PUP 3D-GS: Principled Uncertainty Pruning for 3D Gaussian Splatting

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CVPR Nashville JUNE 11-15, 2025

pup3dgs.github.io

Motivation

3D-GS | PUP 3D-GS (Ours) | LightGaussian

2.65M Gaussians 76.65 FPS | 0.265M Gaussians 318.06 FPS | 0.265M Gaussians 261.27 FPS

How can we compress pretrained 3D Gaussian Splatting (3D-GS) models by 10× while preserving image quality?

We introduce a mathematically principled per-Gaussian **pruning score** and an effective **pruning pipeline** that together yield surprisingly strong results.

Method

Pruning Score

We compute a per-Gaussian pruning score U_i as the log determinant of the Hessian of the L_2 reconstruction error for Gaussian $\mathcal{G}_i$, where $\mathcal{P}_{gt}$ is the set of all training poses and $I_\mathcal{G}(\phi)$ is the rendered view for pose ϕ:

$$U_i \approx \log \left|\nabla^2_{\mathcal{G}_i} L_2\right| \approx \log \left| \sum_{\phi \in \mathcal{P}_{gt}} \nabla_{\mathcal{G}_i} I_\mathcal{G}(\phi) \nabla_{\mathcal{G}_i} I_\mathcal{G}(\phi)^T \right|.$$

We find that the Gaussian mean μ_i and scaling s_i parameters produce an effective **spatial sensitivity pruning score**:

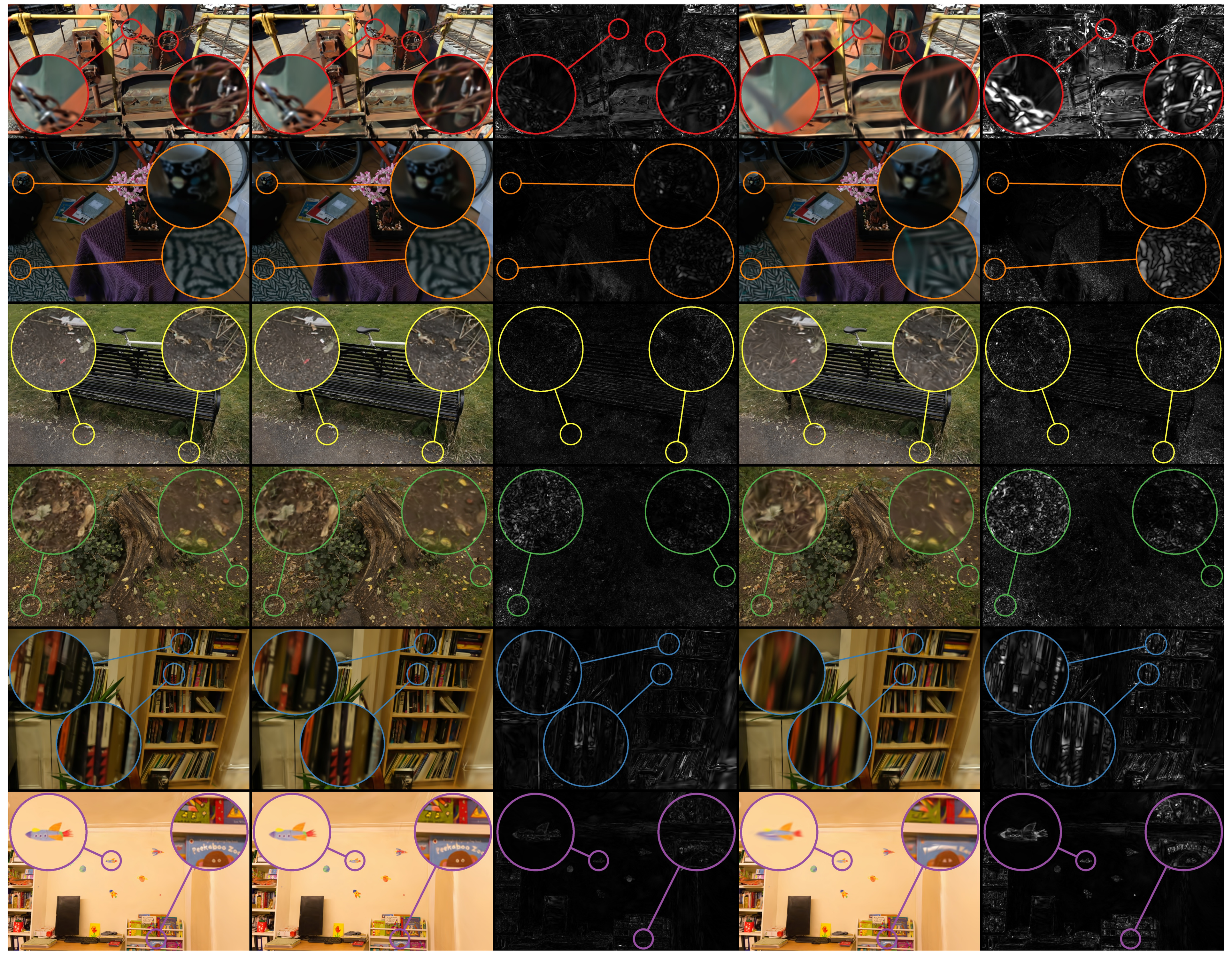
$$U_i = \log \left| \sum_{\phi \in \mathcal{P}_{gt}} \nabla_{\mu_i, s_i} I_\mathcal{G}(\phi) \nabla_{\mu_i, s_i} I_\mathcal{G}(\phi)^T \right|.$$

