

# 3D Tomography with Synchrotron Data

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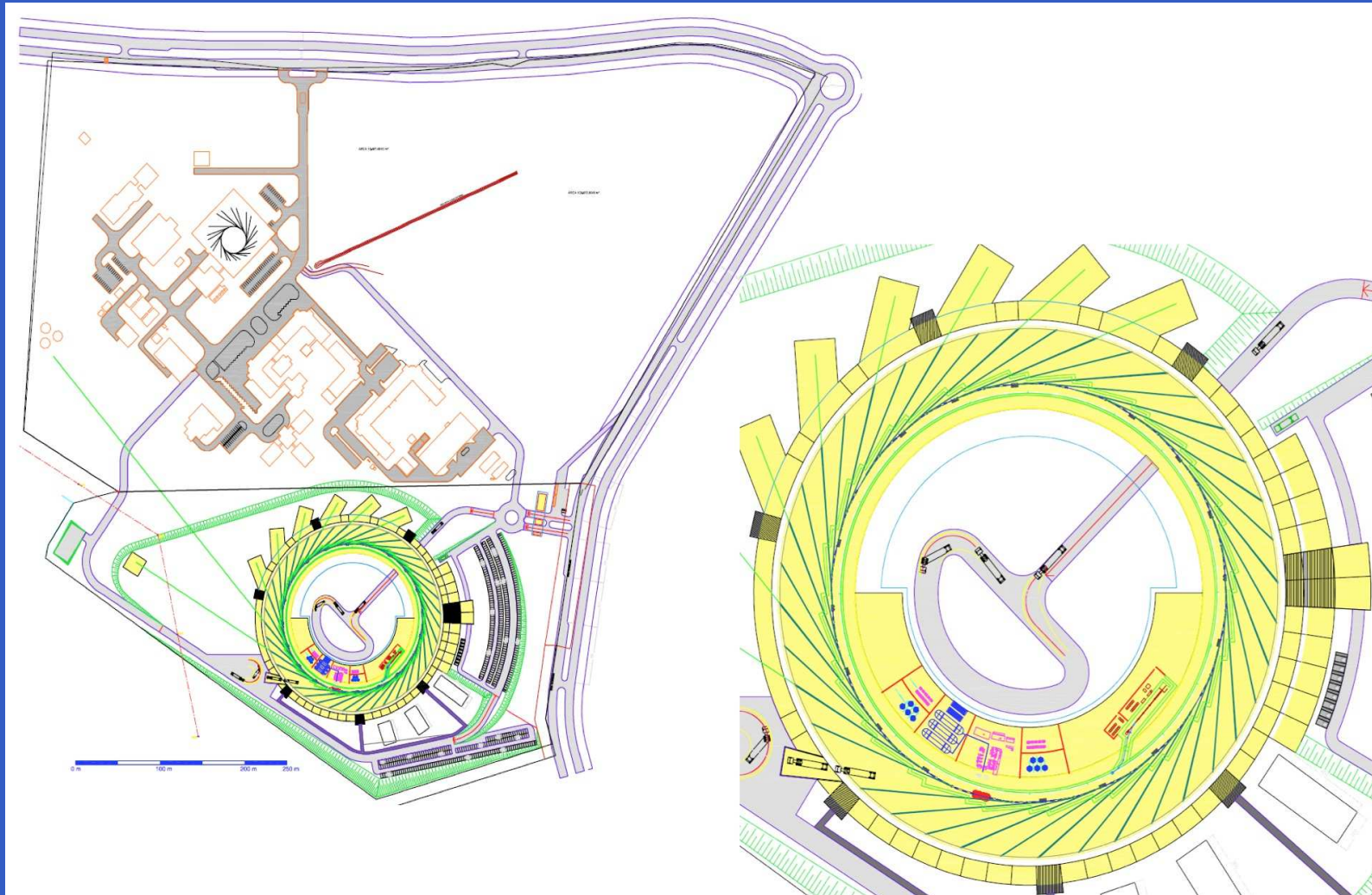
CNPEM - Brazilian Synchrotron Light Source

Campinas, SP - Brazil

# Light Source: 2nd generation



# Future: 3rd generation



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  - First approach: Stacking of 2D images

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  - $\mathbb{Q}$ : your “favorite” reconstruction algorithm!

