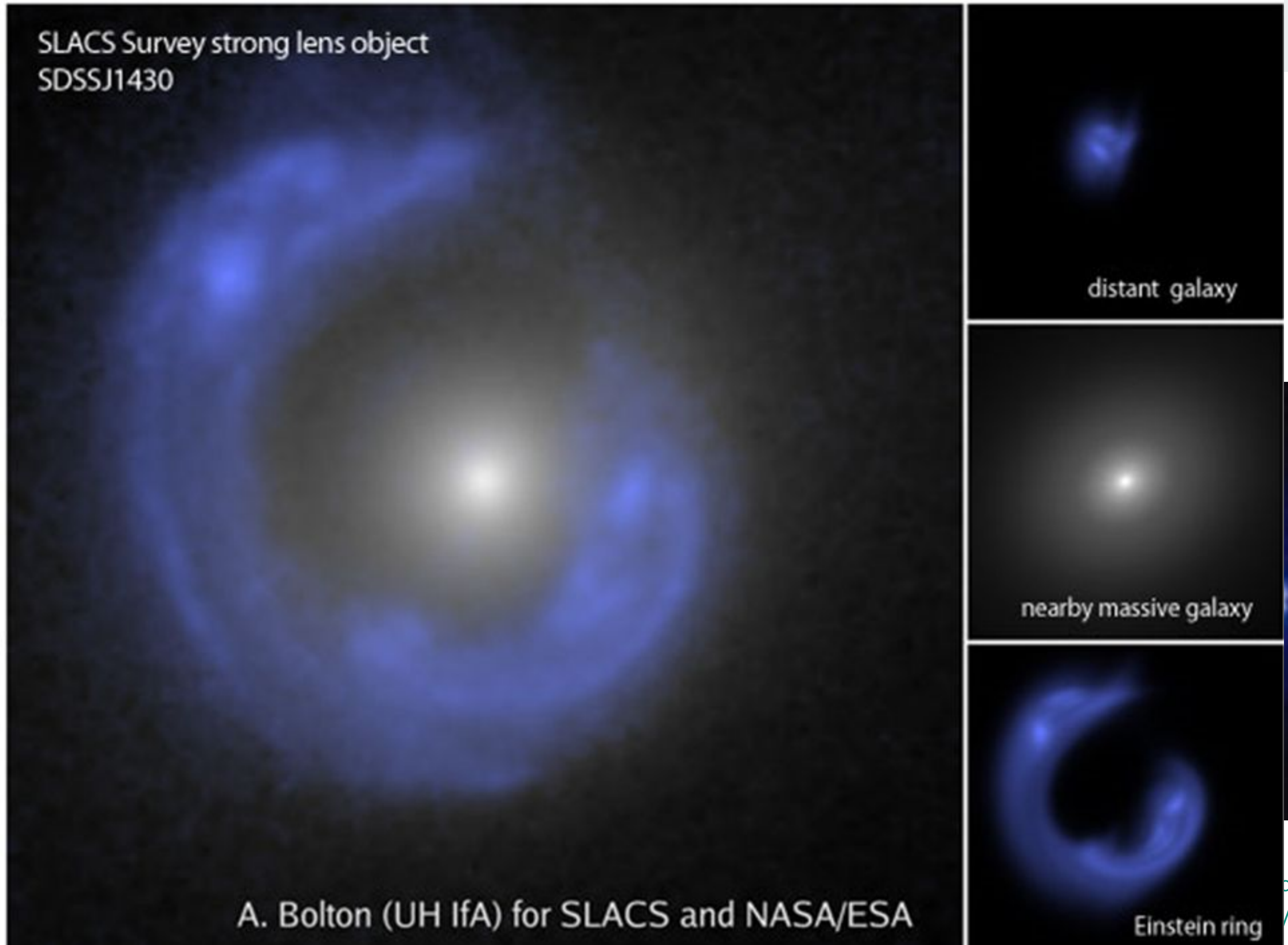
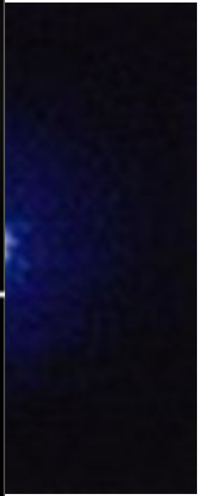
Lenstool-HPC : Mass modelling for Euclid

an HPC based strong gravitational lens mass modelling software

Gr





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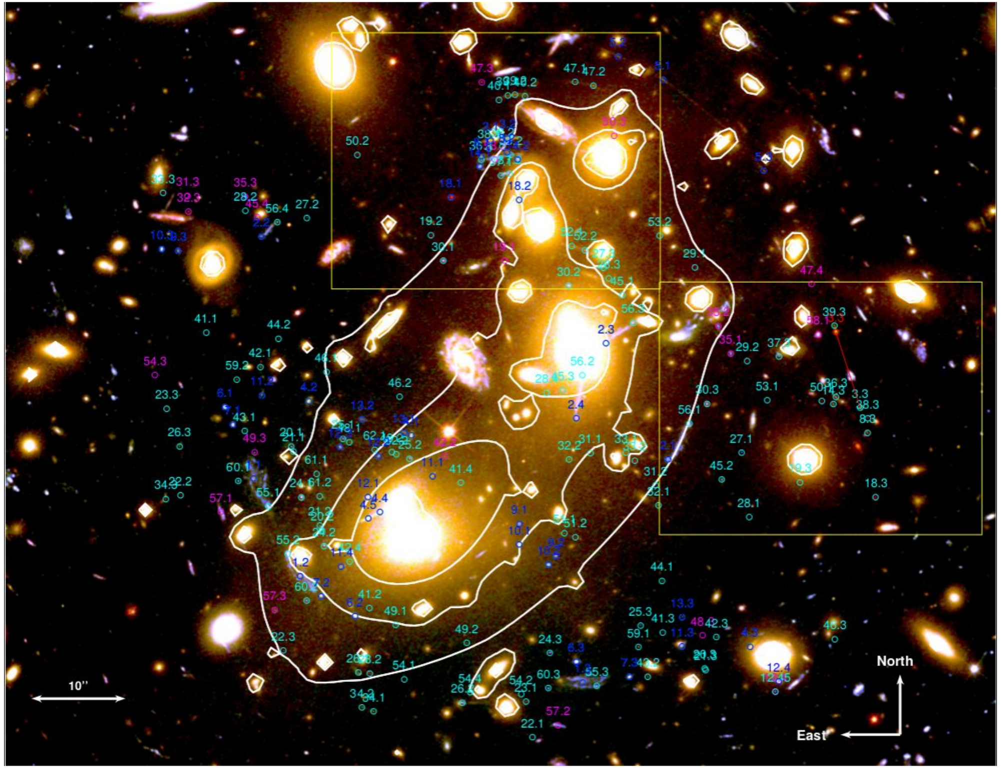
Scientific Motivation

- Mass structures of Galaxies (Dark matter)
  - [More et al.2011, Sonnenfeld et al.2015]
- Galaxy evolution
- Time delay calculation of lensed quasars
  - [Bonvin et al. 2016, Suyu et al. 2017]
- High redshift galaxy detection
  - [Kneib et al.2004, Richard et al.2011].



Cluster A2744 (Credit: Jauzac et al, 2015)

Astronomical Surveys: Creating catalogs of lenses

Ground Based (KiDS) or Space-based (Euclid)

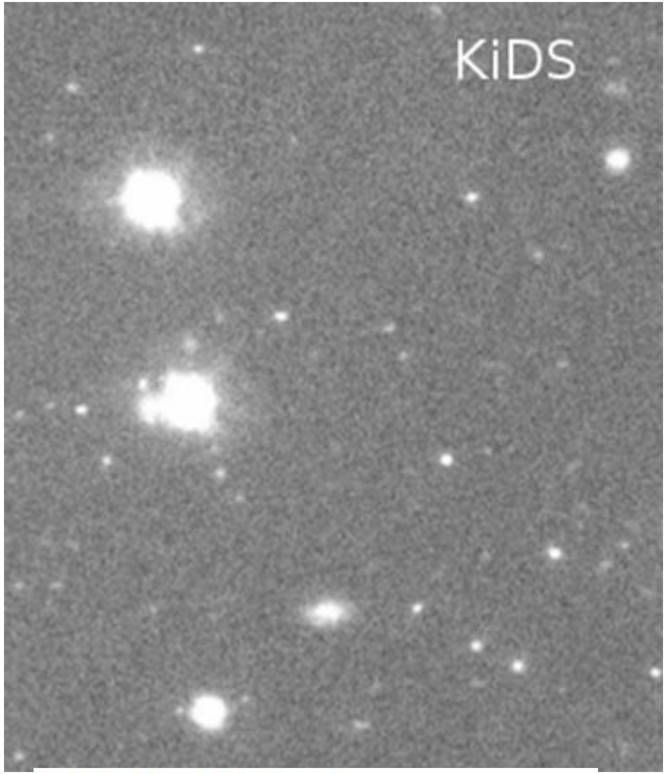
Kilo-Degree Survey

- 1 K estimated galaxy lenses

Euclid (ESA mission)

- 5K-10K estimated cluster and group lenses
- 100 K estimated galaxy lenses

Too much Data ?



KiDs r-band image [2.]

