大数据时代里强引力透镜系统的自动化分析

李楠

国家天文台

黑龙江, 大庆, 2019/11/29

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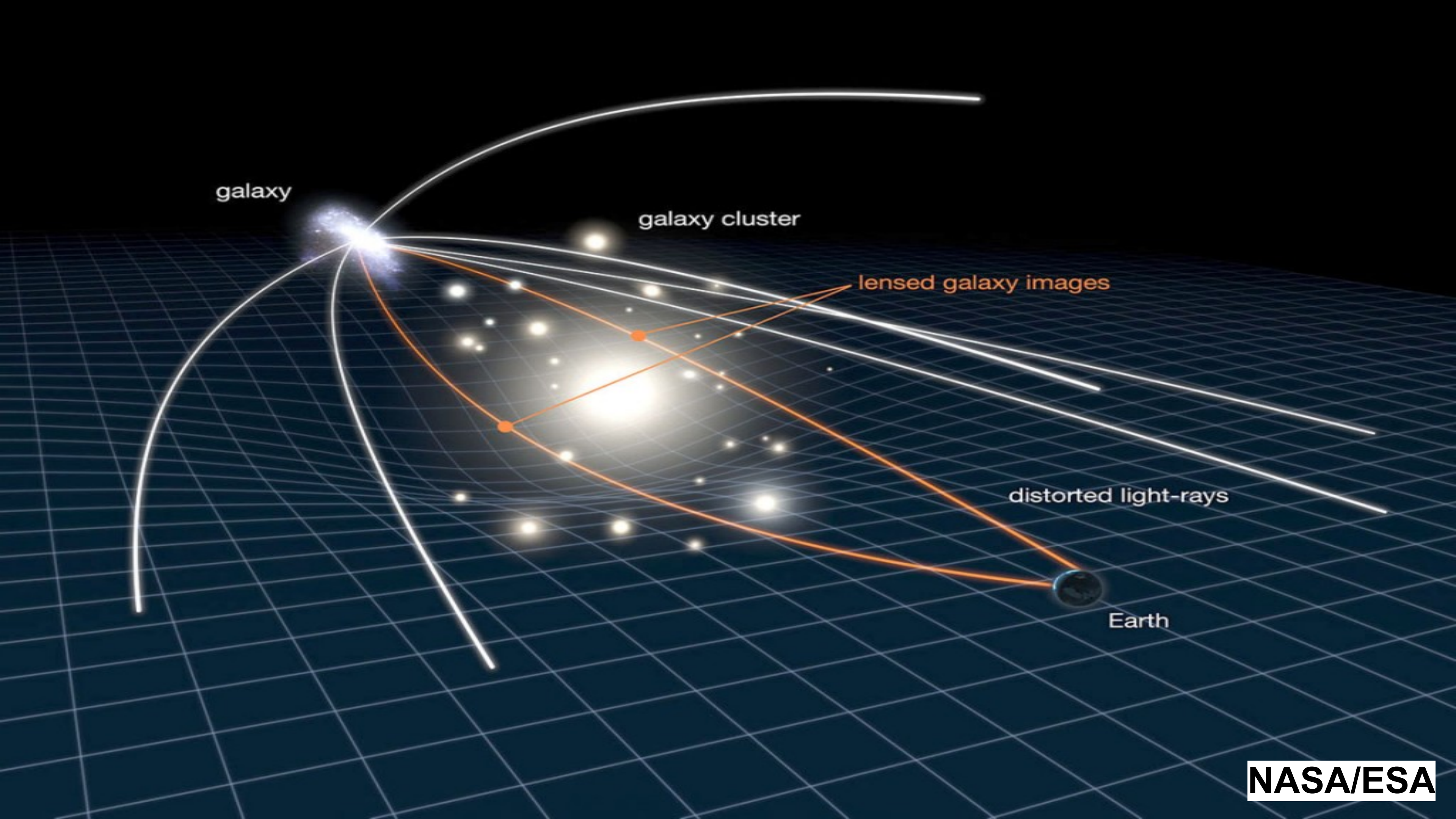
Outline

- Introduction
- Machine Learning and Lens Finding
- Machine Learning and Lens Modeling
- Outlook

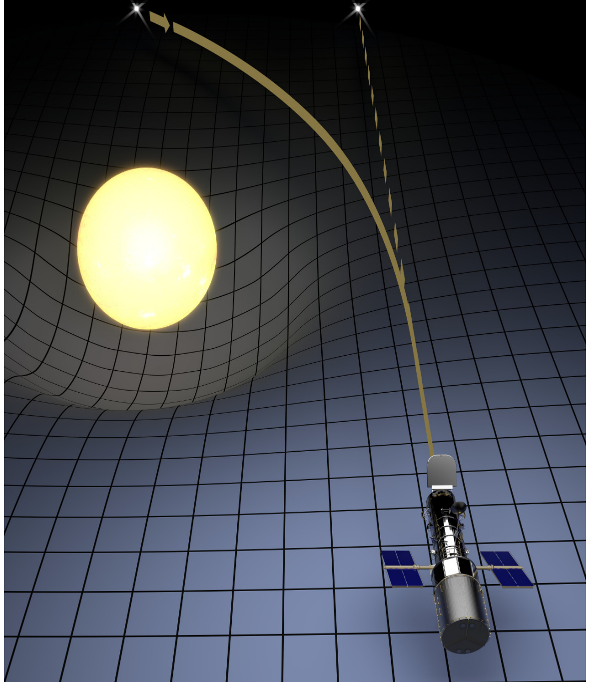

galaxy
galaxy cluster
lensed galaxy images
distorted light-rays
Earth
NASA/ESA

Galaxy Cluster Abell 2218 **HST · WFPC2**

NASA, A. Fruchter and ERO Team (STScI) · STScI-PRC00-08

Applications of Gravitational Lensing

- Test the theory of GR
- Geometry of the space

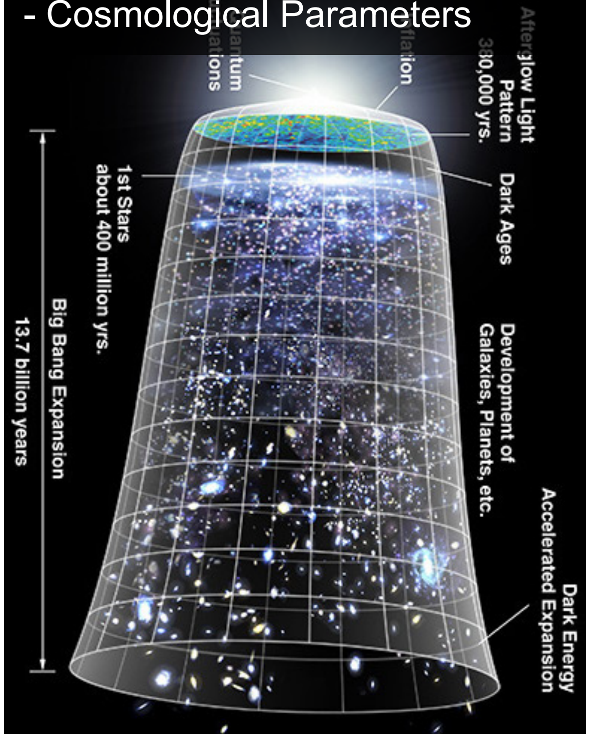


Artwork by Dave Jarvis

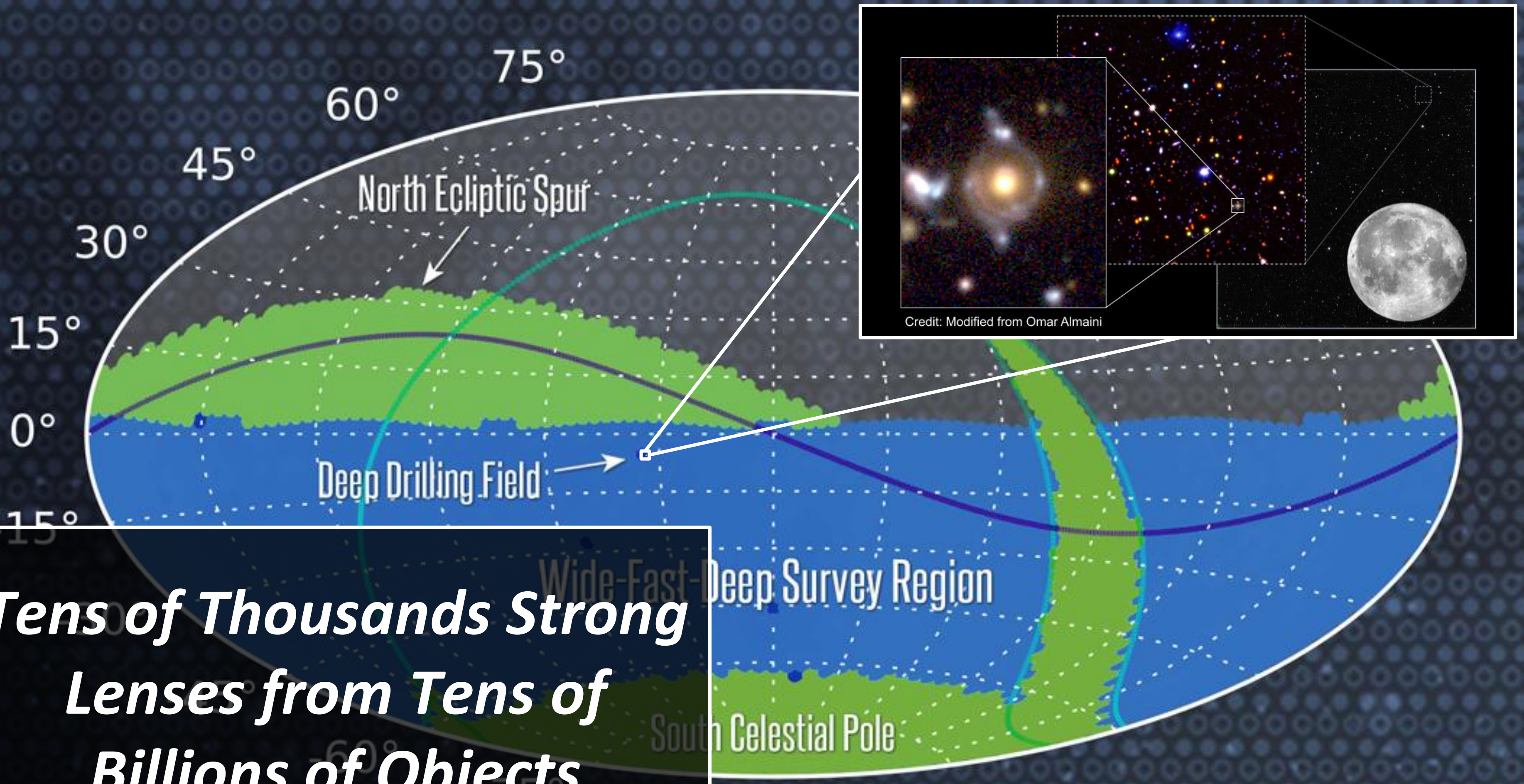
- Mass distribution of lenses
- Dark matter substructures

