Fast, accurate and differentiable simulations of weak cosmic lensing

MADLens

Vanessa Böhm, Yu Feng, Max E. Lee, Biwei Dai

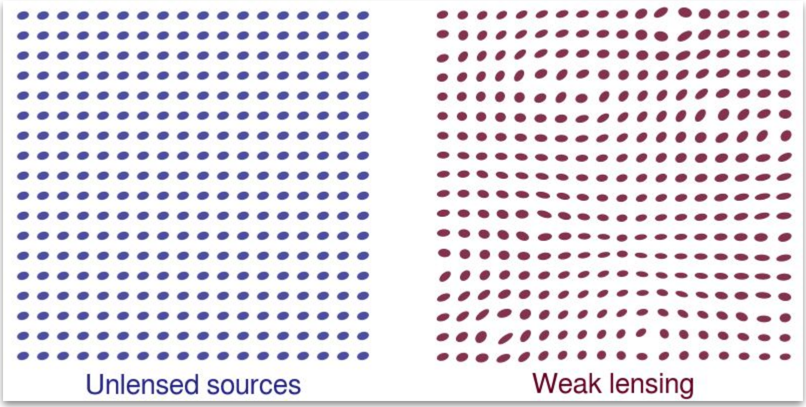
arxiv: 2012.07266

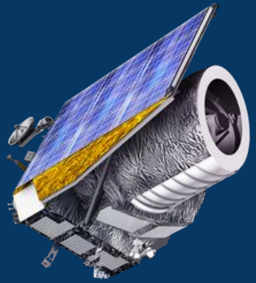
https://github.com/VMBoehm/MADLens

BERKELEY CENTER *for* COSMOLOGICAL PHYSICS

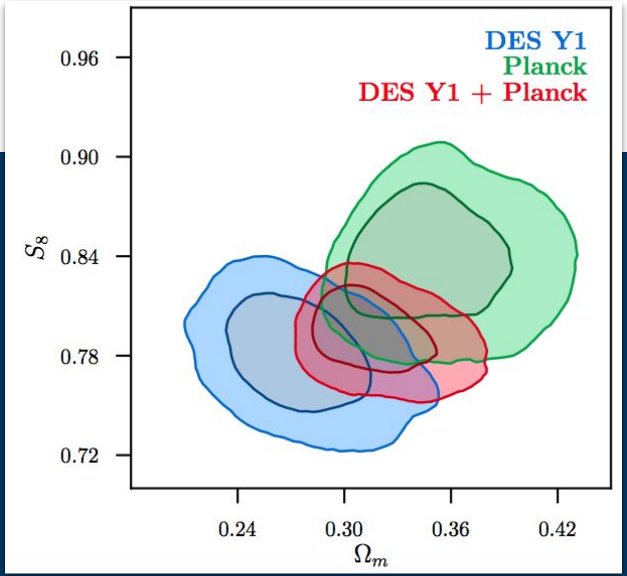
Weak Cosmic Shear

Weak gravitational lensing coherently distorts (shears) observed galaxy shapes.





EUCLID

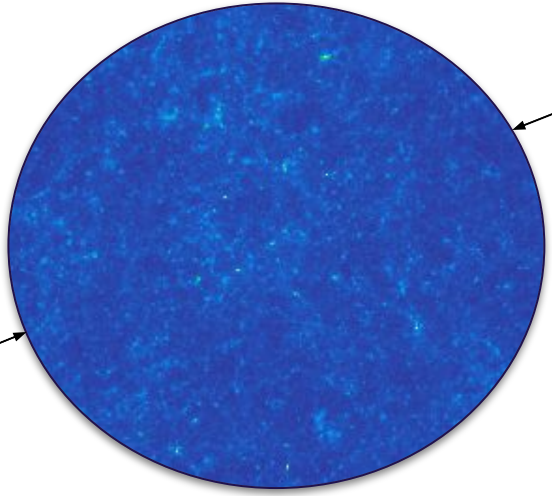


DES Collaboration 2017 (arxiv: 1708.01530)

Lensing is sensitive to

- the total matter parameter ($\boldsymbol{\Omega}_{\mathrm{m}}$)
- the amplitude of matter fluctuations ($\boldsymbol{\sigma}_8$)
- sum of neutrino masses ($\mathbf{M}_\nu$)
- time-varying dark energy (**w**)

Inference from non-Gaussian weak lensing data



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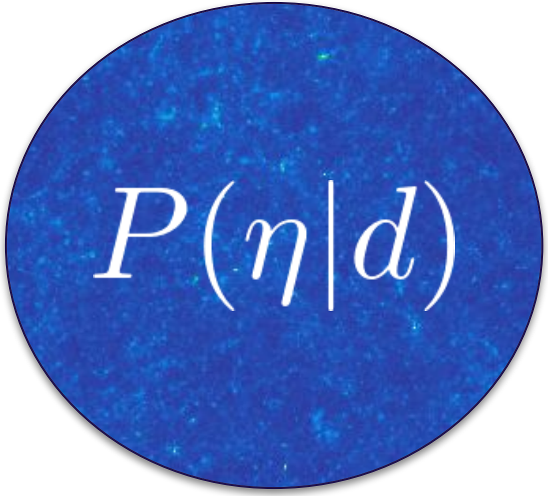