Lenstool: Mass-modeling

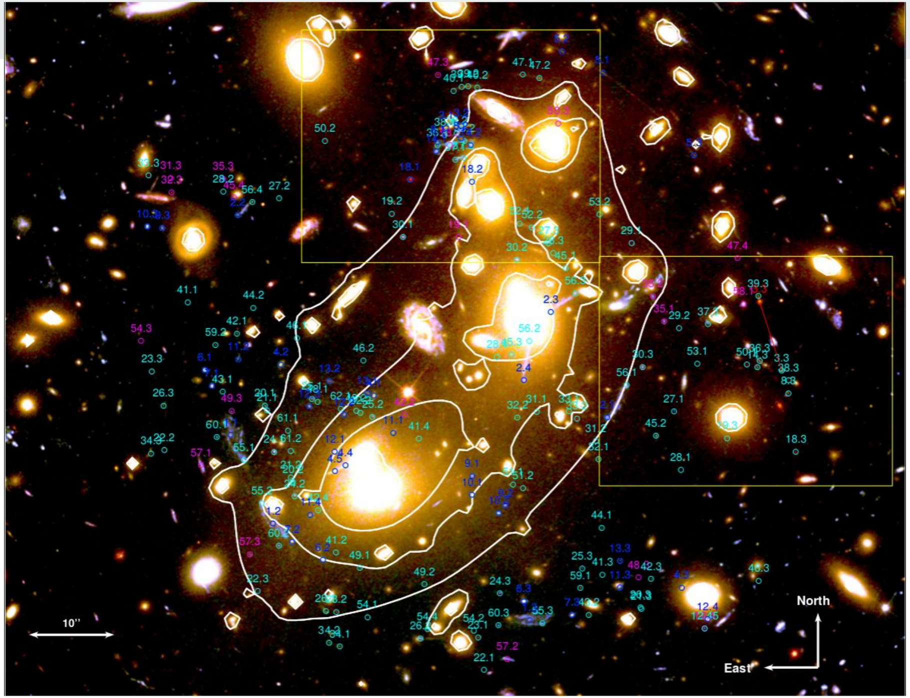
Mass-modelling tool for Gravitational Lenses

based on:

- Parametric mass-models
- MCMC based sampler (Bayesis3)

Multiply imaged sources serve as constraints:

- Parameter space is huge
- Process can take several weeks.



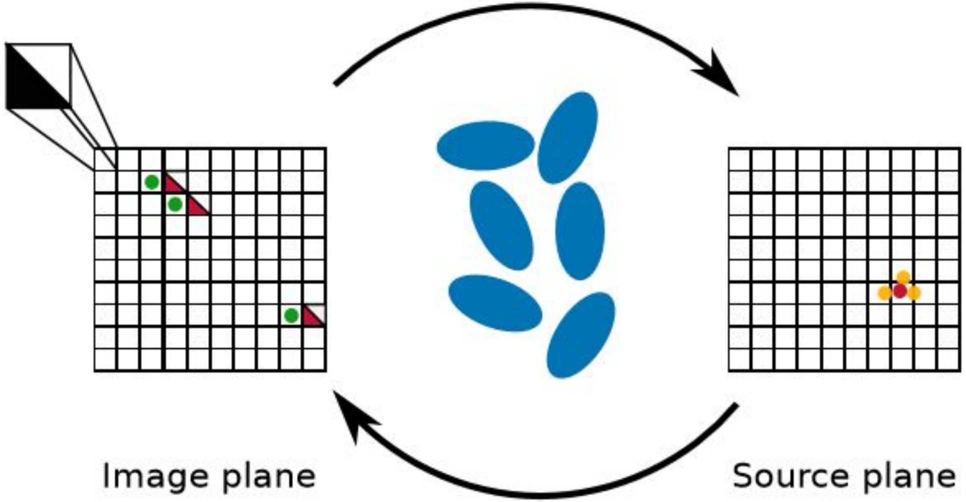
Cluster A2744 (Credit: Jauzac et al, 2015)

$$\chi_i^2 = \sum_{j=1}^{n_i}\left[x^j_{obs} - x^j_{pred}(\theta)\right]^2/\sigma_{ij}^2$$

Lenstool Fit computation

Predicting multiple images :

- Delensing a quadratic grid into the source plane
- Checking each cell for the source
- Attributing cell to closest image



Requires enormous amount of time-consuming deflection angle computations and grid checking

Gradient (PIEMD): $$I^* = \frac{\partial \Phi}{\partial x} + i\,\frac{\partial \Phi}{\partial y} = \frac{(1-\epsilon^2)E_0}{2i\sqrt{\epsilon}} \ln\left\{\left[\frac{1-\epsilon}{1+\epsilon}\,x - i\,\frac{1+\epsilon}{1-\epsilon}\,y + 2i\sqrt{\epsilon}\,\sqrt{\omega^2 + \frac{x^2}{(1+\epsilon)^2} + \frac{y^2}{(1-\epsilon)^2}}\right] \Big/ (x - iy + 2i\omega\sqrt{\epsilon})\right\},$$

HPC techniques for astronomers

Goal: Increase Computation Speed (Throughput) by increasing parallelism

Level of Parallelism:

- Transaction level parallelism
- GPU (Mixture of TLP and DLP)
- Thread Level parallelism (TLP)
- Data Level parallelism (DLP)
- Instruction Level parallelism (ILP)

CPU

Multiple core (TLP)

Multiple operations (DLP)

GPU

Multiple cores

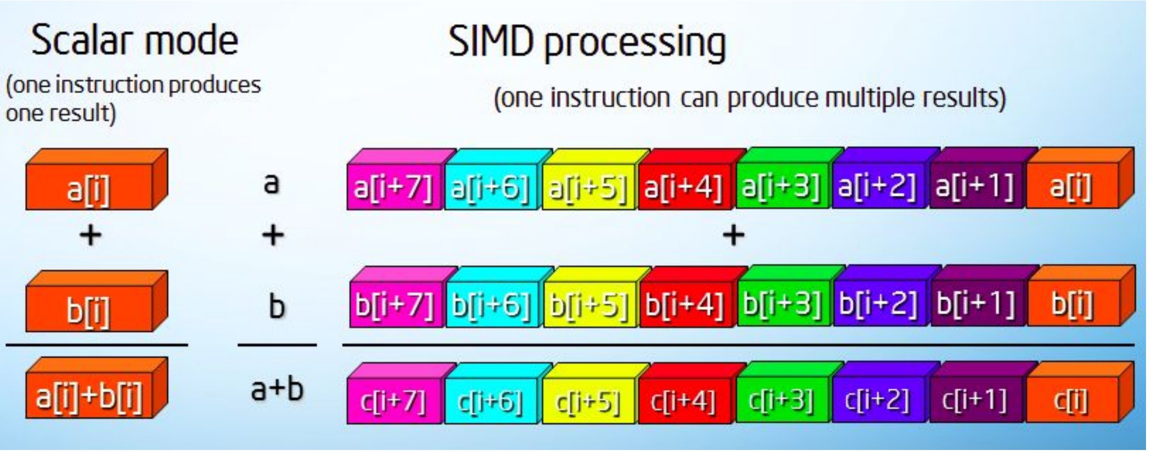
Data Level parallelism (DLP)

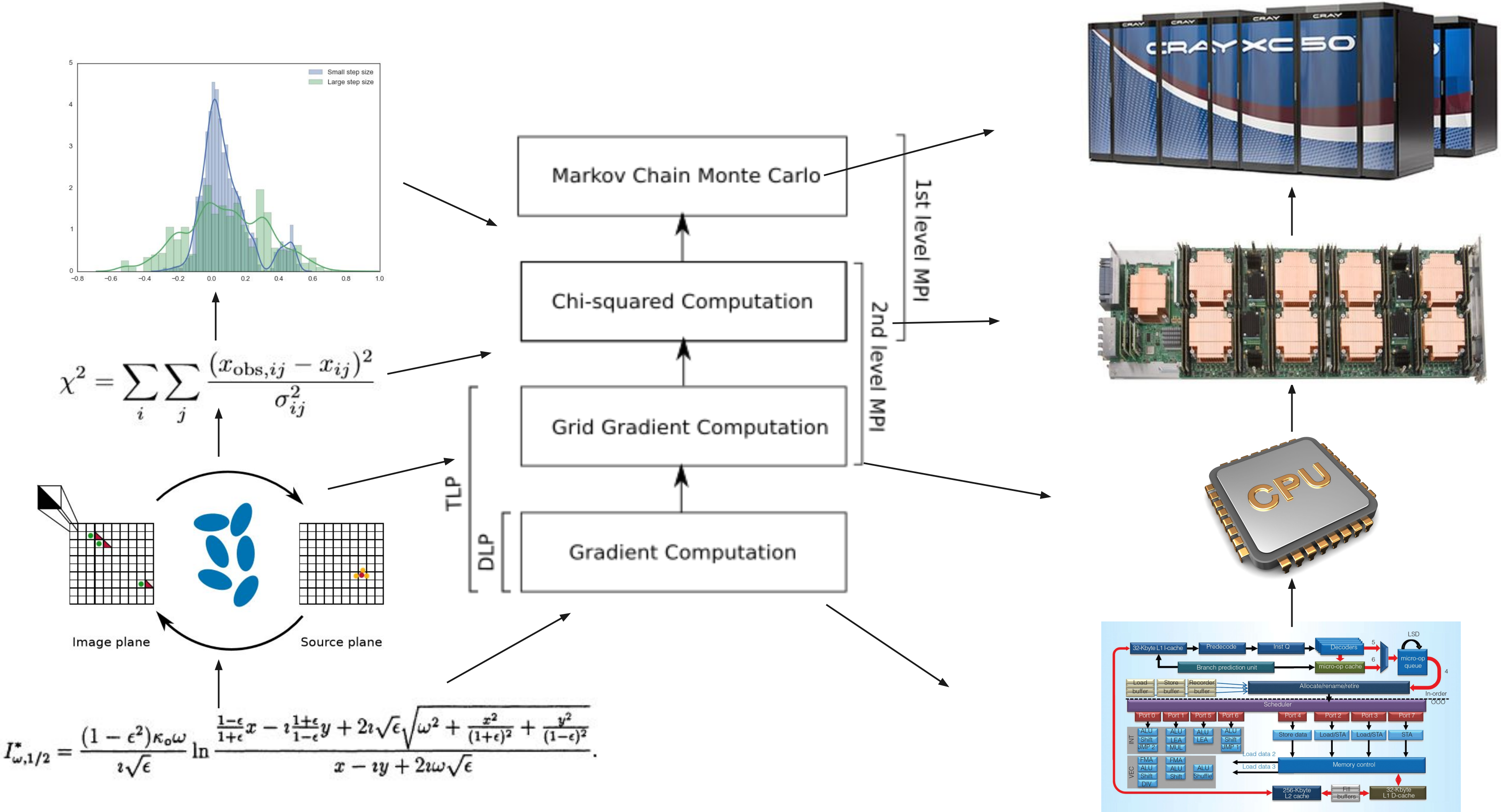
- CPU cores are capable of vectorised operation

