北京大學
PEKING UNIVERSITY

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Dual Prompt Learning for Continual Rain Removal from Single Images

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Background

Image Quality Degradation

- Raindrops obstruct, deform and blur the background scenes
- Generate atmospheric veiling effects similar to mist or fog
- Exhibit strong specular highlights that occlude background scene

Rain Removal Task

Rain Synthesis Model

- O = R + B
- O : Rainy Image R : Rainy Layer B : Background Layer
- Objective : Given O, Estimate B

Deraining Algorithm

Challenge

Diverse Rain in Various Scenes

Domain Shift (1/2)

Training Set

- Limited & Monotonous & Fixed

Rain800

Rain100H

Rain100L

Domain Shift (2/2)

Real World

- Abundant & Diverse & Continually changing

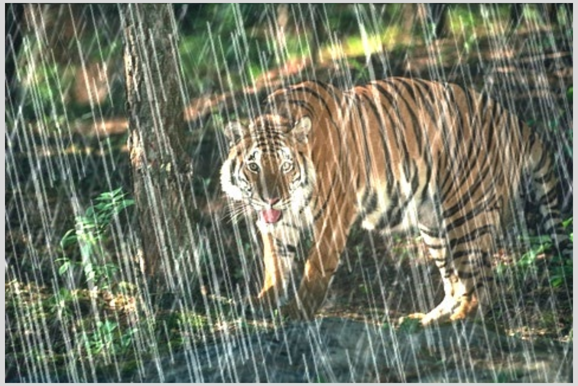
Light Rain in Yangzhou
Spring

Heavy Rain in Beijing
Summer

Rainstorm in Taiwan
Autumn

Can a model handle multiple types of rain?

Rain Type 1



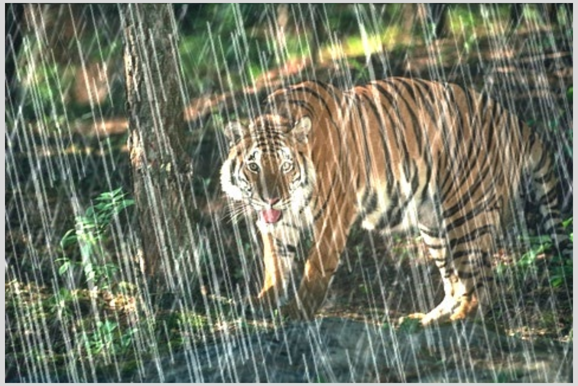
Rain Type 2

Train

Model

Can a model handle multiple types of rain?

Rain Type 1



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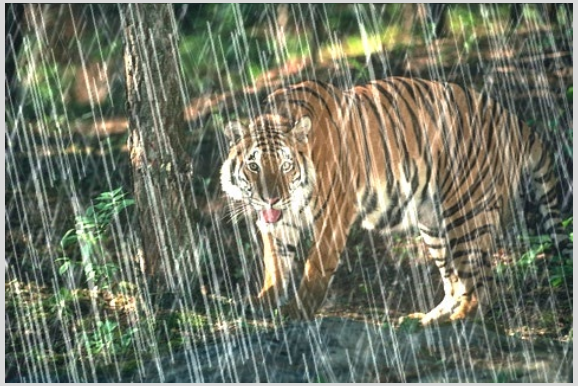


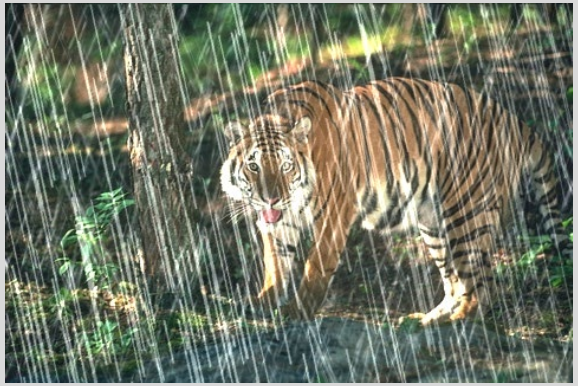
Rain Type 2

Model

Train

Can a model handle multiple types of rain?

