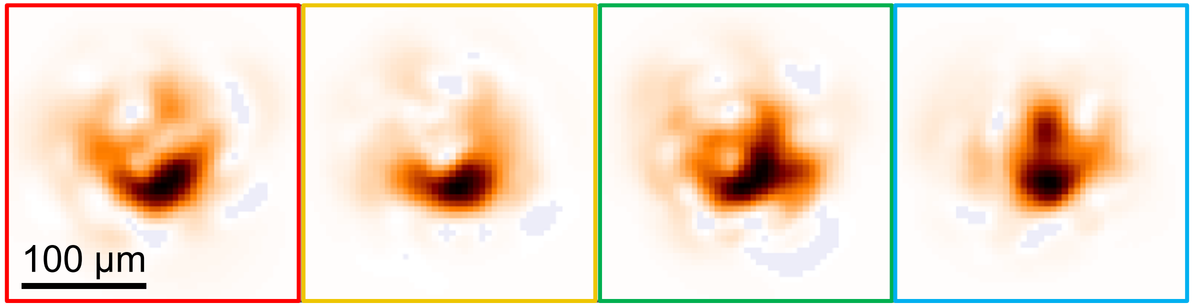
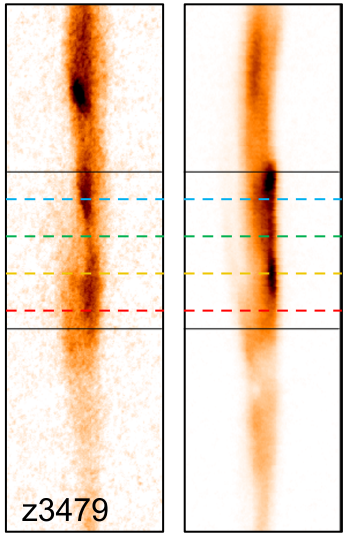
SAND2021-14110C

Tomographic reconstruction of MagLIF emission volumes from orthogonal projections



Reconstructed slices of MagLIF stagnation emission



PRESENTED BY

Jeff Fein

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Sandia National Laboratories, Albuquerque, NM

63rd Annual Meeting of the APS Divisio

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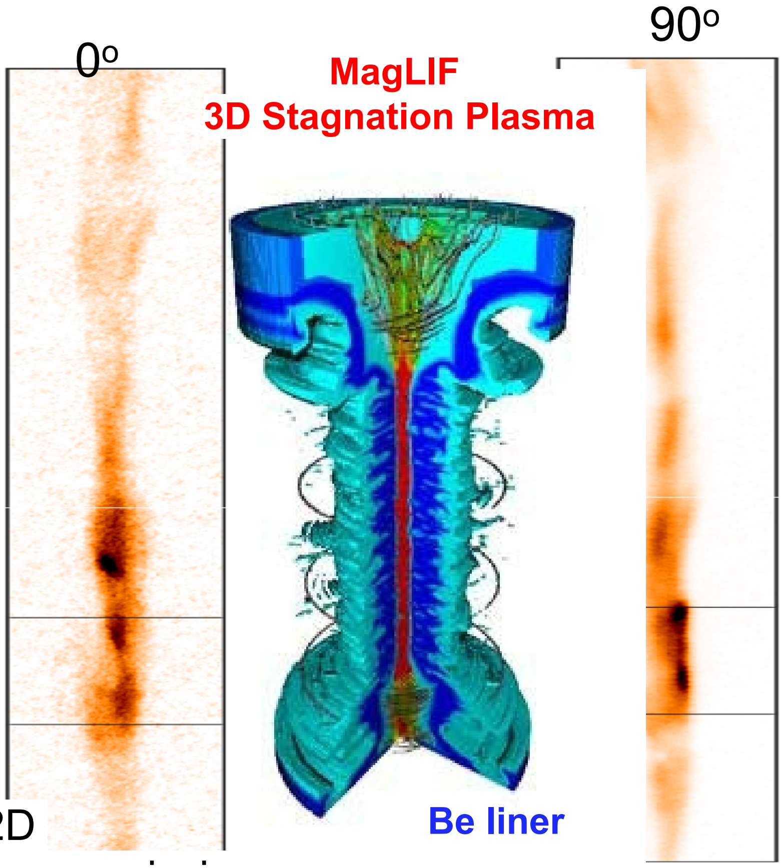
Summary

We are making progress on tomographic reconstruction from limited views in MagLIF to understand stagnation conditions in 3D

- 3D tomographic reconstruction for MagLIF and other high-energy-density experiments is challenging due to limited views from space constraints
- For simple 2D slice reconstruction, orthogonal views may be insufficient for reliable solutions, but a third view in the future could provide enough information for accurate assessment of morphology
- Using learned 3D basis functions with coherent axial structures may adequately constrain 3D reconstructions with just 2 orthogonal views
- Initial 3D reconstructions of MagLIF stagnation columns show irregular hot spot structure

Measuring fuel and mix volumes in 3D is important for MagLIF, but challenging due to limited diagnostic views

Orthogonal projections @ 7.2 keV from spherical crystal imager[1]



2D x-ray emission projections

- Past fuel volume estimates biased by 1D or 2D assumptions
  - Creates bias in inferred stagnation parameters (pressure, mix, etc.)[2]
- Measuring morphology of fuel and liner in 3D is important to understand how mix is degrading performance

Assumption: liner ρR(θ) varies slowly enough over stagnation column width that attenuation can be ignored