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- So,

$$\begin{array}{ll} f = \mathcal{B}[q] & \text{Expensive part} \\ q = \mathbb{F}[p] & \text{Non-expensive part (FFT)} \end{array}$$



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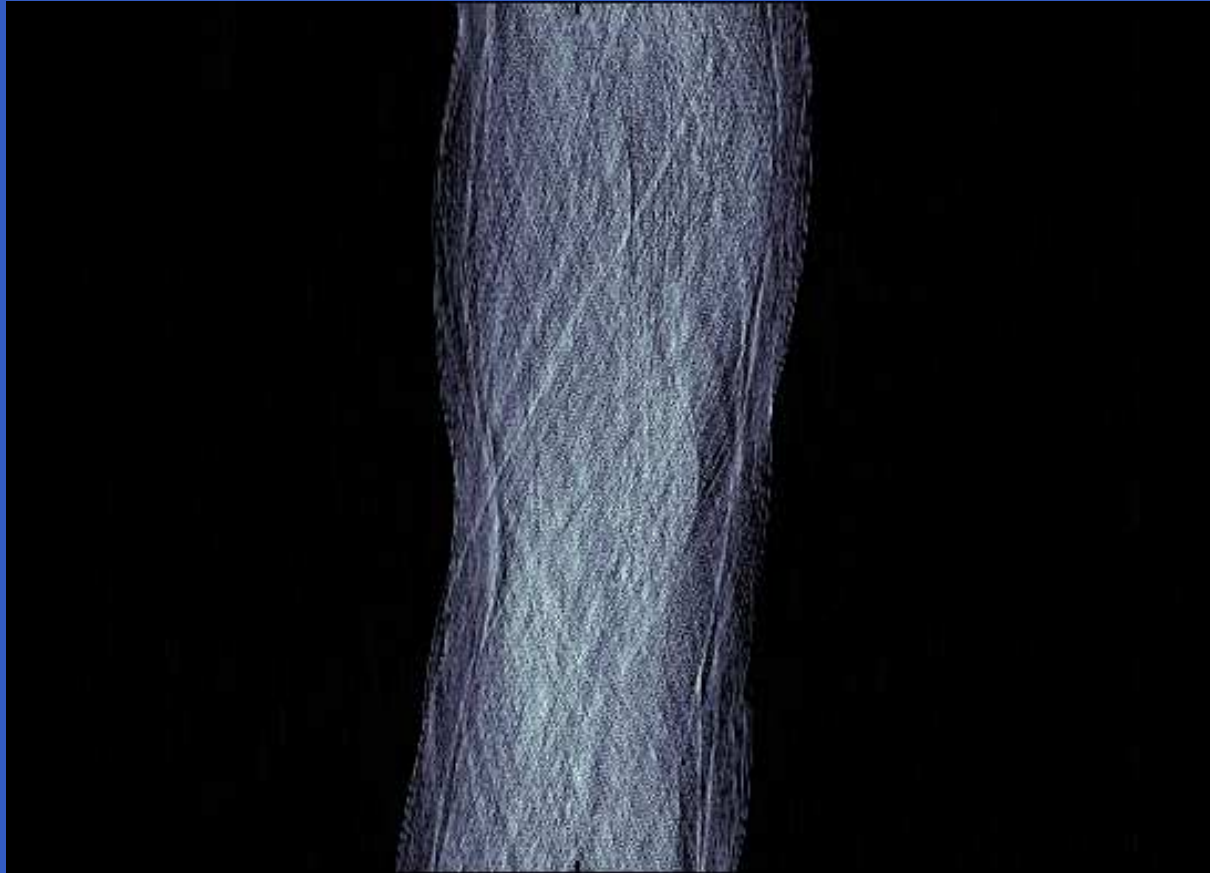
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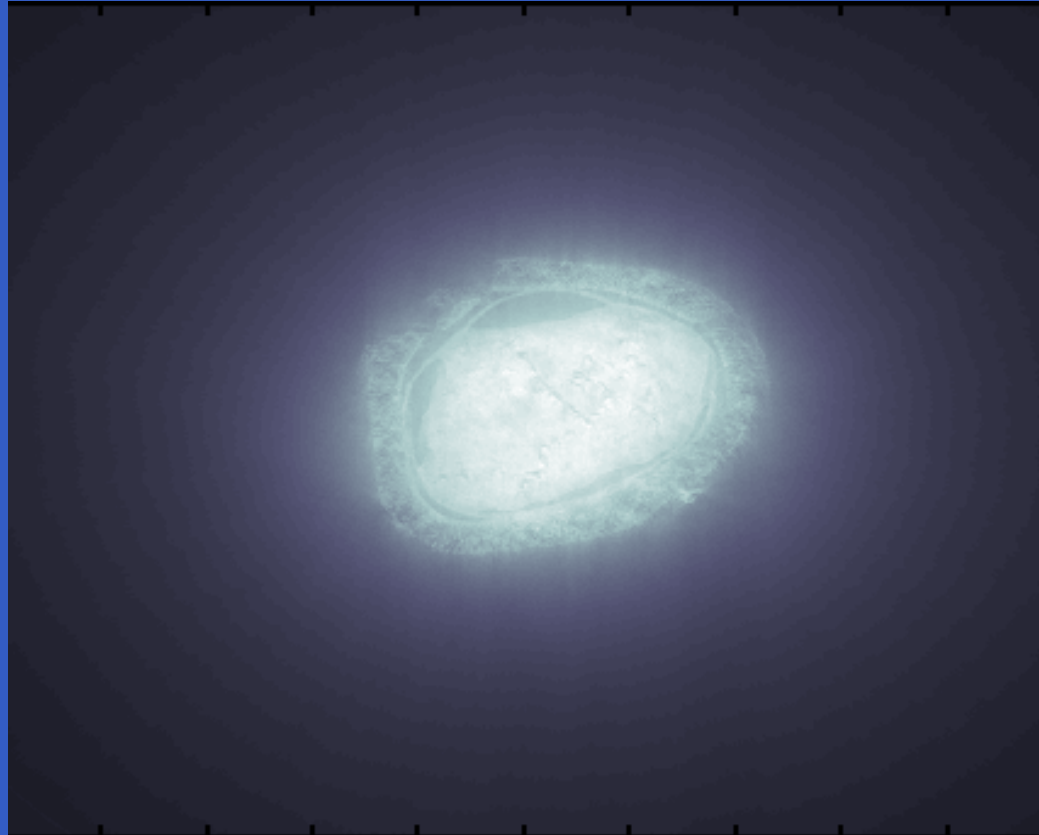
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- 3D:  
 $N$  slices  $\Rightarrow$  total cost:  $O(N^4)$