Rain Type 1



Rain Type 2

Model

Catastrophic Forgetting

Continual Learning

Previous Methods

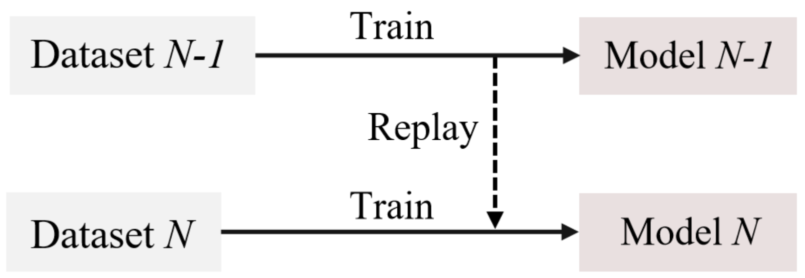
Replay

√ Good performance

√ No additional parameters

× Computationally expensive

× Space increase linearly



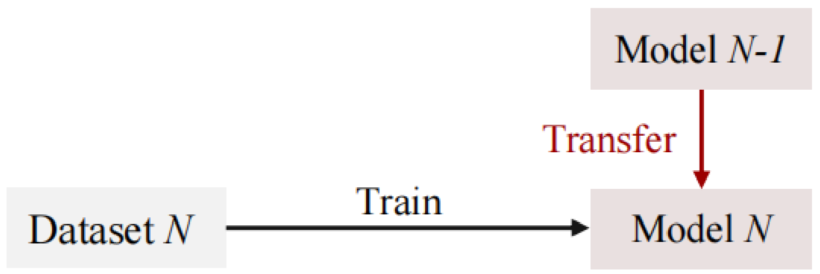
Parameter Regularization

√ Fixed additional space

√ No access to previous data

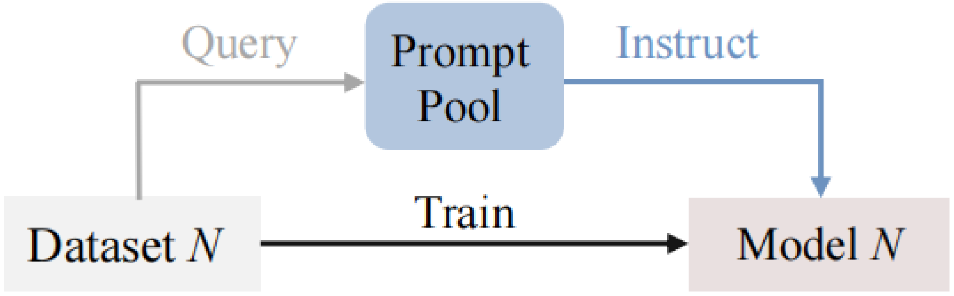
× Costly parameters

× Lacks the flexibility



Prompt Learning for Continual Learning

Prompt Learning
√ Economic parameters
√ Flexibility
× Only designed for high level task (classification)

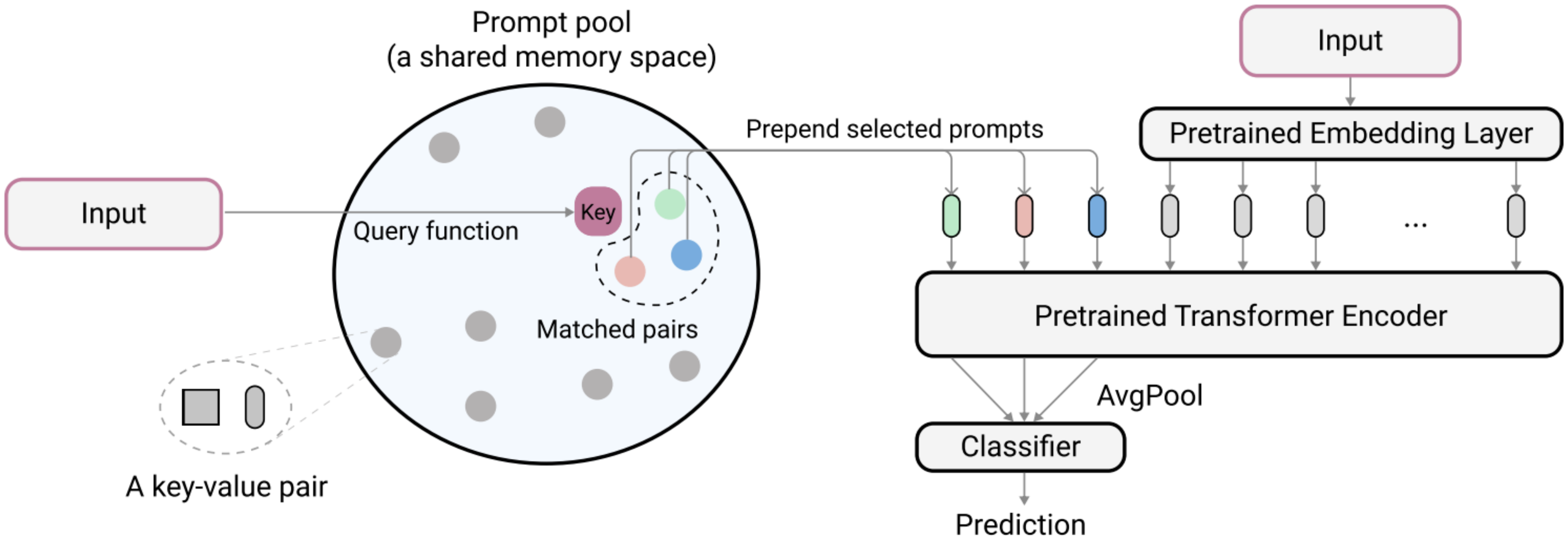


Classification Task ⟶ Global Optimization Problem ⟶ Feature Prompt Pool

Rain Removal Task ⟶ Local and global joint optimization problem ⟶ Dual Prompt Pool

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. CVPR, 2022.

Prompt Learning for Continual Learning



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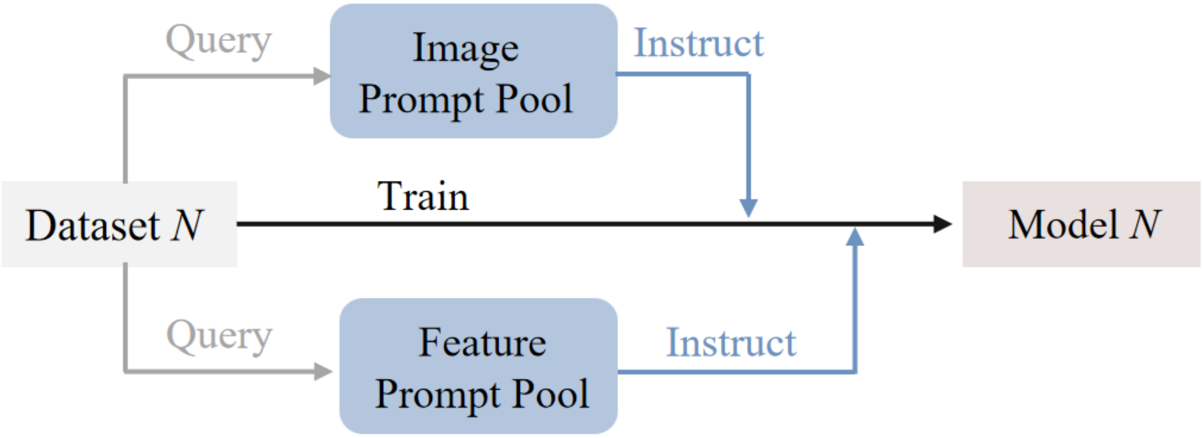
Continual Learning for Rain Removal

