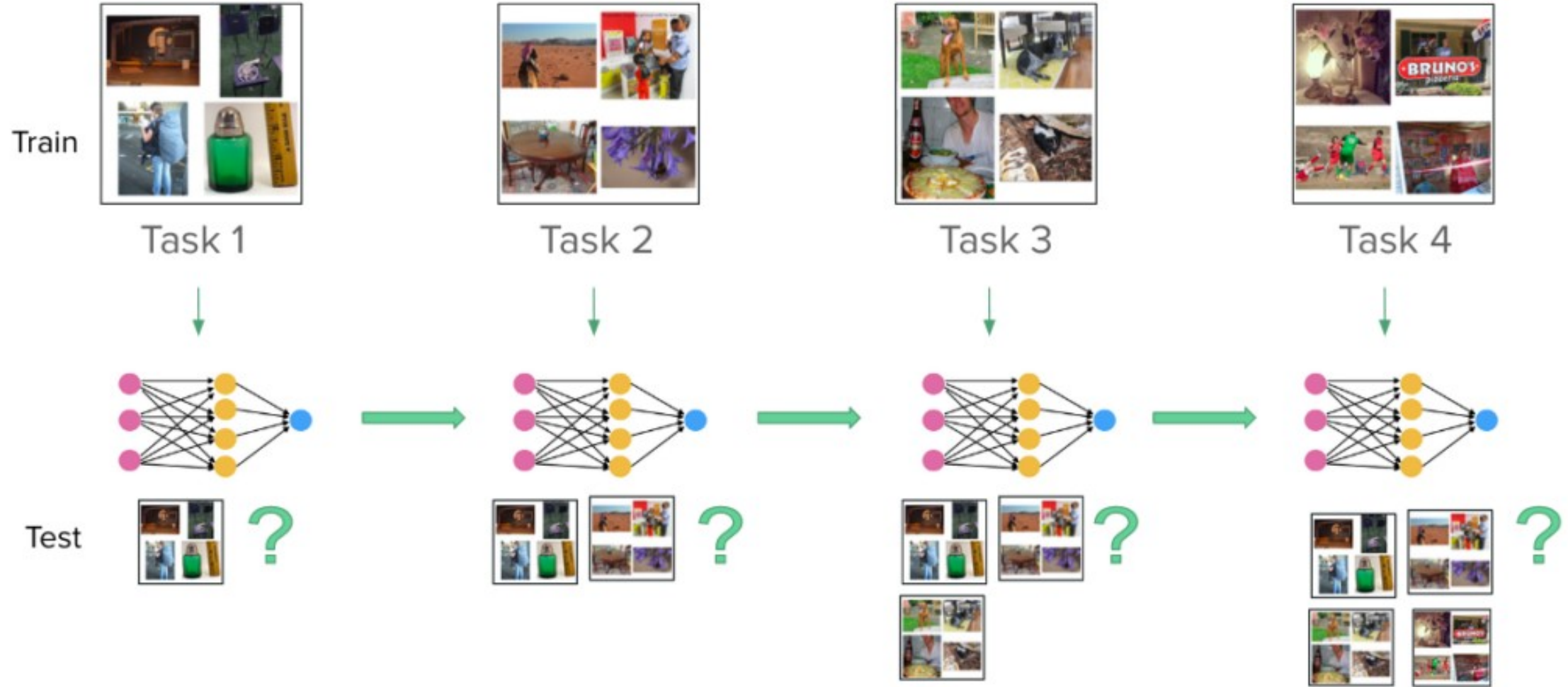


Divide and not forget: Ensemble of selectively trained experts in Continual Learning