- Speed-up of 4 or 8 possible depending on CPU generation

- Vectorisation can be handled implicitly by the compiler

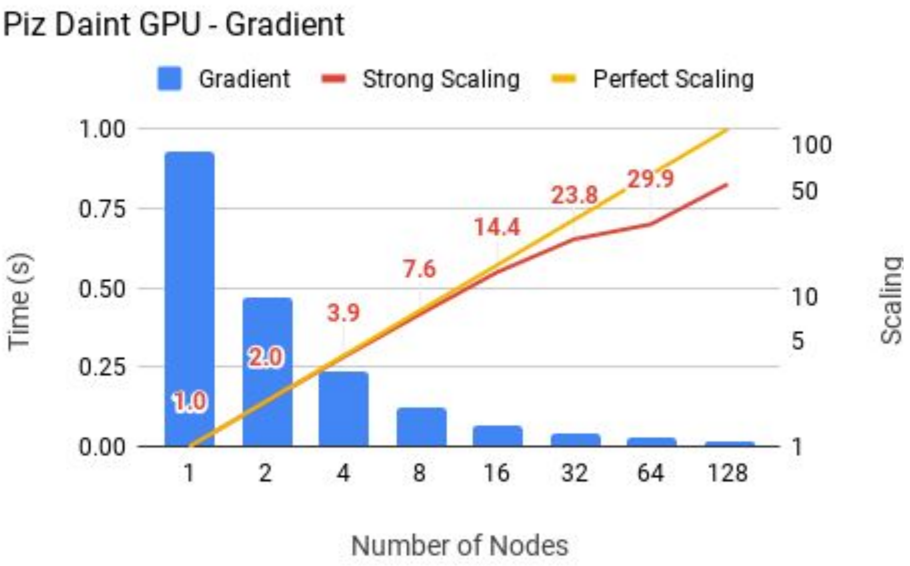
- requires homogenous memory layout: SOA

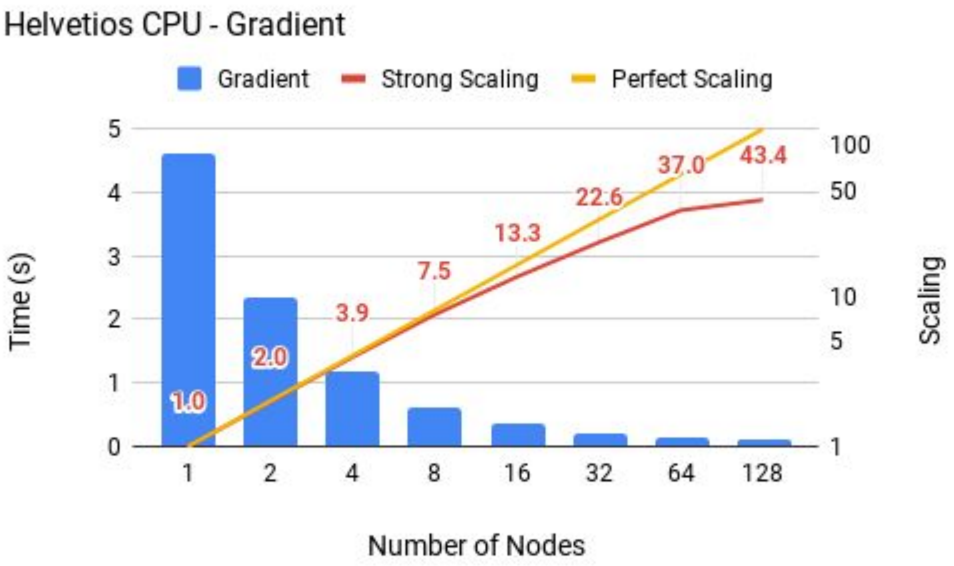




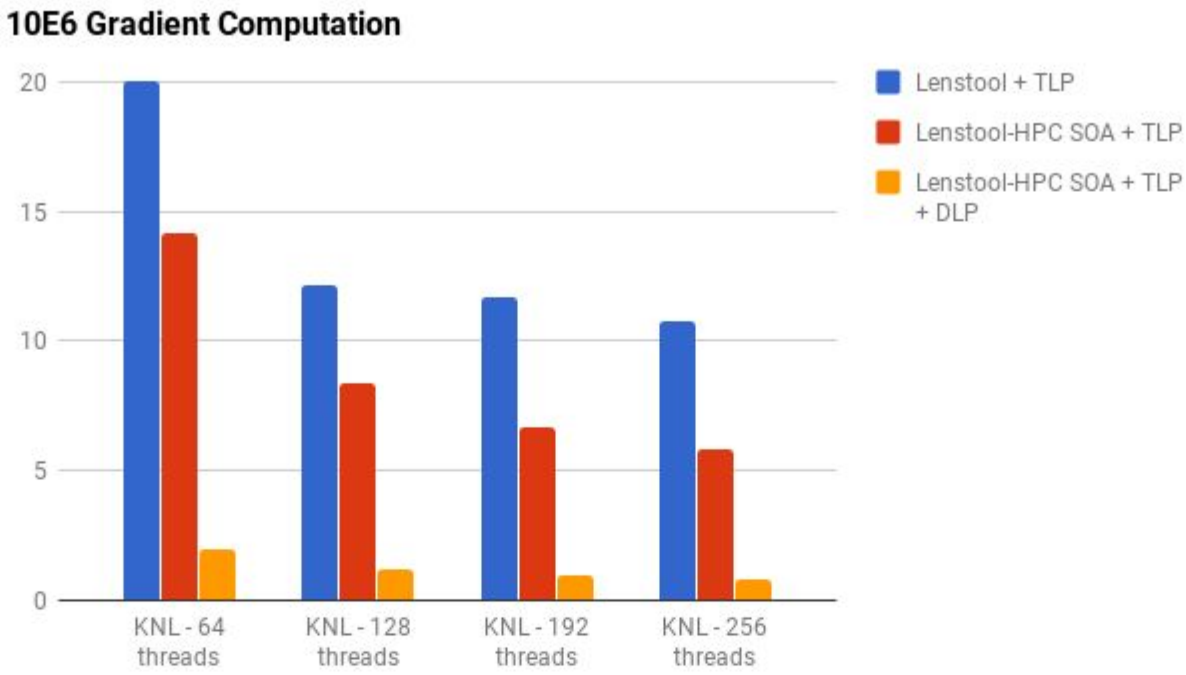
Small step size
Large step size
Markov Chain Monte Carlo
Chi-squared Computation
Grid Gradient Computation
Gradient Computation
1st level MPI
2nd level MPI
TLP
DLP
$\chi^2 = \sum_i \sum_j \frac{(x_{\mathrm{obs},ij} - x_{ij})^2}{\sigma_{ij}^2}$
Image plane
Source plane
$I^*_{\omega,1/2} = \frac{(1-\epsilon^2)\kappa_o\omega}{\imath\sqrt{\epsilon}} \ln \frac{\frac{1-\epsilon}{1+\epsilon}x - \imath\frac{1+\epsilon}{1-\epsilon}y + 2\imath\sqrt{\epsilon}\sqrt{\omega^2 + \frac{x^2}{(1+\epsilon)^2} + \frac{y^2}{(1-\epsilon)^2}}}{x - \imath y + 2\imath\omega\sqrt{\epsilon}}.$
CRAY XC50
CPU

Grid Gradient Benchmark (Step 1)

