

1. Context: 3D Intensity diffraction tomography

► Goal: given $U^i(\mathbf{r})$ and \mathbf{y} , recover $f(\mathbf{r})$, for $\mathbf{r} \in \Omega$.

- Incident planewave $U^i(\mathbf{r}) = e^{i\mathbf{k}^i \cdot \mathbf{r}}$.

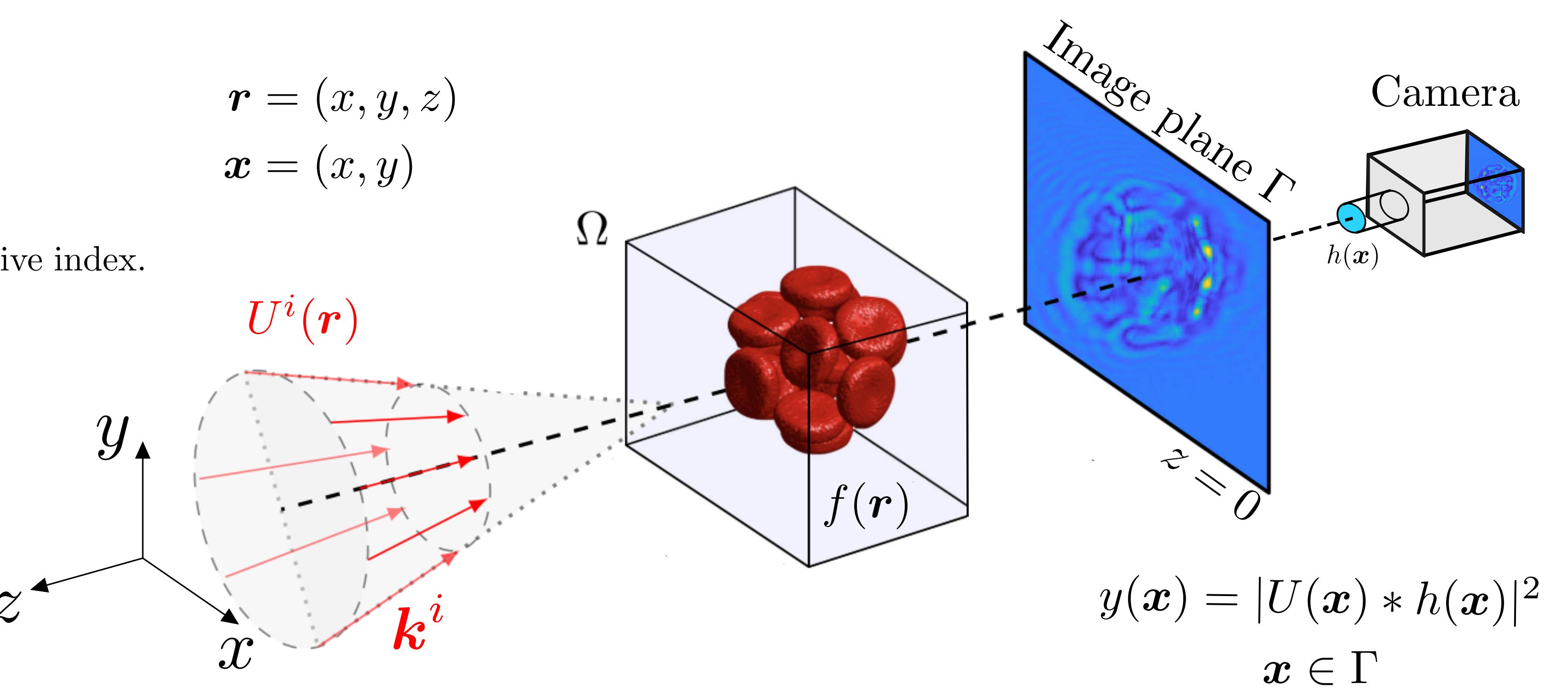
- scattering potential $f(\mathbf{r}) = k_b^2 \left[\left(\frac{n(\mathbf{r})}{n_b} \right)^2 - 1 \right]$ with $n(\mathbf{r})$ the refractive index.

- pupil of the camera: $h(\mathbf{x})$.

► Applications: morphogenesis, oncology, biochemistry.

► Intensity measurements:

- easy and cheap acquisition --- no interferometry setup needed.
- phase recovery problem.