Our Method

Dual Prompt Learning

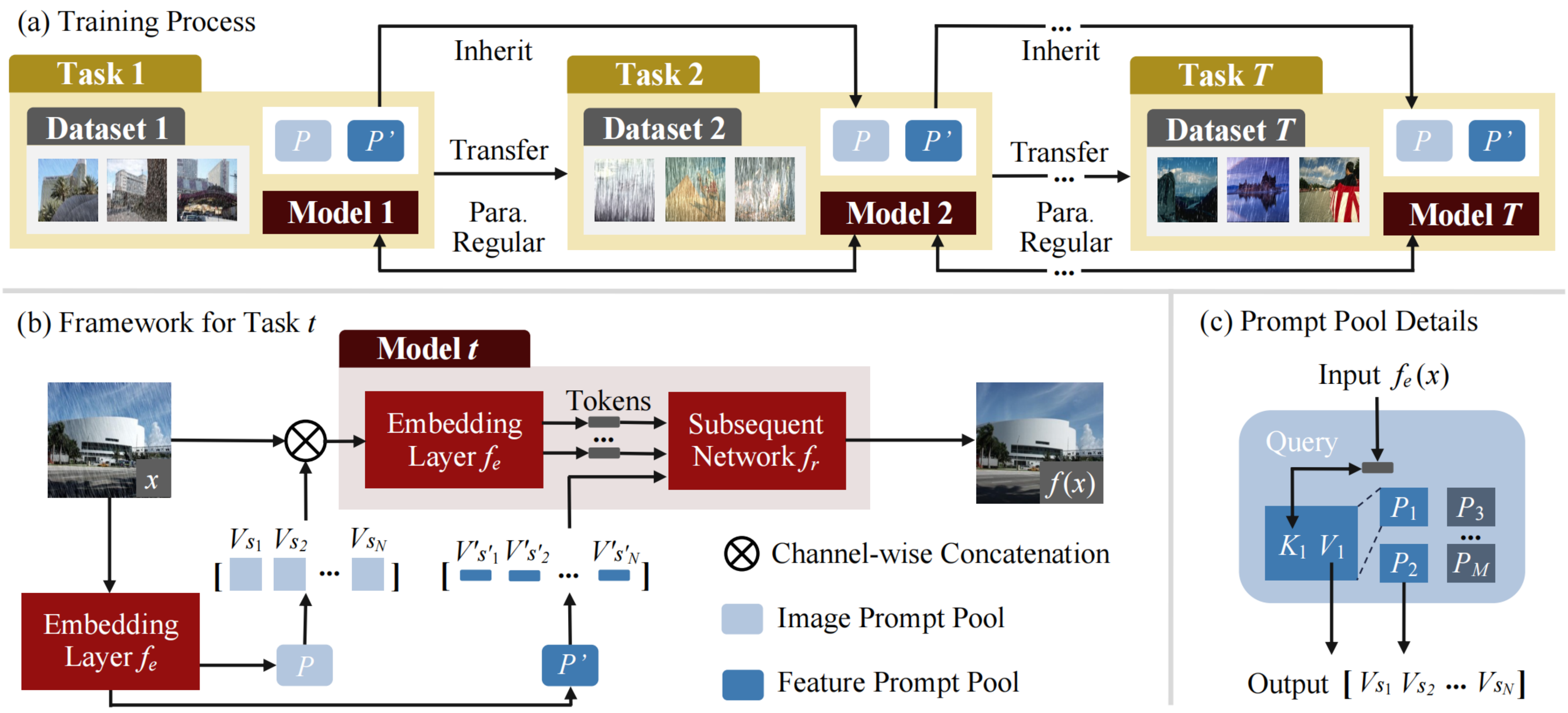
√ Economic parameters
√ Computationally cheap
√ Flexibility
√ Specially designed for rain removal tasks
√ High performance



Our Contributions

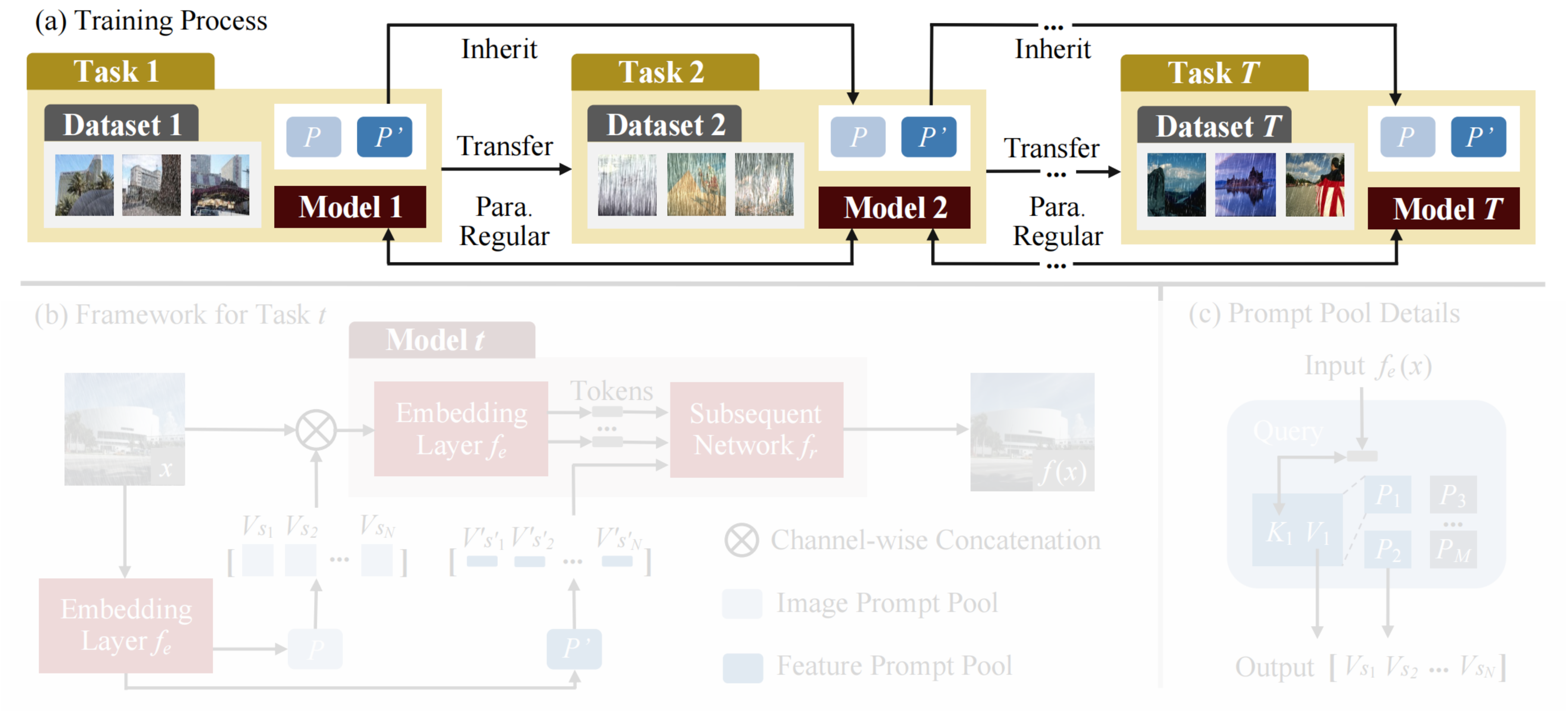
- **Novel prompt learning-based continual learning scheme**
  - Handle different types of rain streaks with a single model, which leads to superior performance on various benchmarks.
- **Dual prompt learning method for deraining**
  - Prompts are applied at both image and feature levels to leverage effectively transferred knowledge of images and features jointly.
- **Competitive results on single dataset**
  - Even though our method is designed for the continual learning scenario, it achieves competitive results against state-of-the-art methods on the stationary distributed data.

