

# Computational light-field microscopy enables high-throughput, scattering-mitigated, volumetric neural activity imaging

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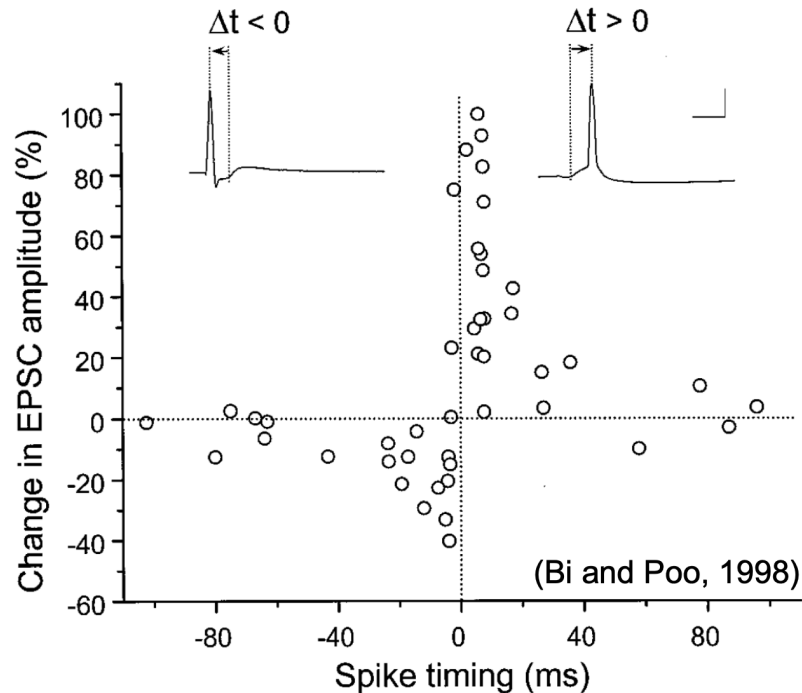
Imperial College London

13 August 2024

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## Why imaging voltage **fast** is important:

Living neuronal network update their weights on millisecond time scales



Studying brain circuits with electrodes is “a dismaying exercise in tedium, like trying to cut the back lawn with a pair of nail scissors.”

Hubel & Wiesel, 2005

“It seems reasonable to imagine an array of 100 photodetectors that would allow simultaneous potential recordings from 100 individual cells.”

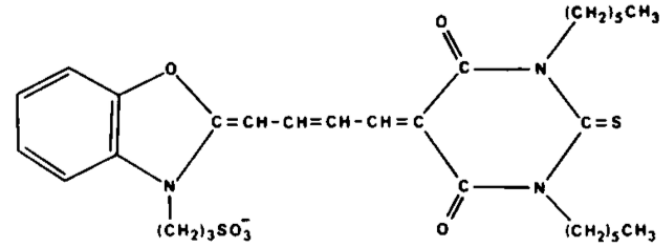
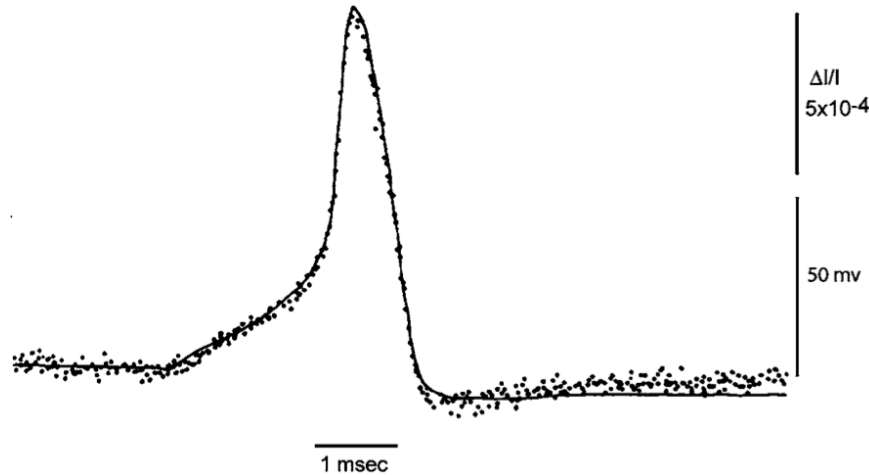
Lawrence B. Cohen, 1977

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# Why imaging voltage **fast** is important:

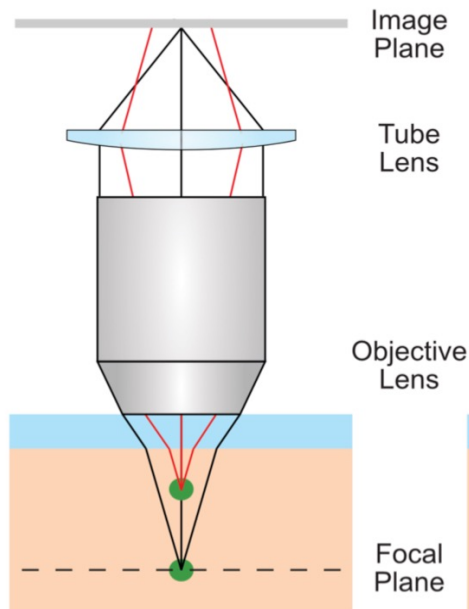
Optical voltage reporters (can) track voltage with microsecond fidelity

