensitivity	$\begin{vmatrix} 98.8 \\ 98.8 \end{vmatrix}$	90.0	83.8	82.6	78.7		
w/o search and sensitivity [27]	98.8	89.3	83.5	81.1	77.4		
w/o contrastive loss	98.8	90.7	86.7	83.2	77.1		
Random search	98.8						



Flowers