Automated Analysis of Strong Lenses with Machine Learning

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In Collaboration with

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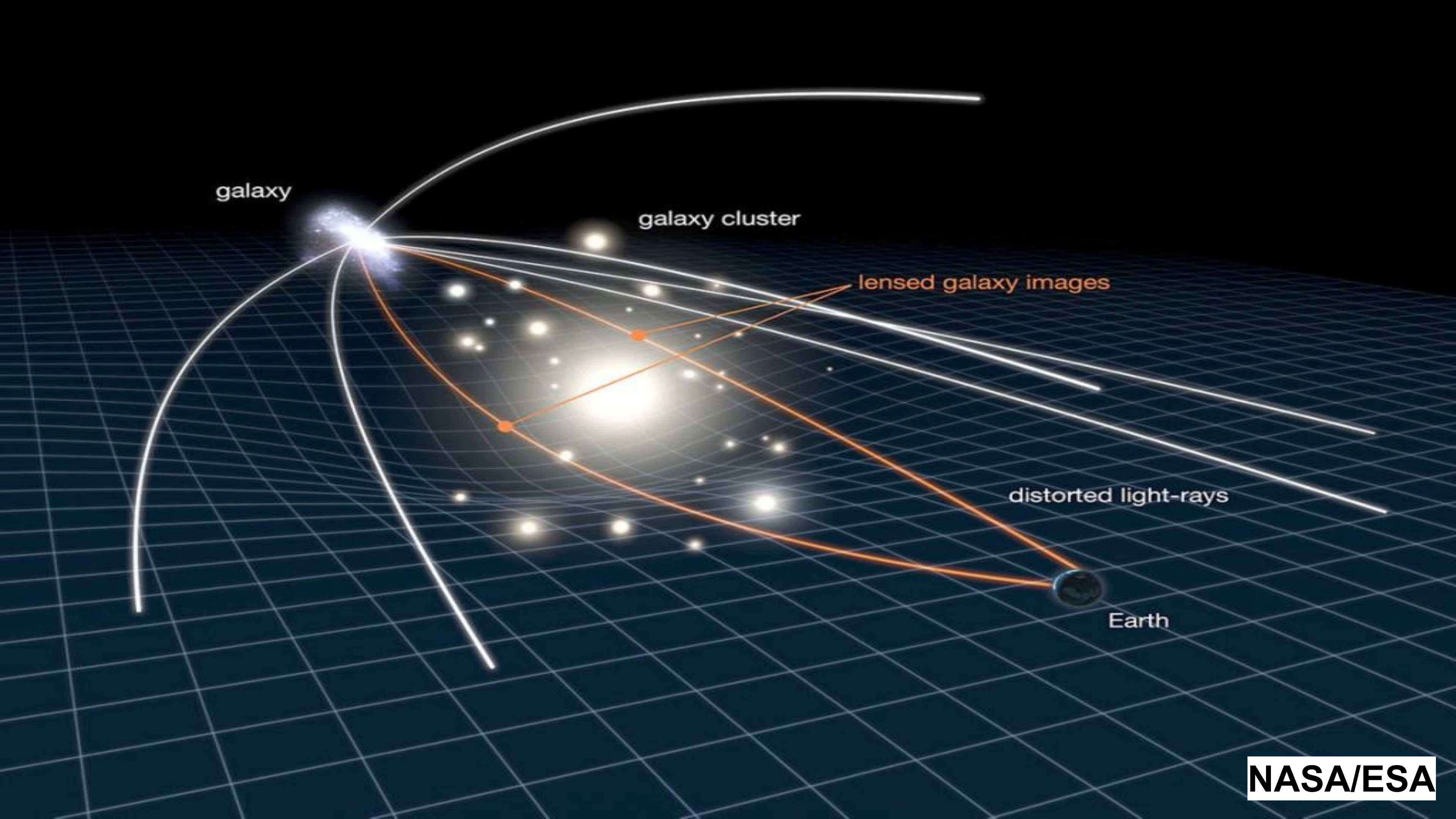
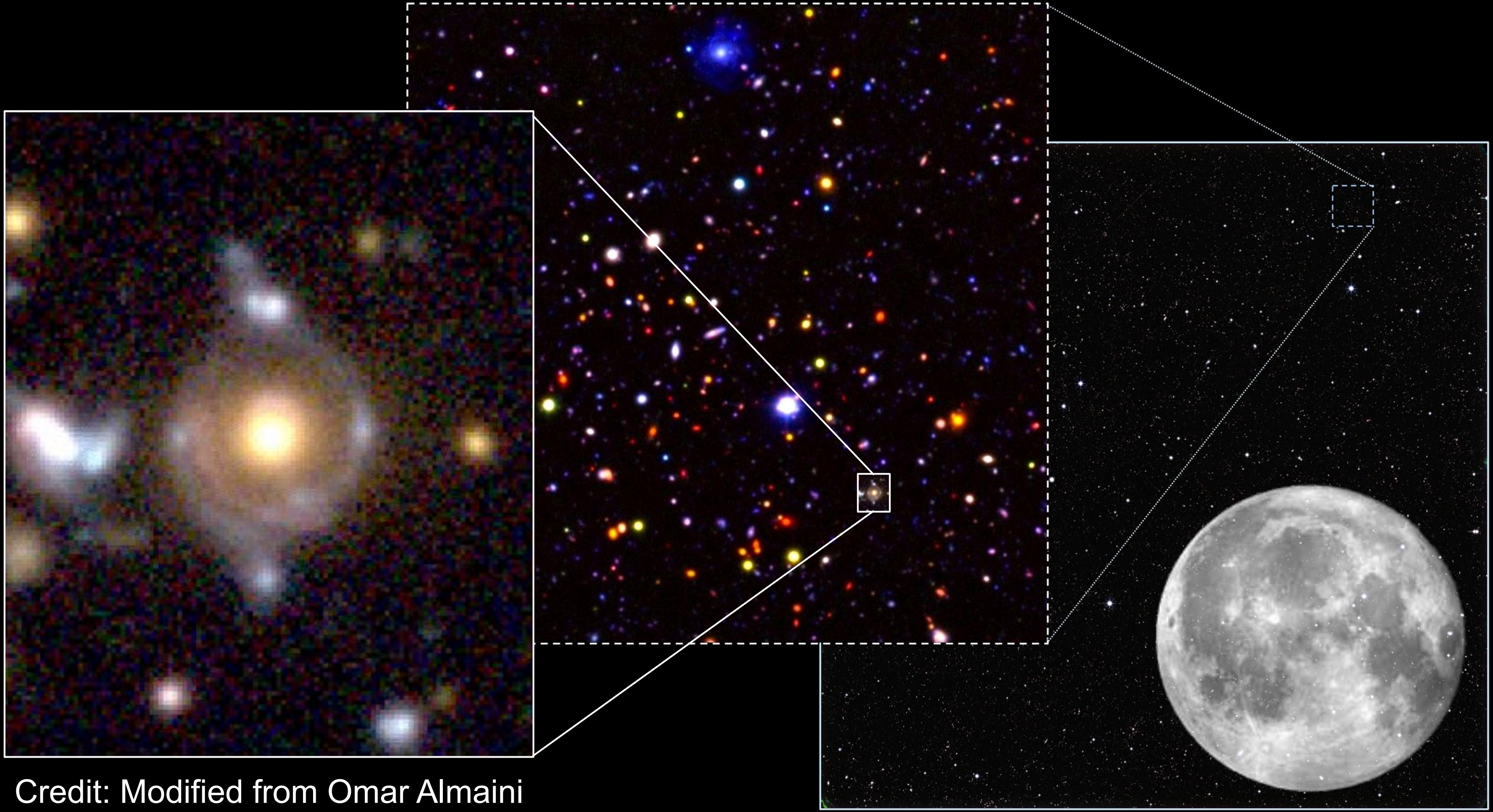
Mike Gladders (UChicago), Katrin Heitmann (Argonne),
Tom Collett (ICG), Camille Avestruz (Uchicago), etc.

