ETH zürich

Universität Basel

Cosmology Group
Optimization of Machine Learning Systems Group

Constraining Cosmology with Deep Learning

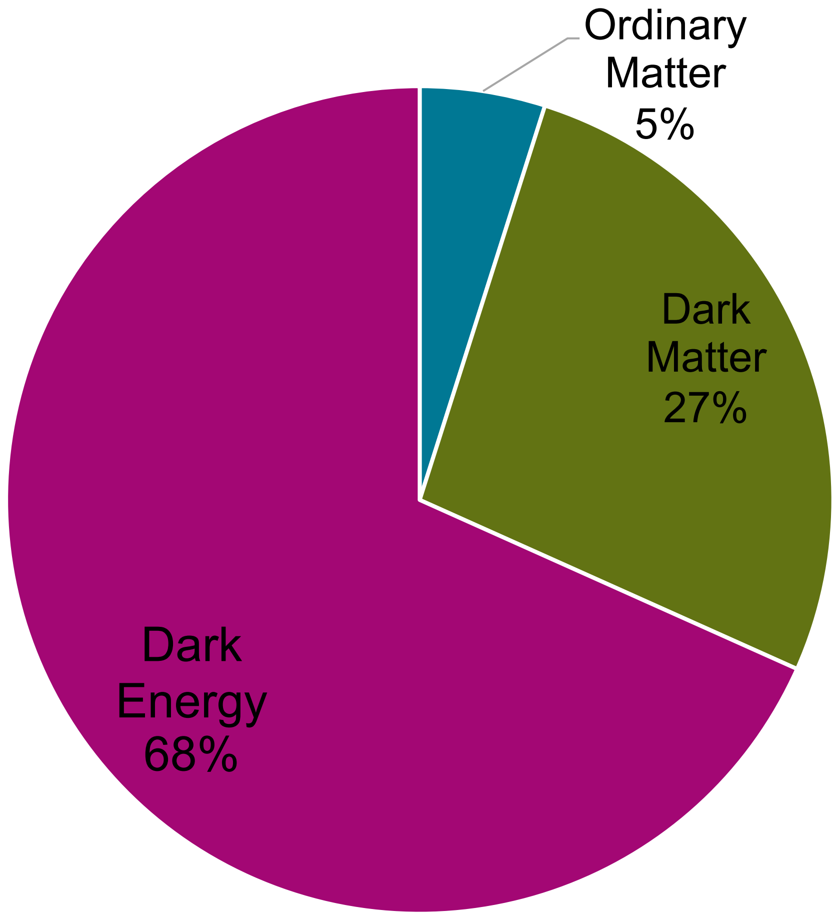
Arne Thomsen

21.03.2023, IPA-ML Workshop

Lambda-CDM

- Refinement of **big bang model**
- Gravity described by **general relativity**
- Major components
  - Ordinary matter
  - Cold dark matter (CDM)
  - Dark energy (Lambda)
- 5 free parameters
  - Mass fraction Ω_M
  - Variance of mass distribution σ_8
  - And $H_0,\ \Omega_b,\ n_s$

