Strong Gravitational Lensing in Big Data Era

Nottingham, 11/09/2018

Nan Li

The University of Nottingham

In Collaboration with

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Mike Gladders (UChicago), Lindsey Bleem (ANL)
Salman Habib (ANL), Huanyuan Shan (AlfA)
Phil Marshall (SLAC), Anupreeta More (IPMU)
Aprajita Amera (Oxford), Tom Collett (ICG)
Ran Li (NAOC), Camille Avestruz (Uchicago)
Michael Florian (NASA), Qingzhi Yan (S.A.P.)

Introduction

What is strong gravitational lensing?

Why is it so important in astrophysics?

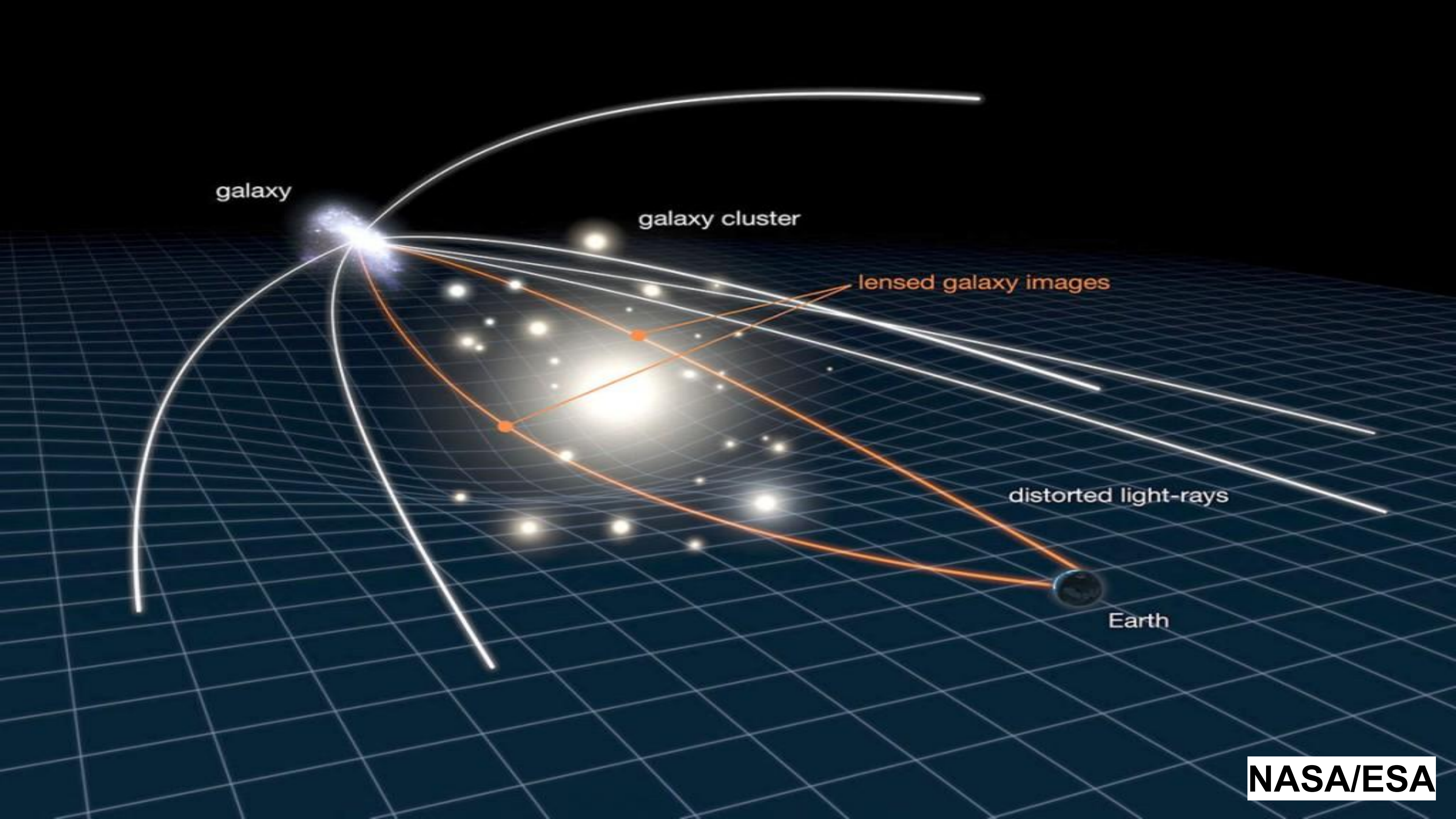
What problems we will encounter in Big Data Era?

