

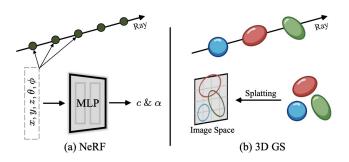
Autoencoders for 2D Gaussian Splats

Rok Mokotar, Federico Harjes Ruiloba

Background

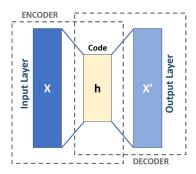
Gaussian Splats

- ML-based scene representation and novel view synthesis -> NeRF: high-quality, continuous representation
- Slow optimization due to the cost of training a NN
- 3D Gaussian Splats: much faster and similar quality, discrete representation



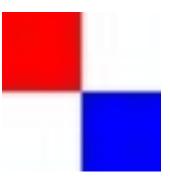
Autoencoders

- Encoder learns a compact representation of the input in the *latent space*
- Decoder then reconstructs the input from the latent space
- Useful for feature extraction and dimensionality reduction, among others



Methodology: Training a Splat Dataset

- Dataset: CIFAR-10
- Splat generation: gsplat
- Hyperparameter Tuning: Optuna
- Added features:
 - Selective learning of splat parameters
 - Support for different rasterization techniques
 - Bilateral guided radiance support
- Initialization strategies:
 - Random 3D initialization
 - Grid-based initialization
 - KNN-based initialization





Methodology: Autoencoding Gaussian Splats

Model Architectures

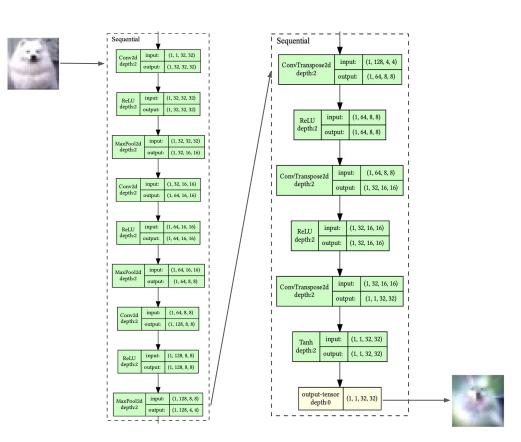
- Simple (Deep) AE
- Convolutional AE
- ResNet-18 AE
- (Abstract AE)

Splat Representations

- Vector-based encoding
- Full-image encoding
- Single-channel encoding
- Independent parameter models

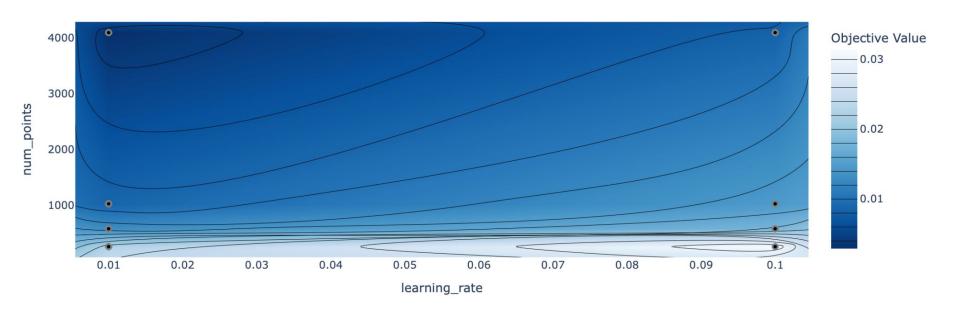
Hyperparameter Tuning (Optuna)