NASA/HST Cluster A370

- Structure Formation History
- Cosmological Parameters

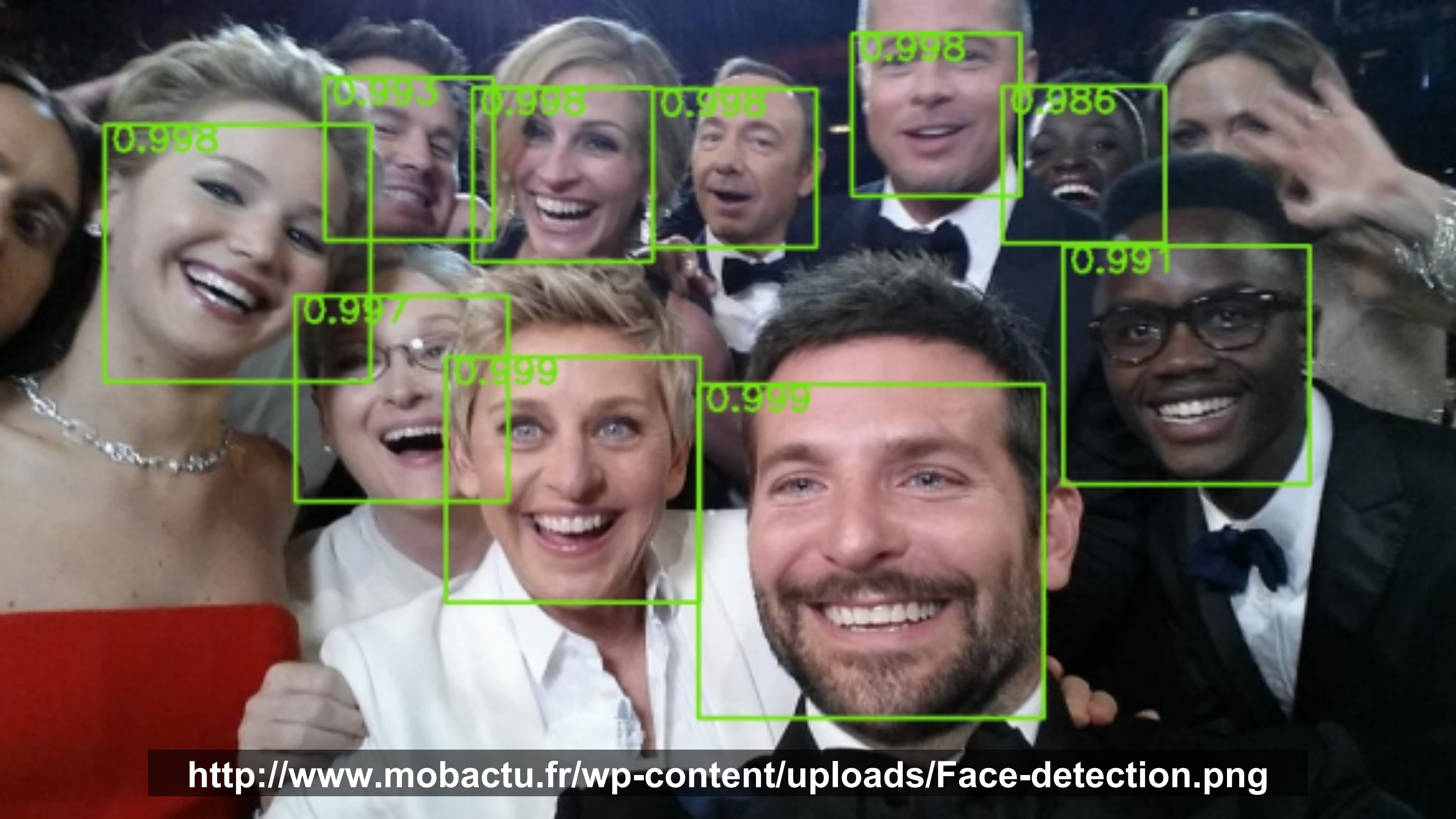


NASA/WMAP Science Team

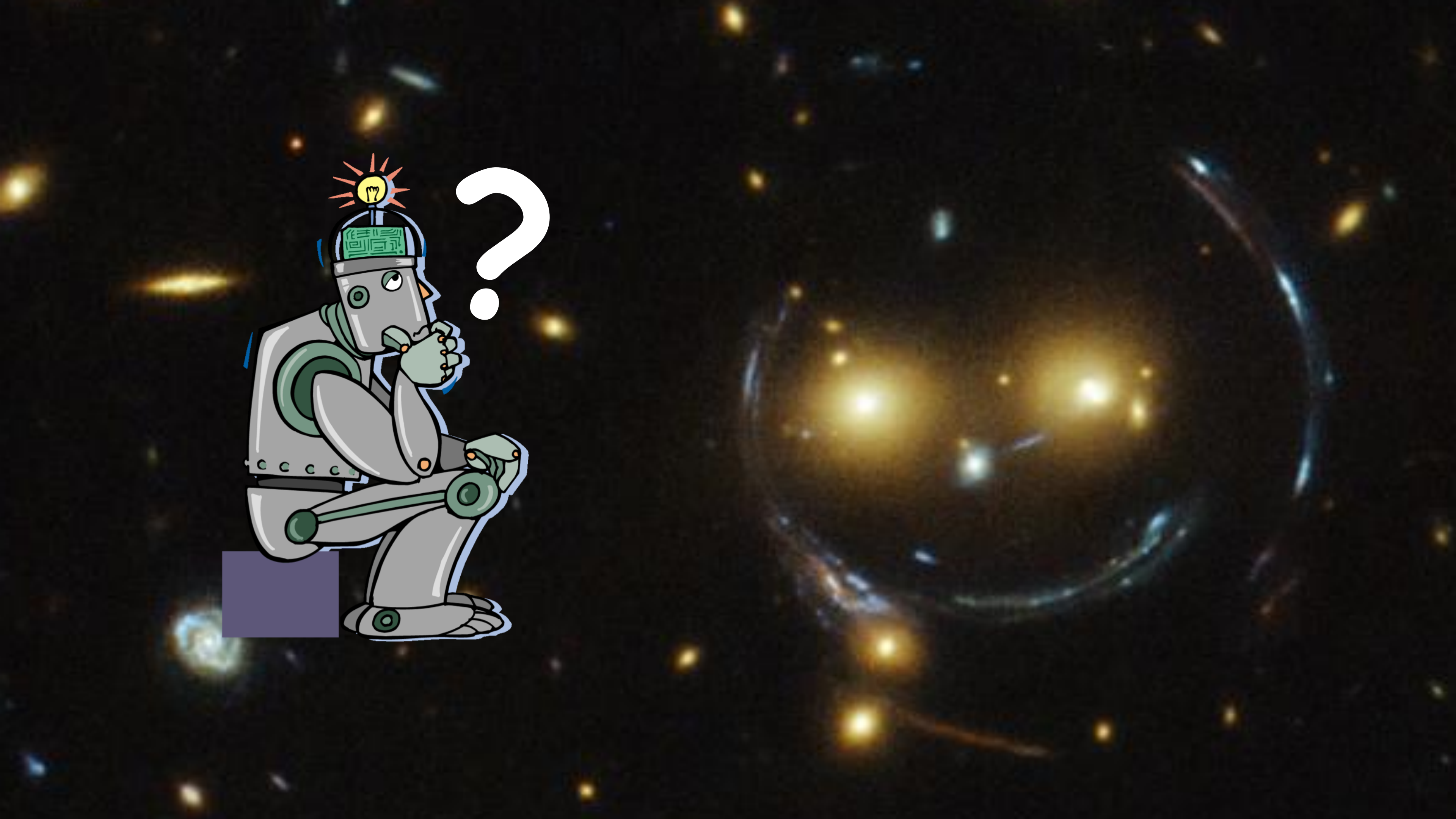


Tens of Thousands Strong Lenses from Tens of Billions of Objects

Credits: LSST OpSim Group



http://www.mobactu.fr/wp-content/uploads/Face-detection.png



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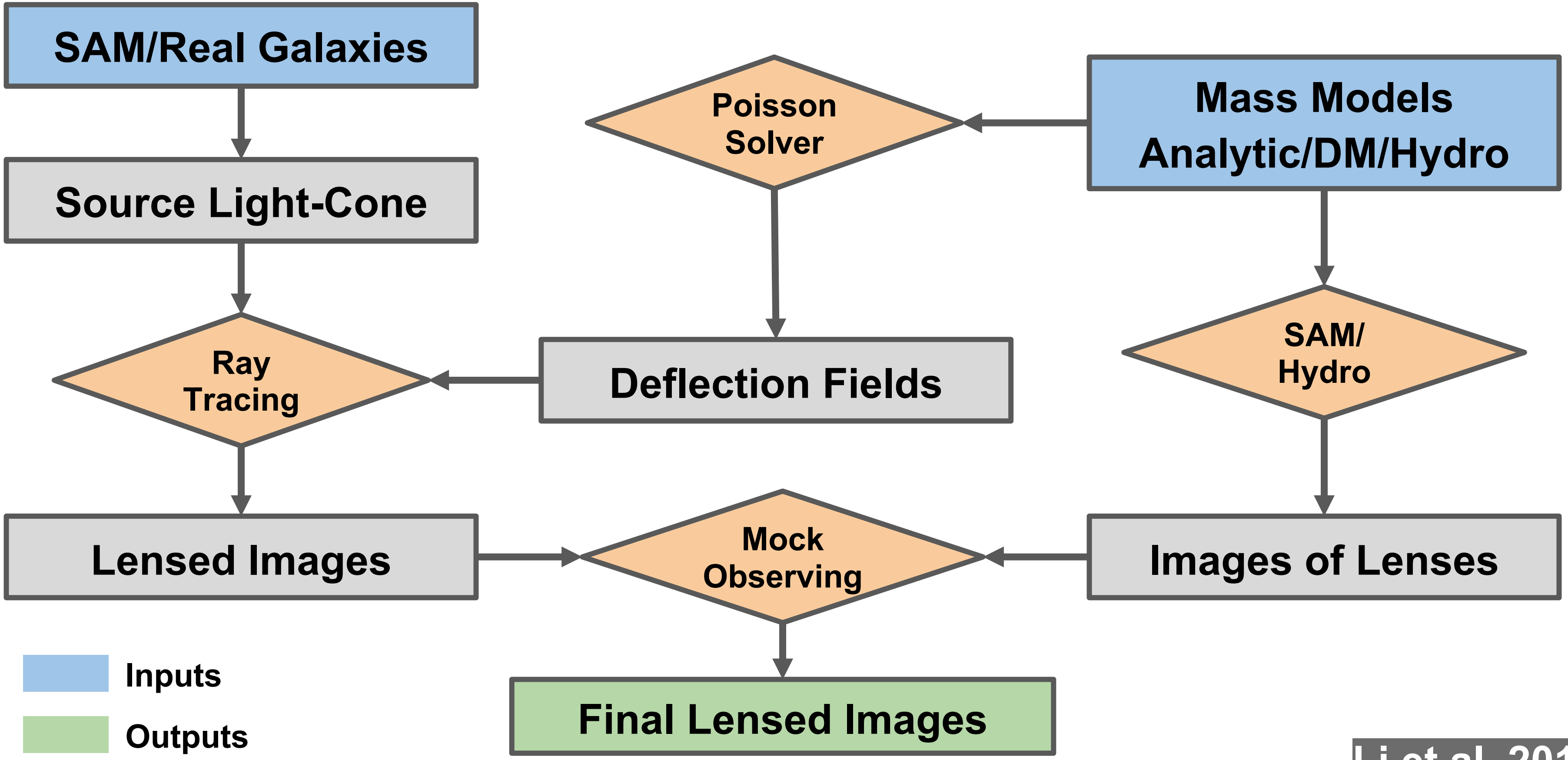
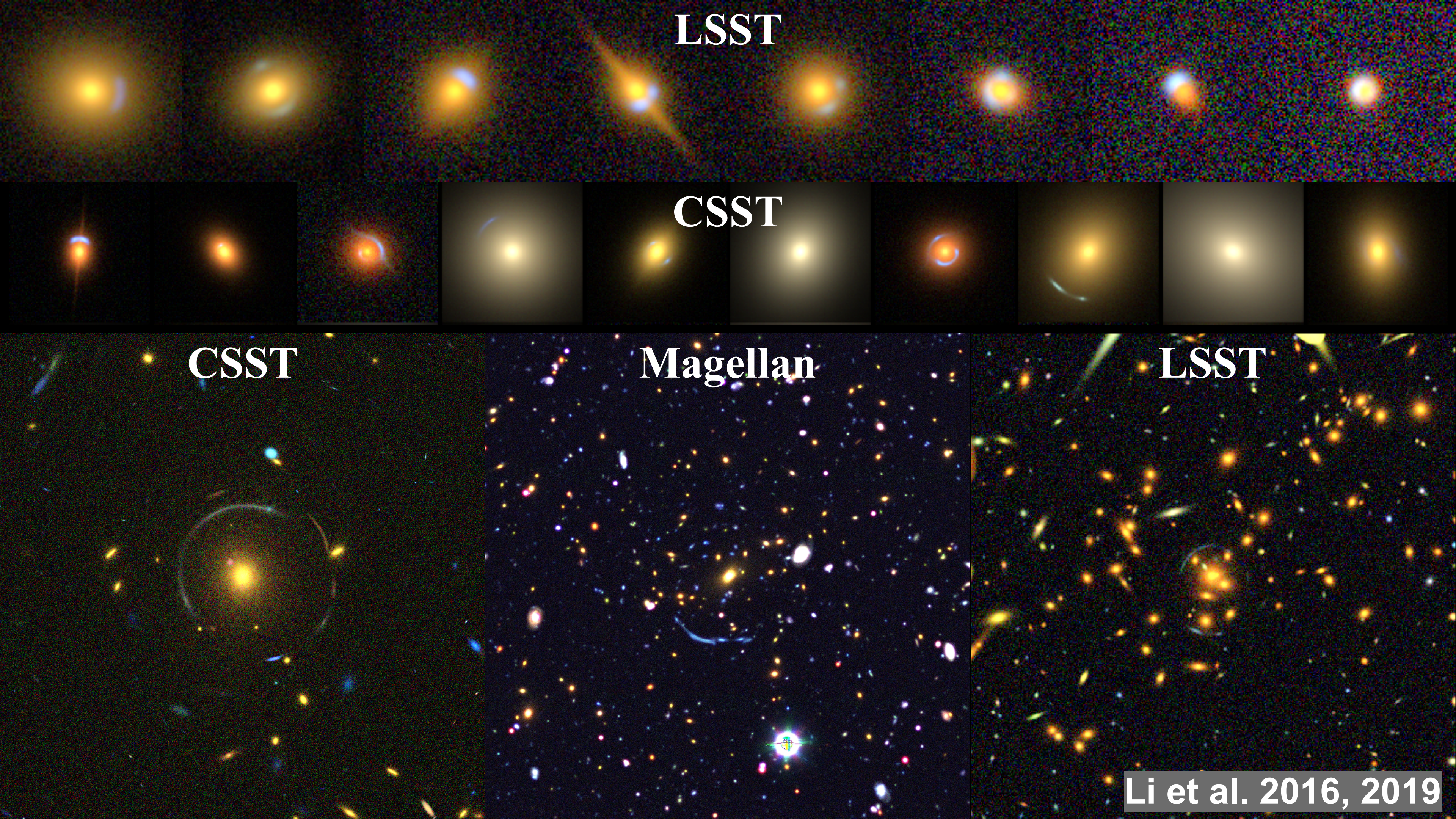
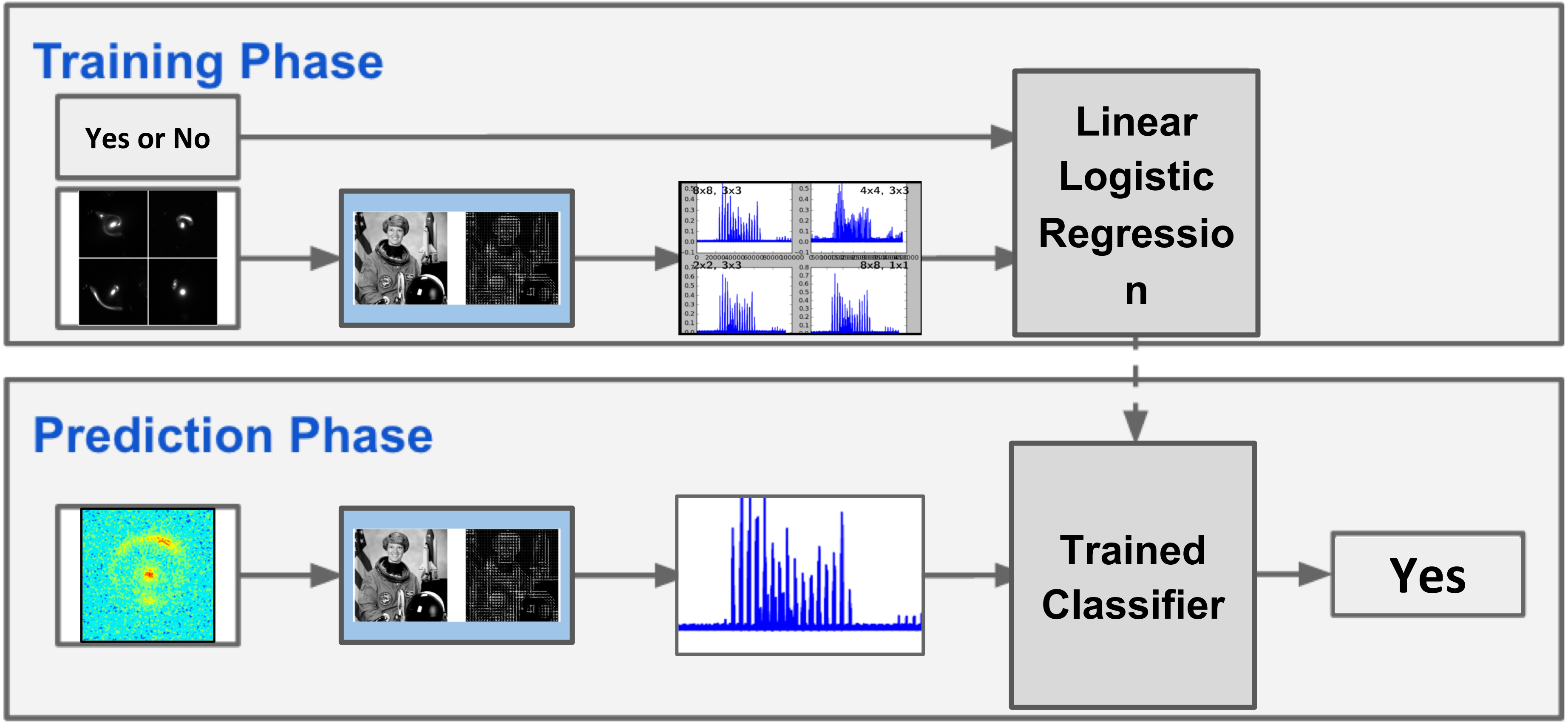
Simulations of Gravitational Lensing (PICS)