Pruning Pipeline

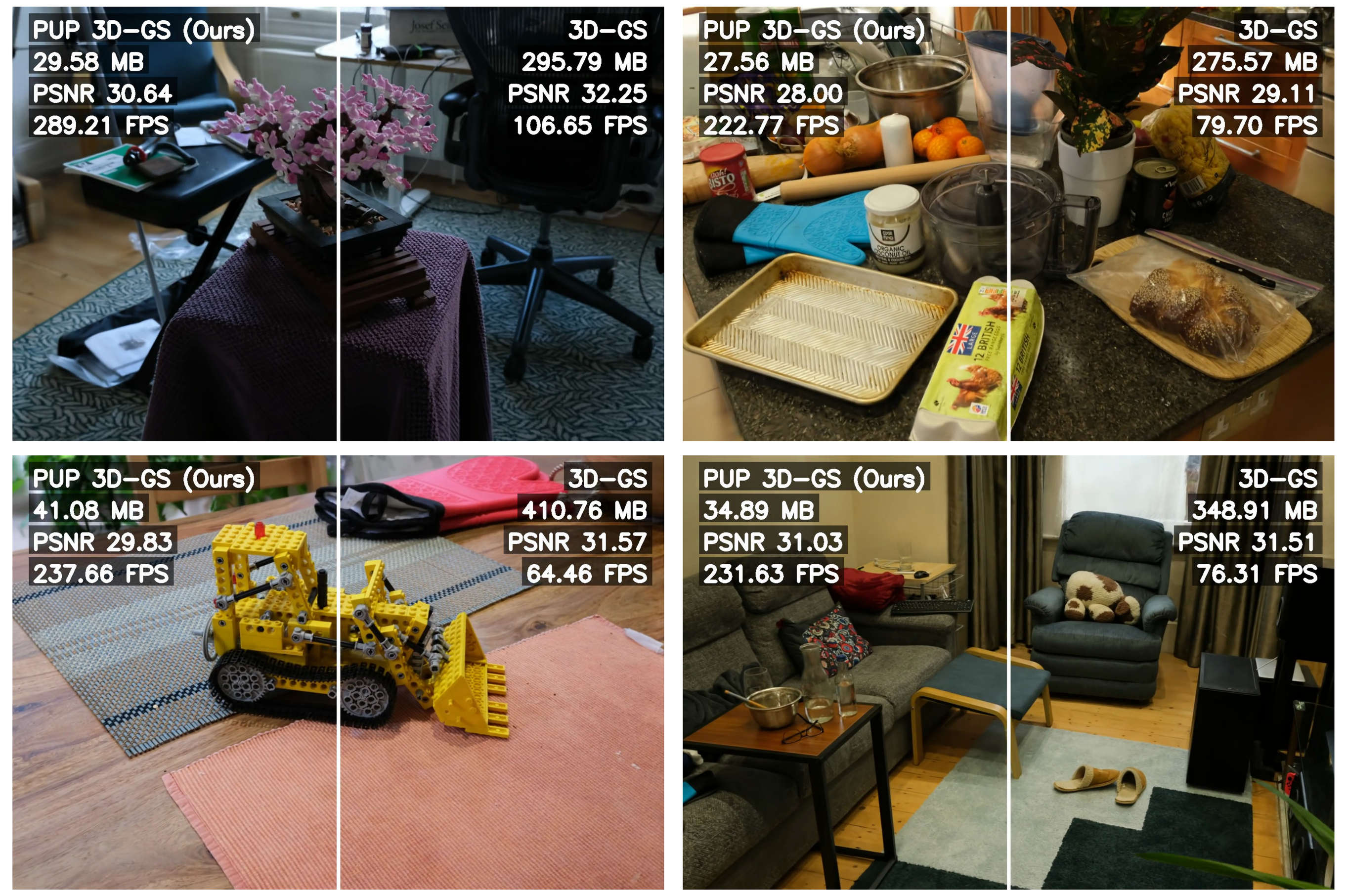
(1) We **prune 80% of Gaussians** and fine-tune for 5,000 iterations, then
(2) **prune 50% of Gaussians** and fine-tune for 5,000 more iterations.
In total, we **prune 90% of Gaussians from the pretrained model**.

