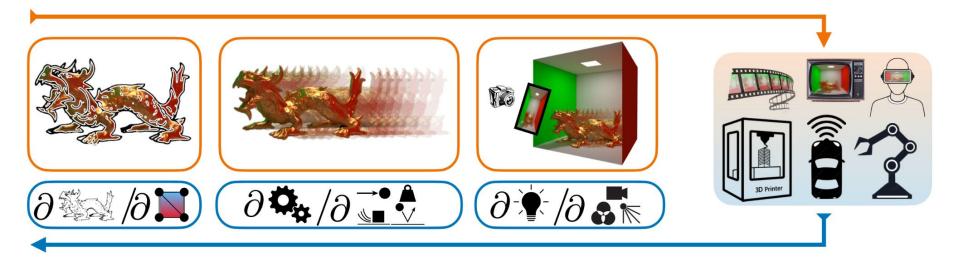
Scene Understanding — Differentiable Graphics

Dr Fangcheng Zhong



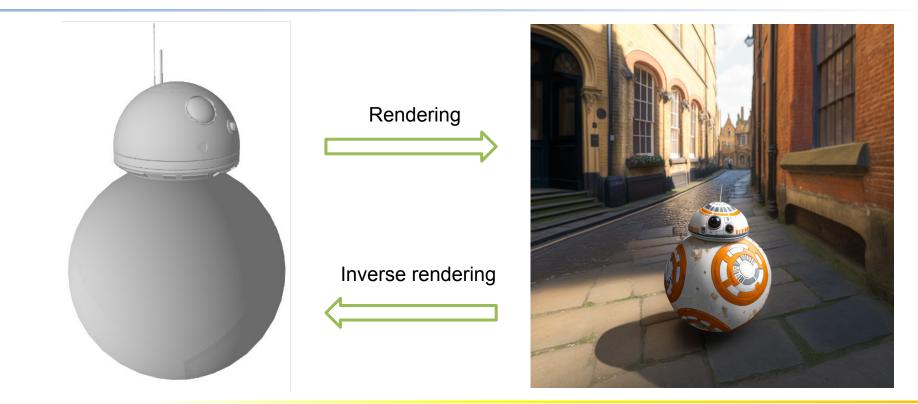


Outline

- Inverse graphics
- Differentiable surface rendering
 - Differentiable rasterization
 - Physically-based differentiable rendering
- Non-surface representations
 - Light fields
 - Neural radiance fields
 - Differentiable volume rendering



Inverse Graphics



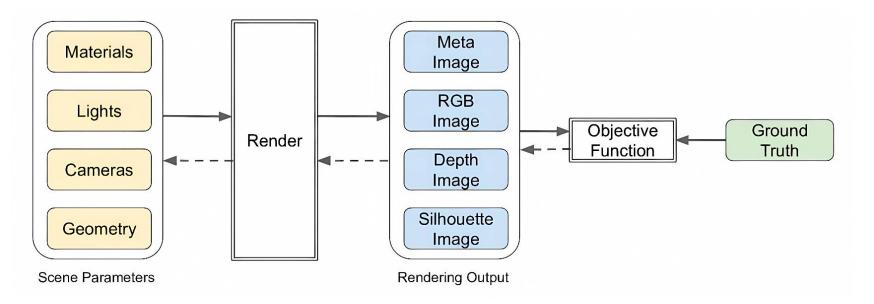


Inverse Graphics

- Traditional approaches
 - SLAM, SfM
 - Light probes, structured light
- Data-driven approaches



