Rep*Mode*: Learning to Re-parameterize Diverse Experts for Subcellular Structure Prediction [CVPR'23 Highlight]



视觉与学习青年学者研讨会 VISION AND LEARNING SEMINAR







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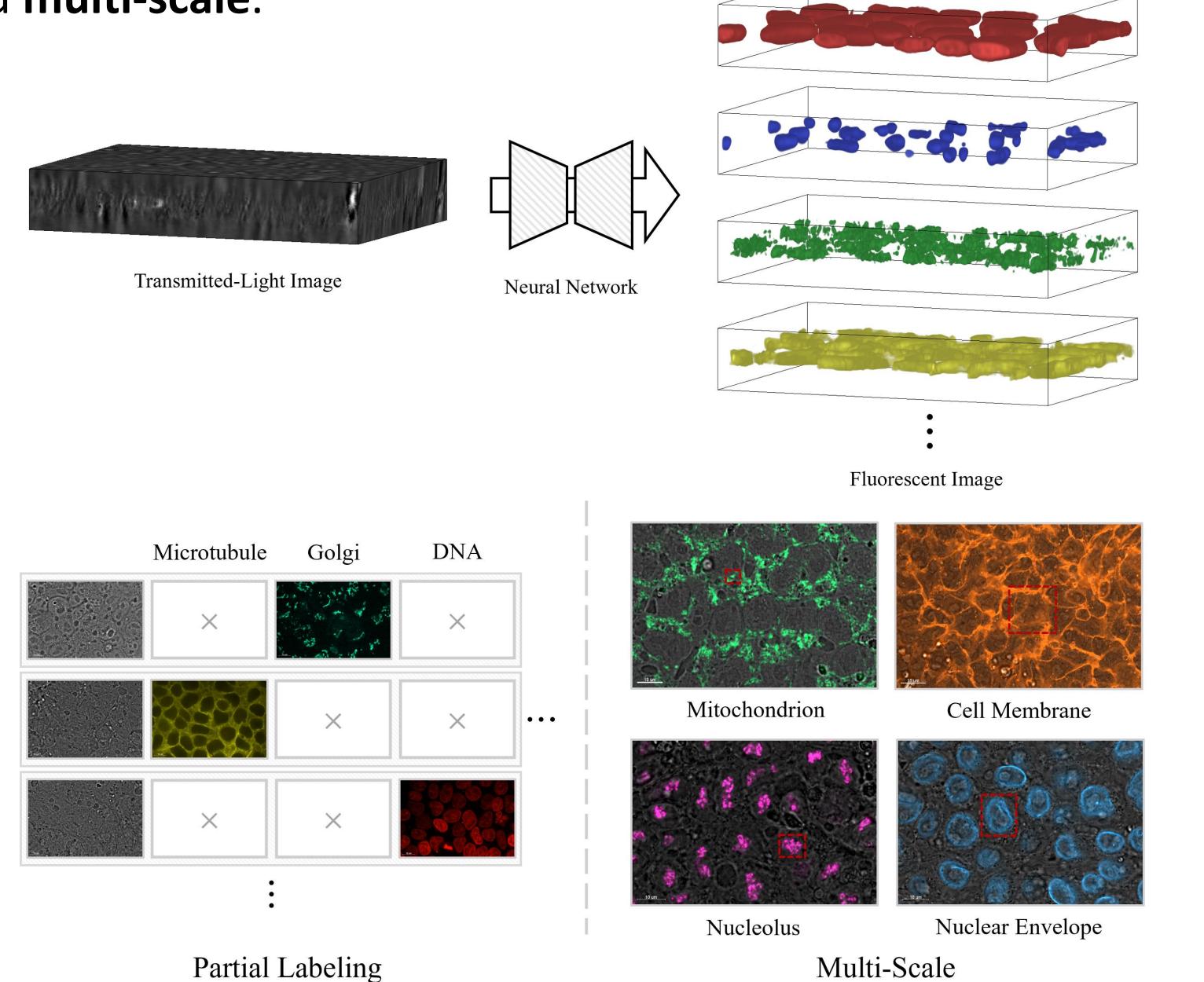
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"Can we recreate Warhol's masterpiece for cells?"