2. Forward model

a. Lippmann-Schwinger equation

► Comes from the wave equation.

$$U(\mathbf{r}) = U^i(\mathbf{r}) + \int_{\Omega} U(\mathbf{r}') f(\mathbf{r}') G(\mathbf{r} - \mathbf{r}') d\mathbf{r}'$$

► Intuitive: $f(\mathbf{r}) = 0 \rightarrow U(\mathbf{r}) = U^i(\mathbf{r})$

► Discrete form $\mathbf{U} = (\mathbf{I} - \mathbf{G} \text{ diag}(\mathbf{f}))^{-1} \mathbf{U}^i$

► $G(\mathbf{r}) := \frac{e^{i k_b \|\mathbf{r}\|}}{4\pi \|\mathbf{r}\|}$ → Singularity, hard numerical computations. Solution in [1].

► \mathbf{G} makes the convolution with $G(\mathbf{r})$.

► solved with:

- BiConjugate Gradient Stabilized Method.
- Neumann series $\mathbf{U} = \sum_{k=0}^{\infty} (\mathbf{G} \text{ diag}(\mathbf{f}))^k \mathbf{U}^i$

b. Intensity measurements

► \mathbf{R}_{Γ} restricts \mathbf{U} to camera plane Γ .

$$\mathbf{y}' = |\mathbf{P} \mathbf{R}_{\Gamma} \mathbf{U}|^2 - |\mathbf{P} \mathbf{R}_{\Gamma} \mathbf{U}^i|^2$$

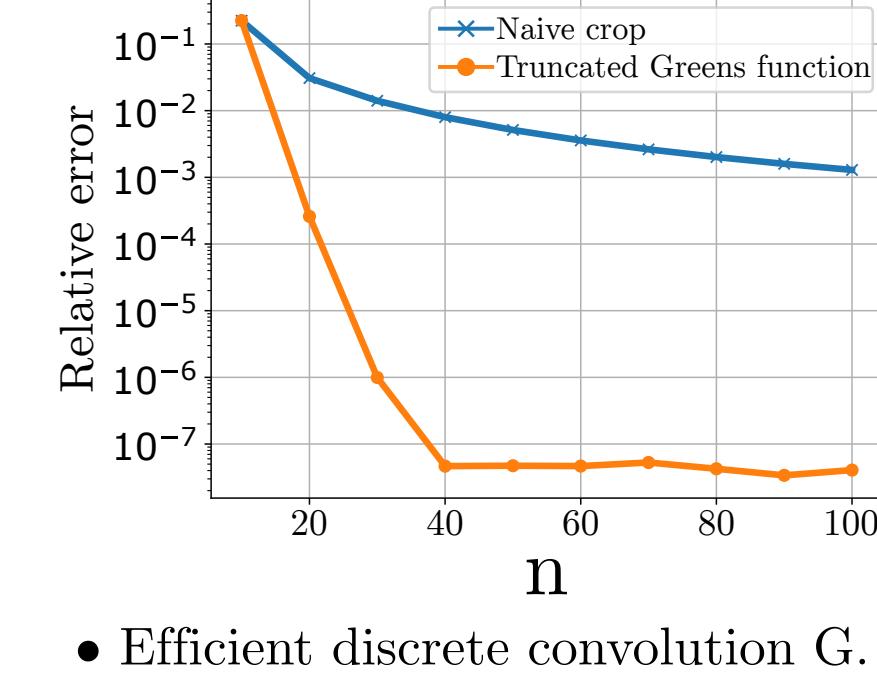
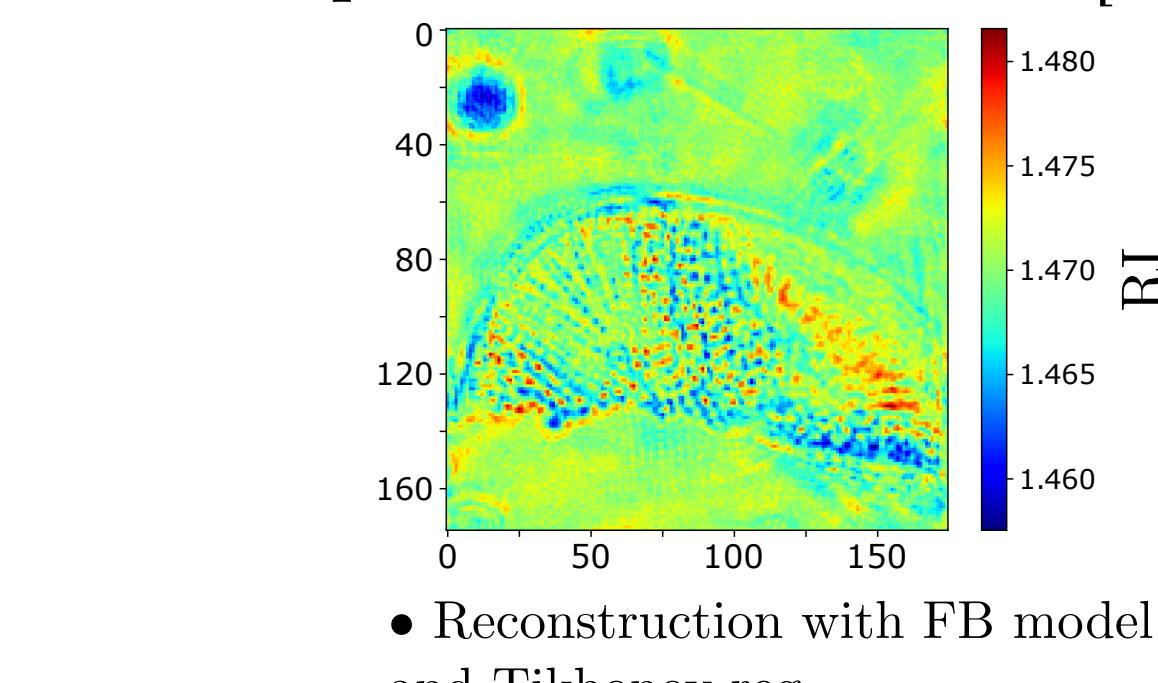
► \mathbf{P} applies the convolution with the pupil function $h(\mathbf{x})$.