Inference from non-Gaussian weak lensing data

prior

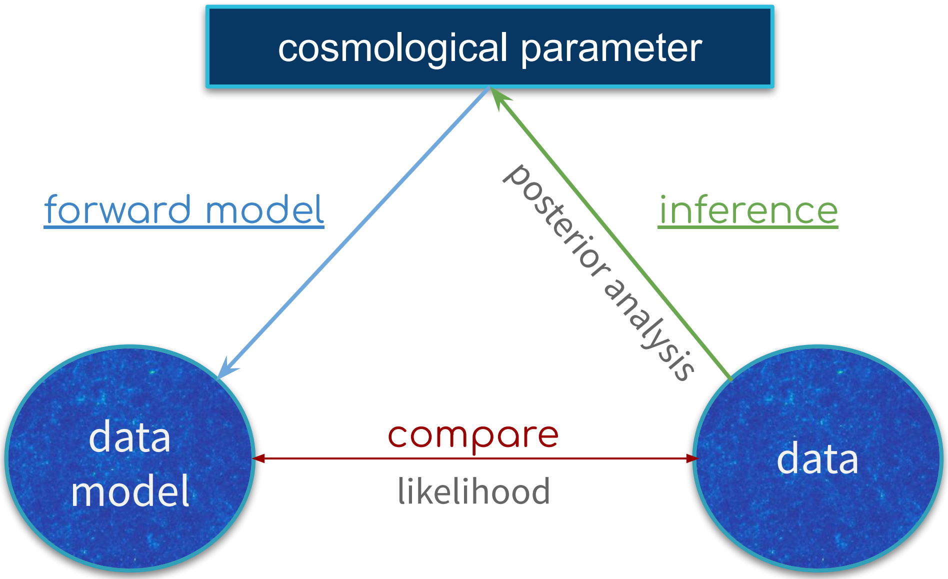
$$P(\eta|d) \sim P(d|\eta)P(\eta)$$

posterior

likelihood

posterior analysis

- ❏ optimization (find maximum)
- ❏ sampling (get contours, mean)



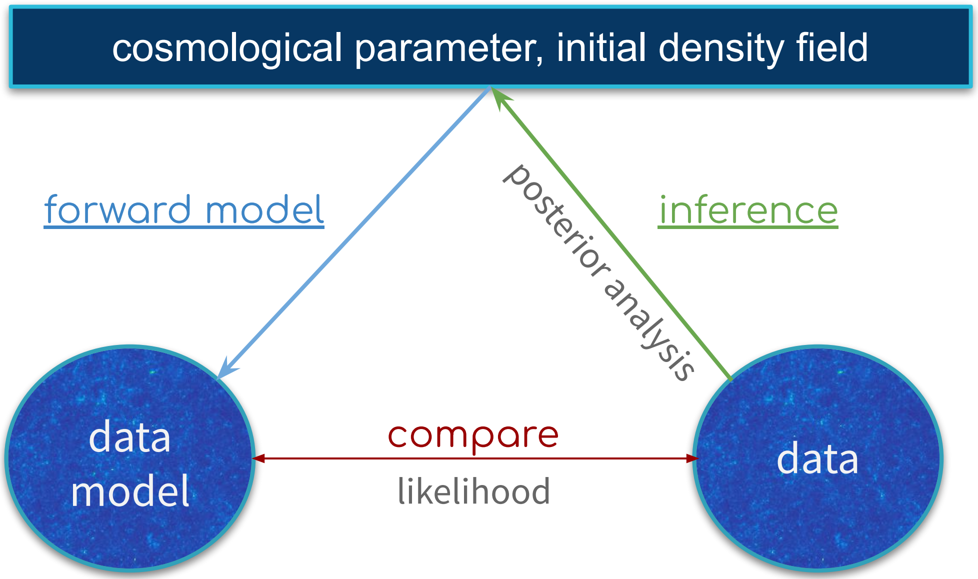
Inference from non-Gaussian weak lensing data

prior

$$P(\eta, s|d) \sim P(d|\eta, s)P(\eta)P(s)$$

posterior

likelihood



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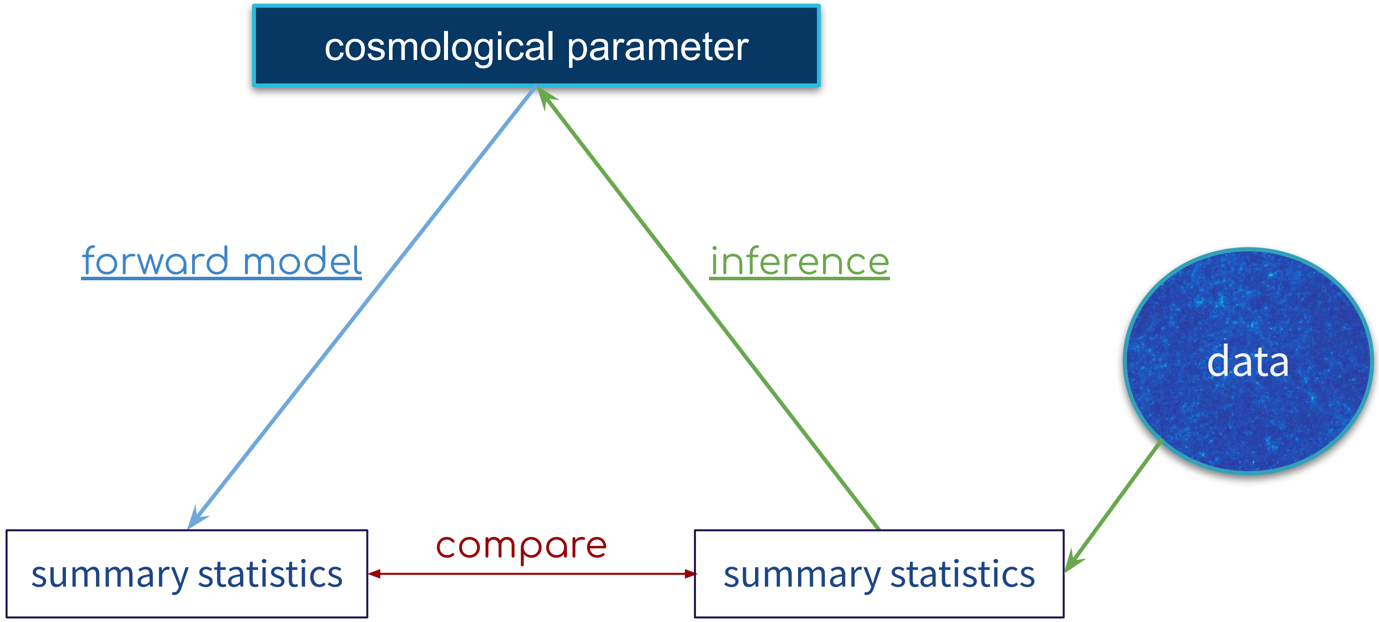