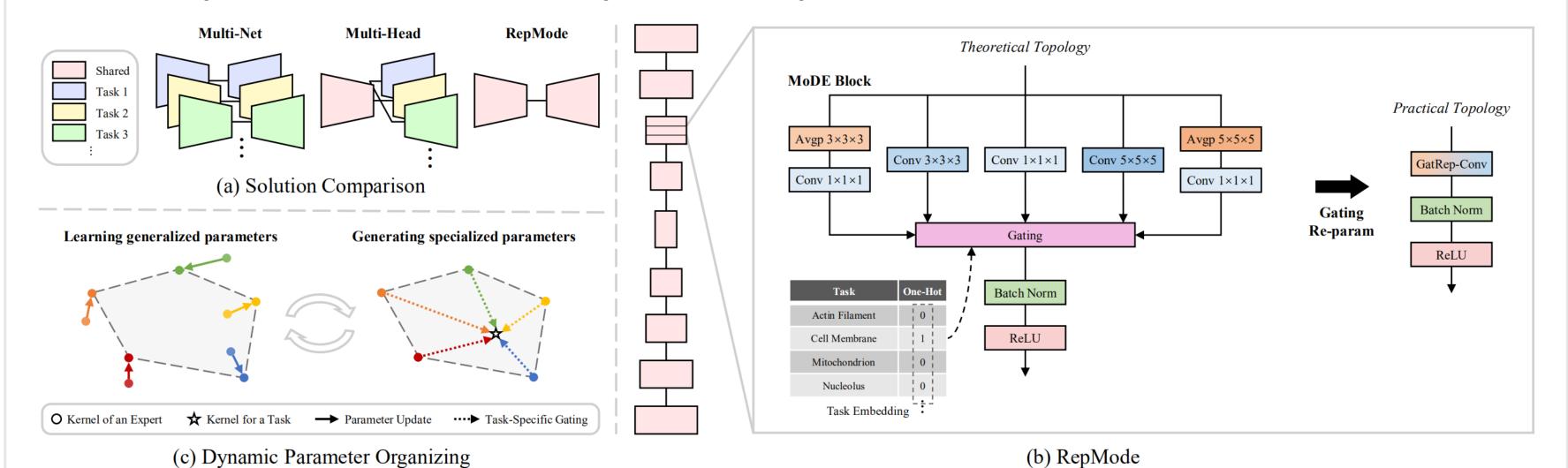
Task and Challenges

We introduce **Subcellular Structure Prediction (SSP)**, which aims to predict 3D fluorescent images of multiple subcellular structures with a 3D transmitted-light image as input, to the CV community. This task faces two challenges, *i.e.* **partial labeling** and **multi-scale**.