SQUID AXON

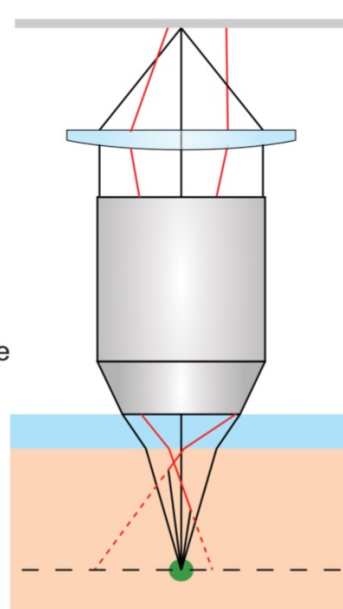


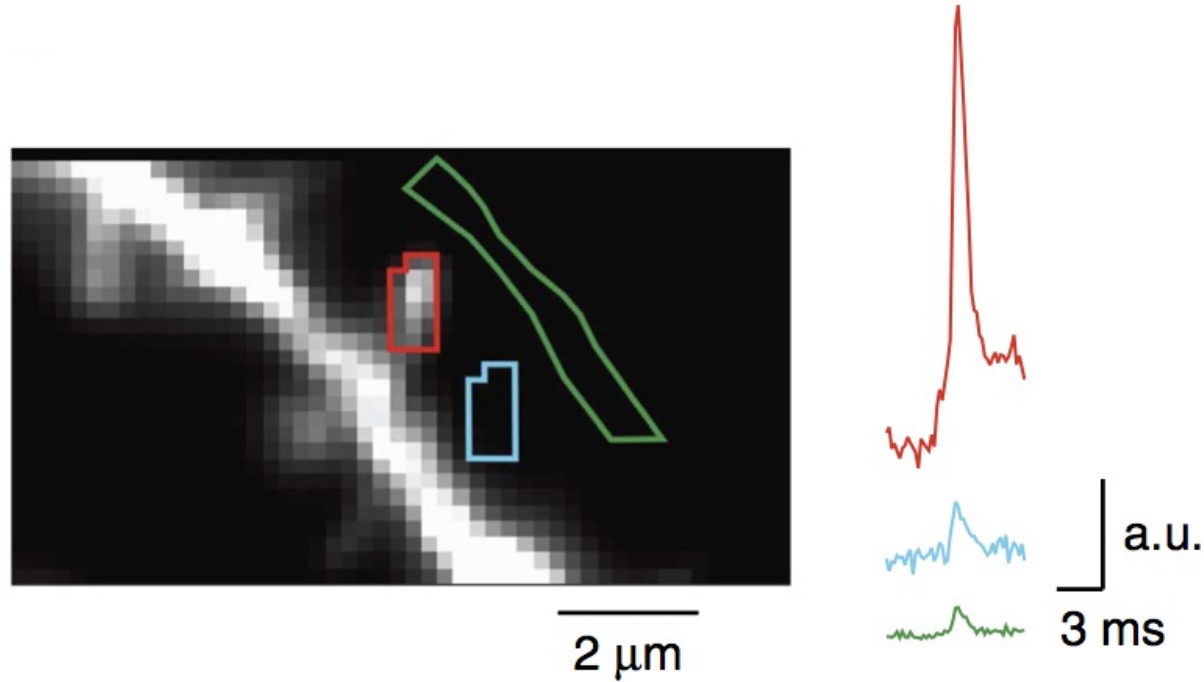


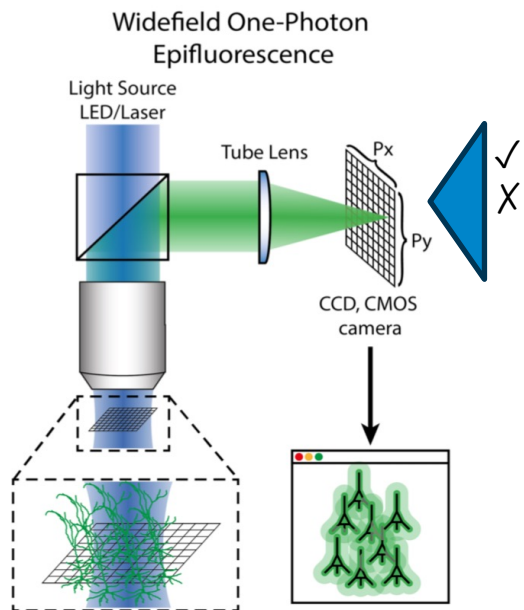
Imaging  
volumes



Scattering

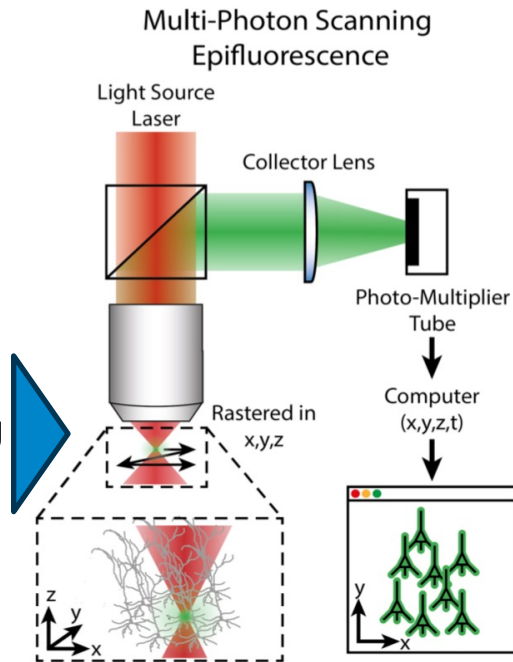




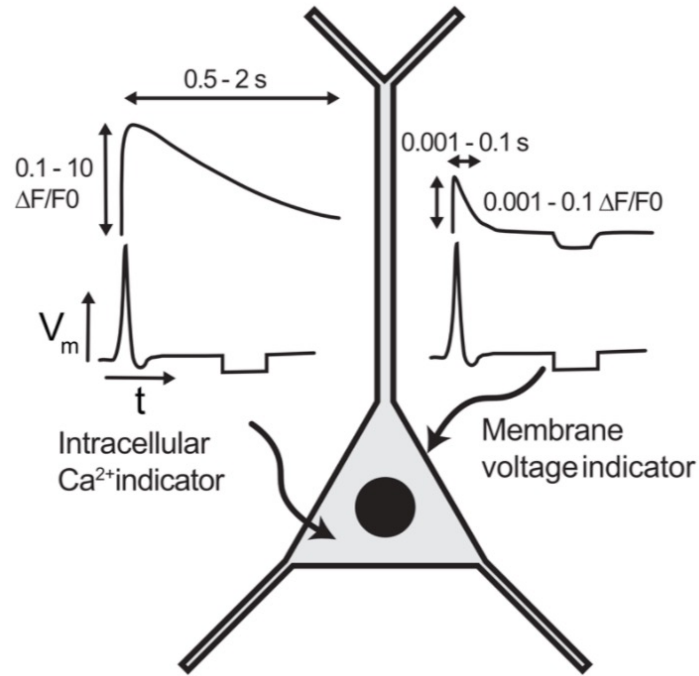


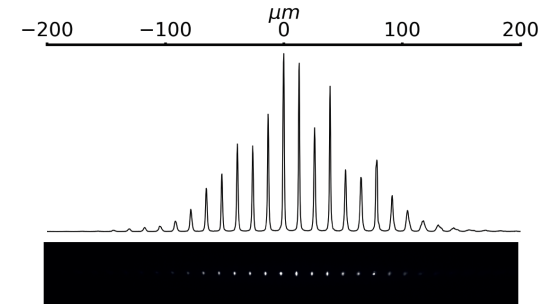
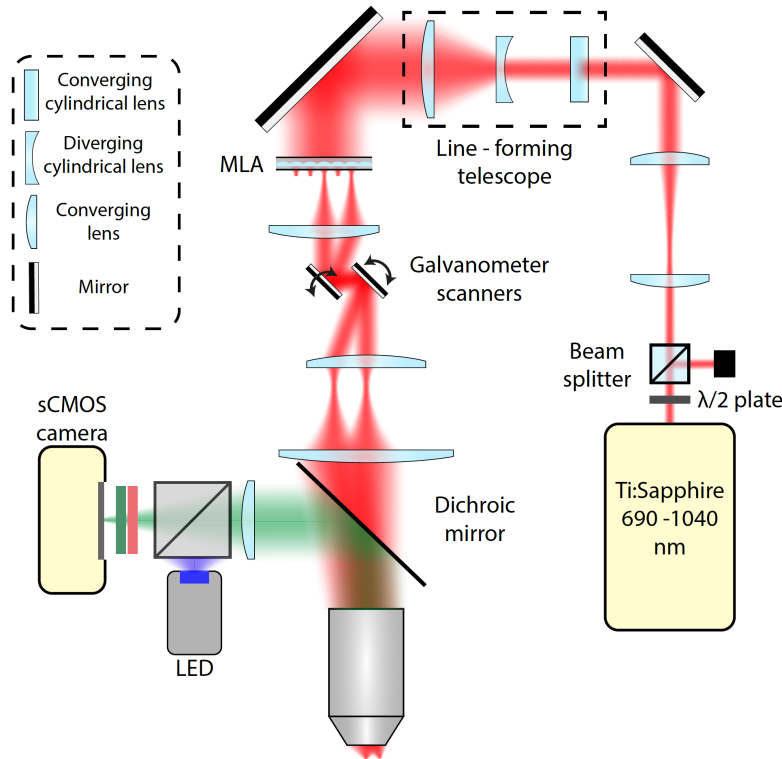
High bandwidth  
Degraded by  
out-of-focus and  
scattered light

- ✓ Optical sectioning
- ✓ Robust to scattering
- ✗ Low-photon budget

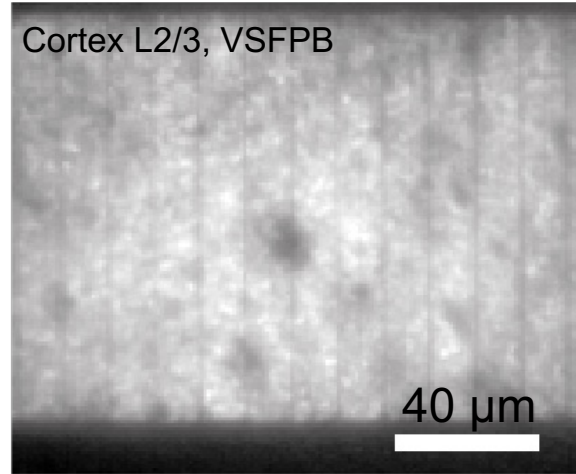


## Solution 1: Image something slower (e.g., calcium)

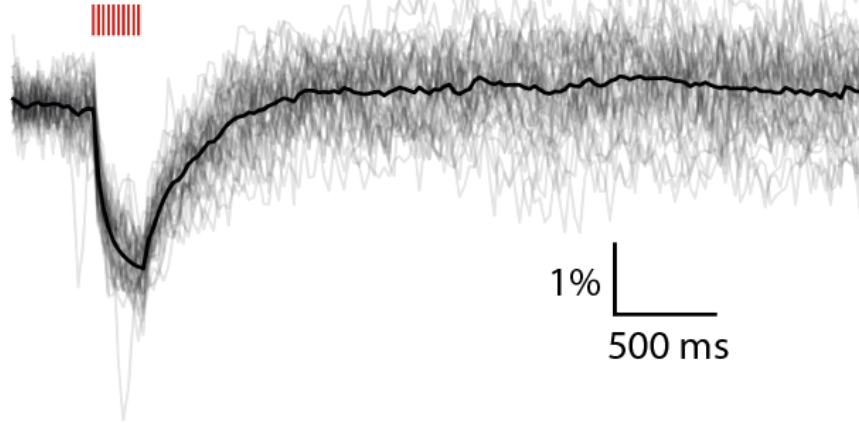




## Solution 2: Scan multiple foci

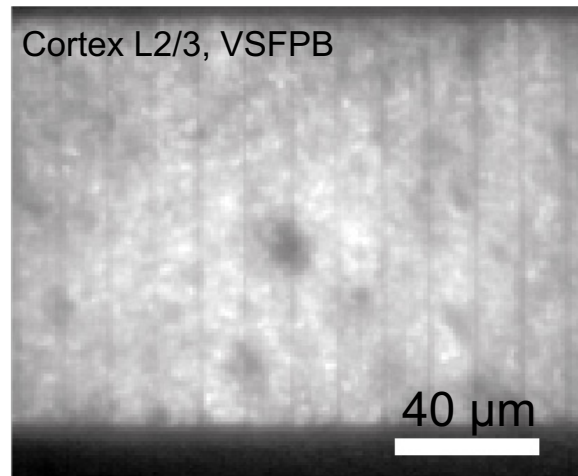


extracellular  
stimulation



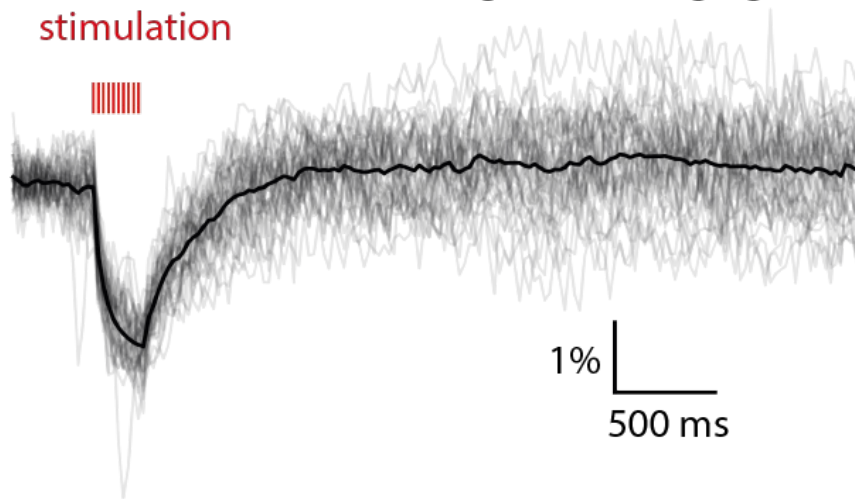
20 fr/s, widefield one-photon, single trial