The Framework of Our Proposed Method



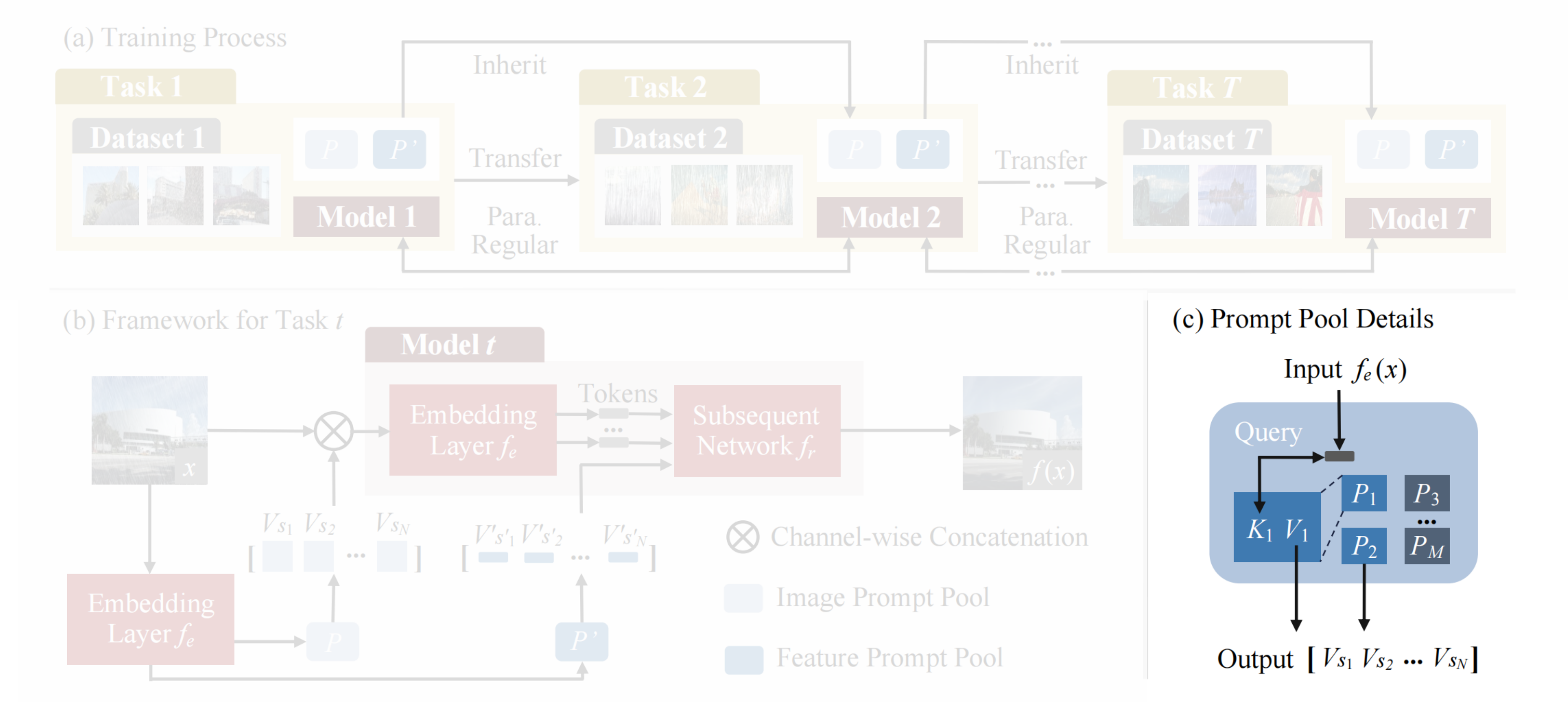
The Framework of Our Proposed Method

The General Training Process

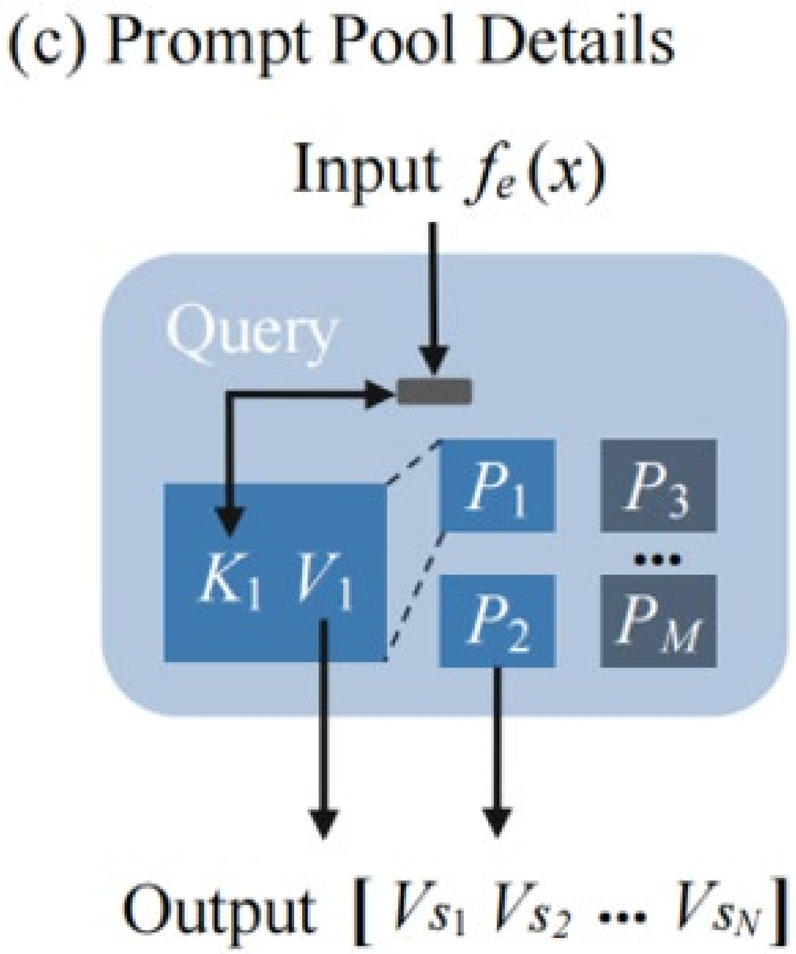


The Framework of Our Proposed Method

The Details of Prompt Pools



The Framework of Our Proposed Method