The University of Nottingham

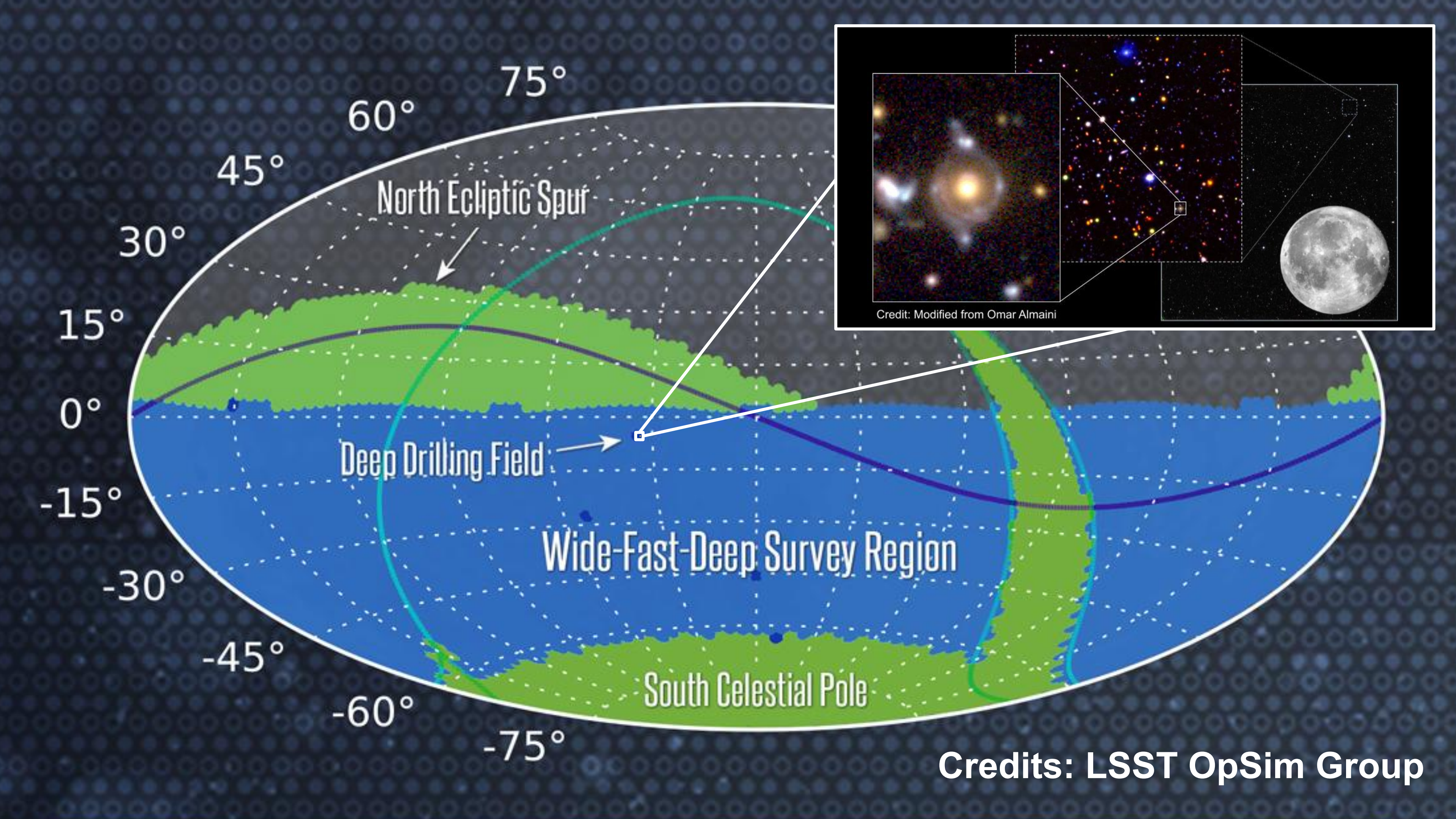

galaxy
galaxy cluster
lensed galaxy images
distorted light-rays
Earth

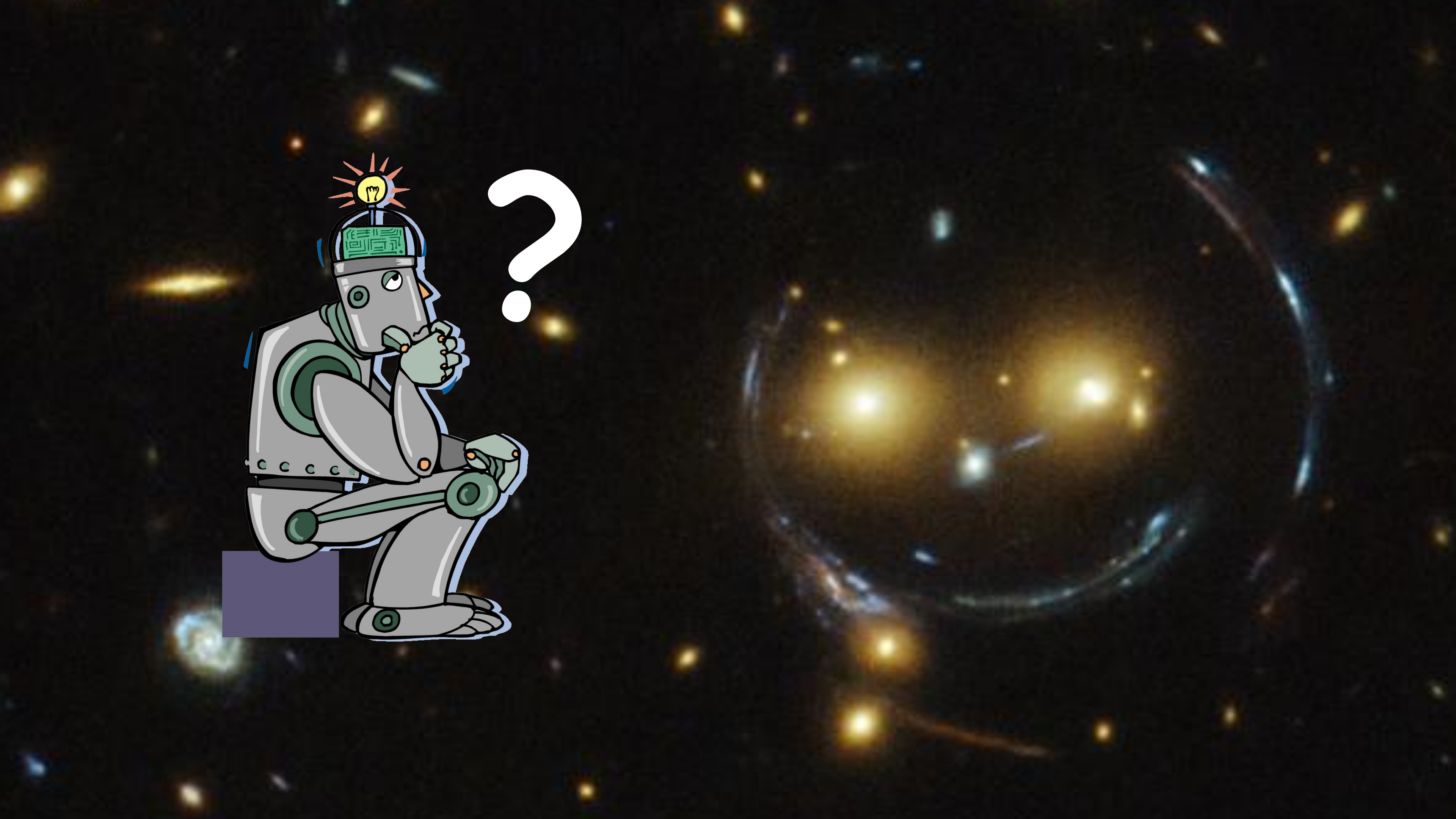
NASA/ESA

“Looking for a needle in a haystack.”