1. E.C. Harding, APS-DPP 2020, 2. P. Knapp, **BI01.00004** (this conference)

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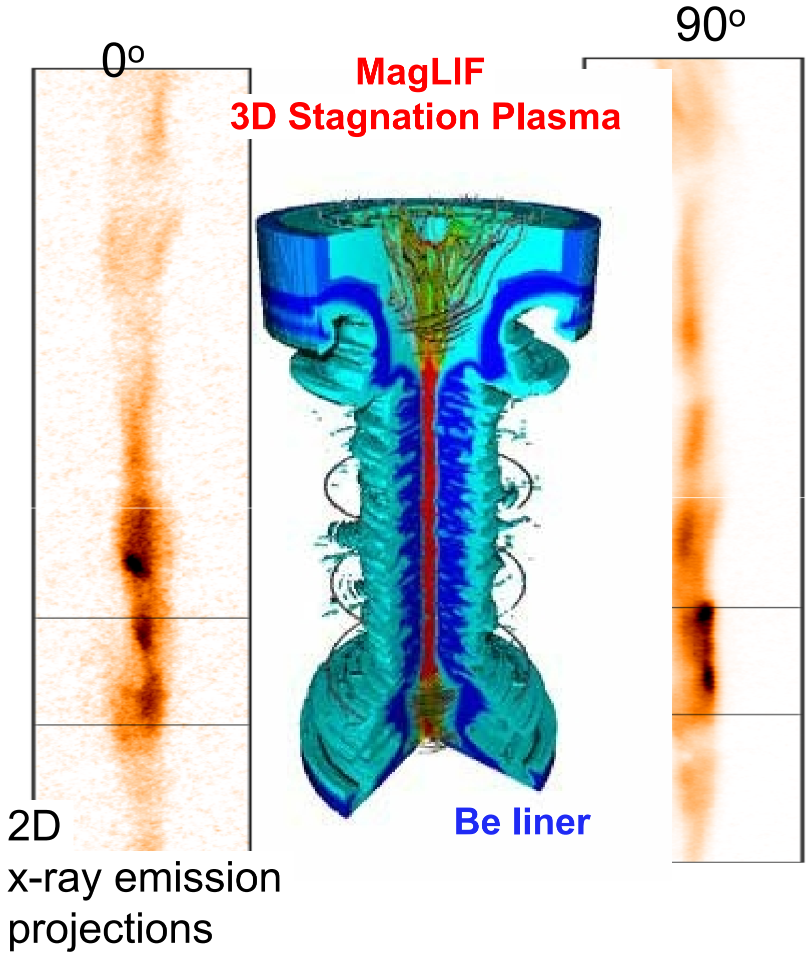

- Past fuel volume estimates biased by 1D or 2D assumptions
  - Creates bias in inferred stagnation parameters (pressure, mix, etc.)[2]
- Measuring morphology of fuel and liner in 3D is important to understand how mix is degrading performance
- Two views have been fielded, but still a very limited data set for uncovering general 3D shape reliably
- Need to add constraints for a more well-posed problem:
  - Smooth solutions, non-negativity (emission), cylindrical/helical structures

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We are using basis-function expansions to better constrain the reconstruction and encode natural geometries into the solutions

Data model:

$$\mathbf{y} = A\mathbf{f} + \epsilon$$

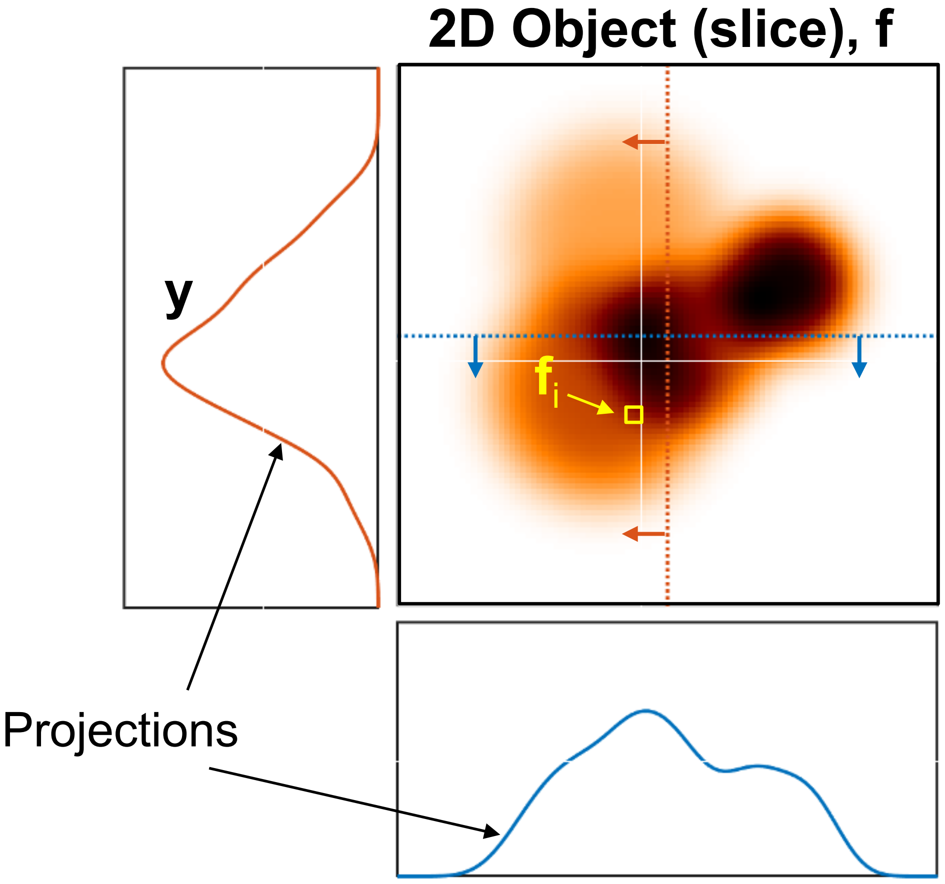
- Projection matrix: A
- Object, array of pixels/voxels: $\mathbf{f}$
- Projection measurements: $\mathbf{y}$
- Noise: ϵ

