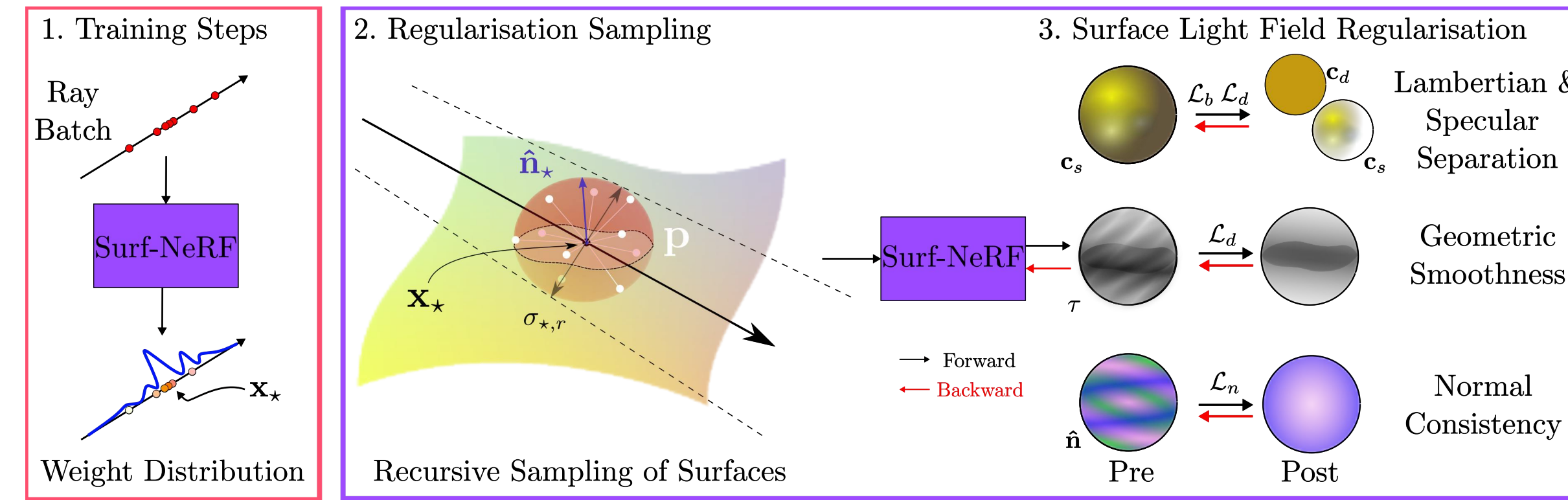


# Surf-NeRF: Surface Regularised Neural Radiance Fields

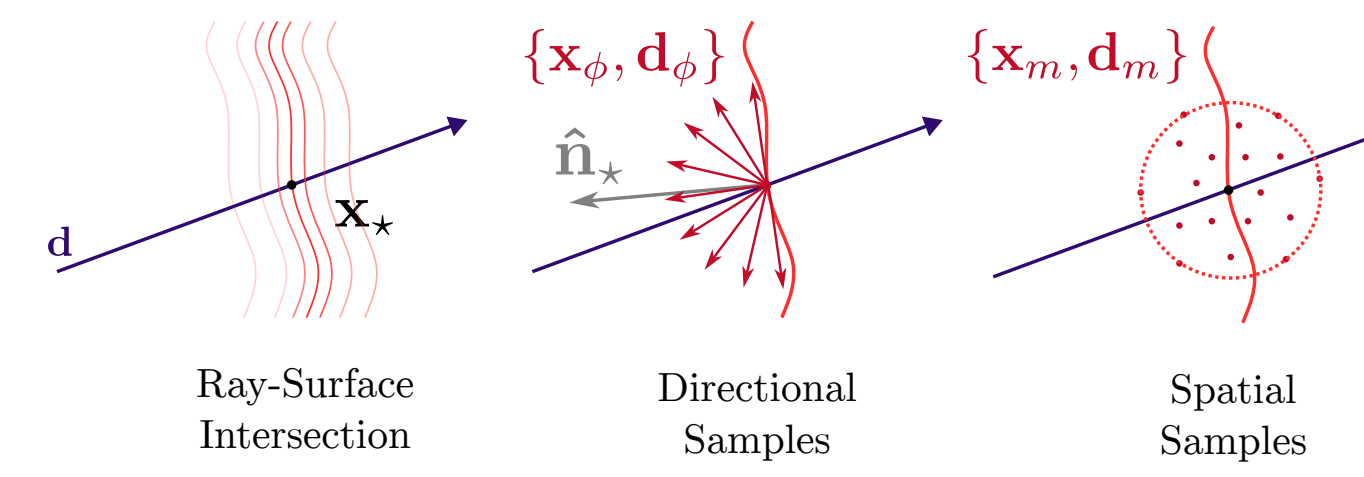
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## Motivation & Contributions