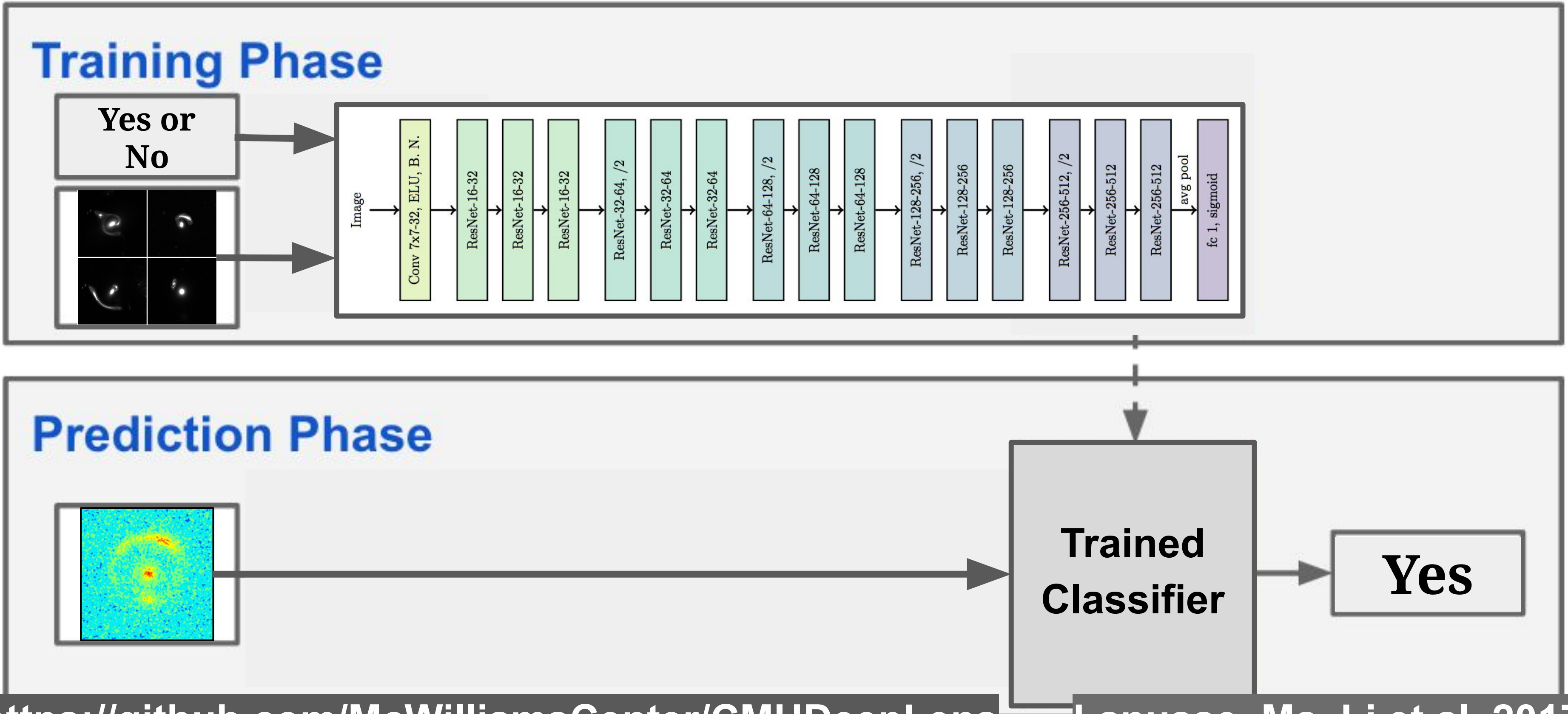


Credit: Modified from Omar Almaini


75°
60°
45°
30°
15°
0°
-15°
-30°
-45°
-60°
-75°
North Ecliptic Spur
Deep Drilling Field
Wide-Fast-Deep Survey Region
South Celestial Pole
Credit: Modified from Omar Almaini
Credits: LSST OpSim Group