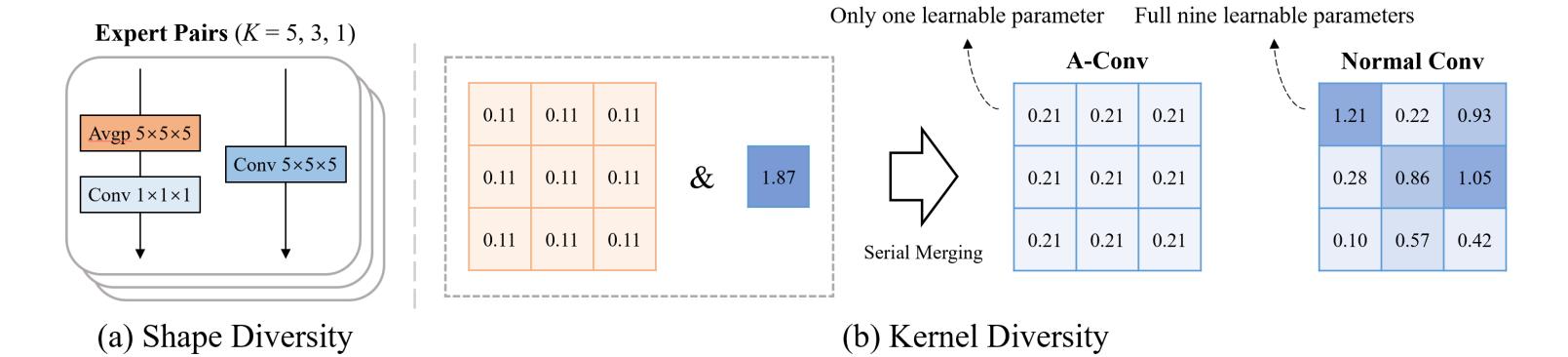


Proposed Method

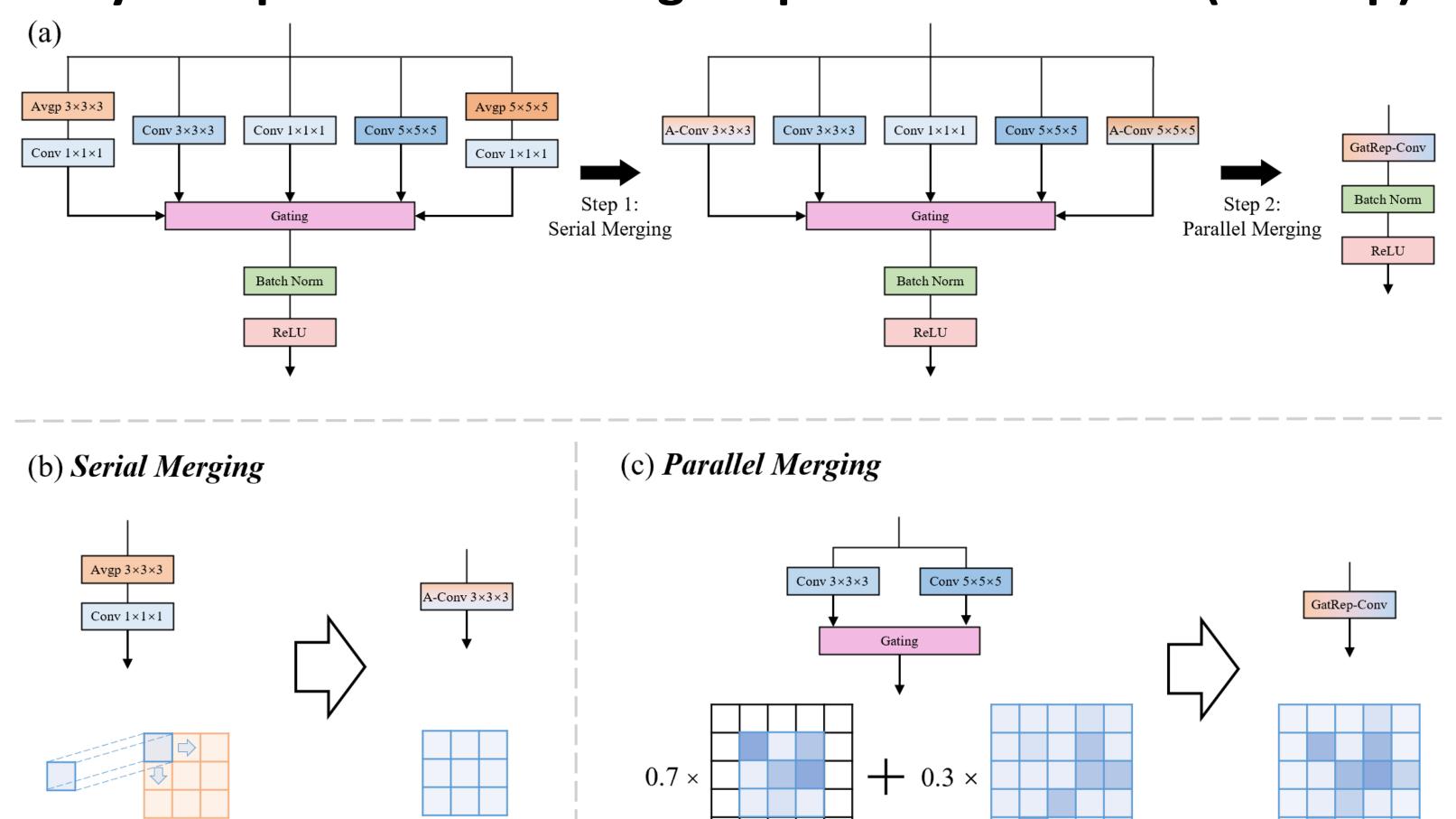
Re-parameterizing Mixture-of-Diverse-Experts (RepMode) is a network that dynamically organizes its parameters with task-aware priors to handle specified prediction tasks of SSP.



