

# Dynamically Managing a Prompt Pool via Self-Enhancement in Continual Learning



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# (a) Existing works<sup>[1,2,3]</sup>: : Initialized prompt (b) CoEn (Ours): : Prompt pool ... Self-Enhancement

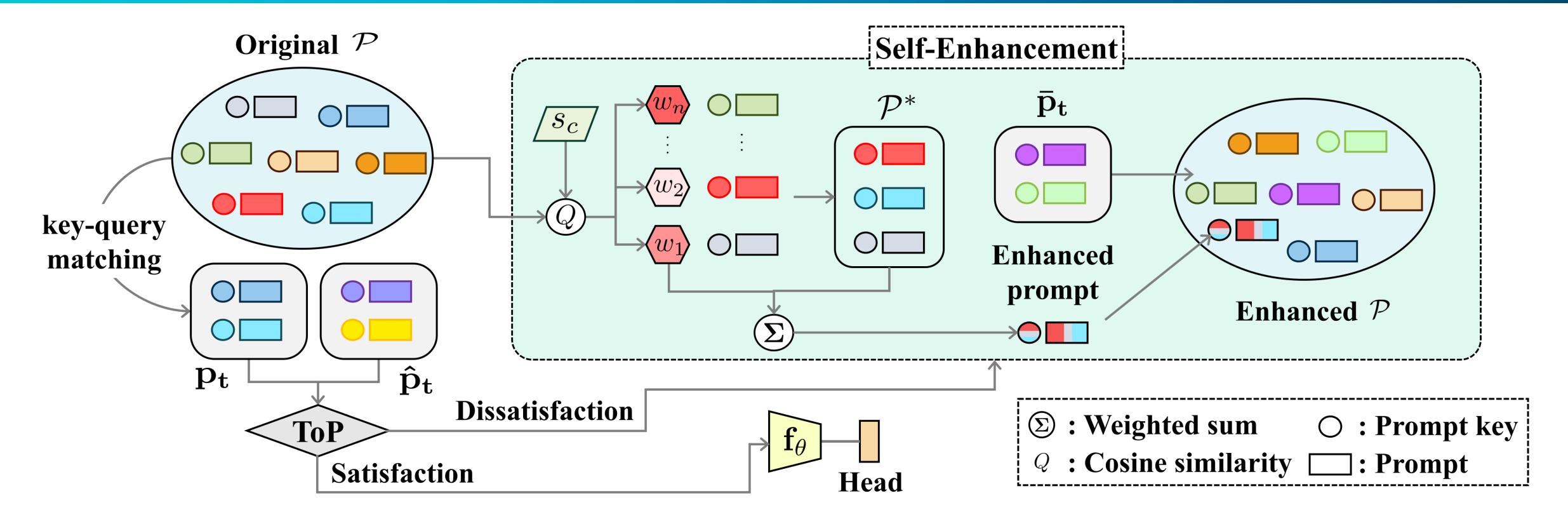
### Existing prompt-based continual learning (a)

• Select similar prompt via key-query matching; uncertainty in positive knowledge transfer.

### Dynamic prompt pool management of CoEn (b)

• Self-Enhancement mechanism; better new knowledge integration and enhanced knowledge retention.

# CoEn: Continual Enhanced prompt pool



# Transferability of the prompt pool (ToP)

$$\operatorname{ToP}^{(t)}[p_t] = \begin{cases} 1, & \text{if } \mathbb{E}_{(x^t, y^t)}[\mathcal{L}(f_{\theta}(x^t, p_t), y^t)] > \mathbb{E}_{(x^t, y^t)}[\mathcal{L}(f_{\theta}(x^t, \hat{p}_t), y^t)], \\ 0, & \text{otherwise,} \end{cases}$$

• Assess positive knowledge transfer via statistical risk; enhance prompt pool if ToP fails.

### **Enhanced prompt**

$$w_{i} = \frac{1}{C} \sum_{c=1}^{C} sim(k_{i}, s_{c}), i \in \{0, \dots, N\},$$

$$k_{enh} = \sum_{i=1}^{h} \frac{w_{\rho(i)} k_{\rho(i)}}{\sum_{i=1}^{h} w_{\rho(i)}}, \quad p_{enh} = \sum_{i=1}^{h} \frac{w_{\rho(i)} p_{\rho(i)}}{\sum_{i=1}^{h} w_{\rho(i)}}.$$

• Low-relevance k and p are aggregated to enhanced one.