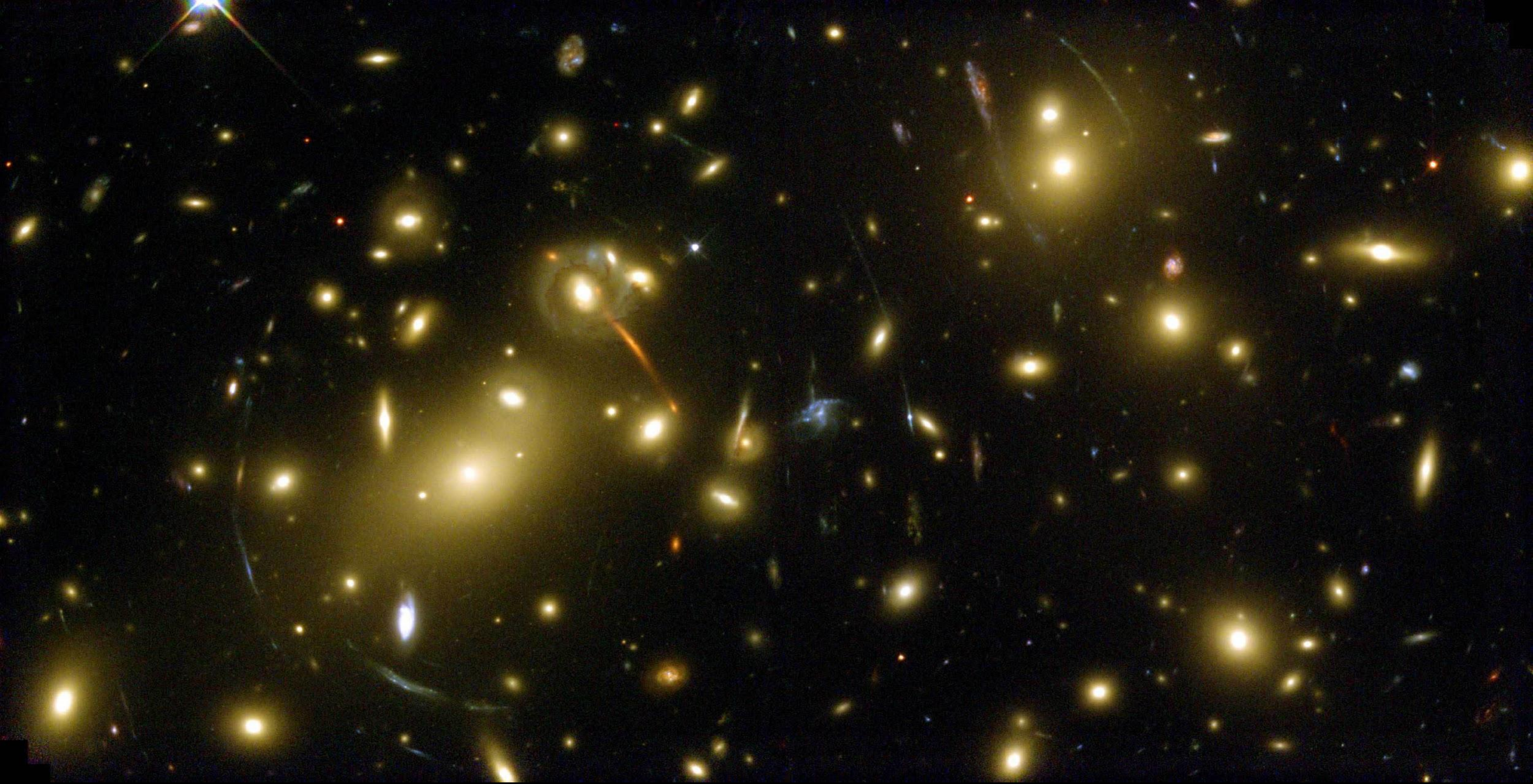
Machine Learning and Strong Lensing

Beyond Machine Learning

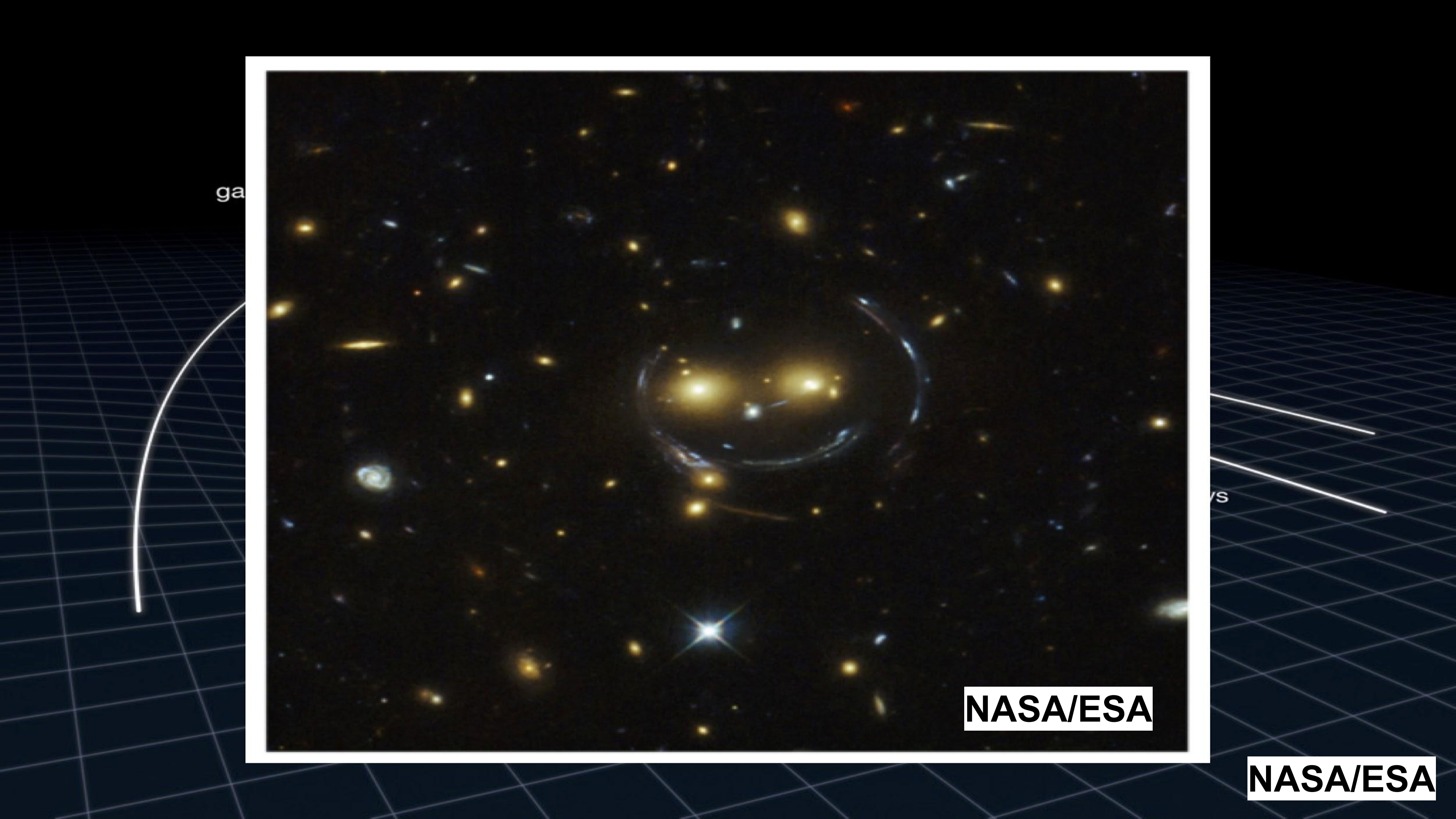
Summary and Future Work

The University of Nottingham