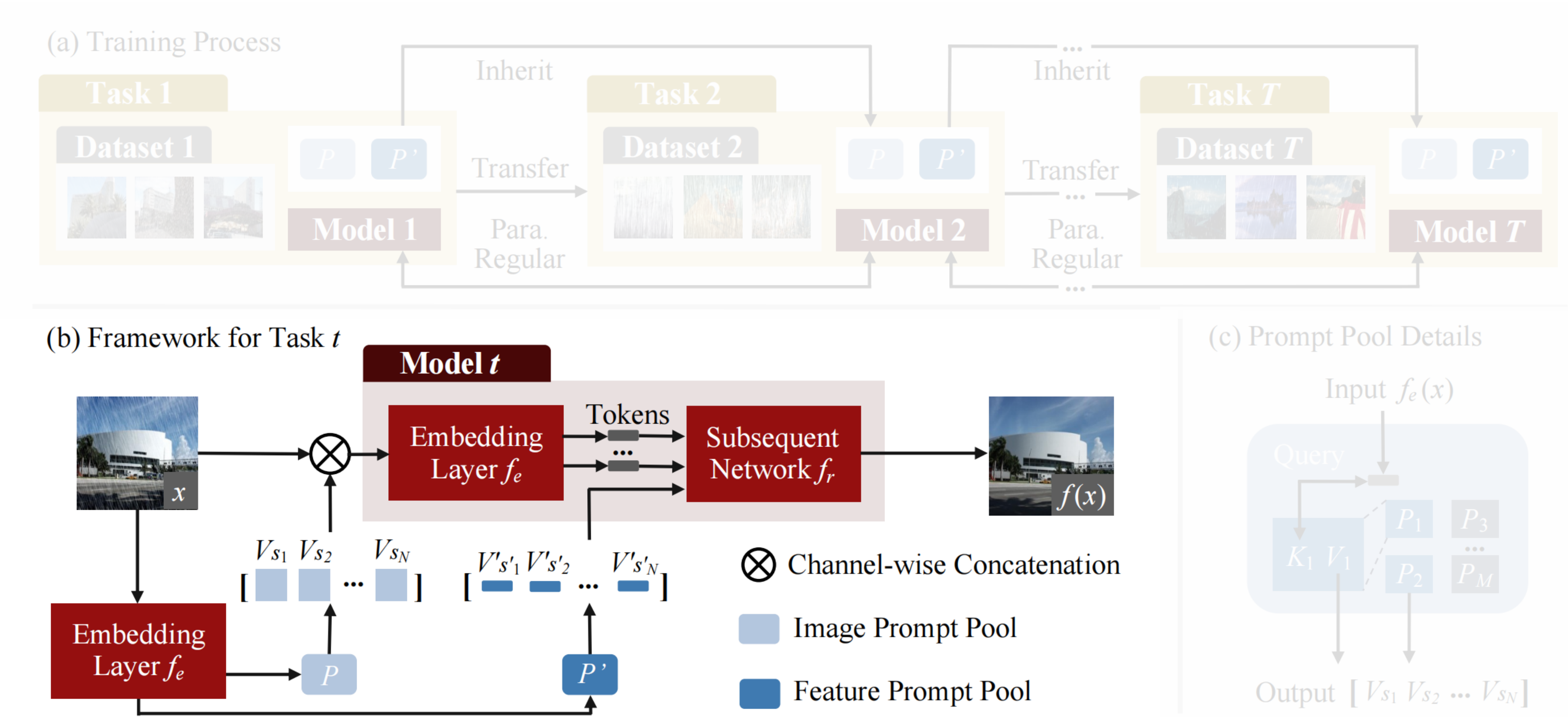


$$\mathcal{P}_x = \underset{\{s_i\}_{i=1}^{N} \subseteq [1,M]}{\arg\min} \sum_{i=1}^{N} \gamma\left(K_{s_i}, f_e(x)\right) \cdot q_{s_i}^{n}$$

$$\mathcal{P}'_x = \underset{\{s'_i\}_{i=1}^{N} \subseteq [1,M]}{\arg\min} \sum_{i=1}^{N} \gamma\left(K'_{s'_i}, f_e(x)\right) \cdot {q_{s'_i}^{n}}'$$