Key Component #1: Mixture of Diverse Expert (MoDE) Block



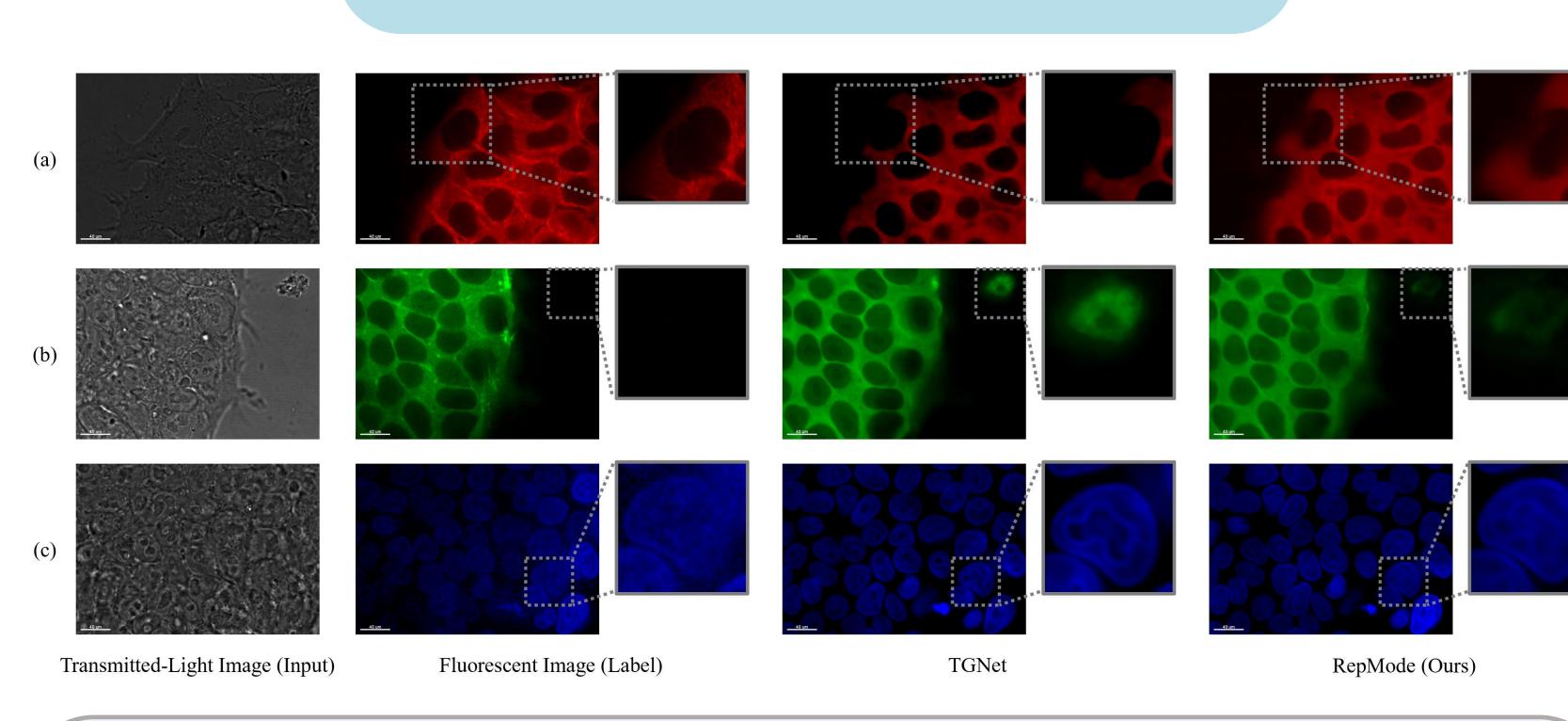
Key Component #2: Gating Re-parameterization (GatRep)