► remove the background intensity.

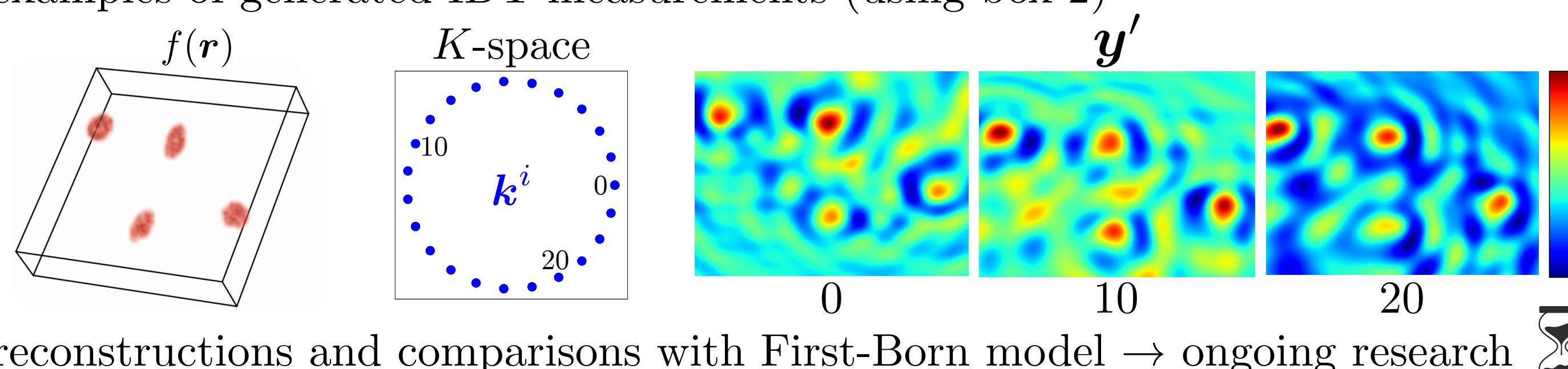
$$\mathbf{y}' = \mathcal{A}(\mathbf{f})$$

4. Numerical experiments

► validated previous results from [1-3].