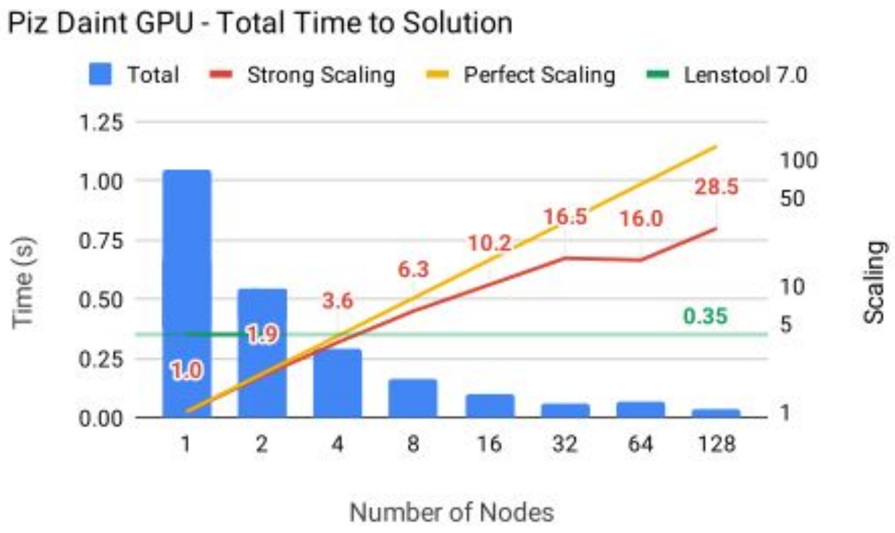


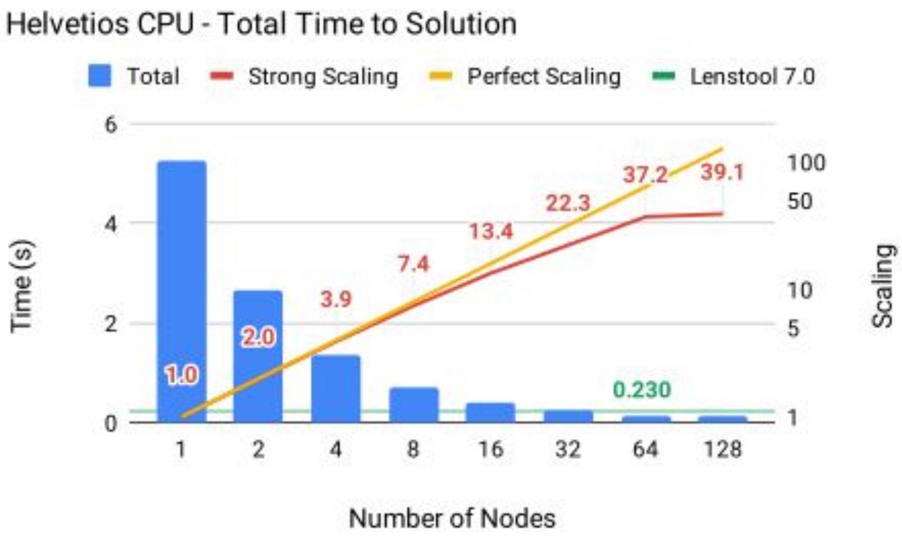


Gradient Benchmark Results (Step 0)



Chi2 (Step 2) Strong Scaling





Lenstool-HPC: Conclusion

Lenstool-HPC achieves only hardware limited speed-up for Lens map generation and Fit computation

Public code on gitlab "https://git-cral.univ-lyon1.fr/lenstool/LENSTOOL-HPC/"

For more details, please refer to [Rexroth et al 2020, Schaefer et al 2020]

Ongoing Development:

- MCMC (Part 3) still under development, taken over by Lyon and Marseille
- Opens up new research options: Combining Weak Lensing and Strong Lensing models

Questions?

Conclusion

Structure of Array (SOA) vs Array of Structures (AOS)

AOS:

- Intuitive
- Heterogenous Layout

SOA:

- Homogenous Layout
- Efficient Loading
- Allows implicit Vectorisation

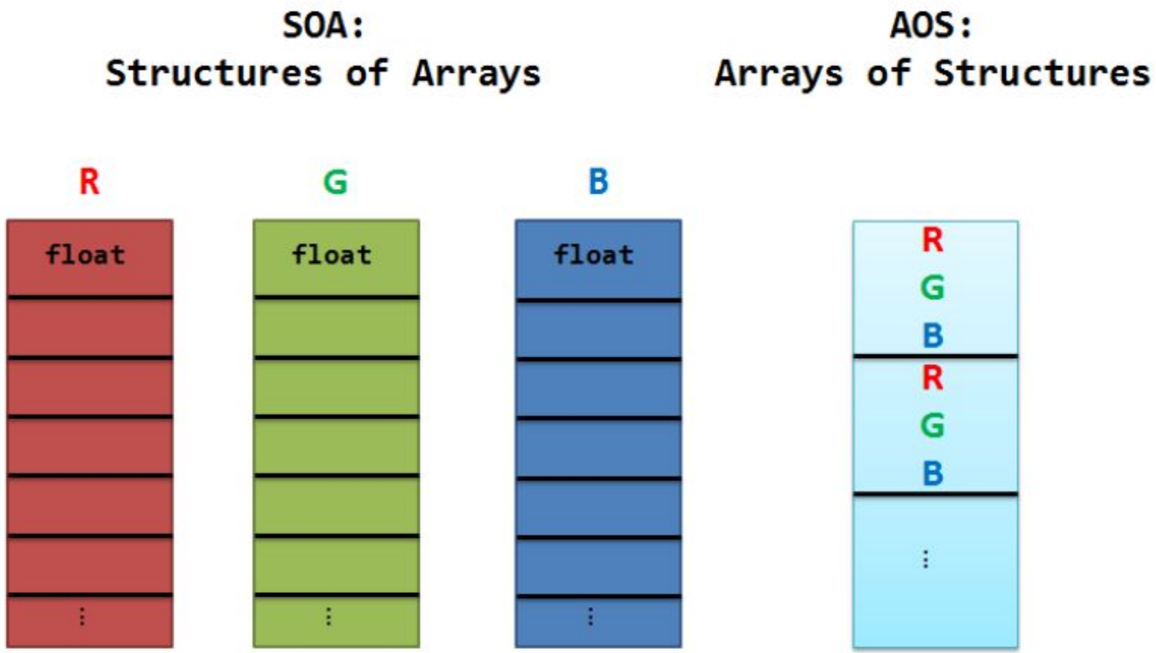
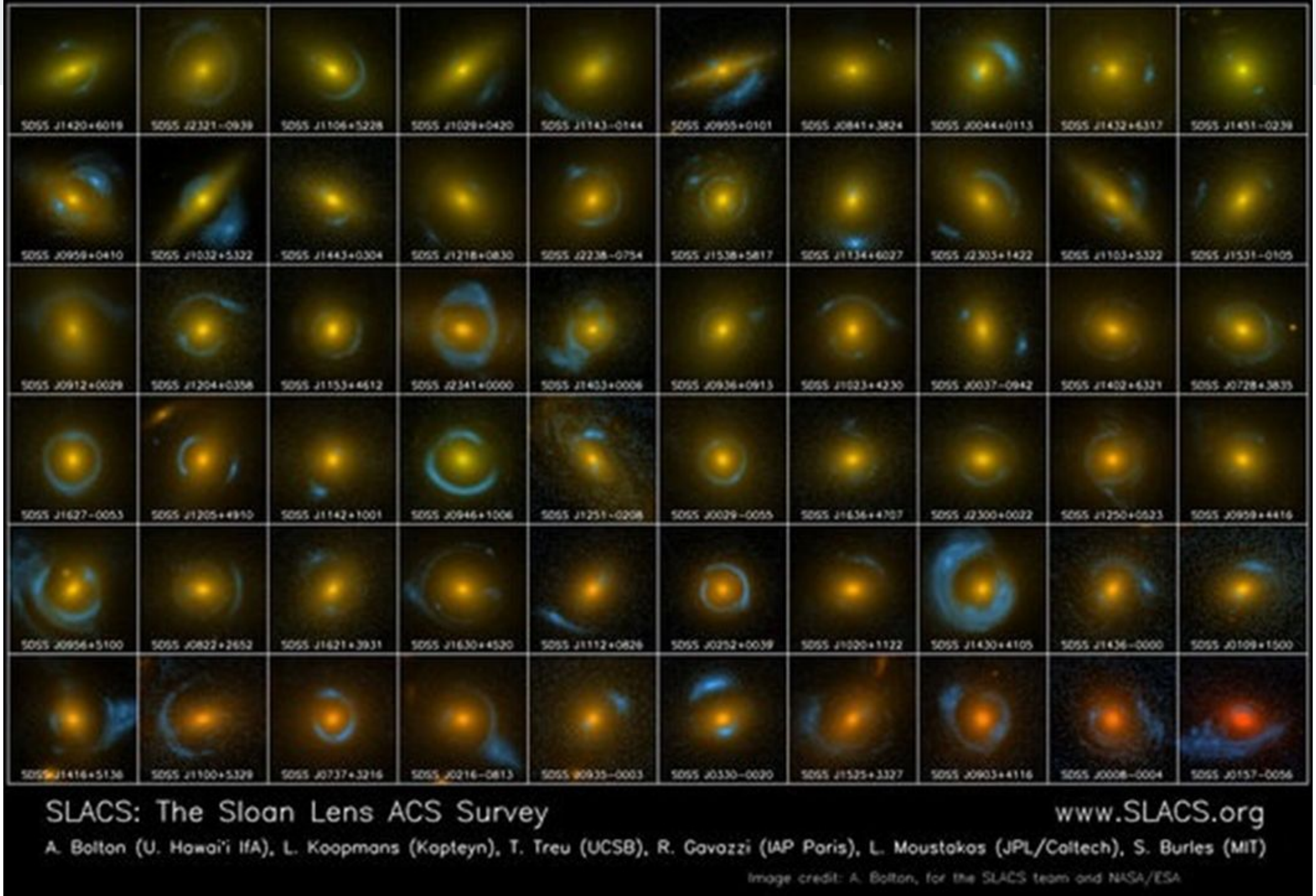
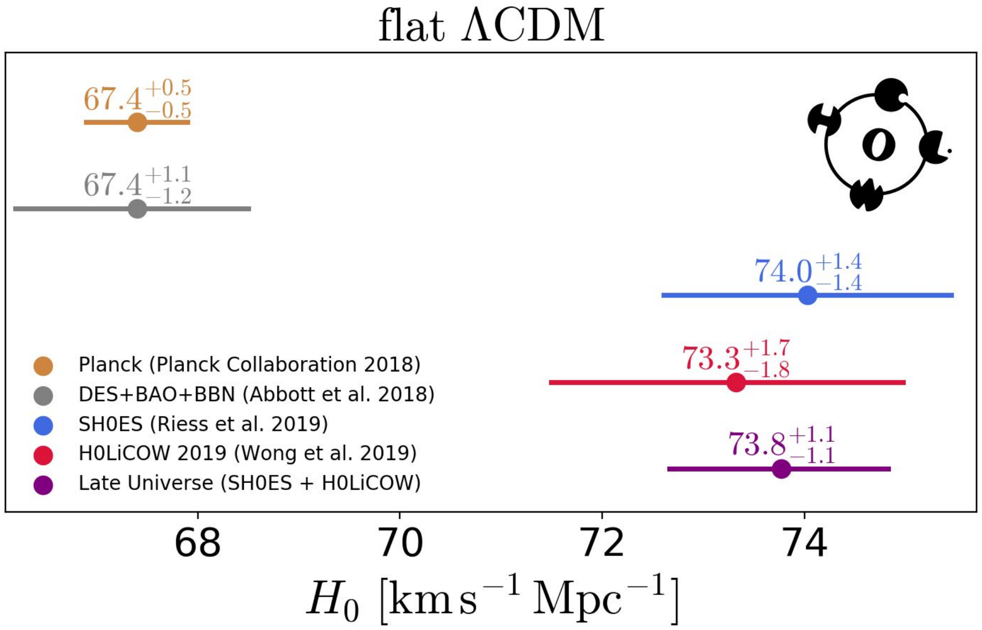