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

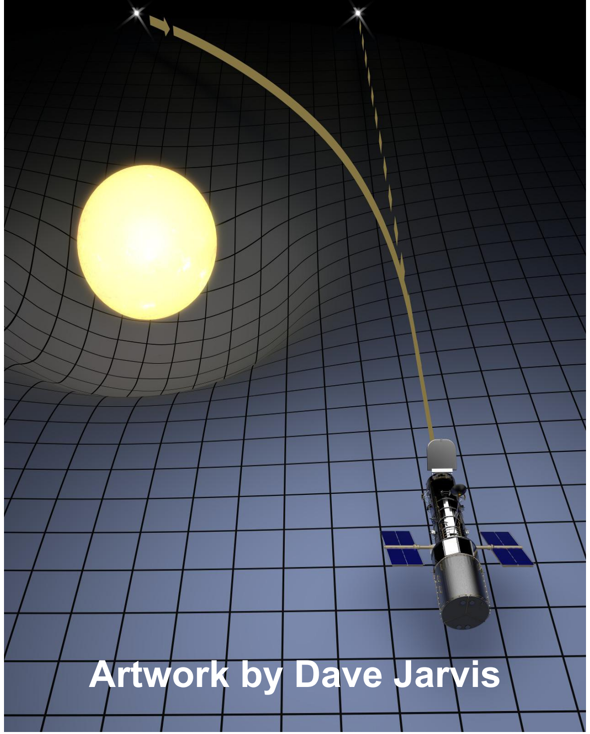


http://www.roe.ac.uk/~heymans/website_images/abell2218.jpg


NASA/ESA
NASA/ESA