Basis function expansion:

$$f(x,y) = \sum_{b}^{B} a_b d_b(x,y) \Rightarrow \mathbf{f} = D\mathbf{a}$$

"Dictionary": D

- Pixel Basis (solve for each pixel, $\mathbf{f}_i$)
  - Significant line-of-sight/streaking artifacts with few views
- **Global basis functions**
  - Encode natural geometries, smoothness, etc.
  - Circular harmonics, SVD, etc.
- Learning-based (train convolutional neural networks)



SVD = Singular Value Decomposition

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Projection measurements → $\mathbf{y}$; Noise → ϵ

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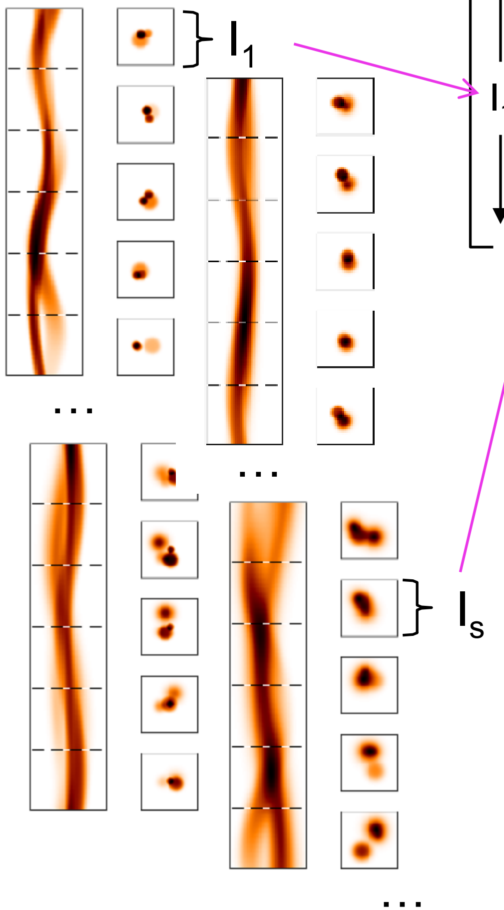
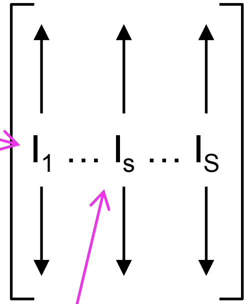
"Optimal" basis functions, calculated from SVD on training volumes

"Training Data"
(slices of helical blobs)

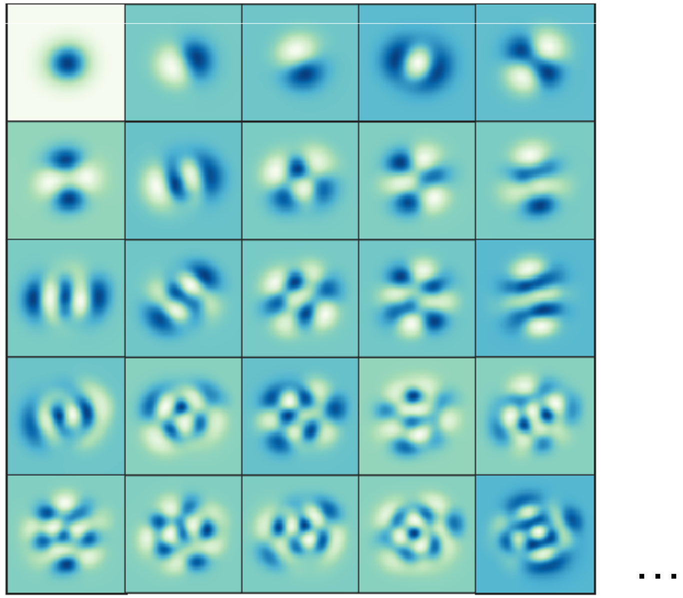


Matrix of slices/volumes



$$= X = U\Sigma V^{\mathsf{T}}$$

U: Left singular vectors ~ principal components



First 25 modes

SVD = Singular Value Decomposition

Even a highly reduced problem using basis expansions for a 2D slice demonstrates data sparsity using just 2 views