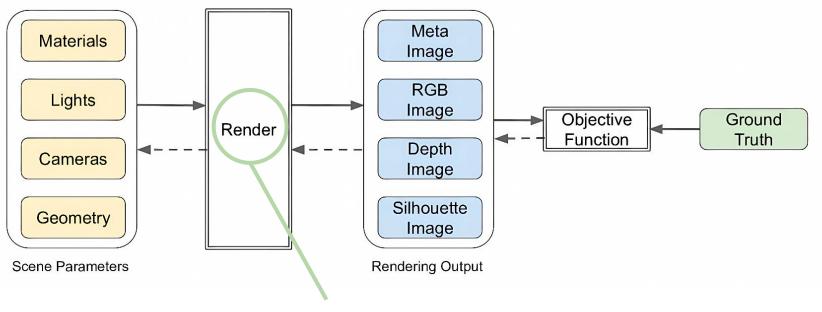
Differentiable Rendering



generalised reprojection error minimisation



Differentiable Rendering

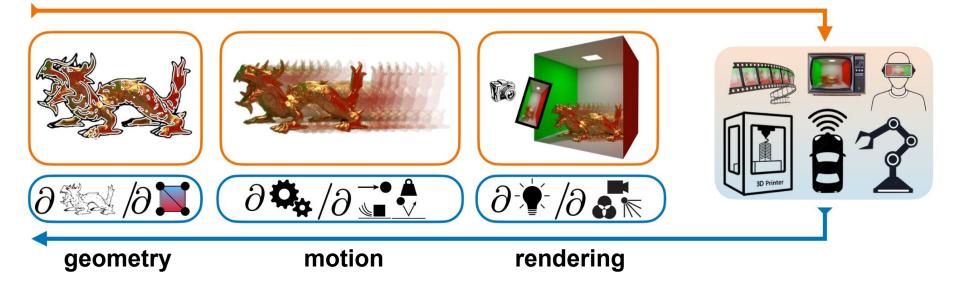


Derive useful gradients in rendering



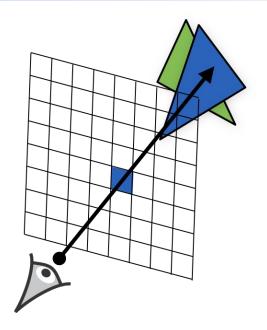
Differentiable Graphics

Everything differentiable can be integrated!





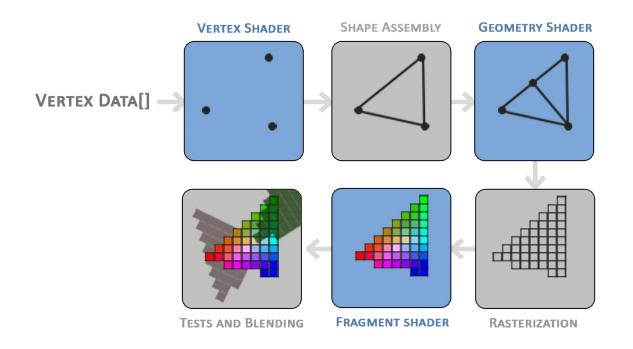
Differentiable Graphics



Visibility has no well-defined gradient



OpenGL Rendering Pipeline



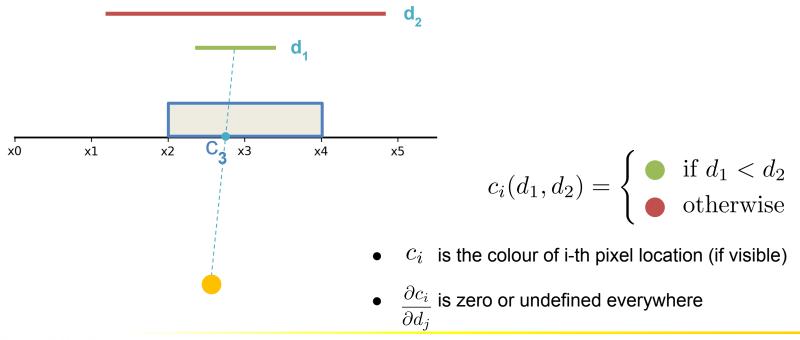


Rasterization has no gradient

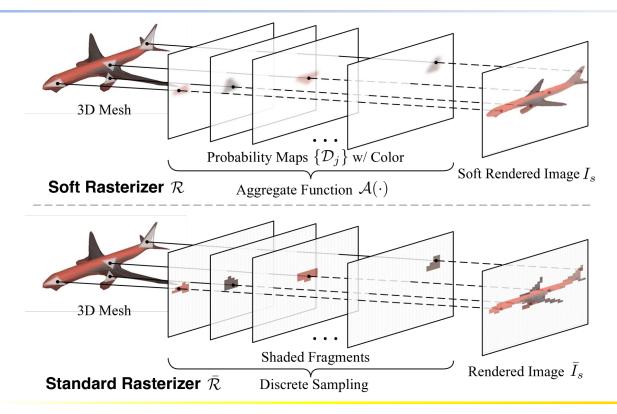
x3 x0 `x2 $\mathbf{f_5} \quad \begin{array}{l} \overset{\mathsf{x5}}{f_1(t_0, t_1)} = \begin{cases} 1 & \text{if } [t_0, t_1] \cap [x_i, x_{i-1}] < \frac{x_i - x_{i-1}}{2} \\ 0 & \text{otherwise} \end{cases}$ x1 x4 f₃ f_i is the visibility of —— at the i-th pixel location • $\frac{\partial f_i}{\partial t_i}$ is zero or undefined everywhere