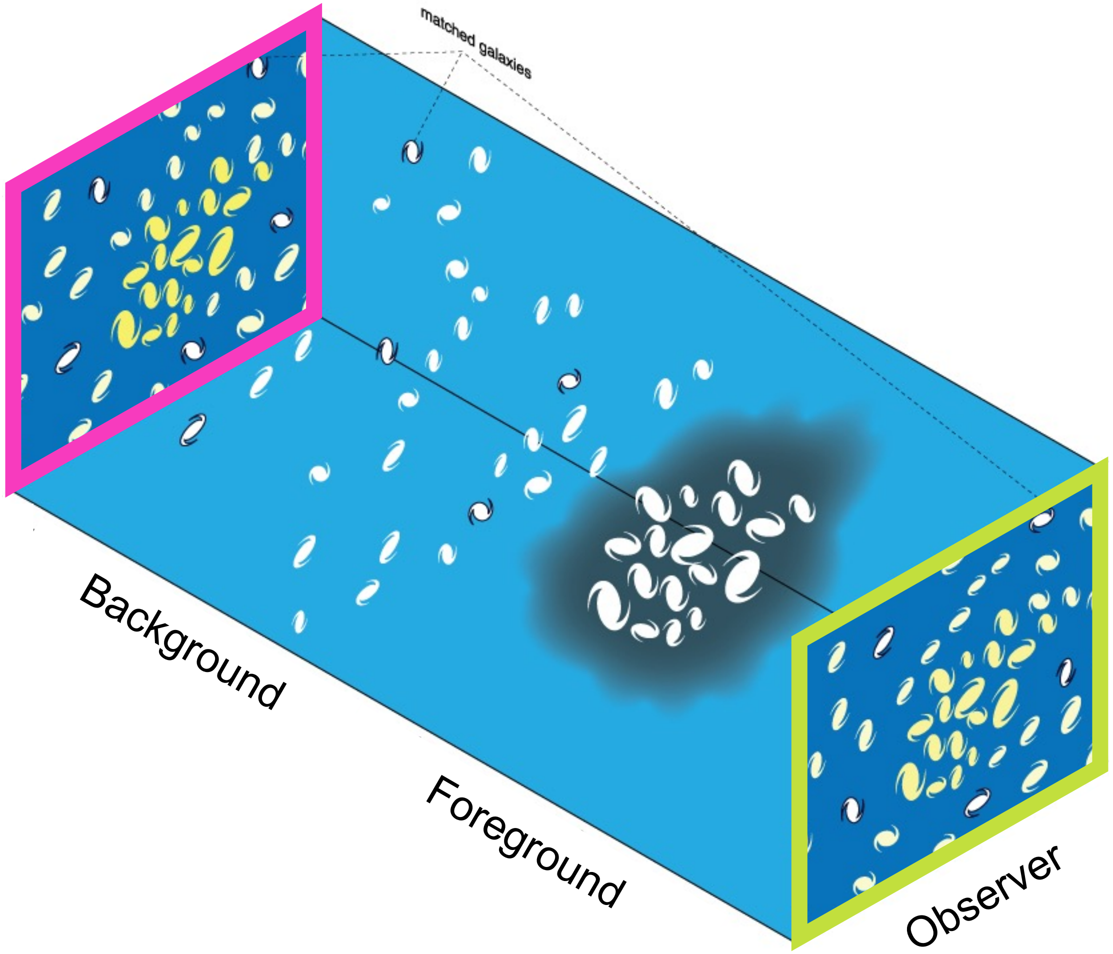
→ Improve constraints



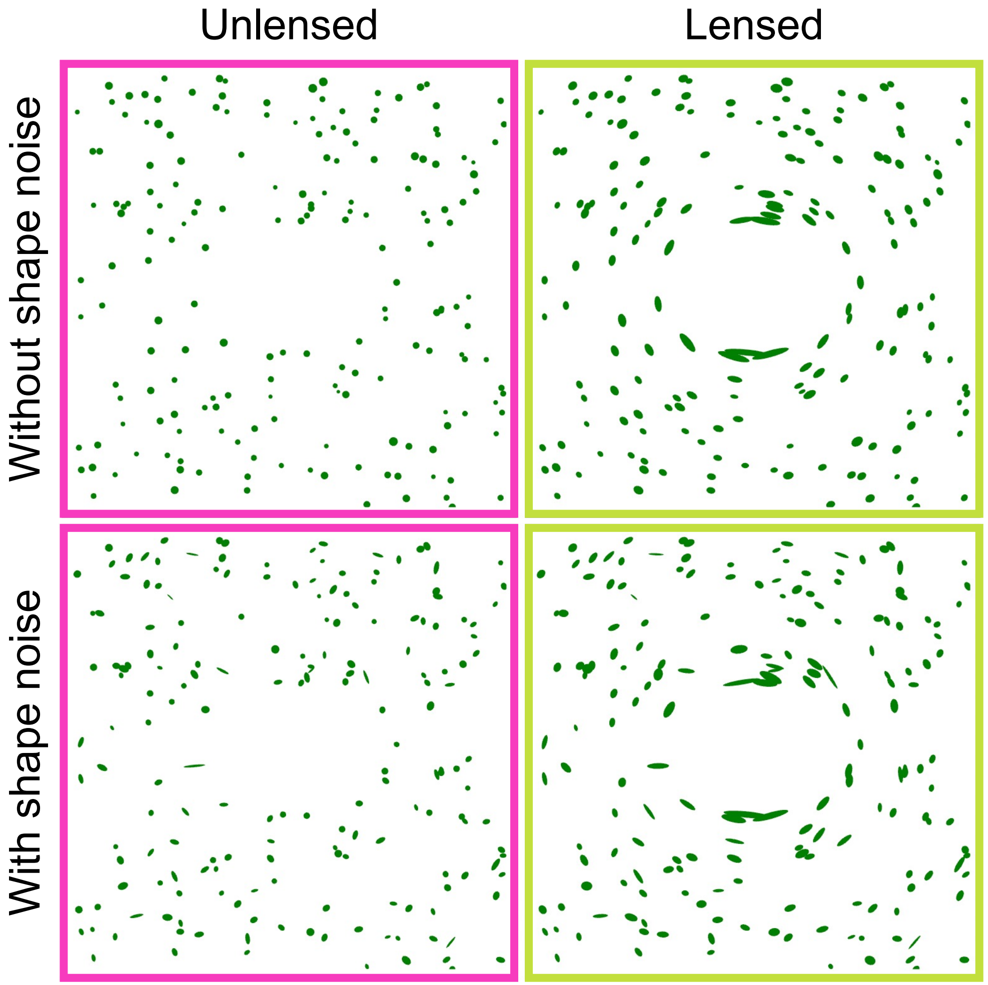
Energy content of the Universe today

Weak (gravitational) lensing

Image credit: [Wikipedia]