► examples of generated IDT measurements (using box 2)



► reconstructions and comparisons with First-Born model → ongoing research

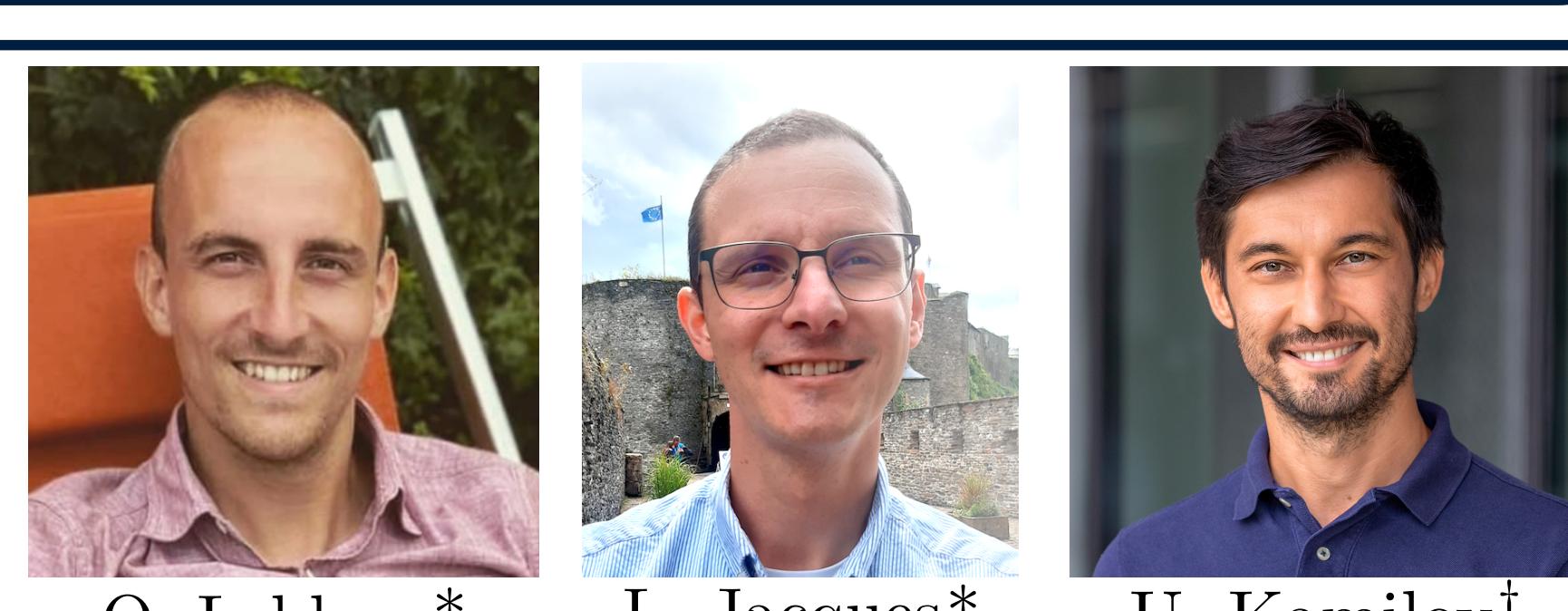
References

- [1] T. Pham, E. Soubies, A. Ayoub, J. Lim, D. Psaltis, and M. Unser, Three-Dimensional Optical Diffraction Tomography With Lippmann-Schwinger Model, IEEE Trans. Comput. Imaging, 6 (2020), p. 727–738
- [2] R. Liu, Y. Sun, J. Zhu, L. Tian, and U. Kamilov, Recovery of Continuous 3D Refractive Index Maps from Discrete Intensity-Only Measurements using Neural Fields, Nat Mach Intell 4, (2022), p. 781–791
- [3] J. Li, A. Matlock, Y. Li, Q. Chen, C. Zuo, L. Tian, High-speed in vitro intensity diffraction tomography, Adv. Photon., 1, (2019)