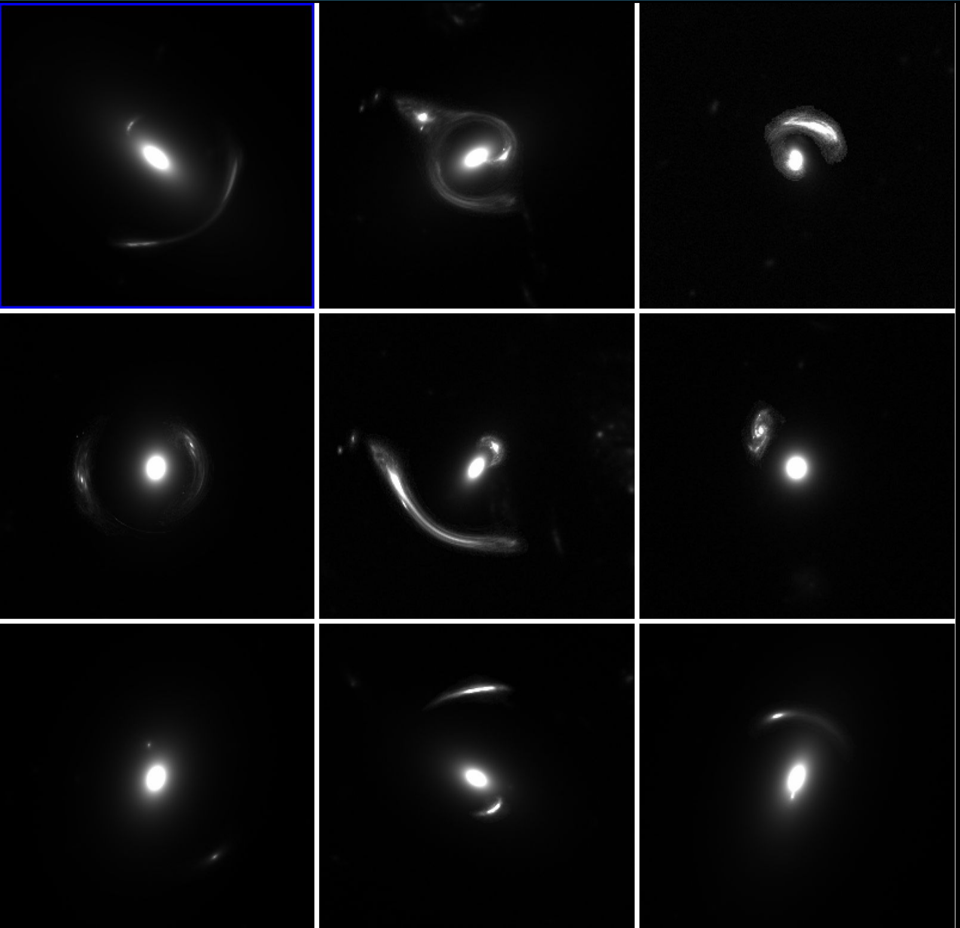
Lens Finding with Deep Learning

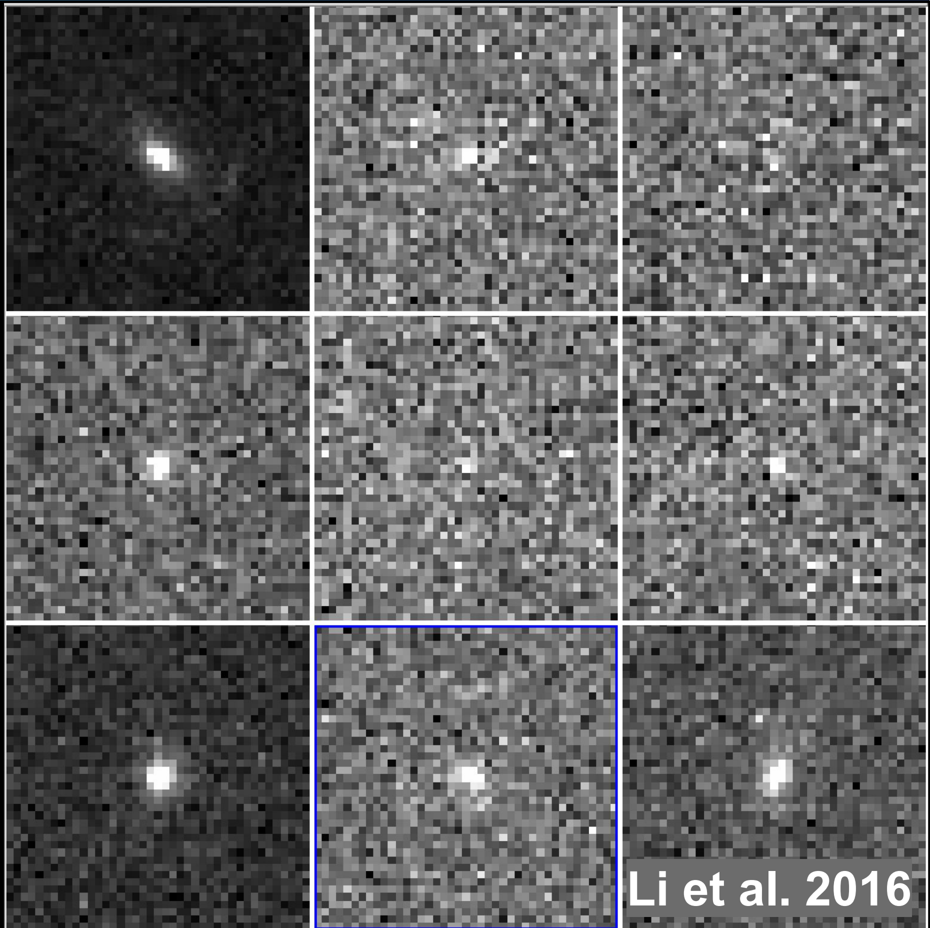


https://github.com/McWilliamsCenter/CMUDeepLens

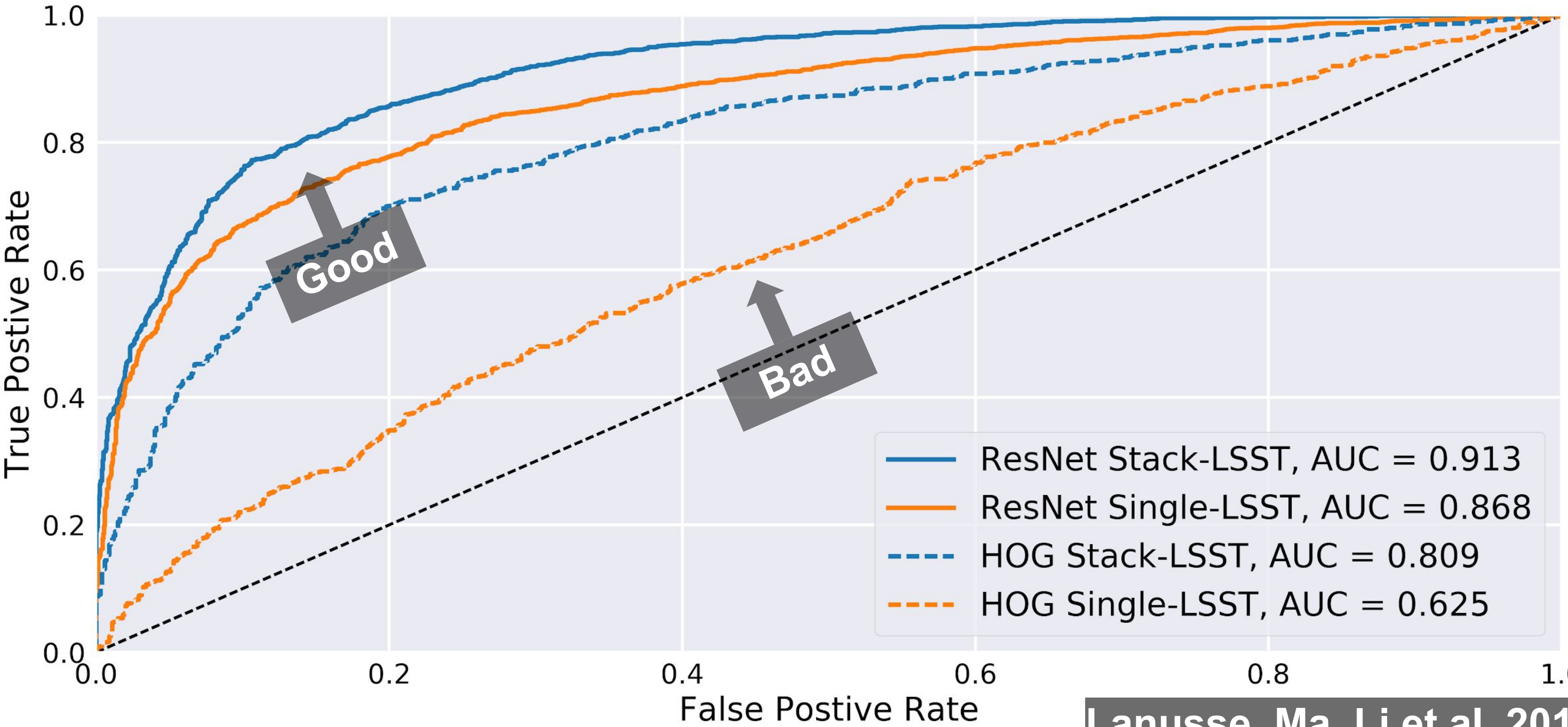
Lanusse, Ma, Li et al. 2017

Training Sets





Receiver Operating Characteristic Curves



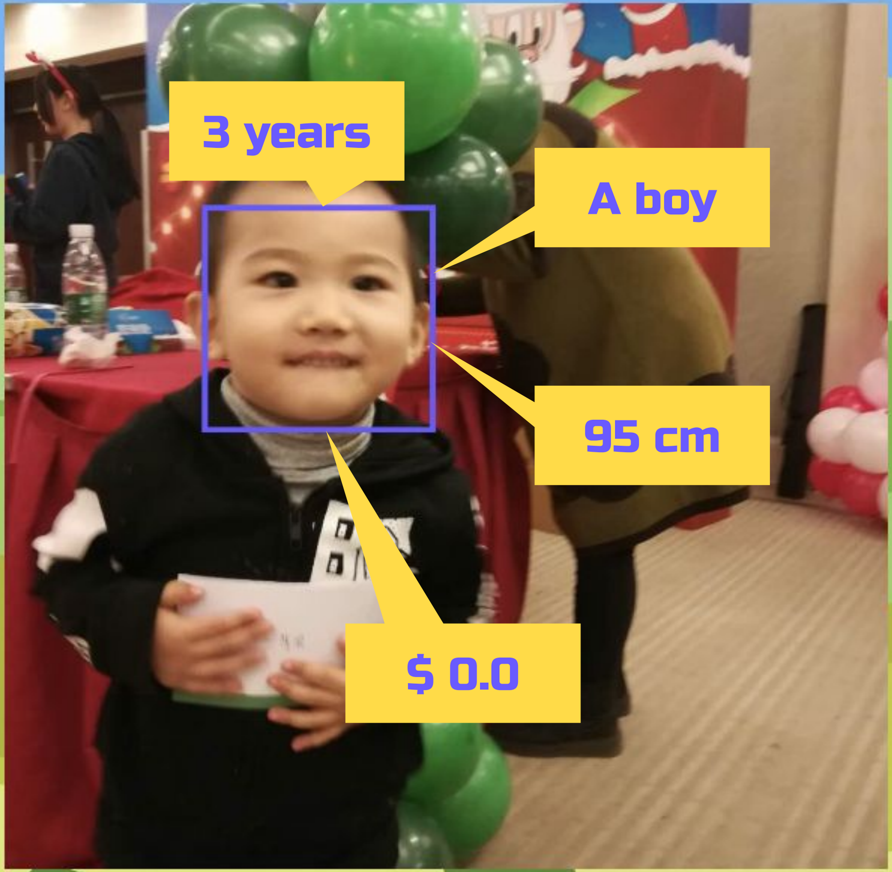
Lanusse, Ma, Li et al. 2017

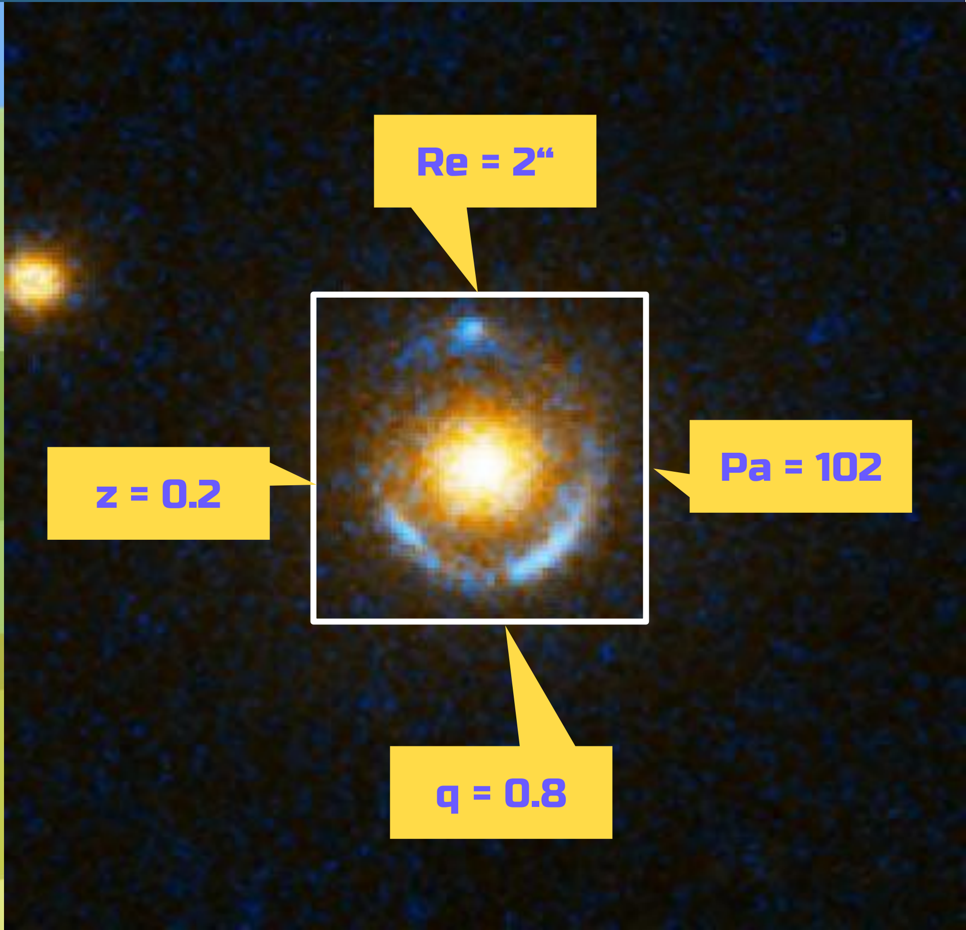
Sorted by area under the ROC curve

##		Team_name_submit	type	AUROC	TPR0	TPR10	description_short	author.1
##	14	resnet_ground_7bf8089	Ground-Based	0.9814321	8.993713e-02	0.4534297041	CNN	Francois Lanusse
##	10	CMU-DeepLens-Resnet-Voting	Ground-Based	0.9804913	2.445130e-02	0.1027314963	CNN	Quanbin Ma
##	20	LASTRO EPFL (11i)	Ground-Based	0.9749255	7.493794e-02	0.1131977256	CNN	Mario Geiger
##	3	cas_convnet_mean	Ground-Based	0.9634215	2.022629e-02	0.0761790327	CNN	Colin Jacobs
##	22	Ground	Ground-Based	0.9557059	0.000000e+00	0.0071018193	CNN	Emmanuel Bertin
##	23	Ground	Ground-Based	0.9557059	0.000000e+00	0.0071018193	CNN	Emmanuel Bertin
##	24	Ground_fixed	Ground-Based	0.9557059	0.000000e+00	0.0071018193	CNN	Emmanuel Bertin
##	25	Ground_fixed	Ground-Based	0.9557059	0.000000e+00	0.0071018193	CNN	Emmanuel Bertin
##	9	Philippa Hartley2	Ground-Based	0.9310191	2.237273e-01	0.3453159911	SVM / Gabor	Philippa Hartley
##	7	Philippa Hartley	Ground-Based	0.9293543	2.123763e-01	0.3316908714	SVM / Gabor	Philippa Hartley
##	27	Manchester-NA2	Ground-Based	0.8913778	2.803645e-04	0.0075297887	Human Inspection	Neal Jackson
##	28	Manchester-NA2	Ground-Based	0.8913778	2.803645e-04	0.0075297887	Human Inspection	Neal Jackson
##	29	Manchester-NA2-Submission2	Ground-Based	0.8913778	2.803645e-04	0.0075297887	Human Inspection	Neal Jackson
##	30	Manchester-NA2-Submission2	Ground-Based	0.8913778	2.803645e-04	0.0075297887	Human Inspection	Neal Jackson
##	4	All-star	Ground-Based	0.8365358	7.181615e-03	0.0186123524	edges/gradiants and Logistic Reg.	