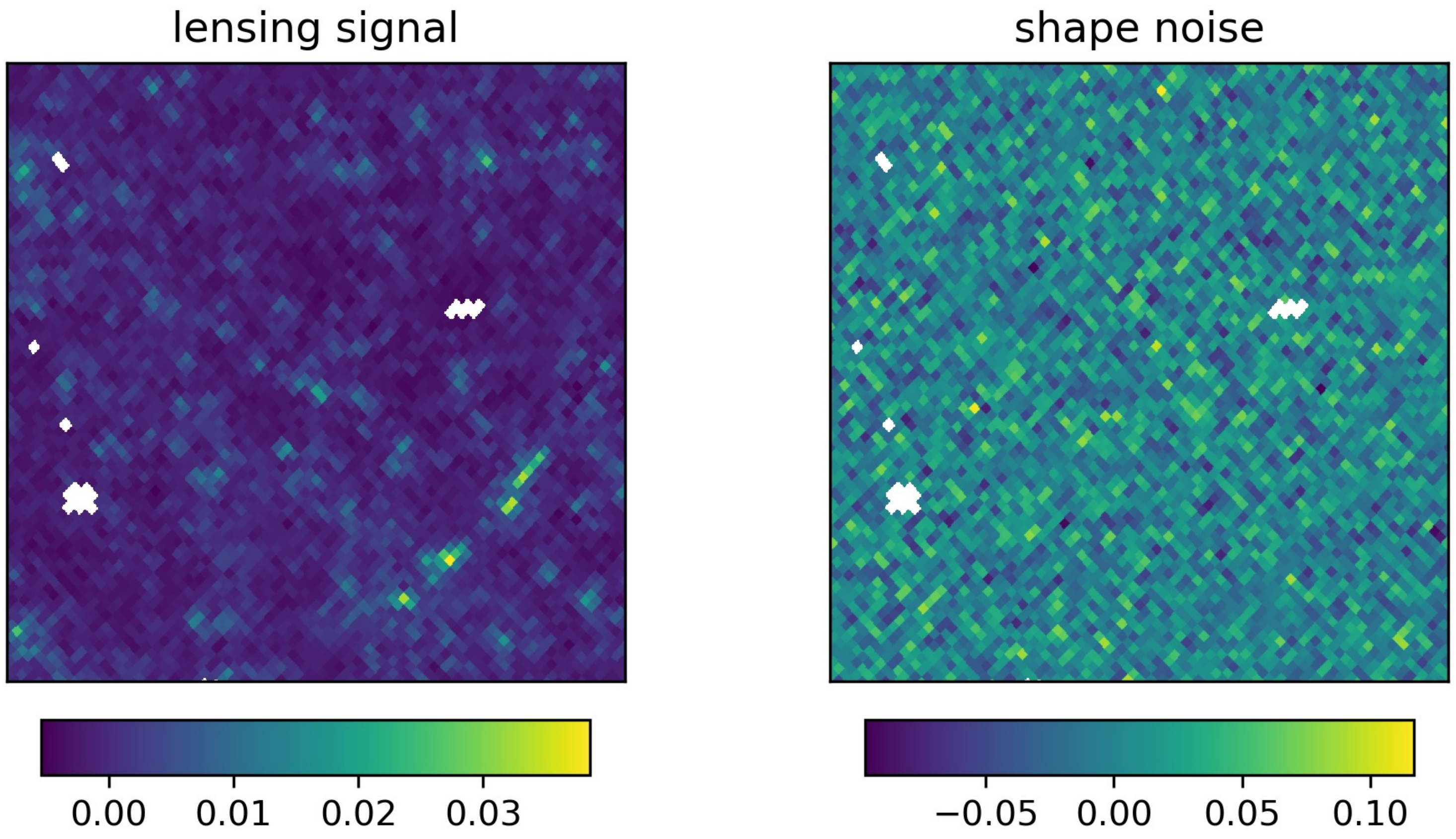


Matter arrangement

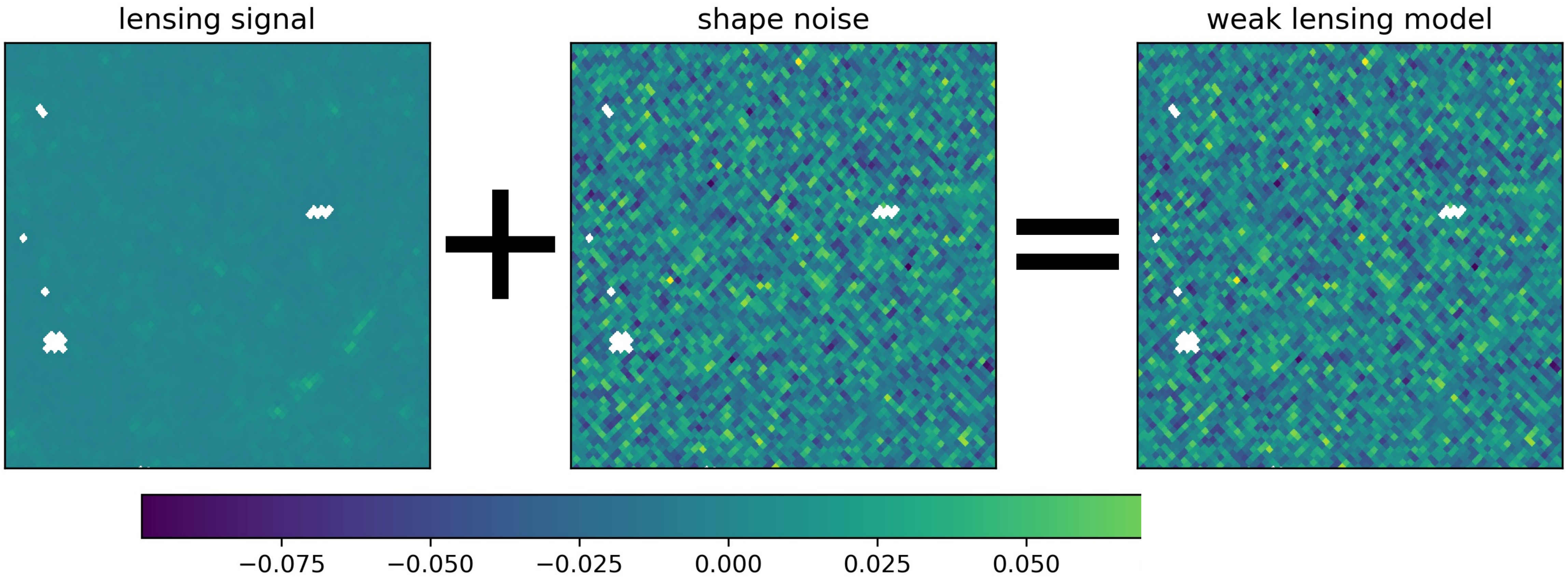


Galaxy shapes

Weak (gravitational) lensing



Weak (gravitational) lensing



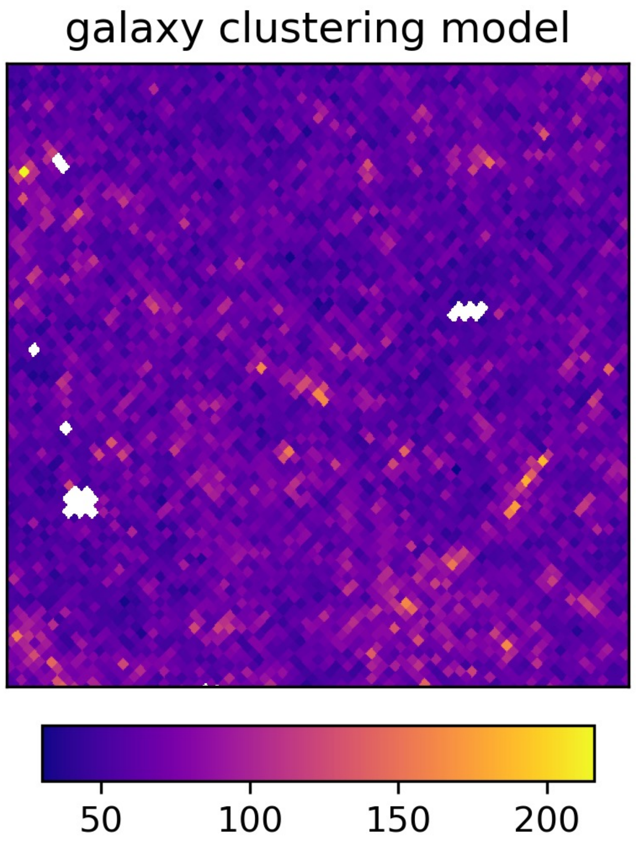
Combined probes of large scale structure

