

# Hollowed Net for On-device Personalization of Text-to-Image Diffusion Models

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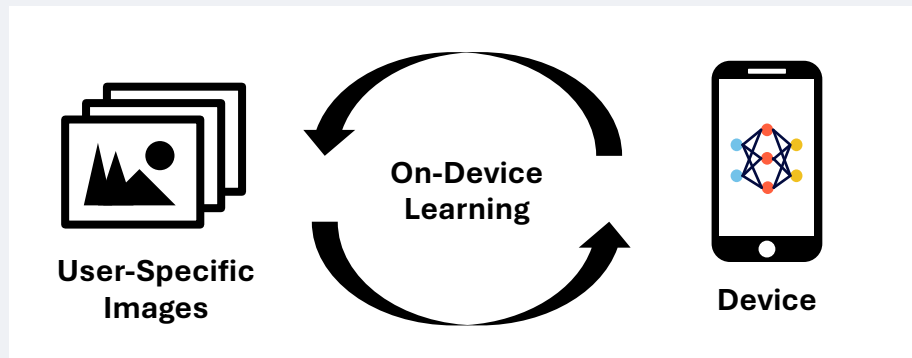
Interim Engineering Intern



# On-Device Personalization of T2I Diffusion Models

## Task Definition

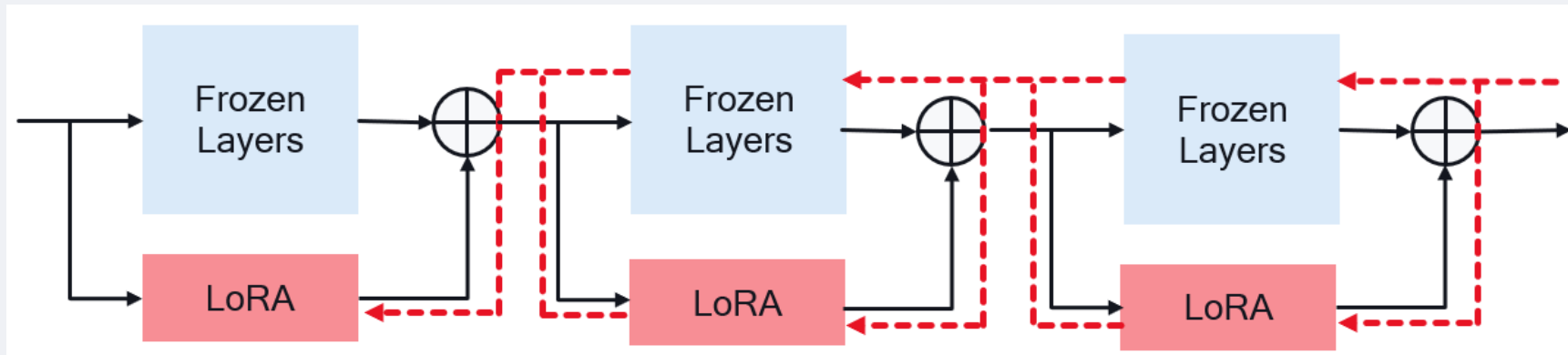
- We aim to enable **on-device personalization** of T2I diffusion models, by **fine-tuning** models on the mobile devices **with user-specific images** for customized generation.
- On-device personalization can make the entire user experience **all-the-more personal** and help **protect users' privacy** since personal information remain solely on the device.



