



SPARSITY TO THE RESCUE
OF 3D WEAK LENSING MASS-MAPPING
STATISTICAL CHALLENGES IN MODERN ASTRONOMY VI

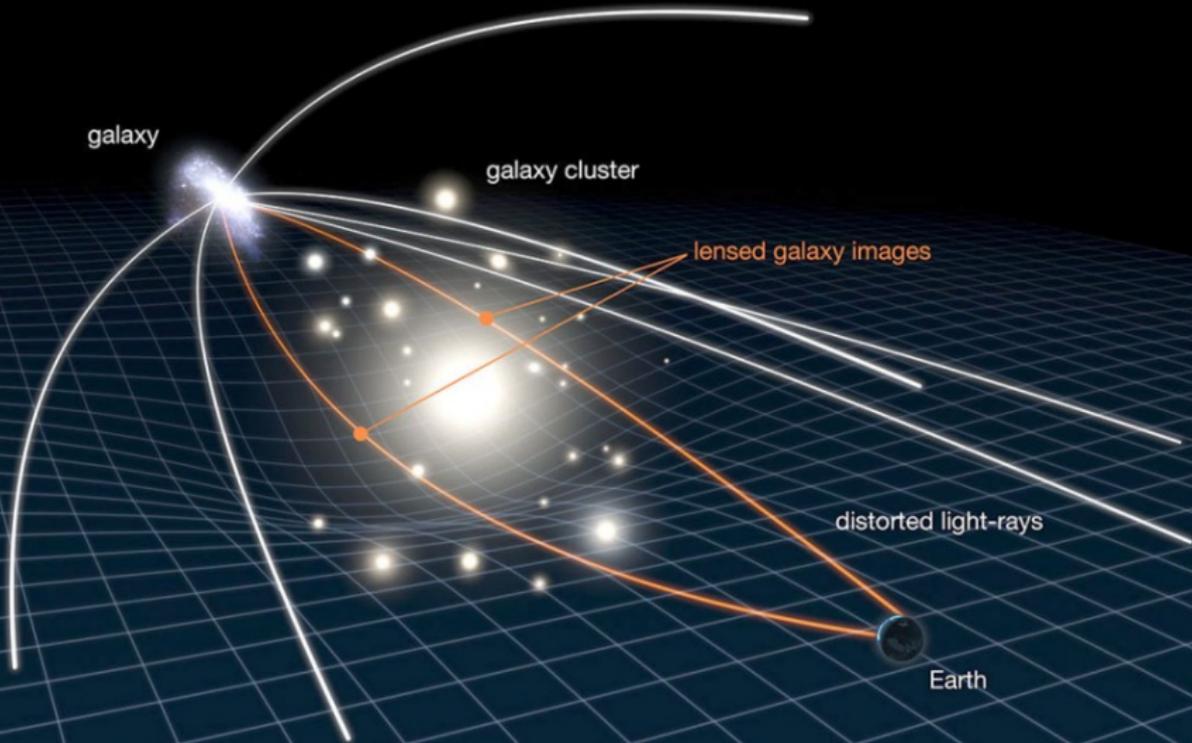
François Lanusse
Carnegie Mellon University