Comparison

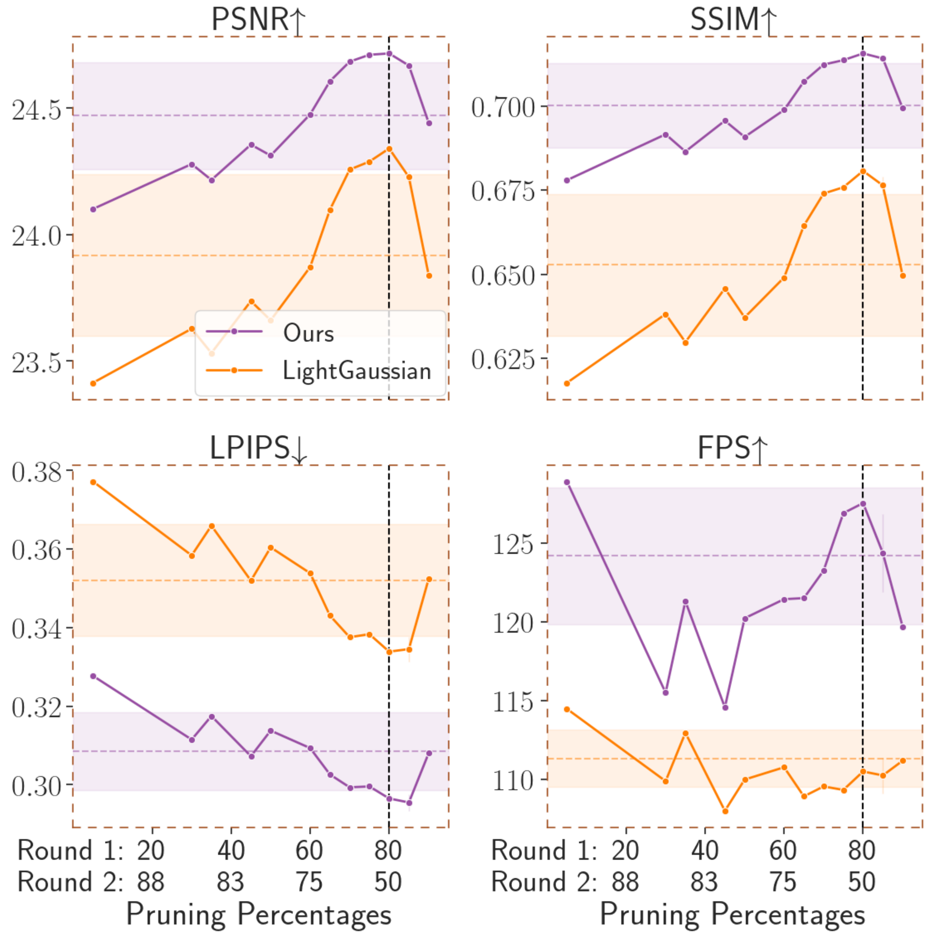
3D−GS | Ours | Ours GS L1 Error | LightGaussian | LG GS L1 Error



PUP 3D-GS **retains more fine details** than previous methods when **pruning 90% of Gaussians** from 3D-GS.



Results



When applied to pretrained 3D-GS models,

PUP 3D-GS achieves **3.56× FPS** and **10× smaller model sizes**

while preserving image quality and salient foreground information.

Datasets	Methods	PSNR ↑	SSIM ↑	LPIPS ↓	FPS ↑	Size (MB) ↓
MipNeRF-360	3D-GS	*27.47*	*0.8123*	*0.2216*	*64.07*	*746.46*
	LightGaussian	26.28	0.7622	0.3054	162.12	74.65
	Ours	26.67	0.7862	0.2719	204.81	74.65
Tanks & Temples	3D-GS	*23.77*	*0.8458*	*0.1777*	*97.86*	*433.24*
	LightGaussian	23.08	0.7950	0.2634	329.03	43.33
	Ours	22.72	0.8013	0.2441	391.10	43.33
Deep Blending	3D-GS	*28.98*	*0.8816*	*0.2859*	*66.79*	*699.19*
	LightGaussian	28.51	0.8675	0.3292	234.10	69.92
	Ours	28.85	0.8810	0.3015	301.43	69.92

Acknowledgements

This research is based upon work supported by the Office of the Director of National Intelligence (ODNI), Intelligence Advanced Research Projects Activity (IARPA), via IARPA R&D Contract No. 140D0423C0076. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of the ODNI, IARPA, or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Governmental purposes notwithstanding any copyright annotation thereon. Additional support was provided by ONR MURI program and the AFOSR MURI program. Commercial support was provided by Capital One Bank, the Amazon Research Award program, and Open Philanthropy. Zwicker was additionally supported by the National Science Foundation (IIS-2126407). Goldstein was additionally supported by the National Science Foundation (IIS-2212182) and by the NSF TRAILS Institute (2229885).