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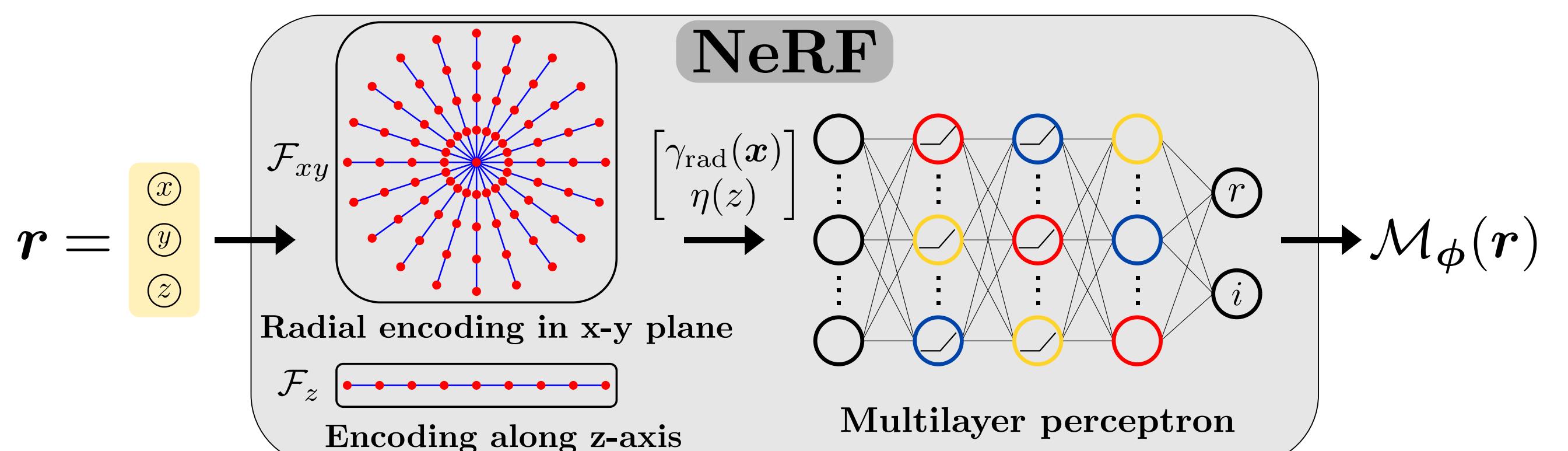
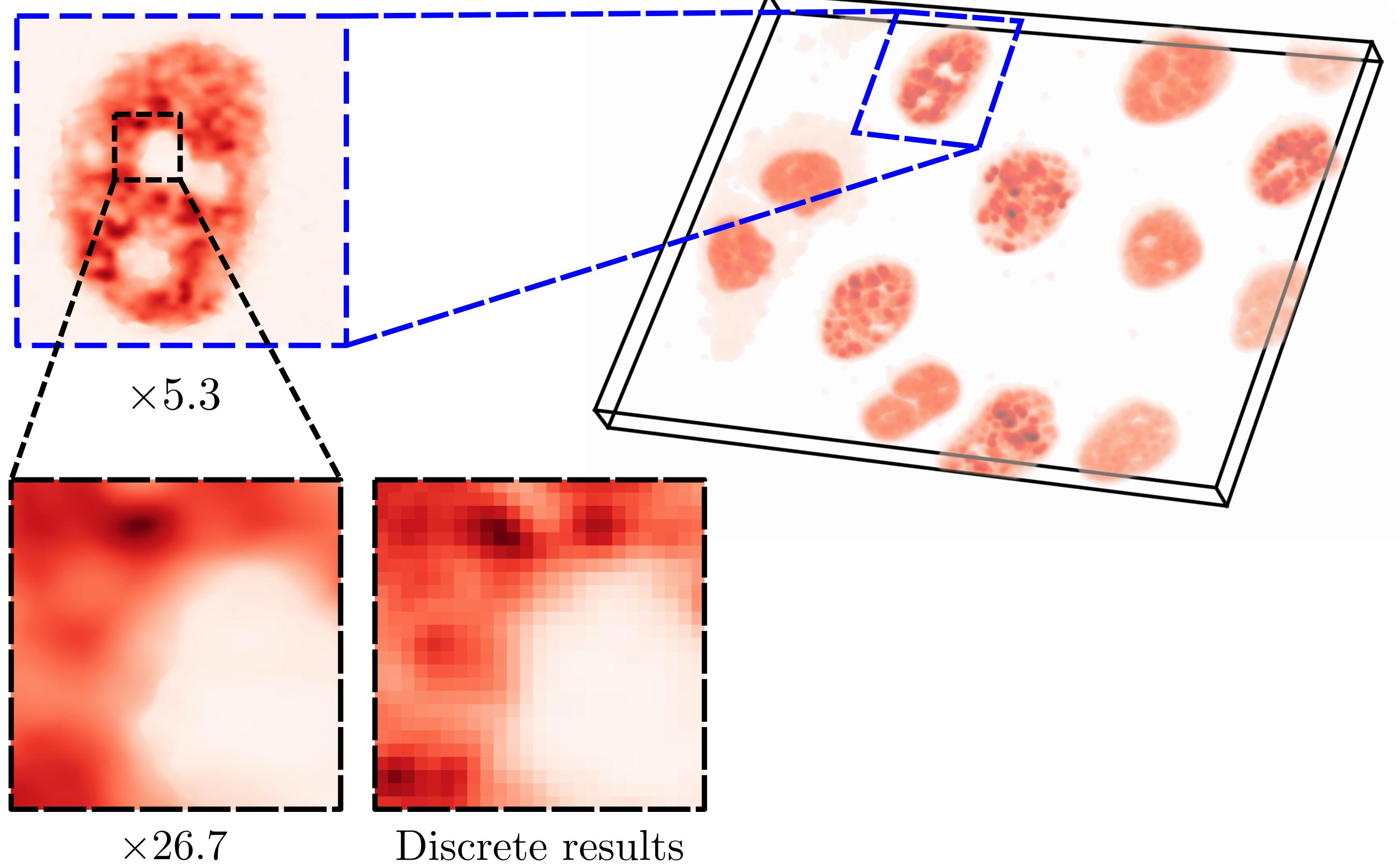
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3. Inverse problem

