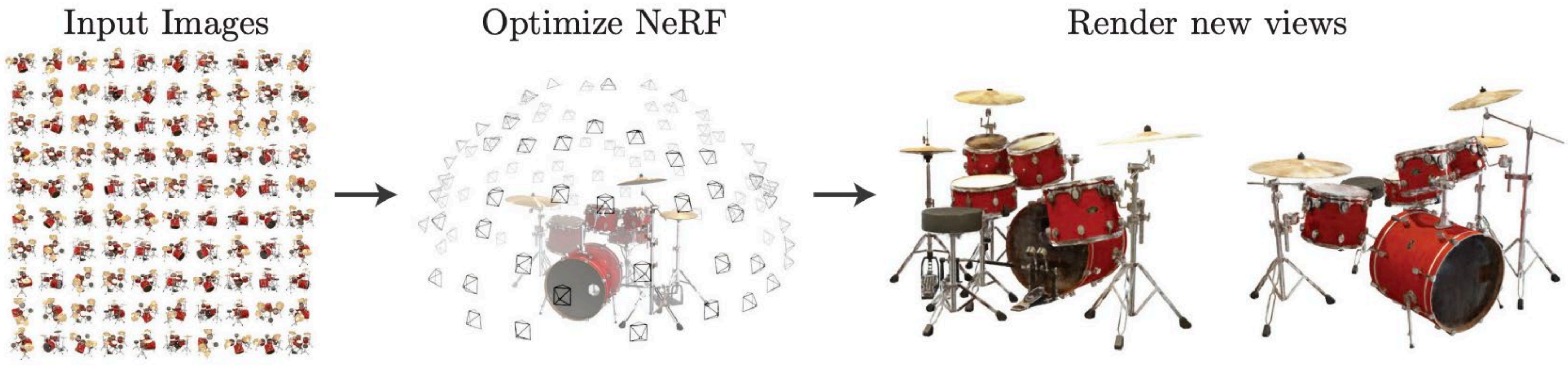
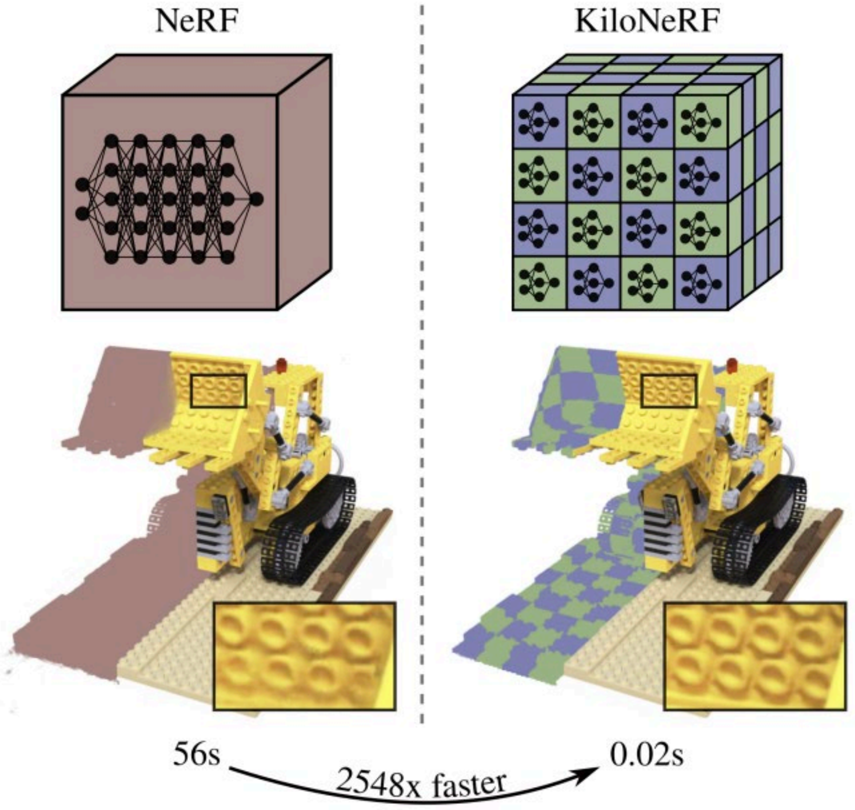
Instant Neural Graphics Primitives with a Multiresolution Hash Encoding