# On-Device Personalization of T2I Diffusion Models

## Challenges

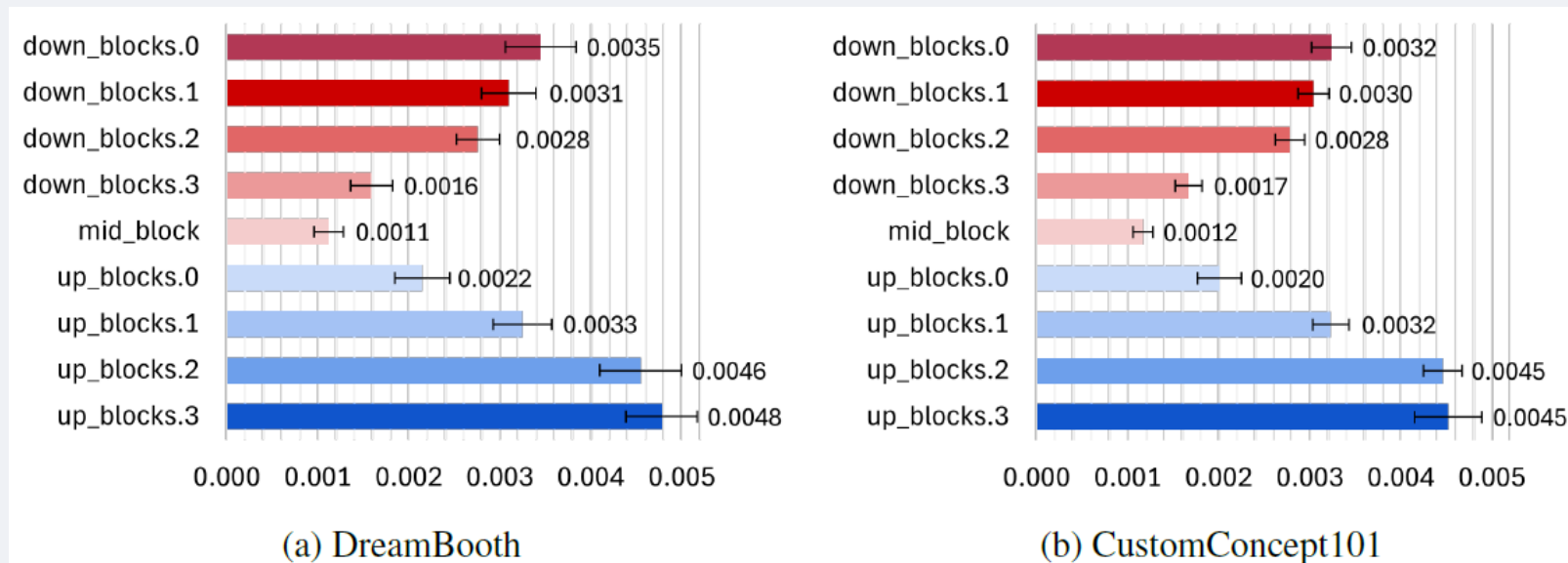
- The challenge of on-device learning stems from **limited computational resources** of end device, particularly in terms of **memory I/O**.
- Existing PEFT methods are **limited in extremely low memory resources** as they require backpropagation over large diffusion models and **do not reduce memory usage from loading model weights**.



# LoRA personalization with Hollowed Net

## Motivation

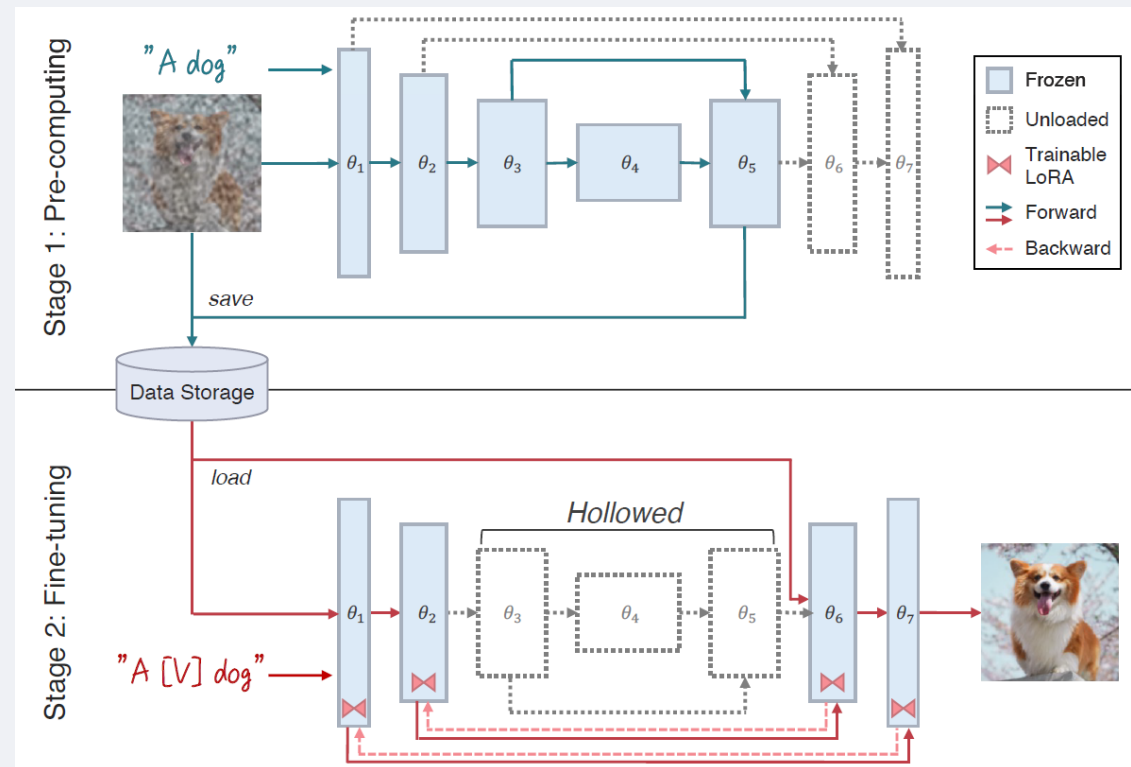
- We find that **the blocks around the center** of the diffusion U-Net are **less involved in the personalization**.
- Building on this insight, we design Hollowed Net, which can **temporarily excluding these less significant layers during fine-tuning** to reduce peak memory usage.