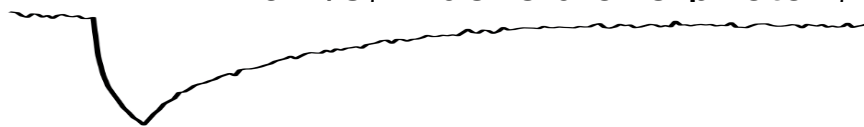


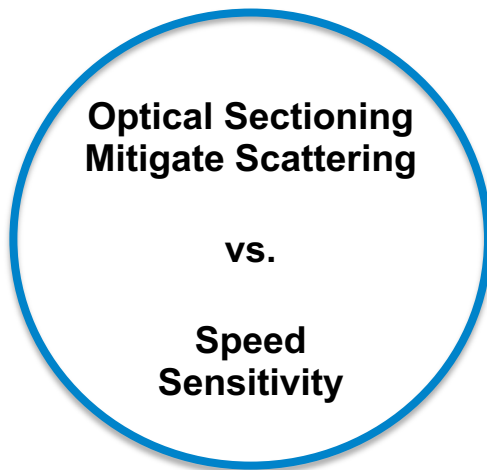
$$S/N \propto \frac{\Delta F}{F} \sqrt{\phi}$$

extracellular  
stimulation



20 fr/s, widefield one-photon, single trial







# Voltage Imaging Competing Requirements

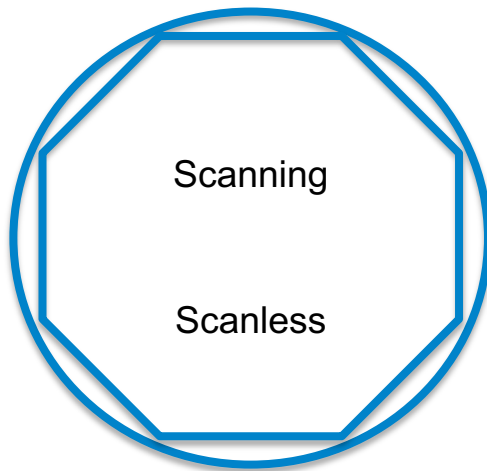
Scanning

**Optical Sectioning  
Mitigate Scattering**

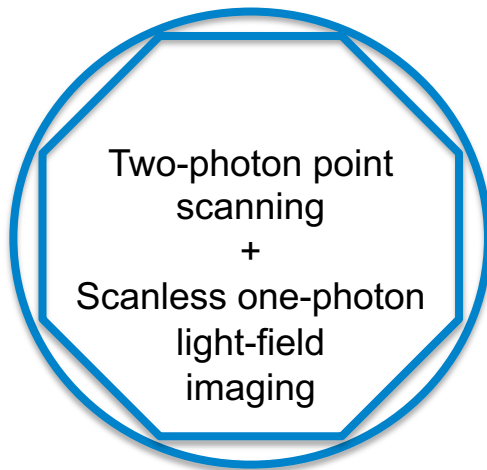
**vs.**

**Speed  
Sensitivity**

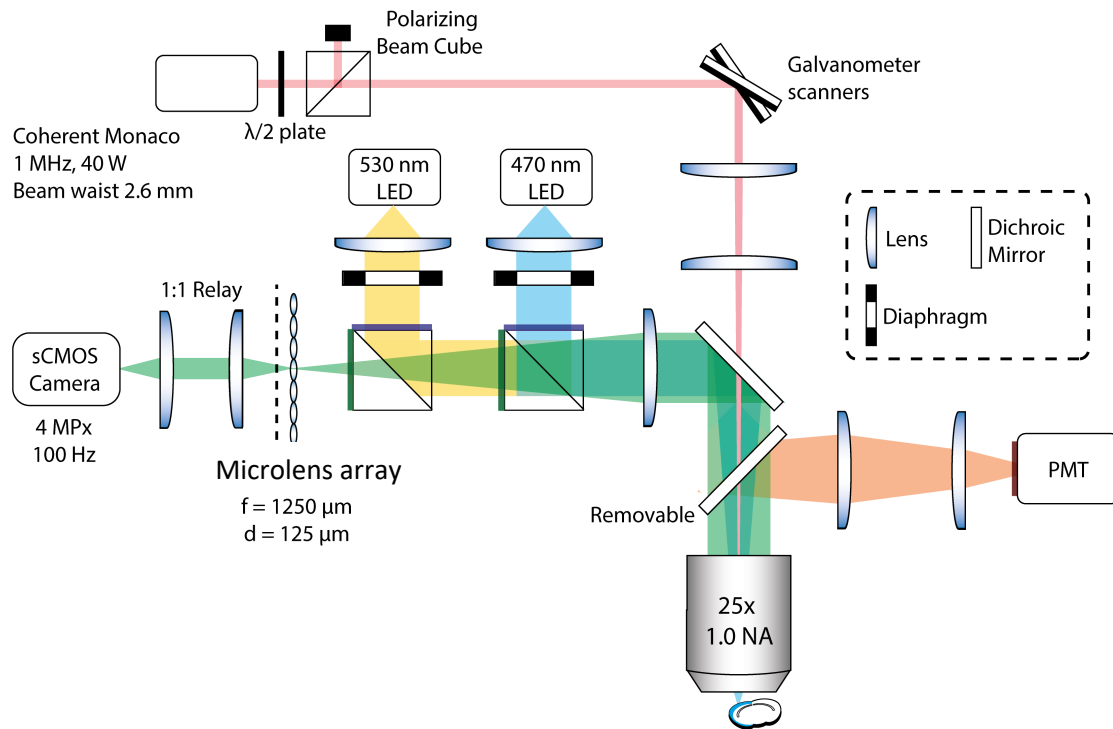
Scanless



# Voltage Imaging Competing Requirements

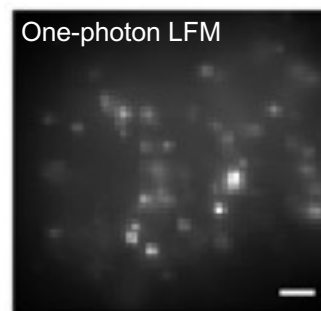
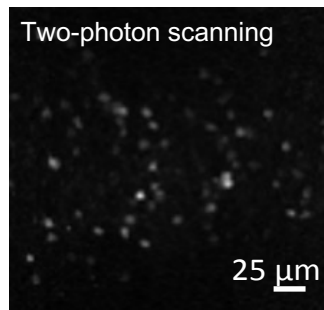


# Our Solution: Scattering-robust structural volumes + high-bandwidth, scanless functional volumes

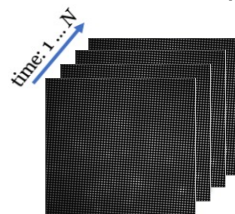


## Our Solution: Scattering-robust structural volumes + high-bandwidth, scanless functional volumes

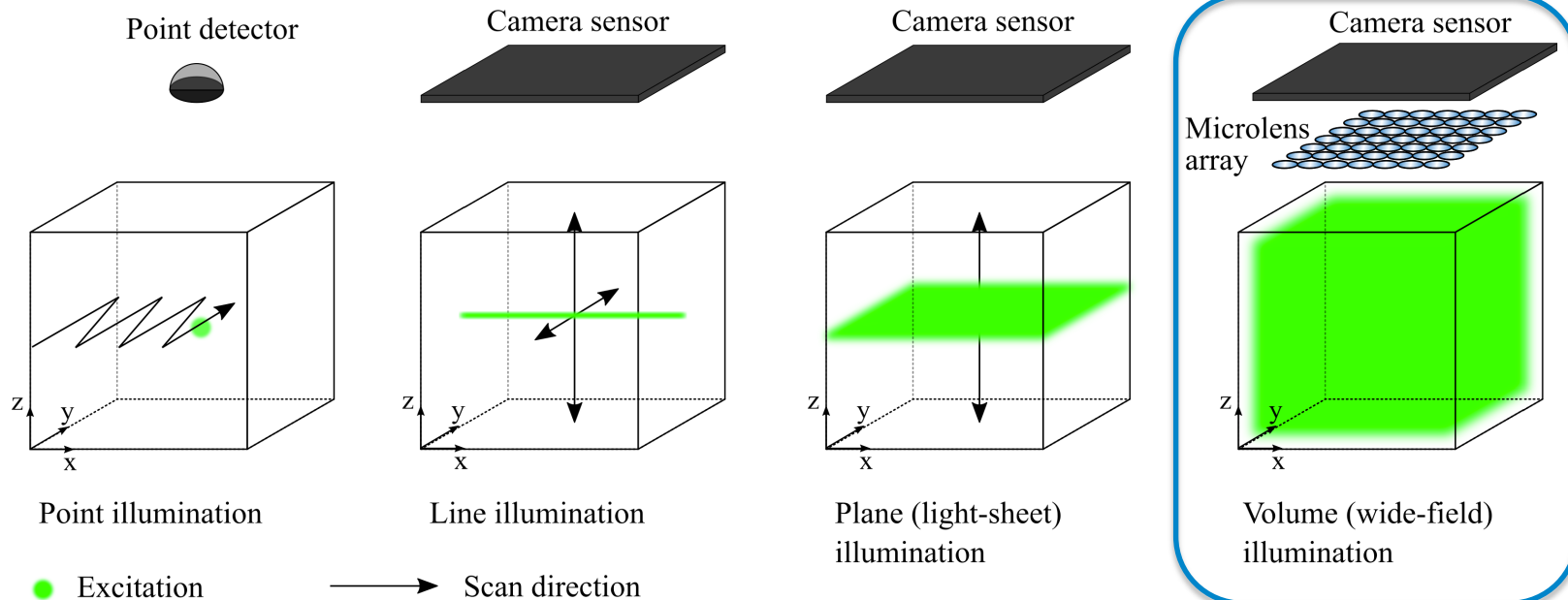
tdTomato structural marker



jRCaMP8f (world's fastest calcium indicator protein ):  
one-photon LFM at 100 Hz