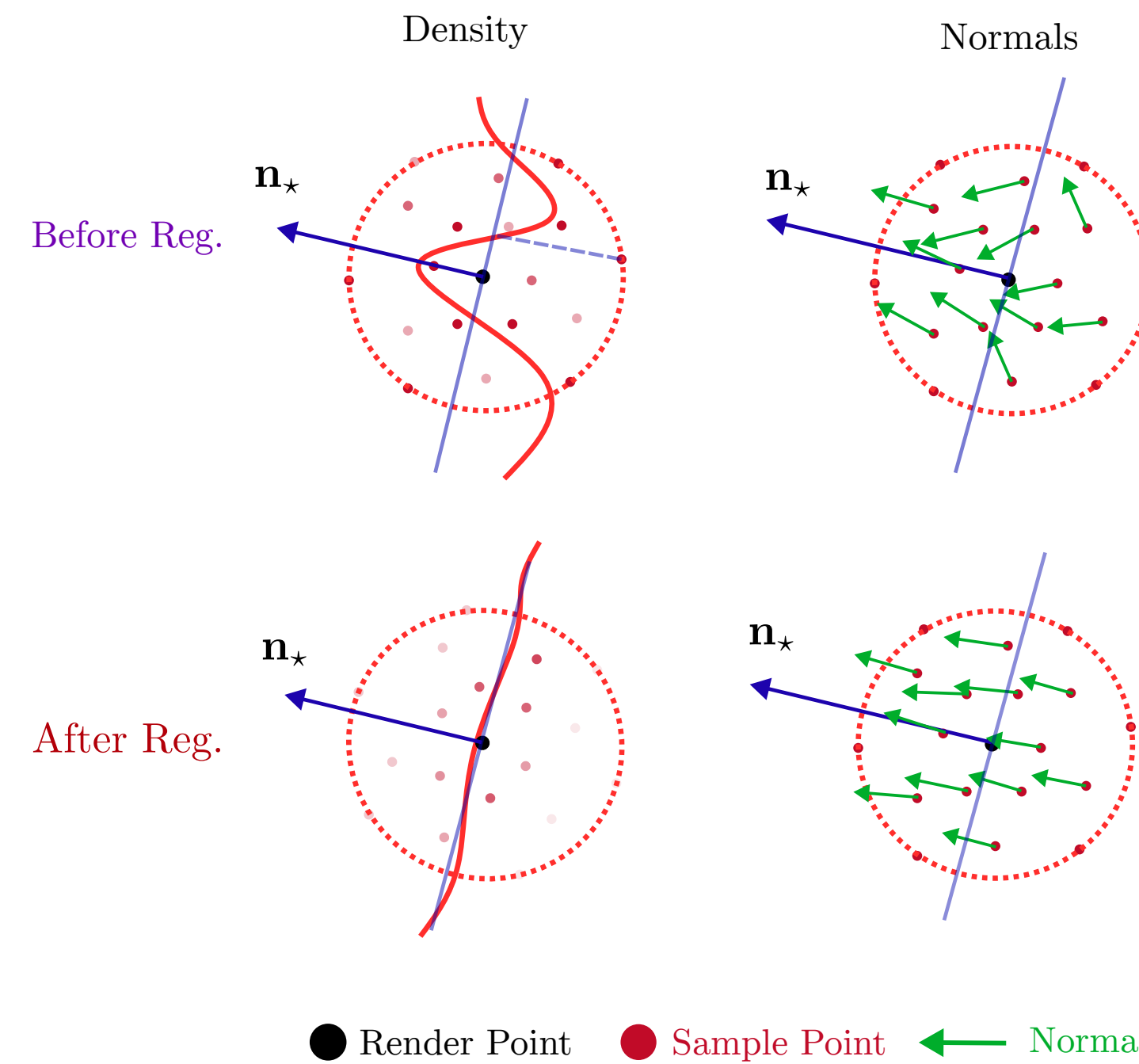
- Radiance-based representations produce realistic novel views of a scene, but have poor geometric representation around non-Lambertian scene elements.
- Reflection parameterisations [1] improve geometry, but still suffer from shape-radiance ambiguity.
- Other models of radiance (e.g. surface light fields) have priors on model of appearance AND geometry [2]
- We propose Surf-NeRF consisting of: 1) representation driven regularisation towards a surface light field model, 2) improved positional encoding for non-planar geometry which we benchmark on a 3) new captured dataset.