# LoRA personalization with Hollowed Net

## Training w/ Hollowed Net

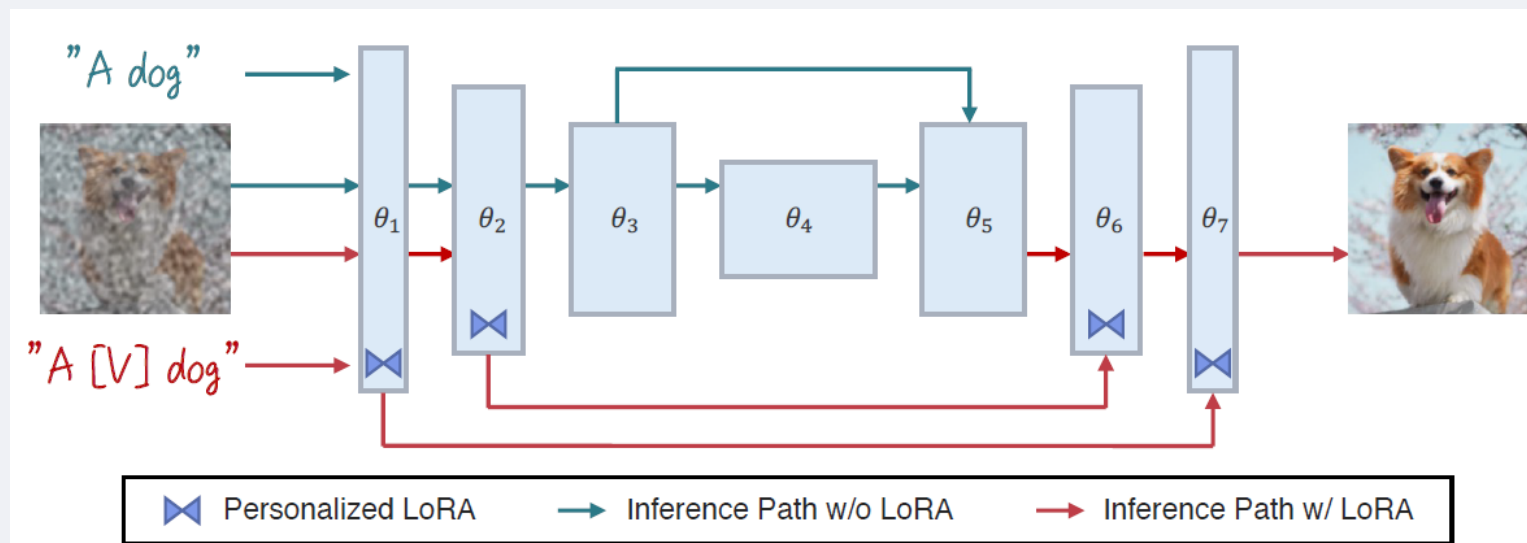
- We propose **two-stage fine-tuning strategy**:
  1. **Pre-computing** intermediate activations of the original diffusion U-Net
  2. **Fine-tuning** the Hollowed Net using the pre-computed activations



# LoRA personalization with Hologated Net

## Inference w/ Personalized LoRA

- Hologated Net **does not need to be held during inference**, by transferring personalized LoRA parameters to the original U-Net.
- We sequentially execute two inference paths, respectively corresponding to each stage of fine-tuning.



# Experimental Results

## Comparison with Full / LoRA FT

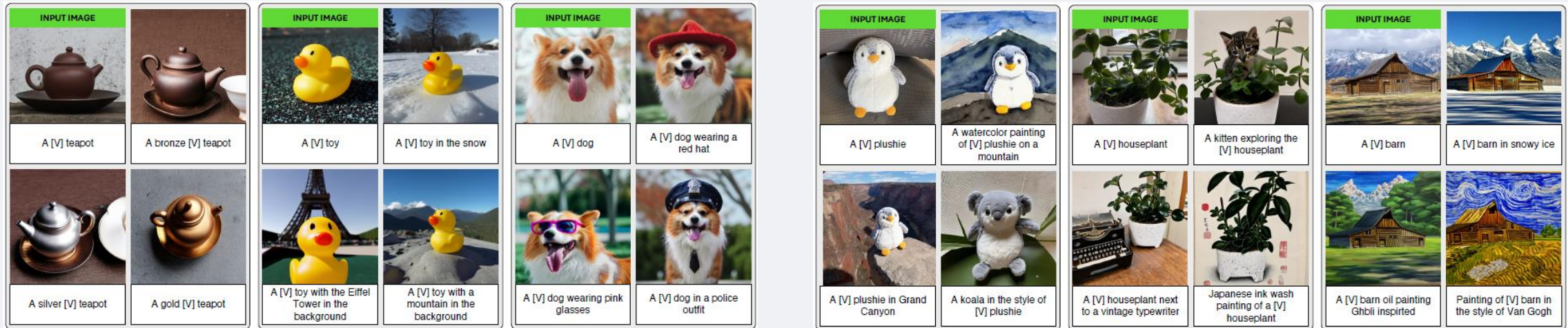
- We conduct experiments with 131 subjects and demonstrate that Hollowed Net achieves high-fidelity personalization results comparable to Full FT while requiring 77% (12.74GB) less GPU memory.
- The required memory for Hollowed Net fine-tuning is only 11% (390MB) more than needed for inference.