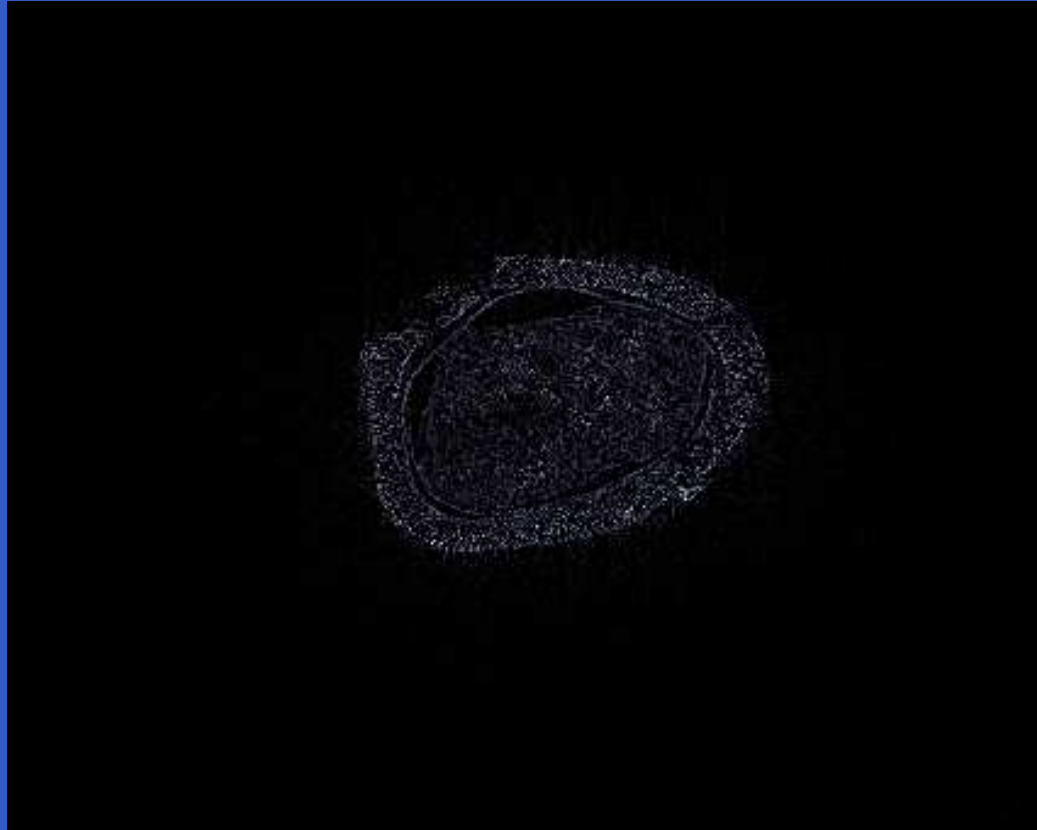
# Real sinogram: Fiber



# Backprojection



# Filtered Backprojection



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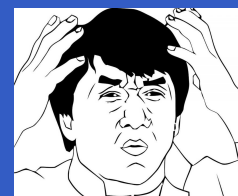