June 6, 2016

Carnegie Mellon University
McWilliams Center for Cosmology

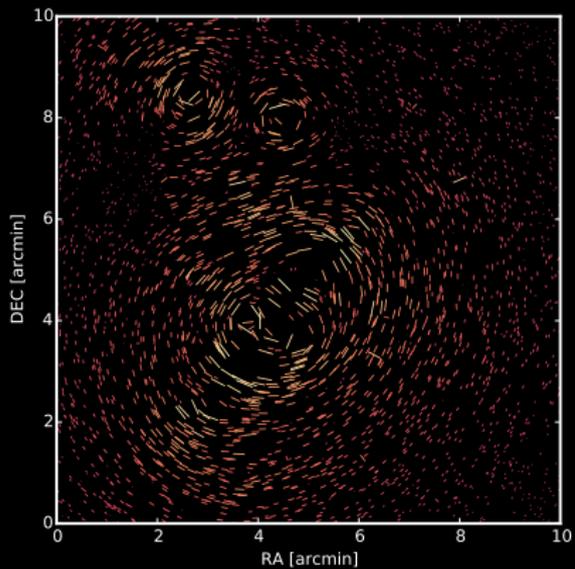
THE 3D MASS-MAPPING PROBLEM

GRAVITATIONAL LENSING BY A MASSIVE CLUSTER



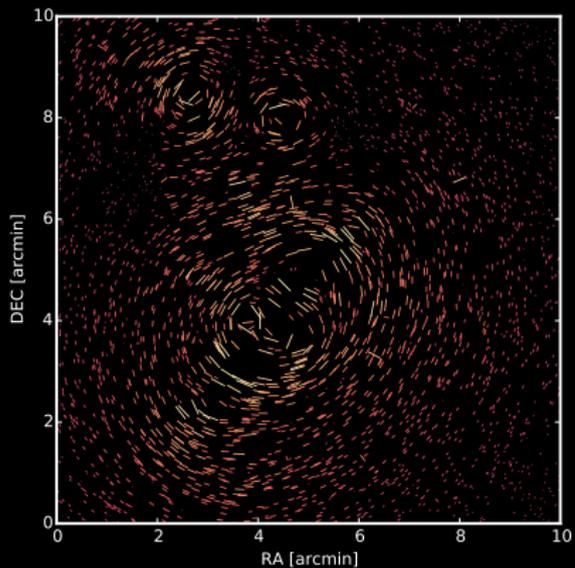
2D MASS MAPPING

Shear γ

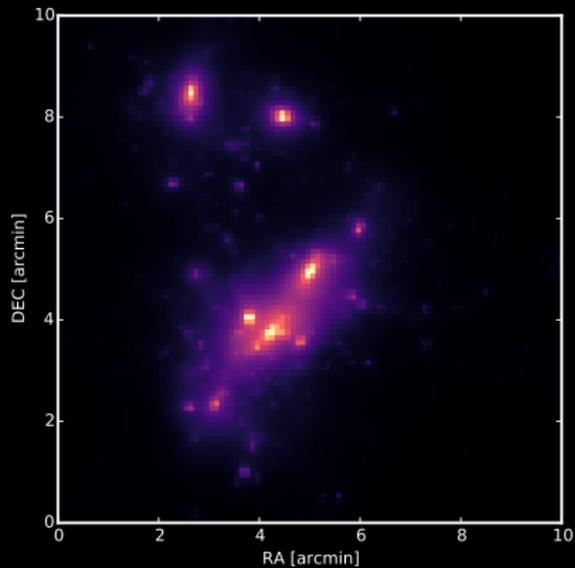


2D MASS MAPPING

Shear γ

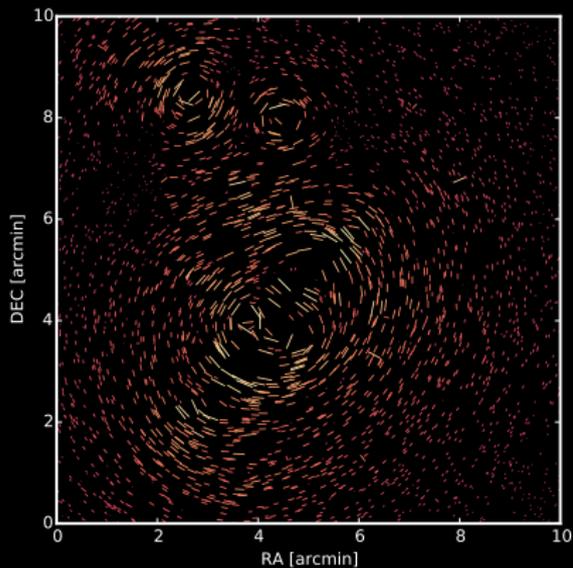


Convergence κ

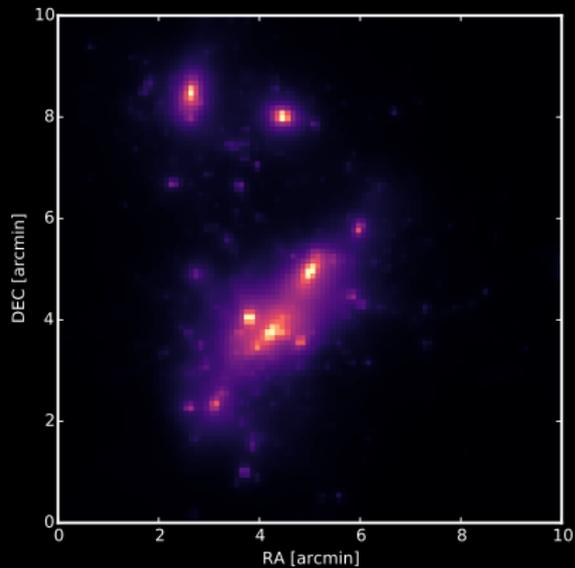


2D MASS MAPPING

Shear γ



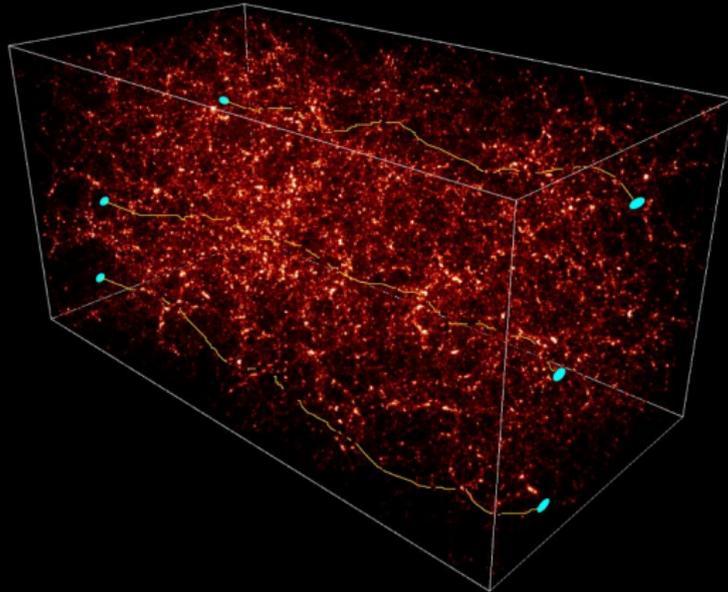
Convergence κ



$$\gamma = \mathbf{P} \kappa$$

PROBING THE MATTER DISTRIBUTION IN 3D

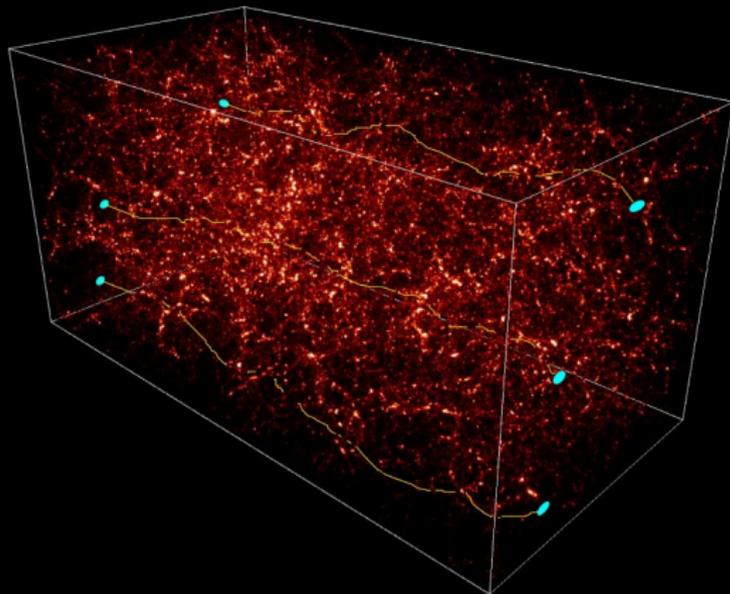
DEFLECTION OF LIGHT RAYS CROSSING THE UNIVERSE, EMITTED BY DISTANT GALAXIES



SIMULATION: COURTESY MC GROUP, S. COLOMBI, IAP.

PROBING THE MATTER DISTRIBUTION IN 3D

DEFLECTION OF LIGHT RAYS CROSSING THE UNIVERSE, EMITTED BY DISTANT GALAXIES

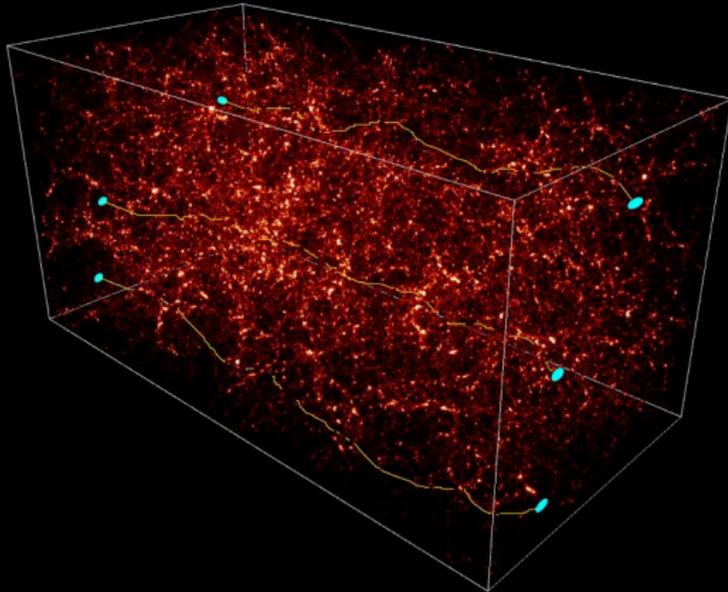


SIMULATION: COURTESY MC GROUP, S. COLOMBI, IAP.

$$\gamma(z) = P \int dz' Q(z, z') \delta(\theta, z')$$

PROBING THE MATTER DISTRIBUTION IN 3D

DEFLECTION OF LIGHT RAYS CROSSING THE UNIVERSE, EMITTED BY DISTANT GALAXIES



SIMULATION: COURTESY NIC GROUP, S. COLOMBI, IAP.

$$\gamma = \text{P Q } \delta$$

THE 3D RECONSTRUCTION PROBLEM