General motivation

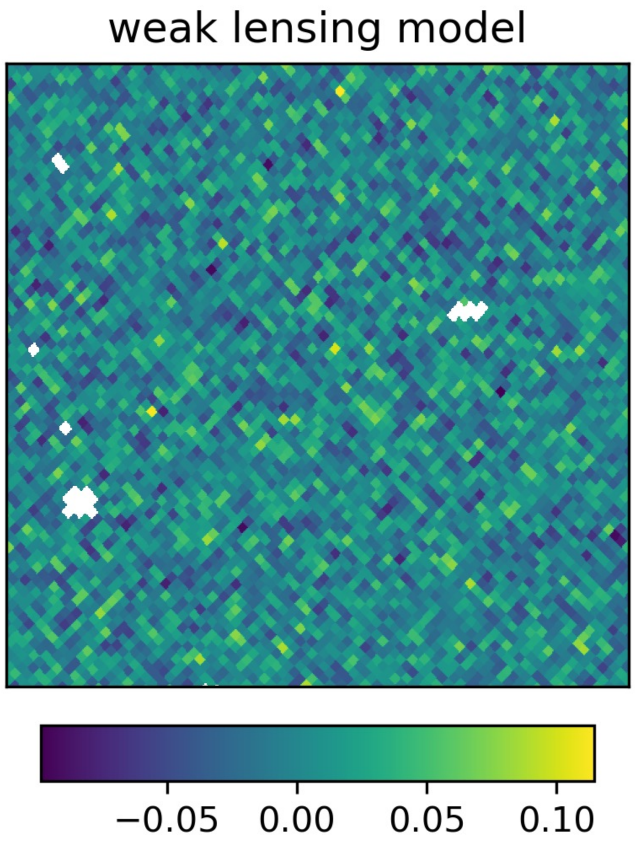
- Breaking of parameter degeneracies
  - Cosmology
  - Astrophysics
  - Measurement

Deep learning specific

- Combining probes in different channels is easy



Number of galaxies per pixel



Convergence value per pixel

Dark Energy Survey (DES)

- International colloboration
  - >400 members
  - 25 institutions
  - USA, Spain, UK, Brazil, Germany, Switzerland, Australia
- 4m telescope in the Chilean Andes
- 570 Megapixel camera with 3 deg field of view
- 758 nights of observations (2013-2019)
- Area of 5000 deg^2 (~1/10 of the sky)
- Half the history of the universe deep

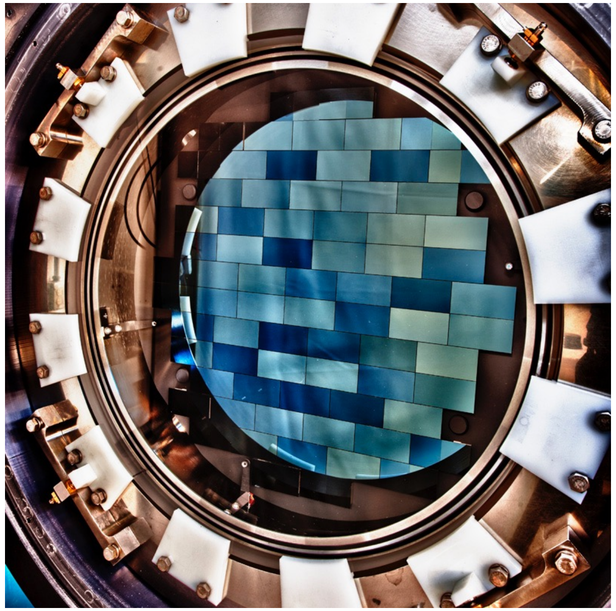
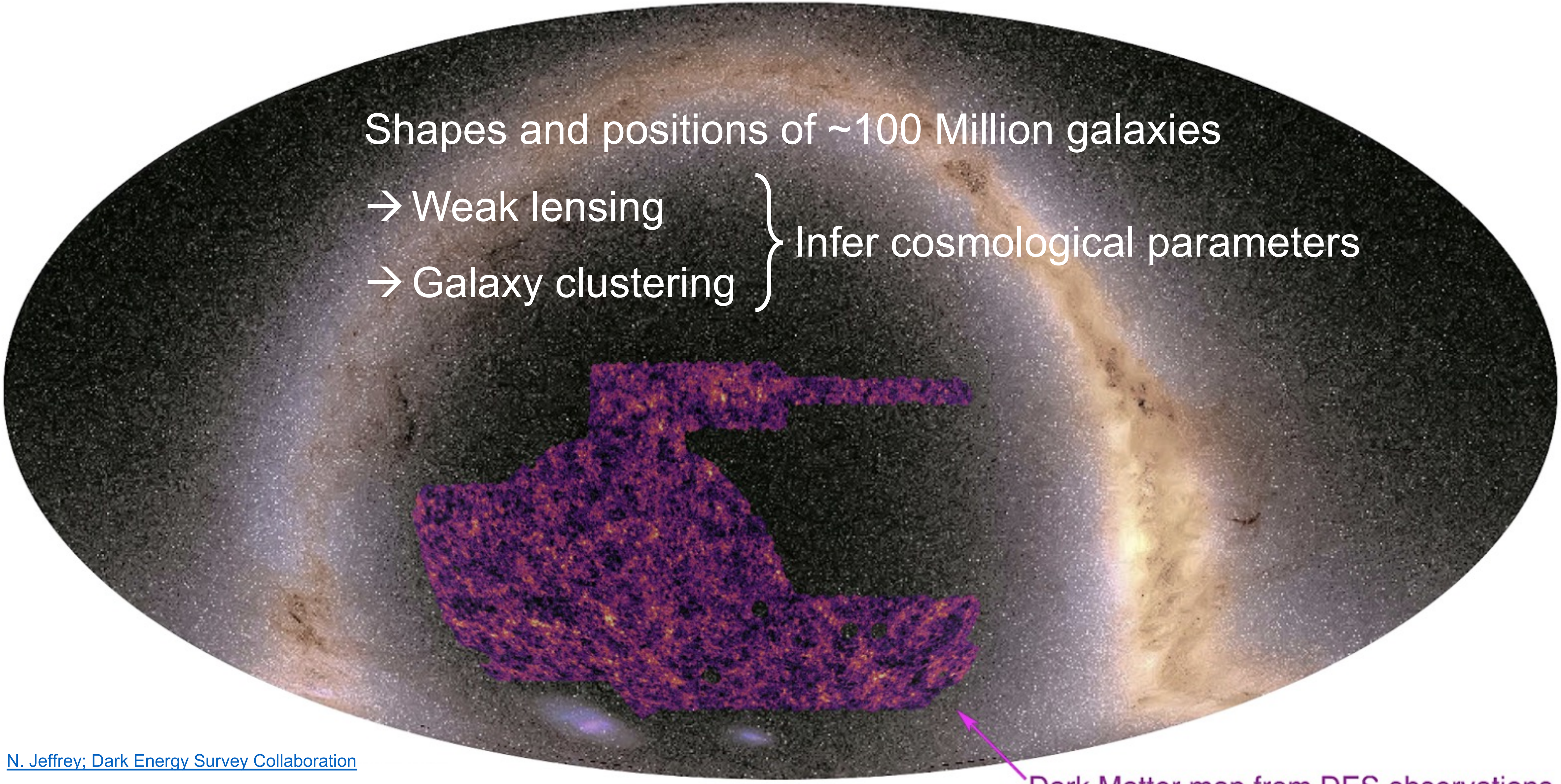