# Light-field Microscopy and Illumination Strategies

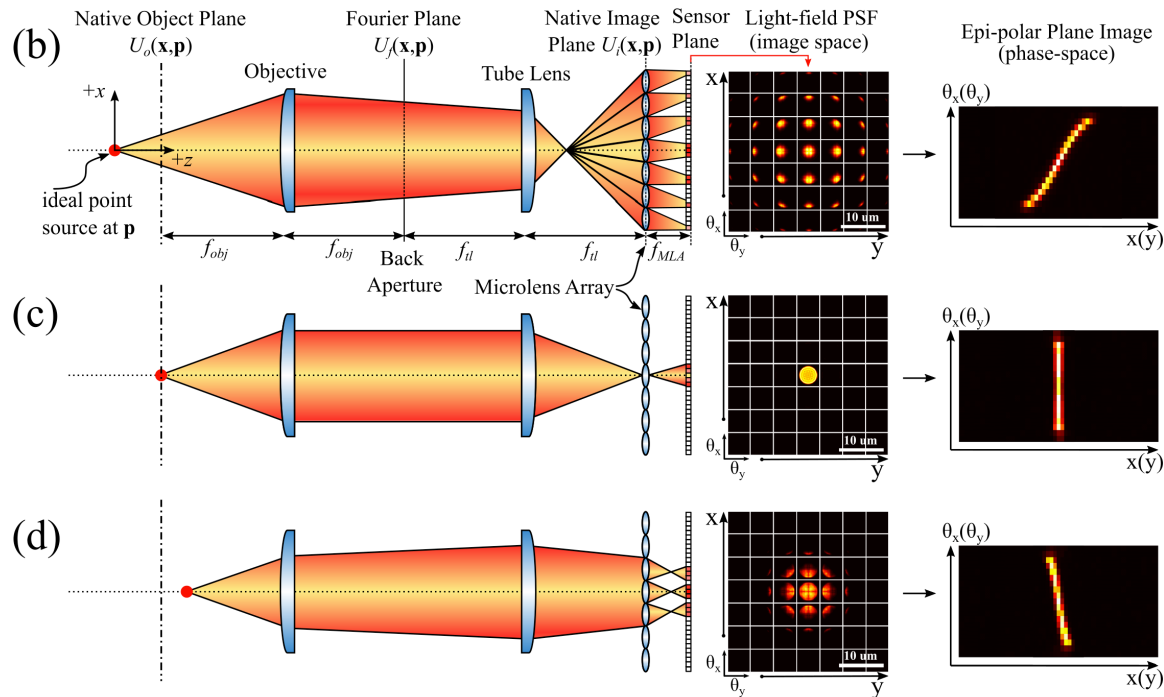
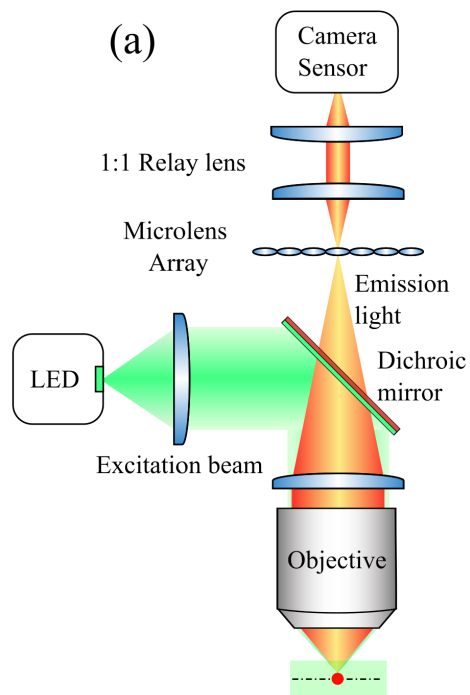


# IBR Results on the Lightfield



*Pearson et al. IEEE TIP 2013*

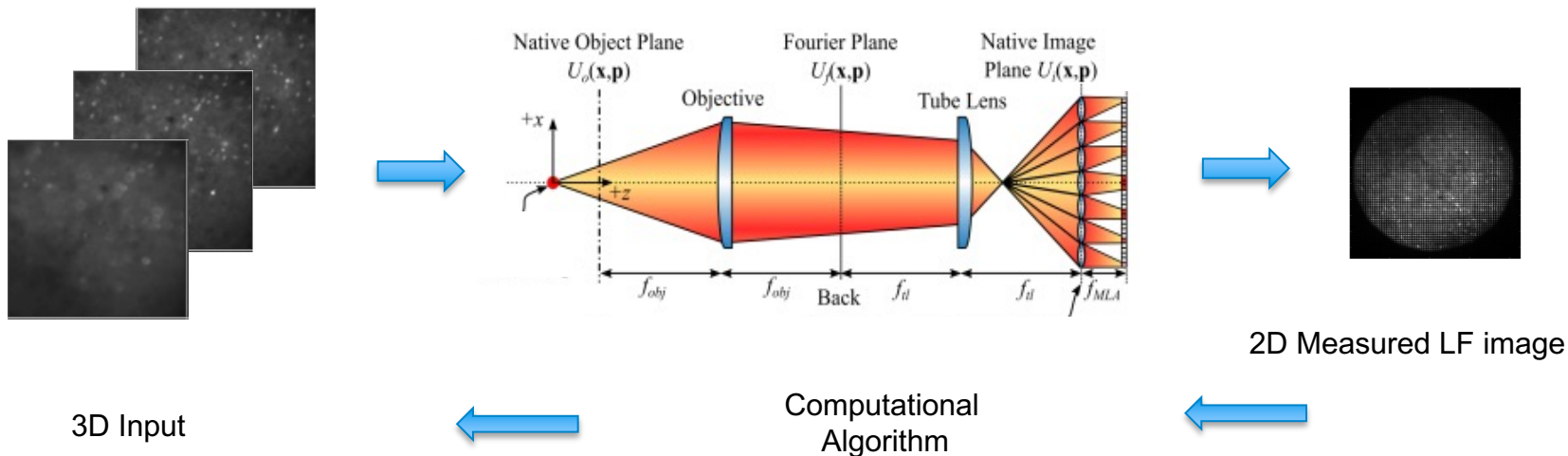
# Light-field Microscopy and EPI





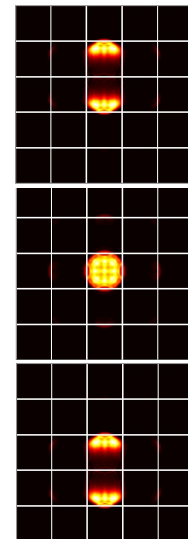
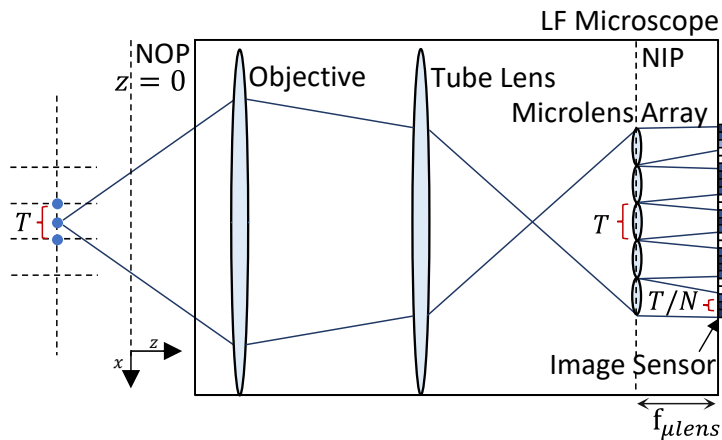
# Light-field Microscopy

**Challenge:** given a sequence of lightfields (2-D signals), need to reconstruct a sequence of volumes (3-D+t)



# Forward Model

- Forward model is linear which means  $y = Hx$ 
  - $H$  is estimated using wave-optics
  - For each depth,  $H$  is block-circulant (periodically shift invariant) and can be modelled with a filter-bank
  - The entire forward model can be modelled using a linear convolutional network with known parameters (given by the wave-optics model)



# Neural network for volume reconstruction

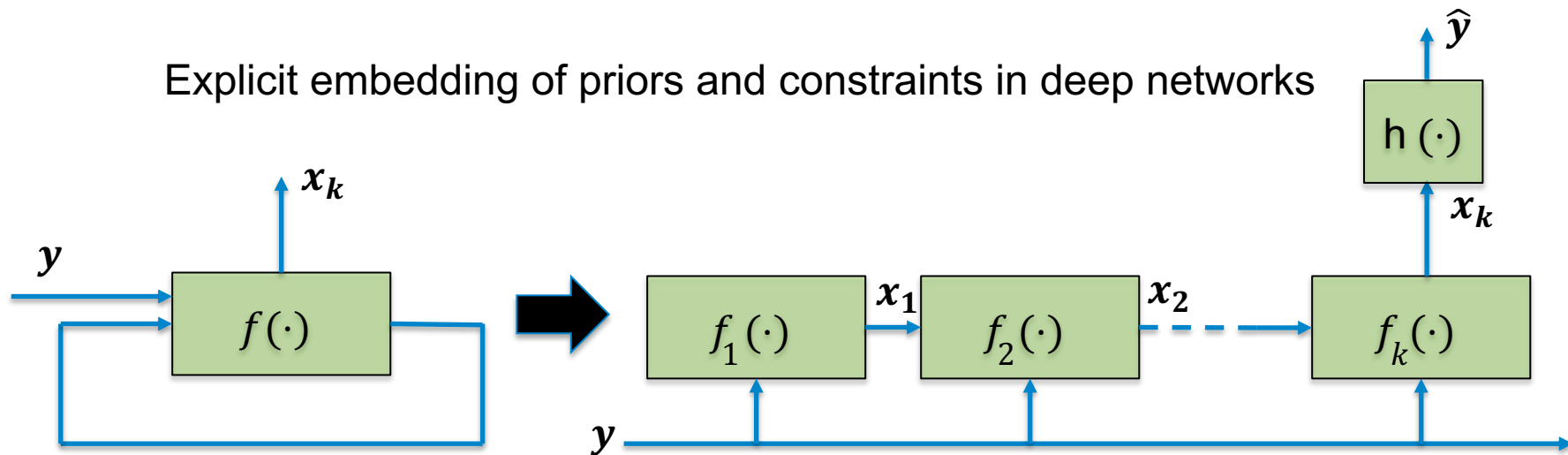
- Data is **sparse** (neurons fire rarely and are localized in space)
- Solve  $\min_x (\|y - Hx\|^2 + \|x\|_1)$  s.t  $x \geq 0$
- This leads to the following iteration:

$$x_{k+1} = \text{ReLU}(x_k - H^T H x_k + H^T y + \lambda)$$

- Approach: Convert the iteration in a deep neural network using the unfolding technique