Camille Avestruz
##	13	CAST-GB	Ground-Based	0.8347916	2.005535e-05	0.0003810517	CNN / SVM	Clecio Roque De Bom
##	31	YattaLensLite	Ground-Based	0.8191702	2.194382e-04	0.0021145867	SExtractor	Alessandro Sonnenfeld
##	16	LASTRO EPFL (13b)	Space-Based	0.9325338	4.773626e-03	0.0779692201	CNN	Mario Geiger
##	8	resnet_5d0aad0	Space-Based	0.9225303	2.206807e-01	0.2904204271	CNN	Francois Lanusse
##	15	GAMOCLASS	Space-Based	0.9210117	7.416406e-02	0.3570444584	DL / CNN	Marc Huertas-Company
##	6	CMU-DeepLens-Resnet-Voting	Space-Based	0.9145407	0.000000e+00	0.0082046692	CNN	Quanbin Ma
##	1	space	Space-Based	0.9143197	6.755404e-04	0.0127852282	CNN	Emmanuel Bertin
##	19	res_bottleneck_87b7e8a	Space-Based	0.9068996	7.506005e-05	0.0038030424	CNN	Eric Ma
##	32	CNN_kapteyn	Space-Based	0.8179482	1.000625e-04	0.0002001251	CNN	Enrico Petrillo
##	21	CAST-SB	Space-Based	0.8128851	6.909326e-02	0.1186942145	CNN	Clecio Roque De Bom
##	5	Manchester1	Space-Based	0.8101726	7.354597e-03	0.1739837398	Human Inspection	Neal Jackson
##	18	Philippa Hartley2	Space-Based	0.8092423	2.859788e-02	0.0812650120	SVM / Gabor	Philippa Hartley
##	17	Philippa Hartley	Space-Based	0.8012731	2.934848e-02	0.0717323859	SVM / Gabor	Philippa Hartley
##	12	Attempt2	Space-Based	0.7626792	0.000000e+00	0.0008265498	CNN / wavelets	Andrew Davies
##	11	YattaLensLite	Space-Based	0.7622929	0.000000e+00	0.0003502802	Arcs / SExtractor	Alessandro Sonnenfeld
##	26	All-now	Space-Based	0.7346352	4.900040e-02	0.0659031545	edges/gradiants and Logistic Reg.	Camille Avestruz
##	2	GAHEC IRAP 1	Space-Based	0.6580909	1.127113e-03	0.0090920476	arc f[illegible]	[illegible]