Li et al. 2016

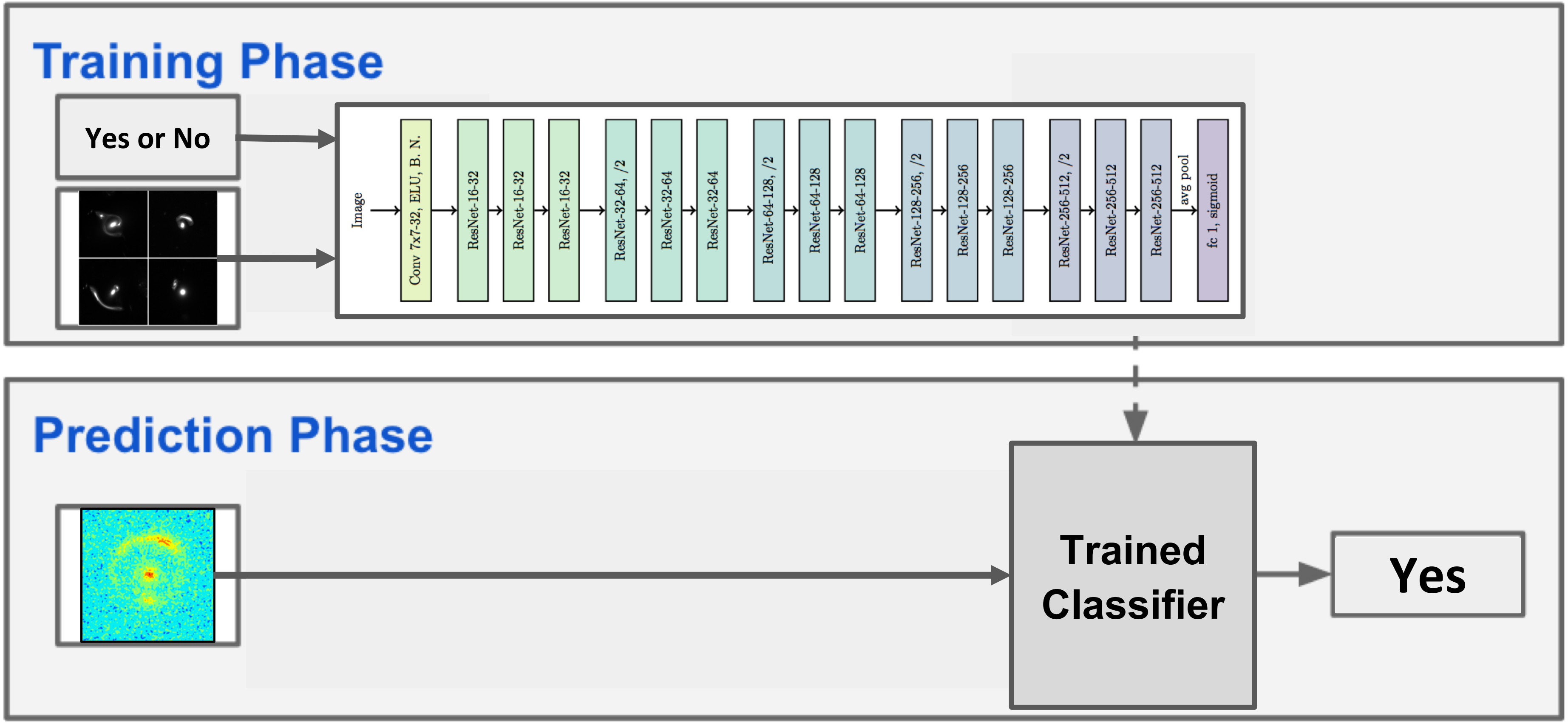

LSST
CSST
CSST
Magellan
LSST
Li et al. 2016, 2019

Traditional Machine Learning and Lens Finding



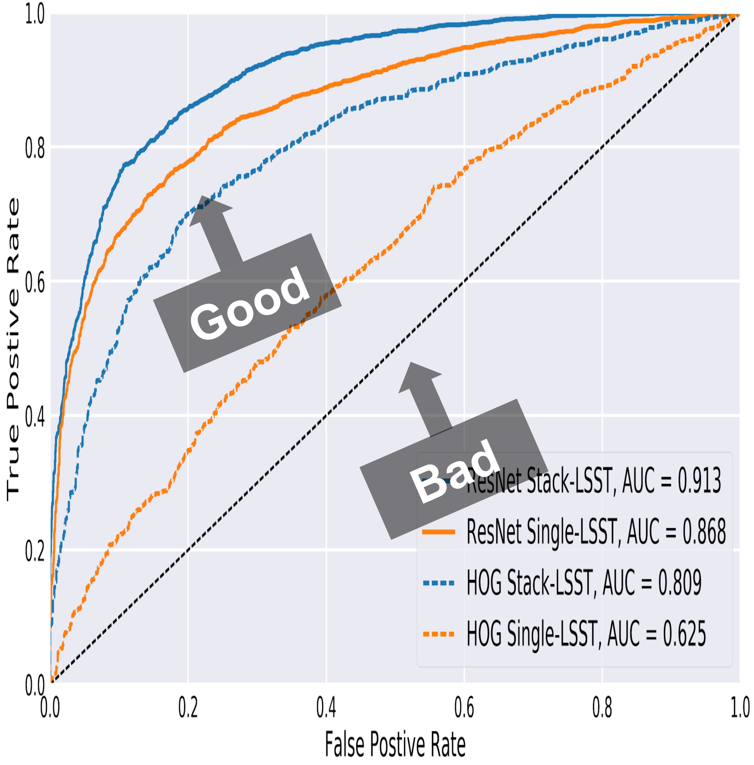
Avestruz, Li et al. 2019

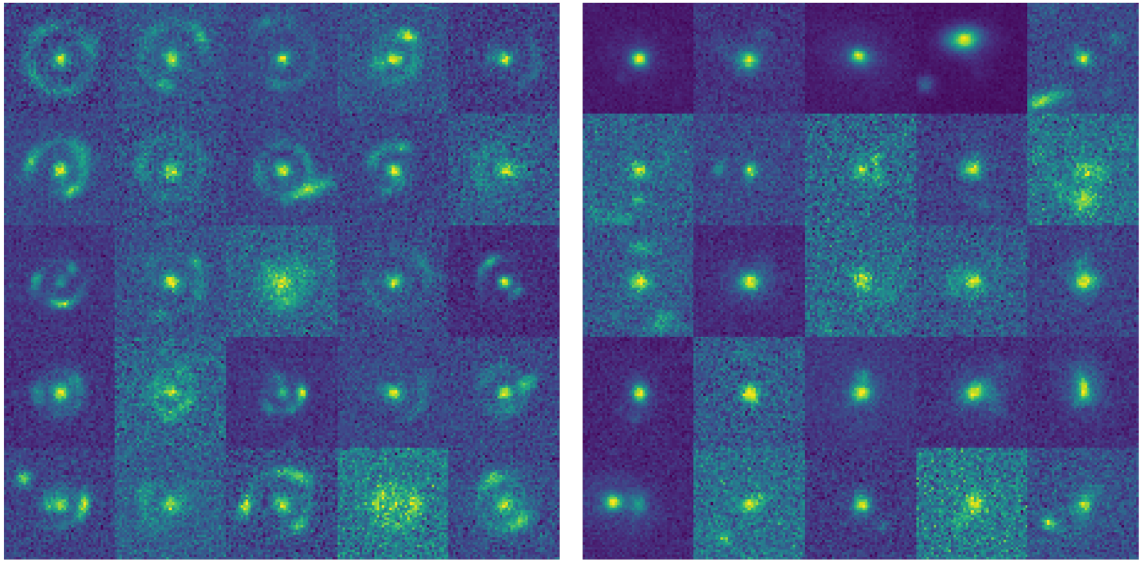
Deep Learning and Lens Finding



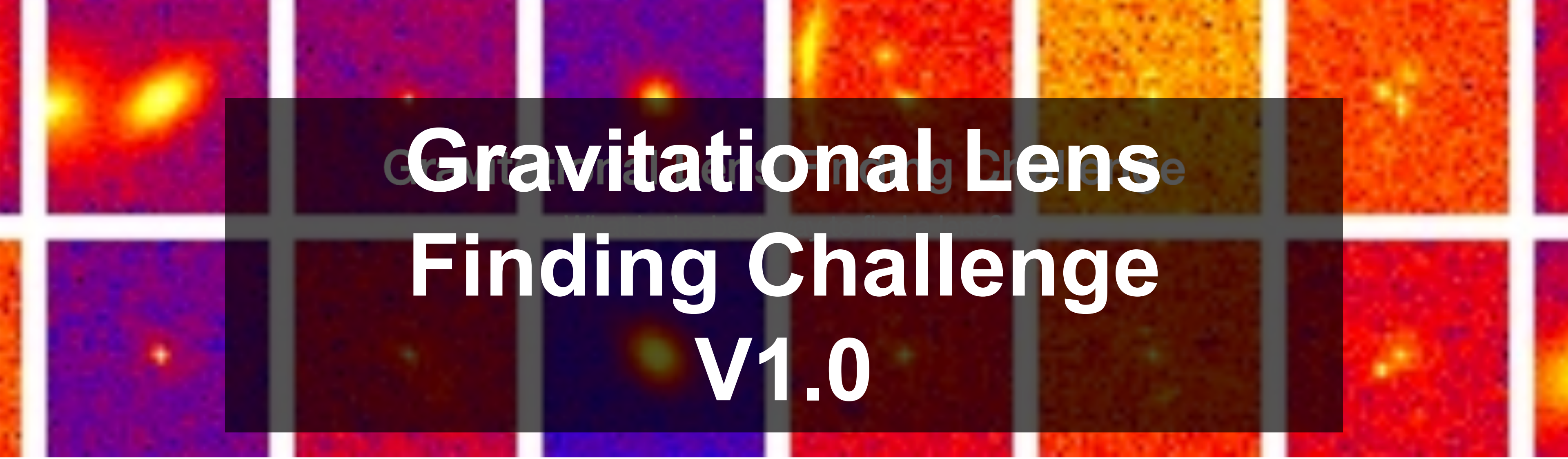
Lanusse, Ma, Li et al. 2017

Traditional Machine Learning VS. Deep Learning





Avestruz, Li et al. 2019 & Lanusse, Ma, Li et al. 2017

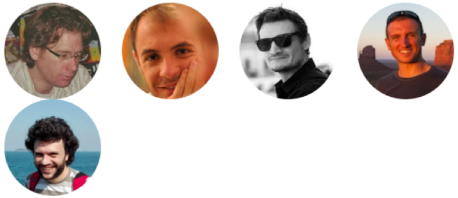


Gravitational Lens Finding Challenge V1.0

Introduction

Finding strong gravitational lenses in the current imaging surveys is difficult. Future surveys will have orders of magnitude more data and more lenses to find. It will become impossible for a single human being to find them by inspection. In addition, to properly interpret the science coming out of strong lens samples it is necessary to accurately quantify the detection efficiency and bias of automated lens detectors. These open challenges are designed as a friendly way of stimulating activity and helping to quantify results in this regard.