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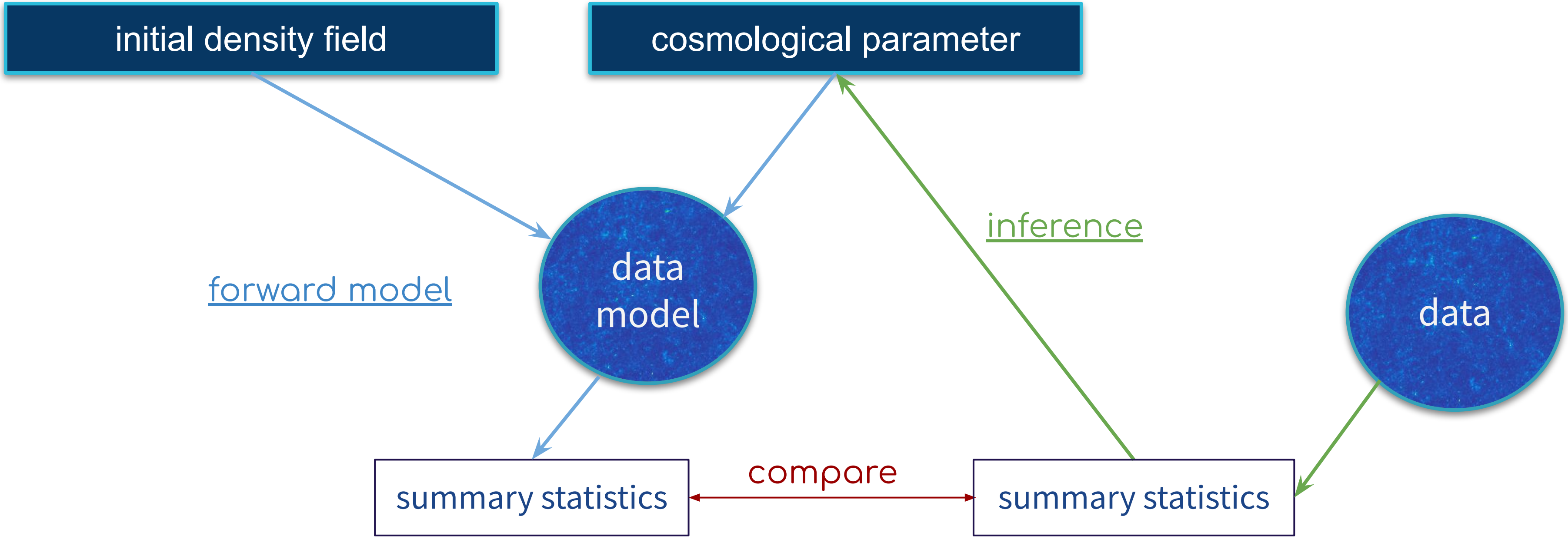
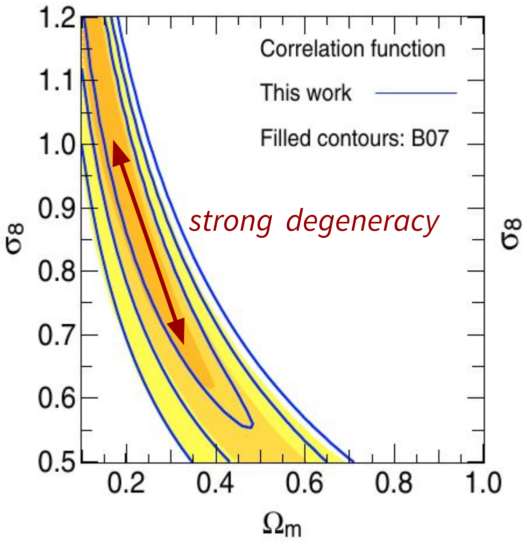


Inference from Gaussian weak lensing data

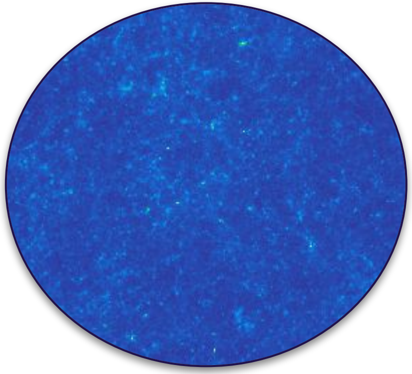
Gaussian summary: 2-point function/power spectrum

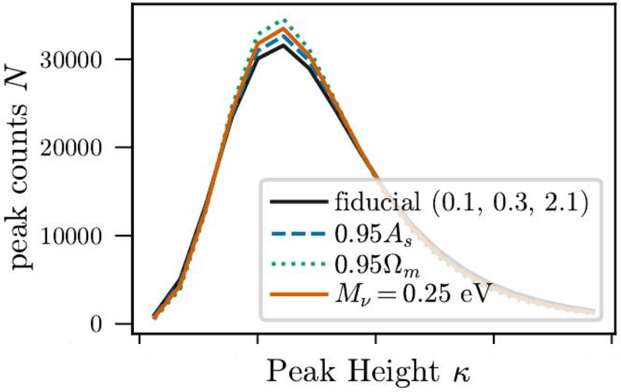


e.g. CFHTLens Analysis, Lu et al. 2008

Inference from non-Gaussian weak lensing data

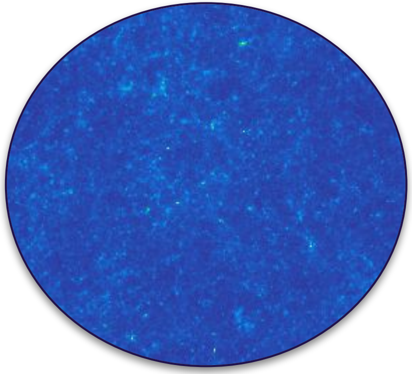
Scientist-defined non-Gaussian summary statistics





e.g. Li et al. 2018 (arxiv: 1810.01781),
Coulton et al. (**VB**) 2018 (arxiv: 1810.02374),
Liu et al. (**VB**) 2016 (arxiv: 1608.03169)