Z-buffering has no gradient

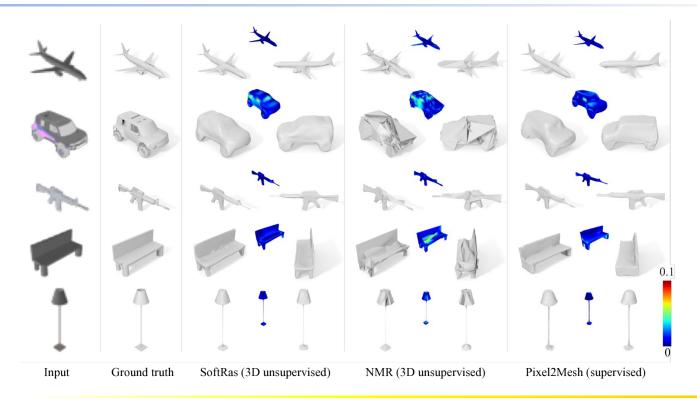






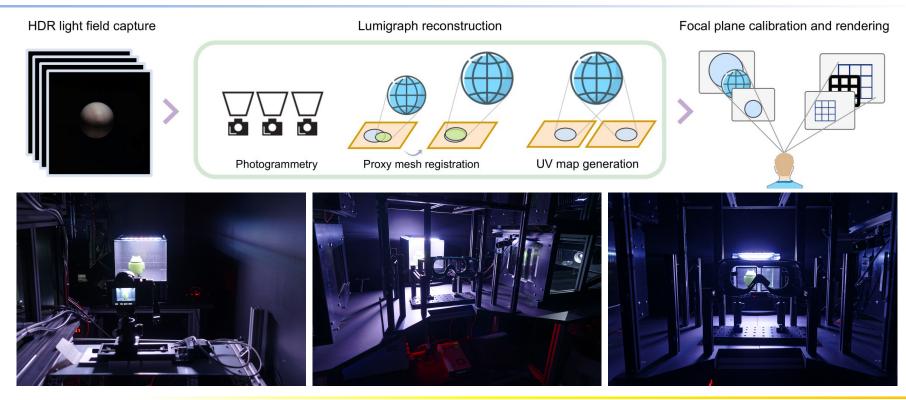


Liu, Shichen, et al. "Soft rasterizer: A differentiable renderer for image-based 3d reasoning." *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019.





Liu, Shichen, et al. "Soft rasterizer: A differentiable renderer for image-based 3d reasoning." *Proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019.





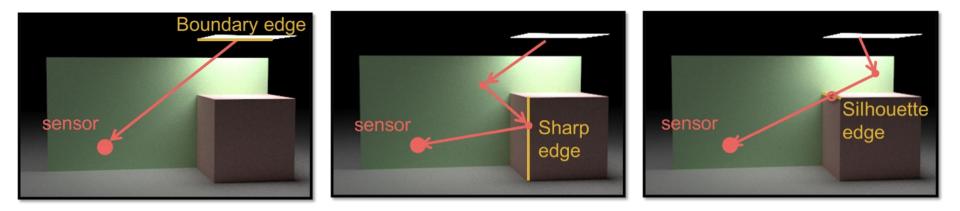
Fangcheng Zhong, Akshay Jindal, Ali Özgür Yöntem, Param Hanji, Simon J. Watt, and Rafał K. Mantiuk. 2021. Reproducing Reality with a High-Dynamic-Range Multi-Focal Stereo Display. ACM Transactions on Graphics (Proceedings of ACM SIGGRAPH Asia, Journal Track), 2021

Physically-based Rendering

The rendering equation

$$L_o(\mathbf{x}, \omega_o) = L_e(\mathbf{x}, \omega_o) + \int_{\Omega} f_r(\mathbf{x}, \omega_i, \omega_o) L_i(\mathbf{x}, \omega_i) \cos(\theta) d\omega_i$$

discontinuous!





