





ICLR 2025

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Code: https://github.com/yihangchen-ee/fcgs/

Page: https://yihangchen-ee.github.io/project_fcgs/

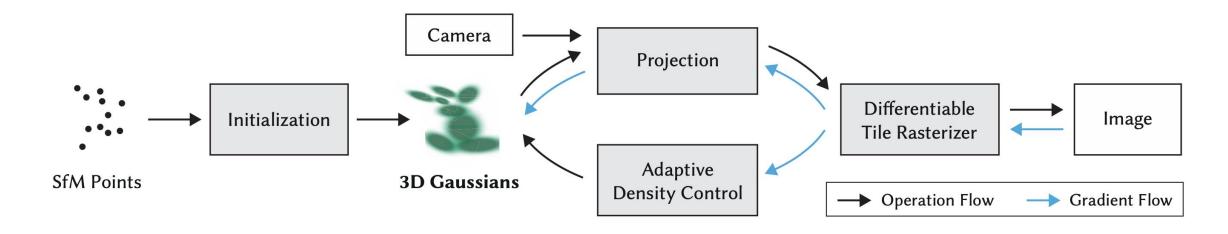








Background: 3D Gaussian Splatting (3DGS)



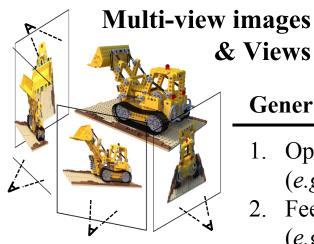
- 1. 3DGS represents scenes using explicit learnable attributed Gaussian points.
- 2. Millions of Gaussians in the scene leads to LARGE storage size!!

Kerbl B, Kopanas G, Leimkühler T, et al. 3D Gaussian Splatting for Real-Time Radiance Field Rendering[J]. ACM Trans. Graph., 2023, 42(4): 139:1-139:14.





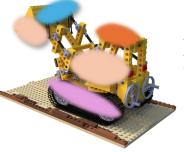




Generate 3DGS via:

- 1. Optimization (*Minutes*) (*e.g.*, vanilla 3DGS [1])
- 2. Feed-forward models (*Seconds*) (*e.g.*, MVSplat[2], LGM [3])





How to Compress it? Compressed bitstreams

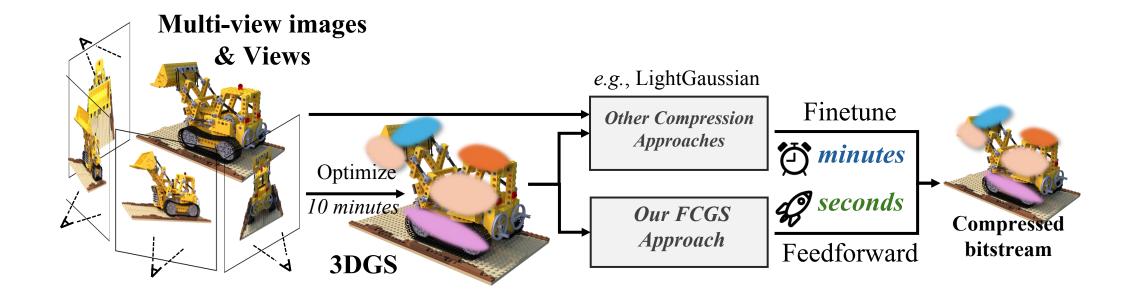
- 1. Pruning, Vector quantization ...
- 2. Entropy constraints, Context model ...

- [1] Kerbl B, Kopanas G, Leimkühler T, et al. 3D Gaussian Splatting for Real-Time Radiance Field Rendering[J]. ACM Trans. Graph., 2023, 42(4): 139:1-139:14.
- [2] Chen Y, Xu H, Zheng C, et al. Mvsplat: Efficient 3d gaussian splatting from sparse multi-view images[C]//ECCV 2024: 370-386.
- [3] Tang J, Chen Z, Chen X, et al. Lgm: Large multi-view gaussian model for high-resolution 3d content creation[C]//ECCV 2024: 1-18.









• Per-scene optimization pipeline.

Pros: Per-scene adaptation for better RD performance.

Cons: Slow, computationally expensive, need GT.

• Generalizable optimization-free pipeline.

Pros: Fast, low computation cost, hassle-free.