Thomas Müller   Alex Evans   Christoph Schied   Alexander Keller

NeRF

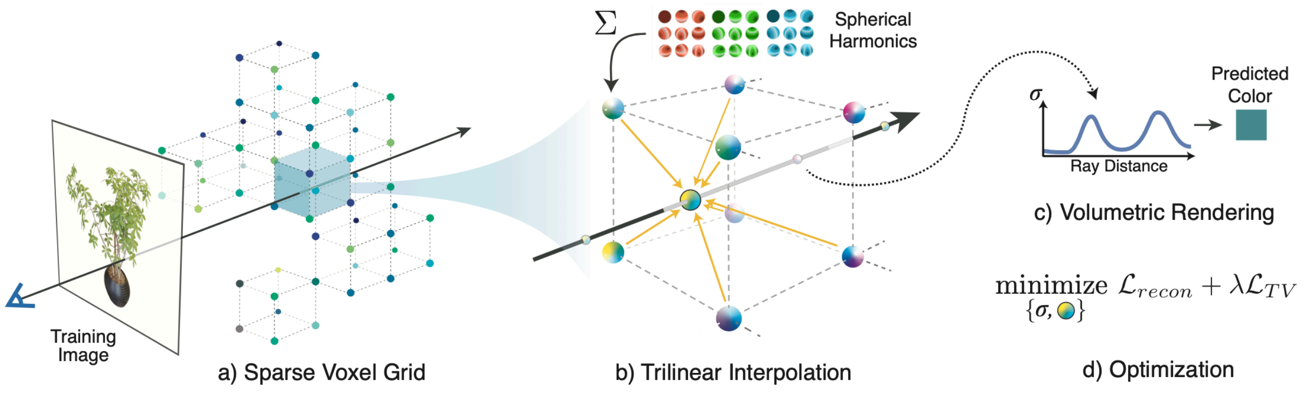


- NeRF Pros: simple representation, differentiable rendering model
- NeRF Cons: dumb brute force, insanely slow
- How can we improve the speed of volumetric rendering?



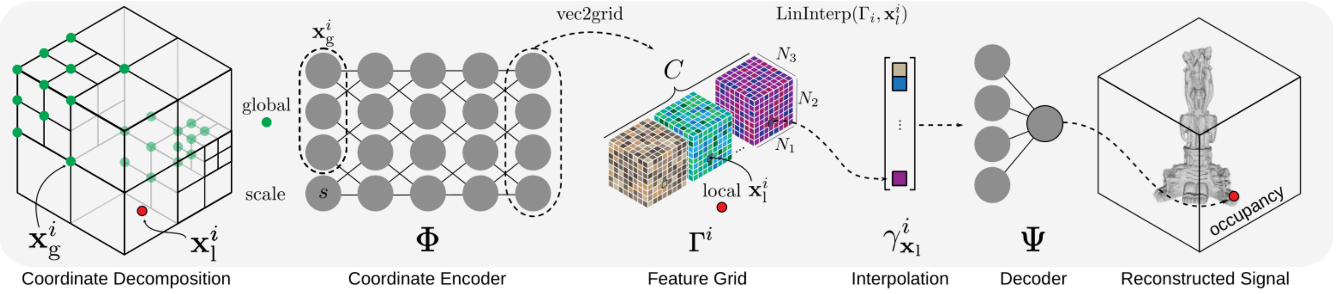
- smaller MLPs

KiloNeRF: break up space into 163 or 323 voxels, each with its own set of (small) MLP weights



- direct voxel lookups

Plenoxels: 512^3 voxel grid with density and spherical harmonics



- Acorn: adaptive feature-grid with a lightweight MLP to decode

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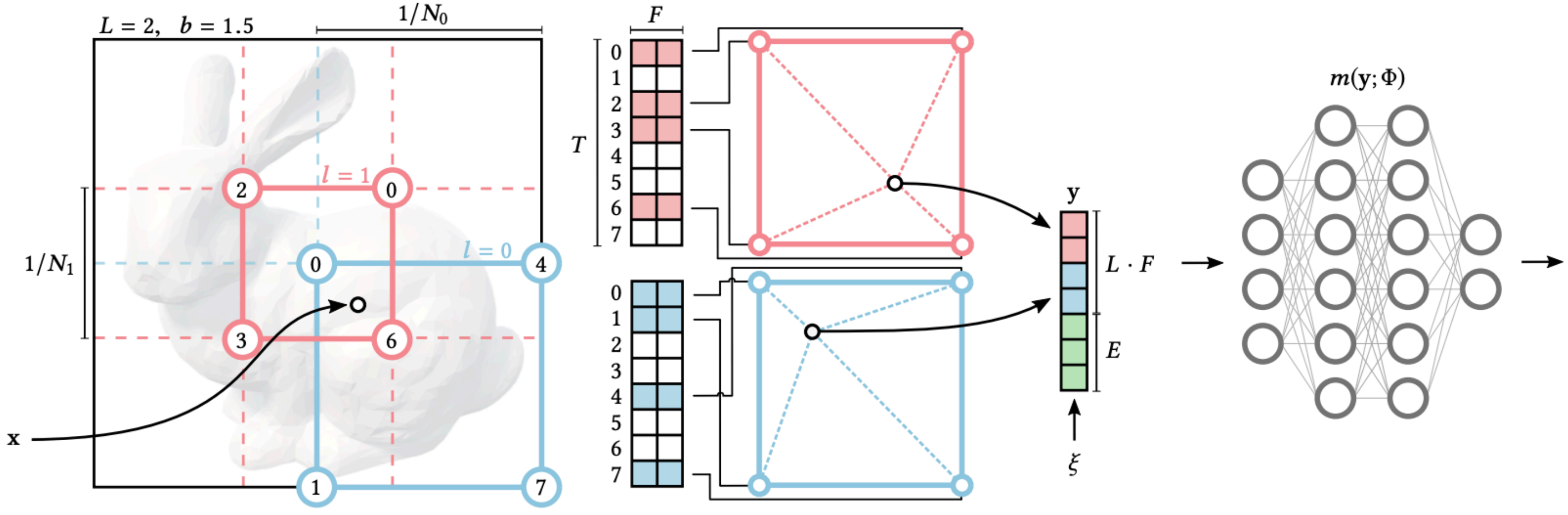
The approach