The Framework of Our Proposed Method

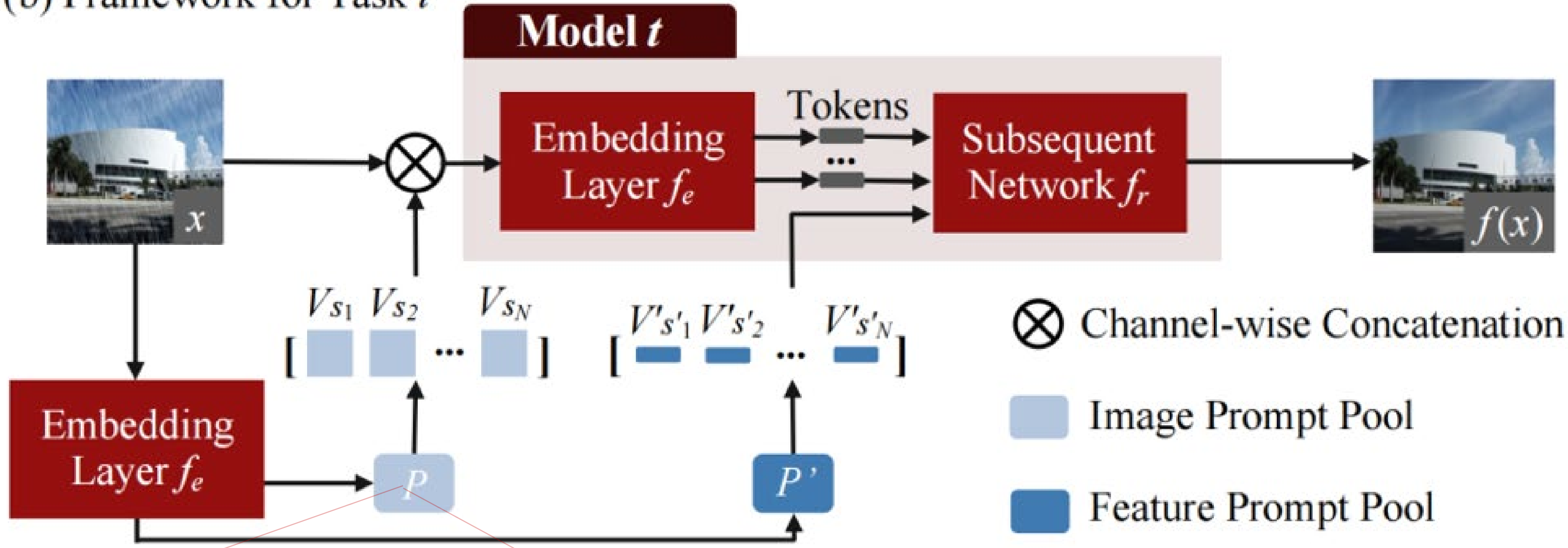
The Details of Training Process for a Task



The Framework of Our Proposed Method

Image Prompt Pool's Selection

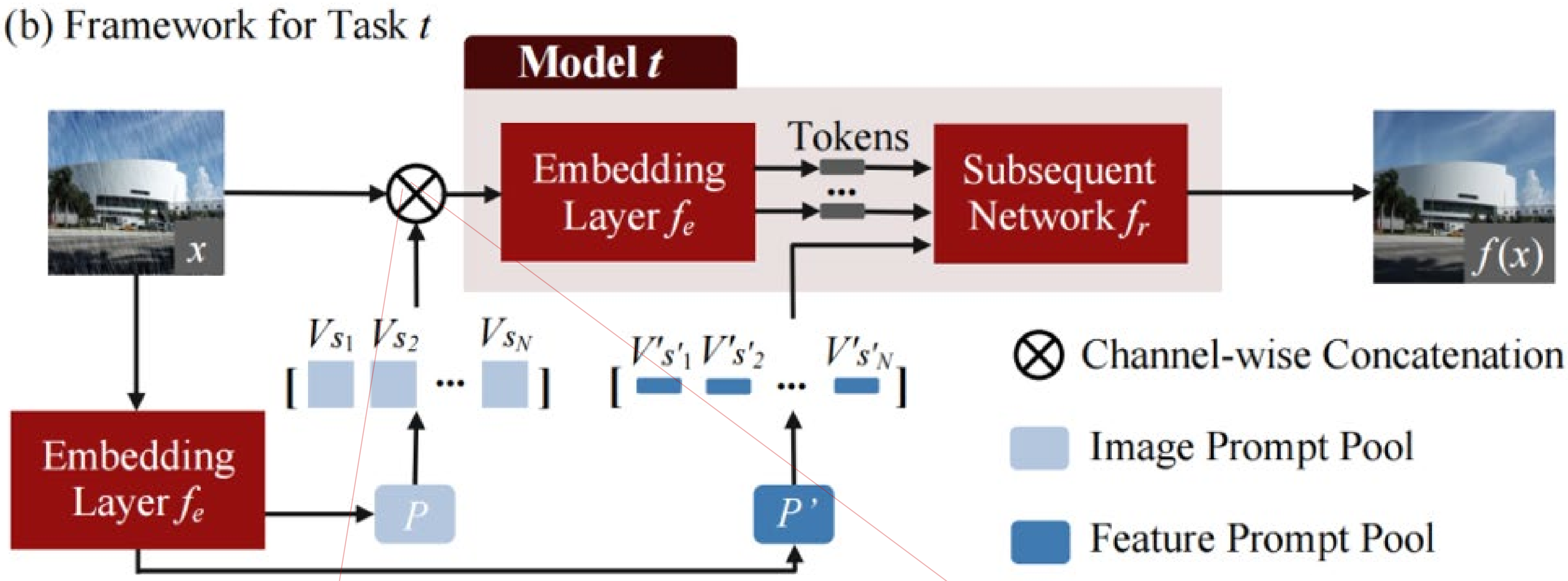
(b) Framework for Task t



$$\mathcal{P}_x = \underset{\{s_i\}_{i=1}^{N} \subseteq [1,M]}{\arg\min} \sum_{i=1}^{N} \gamma\left(K_{s_i}, f_e(x)\right) \cdot q_{s_i}^{n}$$