$$\underbrace{\gamma}_{\text{shear}} = \mathbf{P} \mathbf{Q} \underbrace{\delta}_{\text{overdensity}} + \underbrace{n}_{\text{noise}}$$

P and Q are the **tangential** and **line of sight** lensing operators

THE 3D RECONSTRUCTION PROBLEM

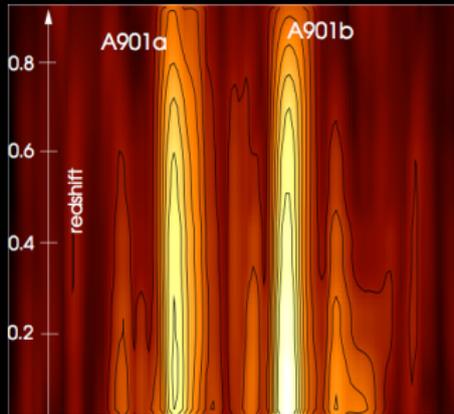
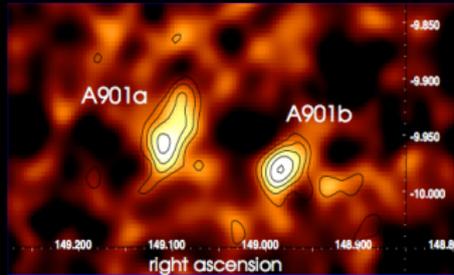
$$\underbrace{\gamma}_{\text{shear}} = \mathbf{P} \mathbf{Q} \underbrace{\delta}_{\text{overdensity}} + \underbrace{n}_{\text{noise}}$$

P and Q are the **tangential** and **line of sight** lensing operators

Difficulty of 3D mass-mapping

- P is non-invertible when the shear is irregularly sampled
- Q is ill-posed, direct inversion impossible

WIENER FILTER RECONSTRUCTION OF ABELL901/902



SPARSE REGULARISATION FOR 2D MAPPING

$$\gamma_1 = \frac{1}{2}(\partial_1^2 - \partial_2^2) \Psi \quad \gamma_2 = \partial_1 \partial_2 \Psi \quad \kappa = \frac{1}{2}(\partial_1^2 + \partial_2^2) \Psi$$

- Explicit solution in Fourier space:

$$\hat{\kappa} = \frac{k_1^2 - k_2^2}{k_1^2 + k_2^2} \hat{\gamma}_1 + \frac{2k_1 k_2}{k_1^2 + k_2^2} \hat{\gamma}_2$$

$$\gamma_1 = \frac{1}{2}(\partial_1^2 - \partial_2^2) \Psi \quad \gamma_2 = \partial_1 \partial_2 \Psi \quad \kappa = \frac{1}{2}(\partial_1^2 + \partial_2^2) \Psi$$