Differentiating the rendering equation

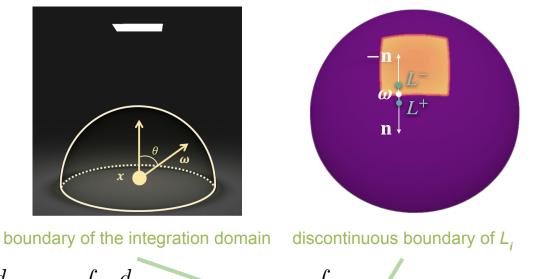
$$L_o(\mathbf{x}, \omega_o; \Theta) = L_e(\mathbf{x}, \omega_o; \Theta) + \int_{\Omega} f_r(\mathbf{x}, \omega_i, \omega_o; \Theta) L_i(\mathbf{x}, \omega_i; \Theta) \cos(\theta) d\omega_i$$

scene parameters

$$\frac{d}{d\Theta}L_o(\mathbf{x},\omega_o;\Theta) \bigotimes \frac{d}{d\Theta}L_e(\mathbf{x},\omega_o;\Theta) + \int_{\Omega} \frac{d}{d\Theta}f_r(\mathbf{x},\omega_i,\omega_o;\Theta)L_i(\mathbf{x},\omega_i;\Theta)\cos(\theta)d\omega_i$$

Only true when the integrand is continuous





$$\frac{d}{d\Theta}L_o = \frac{d}{d\Theta}L_e + \int_{\Omega} \frac{d}{d\Theta}f_r L_i \cos d\omega_i + \int_{\partial\Omega \cup \Omega^*} \mathbf{v} \cdot \mathbf{n} (L_i^- - L_i^+) f_r \cos d\mathcal{S}$$
differential rendering equation movement of S w.t. theta

differential rendering equation

movement of S w.r.t. theta in the normal direction



Leibniz integral rule

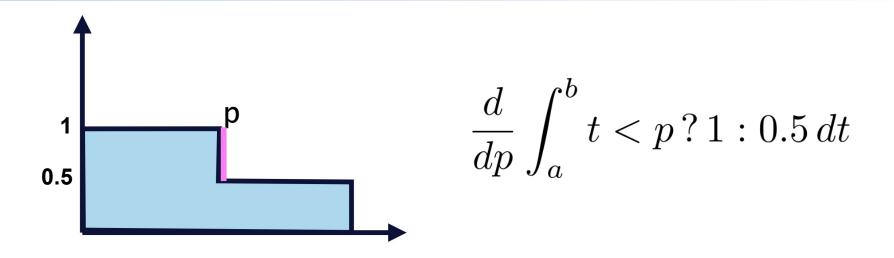
General form:

$$\frac{d}{dx}\int_{a(x)}^{b(x)} f(x,t)\,dt = f(x,b(x))\frac{db}{dx} - f(x,a(x))\frac{da}{dx} + \int_{a(x)}^{b(x)}\frac{\partial}{\partial x}f(x,t)\,dt$$

If i) f(x,t) and its partial derivative $f_x(x,t)$ are continuous; ii) a and b are constant independent of x,

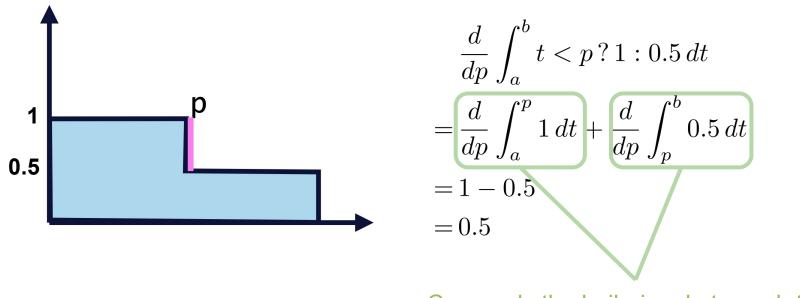
$$\frac{d}{dx}\int_{a}^{b}f(x,t)\,dt = \int_{a}^{b}\frac{\partial}{\partial x}f(x,t)\,dt$$