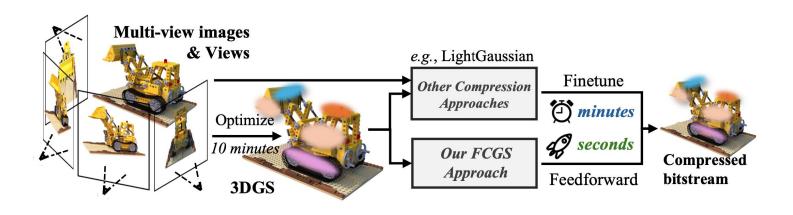
Cons: Limitation in RD performance.

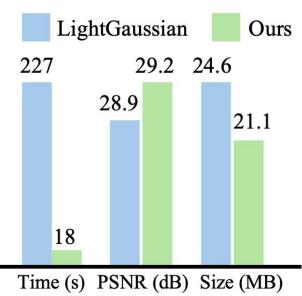
Fan Z, Wang K, Wen K, et al. Lightgaussian: Unbounded 3d gaussian compression with 15x reduction and 200+ fps[C]//NIPS, 2024











We have still achieved excellent compression performance!

DL3DV-GS dataset

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Fan Z, Wang K, Wen K, et al. Lightgaussian: Unbounded 3d gaussian compression with 15x reduction and 200+ fps[C]//NIPS, 2024



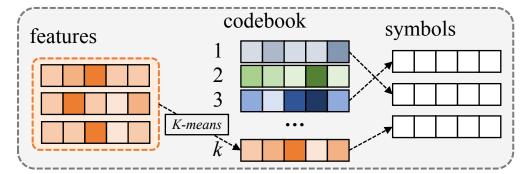




• How to achieve compression without per-scene optimization?

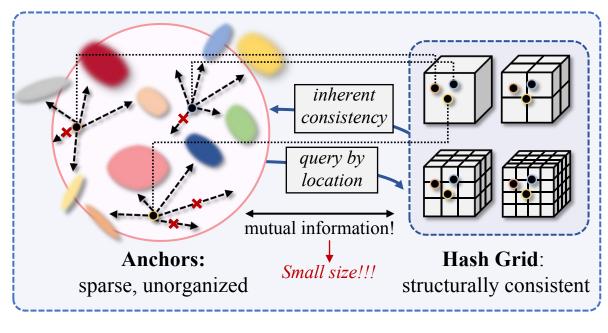


1) Pruning



2) Codebook + Vector Quantization

Pruning & VQ may alter the original values



HAC-like context models

The hash grids need optimization to obtain

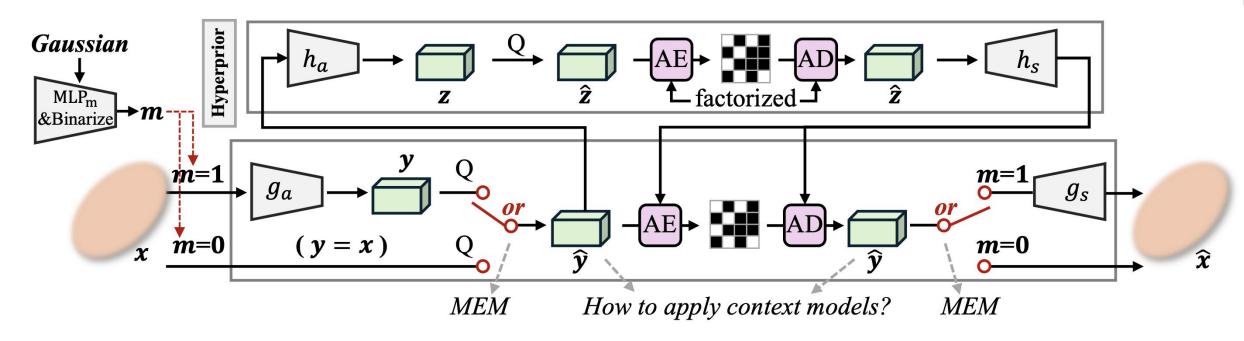
They are not suitable for the optimization-free pipeline







