

Cross-Resolution Gaussian Splatting (XR-GS) for Hybrid Resolution Photography

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Motivation:

Modern 3D Gaussian Splatting (3D-GS) achieves high-quality novel-view synthesis, but it assumes **all training images share a uniform resolution**. In real photography, especially handheld phone capture, this rarely holds:

- Some images are **high-resolution (HR)** → Optical zoom, moved-in close-ups, better cameras
 - Many are **low-resolution (LR)** → Digital zoom, compression, wide shots
- When forced into a single-scale optimization, GS suffers from:
- Hallucinated high-frequency details
 - Over-sharpened edges / inconsistent geometry
 - Overfitting to noise in LR images
 - Unnecessary Gaussian growth (Leading to slow rendering)
 - Loss of genuine fine structure from HR views

Goal:

Enable 3D-GS to *intelligently utilize* mixed-resolution supervision so the model learns **global structure** from LR images and **true detail** from HR images.

By being *resolution-aware*, XR-GS can treat views differently

Dataset:

Created a synthetic hybrid-resolution benchmark using **LLFF (*7 Scenes)**

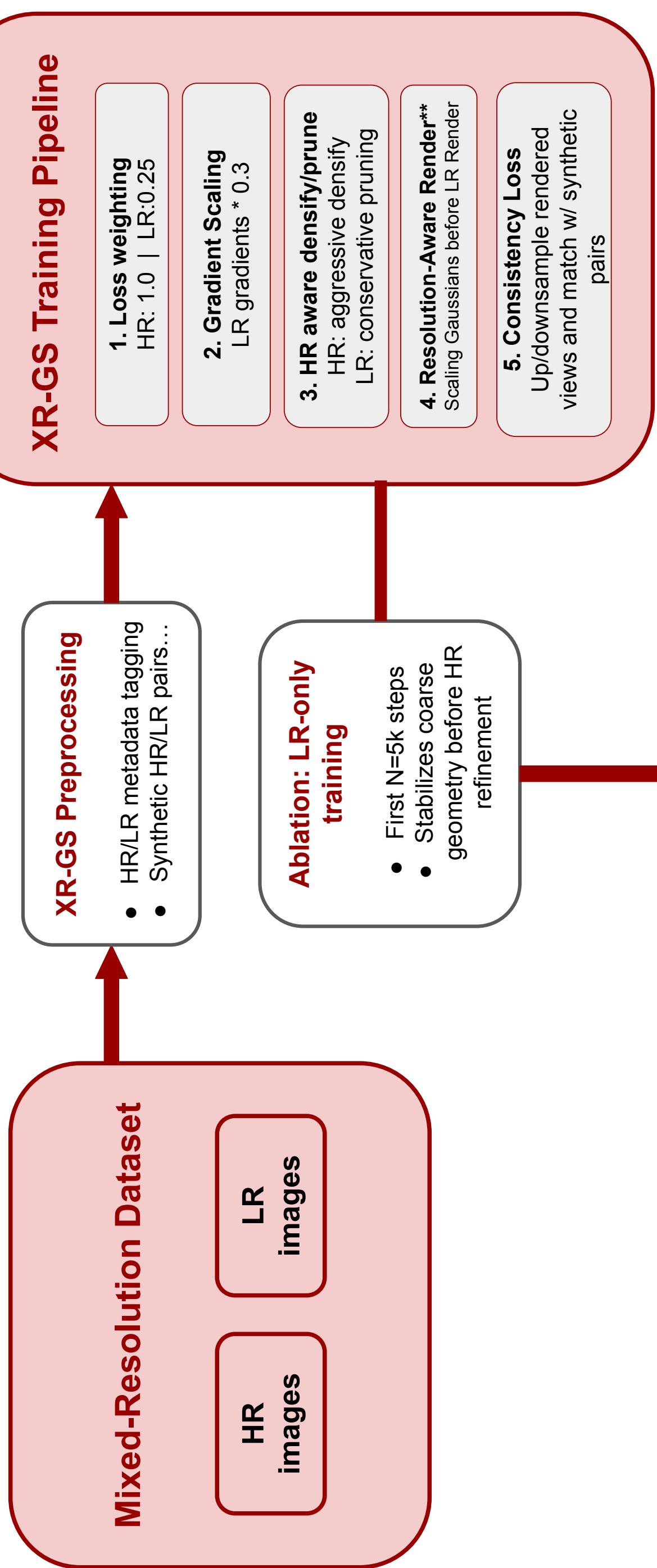
- 30% of Images left as “High-Resolution”, remaining (70%) are downsampled (5x) to be “Low-Resolution”
- COLMAP is re-run on mixed-res images, HR/LR metadata is passed into the dataset for use in XR-GS changes

Captured **2 scenes** ourselves using mixed-resolution situations:

1. Dining room with zoomed out views for HR, close-ups of objects for LR
2. Keychain with 2 different cameras (1 having a higher megapixel count)

Approach:

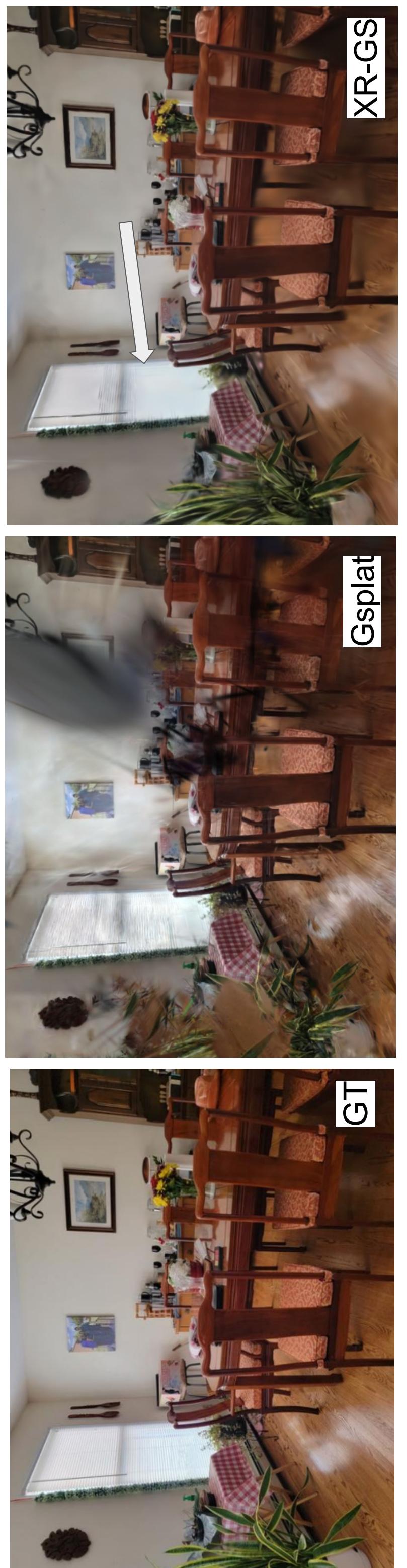
Cross-Resolution Gaussian Splatting (XR-GS)



- Output: XR-GS 3D Gaussian Scene**
- Finer/fine details where anchor sees
 - Stable geometry from LR coverage
 - Smooth HR/LR resolution transition
 - Reduced rendering time, no. of gaussians, and memory
 - Comparable/At times improved PSNR, LPIPS, SSIM
 - Sometimes over-smoothed / blurry render

Analysis:

Resolution-Aware Density Prune Strategy → HR views focus Gaussian capacity on fine structure; LR views avoid over-densifying noise. Leads to structure preservation, less graininess but possible over smoothing



XR-GS helps in cluttered/heavily textured scenes (plants/trees, busy rooms, etc.) but can struggle in singular object scenes. Resource usage gains remain:

Metric	Average % Change from Base Gsplat to XR-GS (w/ Scaled Losses, Gradients, Densify/Prune, and Consistency Loss)
Training Time	-44.57
Num Gaussians	-69.68
Memory Used	-46.50
LPIPS	23.15
SSIM	0.45
PSNR	-0.80

Metric	Dining Room (% Change)	Keychain (% Change)
Training Time	-24.87	-16.32
Num Gaussians	-70.99	-66.05
Memory Used	-33.08	-2.59
LPIPS	-8.83	33.23
SSIM	3.60	-1.56
PSNR	3.92	-15.81

- Learning signal for small high-frequency objects (keychain, camera, etc.) being lost with down-weighted LR gradients
- Consistency Loss allows the model to create blur and “get away with it”
- (In synthetic LR views, the blurriness is less noticeable important)
- Same features that lead to improvements in highly textured scenes cause issues here

Conclusion / Extensions:

- By adapting Gsplat with XR-GS, we reduce hallucination artifacts, “over-sharpened” renders and improve *true detail* reconstruction, especially in cluttered/textured scenes
- Significantly reduce the rendering time, number of gaussians rendered, memory required, while maintaining comparable improved PSNR and SSIM
- Future Work: Network for learning scaling parameters;
- Supporting arbitrary resolution differences (not binary HR vs LR); Cross-resolution teacher–student distillation

XR-GS shows that **resolution diversity is a useful supervision signal for 3DGs**

Metric Results on Modified LLFF Dataset (*7 Scenes)

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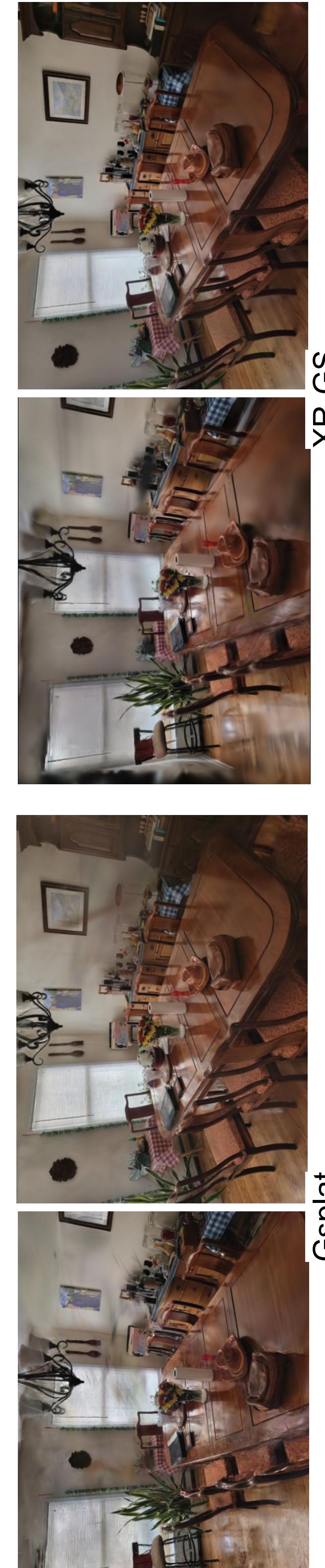
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XR-GS

GSplat

GT

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