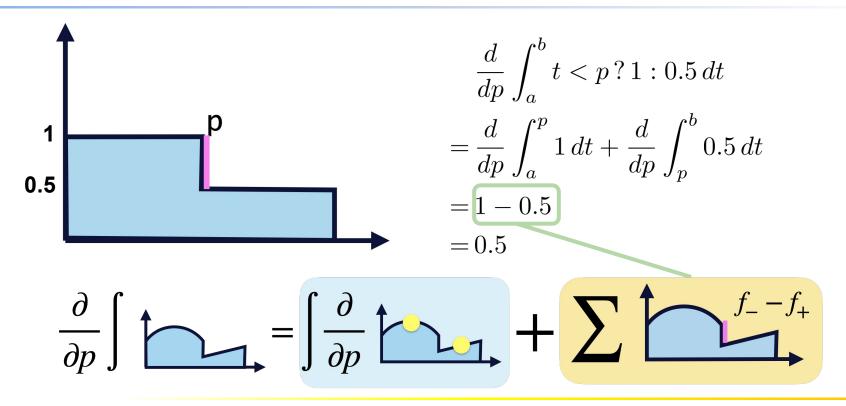
What if the integrand has sharp discontinuities (e.g. visibility)?





Can apply the Leibniz rule to each term







Reynolds transport theorem

$$\frac{d}{dt} \int_{\Omega(t)} f(\mathbf{x}, t) \, dV(\mathbf{x}) = \int_{\Omega(t)} \frac{\partial}{\partial t} f(\mathbf{x}, t) \, dV + \int_{\partial \Omega(t)} f(\mathbf{x}, t) \mathbf{v} \cdot \mathbf{n} \, dA$$

generalisation of the Leibniz integral rule to higher dimensions

$$\frac{\partial}{\partial p} \iint \underbrace{\overleftarrow{\partial p}} = \iint \frac{\partial}{\partial p} \underbrace{\overleftarrow{\partial p}} + \int \underbrace{\overleftarrow{\partial p}}$$



Reparameterizing Discontinuous Integrands for Differentiable Rendering

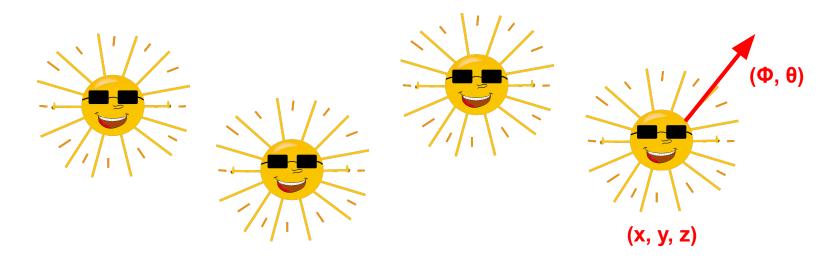
Guillaume Loubet (EPFL) Nicolas Holzschuch (INRIA) Wenzel Jakob (EPFL)

SIGGRAPH Asia 2019



Loubet, Guillaume, Nicolas Holzschuch, and Wenzel Jakob. "Reparameterizing discontinuous integrands for differentiable rendering." *ACM Transactions on Graphics (TOG)* 38.6 (2019): 1-14.

Light Fields



 $f(x, y, z, \phi, \theta)$

Incident radiance at an arbitrary location from an arbitrary direction



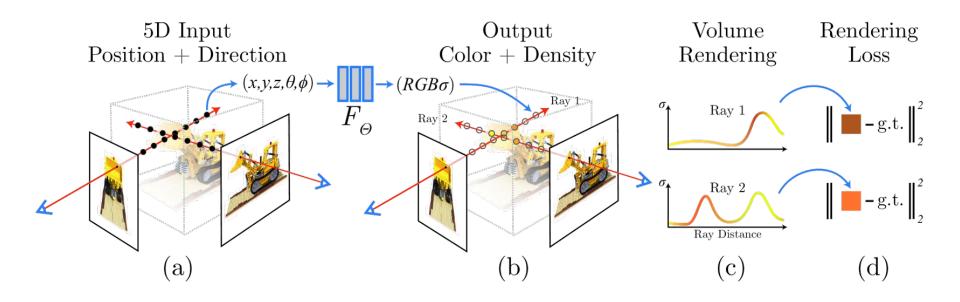
Light Fields





Broxton, Michael, et al. "Immersive light field video with a layered mesh representation." *ACM Transactions on Graphics (TOG)* 39.4 (2020): 86-1. <u>https://augmentedperception.github.io/deepviewvideo/</u>