People



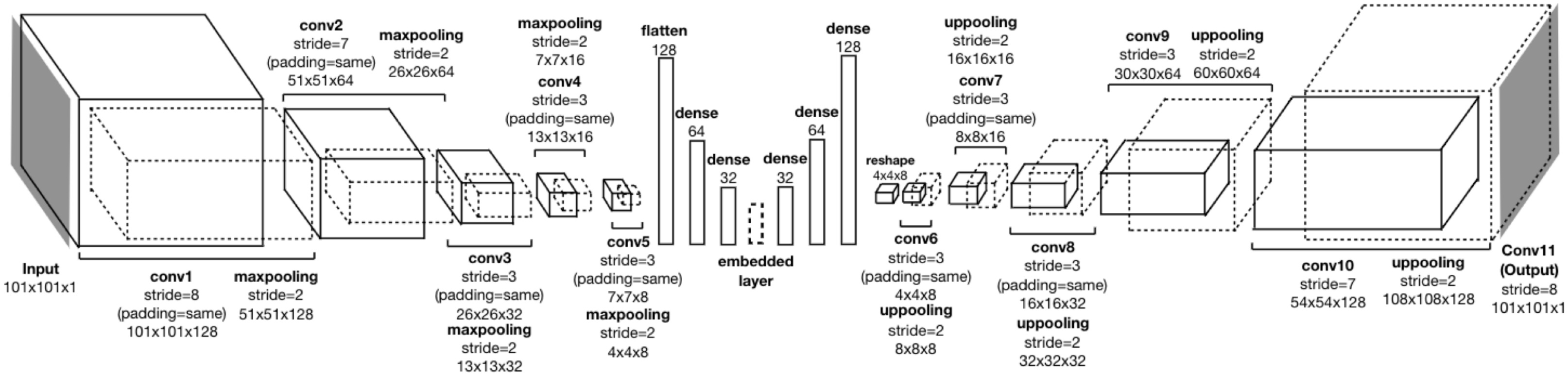
http://metcalf1.difa.unibo.it/blf-portal/gg_challenge.html

Sorted by area under the ROC curve

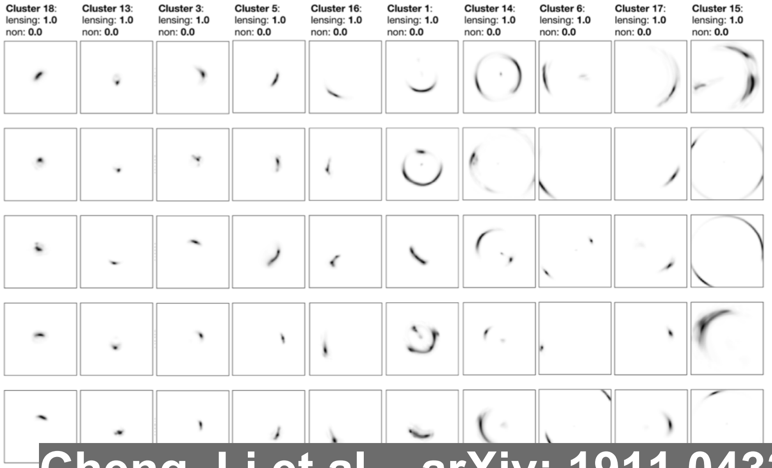
##		Team_name_submit	type	AUROC	TPR0	TPR10	description_short	author.1
##	14	resnet_ground_7bf8089	Ground-Based	0.9814321	8.993713e-02	0.4534297041	CNN	Francois Lanusse
##	10	CMU-DeepLens-Resnet-Voting	Ground-Based	0.9804913	2.445130e-02	0.1027314963	CNN	Quanbin Ma
##	20	LASTRO EPFL (11i)	Ground-Based	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 finder	R Cabanac

Metcalf et al. 2019

Unsupervised Learning and Lens-finding



Name	Author	AUC	TPR_0	TPR_{10}	short description
LASTRO EPFL	Geiger, Schäfer & Kneib	0.93	0.00	0.08	CNN
CMU-DeepLens-Resnet	Francois Lanusse, Ma, C. Li & Ravanbakhsh	0.92	0.22	0.29	CNN
GAMOCLASS	Huertas-Company, Tuccillo, Velasco-Forero & Decencière	0.92	0.07	0.36	CNN
CMU-DeepLens-Resnet-Voting	Ma, Lanusse & C. Li	0.91	0.00	0.01	CNN
AstrOmatic	Bertin	0.91	0.00	0.01	CNN
CMU-DeepLens-Resnet-aug	Ma, Lanusse, Ravanbakhsh & C. Li	0.91	0.00	0.00	CNN
***Unsupervised technique**	**This Work (Training, Fig. 8)**	**0.87**	**0.08**	**0.08**	**Deep Clustering**
****Unsupervised technique**	**This Work (Section 4.2.3)**	**0.83**	**0.00**	**0.00**	**Deep Clustering**
Kapteyn Resnet	Petrillo, Tortora, Kleijn, Koopmans & Vernardos	0.82	0.00	0.00	CNN
CAST	Bom, Valentín & Makler	0.81	0.07	0.12	CNN
Manchester1	Jackson & Tagore	0.81	0.01	0.17	Human Inspection
Manchester SVM	Hartley & Flamary	0.81	0.03	0.08	SVM / Gabor
NeuralNet2	Davies & Serjeant	0.76	0.00	0.00	CNN / wavelets
YattaLensLite	Sonnenfeld	0.76	0.00	0.00	Arcs / SExtractor
All-now	Avestruz, N. Li & Lightman	0.73	0.05	0.07	edges/gradiants and Logistic Reg.
Unsupervised technique	**This Work (Section 4.2.3)**	**0.72**	**0.00**	**0.00**	**Deep Clustering**
GAHEC IRAP	Cabanac	0.66	0.00	0.01	arc finder



Cheng, Li et al., arXiv: 1911.04320

Outline

Introduction

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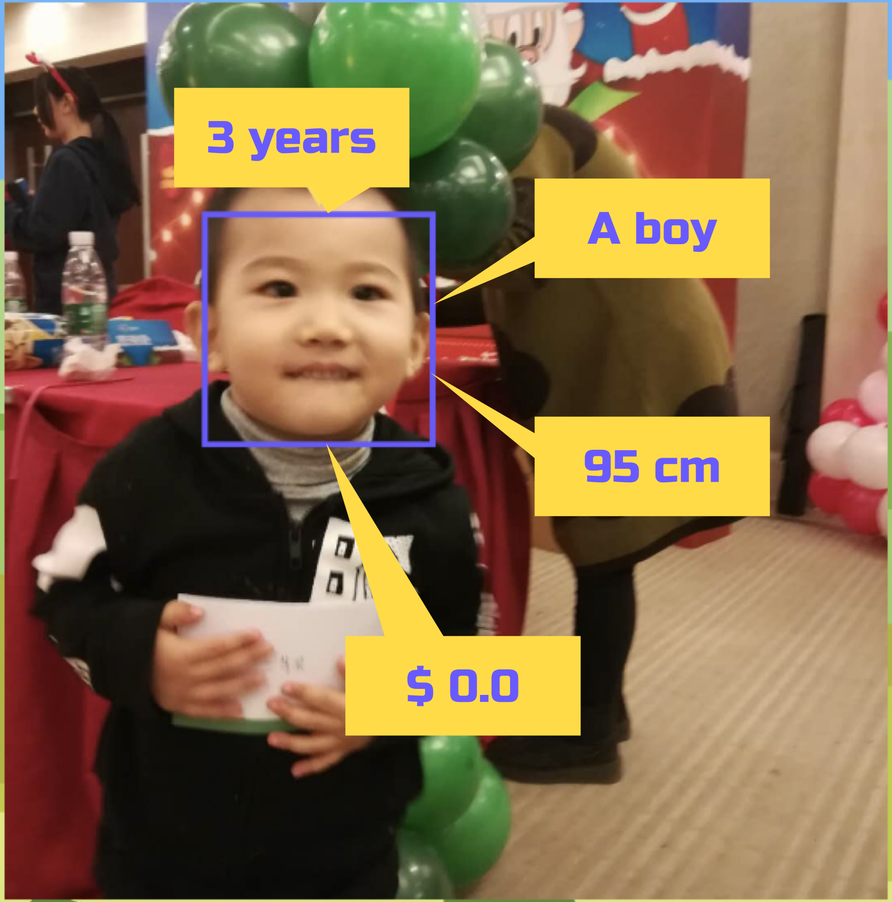
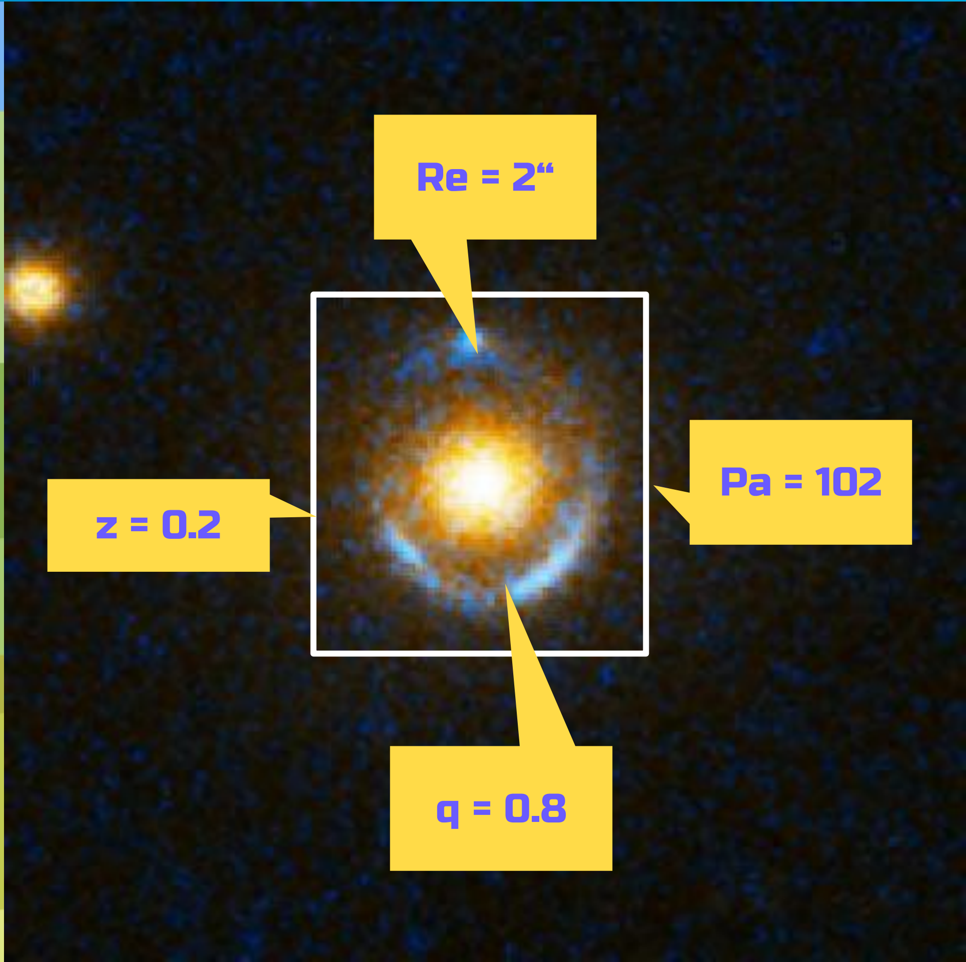
Machine Learning and Lens Modeling

Outlook

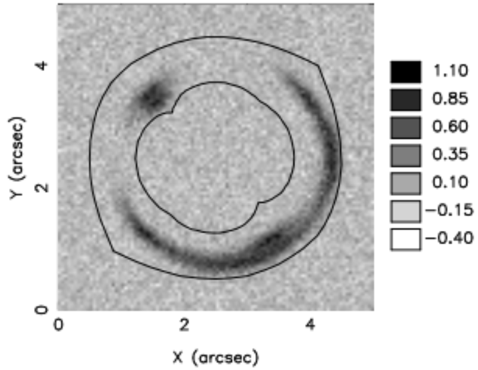
Machine Learning and Lens Modeling

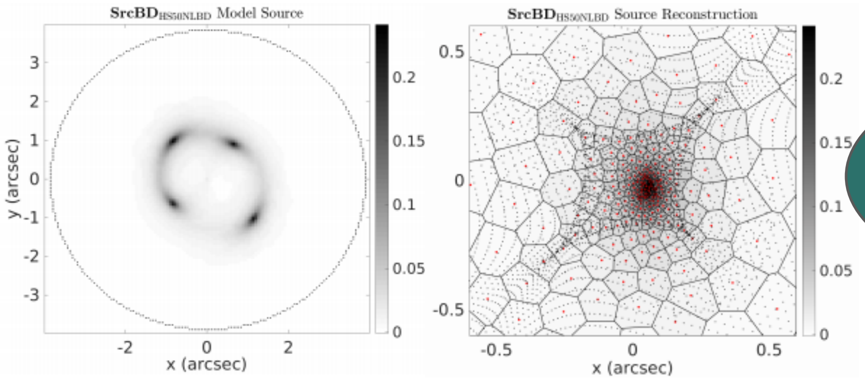




Deep Learning and Lens Modeling

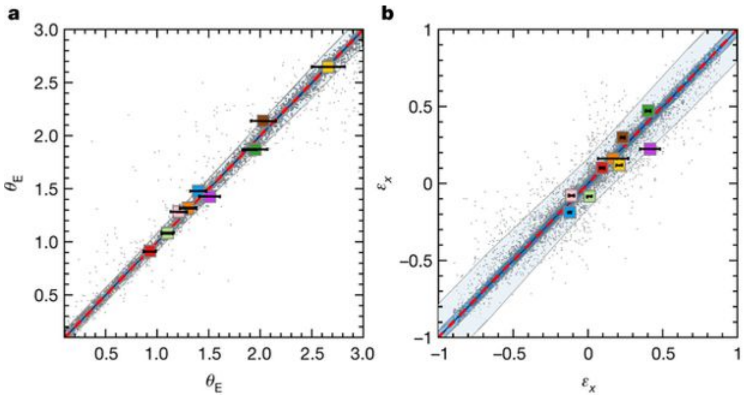
- **Parameter Fitting techniques (e.g. Warren & Dye 2003, Nightingale, Dye & Massey 2018)**





1 Lens/week

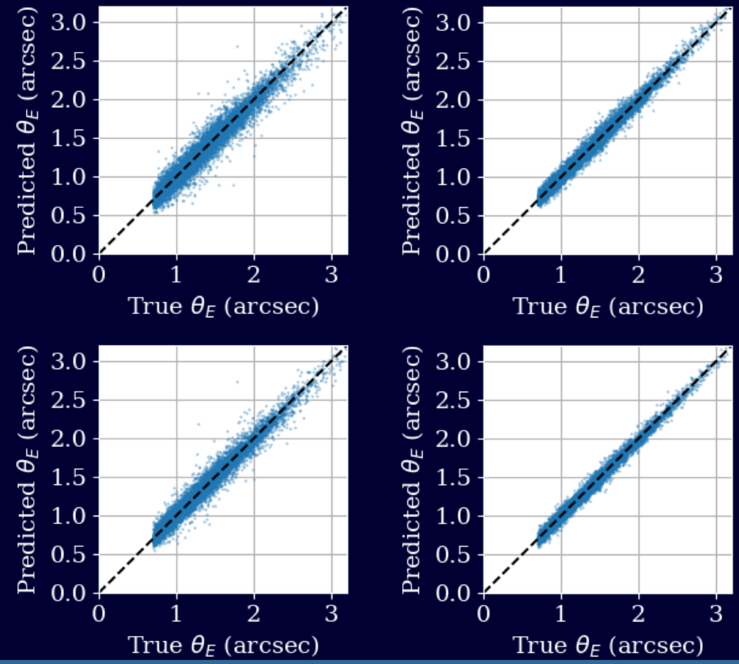
- **CNNs (Hezaveh et al. 2017) -> Speed up of ~7 orders of magnitude!**