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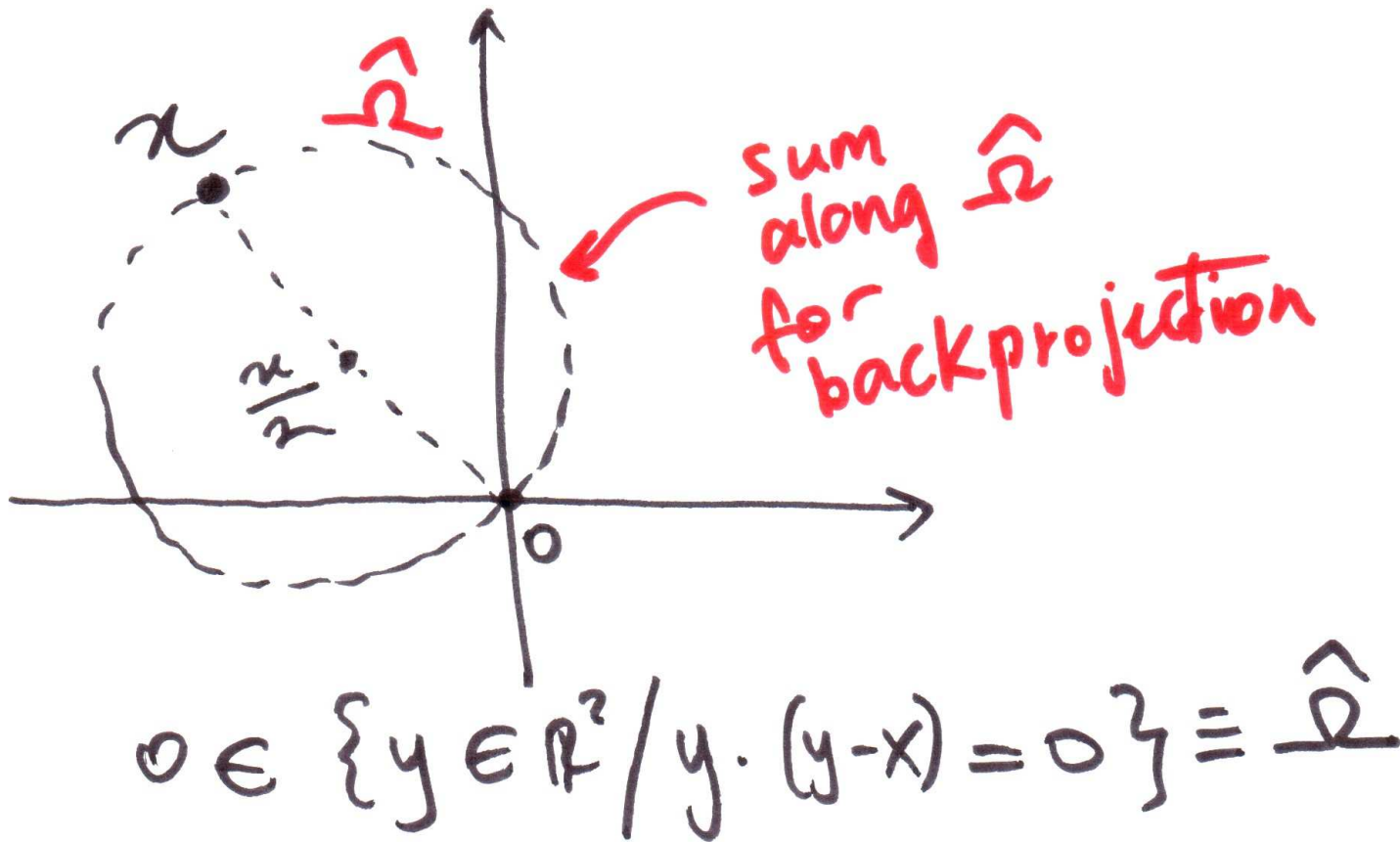
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- $\hat{p}(y)$ : sinogram @ cartesian coordinates
- $y \cdot (y - x) = 0 \iff \|y - \frac{x}{2}\|_2 = \frac{1}{2}\|x\|_2$