# Sparsity and Deep Unfolding Strategy

Explicit embedding of priors and constraints in deep networks



Iterative algorithm with  $x$   
as input and  $I$  as output

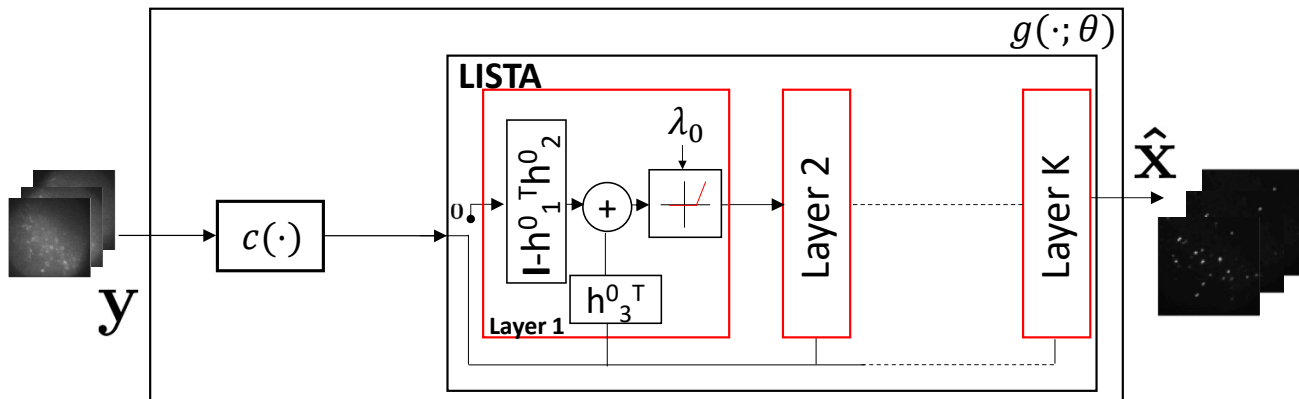
Unfolded version of the iterative algorithm with  
learnable parameters

Need to re-synthesize the input, if self-supervised

# Neural network for volume reconstruction

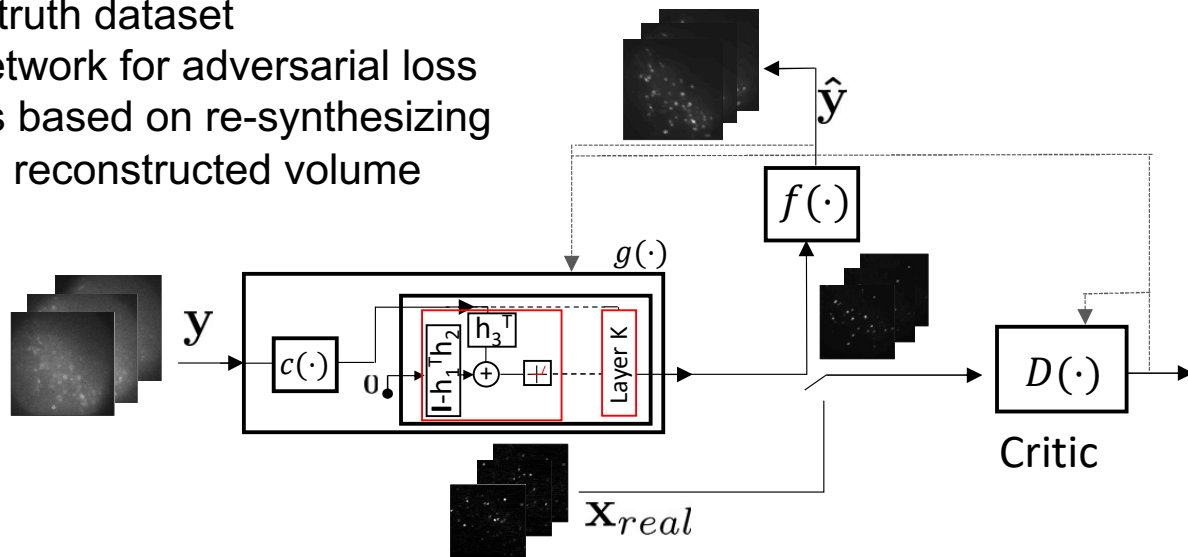
- Convert the iteration in a deep neural network using the unfolding technique

$$x^{k+1} = \text{ReLU}(x^k - H^T H x^k + H^T y + \lambda)$$

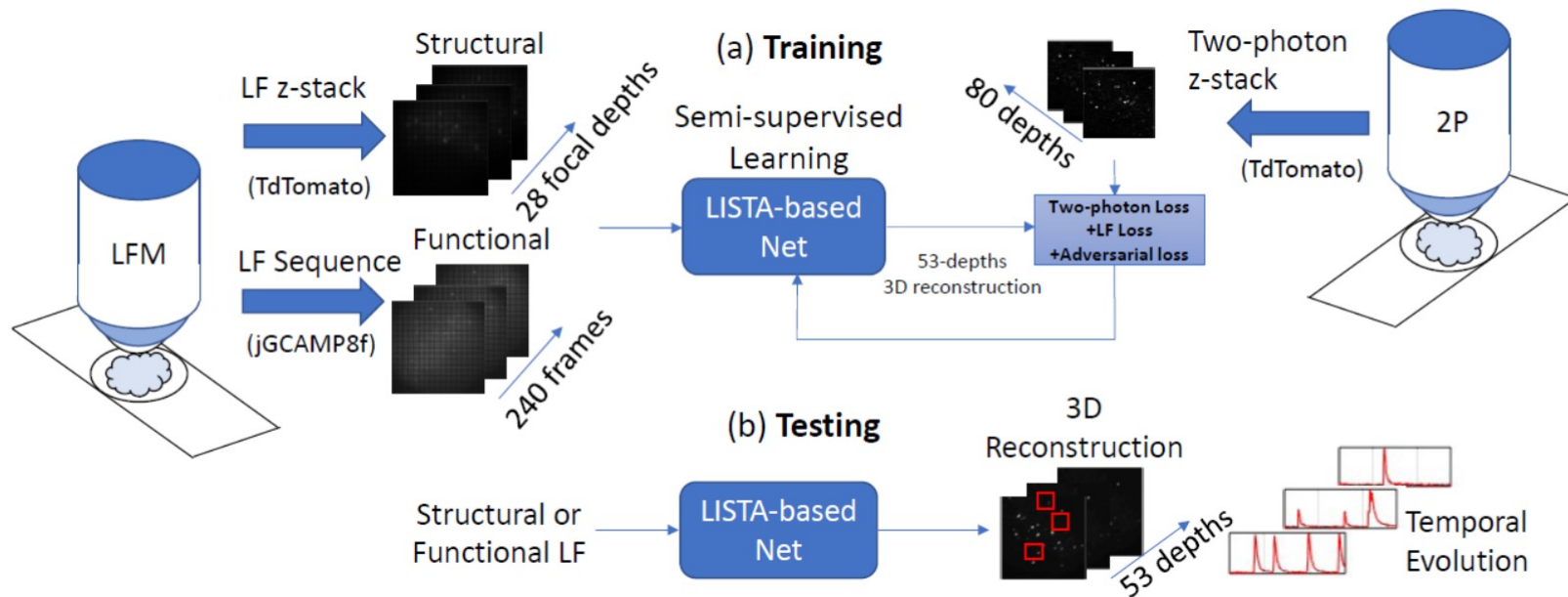


# Training of the neural network

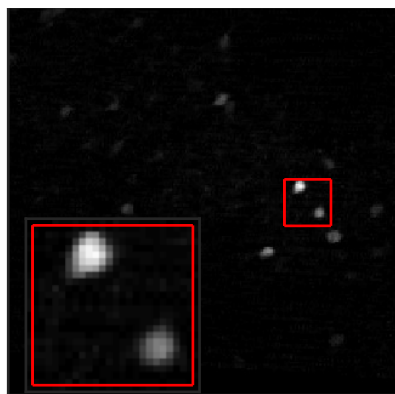
- Training, in this context, is difficult due to lack of ground-truth data
- Our approach: semi supervised learning
  - Small ground truth dataset
  - Adversarial network for adversarial loss
  - Light-field loss based on re-synthesizing light-field from reconstructed volume