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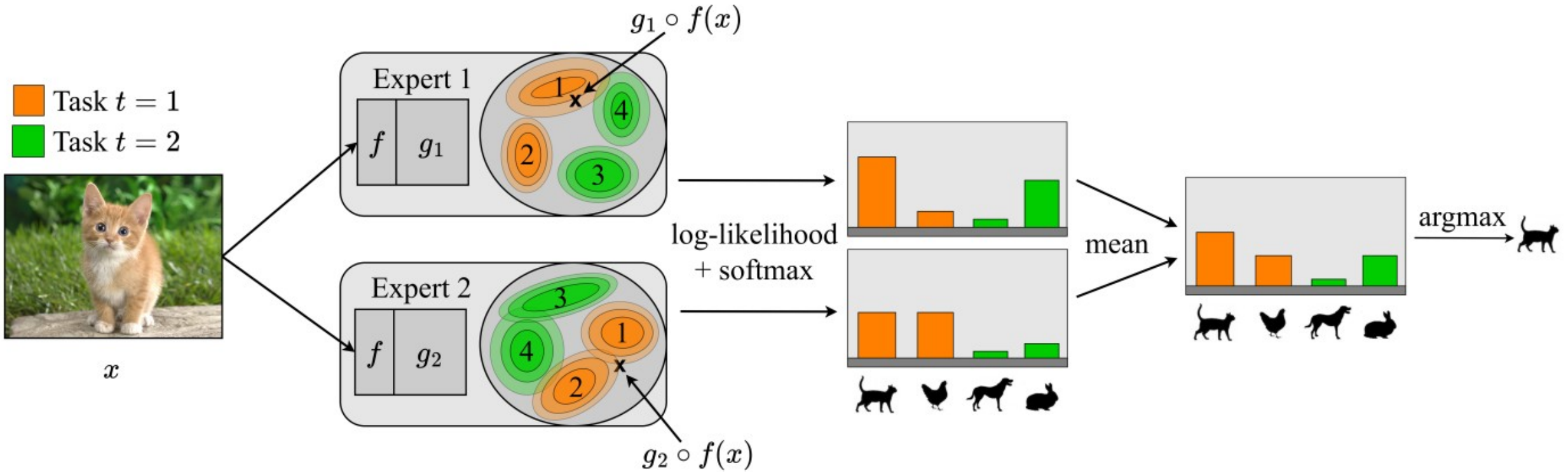
Exemplar-Free Class and Task Incremental Learning



van de Ven, Gido M., and Andreas S. Tolias. "Three scenarios for continual learning." arXiv e-prints (2019): arXiv-1904.

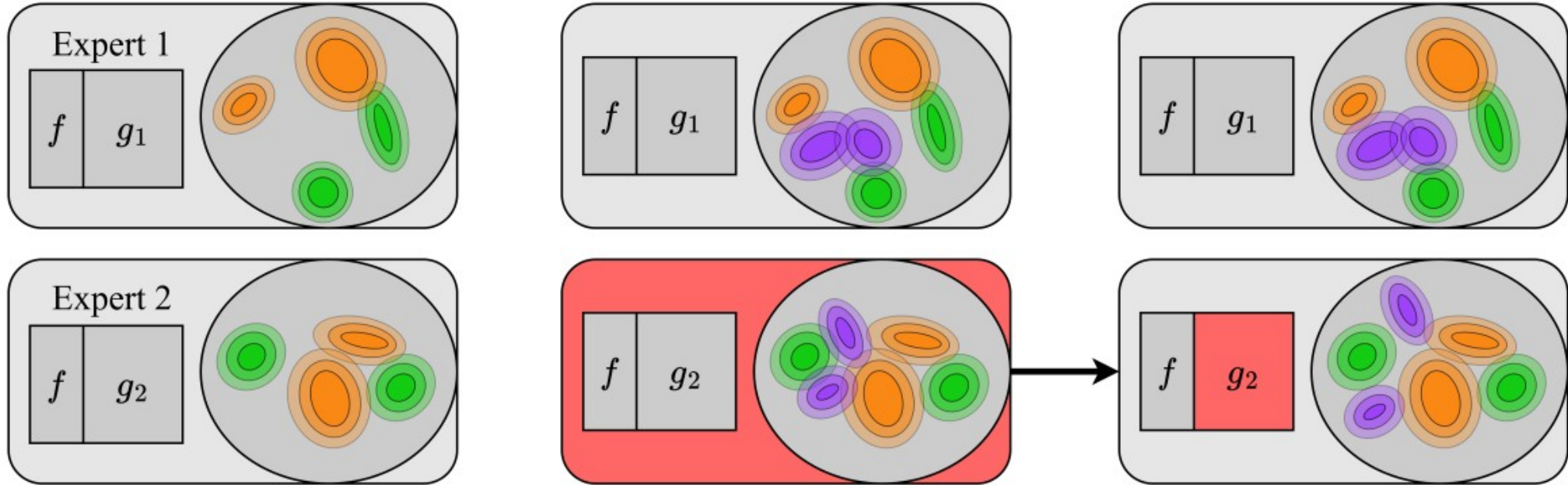
- Unlike existing ensembling methods we train only a single expert on a task, but perform inference using all experts
- Each expert is a deep network and a set of Multivariate Gaussian distributions representing classes
- We utilize ensemble of Bayes classifiers for inference
- Expert diversification is obtained by training them on different data