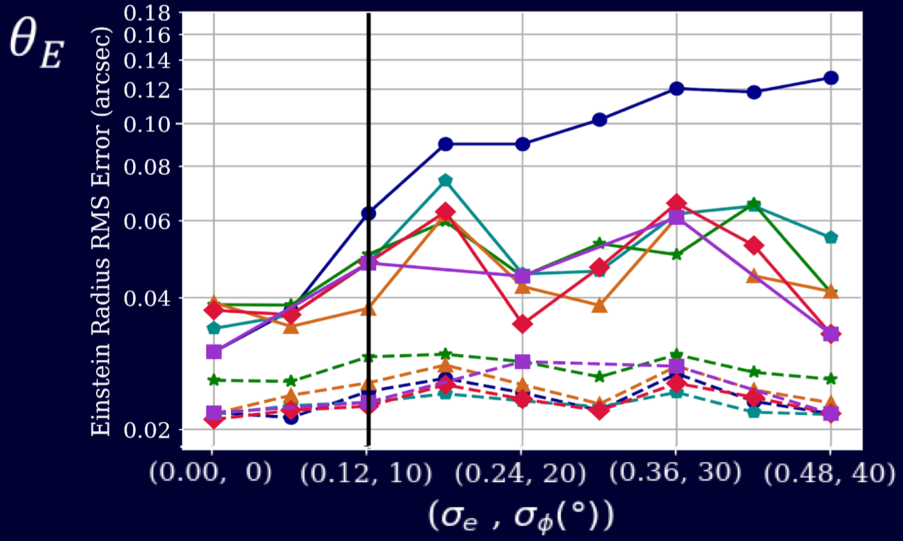


Created my own CNN to investigate:

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

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





When training a neural network, mass-light alignment *must be* taken into account. ***Removing lens light can get rid of the influences.***

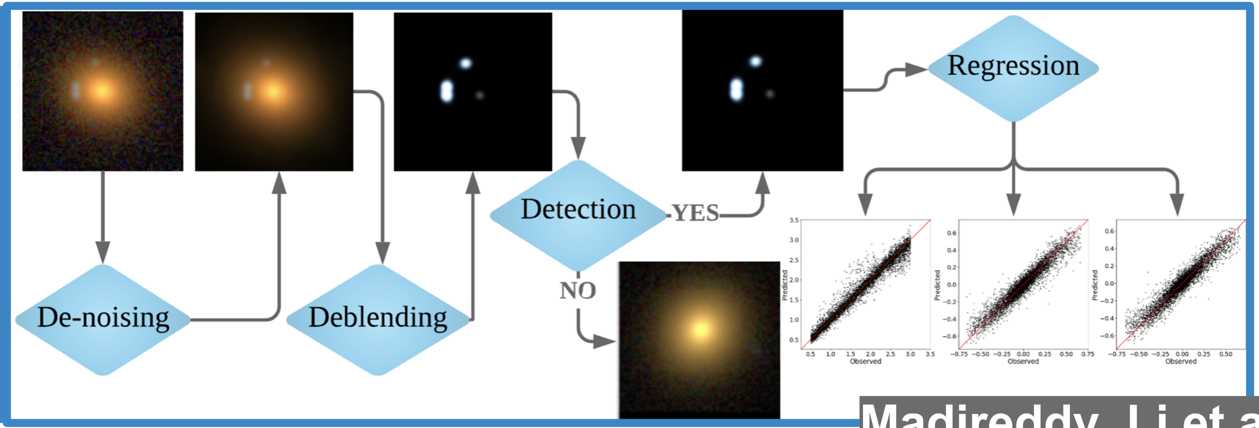
Pearson, Li, Dye 2019

Original Images

Denoise

Deblend

An End2End pipeline for the analysis of GGSLs



Madireddy, Li et al. 2019

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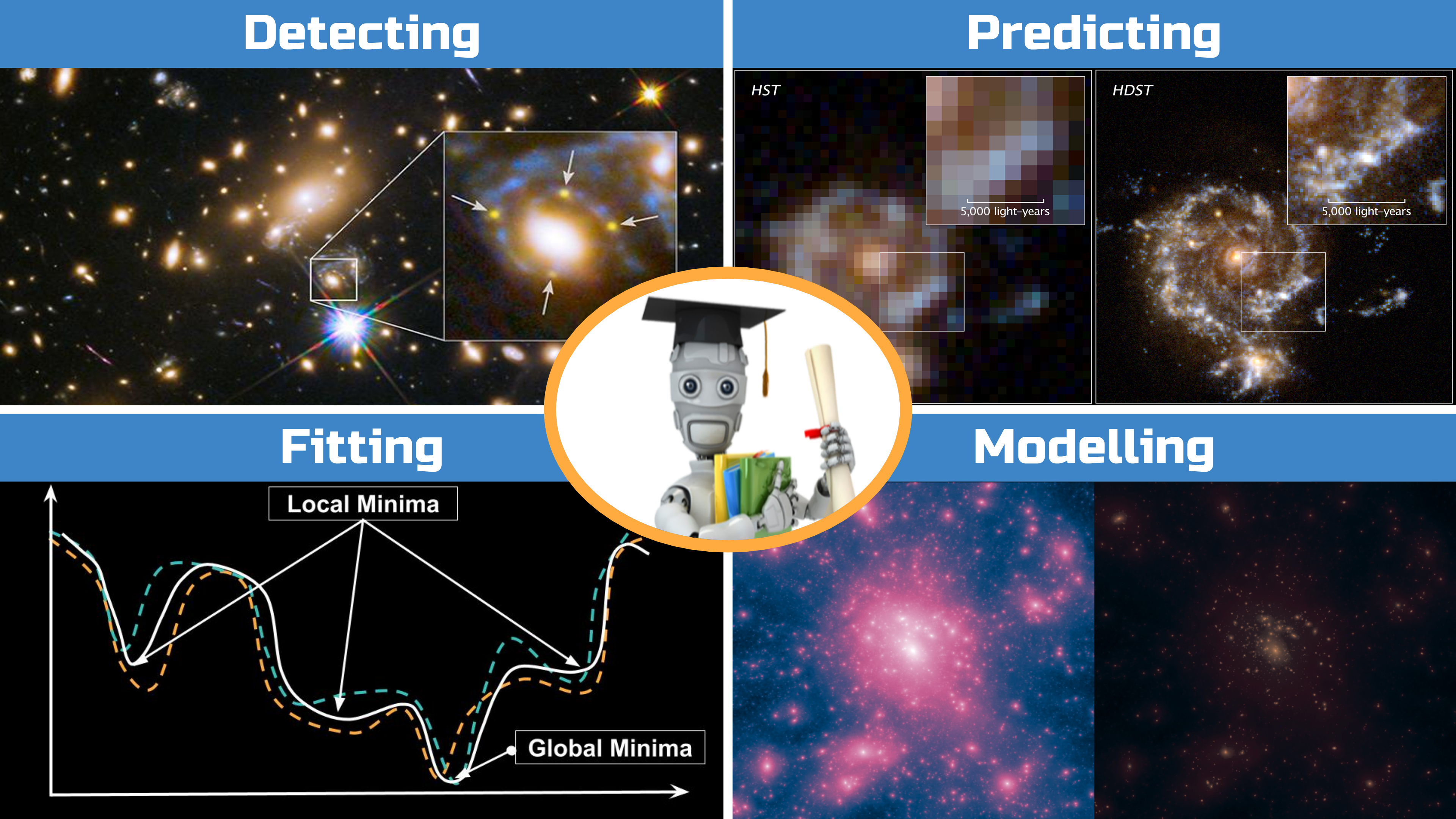
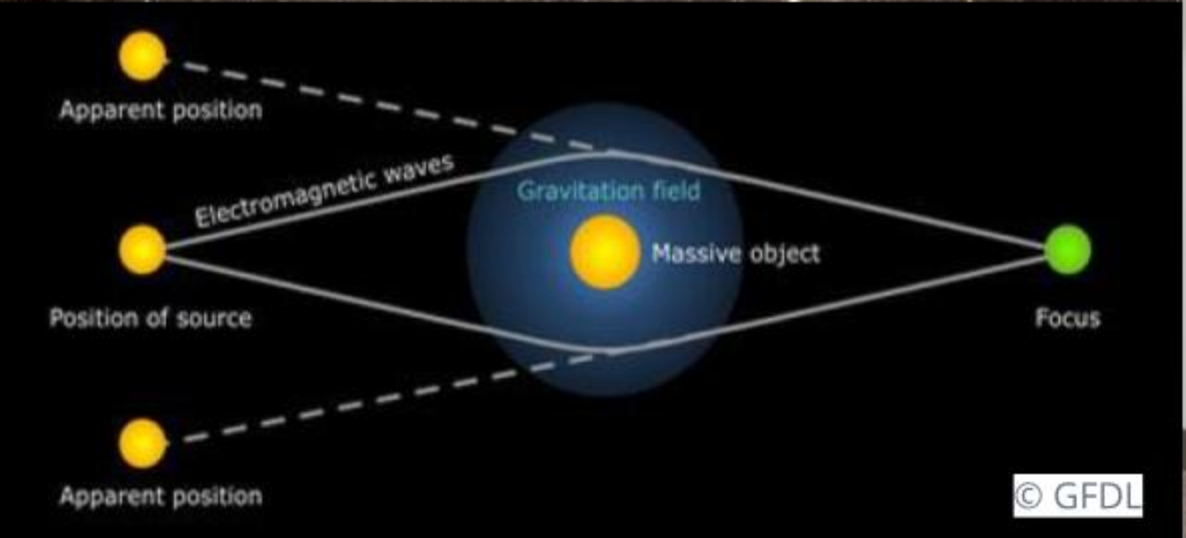
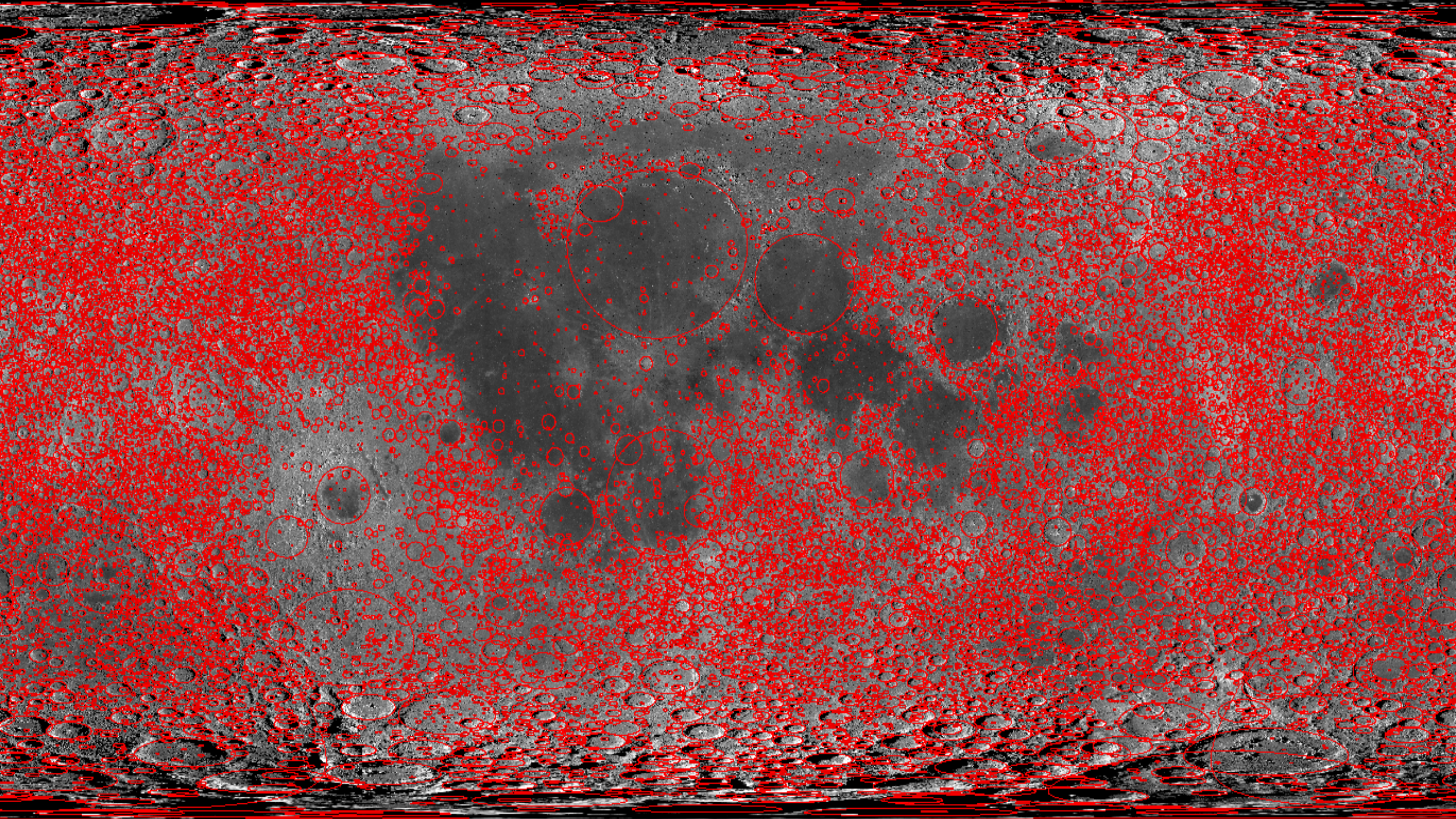
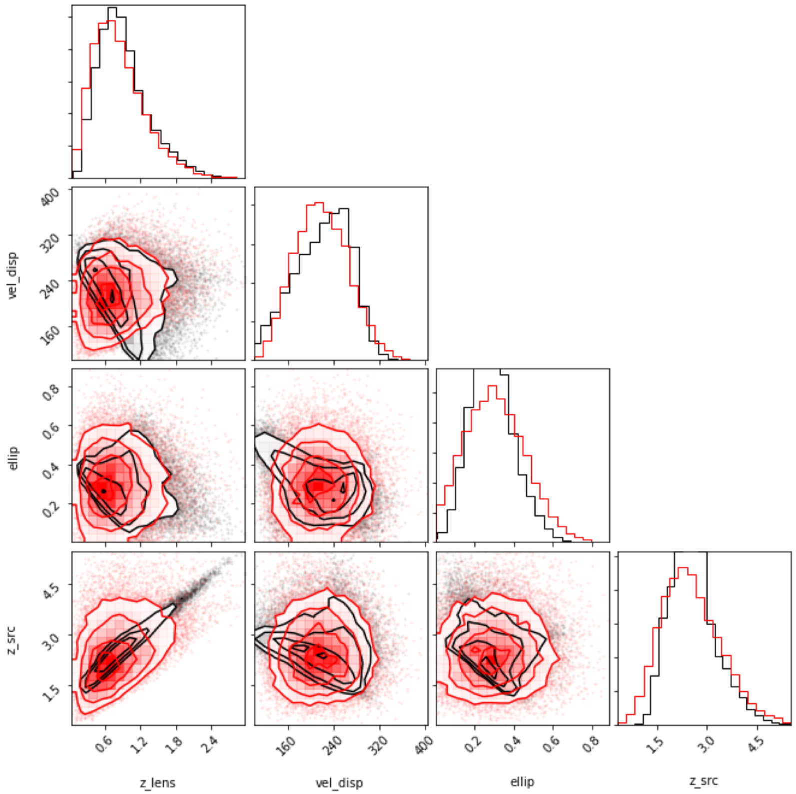
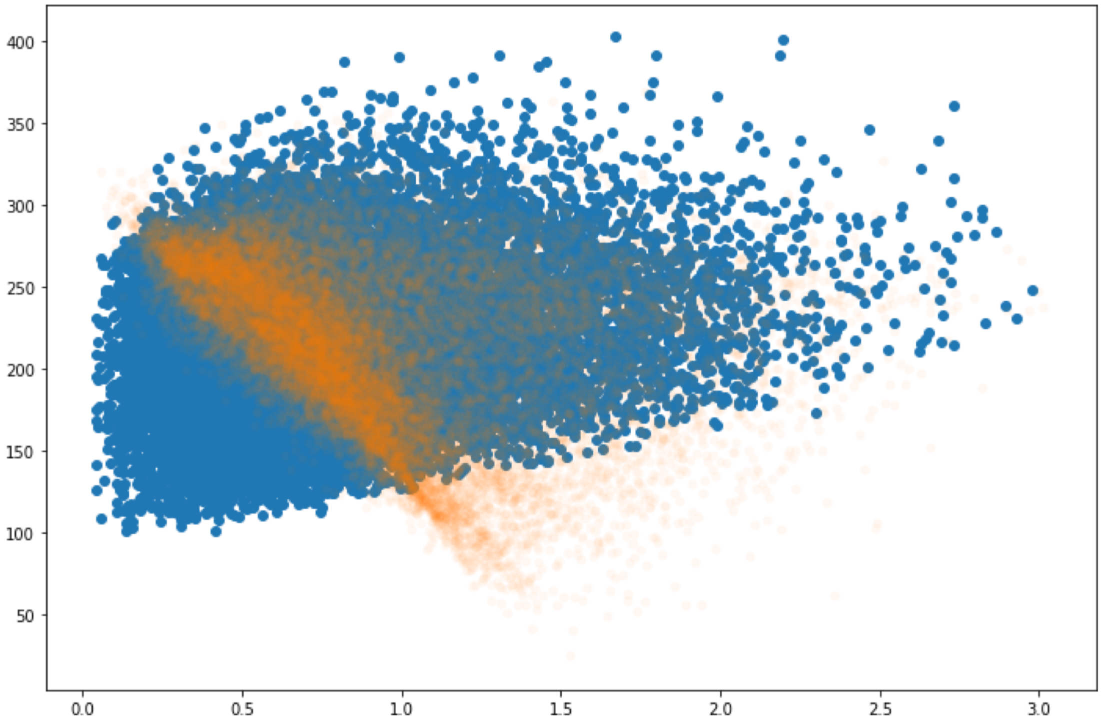