The Framework of Our Proposed Method

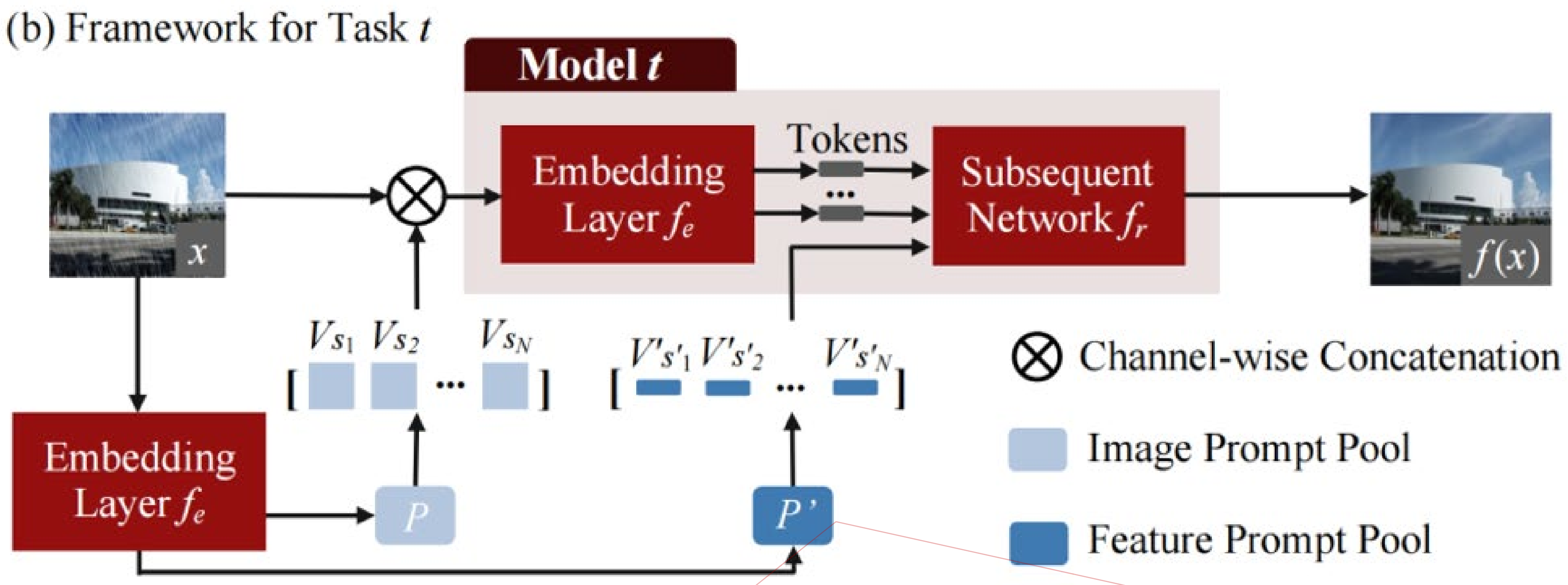
Concatenate along the Channel Dimension



$$x_1 = [V_{s_1}; V_{s_2}; \cdots ; V_{s_N}; x]$$

The Framework of Our Proposed Method

Feature Prompt Pool's Selection

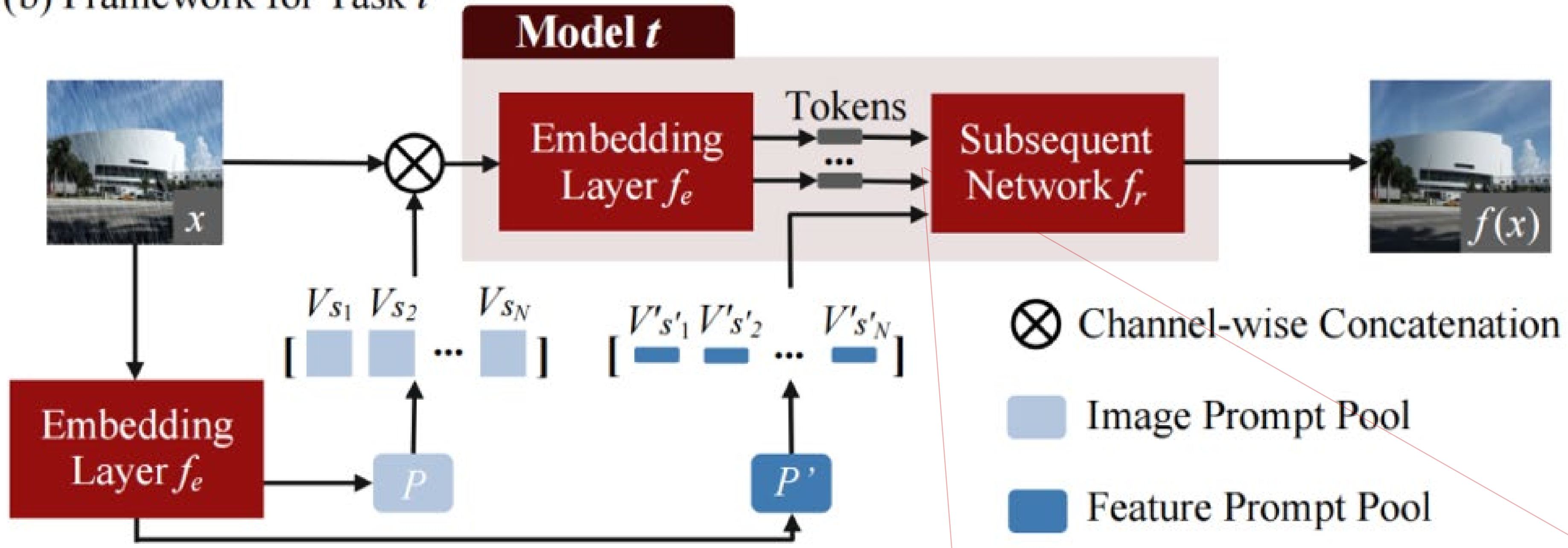


$$\mathcal{P}'_x = \underset{\{s'_i\}_{i=1}^{N} \subseteq [1,M]}{\arg\min} \sum_{i=1}^{N} \gamma\left(K'_{s'_i}, f_e(x)\right) \cdot q_{s'_i}^{n\,\prime}$$