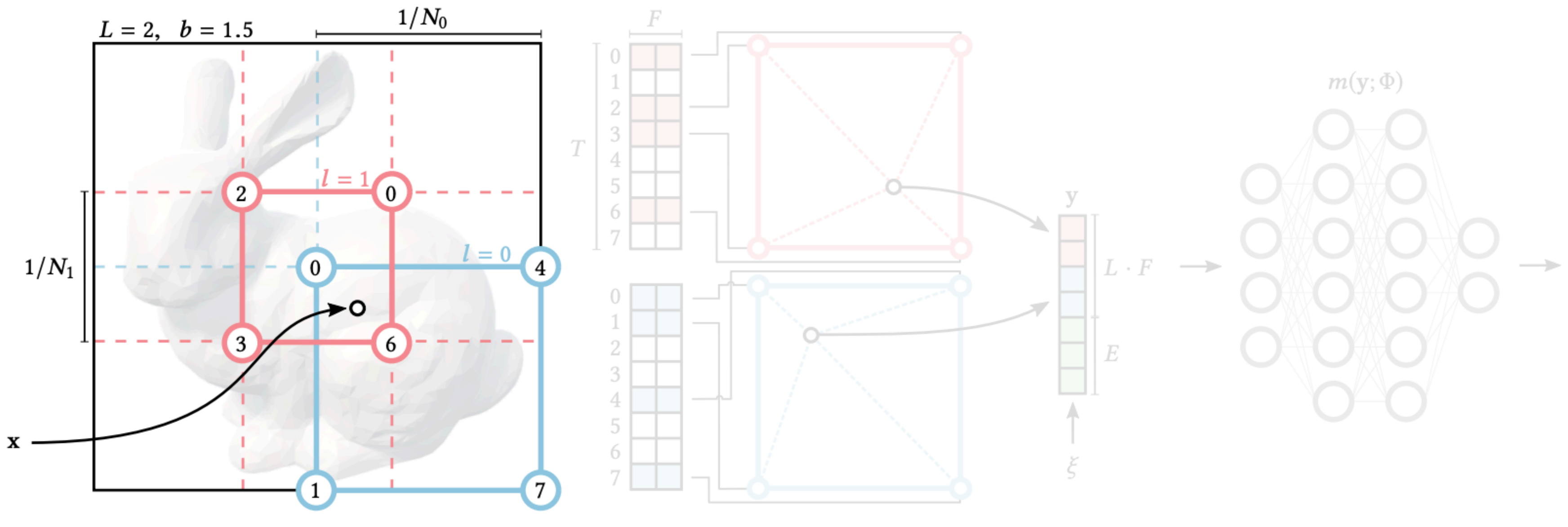
(1) Hashing of voxel vertices (2) Lookup (3) Linear interpolation (4) Concatenation (5) Neural network

1. For a given input coordinate x, we find the surrounding voxels at L resolution levels and assign indices to their corners by hashing their integer coordinates

$$h(\mathbf{x}) = \left(\bigoplus_{i=1}^{d} x_i \pi_i \right) \mod T\,,$$

2. For all resulting corner indices, we look up the corresponding F-dimensional feature vectors from the hash tables
3. Linearly interpolate them according to the relative position of x within the respective l-th voxel.
4. Concatenate + auxiliary inputs (the encoded view, etc.)
5. MLP

The approach



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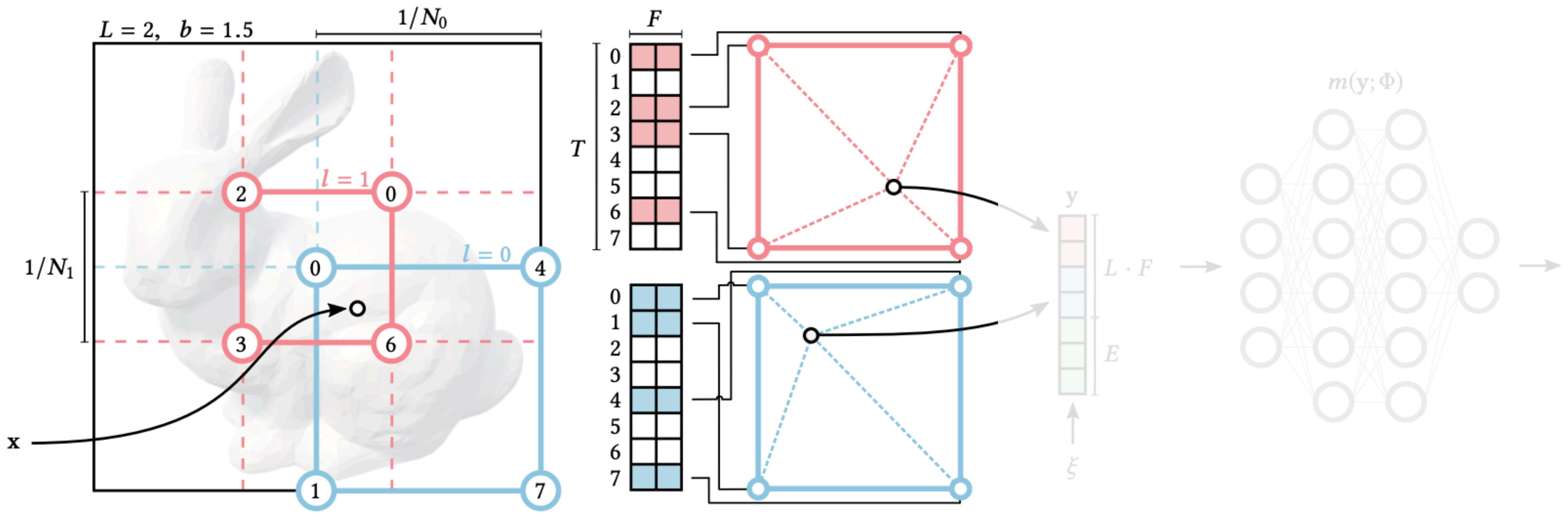