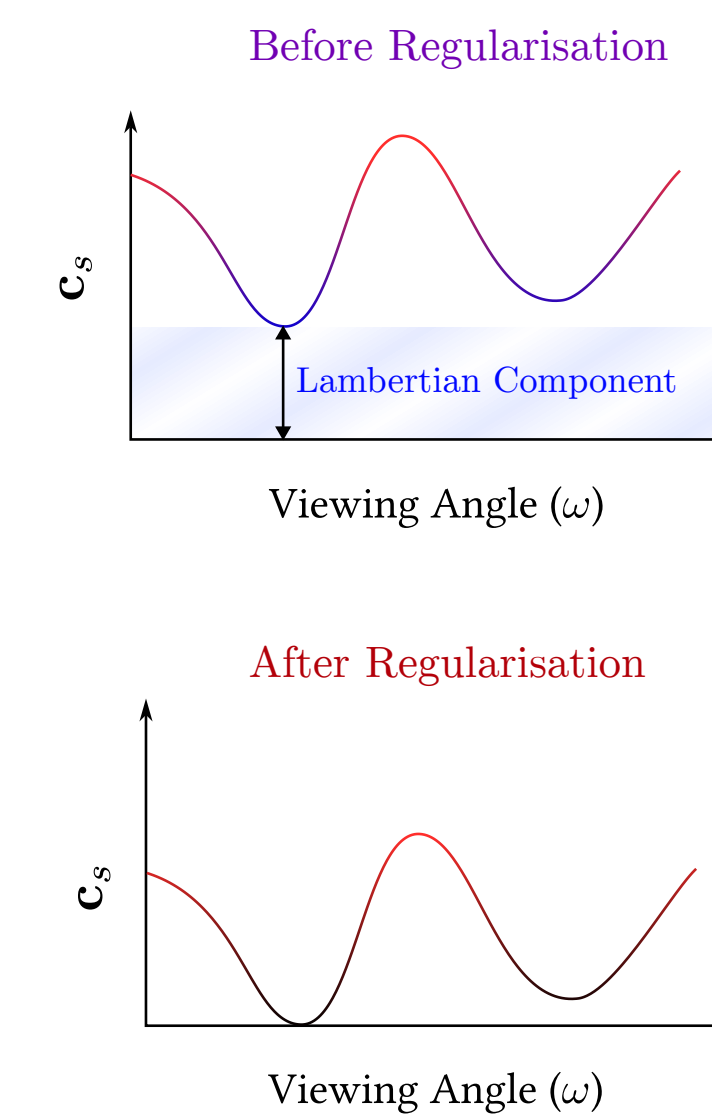
- Sample surface spatially and directionally
- Regularise towards a surface light-field model of appearance and geometry