Inference from non-Gaussian weak lensing data



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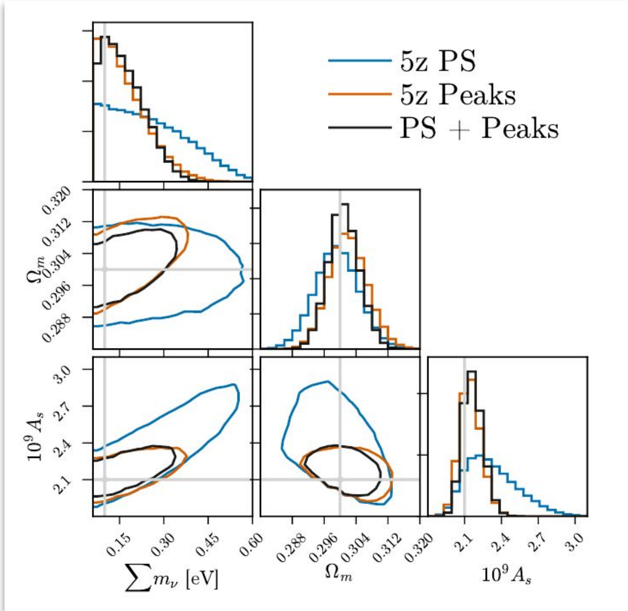

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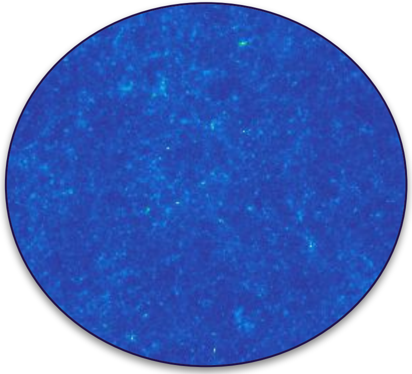
Inference from non-Gaussian weak lensing data

large &
accurate
simulation sets



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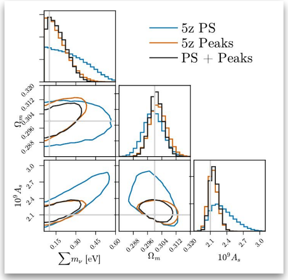

fast (and differentiable) data models

Inference from non-Gaussian weak lensing data

ML- defined non-Gaussian summary statistics

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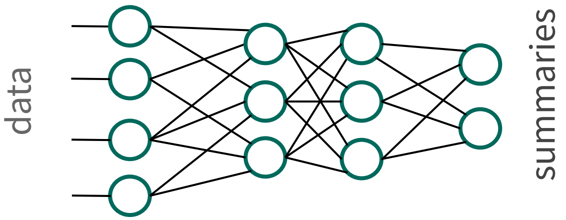
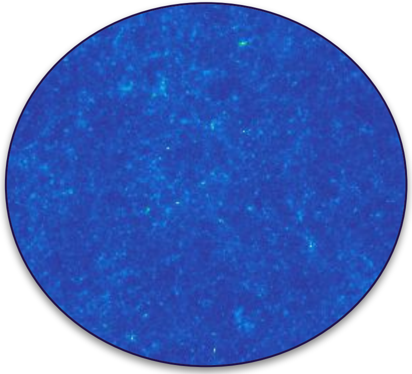
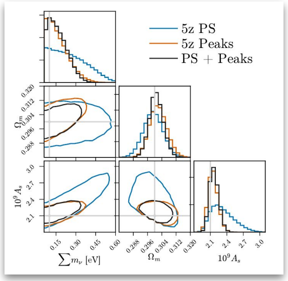
Scientist-defined non-Gaussian summary statistics







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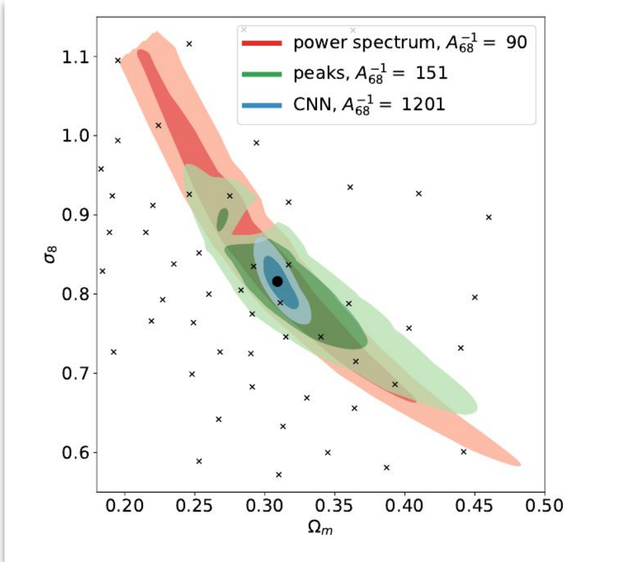

e.g. Ribli et al. 2019 (arxiv:1902.03663),
Fluri et al. 2019 (arxiv: 1906.03156),
Jeffrey et al. 2020 (arxiv:2009.08459),
Taylor et al. 2019 (arxiv:1904.05364)

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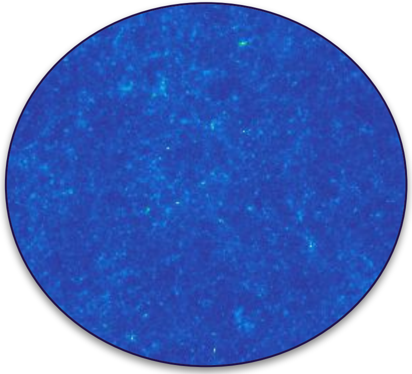
simulation sets



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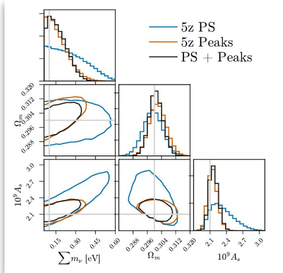

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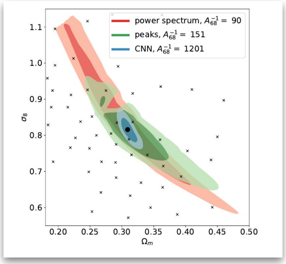