Neural Radiance Field (NeRF)





Ben Mildenhall, Pratul P. Srinivasan, Matthew Tancik, Jonathan T. Barron, Ravi Ramamoorthi, and Ren Ng. Nerf: Representing scenes as neural radiance fields for view synthesis. In ECCV, 2020



view synthesis



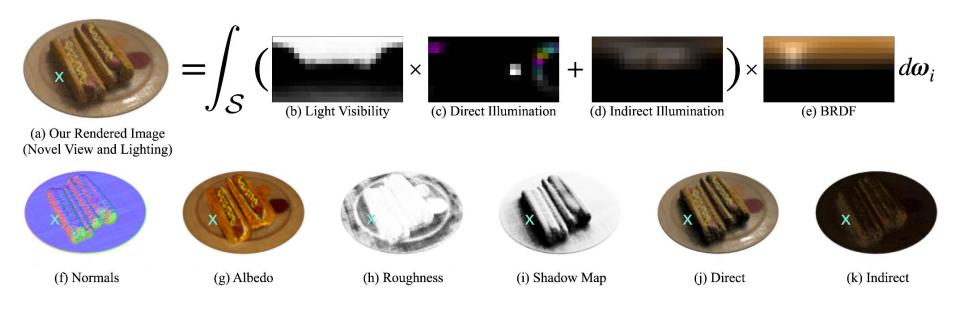
Ben Mildenhall, Pratul P. Srinivasan, Matthew Tancik, Jonathan T. Barron, Ravi Ramamoorthi, and Ren Ng. Nerf: Representing scenes as neural radiance fields for view synthesis. In ECCV, 2020



relighting



Srinivasan, P.P., Deng, B., Zhang, X., Tancik, M., Mildenhall, B. and Barron, J.T. Nerv: Neural reflectance and visibility fields for relighting and view synthesis. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* 2021 (pp. 7495-7504).



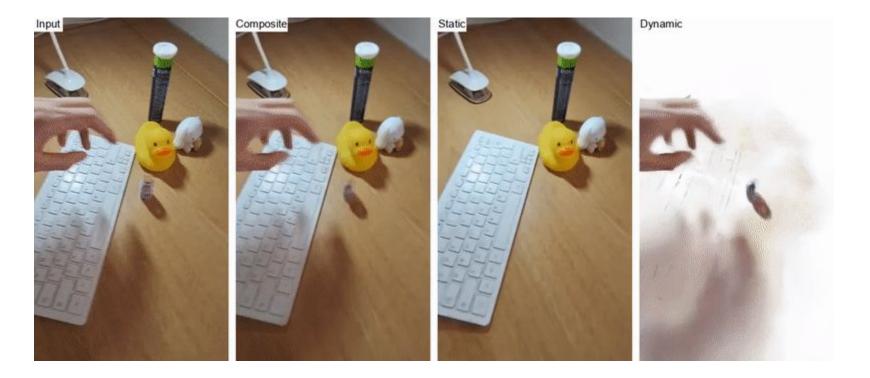


Srinivasan, P.P., Deng, B., Zhang, X., Tancik, M., Mildenhall, B. and Barron, J.T. Nerv: Neural reflectance and visibility fields for relighting and view synthesis. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* 2021 (pp. 7495-7504).





Zhang, Jason, et al. "NeRS: neural reflectance surfaces for sparse-view 3D reconstruction in the wild." *Advances in Neural Information Processing Systems* 34 (2021): 29835-29847.





Tianhao Wu, Fangcheng Zhong, Andrea Tagliasacchi, Forrester Cole, and Cengiz Oztireli. D2NeRF: Self-Supervised Decoupling of Dynamic and Static Objects from a Monocular Video. In NeurIPS, 2022

Differentiable Graphics

- Unified framework to simultaneously infer multiple scene parameters
- Self-supervision
- Generalisability
- Cross regularisation
- Physics consistency in geometry and lighting