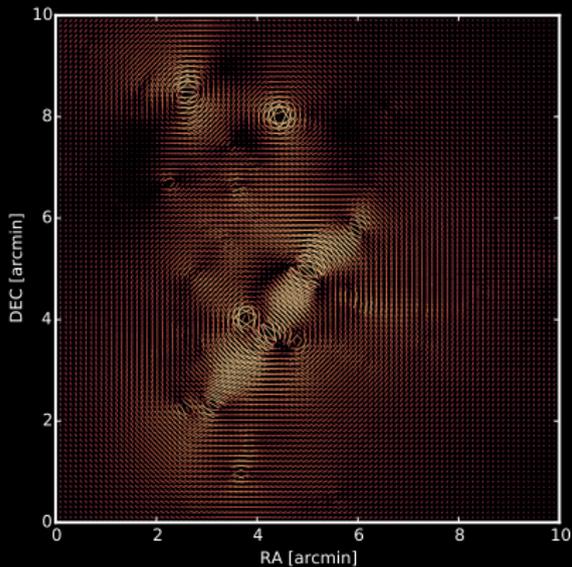
- Explicit solution in Fourier space:

$$\hat{\kappa} = \mathbf{P}^* \hat{\gamma}$$

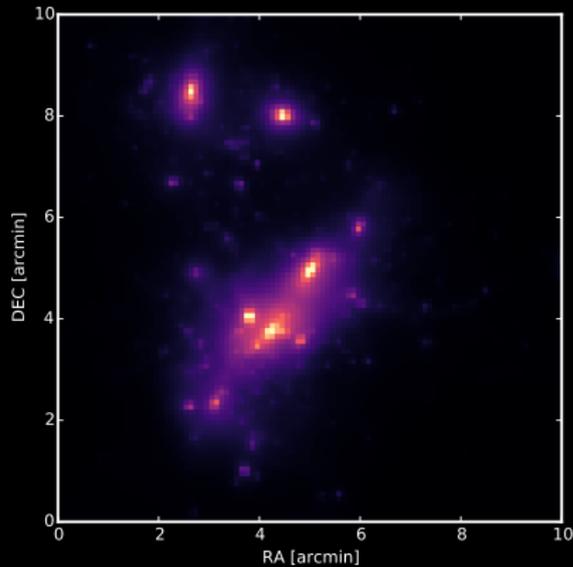
- Difficulties of the inversion:
 - Irregularly sampled or missing data.
 - Individual measurements extremely noise dominated.