Experiments and Analysis

Ablation	Methods	MSE	MAE	R^2					**			~											~ .			
Scope	only in Dec.	.5097	.4139	.4590	Methods		in Filamo			m. Bund			Membra			mosome	0	DN		_	p. Retio			i Appara		
	only in Enc.	.5079	.4184	.4607			MAE			MAE			MAE			MAE R			$E R^2$		MAE			MAE		
Expert	w/o $1 \times 1 \times 1$ expert pair	.5027	.4106	.4662	Multi-Net [47] Multi-Head (Dec.)											5640 .01										
	w/o $3 \times 3 \times 3$ expert pair	.5080	.4141	.4605	Multi-Head (Las.)											5637 .01										
	$\frac{1}{2}$ w/o 5 × 5 × 5 expert pair	.5017	.4108	.4672	CondNet [15]											5655 .01	1111									
	• •	.5631	.4346	.4042	TSNs [56]	.4279	.4779 .	.5656	.6691	.4111	3174	.5309	.4346 .4	4575	.8392	5630 .01	60 .49	74 .46	82 .470	2 .4362	.4785	.5543	.7892	.5777	0949	
	w/o Conv expert	.5037	.4340	.4651	PIPO-FAN [16]											5674 .01										
	w/o Avgp - Conv expert	.3037	.4101	.4031	DoDNet [71] TGNet [63]	111										5633 .01 5654 .01										
Average Pooling	w/o Avgp	.4999	.4112	.4691	RepMode											5619 .01										
	all use $3 \times 3 \times 3$ Avgp	.4974	.4072	.4716		Microtubule			Mitochondria			Nuclear Envelope			Nucleolus			Tight Junction			All			$\Delta_{\mathrm{Imp}}(\%)$		
	all use $5 \times 5 \times 5$ Avgp	.4964	.4091	.4725	Methods		MAE			MAE	11111		MAE	•		MAE R			$\frac{1}{1000}$ $\frac{1}{1000}$ $\frac{1}{1000}$ $\frac{1}{1000}$	MCE	MAE	D2		MAE	11020	
Gating	use Gauss. task embedding	.5071	.4155	.4616	N. 10 N. 45471		1 7 711 11711		100000000000000000000000000000000000000					-	101000000000000000000000000000000000000	The state of the s			in the state of th							
	use two-layer FCN	.4980	.4060	.4710	Multi-Net [47] Multi-Head (Dec.)											1789 .78 1762 .78										
	use Sigmoid activation	.4992	.4094	.4698	Multi-Head (Las.)											1870 .77										
Original	RepMode	.4956	.4078	.4735	CondNet [15]									1		1865 .77										
Original	Repivioue	.4750	.4070		TSNs [56]	.3407	.4235 .	.6572	.4625	.3956	5233	.2904	.2991 .7	7064	.2116	1751 .78	74 .64	79 .33	20 .336	7 .5113	.4192	.4572	4.263	1.804	5.437	
Experimental results of ablation studies from four aspects.					PIPO-FAN [16]											1782 .78										
					DoDNet [71]						1111					1934 .77										
					TGNet [63]											1799 .78 1682 .79										
					RepMode	.5369	.41/1 .	.0390	.4437	.3003	3404	.2031	.2020 .	7340	1993	1002 .79	.01	.52	+5 ,500	3 .4930	.4070	.4/33	7.209	4.402	9.1 70	
Conv 1×1:	41		Ехрен	rimenta	l resul	lts of t	he prop	posed	RepM	lode an	nd the	compo	ring me	thods	on twe	lve pre	diction	tasks o	of SSP.							
Conv 1×1×1 Mitochondrion — Cell Membrane — Nucleolus — Nuclear Envelope Nuclear Envelope Conv 1×1×1 Experimental results of the proposed Repivious and the Comparing methods on twetve prediction tasks of SSF.											_															
Conv 3×3×3 Conv 5×5×5 Conv 3×8×3 Conv 5×5×5																										
				Methods	Strategies Nucleolu MSE MAE					Cell Membrane R^2 MSE MAE R^2 Avgp 3×3									5×5×5		_ [Fr	ozen			
Avgp 3×3×3 - Conv 1×1×1	Avgp 5×5×5 - Conv 1×1×1 Avgp 3×3×3 - Con	w 1×1×1	Avgp 5×5×5 -	Conv 1×1×1	Multi-Head (Dec.)	Fine-Tu	dual Training .2164 .1789 .7826 .5940 .4351 .3930 .2121 .1811 .7870 .5339 .4097 .4543 .5260 .4077 .4625								Conv 3×3×	(3)	Fi	ne-Tuned								
(a) Encod	Experimental results of task-incremental learning.																									
Visualization whi													•													

Visualization Results







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Scanning for the paper (3)