Detecting
Predicting
HST
5,000 light-years
HDST
5,000 light-years
Fitting
Local Minima
Global Minima
Modelling

Backup Slides

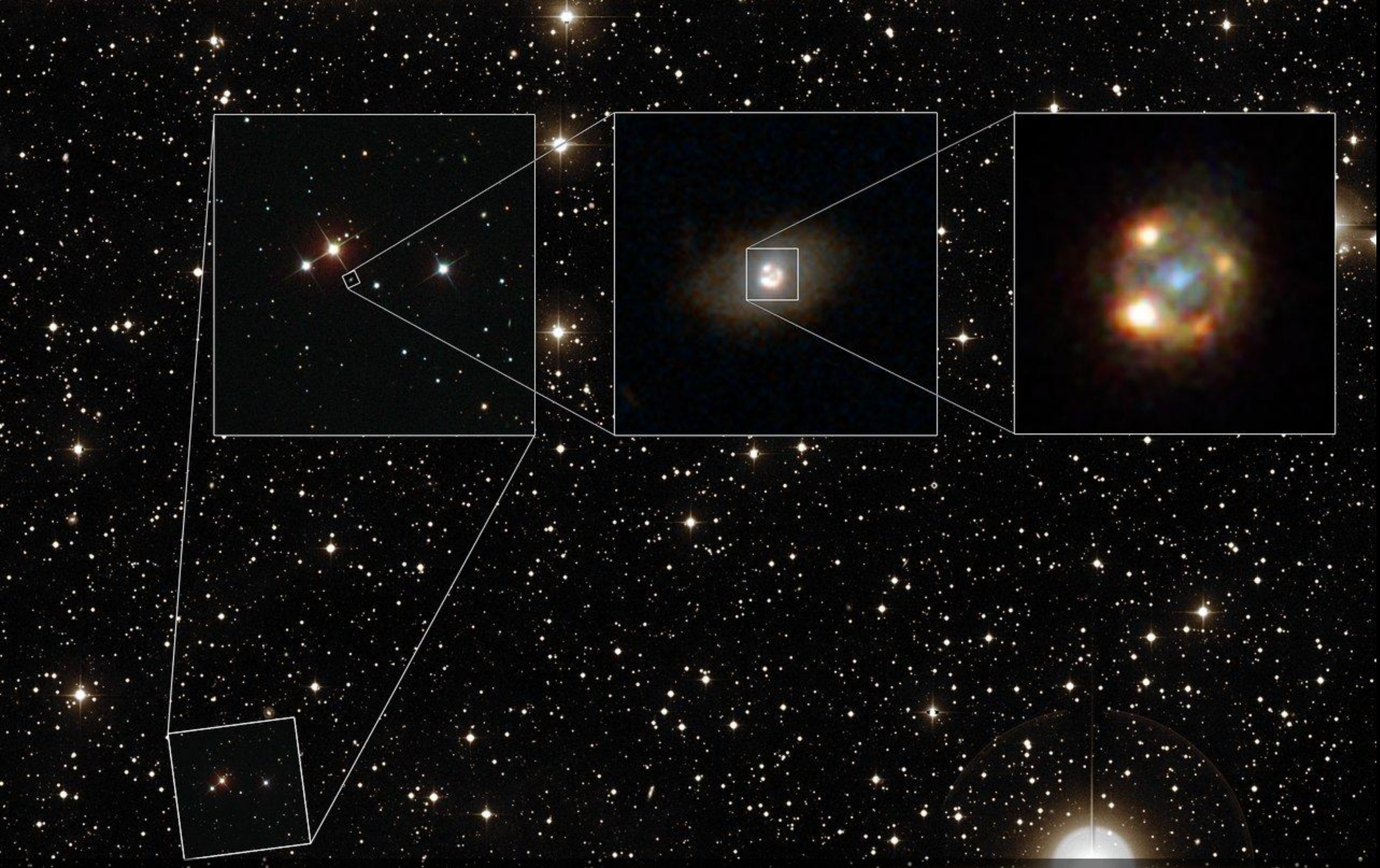

Apparent position
Electromagnetic waves
Gravitation field
Massive object
Position of source
Focus
Apparent position
© GFDL







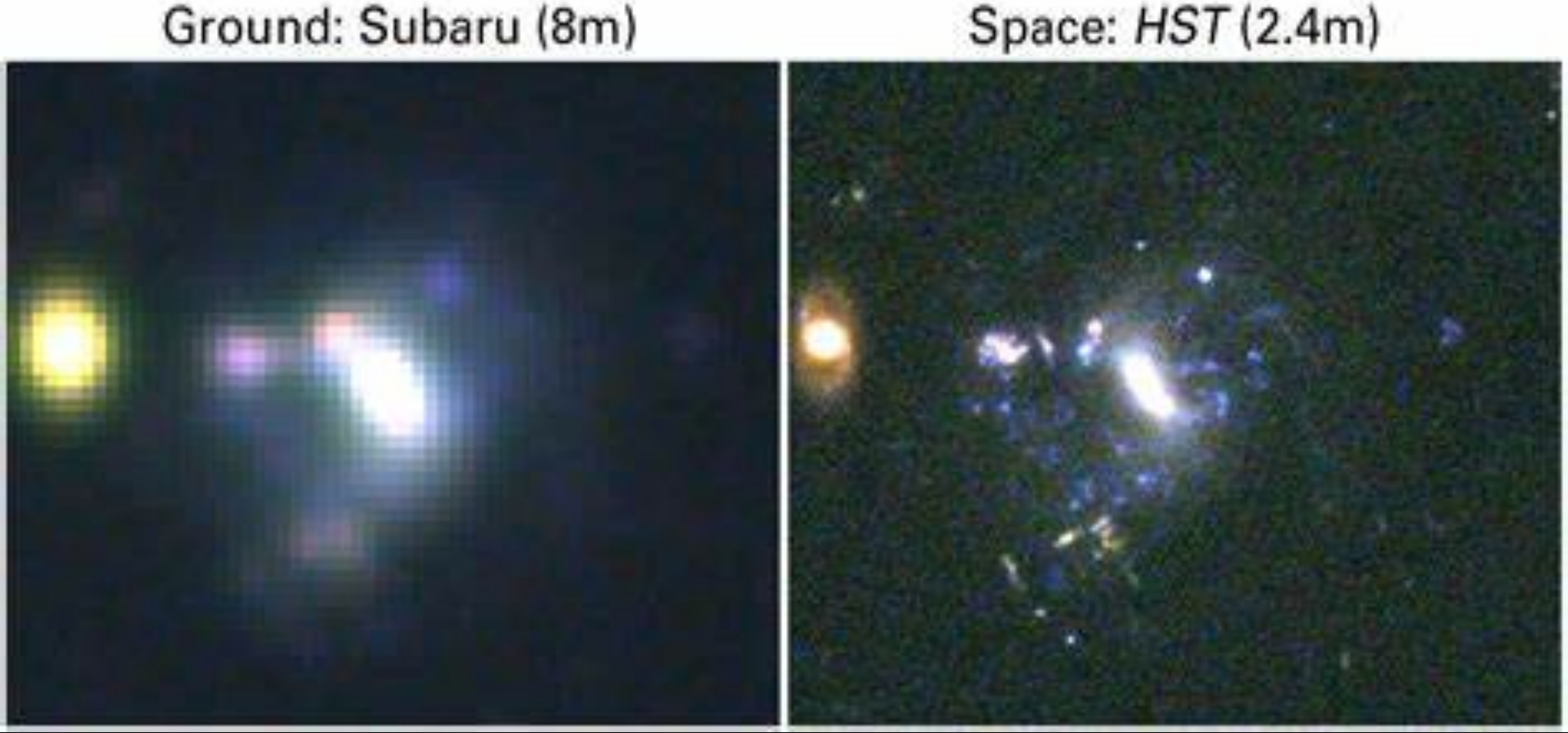
https://colab.research.google.com/drive/17zCysoAcweipj6P37TygZOVwMtu5HITt



Faster RCNN

How to detect specific objects without cutting out stamps from the field of view?

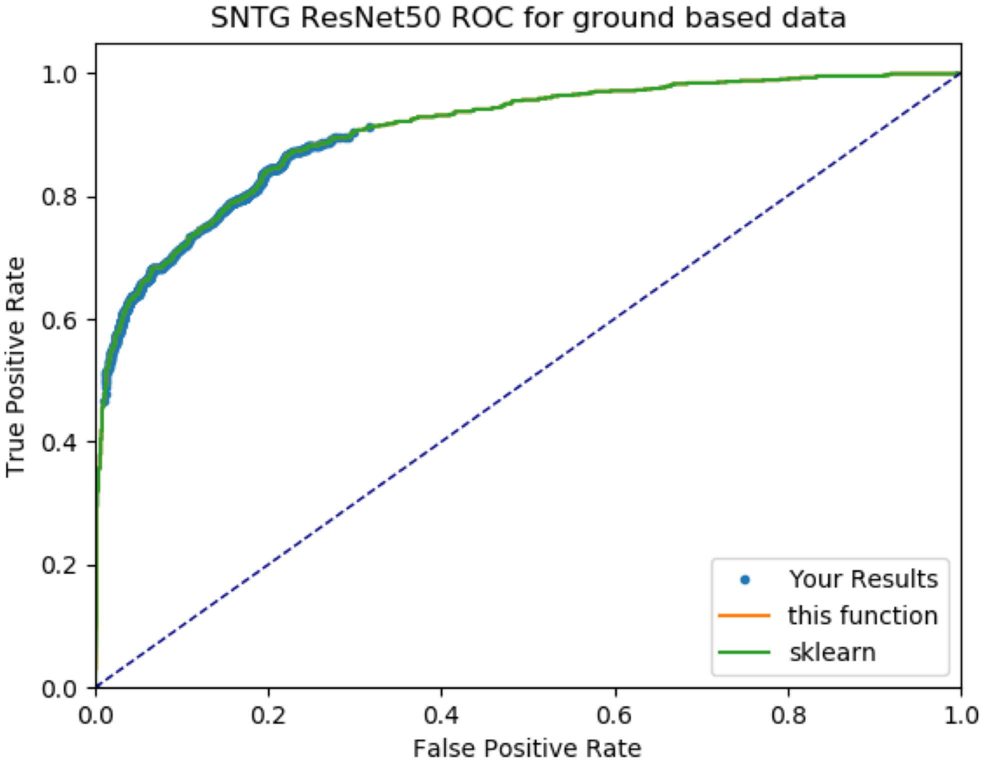
https://github.com/rbgirshick/py-faster-rcnn