- **Reconstruction**:*

L-1 norm encourages sparsity

Minimize w.r.t. $\mathbf{a}$: $$\frac{1}{2}\|\mathbf{y} - A\,D\mathbf{a}\|^2 + \alpha\|\mathbf{a}\|_1$$

s.t. $$D\mathbf{a} = \mathbf{f} \geq 0$$

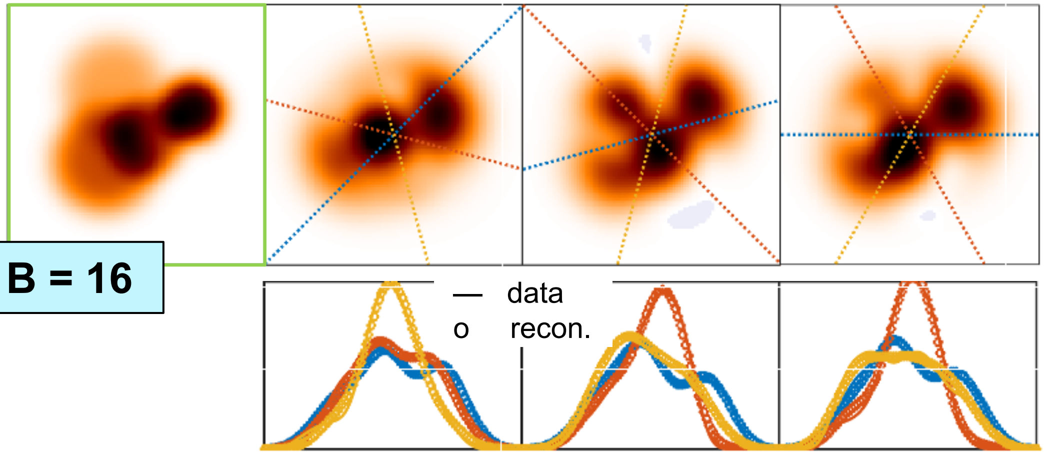
- Solution is highly sensitive to which projections are used
- Can add modes, change value of α, etc., but reconstructions still exhibit pathologies

Adding a third view substantially improves "convergence" to a common solution

α = 5e-5

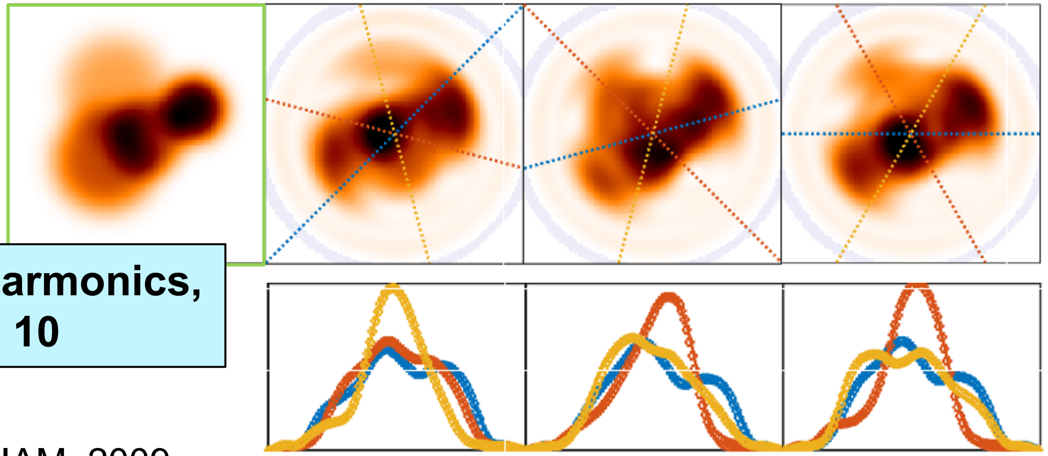
Reconstructions, rotating projections

Ground Truth



SVD, B = 16

Projections

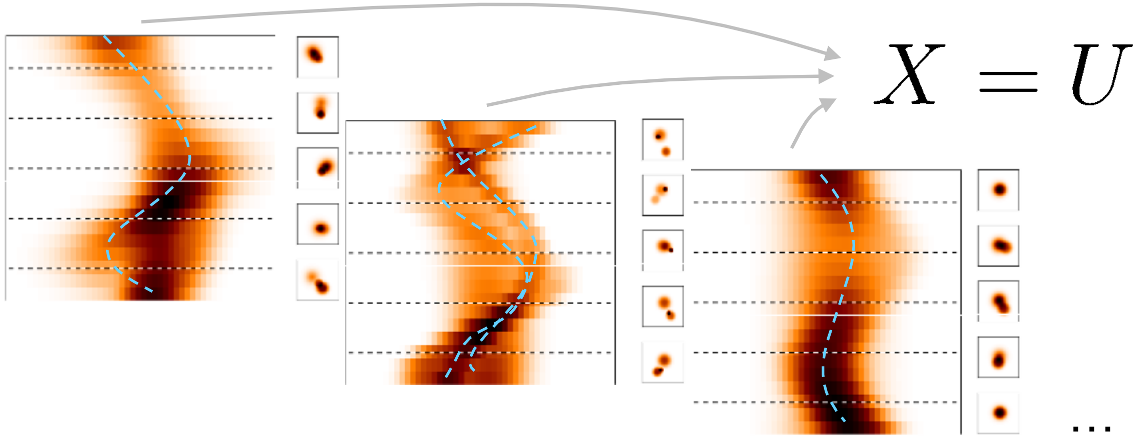


Circular harmonics, M = 5, K = 10

*Solve with Fast-Iterative Shrinkage Thresholding Algorithm: Beck & Teboulle, SIAM, 2009