## Geometry

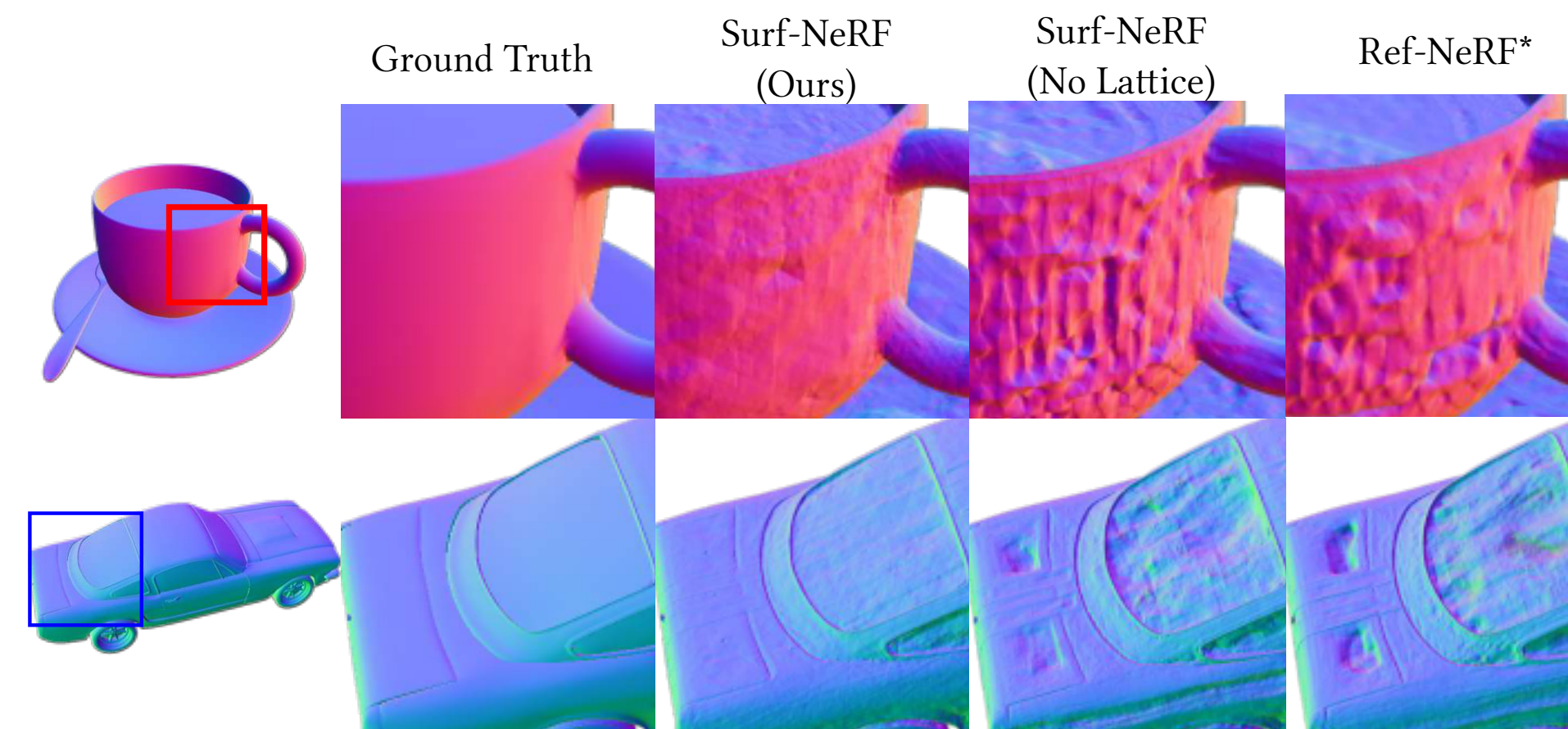


## Appearance