Metcalf et al. 2019

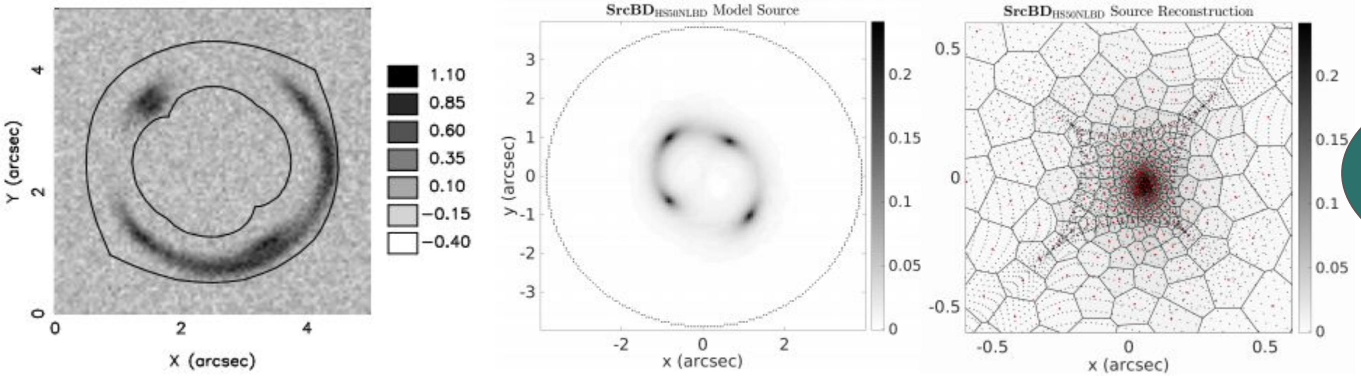
Lens Modelling with Machine Learning





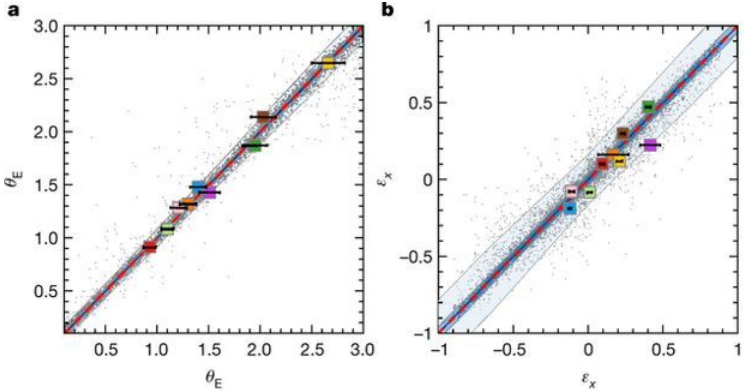
Lens Modelling with Deep Learning

- **Parameter Fitting techniques** (e.g. Warren & Dye 2003, Nightingale, Dye & Massey 2018)



