POP-GS: Next Best View in 3D-Gaussian Splatting with P-Optimality

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Motivation

- **Training cost scales** with number of images and acquiring **new training views** is expensive.
- Current information formulations for 3D-GS are **rigid**/constrained to one function.
- Classical approaches formulate view selection through **optimal experimental design**, yet application is **non-trivial**.

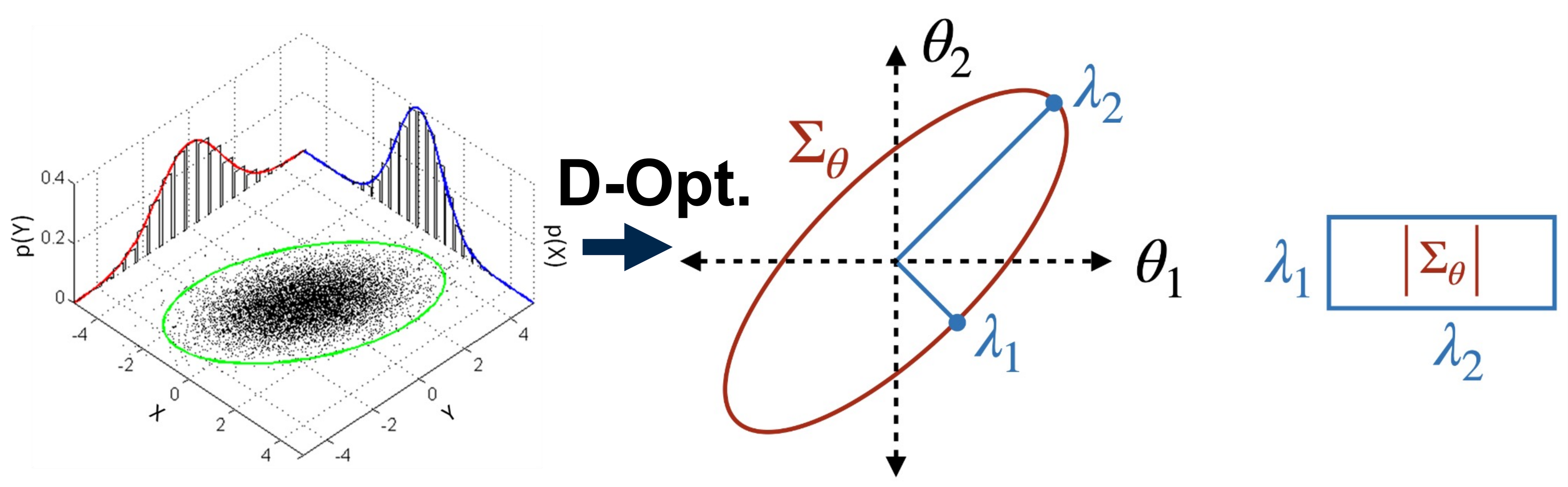
P-Optimality (T.O.E.D.)

- Formulate **information gain** as a reduction of uncertainty.
- Quantified as a **function of covariance** matrix, depending on a scalar p [1].