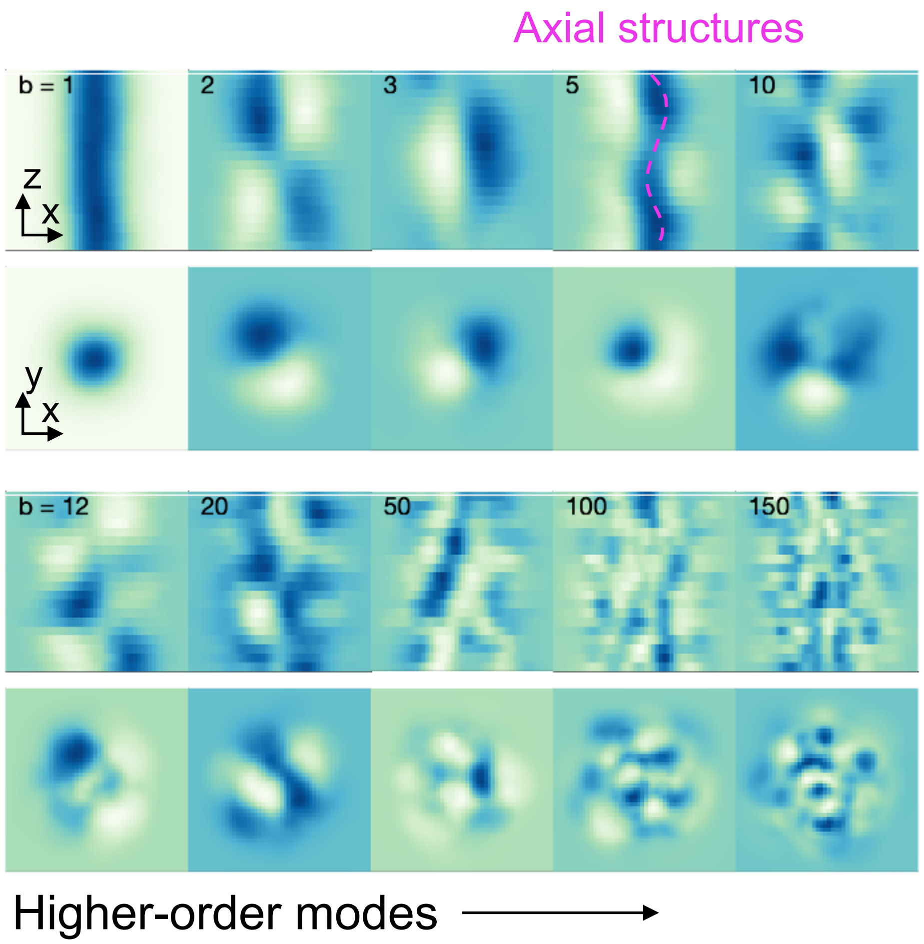
3D basis functions (calculated with SVD) can incorporate axially coherent structures, further constraining solution

3D training data volumes (helical blobs)