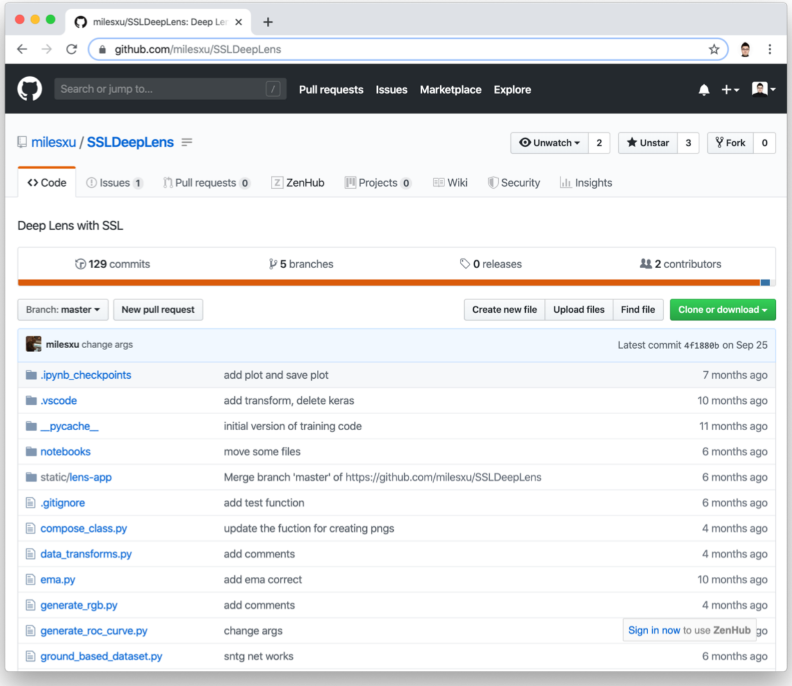


How to Generate Realistic Galaxy Images using GANs?

https://github.com/tycheng-sunny/VQ-VAE-for-emulating-galaxy-images

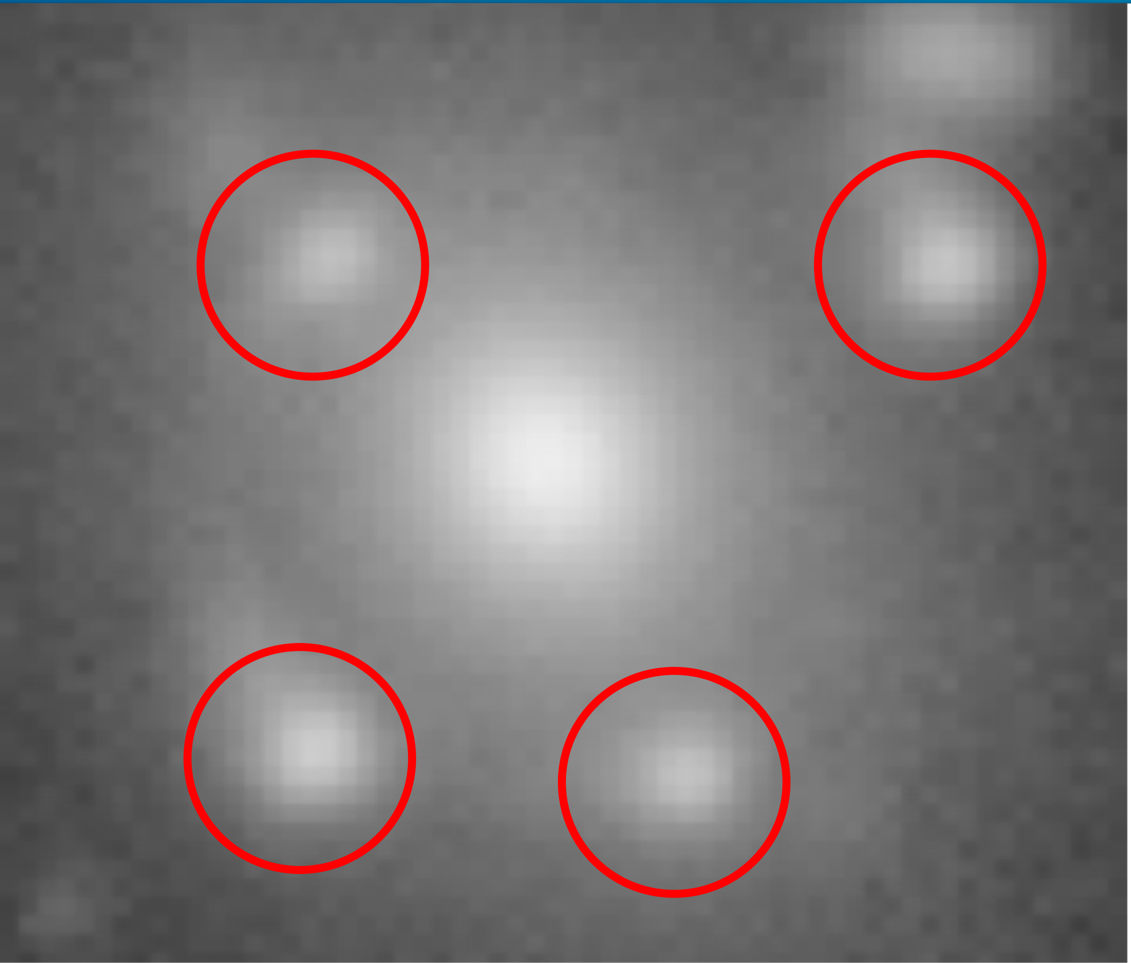
Semi-supervised Learning and Lens-finding

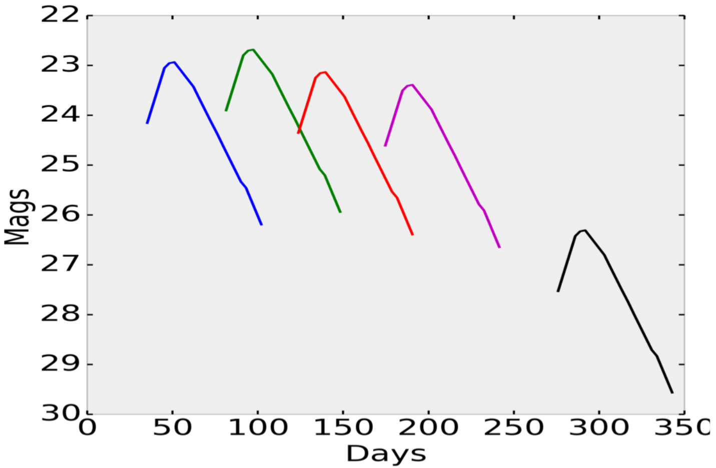


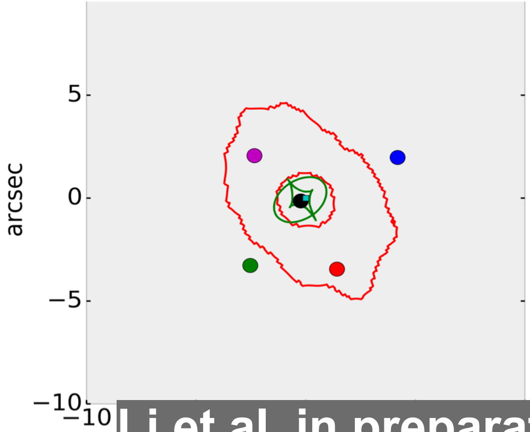


https://github.com/milesxu/SSLDeepLens

simulations of strongly lensed supernovae

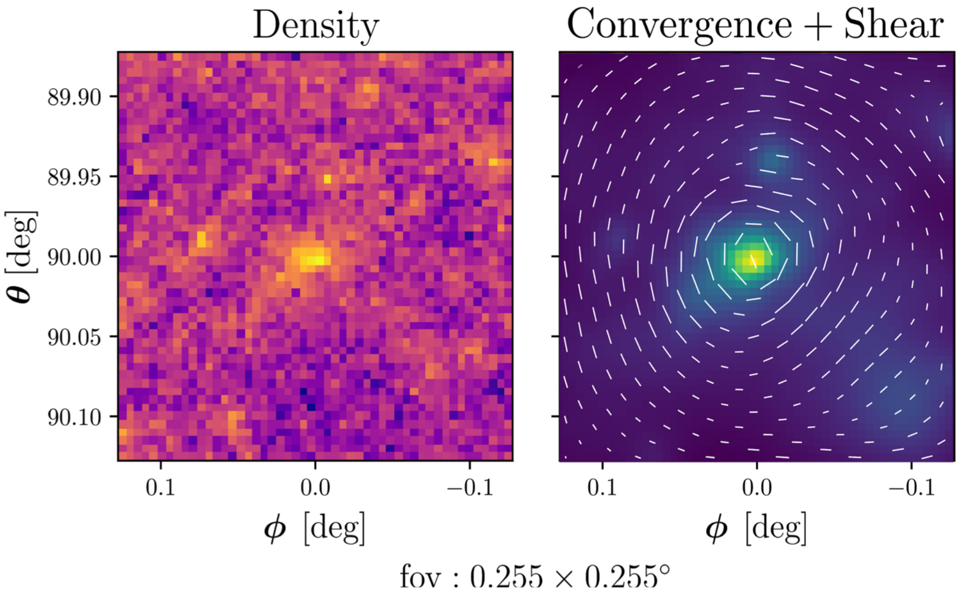






Li et al. in preparation

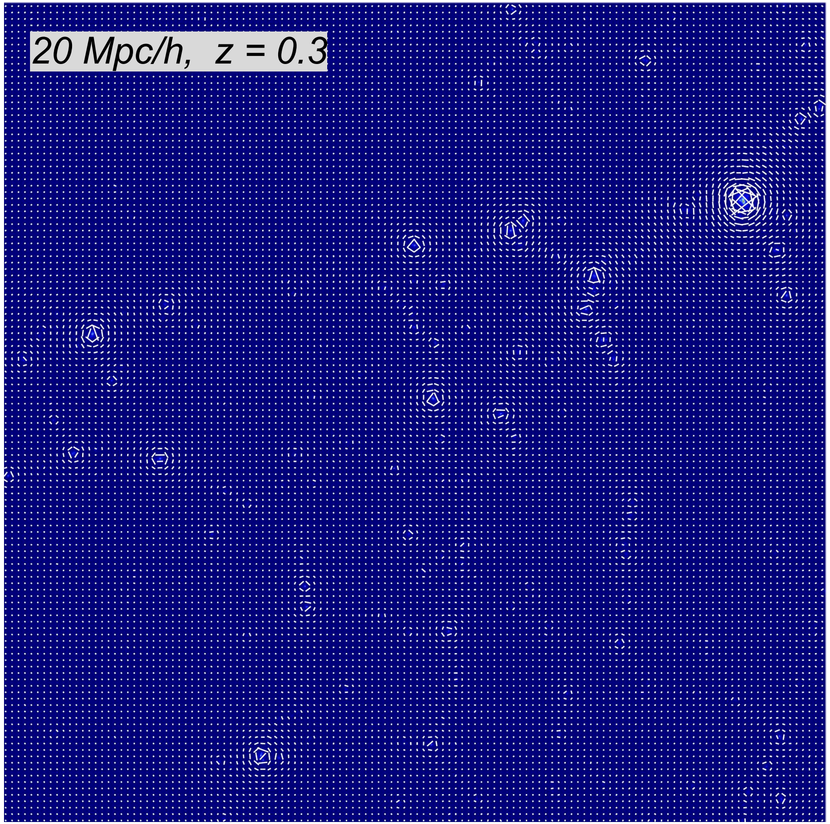
Simulations of weak lensing



$$z = 0.503$$

$$M = 2.703 \times 10^{14} \mathrm{M}_{\odot} h^{-1}$$

Credit: J. Hollowed

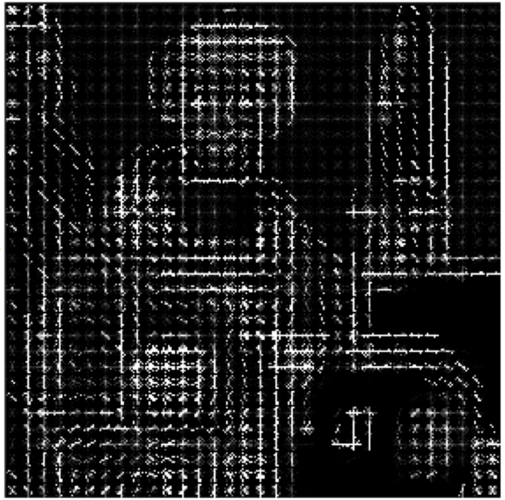


Credit: N. Li

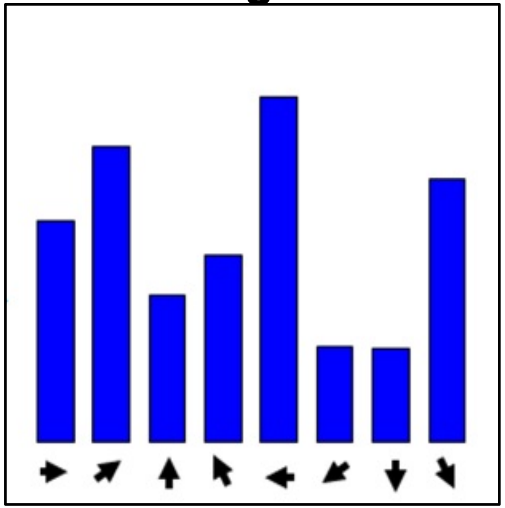
Histogram of Oriented Gradients (HOG)