Solution: An autoencoder-based network architecture with context models



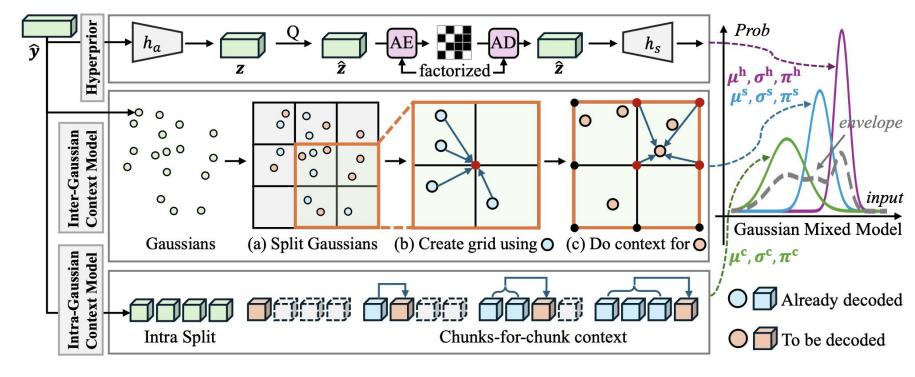
- 1. A Multi-path Entropy Module (MEM) for adaptive balance of fidelity and size of each Gaussian.
 - 1) For **geometry attributes**, they are all in the m=0 path to maintain fidelity.
 - 2) For **color attributes**, *m* can be either 0 or 1 to either maintain fidelity or eliminate redundancies.







Solution: An autoencoder-based network architecture with context models



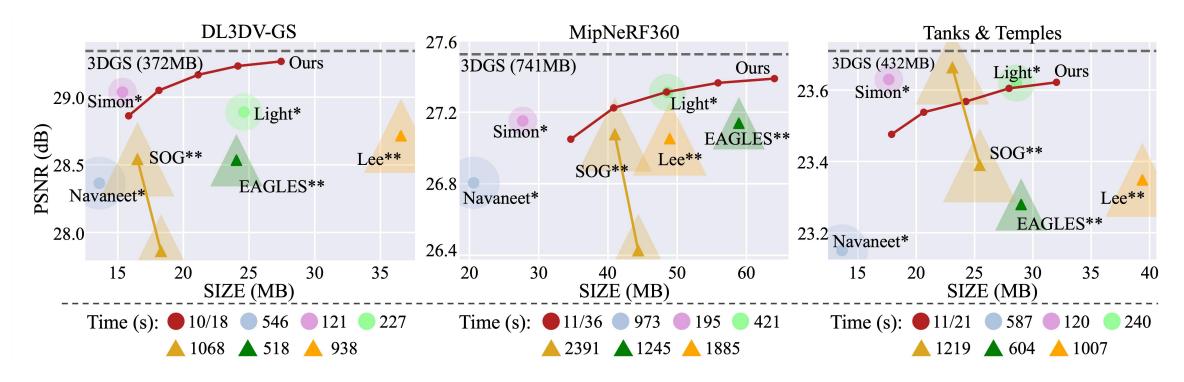
- 2. Inter- and intra-Gaussian context models to build relations among Gaussians for entropy modeling.
 - 1) Inter-Gaussian context models can *create* grids for context, instead of learning hash grids.
 - 2) Intra-Gaussian context models construct contextual relations along channels.
 - 3) Gaussian Mixed Model (GMM) is utilized to fuse the three sets of Gaussian probabilities.







Performance: Compress 3DGS from optimization



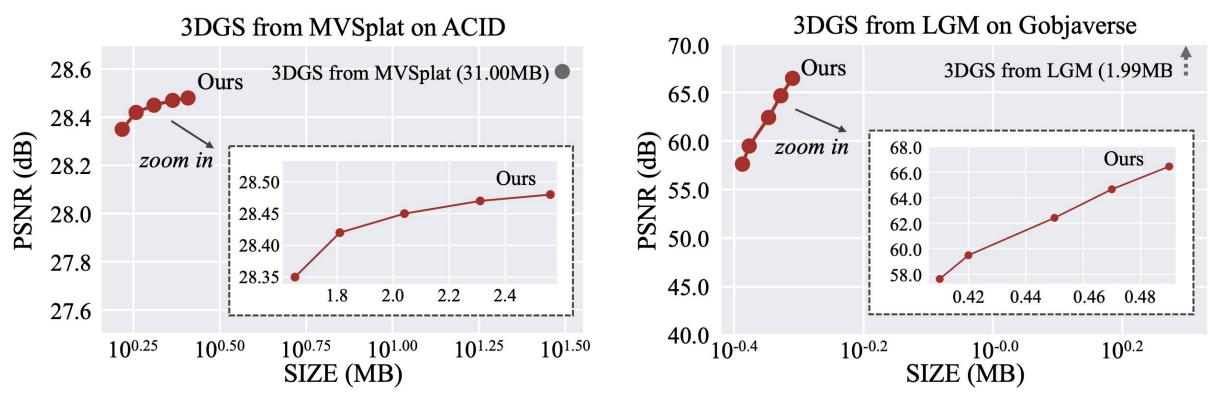
- 1. Although unable to do per-scene optimization, FCGS still surpasses most optimization-based approaches.
- 2. Much **faster runtime** to achieve compression, from *minutes* to *seconds*.