IMPACT OF IRREGULAR SAMPLING

Shear γ



Convergence κ

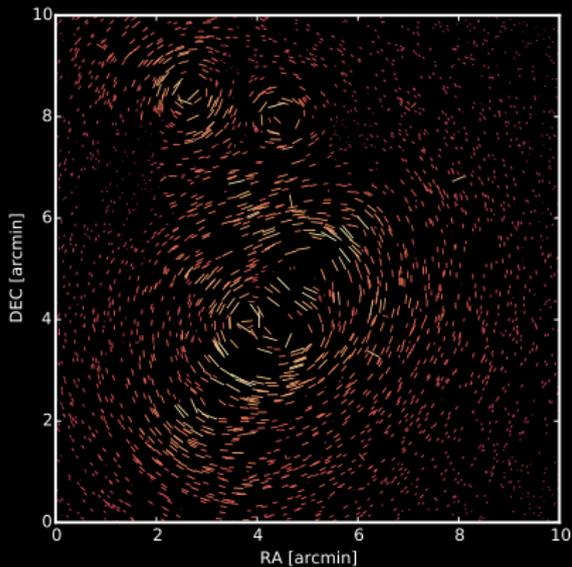


Regular shear sampling

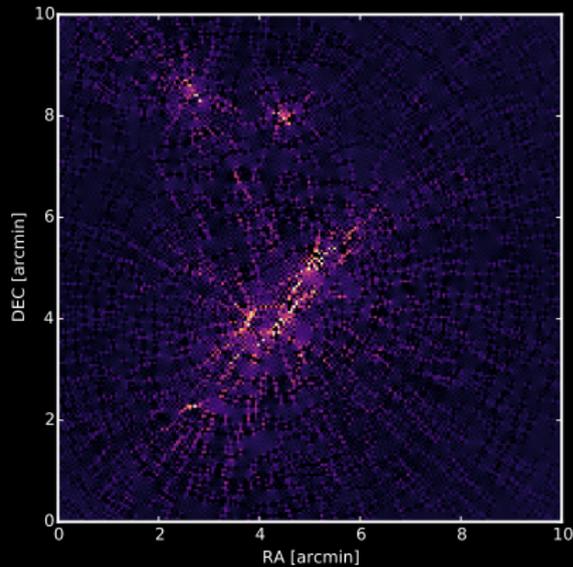
$$\kappa = F^* P^* F \gamma$$

IMPACT OF IRREGULAR SAMPLING

Shear γ



Convergence κ

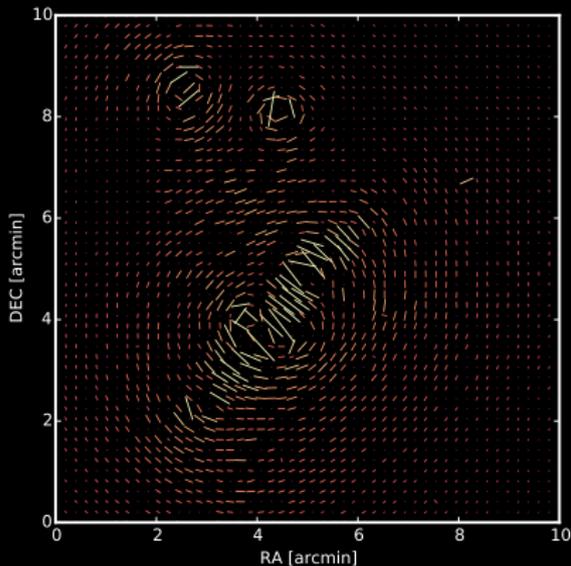


Irregular shear sampling

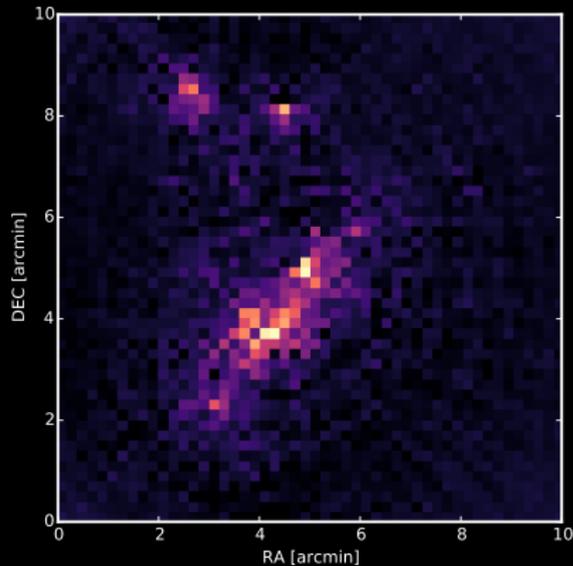
$$\kappa = F^* P^* F M \gamma$$

IMPACT OF IRREGULAR SAMPLING

Shear γ



Convergence κ

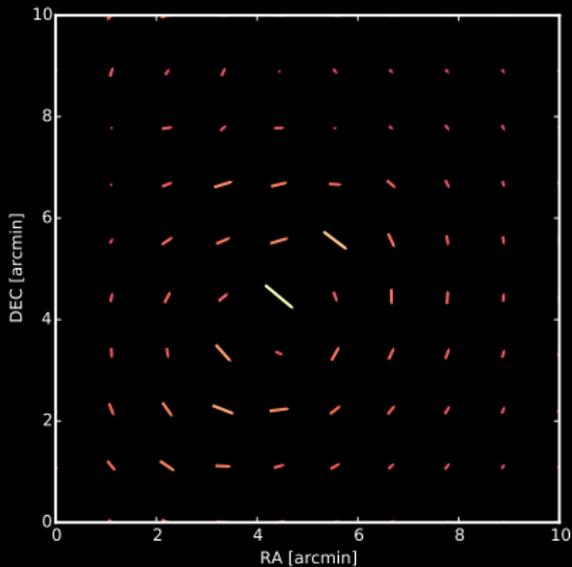


Regularly binned shear (0.2 arcmin)

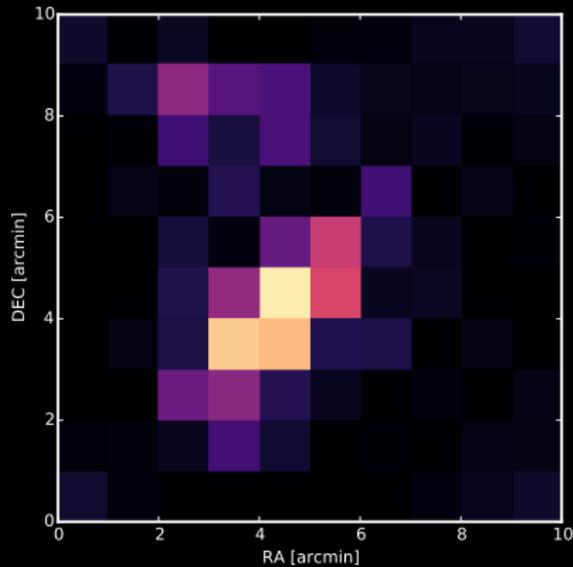
$$\kappa = F^* P^* F M \gamma$$

IMPACT OF IRREGULAR SAMPLING

Shear γ



Convergence κ



Regularly binned shear (1 arcmin)

$$\kappa = F^* P^* F M \gamma$$

OUR MODELING

From a regularly sampled convergence map κ we compute the shear at each galaxy position: **no binning**.

$$\gamma = \mathbf{TPF} \kappa$$

Non Equispaced Discrete Fourier Transform (NDFT)

Fourier transform from a regular grid to an irregular grid x_l :

$$f = \mathbf{T}\hat{f} \quad \text{with} \quad T_{lk} = \frac{1}{\sqrt{N}} e^{2\pi i k x_l}$$

\mathbf{T} is no longer directly invertible \Rightarrow Linear inverse problem.

- Extremely analogous to radio-interferometry and MRI

SPARSE REGULARISATION - SIMPLIFIED PROBLEM

$$\arg \min_{\kappa} \frac{1}{2} \|\gamma - \text{TPF } \kappa\|_2^2 + \lambda \|\Phi^* \kappa\|_1$$

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Data fidelity

SPARSE REGULARISATION - SIMPLIFIED PROBLEM

$$\operatorname{argmin}_{\kappa} \underbrace{\frac{1}{2} \|\gamma - \text{TPF } \kappa\|_2^2}_{\text{Data fidelity}} + \underbrace{\lambda \|\Phi^* \kappa\|_1}_{\text{Sparsity prior}}$$

SPARSE REGULARISATION - SIMPLIFIED PROBLEM

$$\operatorname{argmin}_{\kappa} \frac{1}{2} \|\gamma - \text{TPF } \kappa\|_2^2 + \lambda \|\Phi^* \kappa\|_1$$