# Geometrically...



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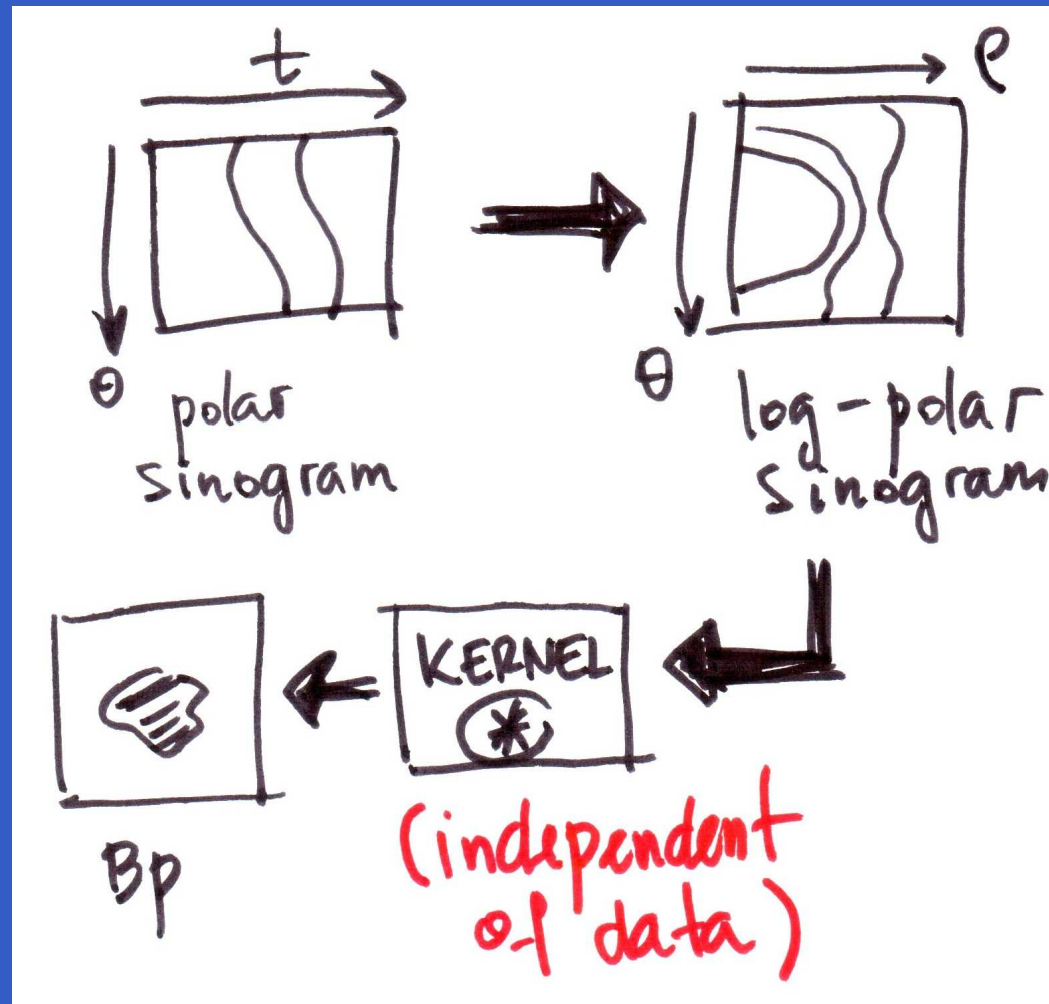
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- $\ell, z$  are *log-polar* coordinates