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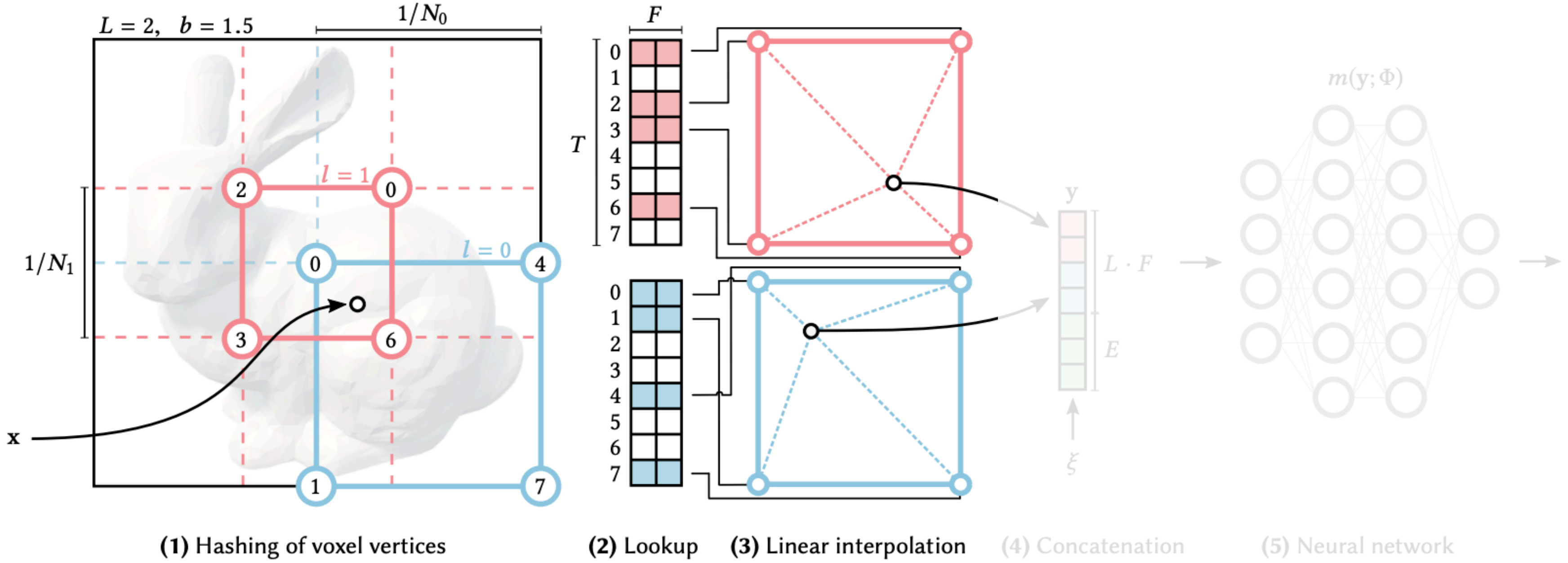