Image credit: Reider Hahn, Fermilab

DES: Survey footprint

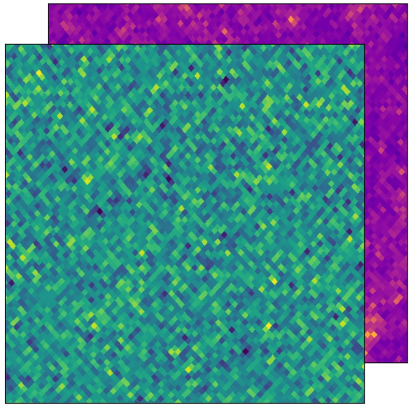


Dark Matter map from DES observations

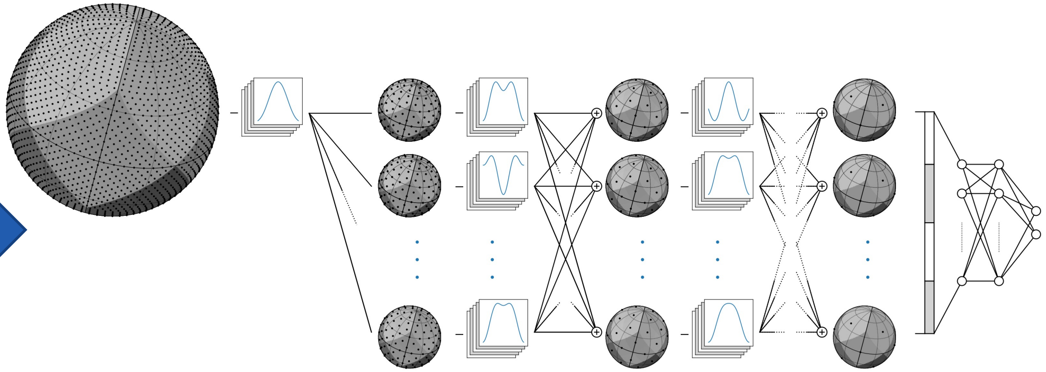
N. Jeffrey; Dark Energy Survey Collaboration

Inference with deep learning

Observation

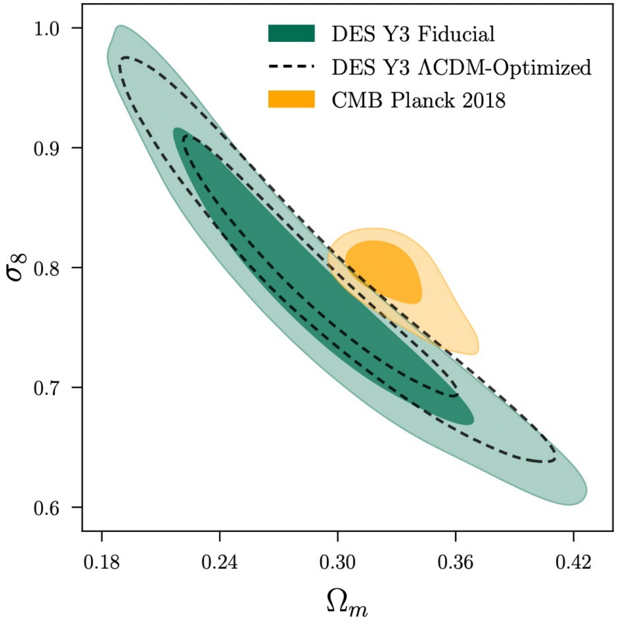


Learned summary statistic



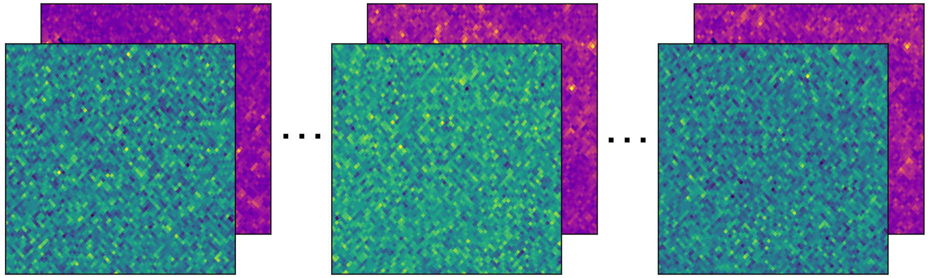
N. Perraudin et al. 2019

Simulation based inference



L. F. Secco et al. 2022

Forward model



Computing resources

- Perlmutter GPU cluster
- National Energy Research Scientific Computing Center (NERSC)
- 8th fastest (TOP500)