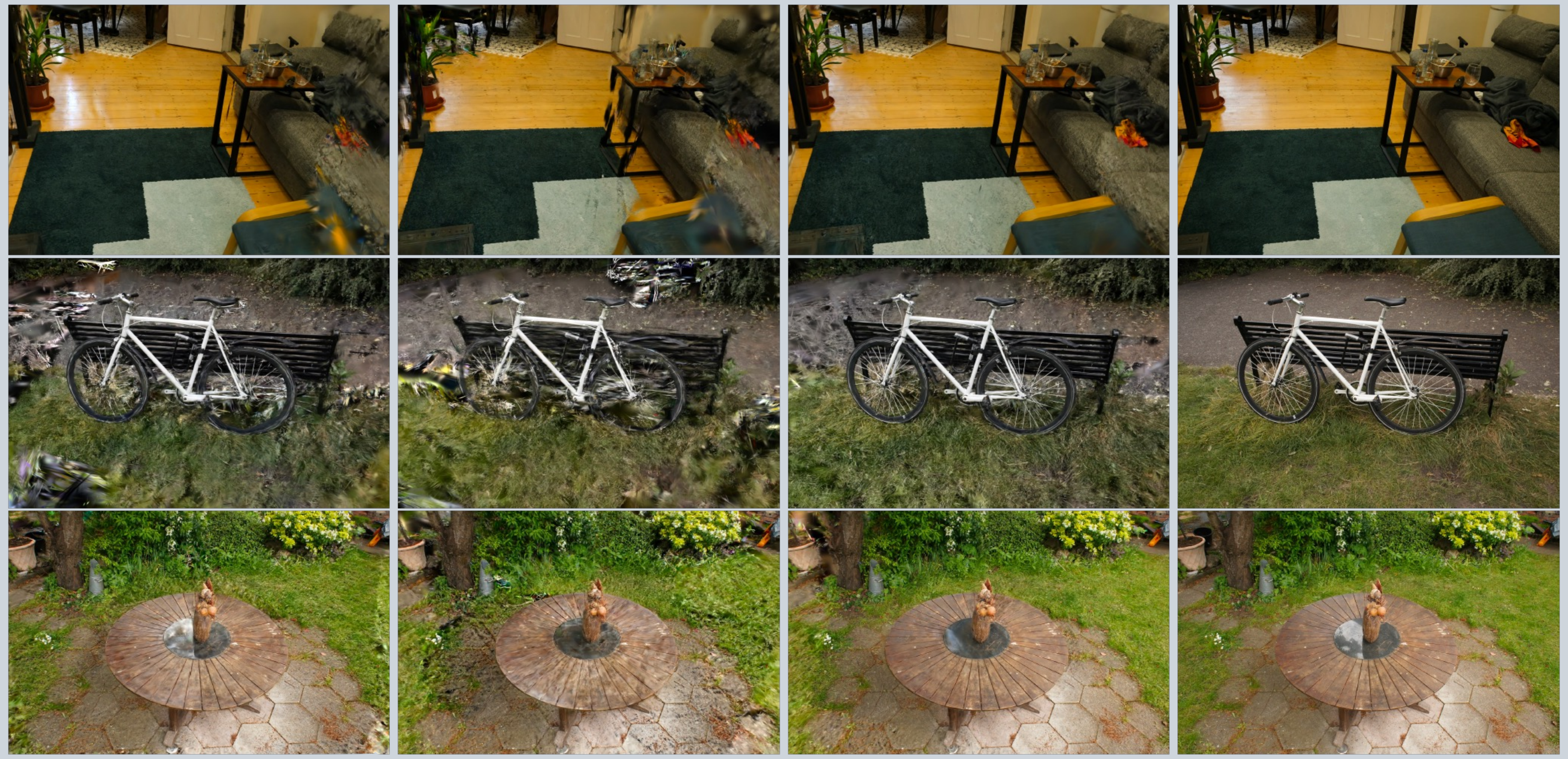
Table 1. Properties of P-Optimality for different values of p. Note: λ_k represent the eigenvalues of the covariance matrix Σ_i.

	T-optimality	A-optimality	D-optimality	E-optimality
p	1	-1	0	$\mp\infty$
Equivalent Formulae	$\frac{1}{l}\mathrm{tr}\left(\Sigma_i\right) = \frac{1}{l}\sum_k^l \lambda_k$	$\left(\frac{1}{l}\mathrm{tr}\left(\boldsymbol{H}_i\right)\right)^{-1} = \left(\frac{1}{l}\sum_k^l \lambda_k^{-1}\right)^{-1}$	$\sqrt[l]{\lvert\Sigma_i\rvert} = \exp\left(\frac{1}{l}\sum_k^l \log \lambda_k\right)$	$\min_{\lambda_k}$ $\max_{\lambda_k}$
Meaning	Average Variance	Harmonic Mean Variance	Volume of covariance hyper-ellipsoid	Single extreme eigenvalue

- Each has a unique **geometric interpretation**



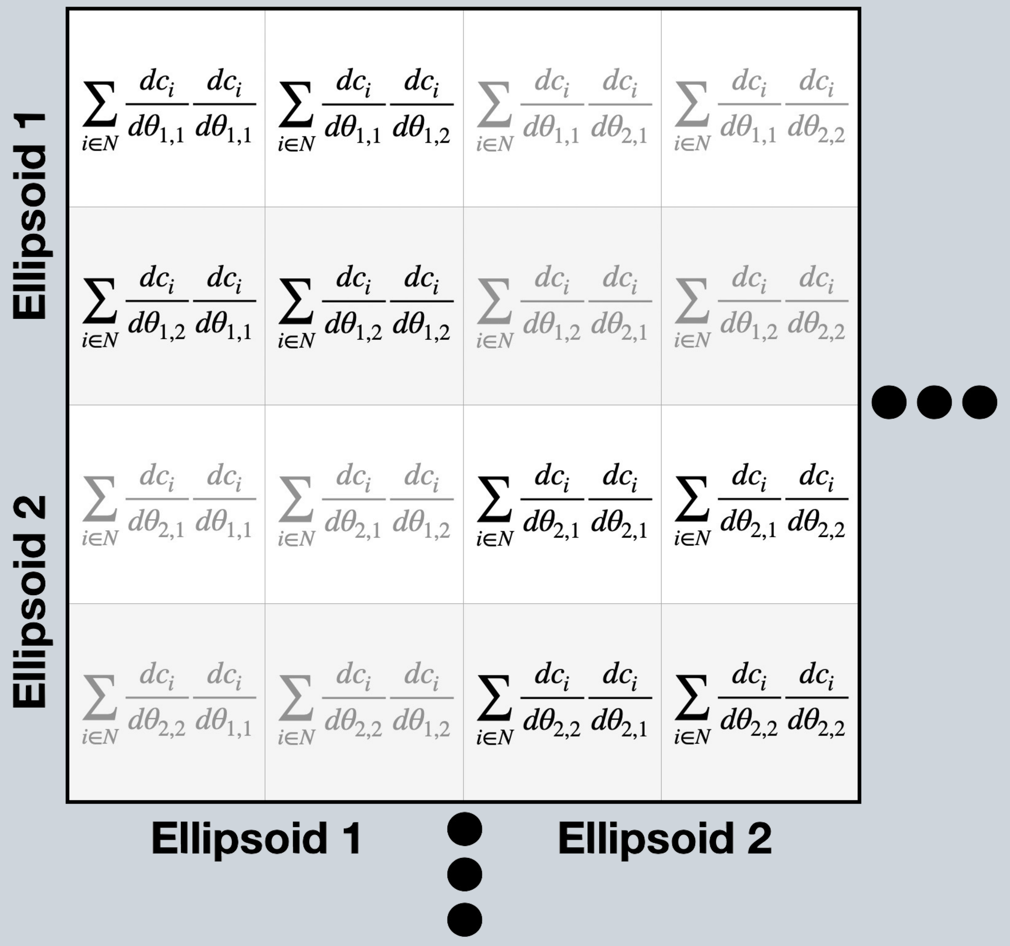
Efficient and flexible information quantification in 3D-GS for active exploration and keyframe selection.