Figure 3.1: Example of structure of arrays vs. array of structures.


SLACS: The Sloan Lens ACS Survey
www.SLACS.org
A. Bolton (U. Hawai'i IfA), L. Koopmans (Kapteyn), T. Treu (UCSB), R. Gavazzi (IAP Paris), L. Moustakas (JPL/Caltech), S. Burles (MIT)
Image credit: A. Bolton, for the SLACS team and NASA/ESA

Cosmography and natural telescopes

- Time delays => Hubble constant
  - Planck H_0 Controversy
  - Substructure detection
- High Redshift Objects observed
  - at z = 1-4 for galaxy scale
  - Up to z = 9-12 for cluster lenses
  - Individual star at redshift z = 1.49 (dubbed MACS J1149 Lensed Star 1) magnified by more than ×2,000 [Kelly et al, 2018]

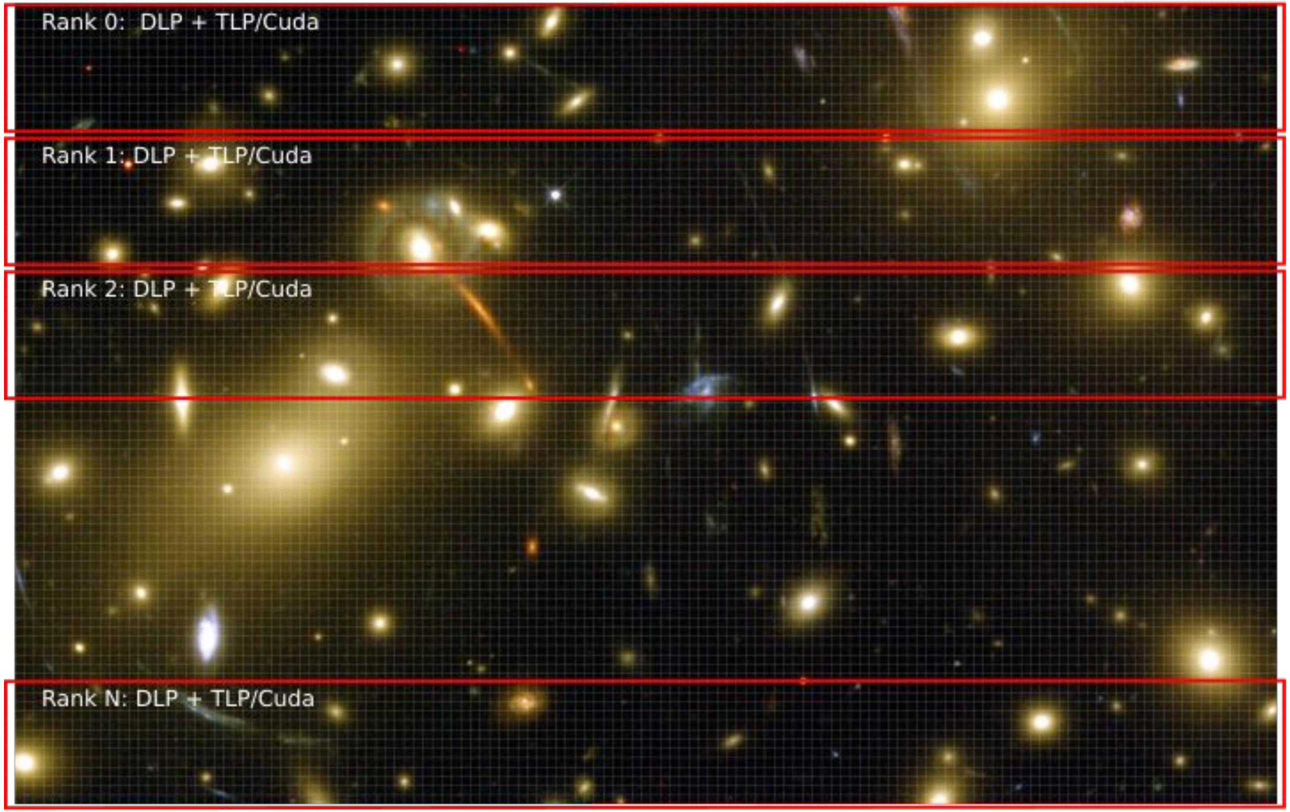


Credit: Holycow collaboration

Distributed Grid Gradient

Grid Gradient computation distribution (step 1):

- Images split into regular subdomains with MPI
- Subdomains are handled using OpenMP/CUDA



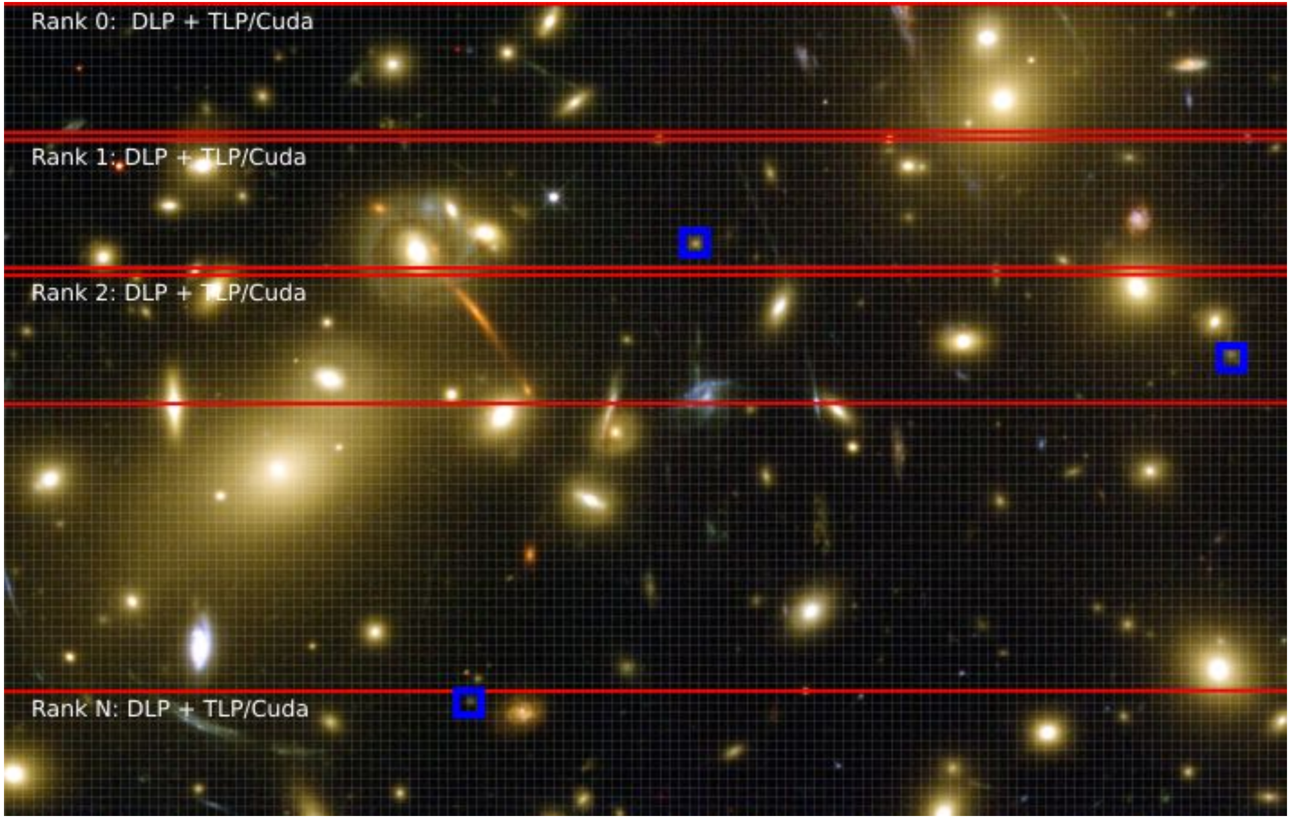
Chi^2 computation

The **Chi^2** is computed by computing the distance between the original images and their computed unlensed/relensed projections from steps 1a and 1b

The blue dots correspond to the same image in the source plane

- Each distance for the same source (in blue) are reduced to Rank 0 using MPI_Pack
- The Chi2 is computed on Rank 0