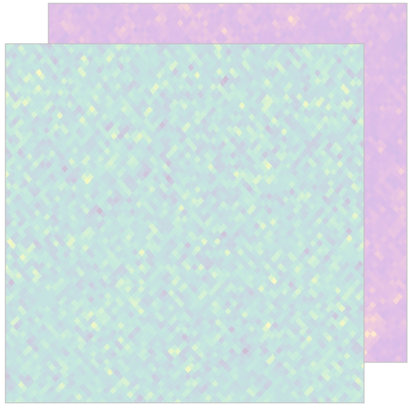
➡ Massive compute resources

➡ Time to solution like standard approach

Image credit: NERSC

Inference with deep learning

Observation



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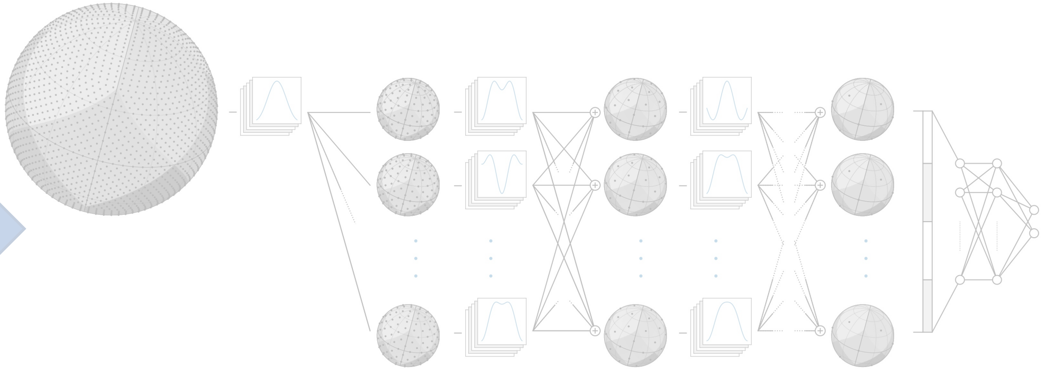

N. Perraudin et al. 2019

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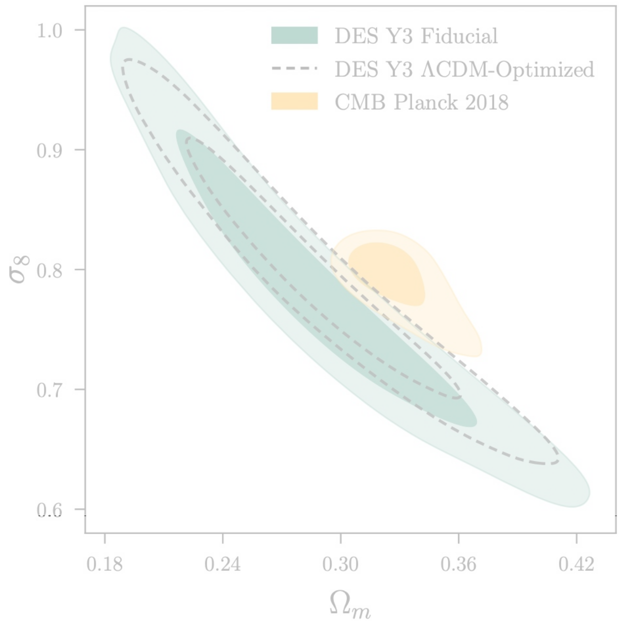

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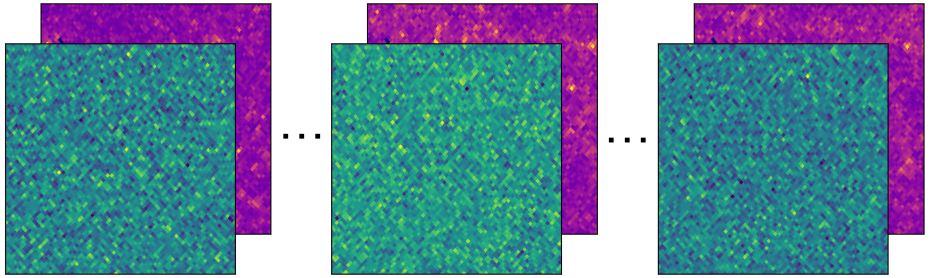
Forward model

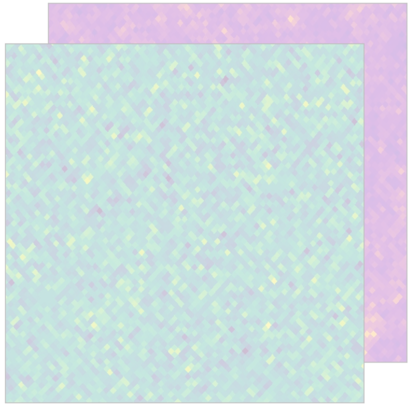


Forward model

General aspects	Deep learning specific
• Data driven approach → Physics is in the modeling	• Fast pipeline required → Trade-off between accuracy and speed
• No analytical prediction summary statistics needed → Flexible choice	• The networks can learn anything → Extra accurate forward model
	• New map level systematics tests

Inference with deep learning

Observation



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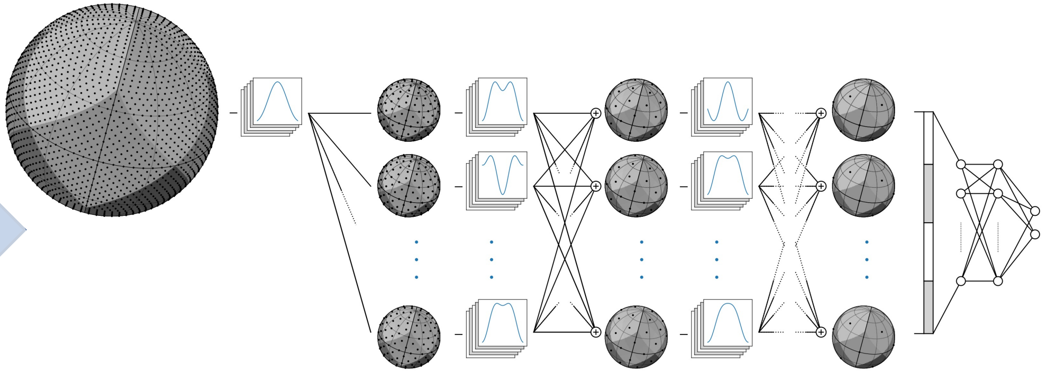