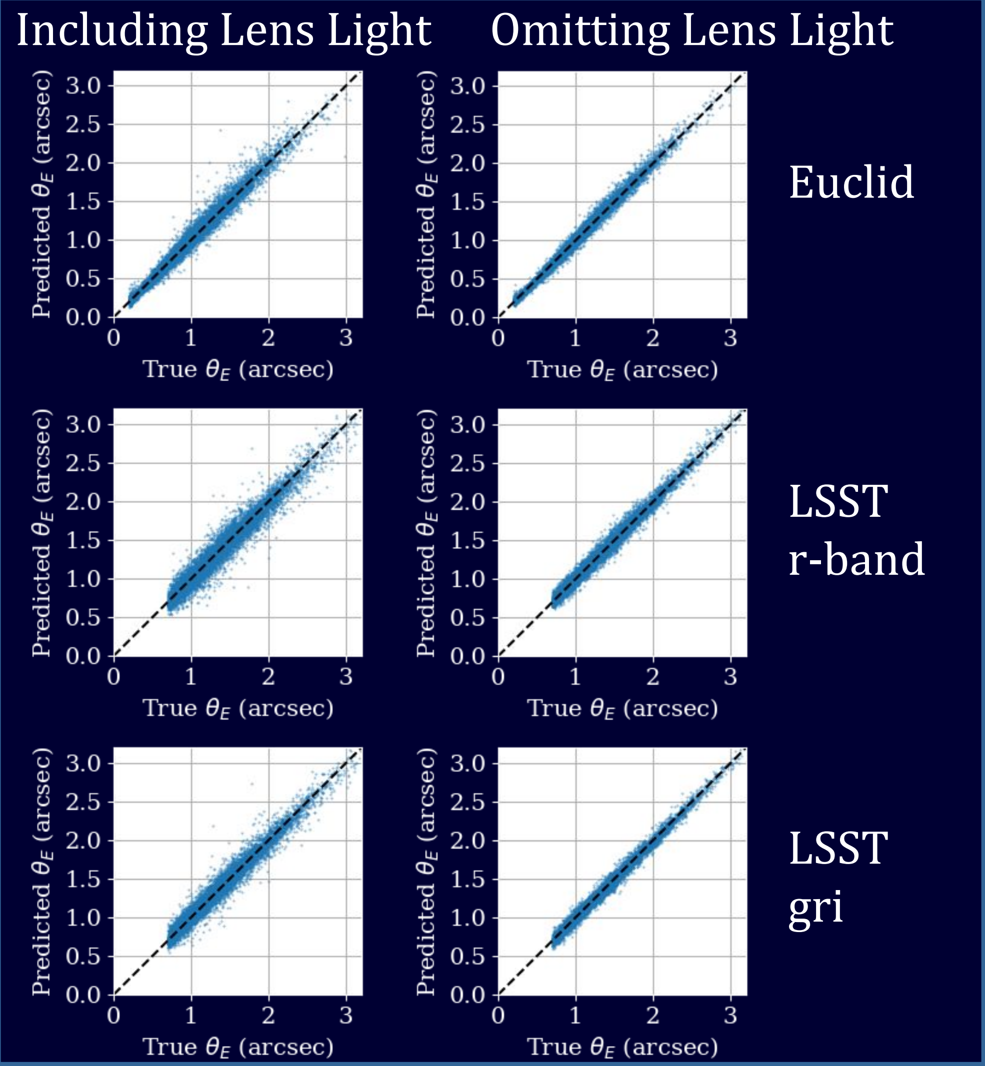
1 Lens/week

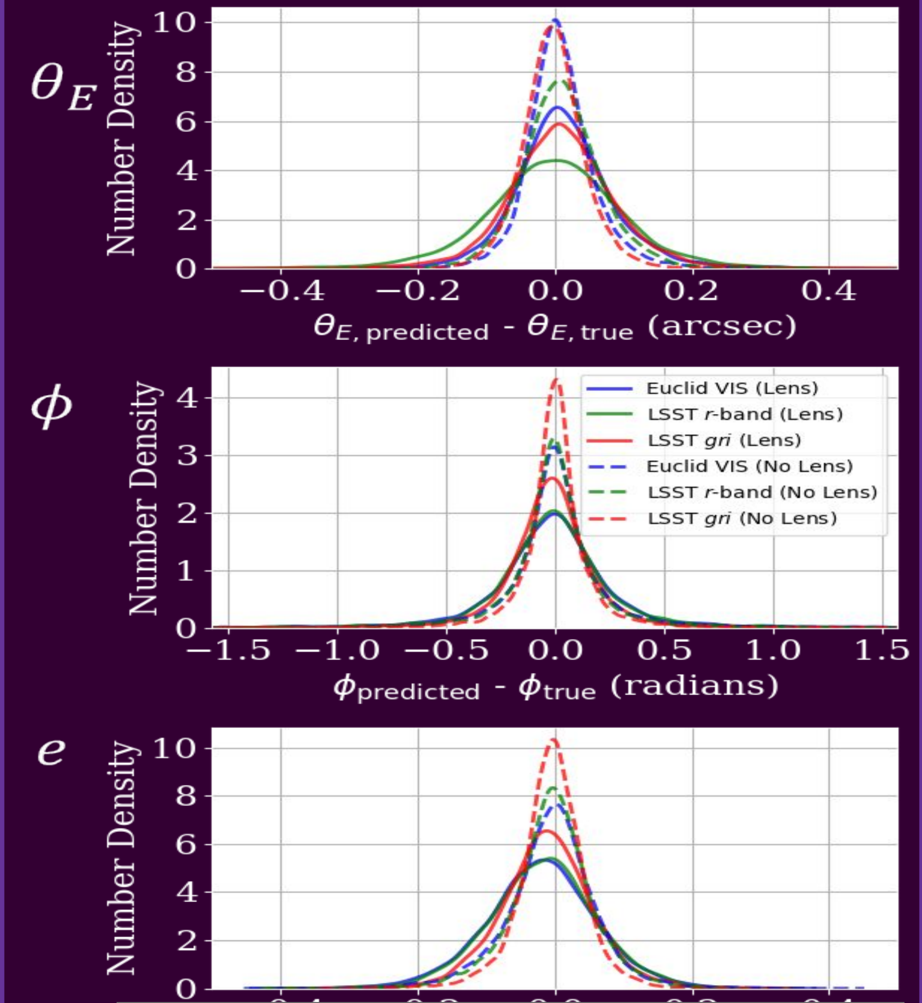
- **CNNs** (Hezaveh et al. 2017) -> **Speed up of ~7 orders of magnitude!**



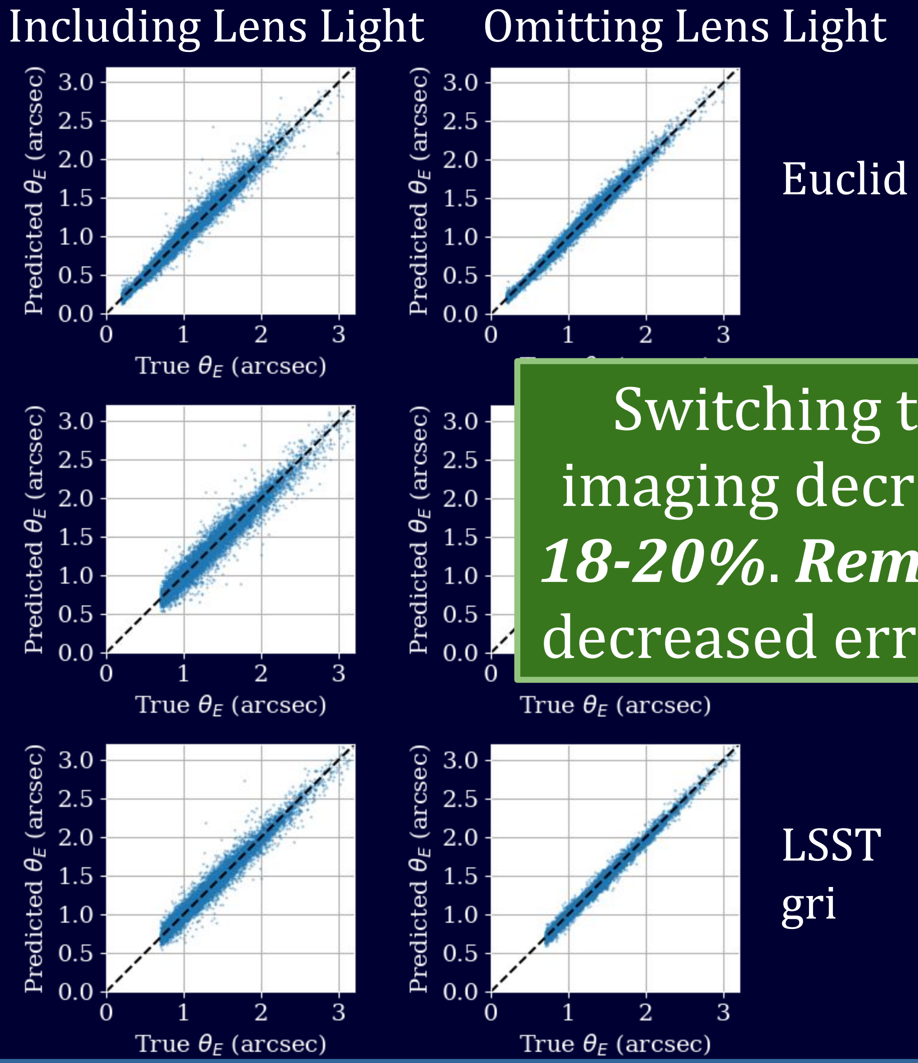
Created my own CNN to investigate:

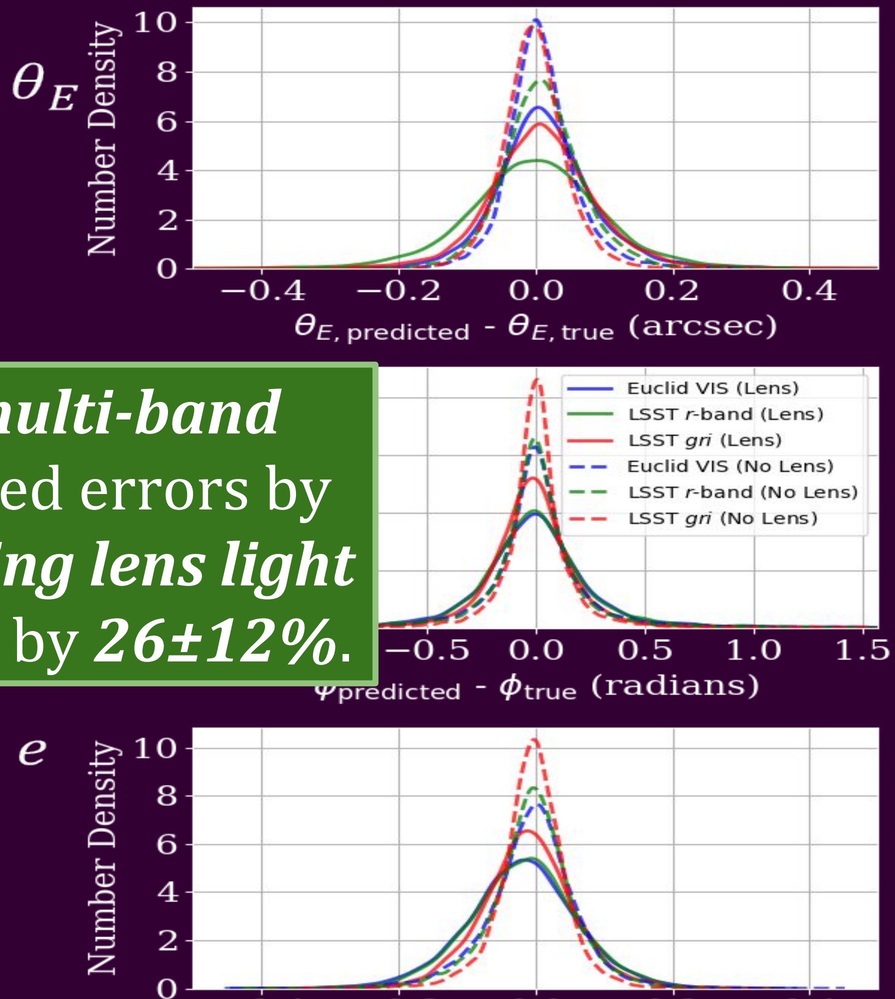
1. the efficiency when applied to **LSST- and Euclid-like images**
2. how accuracy is affected by:
   - the presence of the foreground **lens light**
   - the assumed **mass-light alignment**
   - the use of **multi-band** imaging
   - the use of **stacked** images