# New paradigm for $\mathcal{B}$

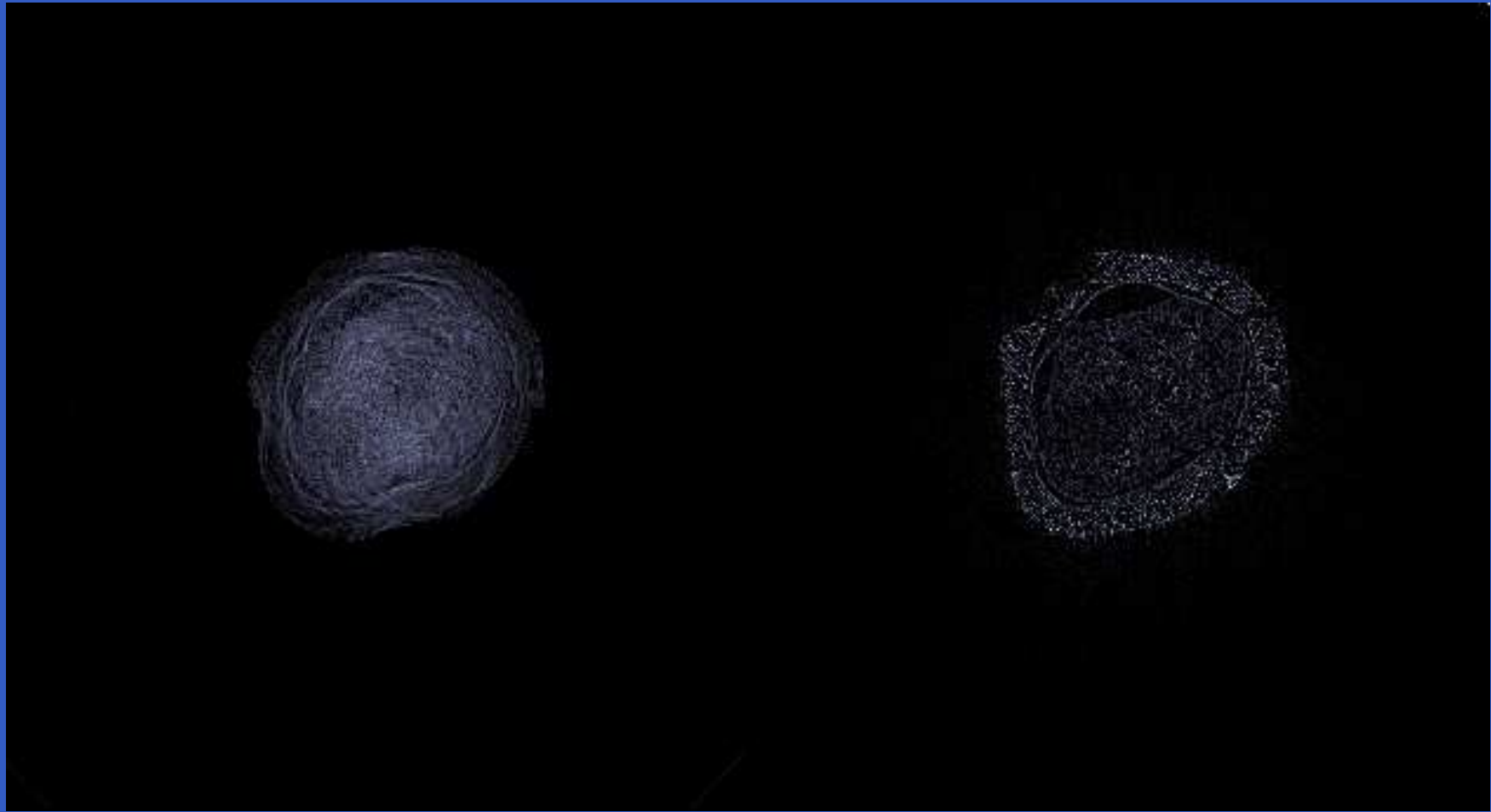


# Example: cartesian sinogram

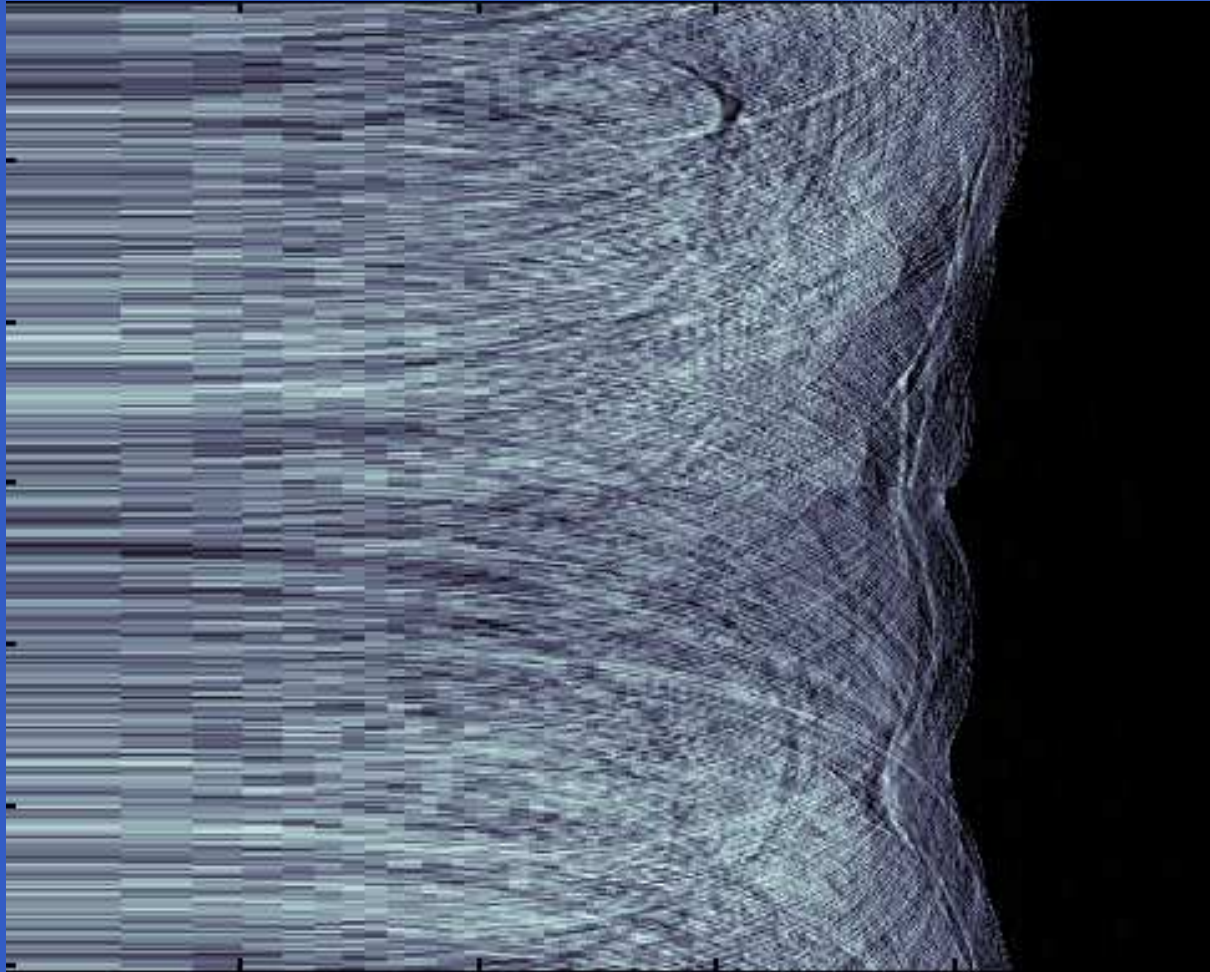