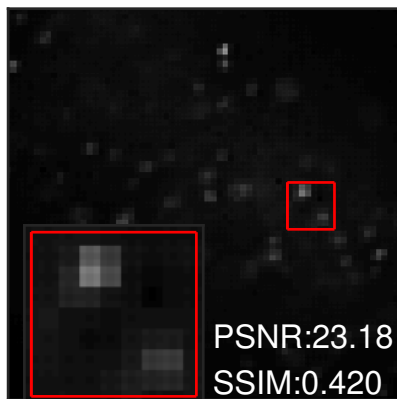
# Training of the neural network



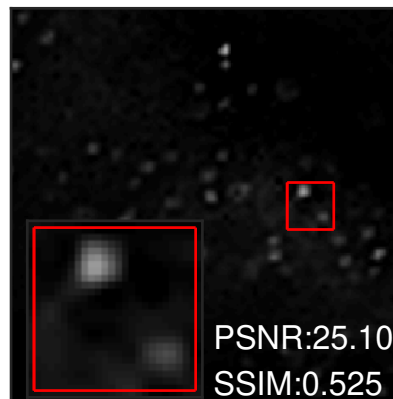
## Results – Structural Data



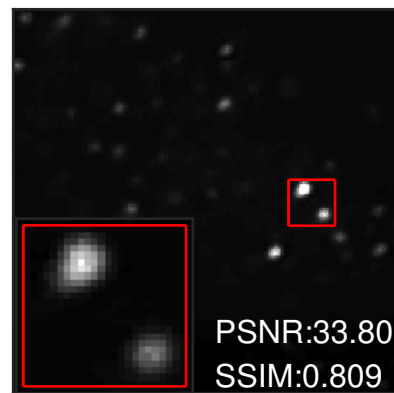
Ground-truth



ISRA



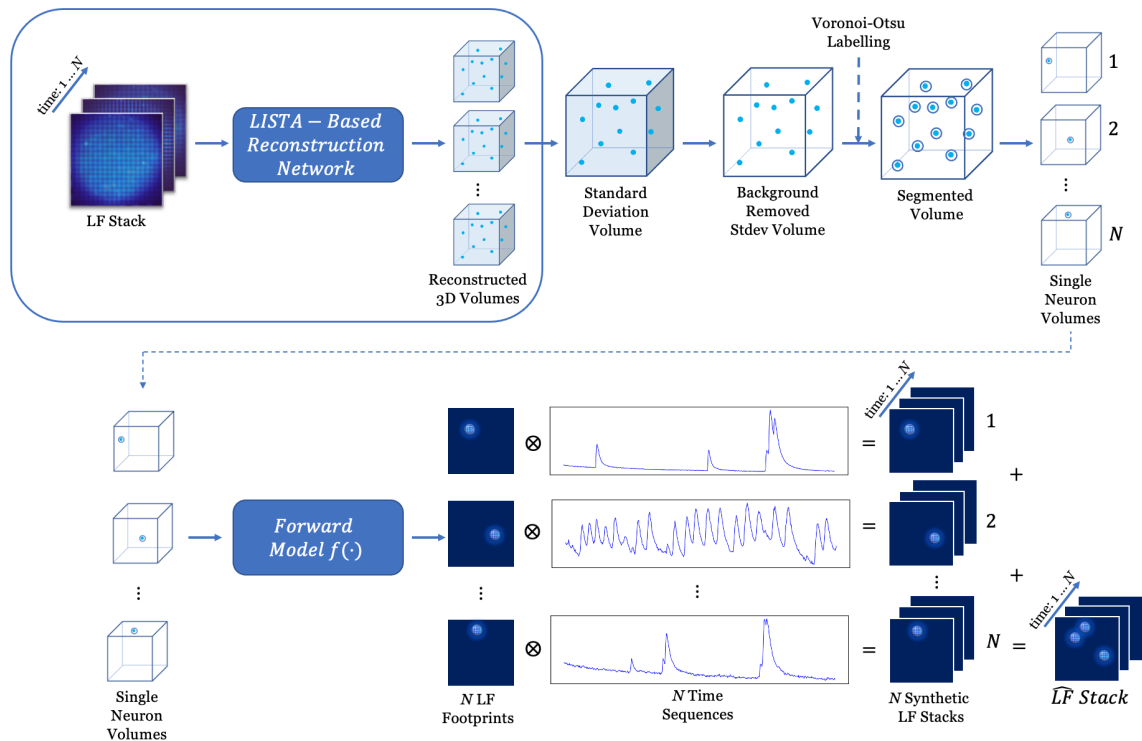
ADMM



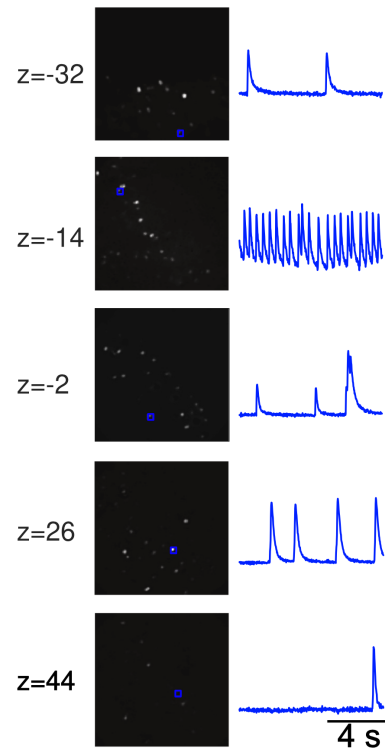
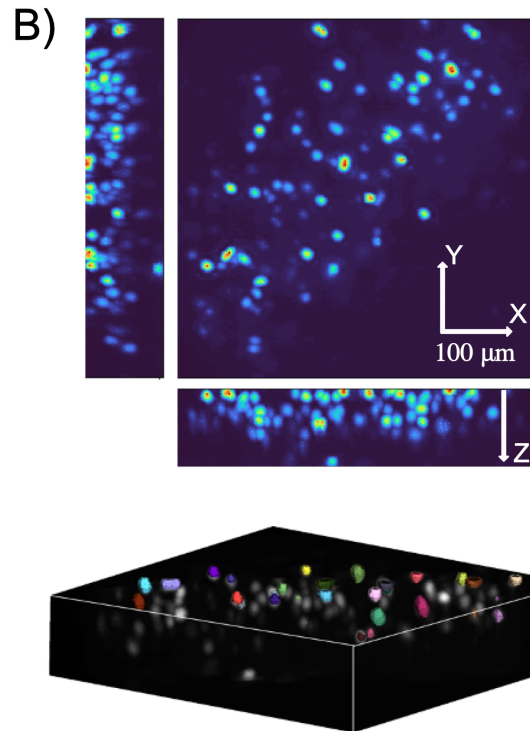
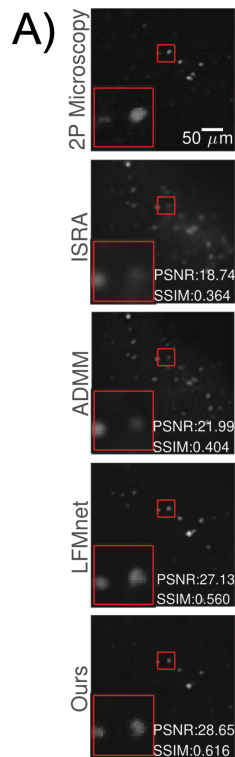
New method (0.3s to  
reconstruct one volume)