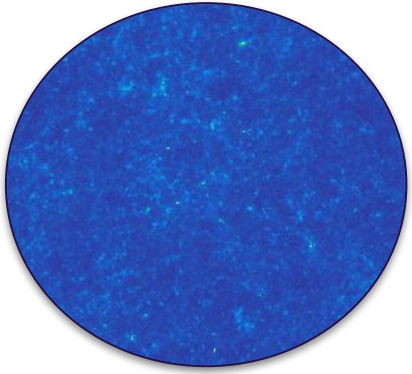

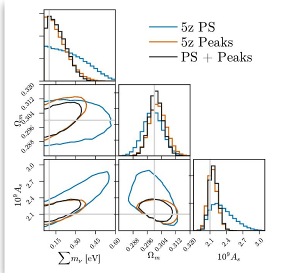

fast (on the fly) simulations

fast (and differentiable) data models

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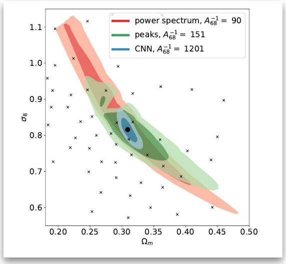

large & accurate simulation sets

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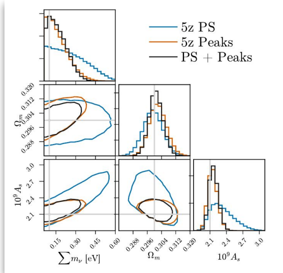
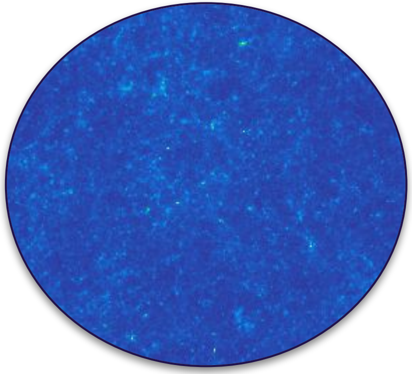
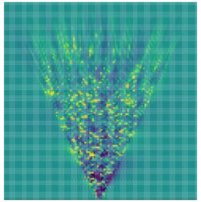


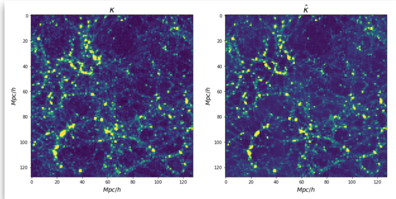


fast (on the fly) simulations

fast (and differentiable) data models

Inference from the full field





VB et al. 2017 (arxiv: 1701.01886),
Seljak et al. 2017 (arxiv:)
Lee et al (**VB**) in prep.

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large & accurate simulation sets

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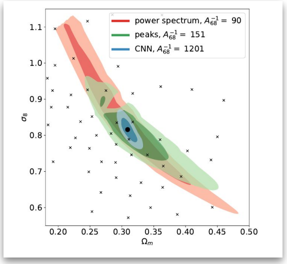

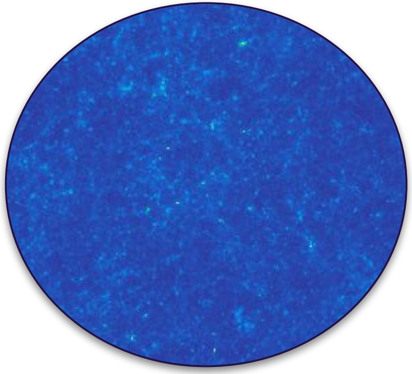

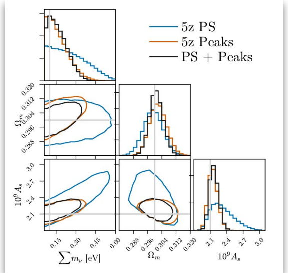

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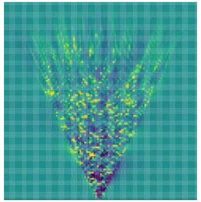

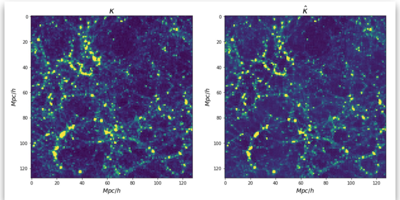

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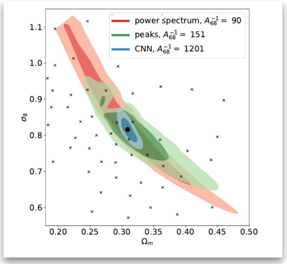

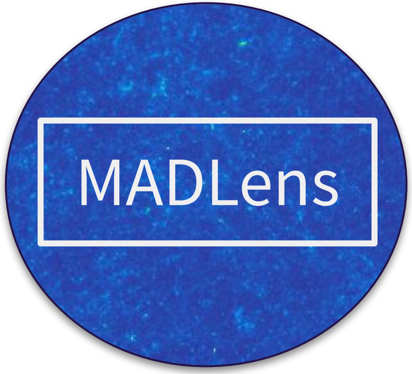

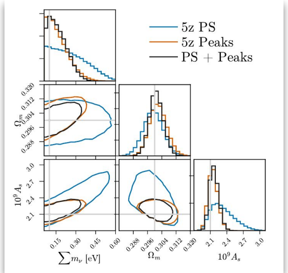

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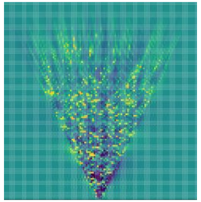
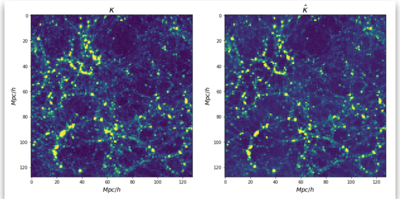
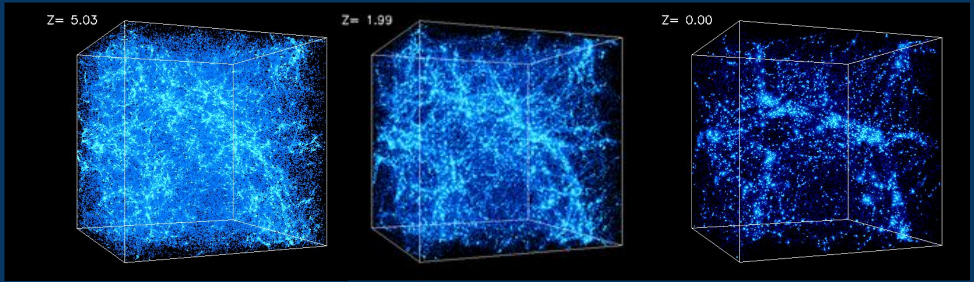