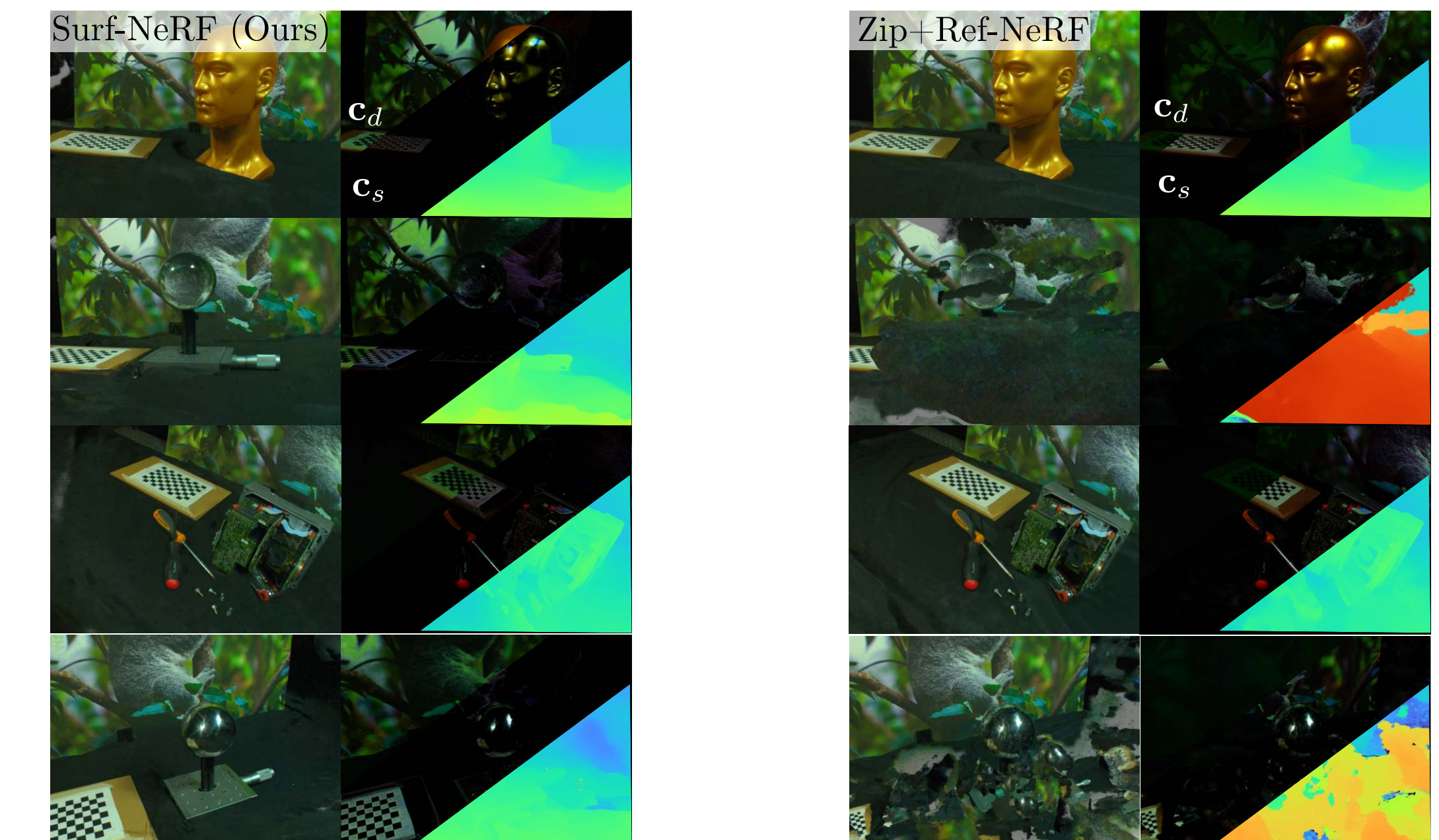
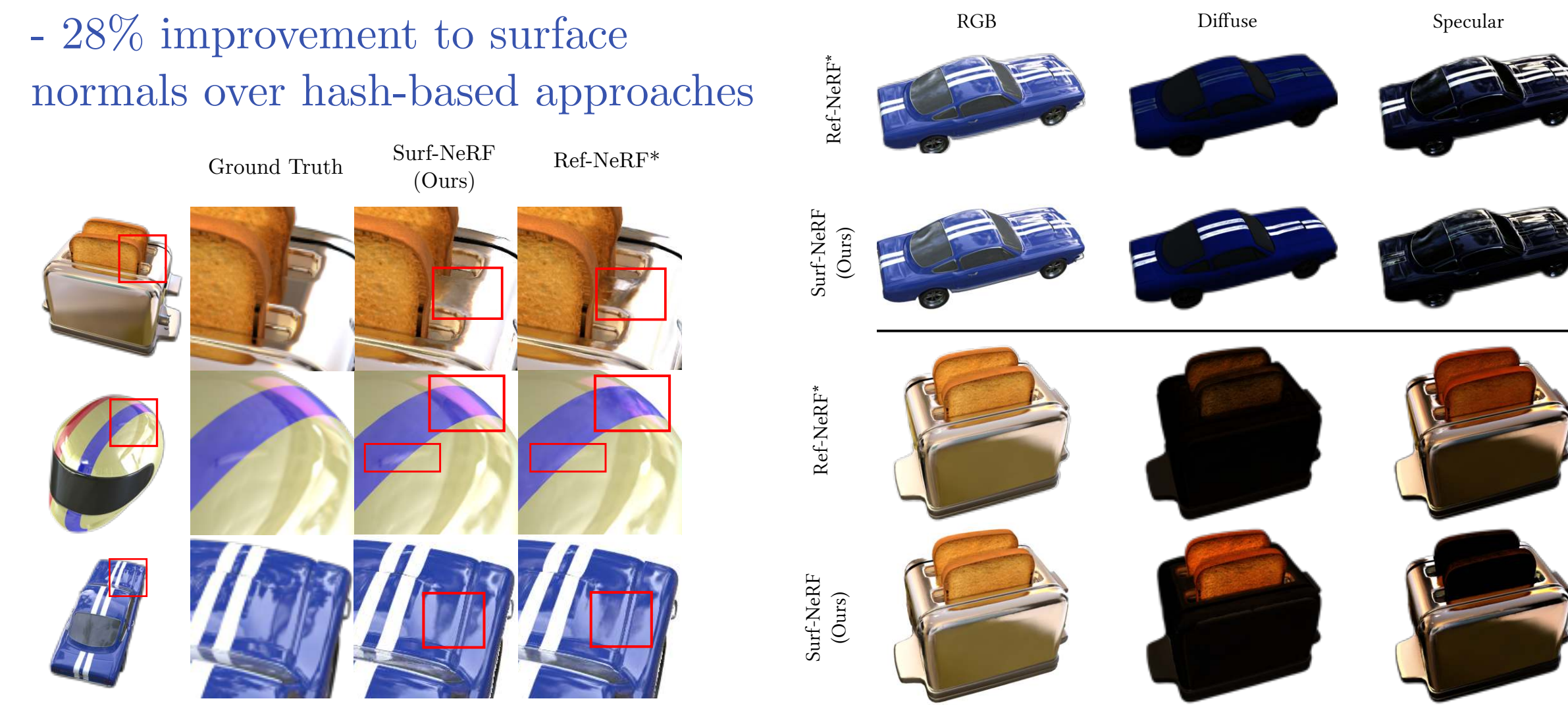
## Results