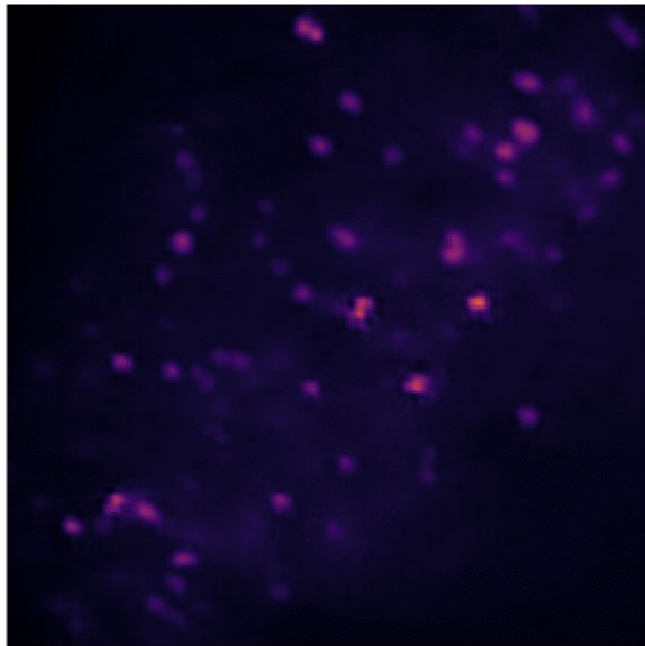


# Neural Activity Extraction



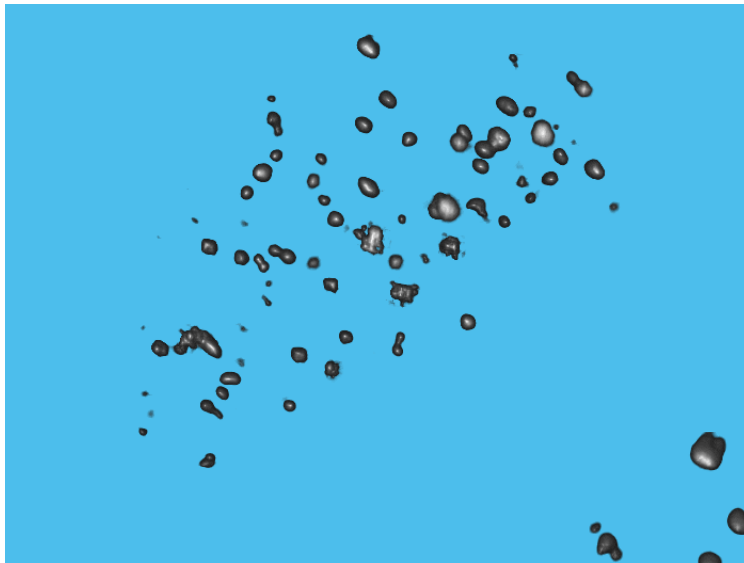
## Results – Functional Data





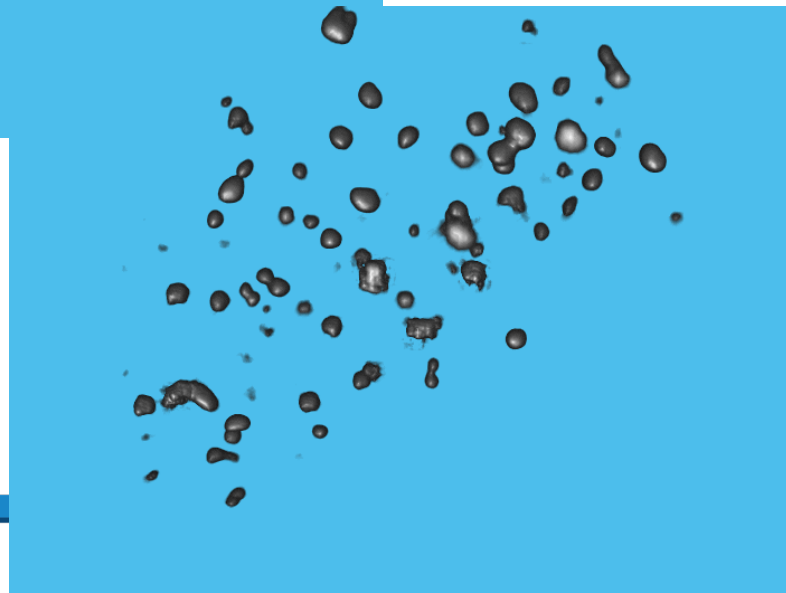
Z

Average

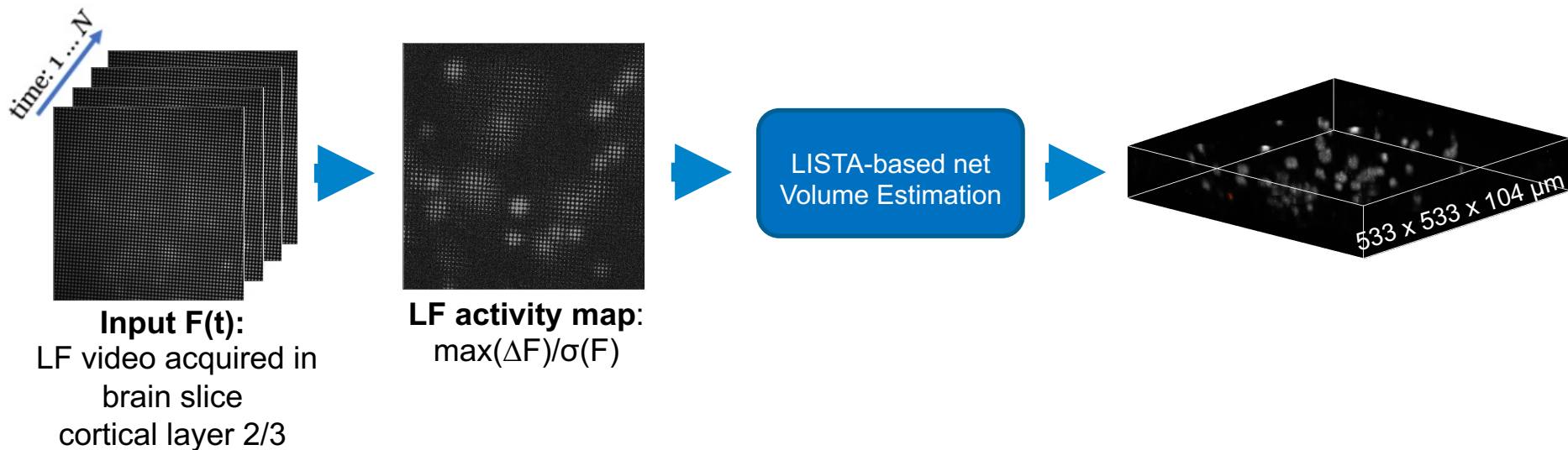


3D  
(view 1)

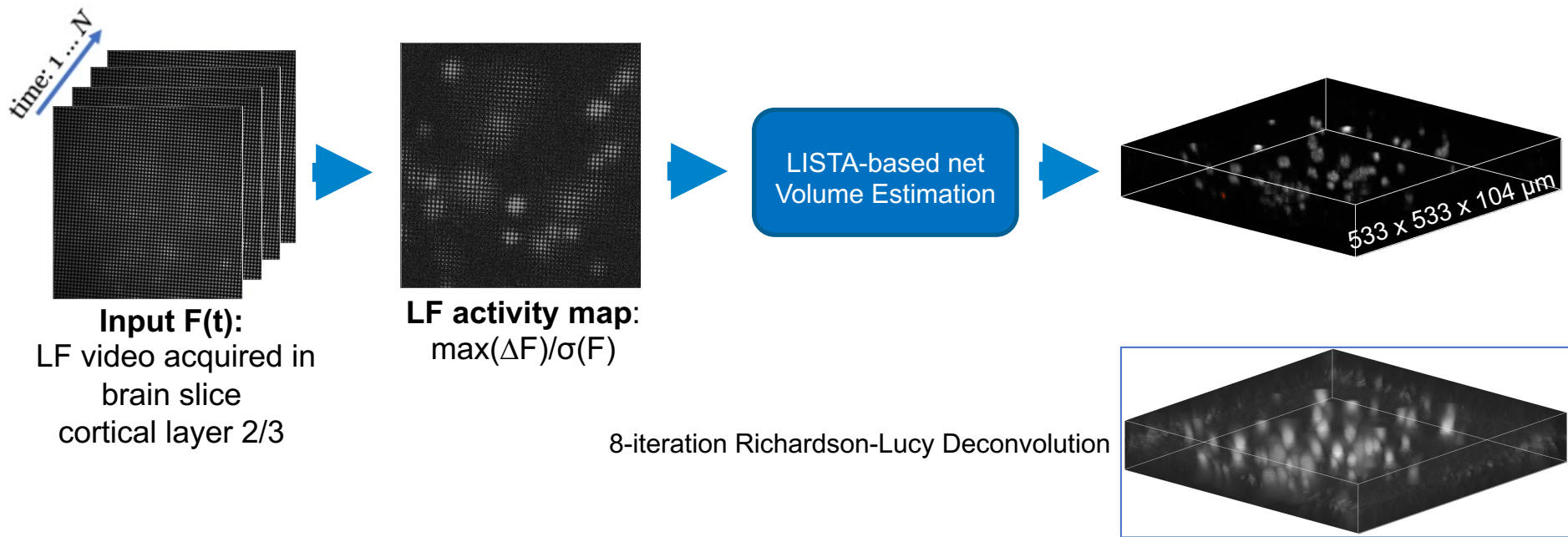
3D  
(view 2)



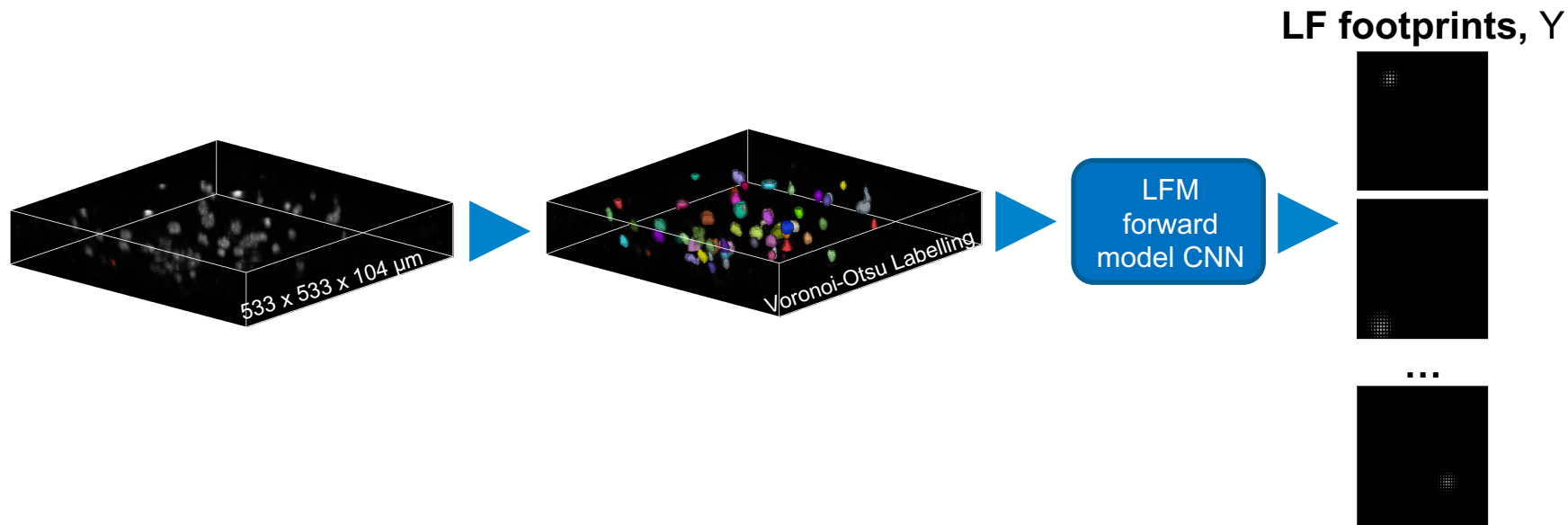
## Fast volumetric jGCaMP8f time-series extraction

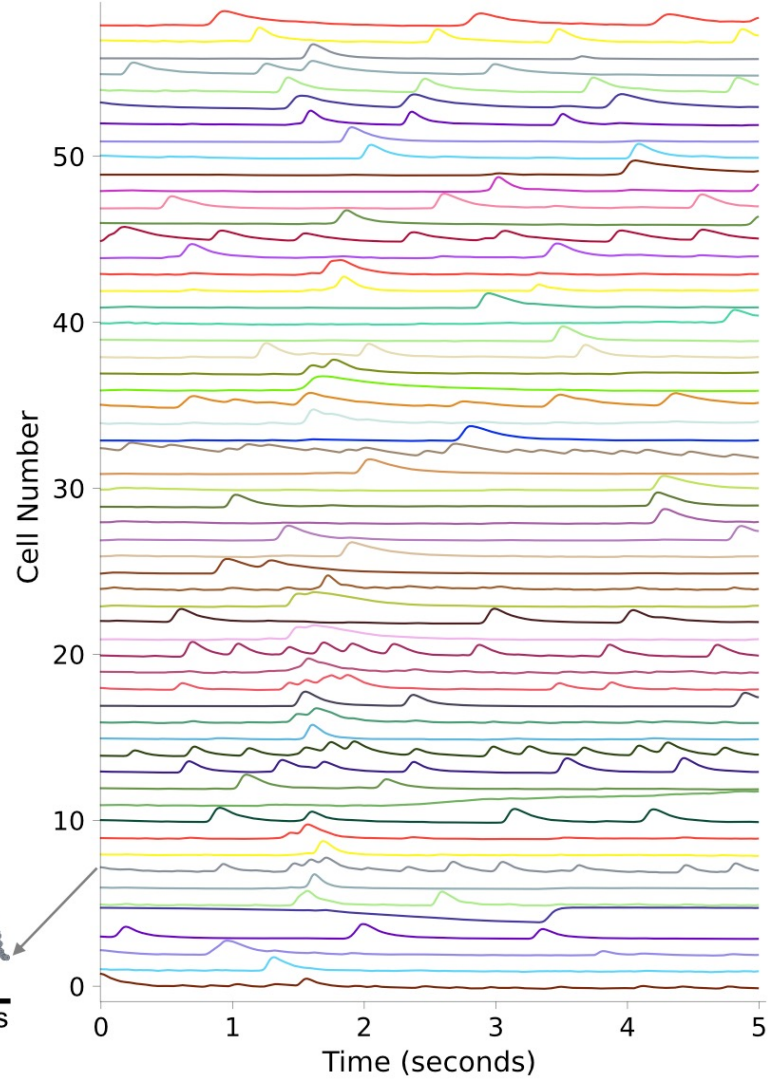
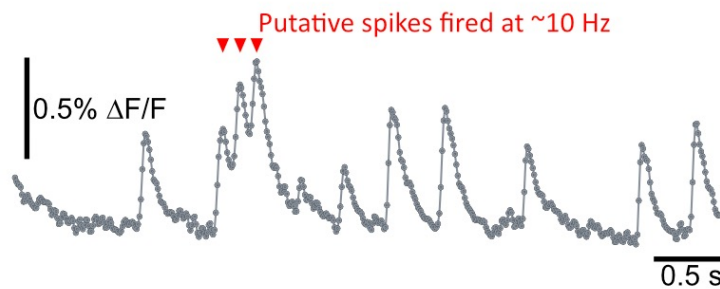
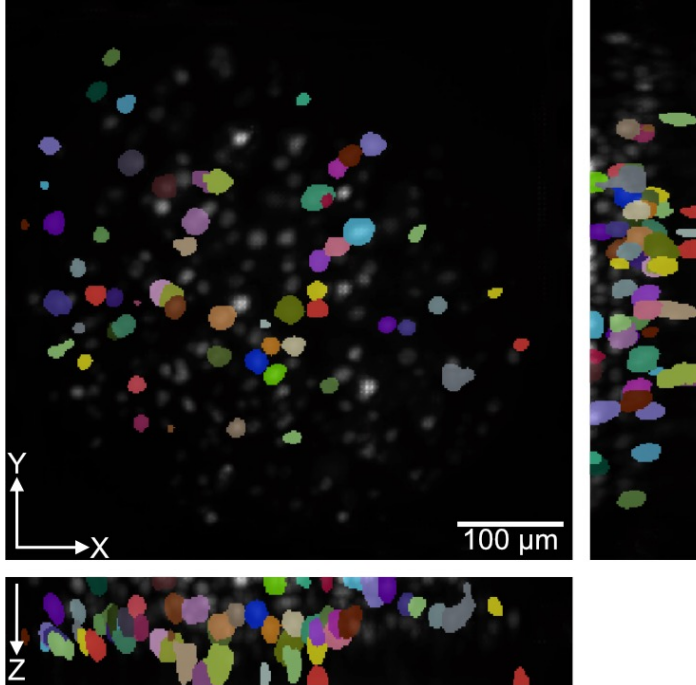