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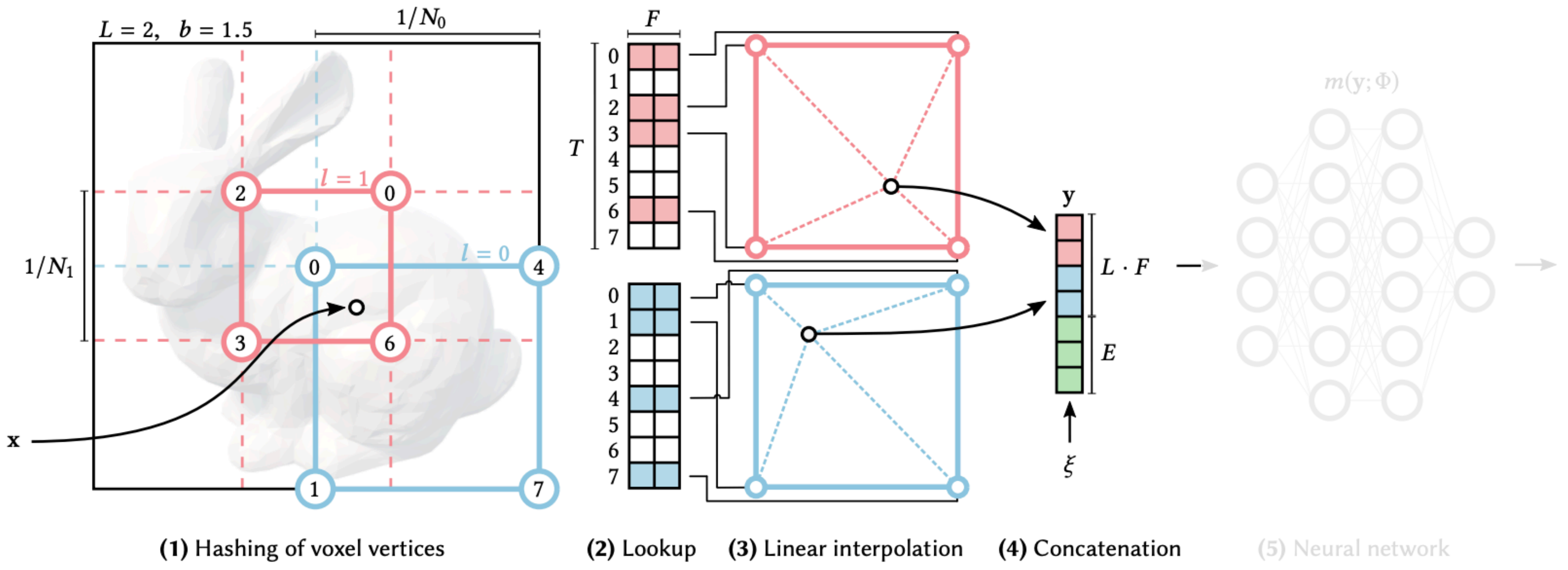

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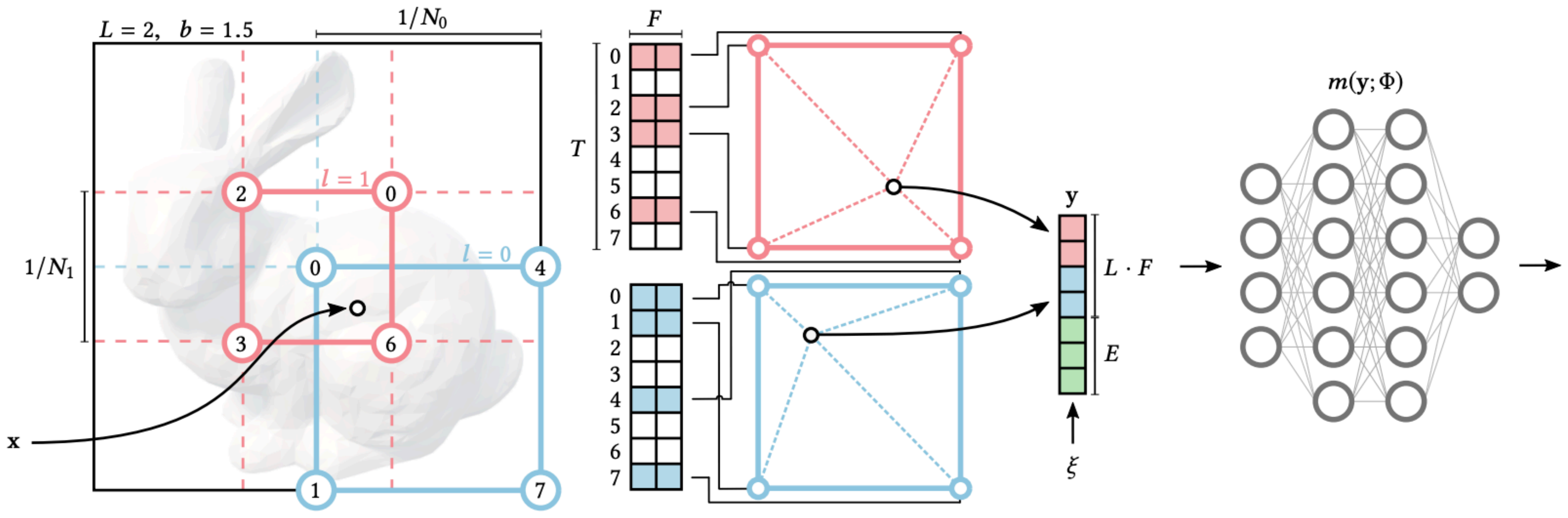