Input Image

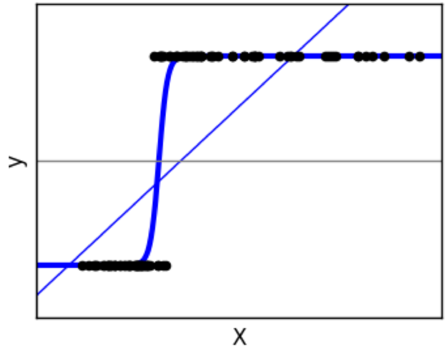
Oriented Gradients

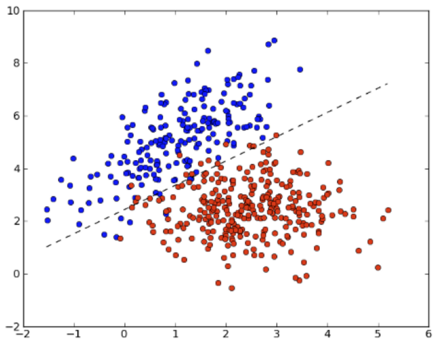


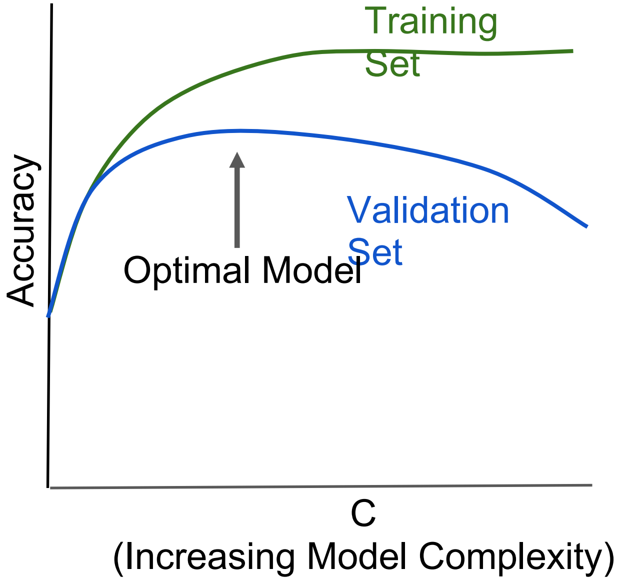
Histogram



Supervised Learning
Logistic Regression



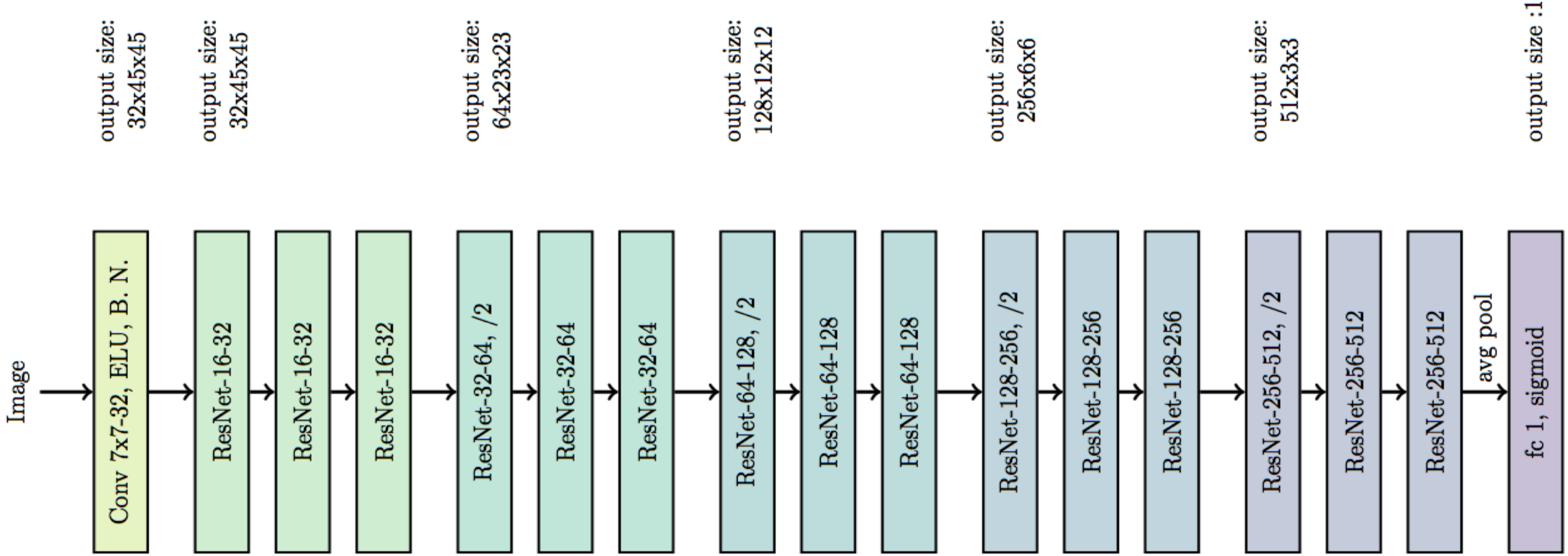




Source: http://stats.stackexchange.com

Model must be regularized to prevent over-fitting. Cross validation on a separate test set is used to decide the optimal amount of regularization.

Architecture of CMU DeepLens



The first block is a single convolutional layer with an ELU activation function and batch normalisation. The last block is a single fully connected layer with a sigmoid activation function, which outputs a probability between 0 and 1.

Lanusse, Ma, Li et al. 2017

Outline

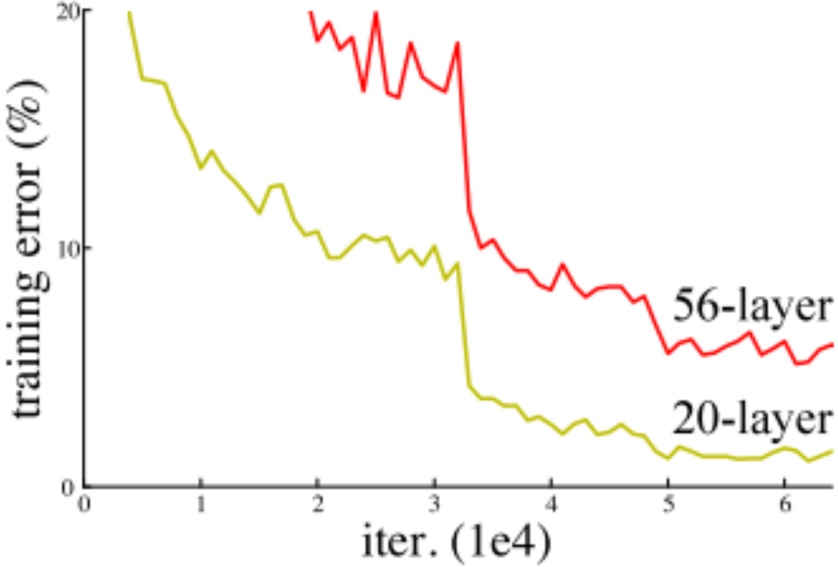
Introduction

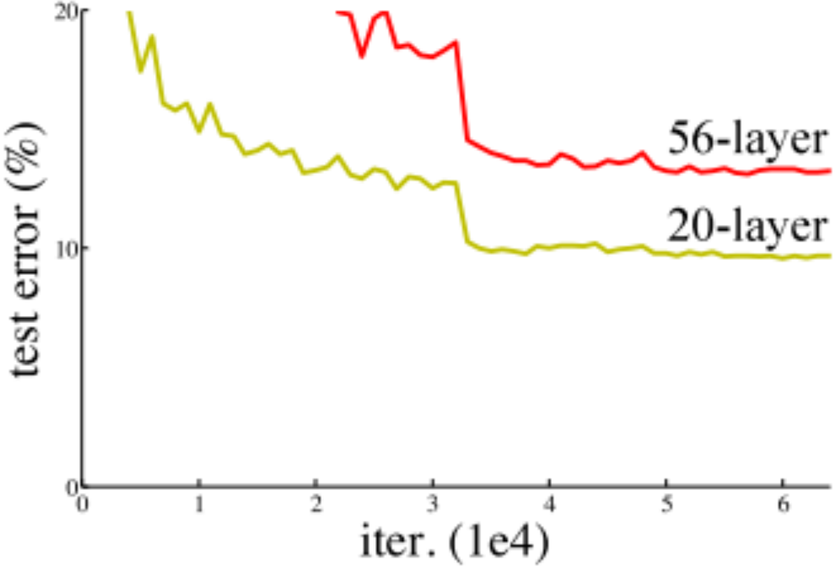
Machine Learning and Lens Finding

Machine Learning and Lens Modeling

Potential Applications of Machine Learning in Astrophysics

The Vanishing Gradient Problem

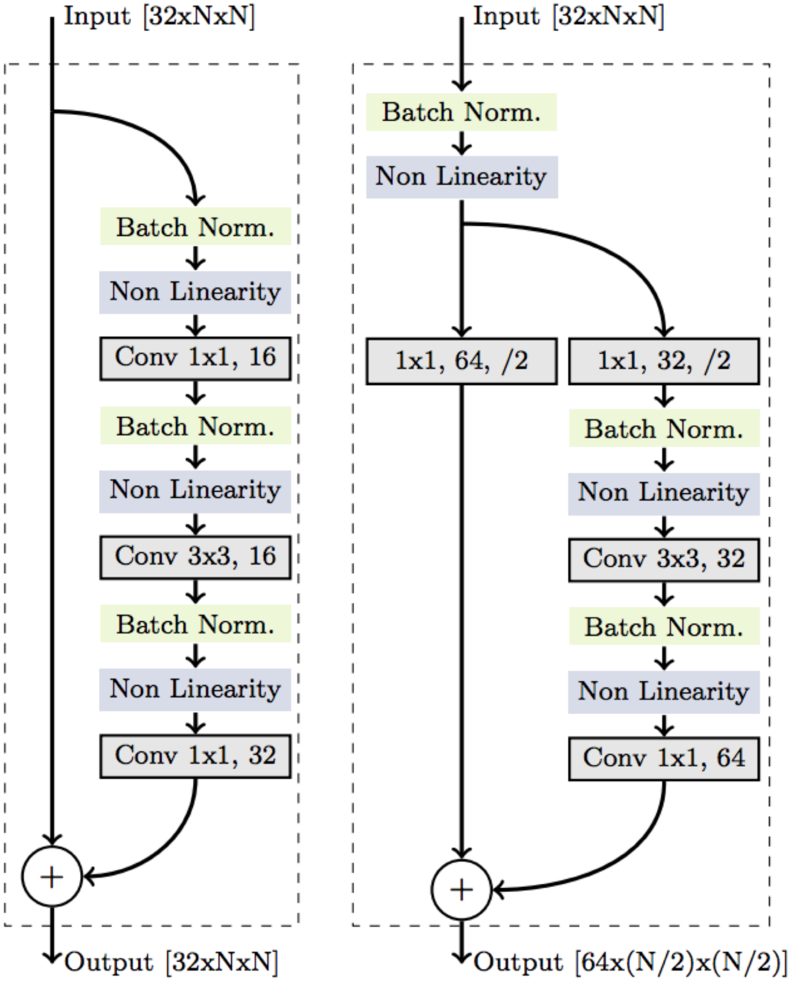




Increasing network depth leads to worse performance

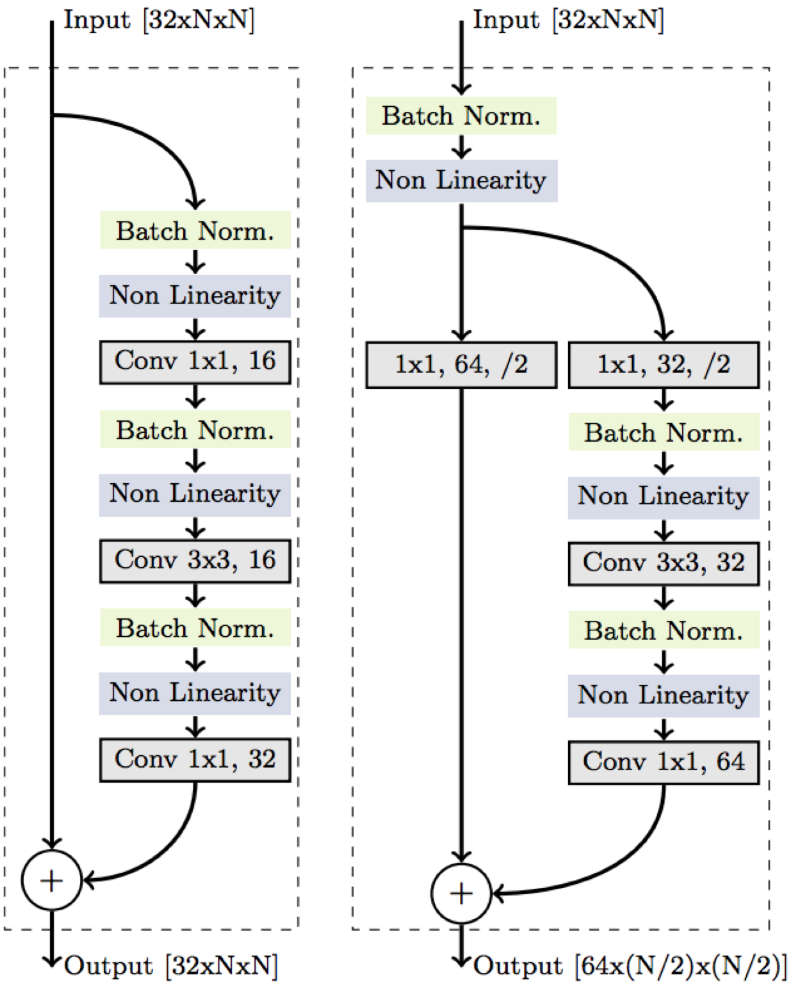
Lanusse, Ma, Li et. al. 2017

The building blocks of a residual network architecture.



(a) ResNet-16-32 (b) ResNet-32-64, /2

- Left: Undecimated ResNet-16-32 unit, preserving the size and depth of the input.
- Right : ResNet-32-64,/2 unit simultaneously increasing the depth of the output (from 32 channels to 64) and down-sampling by a factor 2 its resolution.



(a) ResNet-16-32 (b) ResNet-32-64, /2

Lanusse, Ma, Li et. al. 2017

The building blocks of a residual network architecture.

- Left: Undecimated ResNet-16-32 unit, preserving the size and depth of the input.
- Right : ResNet-32-64,/2 unit simultaneously increasing the depth of the output (from 32 channels to 64) and down-sampling by a factor 2 its resolution.