MADLens

Particle Mesh Simulation + Lensing Projection ⇒ Lensing Convergence



source: http://cosmicweb.uchicago.edu/filaments.html

https://github.com/VMBoehm/MADLens

VB, Y. Feng, M. Lee, B. Dai 2021 (arxiv: 2102.13618)

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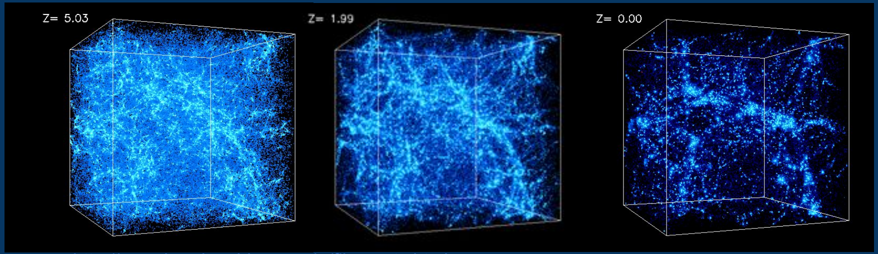

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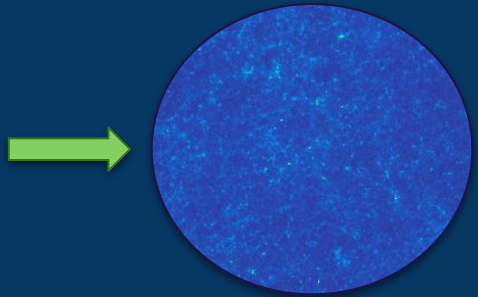

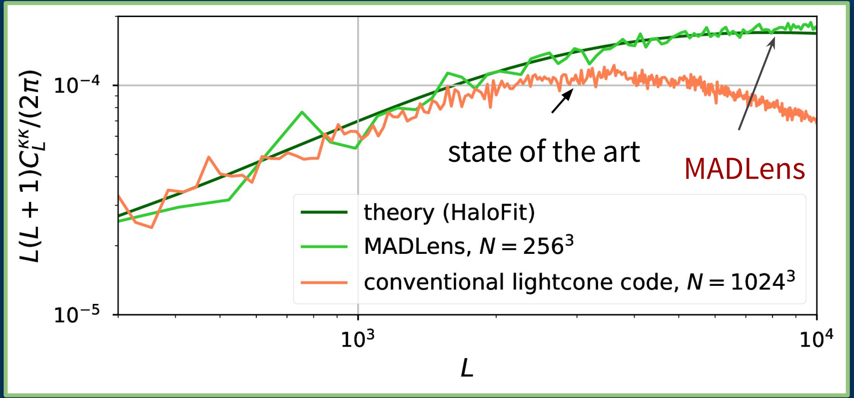

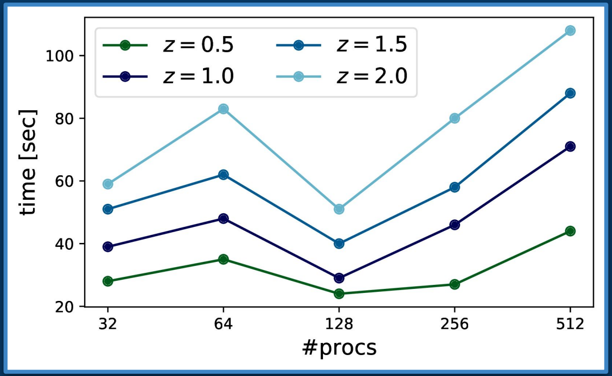

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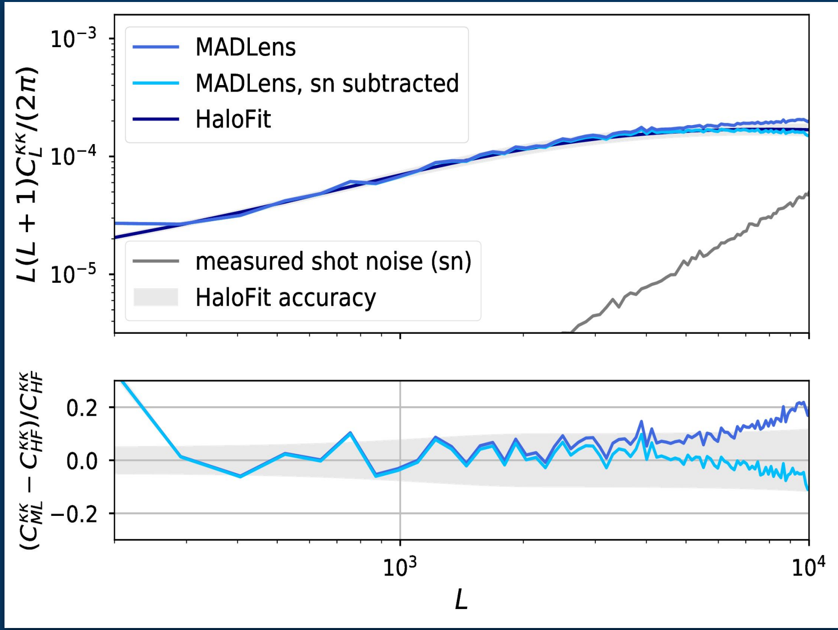
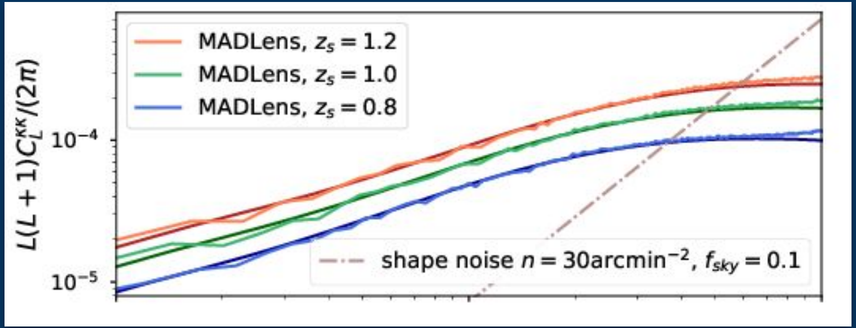
MADLens