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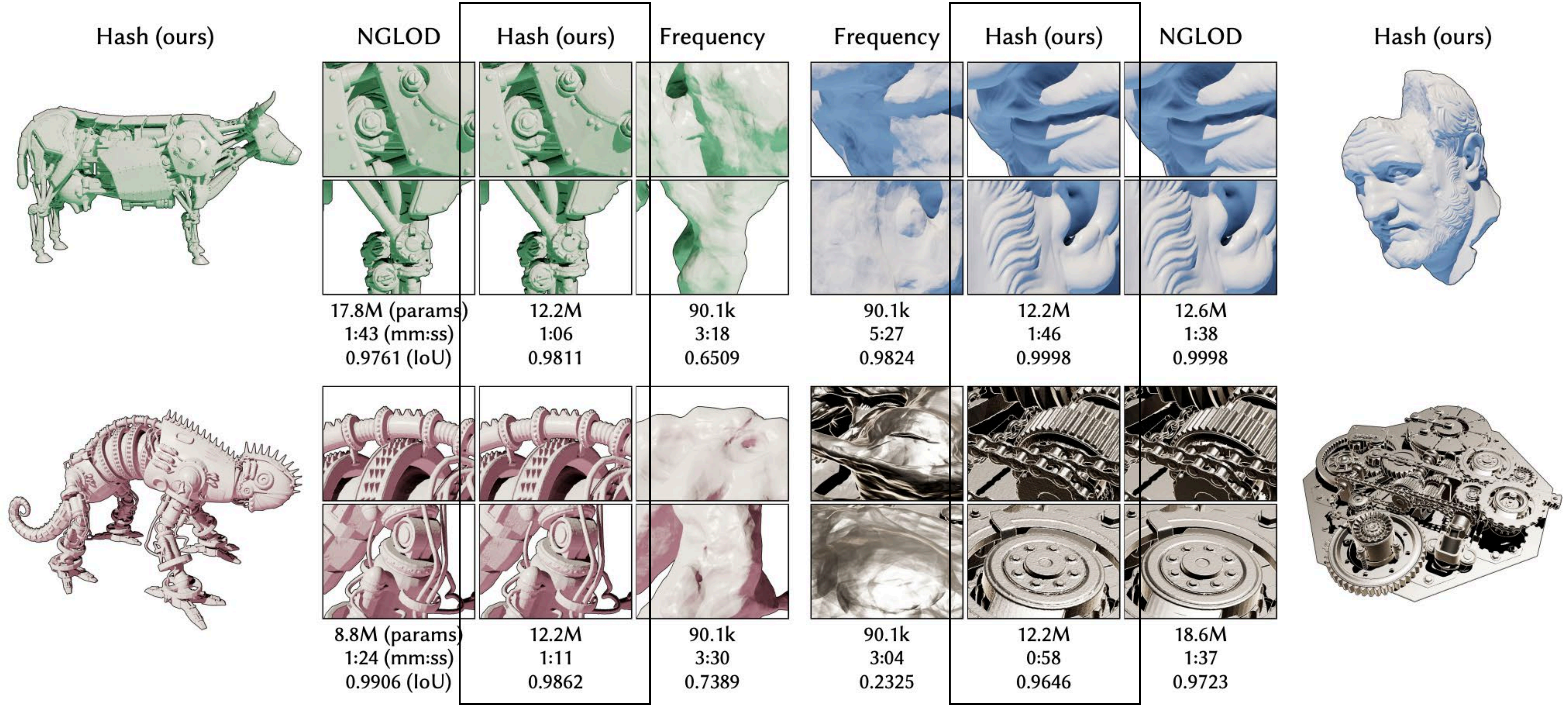
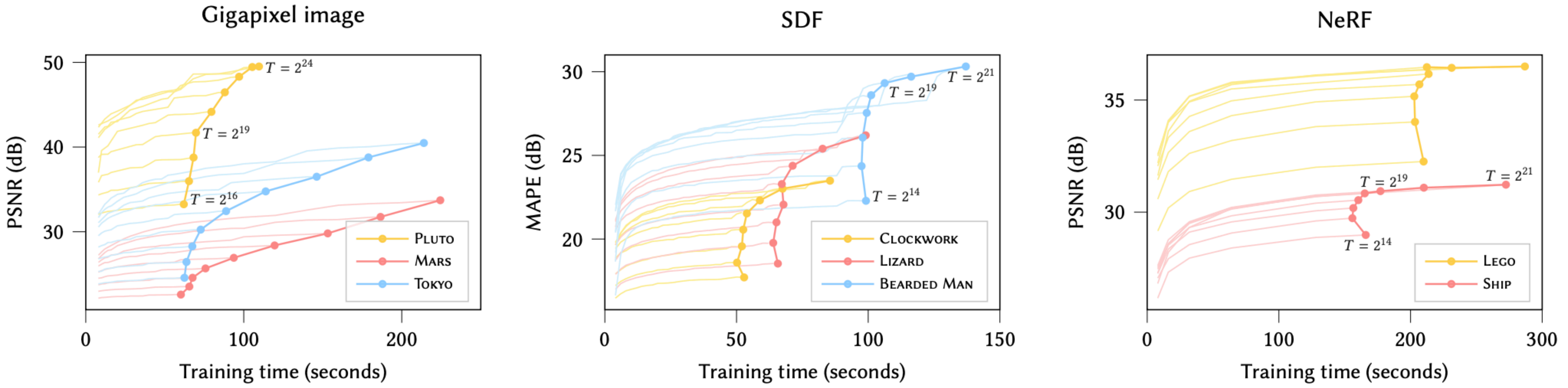
Experiment results - reconstruction quality