SEED - Inference



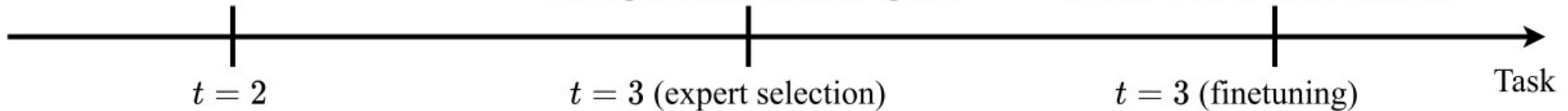
SEED - Training

■ Task $t = 1$
 ■ Task $t = 2$
 ■ Task $t = 3$ distributions



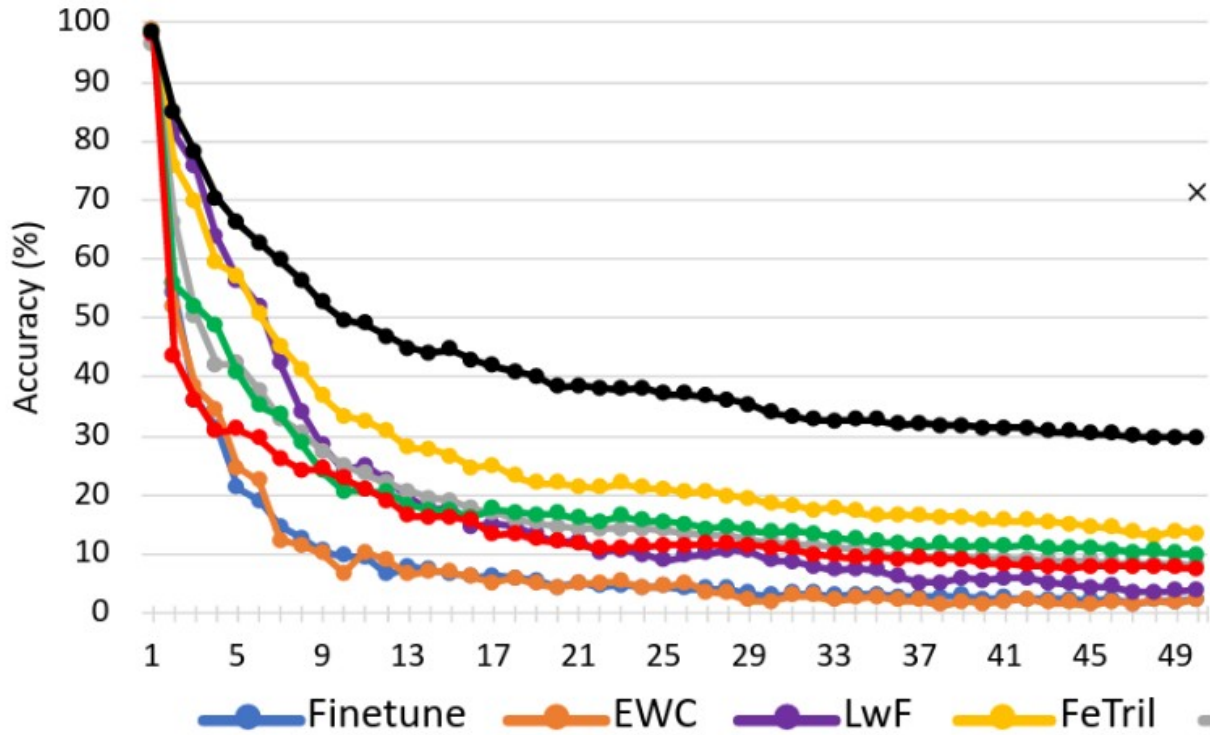
We choose expert 2 because distributions of new class overlap least in its latent space.

We finetune the chosen expert to further increase the separability of new classes' distributions.