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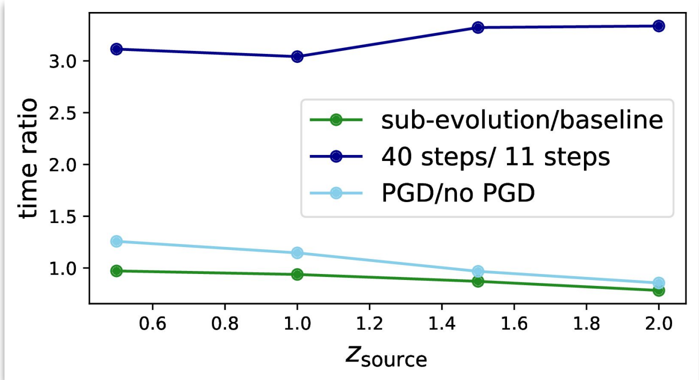
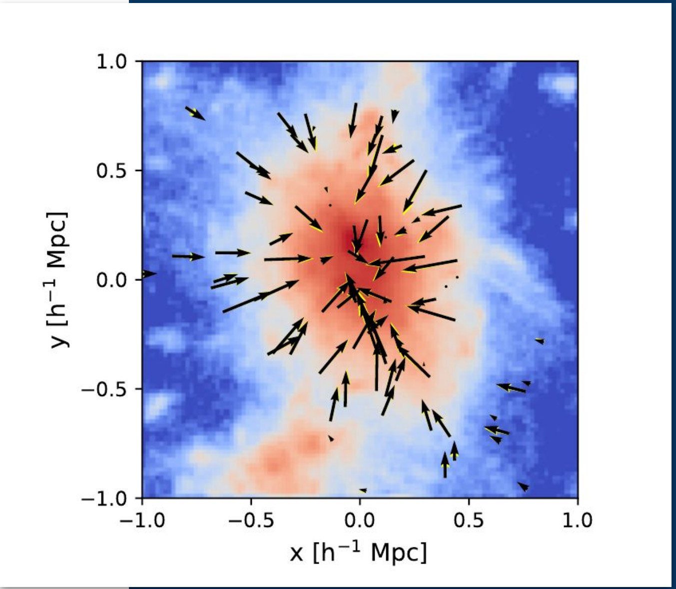
Particle Gradient Descent

Particle Gradient Descent[2] (PGD) displaces particles in every step to recover particle positions of a high resolution simulation.

$$\boxed{\mathbf{S}(x,a) = \alpha(a)/H_0^2\ \nabla\phi_{\text{filtered}}(x,a)}$$



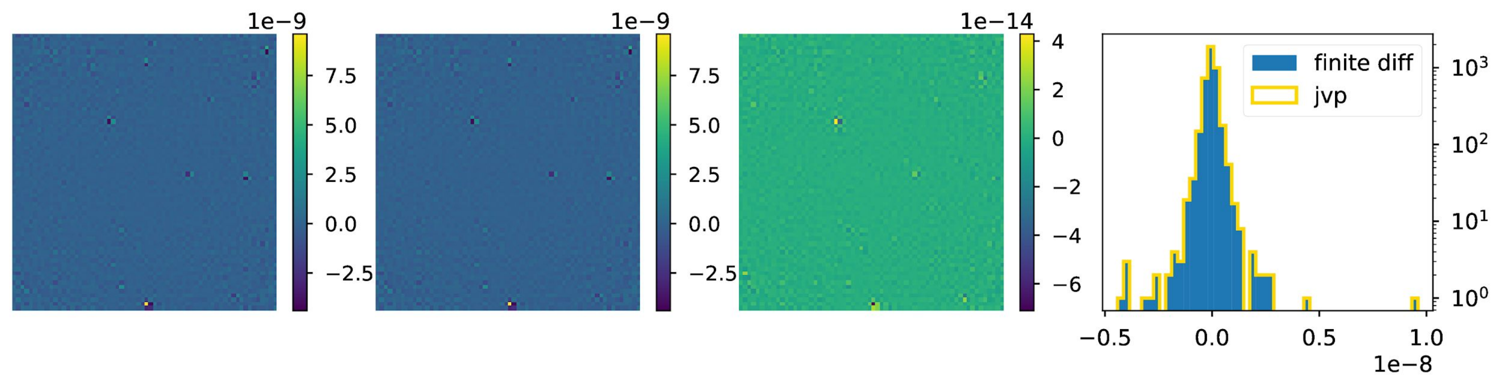


[2]Dai et al. 2016 (arxiv:1603.00476)

Derivatives

MADLens allows the user to take accurate derivatives through the simulation

1) with respect to the initial conditions
2) with respect to cosmological parameters



Derivatives

Memory efficient derivatives of scalar functions rely on reverse mode differentiation, a technique used in deep learning for training neural networks.

$$y = F(x) \qquad y \in R,\ x \in R^N \qquad F = A \circ B \circ C \qquad \begin{aligned} y &= A(a) \\ a &= B(b) \\ b &= C(x) \end{aligned}$$

scalar vector

Forward-mode differentiation:

large matrix

$$\frac{\partial F}{\partial x}\Big|_{x_0} = \frac{\partial A}{\partial a}\Big|_{a_0} \left(\frac{\partial B}{\partial b}\Big|_{b_0} \frac{\partial C}{\partial x}\Big|_{x_0} \right) = J_A \cdot (J_B \cdot J_C)$$

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scalar vector

Reverse-mode differentiation:

vector

$$\frac{\partial F}{\partial x}\Big|_{x_0} = \left(\frac{\partial A}{\partial a}\Big|_{a_0} \frac{\partial B}{\partial b}\Big|_{b_0} \right) \frac{\partial C}{\partial x}\Big|_{x_0} = (J_A \cdot J_B) \cdot J_C$$

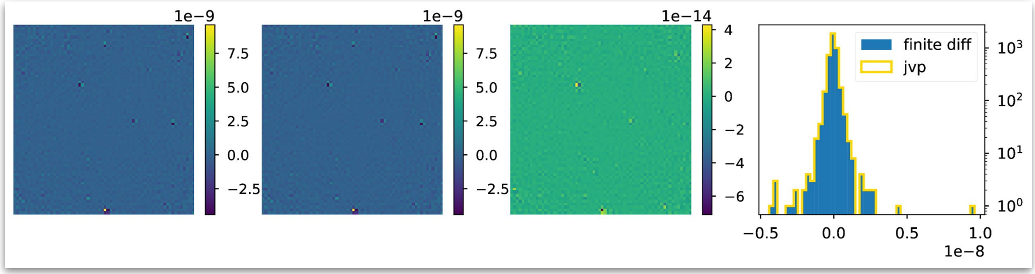
requires saving results of forward pass on a tape