a. Continuous representation

► Query a NeRF $\mathcal{M}_{\phi}(\mathbf{r})$ at any \mathbf{r} with infinite precision [2].



with

$$\bullet \gamma_{\text{rad}}(\mathbf{x}) = \begin{pmatrix} \sin(2^0 \pi \mathbf{R}_{\theta} \mathbf{x}), \cos(2^0 \pi \mathbf{R}_{\theta} \mathbf{x}), \\ \vdots \\ \sin(2^{L-1} \pi \mathbf{R}_{\theta} \mathbf{x}), \cos(2^{L-1} \pi \mathbf{R}_{\theta} \mathbf{x}) \end{pmatrix} \quad \bullet \eta(z) = \begin{pmatrix} \sin(2^0 \pi z), \cos(2^0 \pi z), \\ \vdots \\ \sin(2^{L_z-1} \pi z), \cos(2^{L_z-1} \pi z) \end{pmatrix}$$

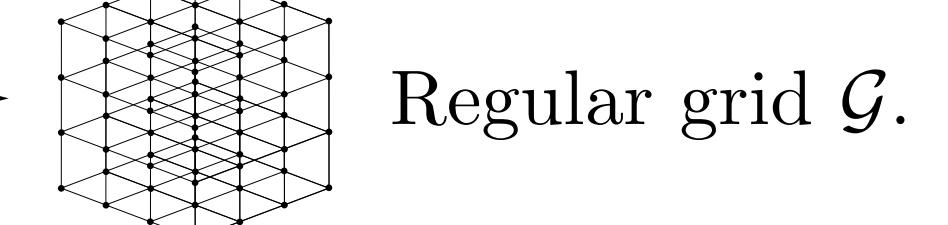
with \mathbf{R}_{θ} a set of K rotation matrices.

b. NeRF-parameterized inverse problem

$$\hat{\phi} = \arg \min_{\phi} \frac{1}{2} \|\mathbf{y} - \mathcal{A}(\mathbf{f})\|_2^2 + \mathcal{R}(\mathbf{f}) \quad \text{s.t. } \mathbf{f} = \{\mathcal{M}_{\phi}(\mathbf{r})\}_{\mathbf{r} \in \mathcal{G}}$$

Data fidelity Regularization

► Solved with automatic differentiation.



Conclusion

► Stabilized discrete physical models.

► Efficient continuous representation with NeRF.

► Upcoming reconstruction results.

► Perspectives

- Combine continuous representation with PINN-like architecture to get direct latent representation to discrete measurements mapping.

- Replace NeRF by COIN++ approach to avoid one NeRF per reconstruction.

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