Slurm: Distributed Training over 10 machines with either 2060 RTX or CPU

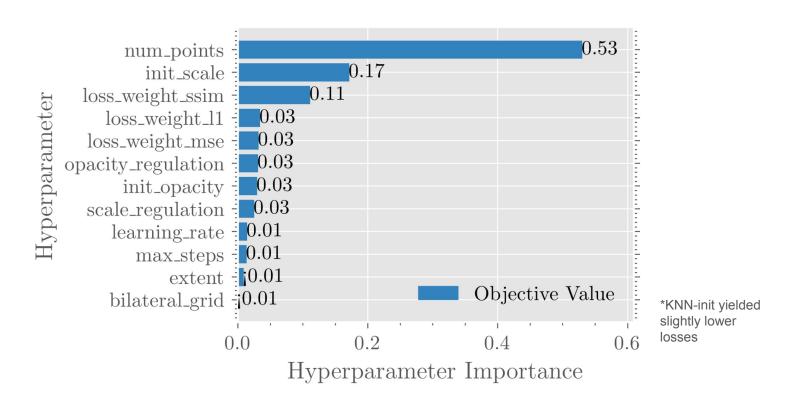


Results: Gaussian Splats - Hyperparameter Tuning

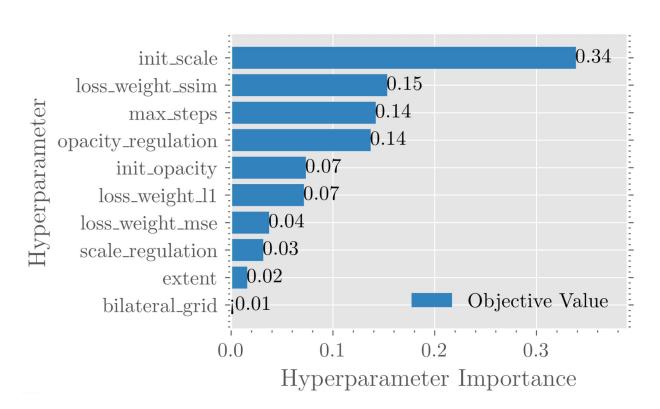
Contour Plot



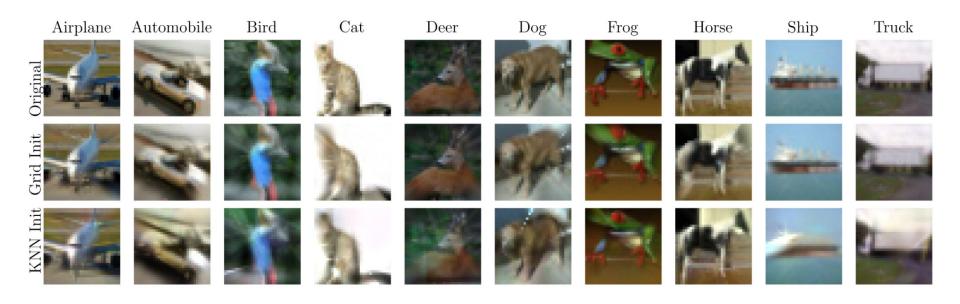
Results: Gaussian Splats - Hyperparameter Tuning