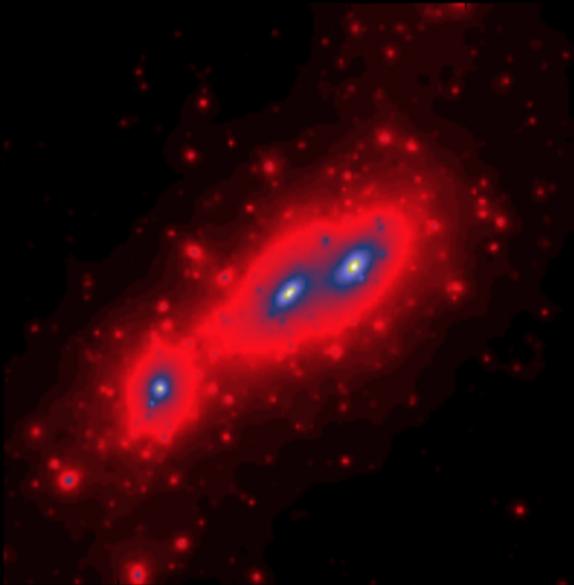
Data fidelity

Sparsity prior

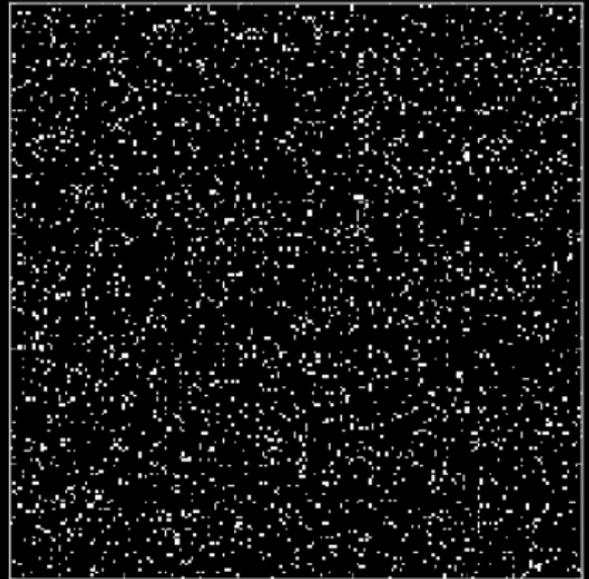
Wavelet based

The diagram illustrates the components of the optimization problem. A horizontal line is drawn under the first term of the equation, $\frac{1}{2} \|\gamma - \text{TPF } \kappa\|_2^2$. A vertical line extends upwards from the center of this horizontal line, and a diagonal line extends from that point to the right, ending at the text 'Data fidelity'. Another horizontal line is drawn under the second term, $\lambda \|\Phi^* \kappa\|_1$. A vertical line extends downwards from the center of this horizontal line, and a diagonal line extends from that point to the right, ending at the text 'Sparsity prior'. A second diagonal line extends from the same vertical line downwards and to the left, ending at the text 'Wavelet based'.