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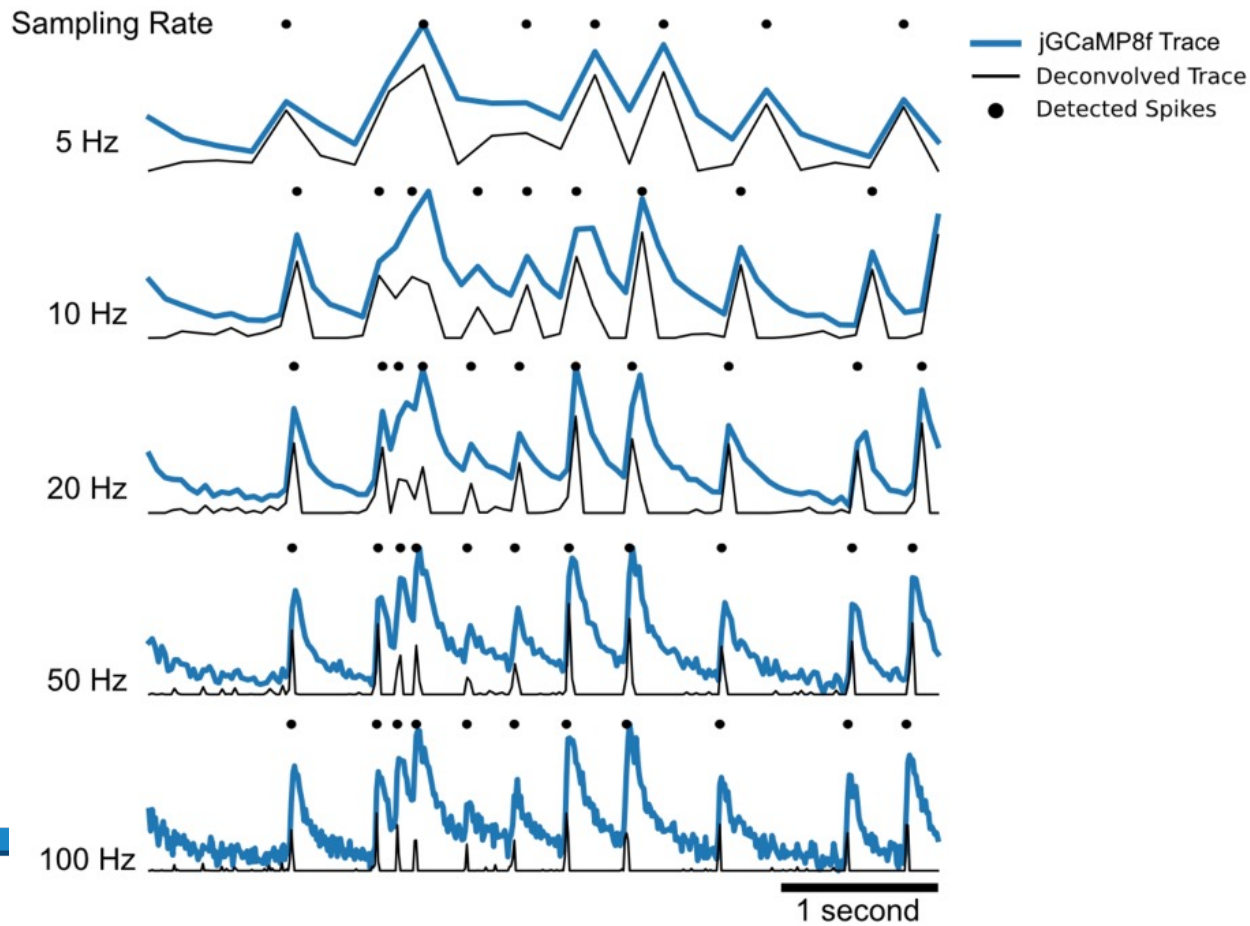


## Fast volumetric jGCaMP8f time-series extraction



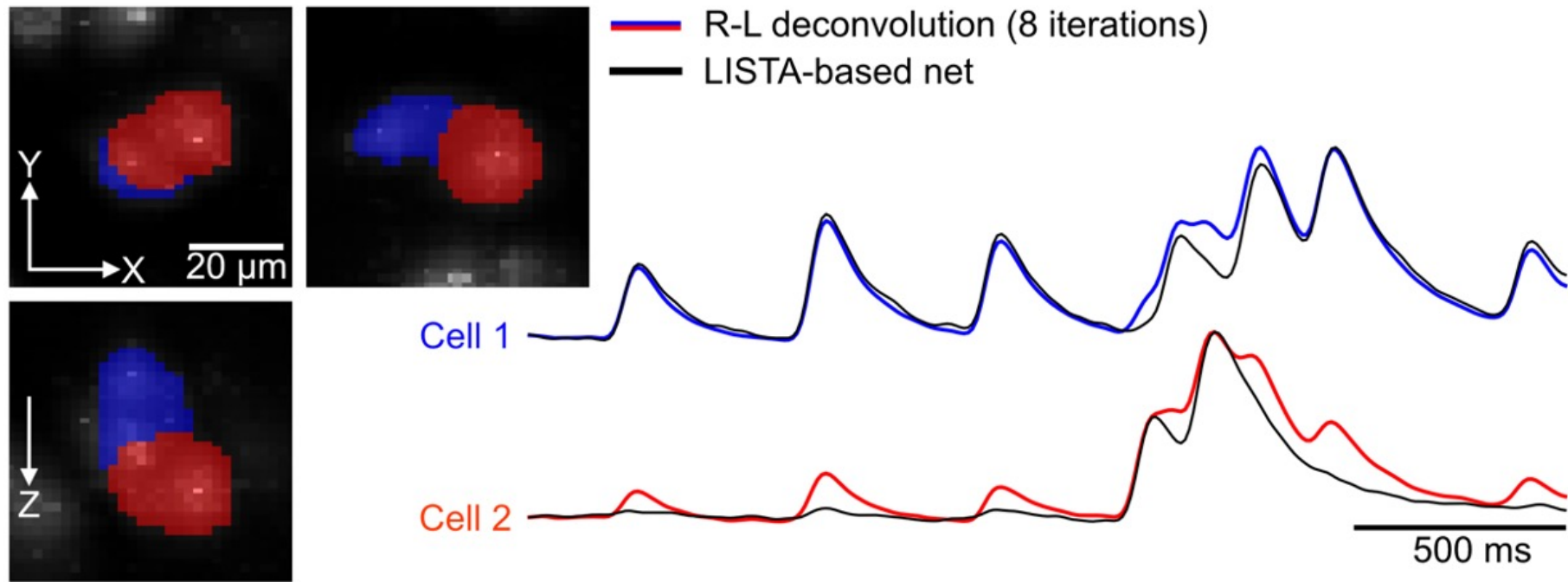


## Why imaging **fast** is important:





## LISTA-based net decreases crosstalk between neighbouring neurons



- Physics-based deep learning can powerfully exploit the advantages of light-field and two-photon microscopy.
- LISTAnet reduces calcium signal crosstalk between neighboring neurons.
- Calcium signals extracted up to 100 microns deep in neocortex. Scope to go deeper with:
  - Red-shifted indicators
  - Integrating structured illumination
- Future applications:
  - Determine living neural network learning rules in-vivo
  - Direct measurement of voltage

## A special thank to:



Kate Zhao

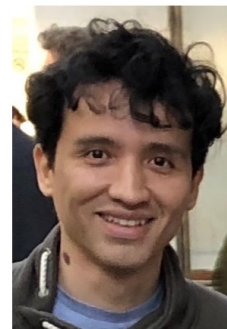


Pingfan Song



Peter Quicke

Herman Verinaz



Carmel Howe

**Thank you!**

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