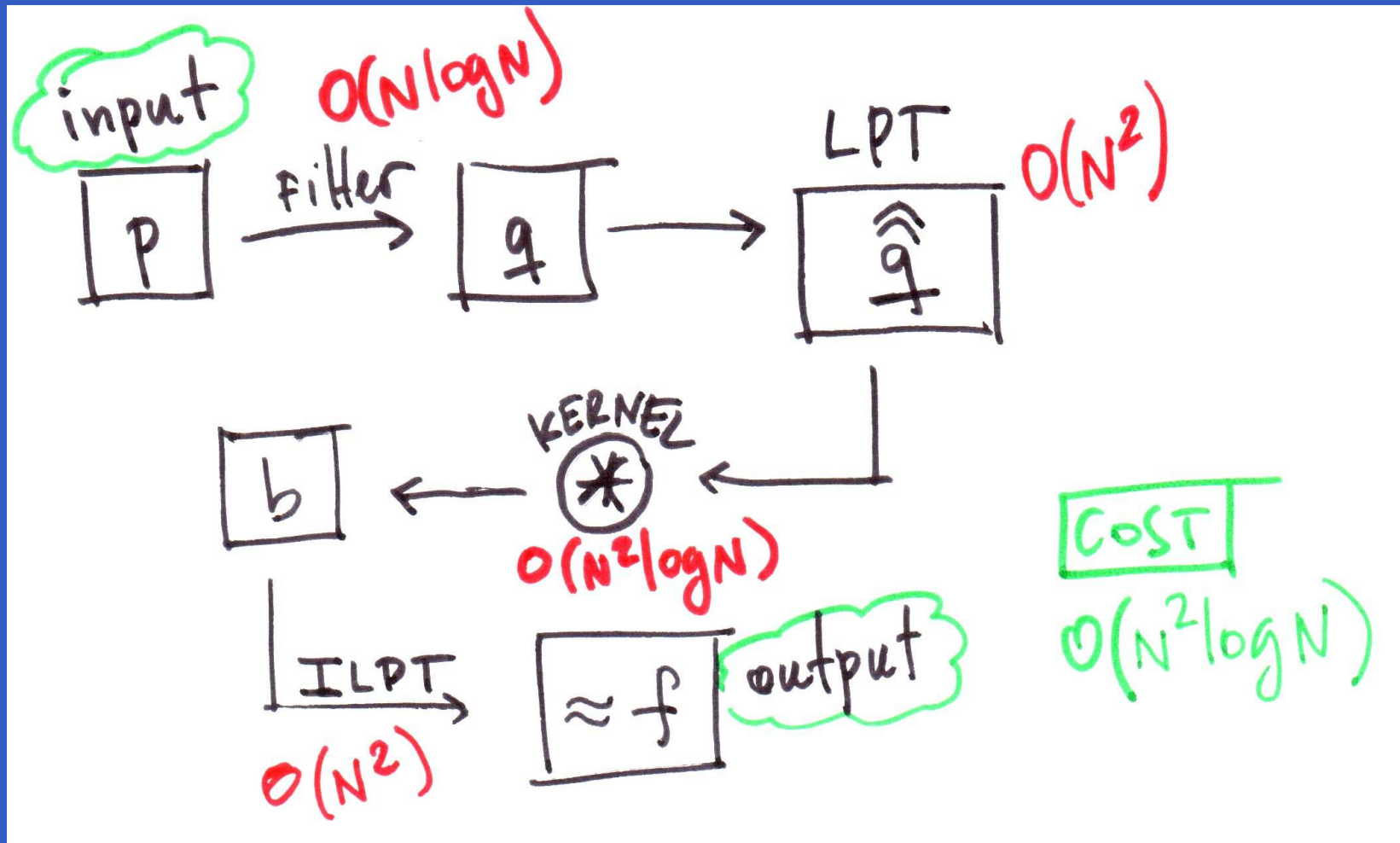
# Example: cartesian sinogram $\times$ FBP



# Example: log-polar sinogram



# Fast 2D reconstruction



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  - Others

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fast and accurate?

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