N. Perraudin et al. 2019

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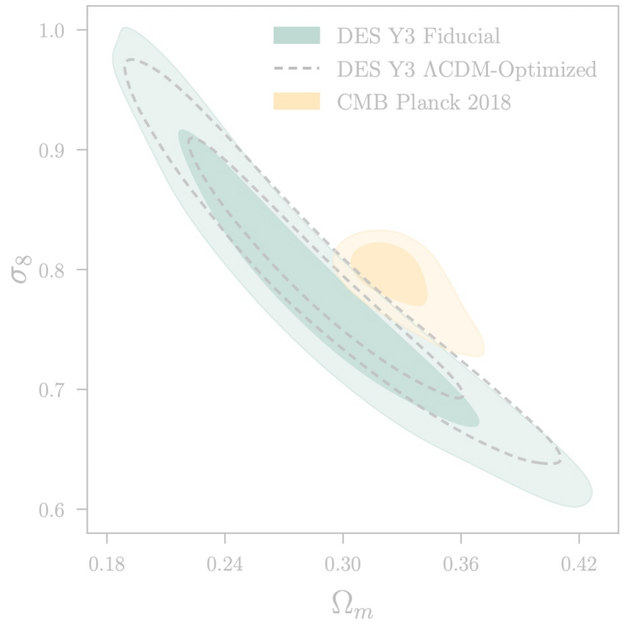

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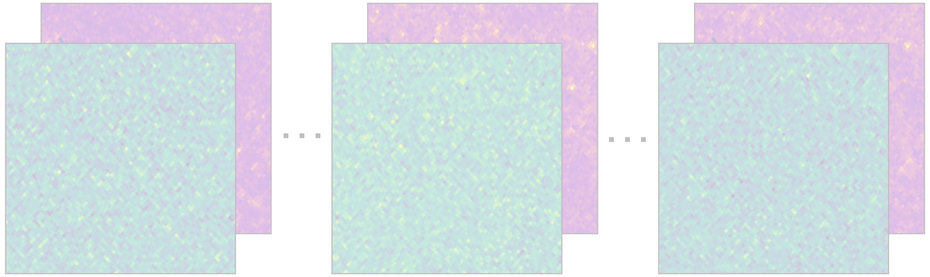
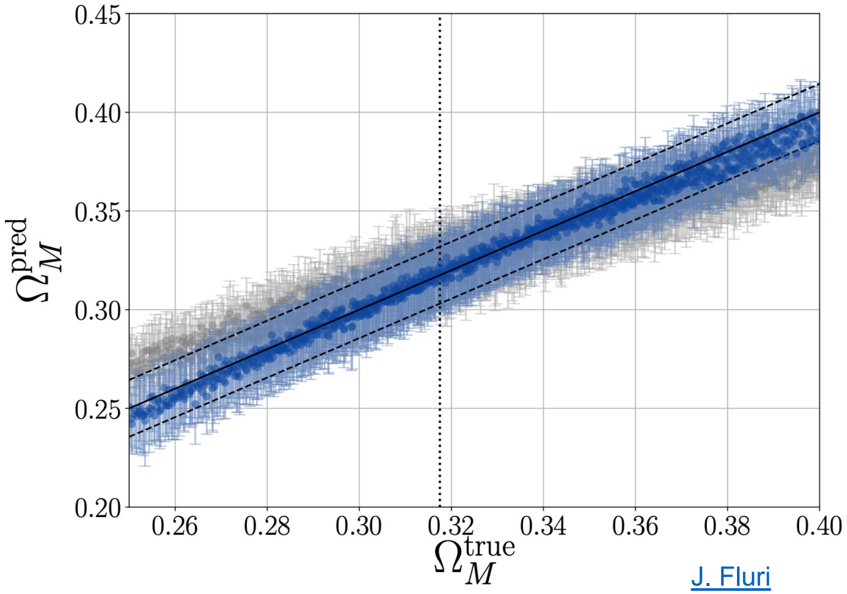
Forward model



Learned summary statistic

General

- Compression $\quad d_\theta \leq d_s \ll d_x$
  - High dimensional input $\quad x \in \mathbb{R}^{d_x}$
  - Low dimensional output $\quad s(x) \in \mathbb{R}^{d_s}$
- Preserve information
  - Ideally Bayesian sufficiency $\quad p(\theta|x) = p(\theta|s(x))$



J. Fluri et al. 2021

Learned

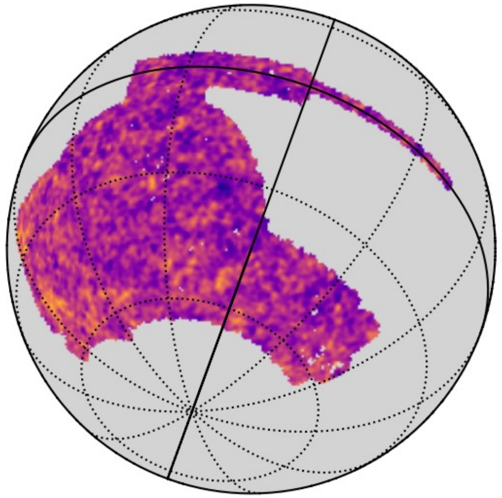
- Loss function
  - Simplest choice: Mean squared error
  - More specialized: Information maximizing loss

$$\underbrace{\mathrm{Cov}_\theta(s) \leq \frac{\partial \Psi_\theta(s)}{\partial \theta} \mathbf{I}(\theta)^{-1} \frac{\partial \Psi_\theta(s)}{\partial \theta}^T}_{\text{Cramér–Rao bound}} \iff -\log\det(\mathbf{I}(\theta)) \leq \overbrace{\log\det\left(\mathrm{Cov}_\theta(s)\right) - 2\log\left|\det\left(\frac{\partial \Psi_\theta(s)}{\partial \theta}\right)\right|}^{\text{Loss function}}$$