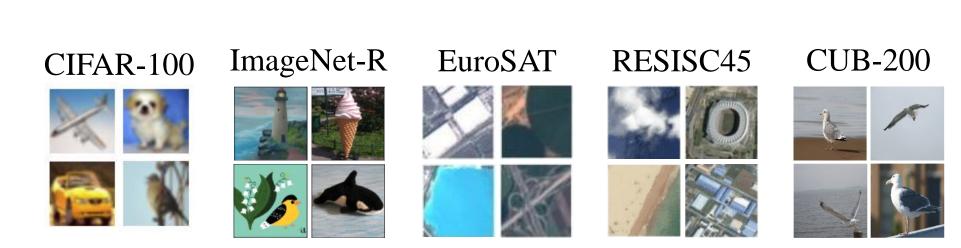
### **Experimental Results**

### General-domain class incremental learning scenario

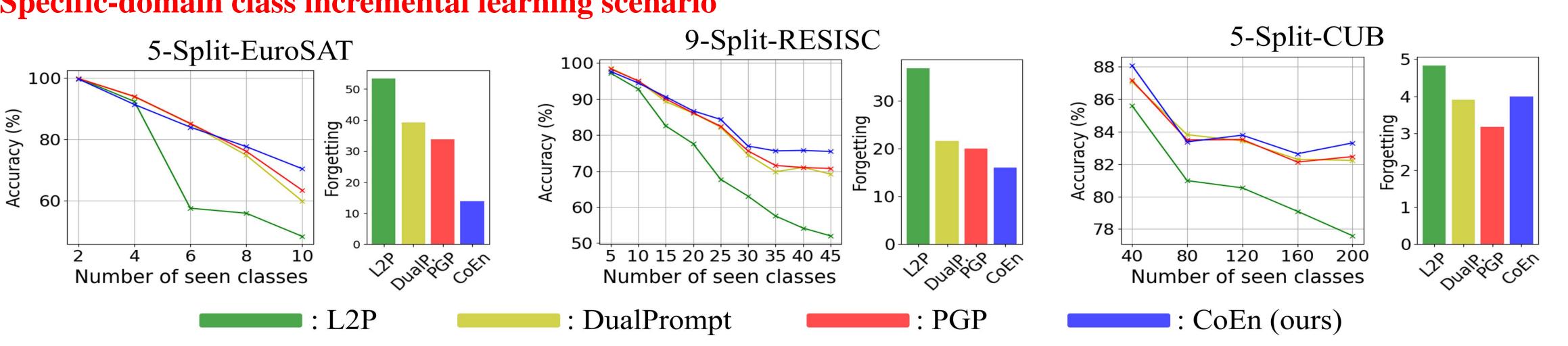
Method _	10-Split- CIFAR100		20-Split- CIFAR100		10-Split- ImageNet-R		20-Split- ImageNet-R	
	Acc	$\mathbf{F}$	Acc	F	Acc	$\mathbf{F}$	Acc	F
L2P <sup>[1]</sup>	83.5	6.9	81.6	9.4	65.1	5.1	57.0	9.5
Dual.P <sup>[2]</sup>	86.1	<b>5.8</b>	83.5	<b>7.8</b>	69.2	<u>4.7</u>	<b>65.7</b>	<u>7.1</u>
$PGP^{[3]}$	86.7	<b>5.5</b>	83.5	<b>8.1</b>	69.1	<b>5.8</b>	<u>65.9</u>	<b>7.1</b>
CoEn	<u>86.8</u>	<u>4.9</u>	<u>84.3</u>	<u>6.4</u>	<u>69.6</u>	<b>5.6</b>	64.9	8.0

## Results

- CoEn: 3.8% accuracy boost.
- Superior to existing methods.
- Enhanced knowledge transfer.
- Dynamic prompt management.



# Specific-domain class incremental learning scenario



[1] Zifeng Wang, Zizhao Zhang, Chen-Yu Lee, Han Zhang, Ruoxi Sun, Xiaoqi Ren, Guolong Su, Vincent Perot, Jennifer Dy, and Tomas Pfister. Learning to prompt for continual learning. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pages139–149, 2022.
[2] Zifeng Wang, Zizhao Zhang, Sayna Ebrahimi, Ruoxi Sun, Han Zhang, Chen-Yu Lee, XiaoqiRen, Guolong Su, Vincent Perot, Jennifer Dy, et al. Dualprompt: Complementary prompting for rehearsal-free continual learning. In European

Conference on Computer Vision, pages 631–648. Springer, 2022.

[3] Jingyang Qiao, Xin Tan, Chengwei Chen, Yanyun Qu, Yong Peng, Yuan Xie, et al. Prompt gradient projection for continual learning. In The Twelfth International Conference on Learning Representations, 2023.