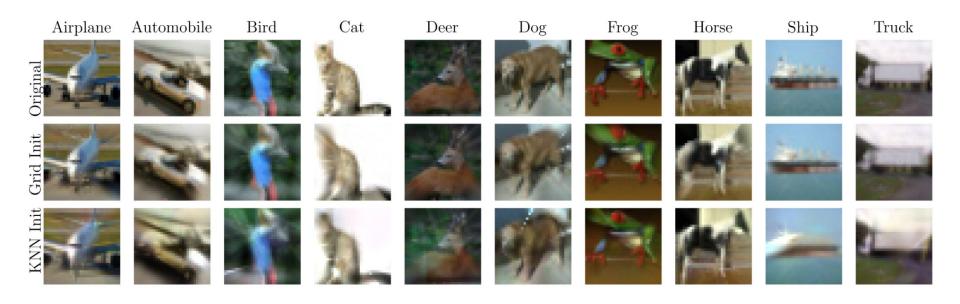
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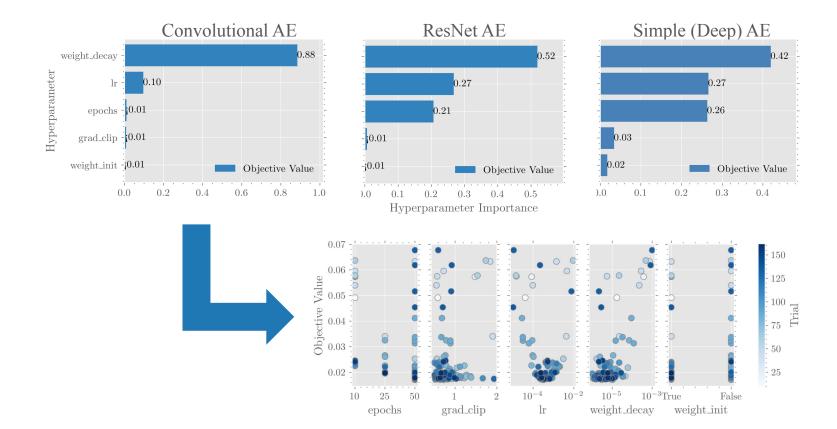
Results: Gaussian Splats - Full Dataset



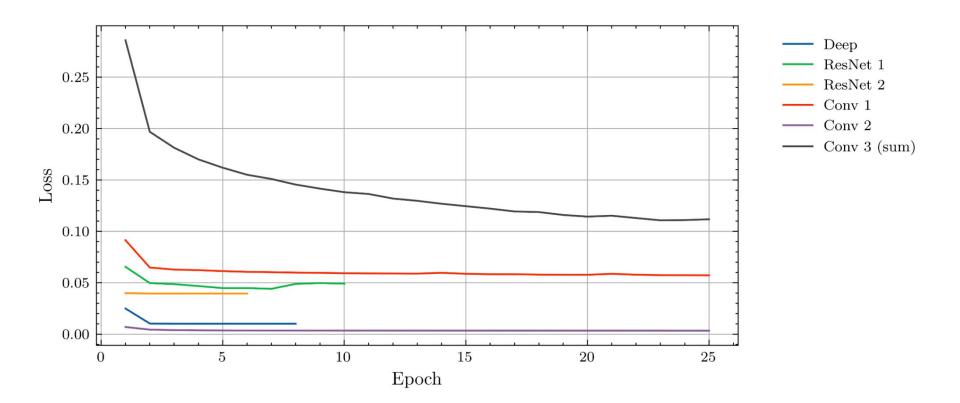
Results: Gaussian Splats - Full Dataset



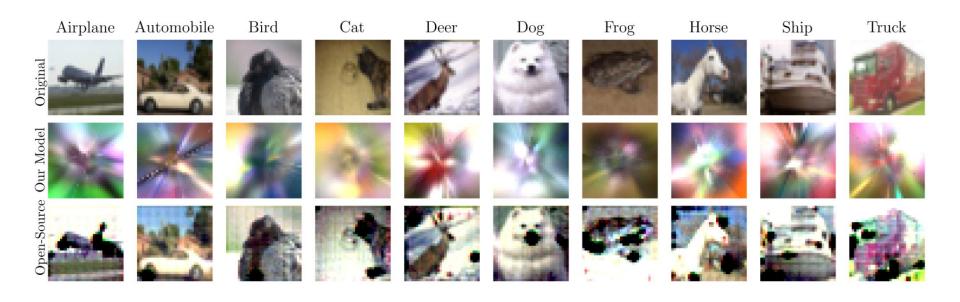
Results: Autoencoding GS - Hyperparameter Tuning