ILLUSTRATION - NOISELESS RECOVERY



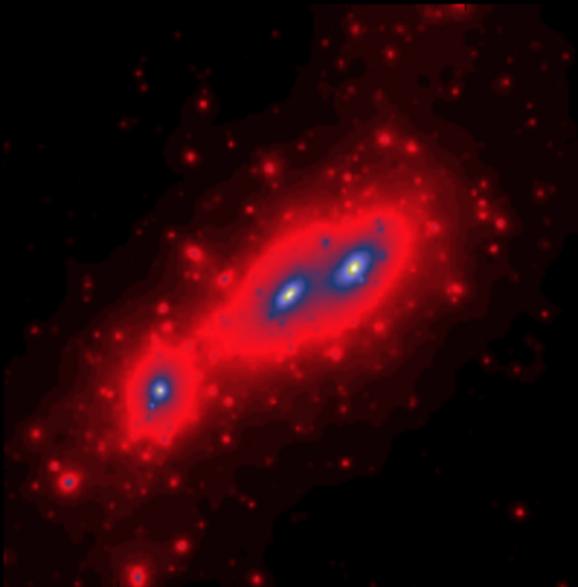
Input map 10×10 arcmin



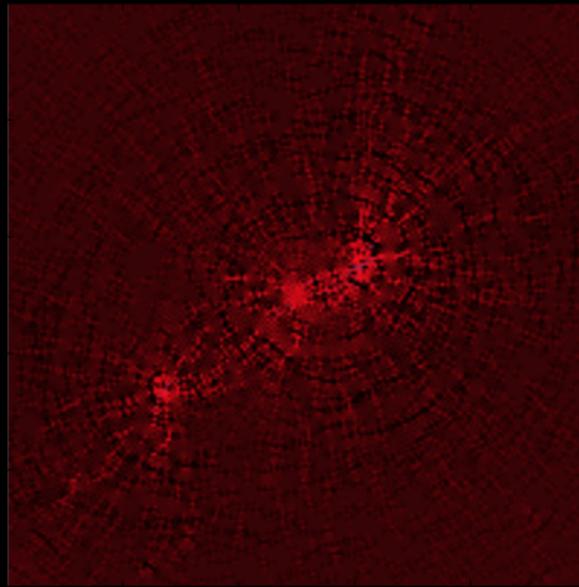
Source distribution

30 gal/arcmin^2 93% of missing data

ILLUSTRATION - NOISELESS RECOVERY



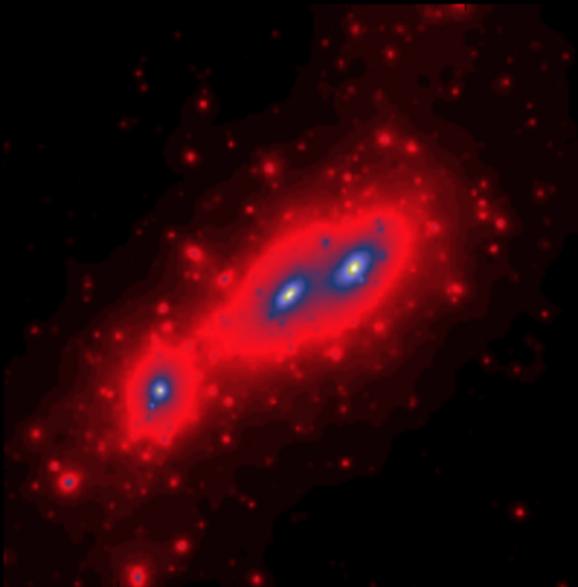
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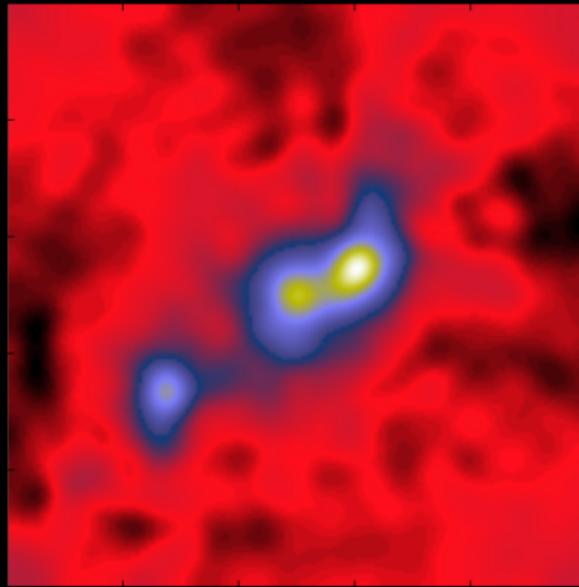
Without regularisation

30 gal/arcmin² 93% of missing data

ILLUSTRATION - NOISELESS RECOVERY



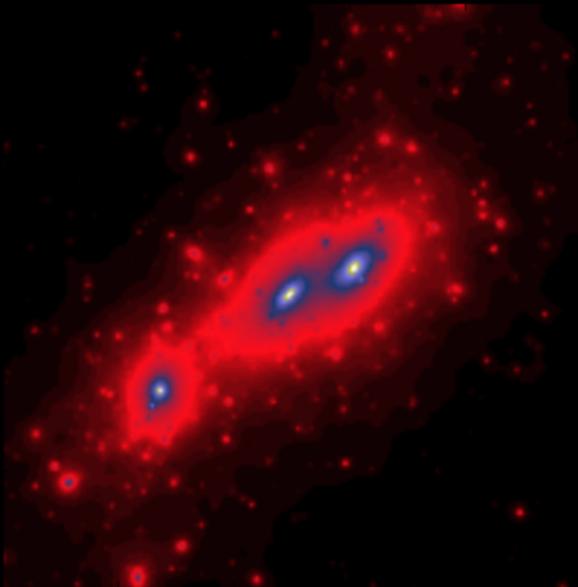
Input map 10×10 arcmin



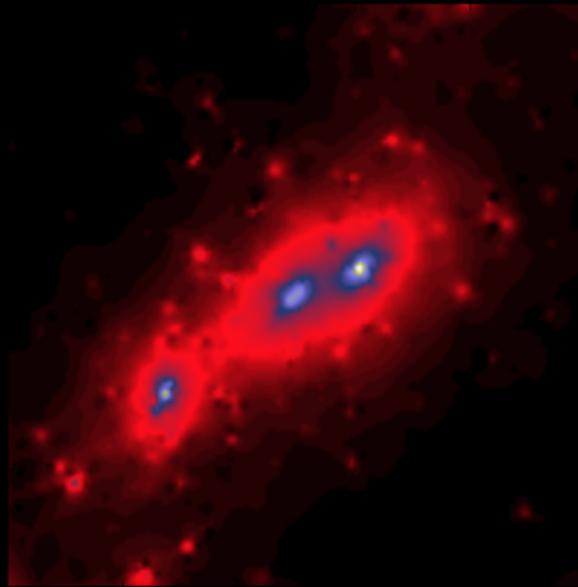
Binning + Gaussian Smoothing

30 gal/arcmin^2 93% of missing data

ILLUSTRATION - NOISELESS RECOVERY



Input map 10×10 arcmin



Sparse regularisation

30 gal/arcmin^2 93% of missing data

SPARSE REGULARISATION - FULL 2D PROBLEM

Lanusse, Starck, Leonard, Pires (2016)

$$\begin{aligned} \arg \min_{\kappa, \tilde{\mathcal{F}}} & \frac{1}{2} \| \mathcal{C}_{\kappa}^{-1} [(1 - ZTF^* \kappa)g - ZTPF^* \kappa] \|_2^2 \\ & + \frac{1}{2} \| \mathcal{C}_{\kappa}^{-1} [(1 - ZTF^* \kappa)F - ZTF^* \tilde{\mathcal{F}}] \|_2^2 \\ & + \lambda \| \mathbf{W} \circ \Phi^t \kappa \|_1 + i_{\text{Im}(\mathbb{R})} \left(\begin{bmatrix} \kappa \\ \tilde{\mathcal{F}} \end{bmatrix} \right) \end{aligned}$$

- Includes reduced shear, reduced flexion, individual redshifts
- Optimally combines shear and flexion
- Tuning of the sparsity constraint based on local noise levels
- Solved using a primal-dual proximal algorithm adapted from (Vu, 2013)