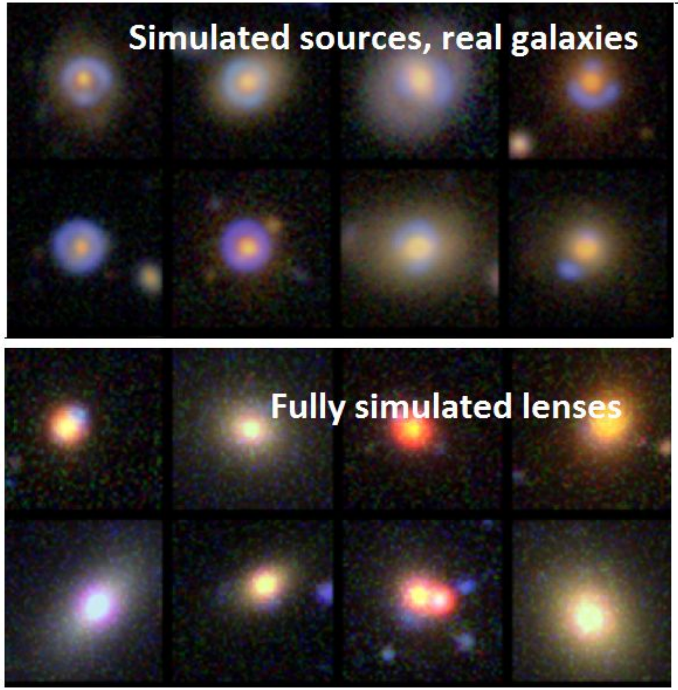
$$\chi^2 = \sum_i \sum_j \frac{(x_{\mathrm{obs},ij} - x_{ij})^2}{\sigma_{ij}^2}$$



Lens simulation

Copy Paste Concept: Simulate Lens and copy unto real Data

- Analytic source and LRG + real sky image (e.g. Jacobs 2019, Jacobs 2017)
- Analytic source + real image of LRG (e.g. Petrillo 2018, Jacobs 2017)
- Use real data for source image + real image of LRG [In the works]
    - Lenstronomy and Glee based simulation by F. Courbin group (Elodie Savary, Karina Rojas & Benjamin Clément) [CFIS Data]



Credit: adapted from Jacobs et al 2017

File Edit View History Bookmarks Tools Help

Strong Gravitational Lens dat ×

127.0.0.1:8000/lenses/KIDS J1422+0033/

Search

KIDS J1422+0033

Right Ascension	Declination	Lens redshift	Source redshift	ESA sky link
215.70692	-0.55323			Link

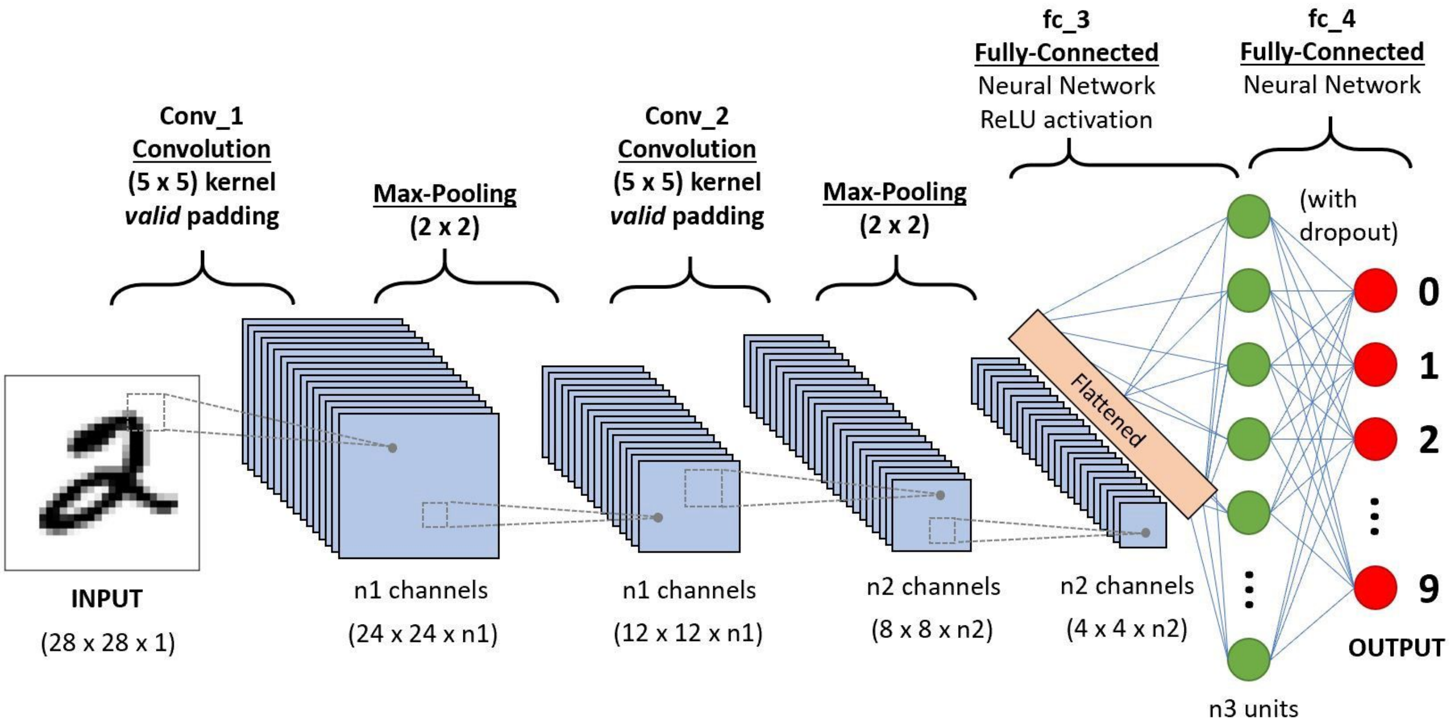
Methods

CNN_Petrillo_2	Score
Morphological classification method based on a Convolutional Neural Network (CNN) for recognizing strong gravitational lenses in 255 square degrees of the Kilo Degree Survey (KiDS), one of the current- generation optical wide surveys. (Second Version) The CNN is currently optimized to recognize lenses with Einstein radii >~1.4 arcsec, about twice the r-band seeing in KiDS.	0.98
Visual_Inspection	**Score**
Found by visual inspection by experts using possibly semi-automatic methods	1.00
Yattalens	**Score**
Looks for arc-like features around massive galaxies and then estimates the likelihood of an object being a lens by performing a lens model fit	1.00
Chitah	**Score**
Modeling-based algorithm originally developed to look for lensed quasars	1.00

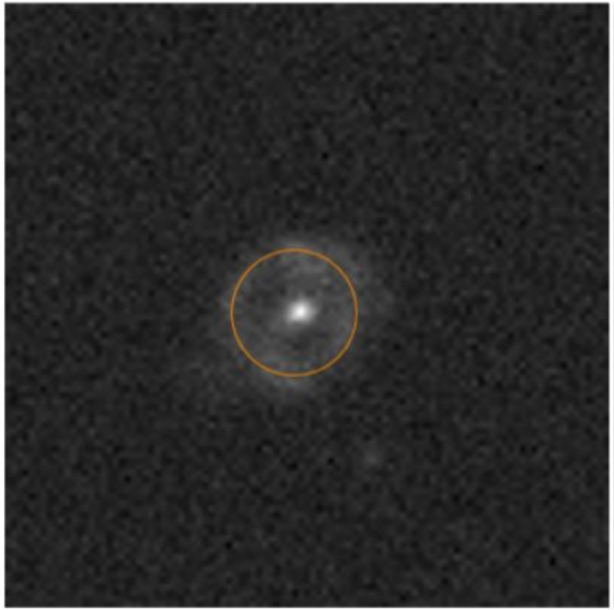
Referencing Paper

SDSS J0822+2652	GAL-GAL	0.24	0.59	8:22:42.32	26:52:43.54	13
SDSS J0841+3824	GAL-GAL	0.12	0.66	8:41:28.80	38:24:13.72	7

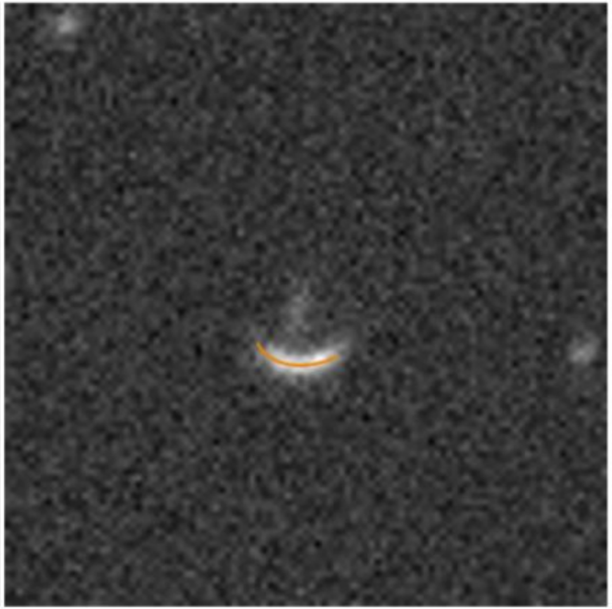
Convolutional Neural Networks (CNN)