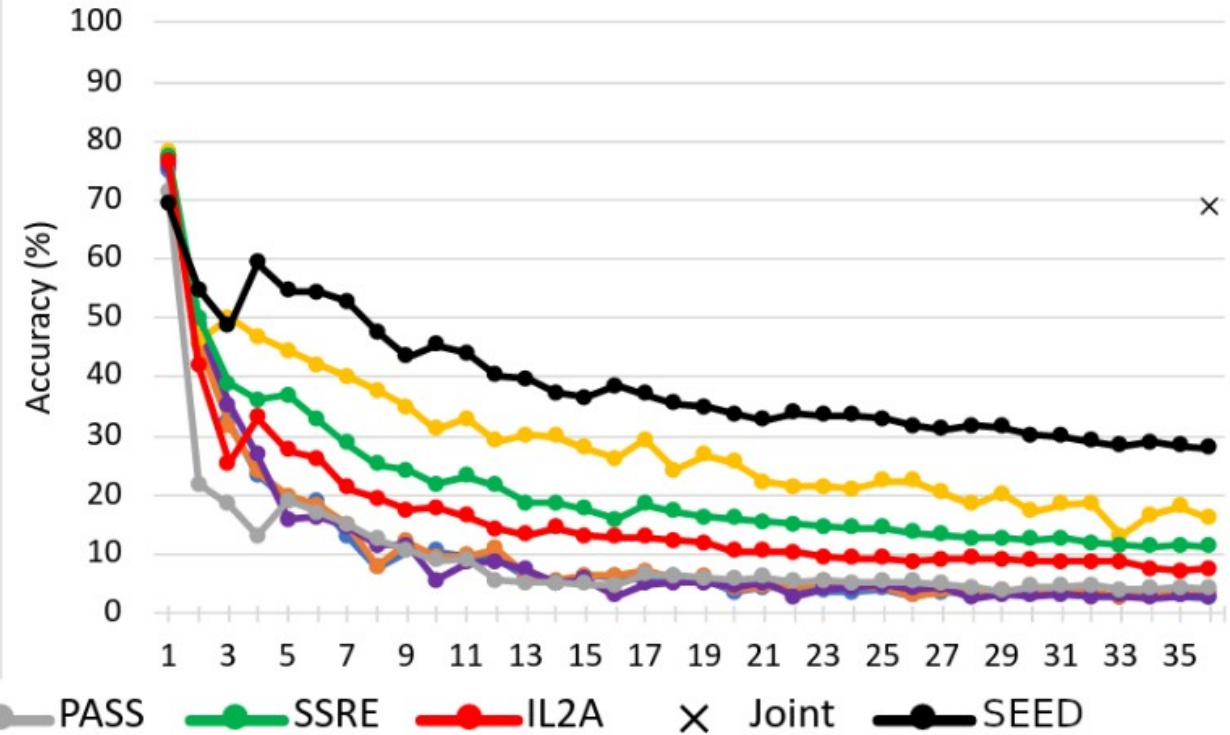


CIL Method	CIFAR-100 (ResNet32)			DomainNet			ImageNet-Subset
	$T=10$	$T=20$	$T=50$	$T=12$	$T=24$	$T=36$	$T=10$
Finetune	26.4±0.1	17.1±0.1	9.4±0.1	17.9±0.3	14.8±0.1	10.9±0.2	27.4±0.4
EWC (Kirkpatrick et al., 2017) (PNAS'17)	37.8±0.8	21.0±0.1	9.2±0.5	19.2±0.2	15.7±0.1	11.1±0.3	29.8±0.3
LwF* (Rebuffi et al., 2017) (CVPR'17)	47.0±0.2	38.5±0.2	18.9±1.2	20.9±0.2	15.1±0.6	10.3±0.7	32.3±0.4
PASS (Zhu et al., 2021b) (CVPR'21)	37.8±1.1	24.5±1.0	19.3±1.7	25.9±0.5	23.1±0.5	9.8±0.3	-
IL2A (Zhu et al., 2021a) (NeurIPS'21)	43.5±0.3	28.3±1.7	16.4±0.9	20.7±0.5	18.2±0.4	16.2±0.4	-
SSRE (Zhu et al., 2022) (CVPR'22)	44.2±0.6	32.1±0.9	21.5±1.8	33.2±0.7	24.0±1.0	22.1±0.7	45.0±0.5
FeTrIL (Petit et al., 2023) (WACV'23)	46.3±0.3	38.7±0.3	27.0±1.2	33.5±0.6	33.9±0.5	27.5±0.7	58.7±0.2
SEED	61.7±0.4	56.2±0.3	42.6±1.4	45.0±0.2	44.9±0.2	39.2±0.3	67.8±0.3
Joint		71.4±0.3		63.7±0.5	69.3±0.4	69.1±0.1	81.5±0.5