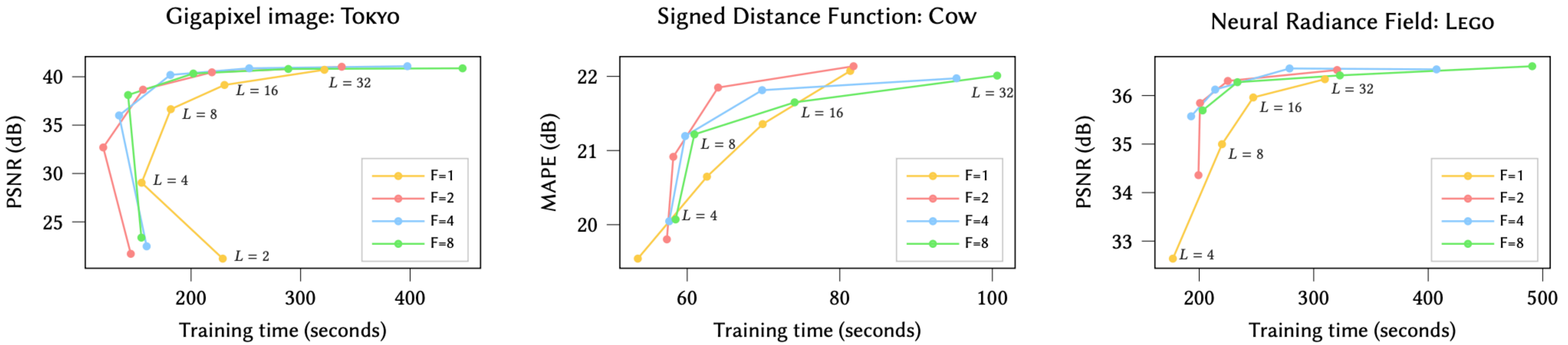
Experiment results



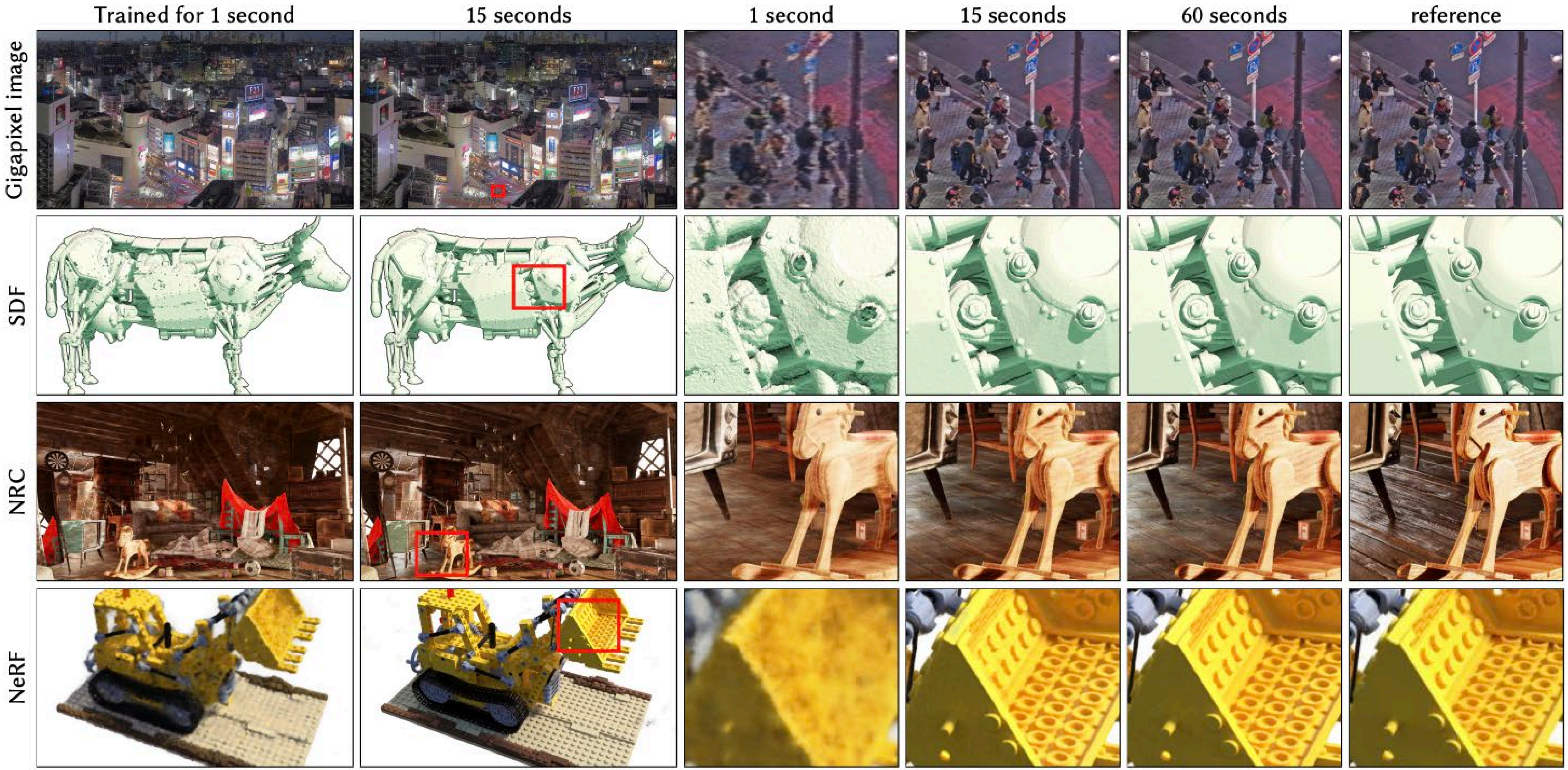
test error over training time for varying hash table size T



Test error over training time for fixed values of feature dimensionality F



Experiment results - runtime



Where does the speedup come from?