Finding gravitational Lenses



Einstein Ring

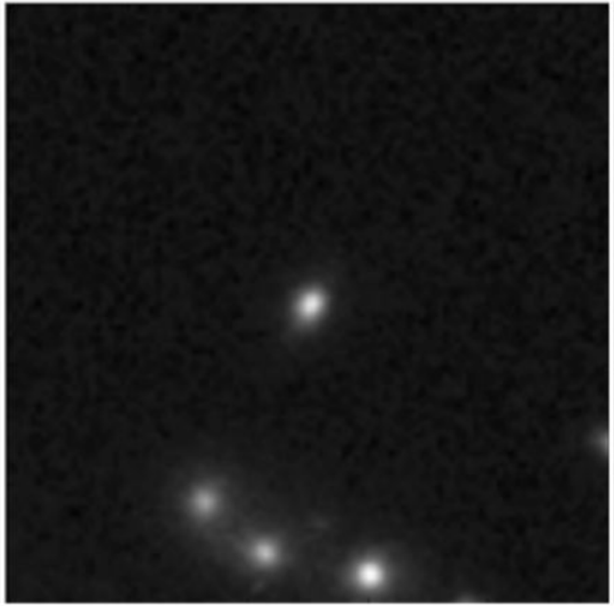


Arcs

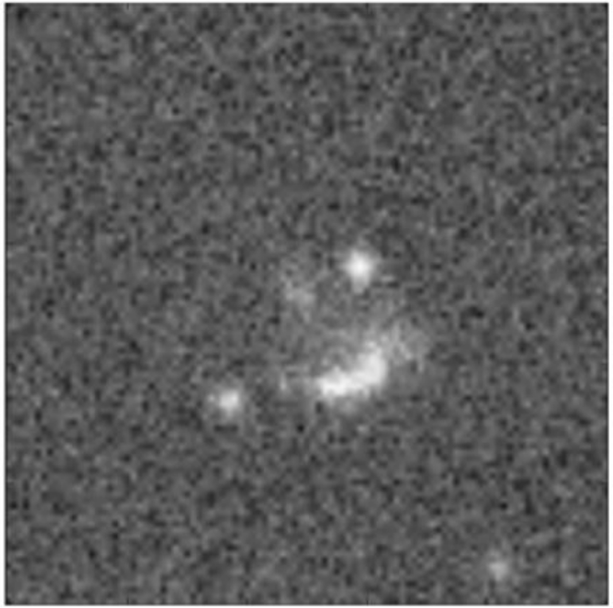
Multiple Images

Likely False Positives

Companions



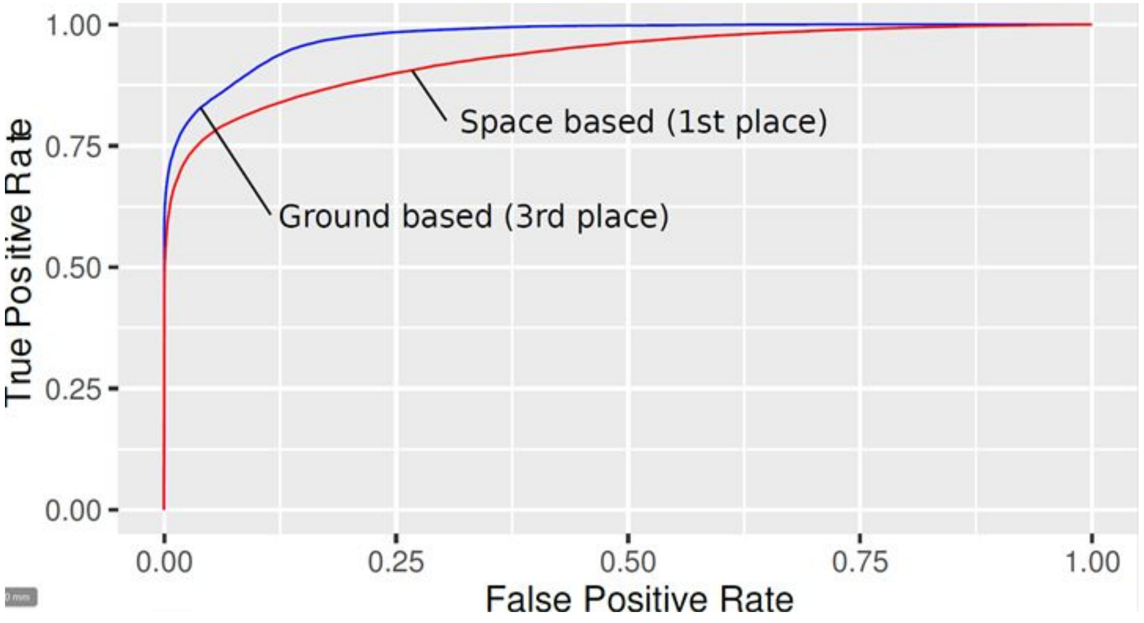
Arc-like structures



Unusual structures

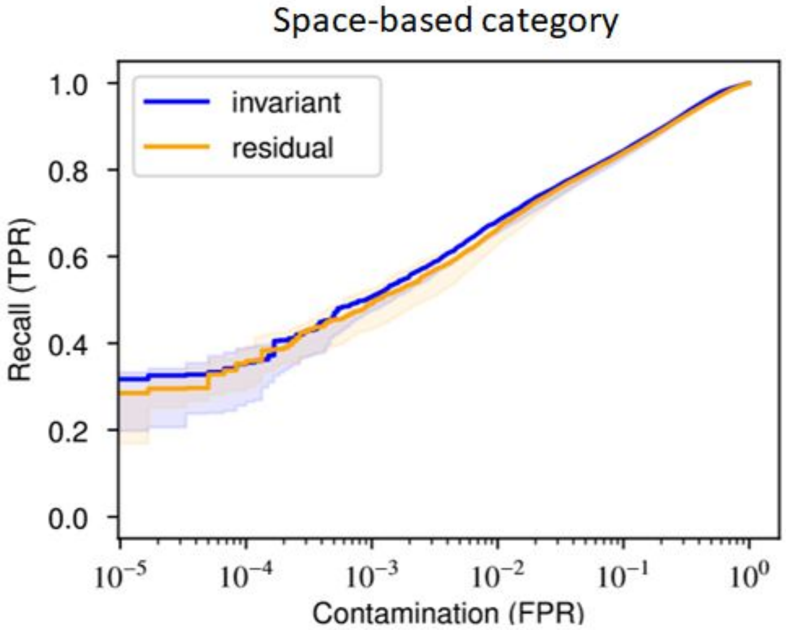
Bologna Lens (SLSWG) Challenge conclusions

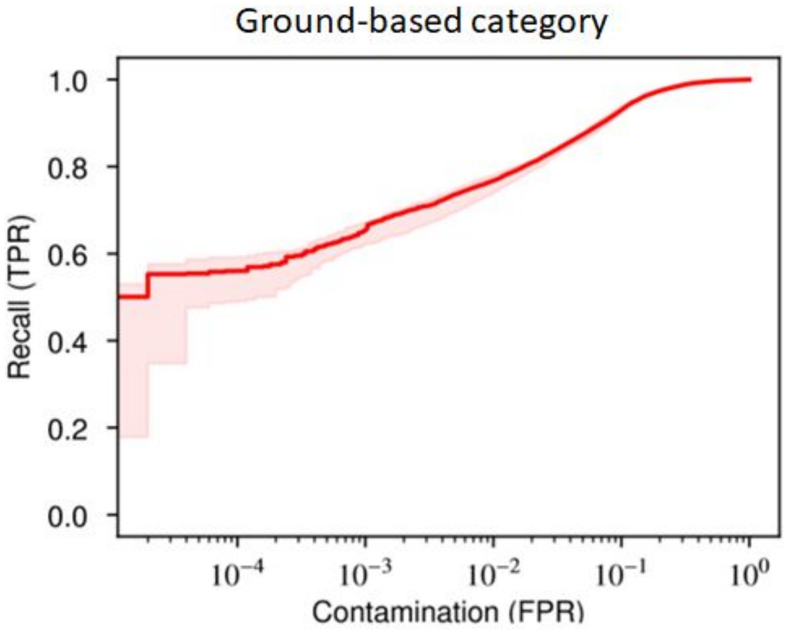
- CNN dominated the AUC score
- CNN deal well with ground based noise
- CNNs performed better on ground-based data
- Better simulations were needed to distinguish between CNNs
- With realistic ratios, False Positive still dominate



[Schaefer et al.2018]. Petrillo et al.2019, Jacobs et al.2019, Metcalf et al 2018

CNN-Lensfinder Committee





The solid line represents the committee ROC curves.