(a) Uniform Sampling (b) FisherRF (c) Ours (d) Ground Truth

Method

1. **Construct Hessian matrix (right) using Gauss-Newton Approximation $H(\theta) = J_\theta^T J_\theta$**
2. **Relate covariance to Hessian** $\Sigma \propto H(\theta)^{-1}$ (asymptotic relationship in MLE for exponential family)
3. **Approximate as diagonal or block-diagonal due to size.**
4. **Measure reduction in covariance with P-Optimality.**



Hessian Matrix Approximation

Results

1. Next Best View

(a) Uniform (b) FisherRF (c) Ours (d) Ground Truth

Method	PSNR (↑)	SSIM (↑)	LPIPS (↓)
Uniform Sampling	23.32	0.885	0.101
FisherRF [2]	24.59	0.897	0.091
A-Opt. (Simple)	22.39	0.876	0.116
E-Opt. (Simple)	21.40	0.862	0.129
T-Opt. (Simple)	25.40	0.908	0.080
D-Opt. (Simple)	**25.52**	**0.909**	**0.078**
D-Opt. (Block)	25.41	0.908	0.078

(a) Mip-Nerf360 [3] Data

Method	PSNR (↑)	SSIM (↑)	LPIPS (↓)
Uniform Sampling	17.29	0.508	0.432
FisherRF [2]	16.81	0.493	0.445
A-Opt. (Simple)	15.55	0.452	0.480
E-Opt. (Simple)	15.33	0.436	0.488
T-Opt. (Simple)	17.91	0.520	0.420
D-Opt. (Simple)	17.95	0.535	0.411
D-Opt. (Block)	**18.15**	**0.548**	**0.401**

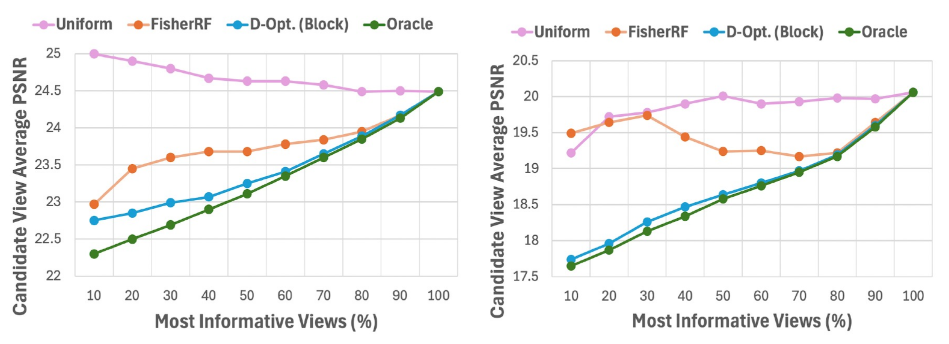
(b) Blender [4] Data

2. Keyframe Selection

Method	PSNR (↑)	SSIM (↑)	LPIPS (↓)
Uniform Sampling	23.47	0.888	0.109
FisherRF	18.37	0.829	0.184
A-Opt. (Simple)	17.05	0.811	0.226
E-Opt. (Simple)	16.55	0.786	0.255
T-Opt. (Simple)	**24.90**	**0.903**	**0.096**
D-Opt. (Simple)	24.26	0.899	0.101
D-Opt. (Block)	24.53	0.902	0.099

➡️ **T and D Opt. most effective**

3. Uncertainty Correlation



(a) Ficus (b) Drums

➡️ **Uncertainty correlated w/ image quality**

References

1. Jack Kiefer, "General equivalence theory for optimum designs (approximate theory)". *The Annals of Statistics*, 1974.
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3. Barron et al., "Mip-NeRF 360: Unbounded Anti-Aliased Neural Radiance Fields", *CVPR*, 2022.
4. Mildenhal et al., "NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis", *ICCV*, 2020.