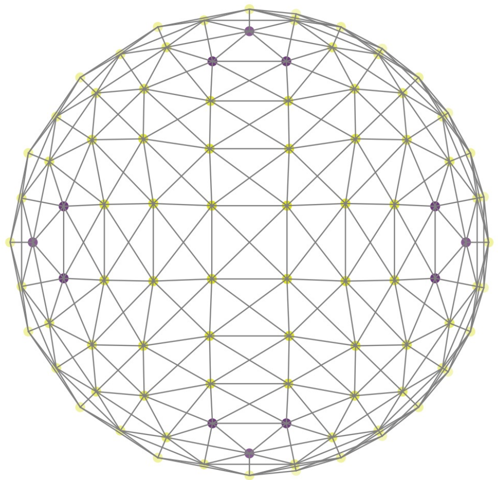
Network architecture

- Large area of the sky → Non-negligible curvature
- Complex survey mask → Graph representation advantageous
- Pixelation of the sphere (HEALPix)

DeepSphere graph convolutional neural networks (https://github.com/deepsphere)

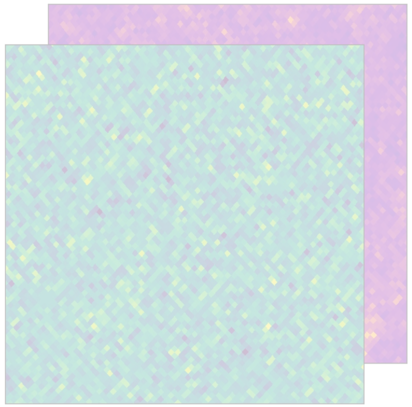


N. Perraudin et al. 2019



Inference with deep learning

Observation



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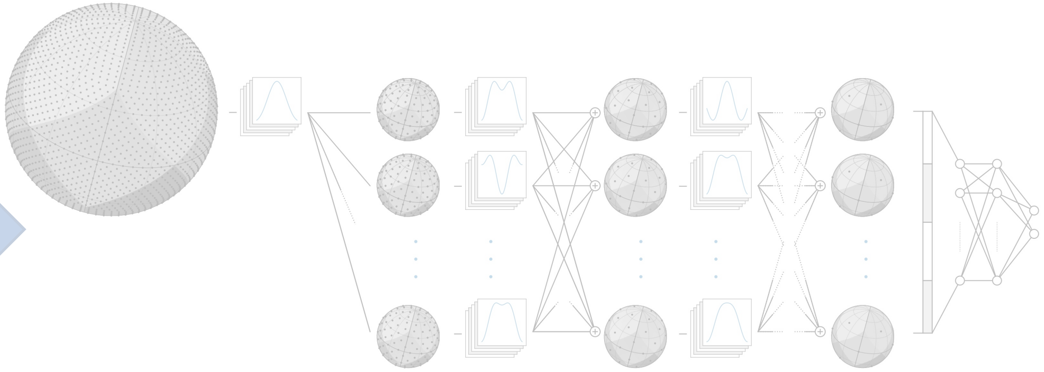

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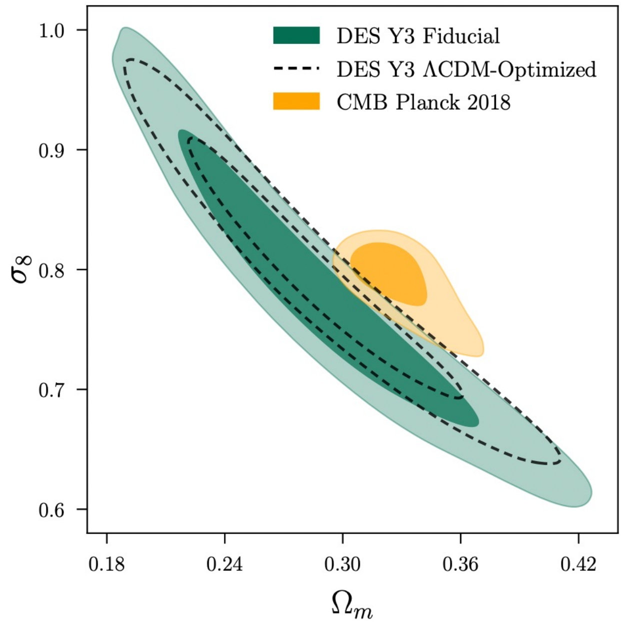
Simulation based inference



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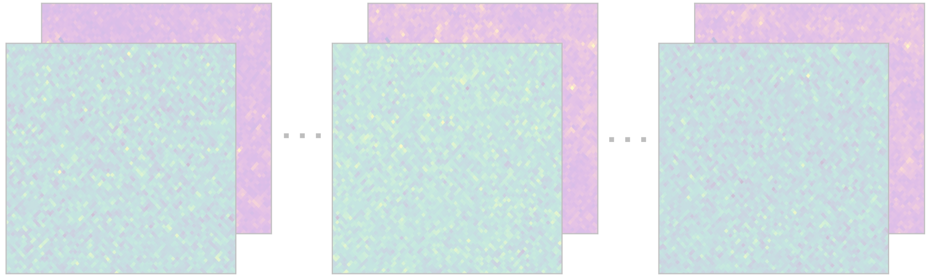
Forward model



Simulation based inference

Goal: Posterior distribution $p(\theta|x) \overset{\text{if sufficient}}{=} p(\theta|s(x))$

- GP ABC J. Fluri et al. 2021
  - Approximate Bayesian (ABC) computation for a kernel K_h

    $$p_{ABC}\left(\theta \mid s_{\text{obs}}\right) \propto \int K_h\left(\left\|s-s_{\text{obs}}\right\|\right) p(s \mid \theta) p(\theta) \mathrm{d} s$$

    - Evaluate on the parameter grid
  - Gaussian process (GP) regression to emulate between grid points
- Neural density estimation
  - Learn $p(s|\theta)$ with a normalizing flow, mixture auf Gaussians, …
  - Get $p(\theta|s_{\text{obs}})$ from Bayes' theorem

Conclusion

Constraining cosmology with deep learning

- Multiple probes of large scale structure
  - Weak lensing
  - Galaxy clustering
- Forward model
  - Contains all physics
- Learned summary statistic
  - Loss function
  - Network architecture
- Parameter inference
  - Approximate Bayesian computation
  - Neural density estimation

Thanks for your attention