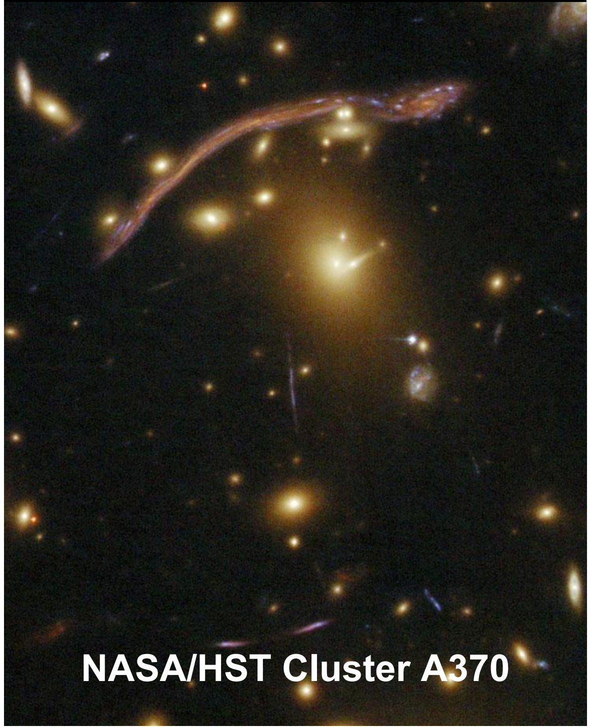
Applications of Gravitational Lensing

- Test the theory of GR
- Geometry of the space



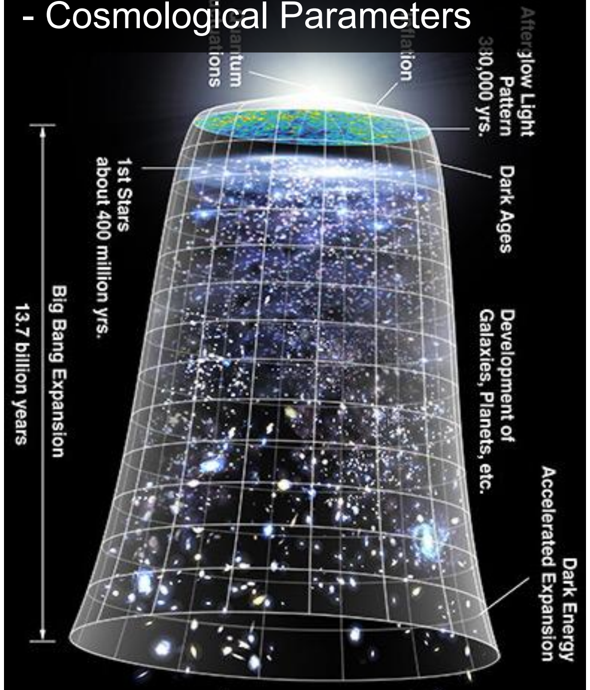
Artwork by Dave Jarvis