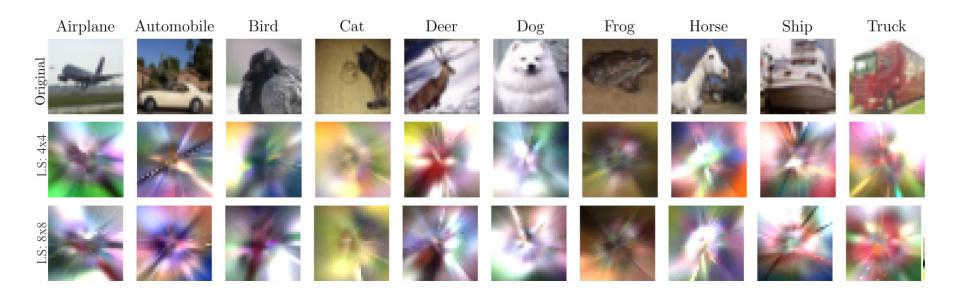
Results: Autoencoding GS - Loss Evolution

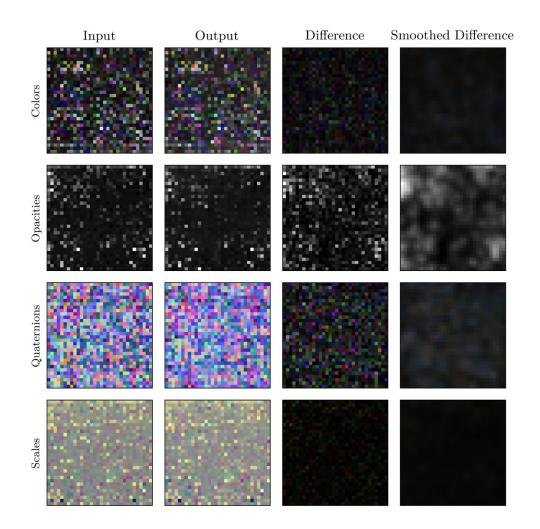


Results: Autoencoding GS - Reconstructed Images



Results: Autoencoding GS - Latent Space Dimension



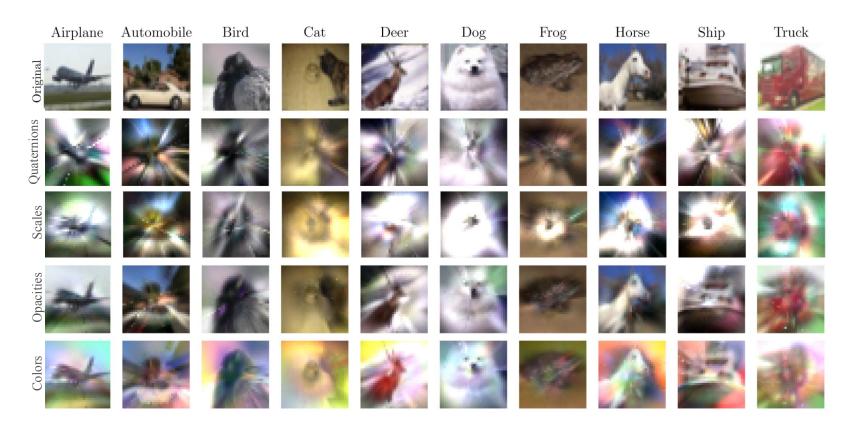


Individual

Parameters

* σ = 1 for the smoothed difference ** quaternions were converted into a rotation matrix

Results: Autoencoding GS - Individual Parameters



Discussion: Interpreting the Results - Insights and Shortcomings

- **Gaussian Splatting:** highly accurate reconstruction of the CIFAR-10 dataset
- Autoencoding: small losses + similar visualizations for all parameters
 - deficient output quality across all AE variants
- Possible causes:
 - Small variations in splat representation might cause large variation in reconstructed image
 - Issues with reconstruction
 - Latent space might be too small (size = 16 for the best model)
- Unlikely that the model is incapable of

Discussion: Future Work

- Improved loss function: include image reconstruction fidelity
- Further exploration of the impact of the latent space size
- Implementation of more complex architectures, such as HiP
- Generative modelling on the latent space
- Gaussian splat generation
- Exploration of the latent space

Methodology: Training Process

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Hyperparameter Tuning (Optuna)