- factor of 10 from tiny-cuda-cnn - optimised CUDA kernels
- factor of 10~100 from smaller MLP due to better encoding
  - Combine many hash maps with cells of different resolutions

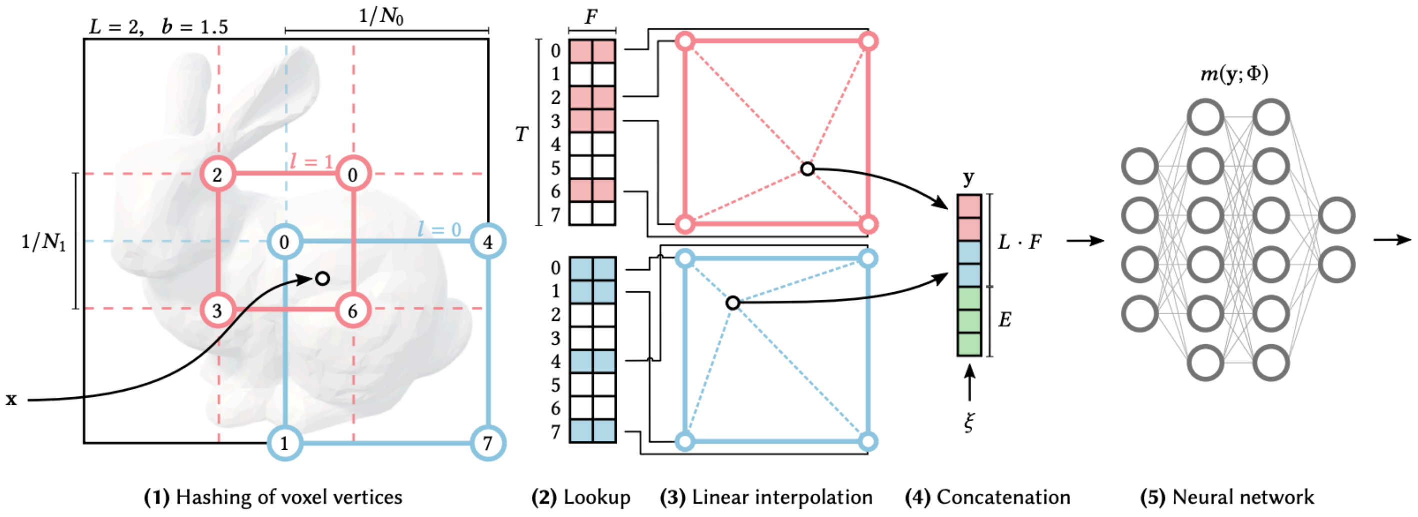
	Mic	Ficus	Chair	Hotdog	Materials	Drums	Ship	Lego	avg.
Ours: Hash (1 s)	26.09	21.30	21.55	21.63	22.07	17.76	20.38	18.83	21.202
Ours: Hash (5 s)	32.60	30.35	30.77	33.42	26.60	23.84	26.38	30.13	29.261
Ours: Hash (15 s)	34.76	32.26	32.95	35.56	28.25	25.23	28.56	33.68	31.407
Ours: Hash (1 min)	35.92	33.05	34.34	36.78	29.33	25.82	30.20	35.63	32.635
Ours: Hash (5 min)	36.22	33.51	35.00	37.40	29.78	26.02	31.10	36.39	33.176
mip-NeRF (~hours)	38.04	33.19	37.14	39.31	32.56	27.02	33.08	35.74	34.510
NSVF (~hours)	34.27	31.23	33.19	37.14	32.68	25.18	27.93	32.29	31.739
NeRF (~hours)	32.91	30.13	33.00	36.18	29.62	25.01	28.65	32.54	31.005
Ours: Frequency (5 min)	31.89	28.74	31.02	34.86	28.93	24.18	28.06	32.77	30.056
Ours: Frequency (1 min)	26.62	24.72	28.51	32.61	26.36	21.33	24.32	28.88	26.669

	Training speed	Rendering speed
Original NeRF	1-2 days	30 sec
KiloNeRF, cached voxels	1-2 days	1/60 sec
Learned voxels	10-15 mins	1/15-1/2 sec
Learned hash maps (Instant NGP)	5 sec - 5 mins	1/60 sec

Ref: http://graphics.stanford.edu/courses/cs348n-22-winter/LectureSlides/FinalSlides/leo_class_nerf_2022.pdf

Hash Collision

- When the same feature vector is used for multiple spatial locations, you average gradients over all of them.
  - When only a small fraction of those locations have interesting things going on (e.g. not empty space), then that feature vector will mostly be used to represent the interesting stuff going on there, since gradients from that location will be largest.



Summary

- multiresolution hash encoding

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- Very small MLP (2-3 layers x 64 channels) decodes the trilinearly interpolated hash map features

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- optimized CUDA kernels