CIFAR100 T=50



DomainNet T=36

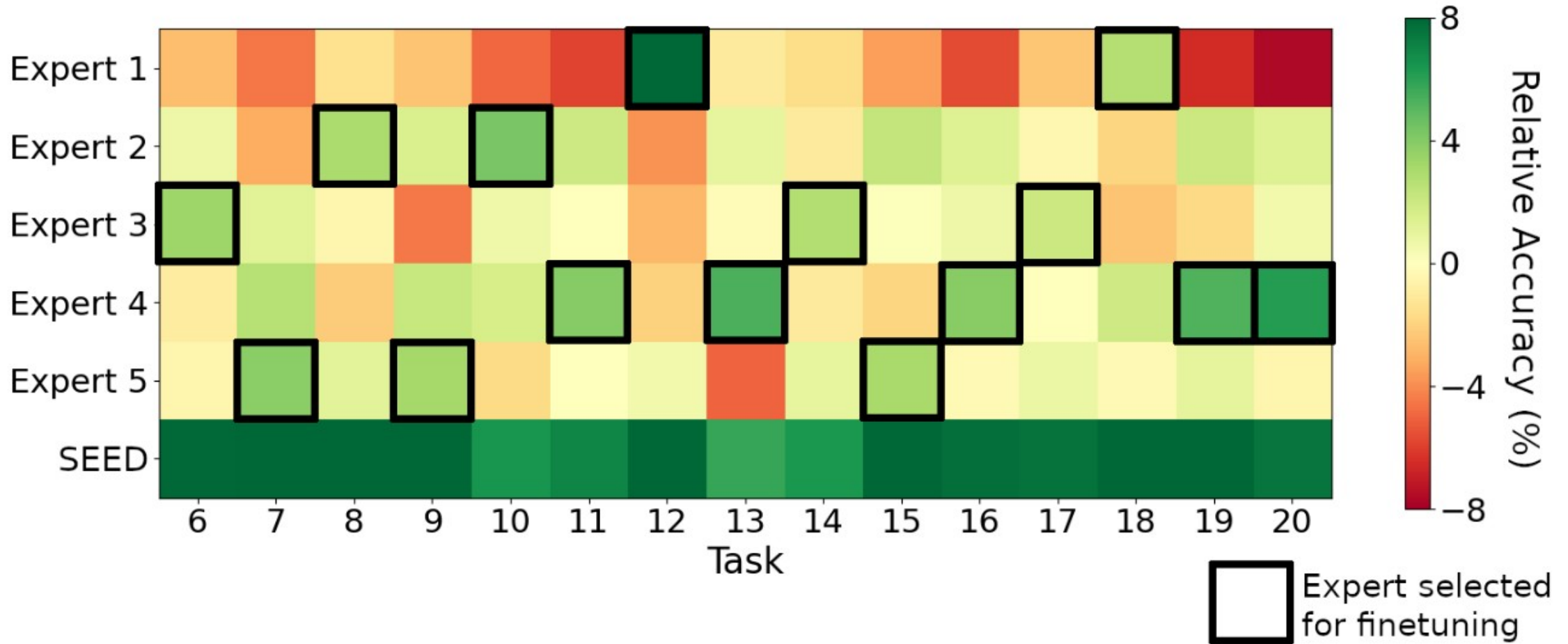


SEED - Task incremental setting + Abelation

Approach	#Params.	20-split	50-split
HAT	6.8M	77.0	80.5
MARK	4.7M	78.3	-
BNS	6.7M	-	82.4
CoSCL(EWC+LWF)	4.6M	79.4±1.0	87.9±1.1
SEED	3.2M	86.8±0.3	91.2±0.4
SEED(1 shared)	3.2M	86.7±0.6	91.2±0.5
SEED(11 shared)	3.1M	85.6±0.3	89.6±0.2
SEED(21 shared)	2.7M	82.4±0.4	88.1±0.5

Approach	Acc.(%)
SEED(5 experts)	61.7 ±0.4
standard ensemble	56.9±0.4
weighted ensemble	57.0±0.5
CoSCL ensemble	57.3±0.4
w/o multivariate Gauss.	53.5±0.5
w/o covariance	54.1±0.3
w/o temp. in softmax	59.2±0.5
w/ ReLU	57.8±0.6

SEED - Diversification of experts



Summary

- We introduce SEED method for CL, that achieves state-of-the-art results
- We develop a novel selection strategy that assigns expert to a task

Link to the paper and code:



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