$$X = U\Sigma V^{\mathsf{T}}$$

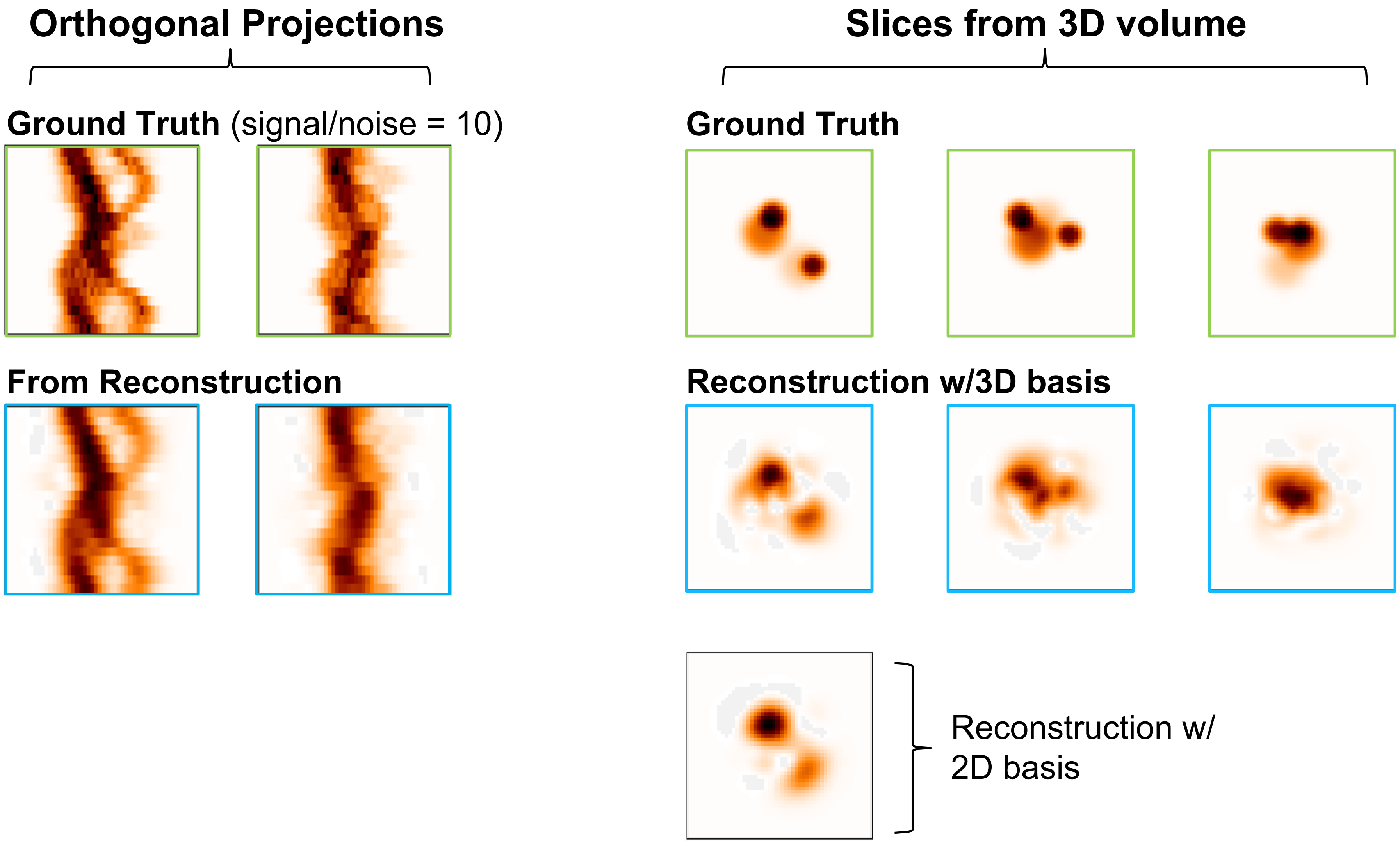
Slices of basis functions from SVD



- Generate a large training data set (N = 200) of 3D volumes with limited axial extent
- Compute SVD on this set of 3D volumes to get fundamental modes and use to reconstruct full 3D volume
- **Future**: Build confidence in training data by using metrics to determine if images from training volumes are in same distribution as exp. images[1]

1. W. Lewis, PP11.00170

Reconstructions on test object (not included in training data) with 3D basis functions shows accurate morphology



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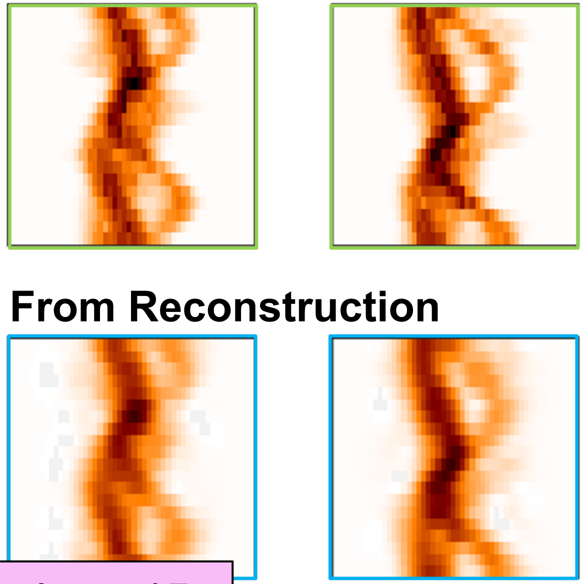
Orthogonal Projections

Ground Truth (signal/noise = 10)