Method	# of Parameters		Training Memory		DreamBooth			CustomConcept101		
	Base	LoRA	Peak	Comp. w/ Inf.	DINO	CLIP-I	CLIP-T	DINO	CLIP-I	CLIP-T
Full FT	866M	-	16.62GB	+376%	0.663 $\pm 0.013$	0.802 $\pm 0.007$	0.302 $\pm 0.002$	0.605 $\pm 0.005$	0.773 $\pm 0.006$	0.302 $\pm 0.002$
LoRA FT ( $r=128$ )	866M	27M	5.23GB	+50%	0.658 $\pm 0.001$	0.806 $\pm 0.005$	0.299 $\pm 0.002$	0.603 $\pm 0.008$	0.773 $\pm 0.005$	0.302 $\pm 0.002$
LoRA FT ( $r=1$ )	866M	207K	4.84GB	+39%	0.516 $\pm 0.011$	0.738 $\pm 0.003$	0.314 $\pm 0.001$	0.522 $\pm 0.008$	0.737 $\pm 0.005$	0.305 $\pm 0.001$
<b>Hollowed Net (Ours)</b>	<b>527M</b>	<b>24M</b>	<b>3.88GB</b>	<b>+11%</b>	0.660 $\pm 0.011$	0.805 $\pm 0.006$	0.300 $\pm 0.001$	0.603 $\pm 0.007$	0.773 $\pm 0.005$	0.302 $\pm 0.002$

# Experimental Results

## Qualitative Results

- Hollowed Net effectively captures the visual details of the target subjects, while maintaining high text-image alignment for different types of applications including property modification, recontextualization, accessorization, and artistic rendition.

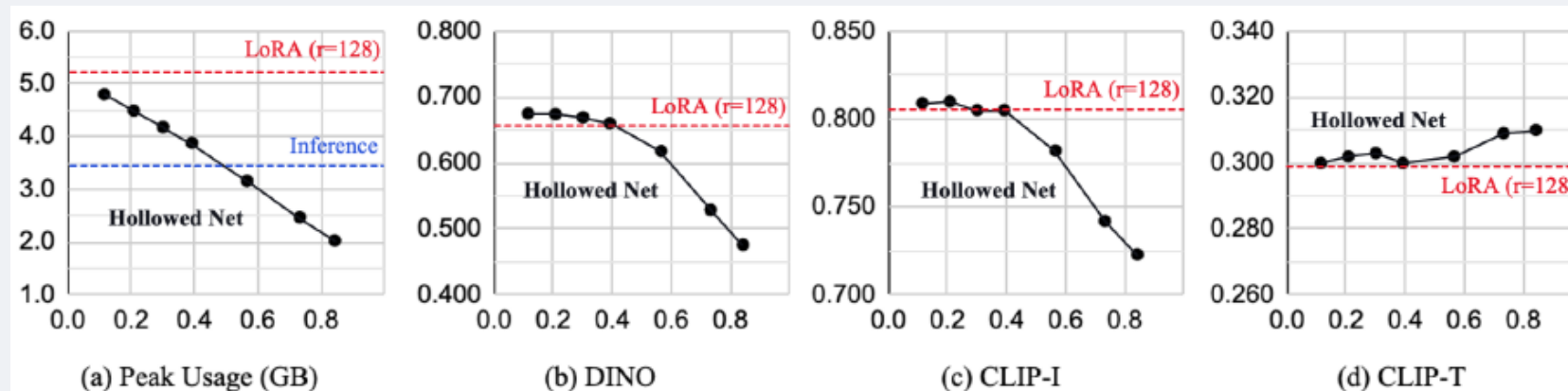




# Experimental Results

## Fractions of Hollowed Layers

- We find that the model's capacity to preserve subject fidelity remains comparable to or slightly better than LoRA FT **until around 39.2% of layers are hollowed**.
- Users can adjust the fraction of hollowed layers to control the trade-offs between performance and memory requirements, depending on the target application and resources.



# Thank you

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