Performance: Compress 3DGS from feed-forward models



FCGS can also compress 3DGS from feed-forward models such as MVSplat [1] and LGM [2].

^[1] Chen Y, Xu H, Zheng C, et al. Mvsplat: Efficient 3d gaussian splatting from sparse multi-view images[C]//ECCV 2024: 370-386.

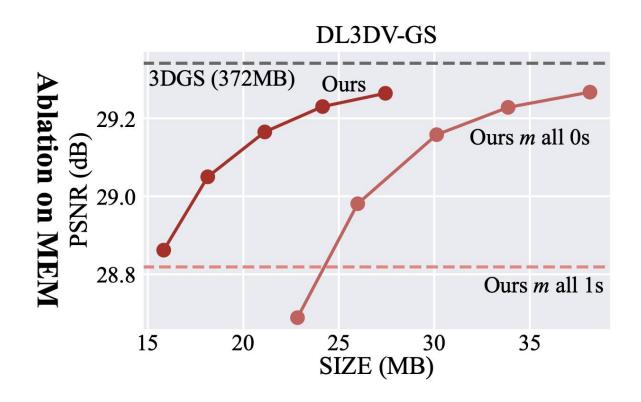
^[2] Tang J, Chen Z, Chen X, et al. Lgm: Large multi-view gaussian model for high-resolution 3d content creation[C]//ECCV 2024: 1-18.

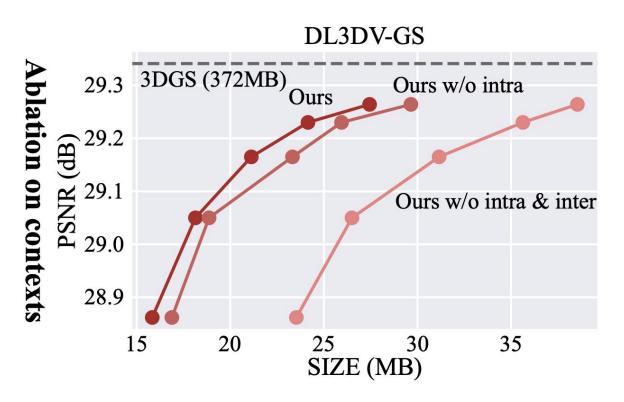






Ablation study





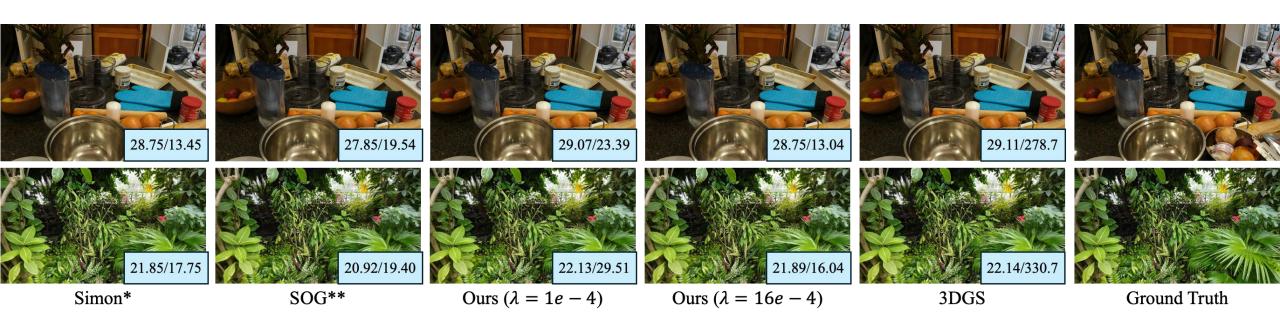
Both the **MEM** module and **context models** are demonstrated to be effective.







Qualitative results









Thank you for your kind attention!