EXTENSION TO THE 3D PROBLEM

SPARSE REGULARISATION OF THE FULL INVERSE PROBLEM

Leonard, Lanusse, Starck (2015)

Leonard, Lanusse, Starck (2014)

Leonard, Dupe, Starck (2012)

$$\hat{\delta} = \arg \min_{\delta} \frac{1}{2} \|\gamma - \mathbf{T P F Q} \delta\|_2^2 + \lambda \|\Phi^* \delta\|_1$$

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Typically solved using FISTA (Fast Iterative Soft Thresholding)

SPARSE REGULARISATION OF THE FULL INVERSE PROBLEM

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Leonard, Dupe, Starck (2012)

Badly conditioned

$$\hat{\delta} = \arg \min_{\delta} \frac{1}{2} \left\| \gamma - \mathbf{T P F} \frac{\mathbf{Q}}{\mathbf{Q}} \delta \right\|_2^2 + \lambda \left\| \Phi^* \delta \right\|_1$$

Typically solved using FISTA (Fast Iterative Soft Thresholding)

PRECONDITIONING OF THE PROBLEM

Lanusse, Starck (2016), in prep.

We use the SVD of \mathbf{Q} to build a preconditioning matrix \mathbf{N} :

$$\mathbf{Q} = \mathbf{U}\mathbf{S}\mathbf{V}^* \quad \mathbf{N} = \mathbf{V} \overline{\mathbf{S}^{-1}} \mathbf{V}^*$$

and we solve the problem:

$$\delta = \mathbf{N} \arg \min_{\delta'} \frac{1}{2} \|\gamma - \mathbf{P} \mathbf{Q}' \delta'\|_2^2 + \lambda \|\Phi^* \mathbf{N} \delta'\|_1$$

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- Convergence rate improved by orders of magnitudes

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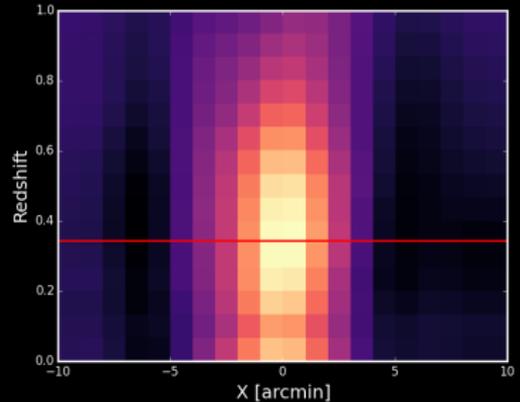
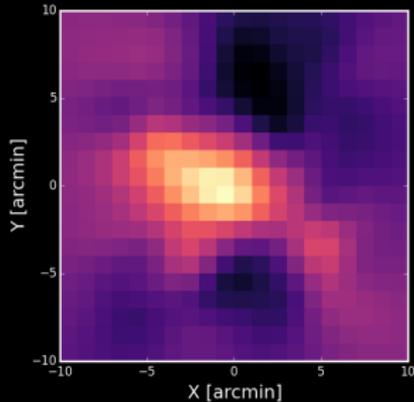
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- Convergence rate improved by orders of magnitudes
- Sparsity constraint more complex to compute
 - Fast Spectral Projected Gradient algorithm
 - GP-GPU parallel implementation

ILLUSTRATION ON A CLUSTER FROM THE MICE N-BODY SIMULATIONS

$10^{15} h^{-1} M_{\odot}$ cluster at $z=0.37$



Reconstruction using transverse Wiener filter from [Simon et al. \(2011\)](#)

ILLUSTRATION ON A CLUSTER FROM THE MICE N-BODY SIMULATIONS

$10^{15} h^{-1} M_{\odot}$ cluster at $z=0.37$

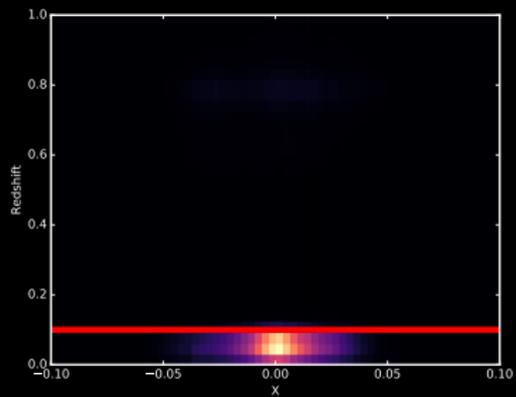
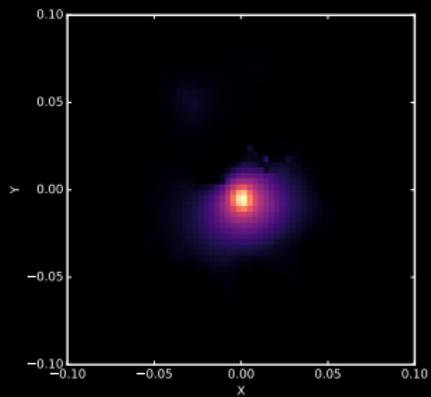
Reconstruction using GLIMPSE

PRELIMINARY RESULTS ON COSMOS

RECONSTRUCTED 3D DENSITY CONTRAST

Lanusse, Starck (2016), in prep.

ZOOM IN ON A CLUSTER AT REDSHIFT 0.12



CONCLUSION

- Incorporates developments introduced in Lanusse et al. (2016):
 - Handles irregularly distributed galaxies (**no binning**)
 - Include **individual redshift pdfs**
 - Accounts for **reduced shear**
- Tractable optimisation thanks to new algorithm
- Promising preliminary results on real data.
- Open-source software. The 2D version already available at:

<https://github.com/CosmoStat/Glimpse>