- Significantly improved geometric representation, normal consistency



- More consistent rendering of specularities
- Separation of diffuse + specular appearance
- 28% improvement to surface normals over hash-based approaches

| Model                  | PSNR $\uparrow$ | SSIM $\uparrow$ | MAE $\downarrow$ | RMSE $\downarrow$ |
|------------------------|-----------------|-----------------|------------------|-------------------|
| PE                     |                 |                 |                  |                   |
| MipNeRF                | 31.29           | 0.943           | 56.17            | 0.125             |
| MipNeRF+Diff           | 30.84           | 0.936           | 60.00            | 0.122             |
| Ref-NeRF               | 33.21           | 0.971           | 25.89            | 0.117             |
| Surf-NeRF (Reg. Only)  | 33.01           | 0.967           | 22.15            | 0.117             |
| Grid                   |                 |                 |                  |                   |
| ZipNeRF                | 31.02           | 0.952           | 19.47            | 0.209             |
| Zip+Ref-NeRF           | 33.14           | 0.964           | 14.70            | 0.195             |
| Lattice+Ref-NeRF       | 33.21           | 0.964           | 13.76            | 0.202             |
| Surf-NeRF (No Lattice) | 32.13           | 0.954           | 13.35            | 0.202             |
| Surf-NeRF (Ours)       | 32.82           | 0.955           | 10.60            | 0.198             |



- Improved separation of diffuse + specular and surface geometry on sparse captured multi-view data (Koala Dataset)

## Conclusions

- Regularisation towards a surface light field model substantially improves geometric representation while maintaining volumetric rendering
- Limitations: 2x steps through network, possible to ablate fine details which are better represented volumetrically, slightly reduced rendering quality
- Future work: we anticipate similar regularisation can be applied to 3DGS/Radiant Foam + other scene representations.