From Reconstruction

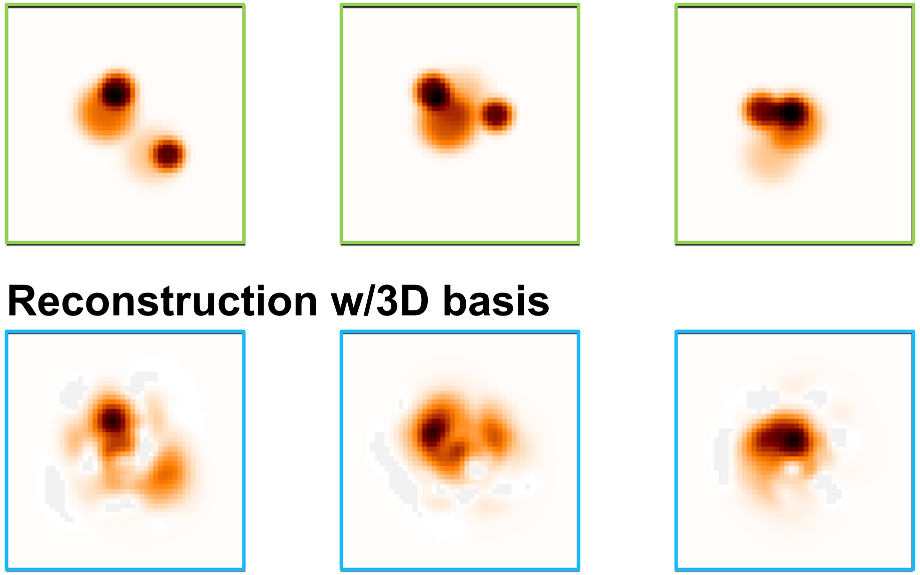


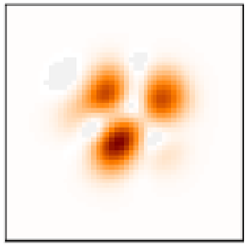
Rotate projections 45º

Slices from 3D volume

Ground Truth

Reconstruction w/3D basis



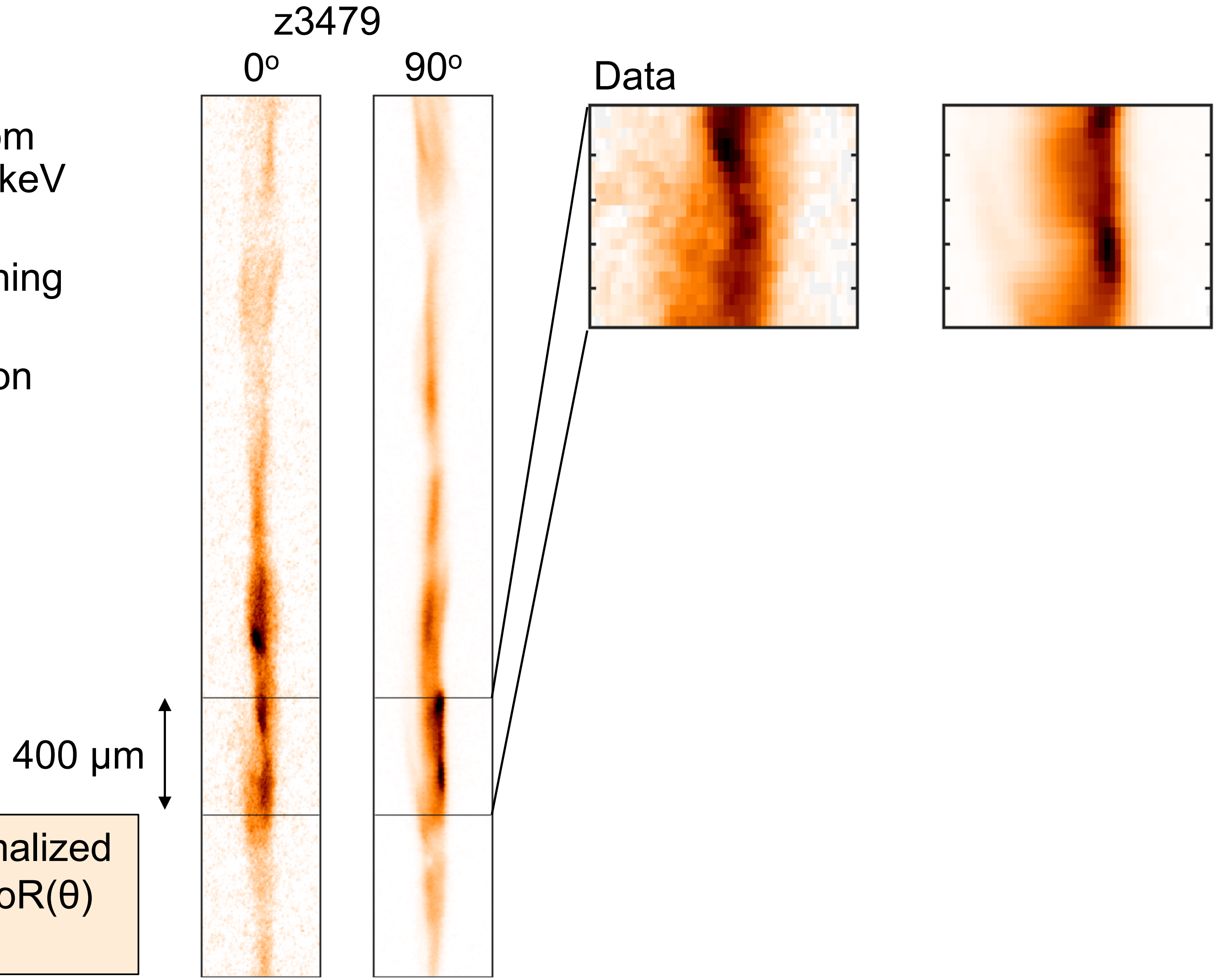


Reconstruction w/ 2D basis

Reconstructions with 3D basis functions are less sensitive to which projections are used!

Initial 3D reconstructions of a MagLIF stagnation column show asymmetric hot spots

- Reconstruct volume patch from orthogonal projections at 7.2 keV using learned 3D SVD basis
- Extend to full volume by stitching overlapping patches together
- Projections from reconstruction match data to within <15%



*Projections are intensity-normalized assuming slowly varying liner ρR(θ) and center-of-mass aligned

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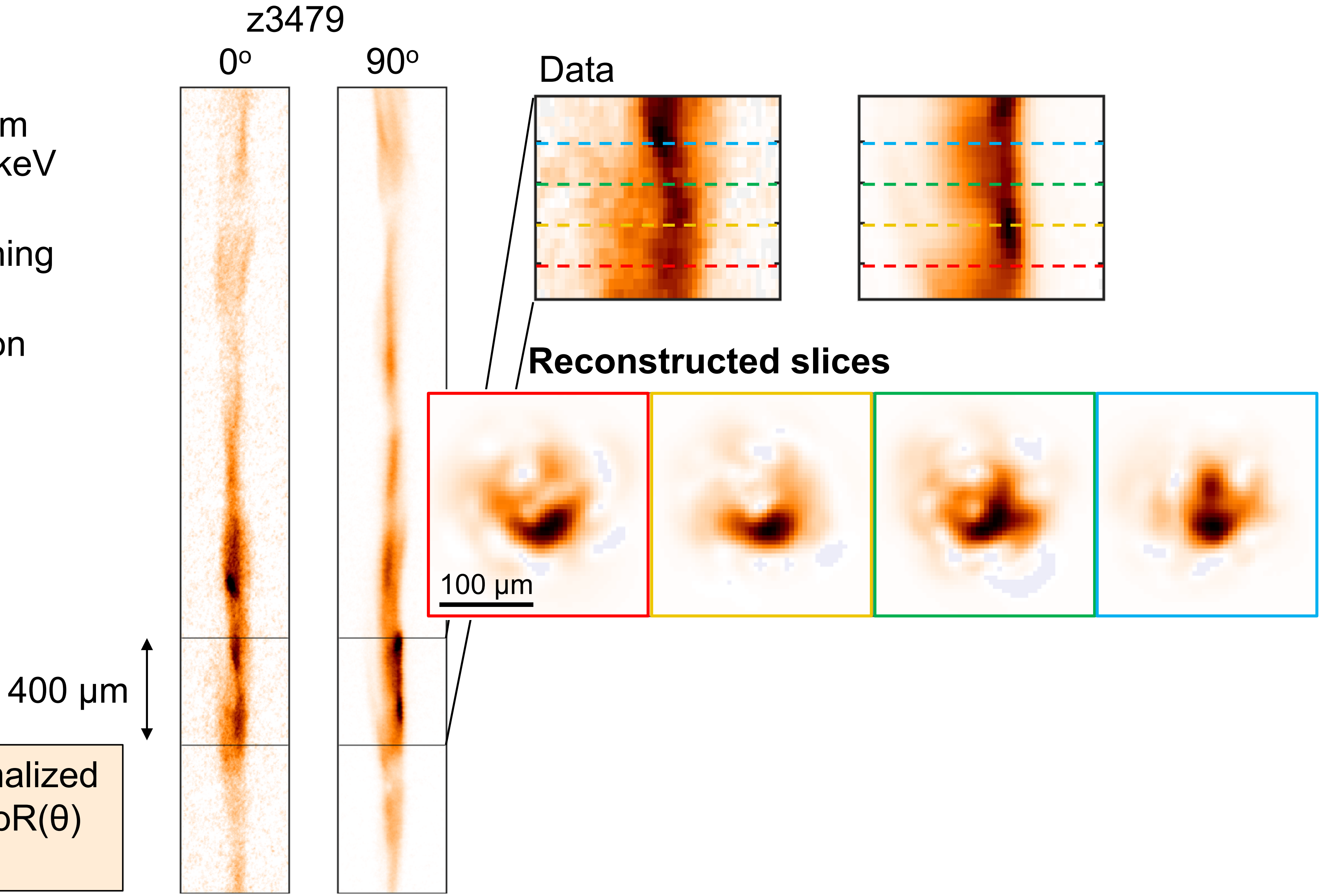