The Framework of Our Proposed Method

Concatenate along the Token Length Dimension

(b) Framework for Task t



$$x_2 = [V'_{s'_1}; V'_{s'_2}; \cdots; V'_{s'_N}; f_e(x_1)], 1 \leq N \leq M$$

The Framework of Our Proposed Method

Joint Regularization of Parameters and Prompts

$$
\begin{aligned}
I\left(\theta^{n+1}\right) &= \Delta f\left(\theta^{n+1}, \theta^{n}, x, y\right) \\
&= \sum_{k=1}^{r+s}\left[l\left(f\left(x, \theta_k^{n+1}\right), y\right) - l\left(f\left(x, \theta_k^{n}\right), y\right)\right] \\
&= \sum_{k=1}^{r+s}\left[\left(\nabla_{\theta_k^n} l\right)^T \cdot \delta\theta_k^n + \frac{1}{2}\left(\delta\theta_k^n\right)^T \cdot H \cdot \left(\delta\theta_k^n\right)\right]
\end{aligned}
$$

The Framework of Our Proposed Method

Loss Functions

$$\begin{aligned}\mathcal{L}_x = \min_{\mathcal{P},\mathcal{P}',\theta} & \alpha L_1\left(f\left(x\right),y\right) + \beta L_p\left(f\left(x\right),y\right) \\ & + \zeta \sum_{\mathcal{P}_x} \gamma\left(f_e\left(P_{s_i}\right), f_e\left(x\right)\right) \cdot q_{s_i}^n \\ & + \eta \sum_{\mathcal{P}'_x} \gamma\left(P'_{s'_i}, f_e\left(x\right)\right) \cdot {q_{s'_i}^n}' + \omega I\left(\theta^n\right).\end{aligned}$$

EXPERIMENTAL RESULTS

Datasets

Rain800
- 700 pairs for training
- 100 pairs for testing

Rain100H
- 1800 pairs for training
- 100 pairs for testing

Rain100L
- 1800 pairs for training
- 100 pairs for testing

Experiments

Performance & Additional Increased Parameter Complexity Comparison

	Replay	Parameter Reg. (PR)	Dual Prompt (DP)	DP+PR
Performance (PSNR)	22.76	22.48	22.96	24.39
Increased Parameter Ratio	100% + 4% × tasks	100%	5.2%	105.2%

Quantitative Evaluation

Training on Rain800-Rain100H, Testing on Rain800

Methods	Training on Rain800-Rain100H		
	PSNR	SSIM	Degradation on Rain800
Baseline (only Rain800)	26.63	0.8583	0, 0
Ours (only Rain800)	27.52	0.8667	-0.89, -0.0084
SI	19.87	0.6451	6.76, 0.2132
EWC	21.64	0.7962	4.99, 0.0621
Replay	22.76	0.8136	3.87, 0.0447
Deep gererative	22.51	0.8162	4.12, 0.0421
PIGWM	22.48	0.8058	4.15, 0.0525
Ours	**24.39**	**0.8365**	**2.24, 0.0218**

Quantitative Evaluation

Training on Rain800-Rain100L, Testing on Rain800

Methods	Training on Rain800-Rain100L		
	PSNR	SSIM	Degradation on Rain800
Baseline (only Rain800)	26.63	0.8583	0, 0
SI	20.42	0.5823	6.21, 0.2760
EWC	23.11	0.7840	3.52, 0.0743
Replay	23.20	0.7758	3.43, 0.0825
Deep gererative	22.25	0.7462	4.38, 0.1121
PIGWM	23.98	0.8049	2.65, 0.0534
Ours	**24.79**	**0.8382**	**1.84, 0.0201**

Visual Results

Input

Task 0

Visual Results

Input

SI Task 1

Visual Results

DPL Task 1

SI Task 1

Visual Results

DPL Task 1

Replay Task 1

Visual Results

DPL Task 1

PIGWM Task 1

Visual Results

Input

Task 0

Visual Results

Input

SI Task 1

Visual Results

DPL Task 1

SI Task 1

Visual Results

DPL Task 1

Replay Task 1

Visual Results

DPL Task 1

PIGWM Task 1

Ablation Study

Training on Rain800-Rain100H, Testing on Rain800					
Image Prompts	Feature Prompts	Parameter Reg.	Prompts Reg.	PSNR	SSIM
√	√	√	√	24.39	0.8365
×	√	√	√	23.82	0.8262
√	×	√	√	22.67	0.8189
√	√	×	√	23.07	0.8311
√	√	√	×	23.54	0.8215

Ablation Study

Input Image

All components are applied

Ablation Study

Input Image

No Image Prompts

Ablation Study

Input Image

No Feature Prompts

Ablation Study

Input Image

No Parameter Regularization

Ablation Study

Input Image

No Prompts Regularization

Sequential tasks Rain800-Rain100H-Rain100L

Method	Testing Set		
	Rain800	Rain100H	Rain100L
SI	21.30/0.7152	16.53/0.5946	36.96/0.9800
Replay	22.77/0.7758	18.78/0.6861	32.12/0.9541
PIGWM	22.80/0.7564	17.44/0.6331	32.58/0.9561
DPL	**24.44/0.8163**	**19.63/0.7282**	**31.93/0.9589**
Reference	26.63/0.8583	28.49/0.8802	37.97/0.9825

Conclusion

- **A novel continual learning scheme for single image deraining——Dual Prompt Learning**
- **This approach can be seamlessly integrated into the training of lower-level task models.**
- **Extensive experiments on various rain streak benchmarks demonstrates the effectiveness of our proposed scheme.**

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Thank You!

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