Pearson, Li, Dye, arXiv:1904.06199

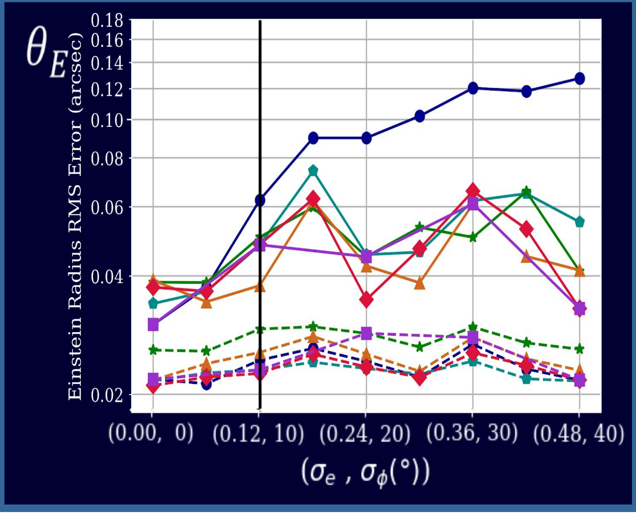


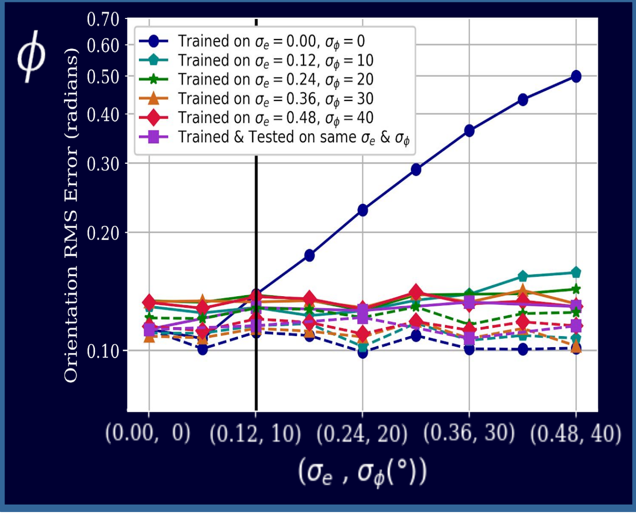


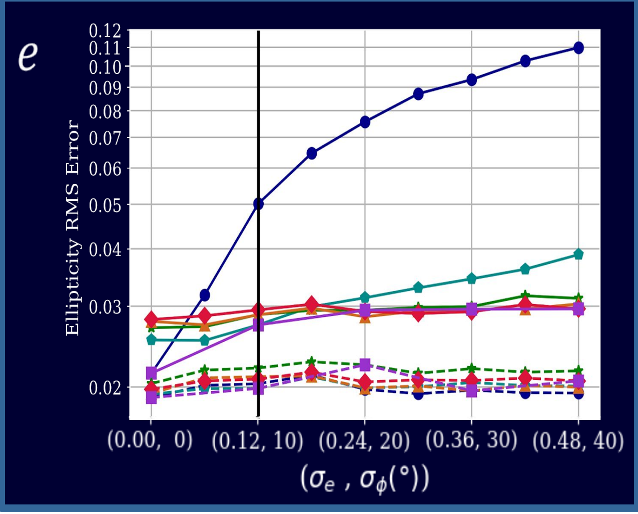
Switching to ***multi-band*** imaging decreased errors by ***18-20%***. ***Removing lens light*** decreased errors by ***26±12%***.

Pearson, Li, Dye, arXiv:1904.06199

Lights & Mass Profile Correction



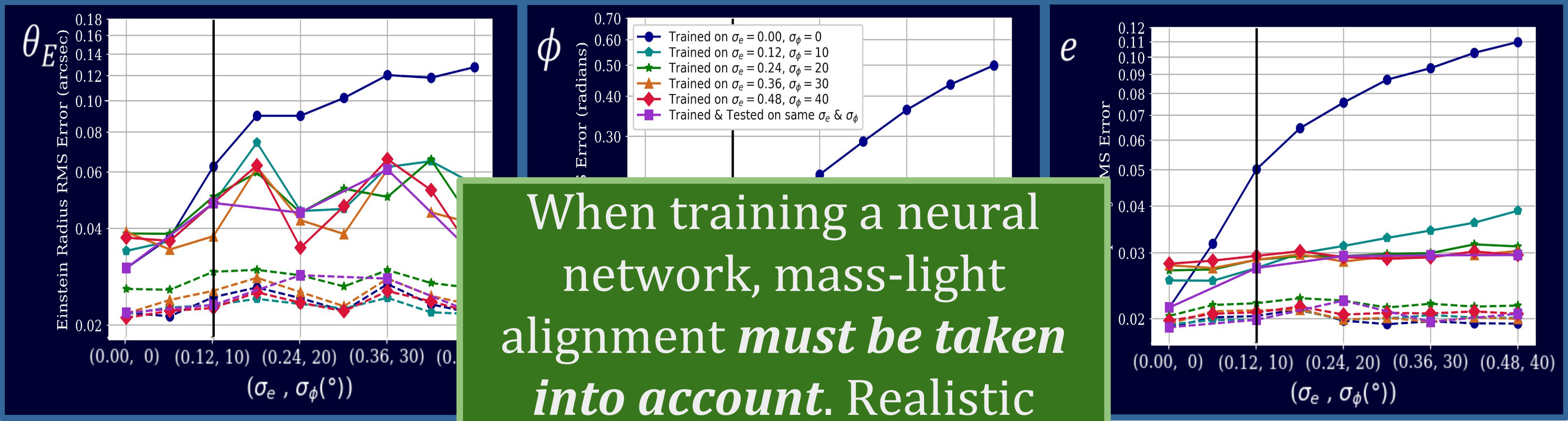




A CNN trained on zero scatter (blue line) uses lens light to predict the mass profile. There is scatter between the mass profiles and light profiles of observed lenses. We scattered both Orientation and Ellipticity to study the influences on the predictions. Solid Lines for "with lens light"; Dashed lines for "without lens light".

Pearson, Li, Dye, arXiv:1904.06199

Lights & Mass Profile Correction



When training a neural network, mass-light alignment ***must be taken into account***. Realistic Training Sets are necessary.

A CNN trained on z … light to predict the mass profile. There i … les and light profiles of observed lenses. We scattered both Orientation and Ellipticity to study the influences on the predictions. Solid Lines for "with lens light"; Dashed lines for "without lens light".

Pearson, Li, Dye, arXiv:1904.06199

Summary

- ❖ **Gravitational lensing is useful in astrophysics and cosmology, but we will encounter some issues in the Era of LSST, such as identifying and modelling strong lenses.**

- ❖ **Deep learning works better than traditional methods and human eyes in the detection of Strong lenses in the first Lens Finding Challenge.**

- ❖ **Lens modelling can be improved by utilising deep learning, including automation and efficiency. But, Realistic Training Sets are necessary.**

- ❖ **By connecting the machine modules mentioned above to traditional lens modelling tools, we are building an end-to-end pipeline for the automated analysis of strong lenses.**