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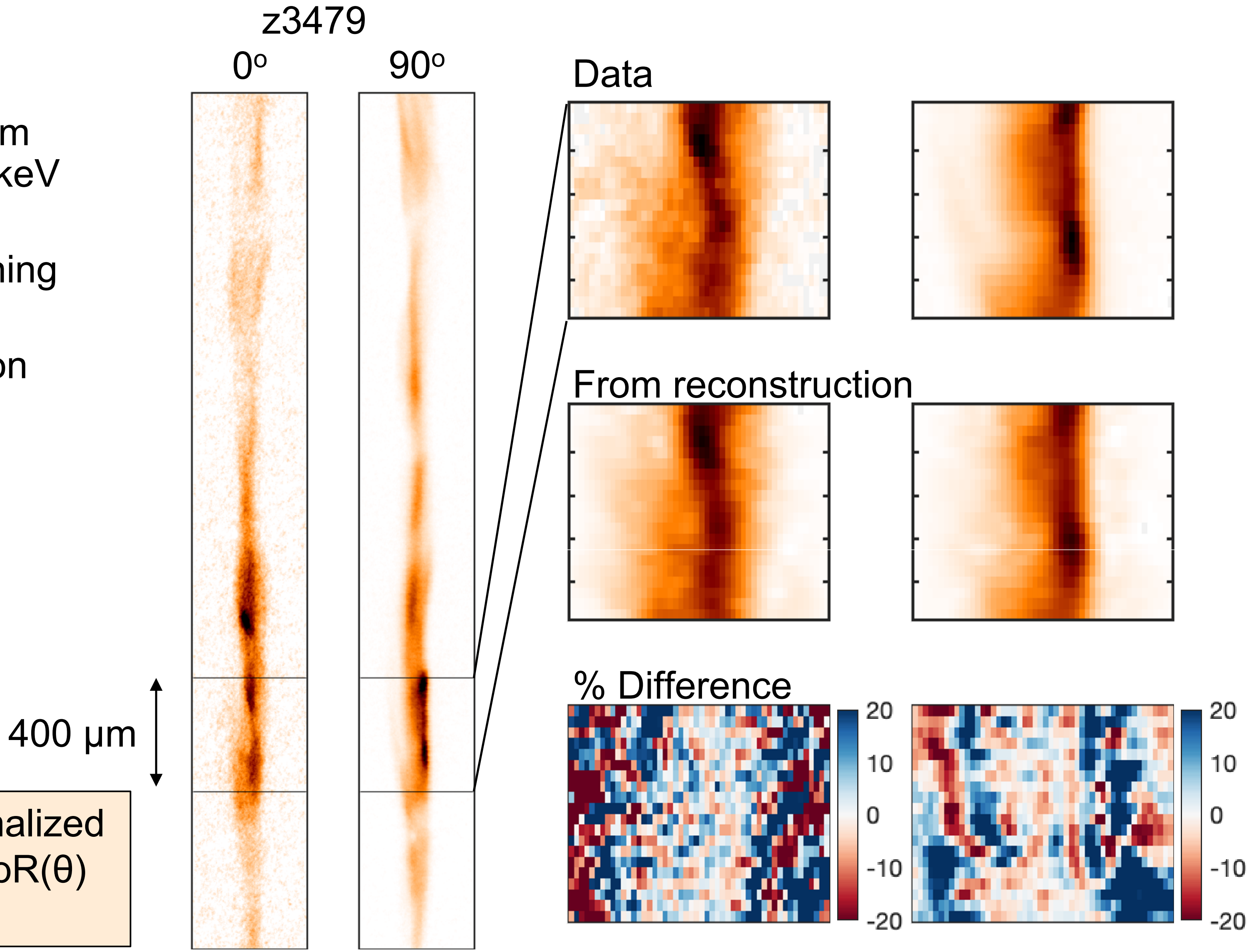

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