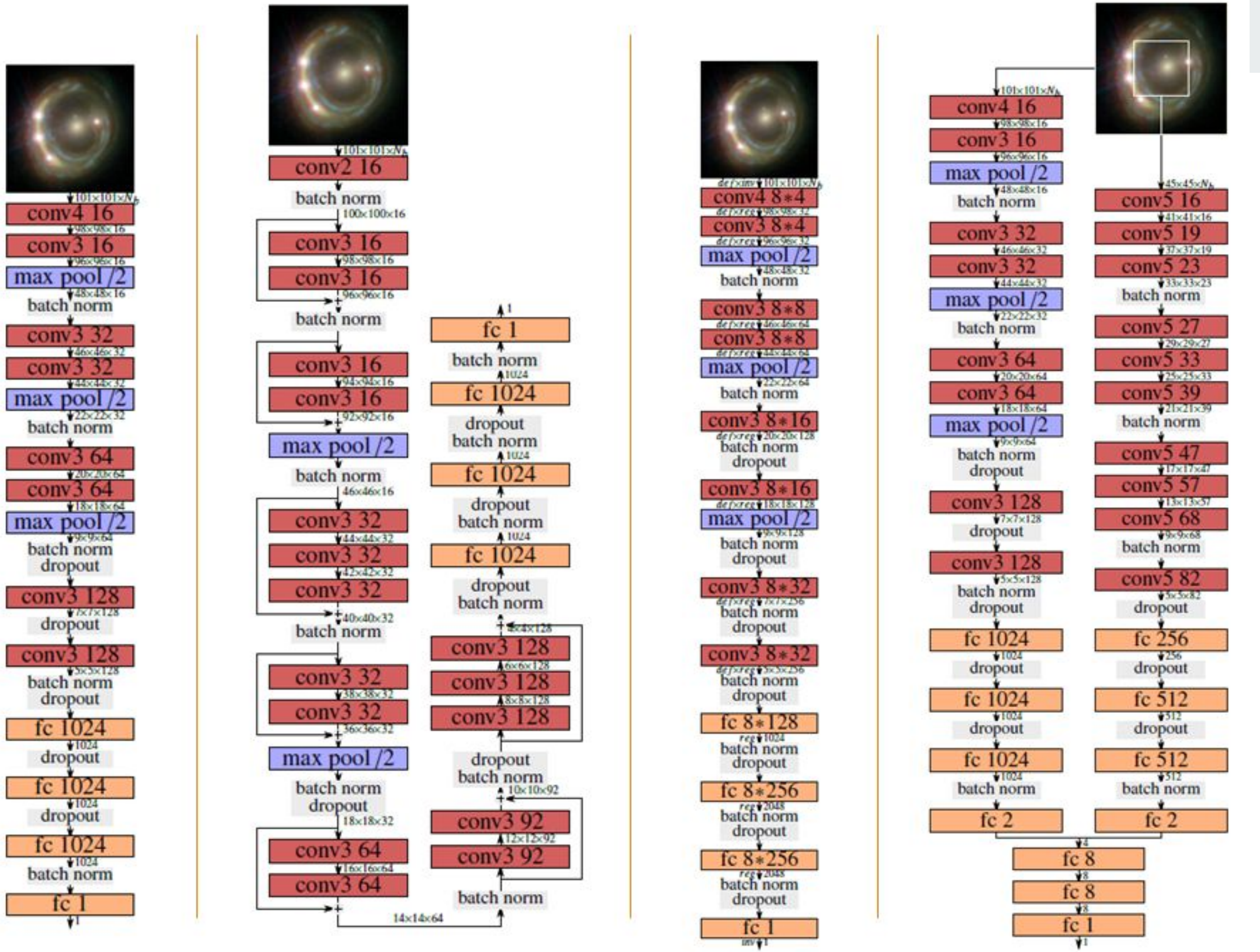
The shaded areas represent the minimum and maximum values from the standalone CNNs.

Problem: Application on real data

- Application on real Data is not trivial when trained on Simulations [Petrillo et al.2019, Jacobs et al.2019].
    - Transfer Learning Problem: The model learned is subtly different from the one needed.
- Not enough Lenses for a complete Training-set
    - Simulations have to be used to complement Training set

Solutions?

- More labelled Data using Citizen Science: Space Warps [In the works]
- More realistic Training set [In the works]



conv4 16
conv3 16
max pool /2
batch norm
conv3 32
conv3 32
max pool /2
batch norm
conv3 64
conv3 64
max pool /2
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dropout
conv3 128
dropout
conv3 128
batch norm
dropout
fc 1024
dropout
fc 1024
dropout
fc 1024
batch norm
fc 1
conv2 16
batch norm
conv3 16
conv3 16
batch norm
conv3 16
conv3 16
max pool /2
batch norm
conv3 32
conv3 32
conv3 32
batch norm
conv3 32
conv3 32
max pool /2
batch norm
dropout
conv3 64
conv3 64
14x14x64
batch norm
conv3 92
conv3 92
dropout
batch norm
conv3 128
conv3 128
conv3 128
dropout
batch norm
fc 1024
dropout
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dropout
batch norm
fc 1024
batch norm
fc 1
conv4 8*4
conv3 8*4
max pool /2
batch norm
conv3 8*8
conv3 8*8
max pool /2
batch norm
conv3 8*16
batch norm
dropout
conv3 8*16
max pool /2
batch norm
dropout
conv3 8*32
batch norm
dropout
conv3 8*32
batch norm
dropout
fc 8*128
batch norm
dropout
fc 8*256
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dropout
fc 1
conv4 16
conv3 16
max pool /2
batch norm
conv3 32
conv3 32
max pool /2
batch norm
conv3 64
conv3 64
max pool /2
batch norm
dropout
conv3 128
dropout
conv3 128
batch norm
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fc 1024
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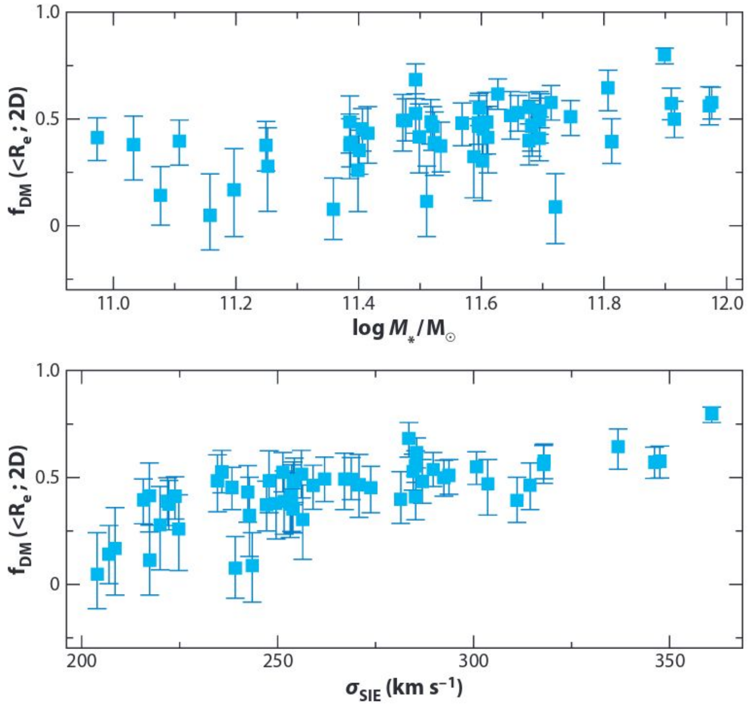
fc 1024
batch norm
fc 2
conv5 16
conv5 19
conv5 23
batch norm
conv5 27
conv5 33
conv5 39
batch norm
conv5 47
conv5 57
conv5 68
batch norm
conv5 82
dropout
fc 256
dropout
fc 512
dropout
fc 512
batch norm
fc 2
fc 8
fc 8
fc 1

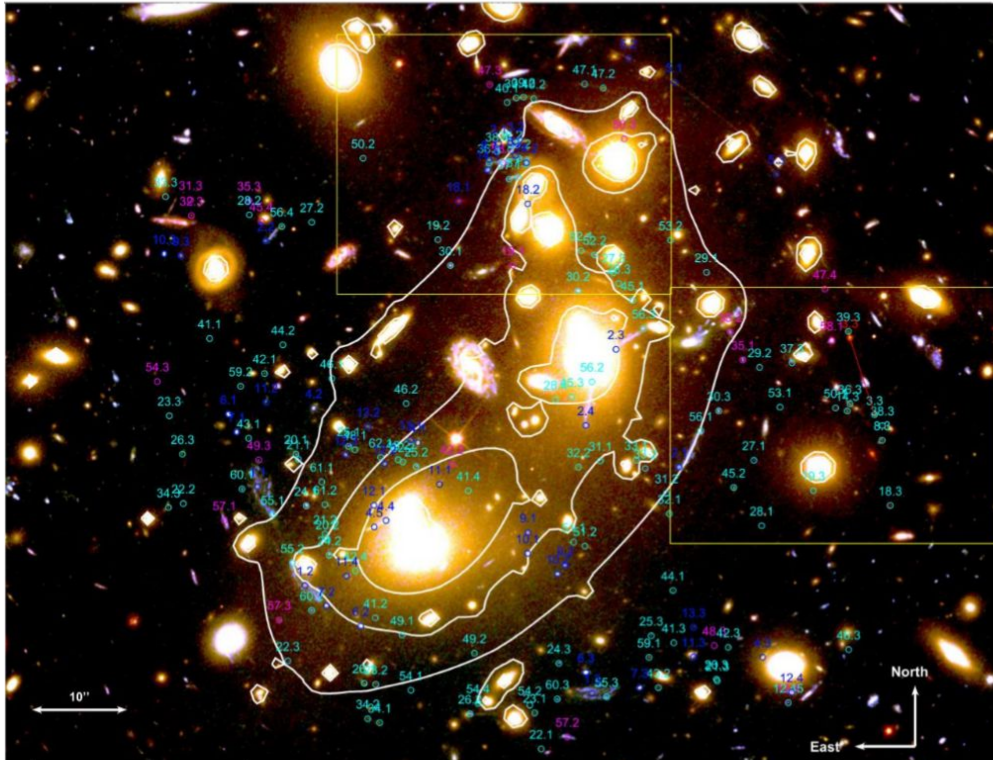
Mass structures of Galaxies

- Dark matter haloes for galaxies
  - Mass constraint inside Einstein radius
- Relative spatial distribution
  - Fraction of DM/Luminous Mass
  - Tilt of fundamental plane (not observed with total mass)
- Slope of the Mass density profile
- Galaxy formation



Substructure in Galaxies

- Substructure analysis
- Too few substructures for CDM
  - Either exist but not luminous enough
  - Or major revision to CDM
- Detection through
  - Flux ratio anomalies
  - Time delay anomalies



Credit: (Jauzac et al 2015b)

Convolutional Neural Networks (CNN)