## References & Acknowledgements

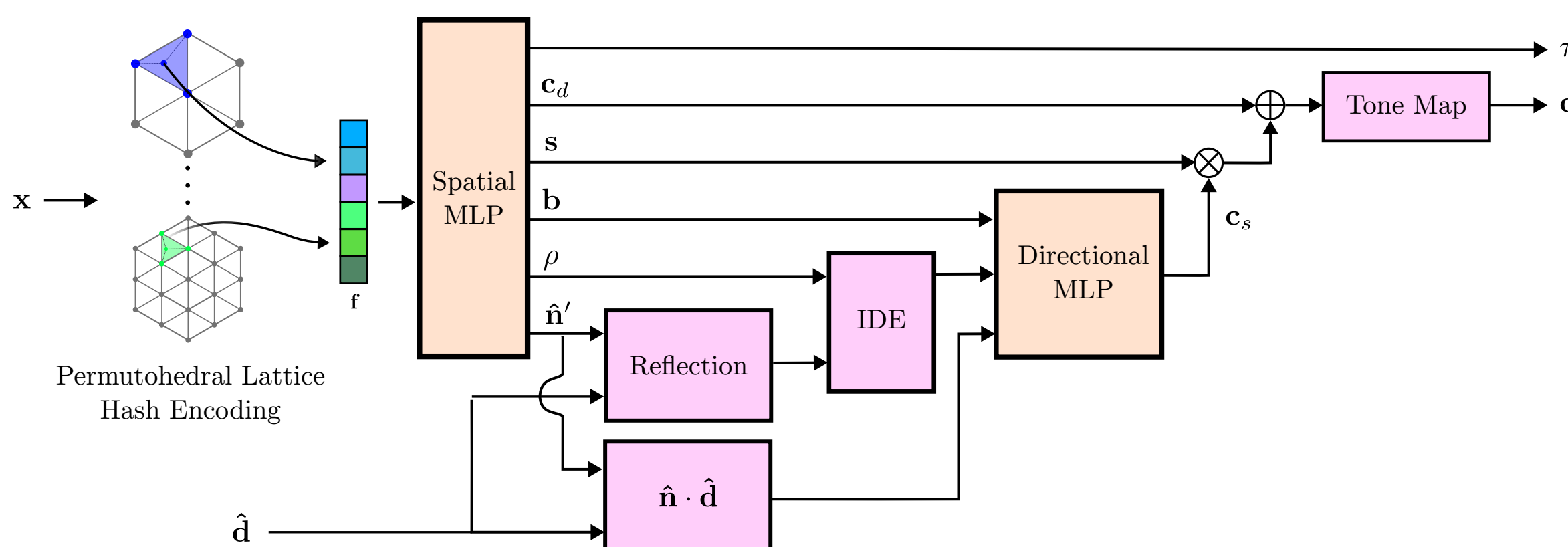
[1] Verbin et al., *Ref-NeRF: Structured View-Dependent Appearance For Neural Radiance Fields*, CVPR, 2022  
 [2] Wood et al., *Surface Light Fields for 3D Photography*, SIGGRAPH, 2000  
 The authors wish to acknowledge Ford Motor Company and ARIAM Hub. Computational aspects of this work were supported by Australia's NCI Gadi, an NVIDIA Academic Grant and Google TPU Research Cloud.

Ref-NeRF

Surf-NeRF (Ours)

## Methodology

- Introduce **permutohedral lattice hash encoding** suitable for smooth surfaces
- Tetrahedrons can better approximate non-planar surfaces compared to voxels



- Curriculum learning of surface: apply regularisation with second pass through network with increasing frequency during training