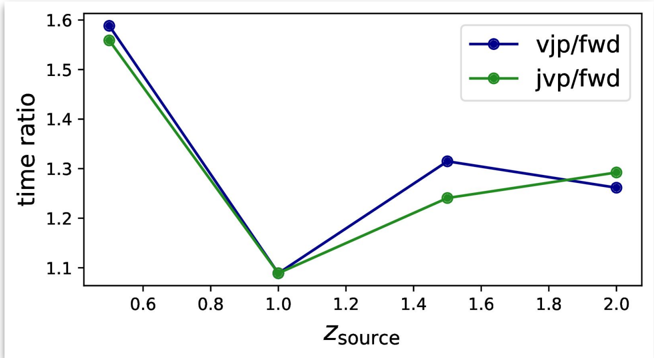
Derivatives

MADLens allows the user to take accurate derivatives through the simulation

1) with respect to the initial conditions
2) with respect to cosmological parameters

Based on backpropagation (a method also used for training neural networks).



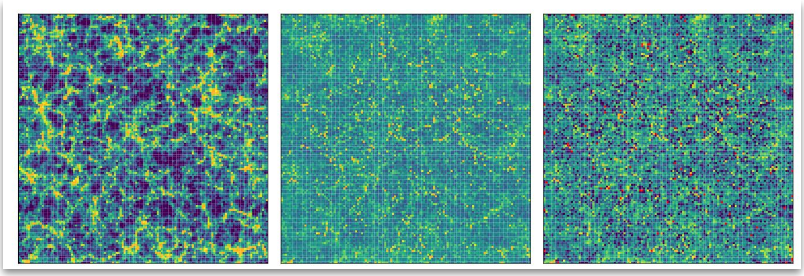


MADLens for Data Analysis

work led by Max E.

$$P(\eta|d) \sim \int \mathrm{d}s\, P(s,\eta|d)$$

VB et al. 2017 (arxiv:1701.01886)



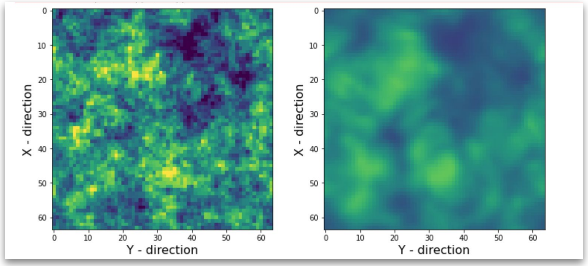
truth

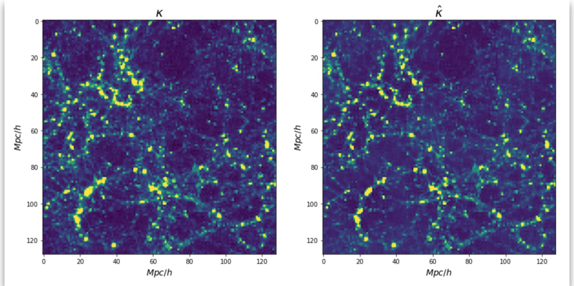
lognormal model reconstruction

Wiener Filter reconstruction

MAP reconstruction with lognormal fwd model

Lee et al. (**VB**) in prep.





MAP reconstruction with MADLens

MADLens for Data Analysis

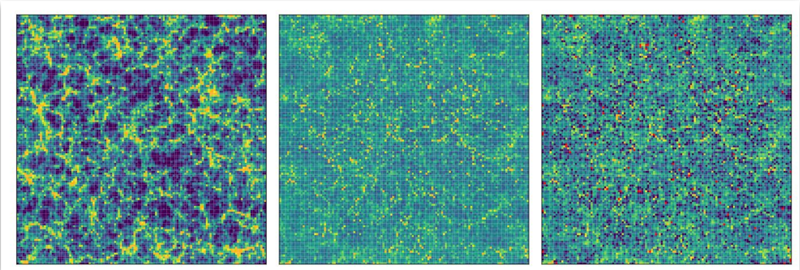
work led by Max E.

Lee

$$P(s|d) \sim P(d|s)P(s)$$

$$P(d|s) \hookleftarrow \mathcal{G}(d|\mathrm{FwdModel}(s), \sigma_e) \qquad P(s) \hookleftarrow \mathcal{G}(s|P_k)$$

VB et al. 2017 (arxiv:1701.01886)



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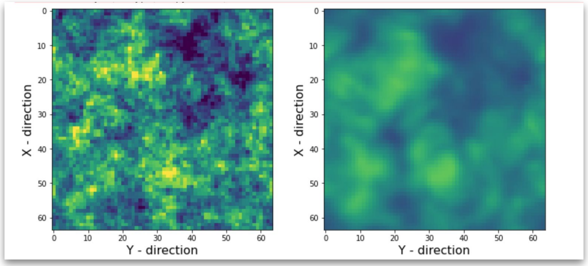
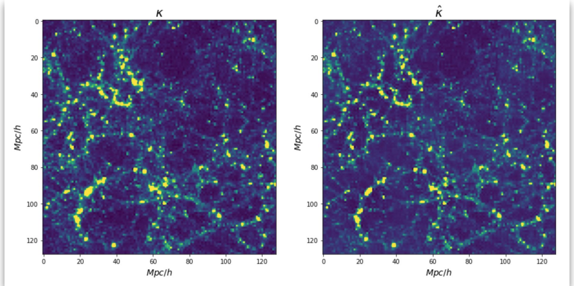
Lee et al. (**VB**) in prep.





MAP reconstruction with MADLens

Final Remarks

MADLens is the most accurate fast lensing code to date - and it is open source!

https://github.com/VMBoehm/MADLens

We can help you get it running for your application and welcome feedback.

We are actively working on extending MADLens (adding observables that are correlated with the convergence field, adding more derivatives).

The MADLens lensing scheme is currently being integrated into FlowPM (Modi et al 2020) - a FastPM version in tensorflow that runs on GPUs.