- Mass distribution of lenses
- Dark matter substructures



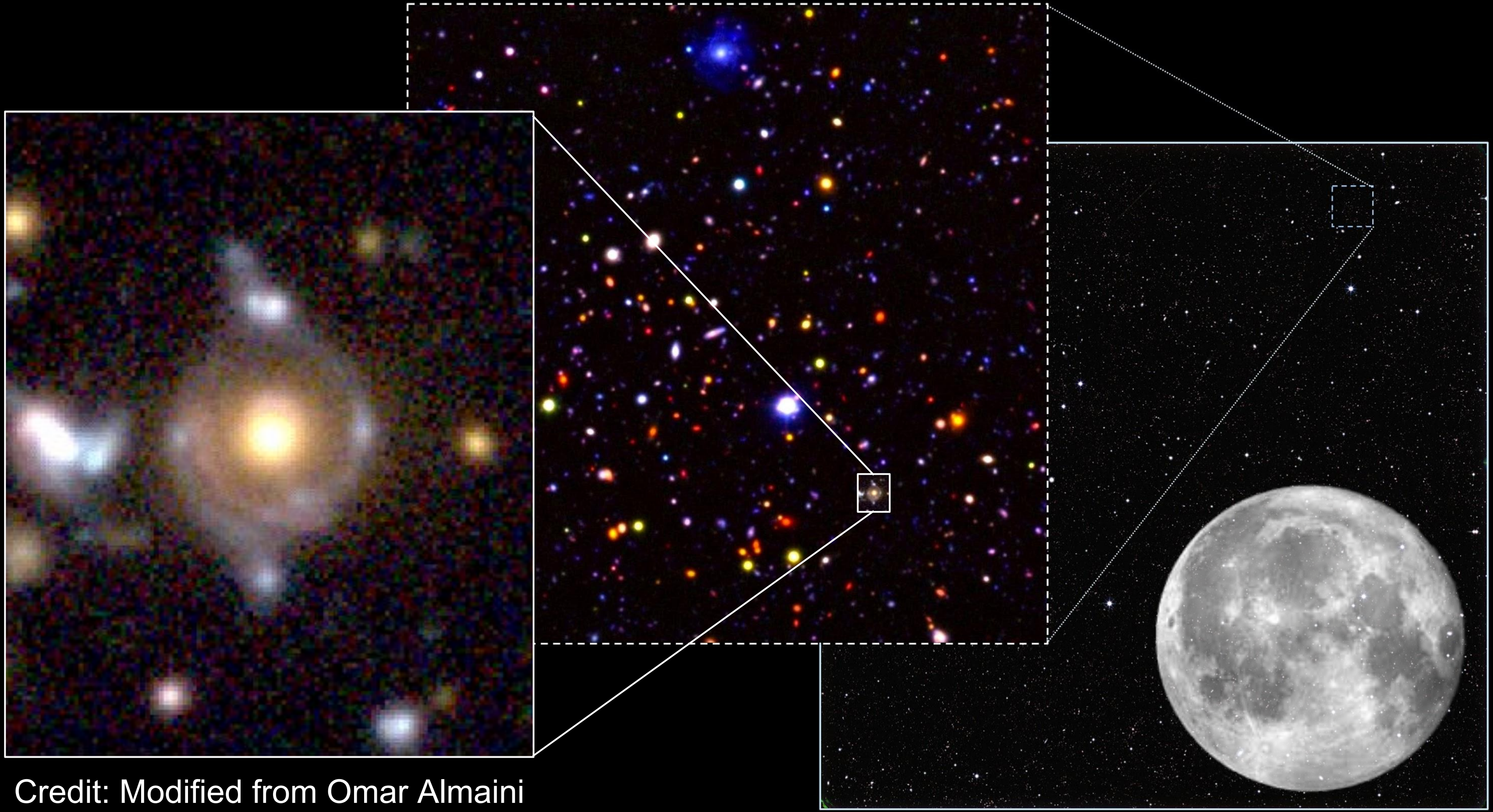
NASA/HST Cluster A370

- Structure Formation History
- Cosmological Parameters

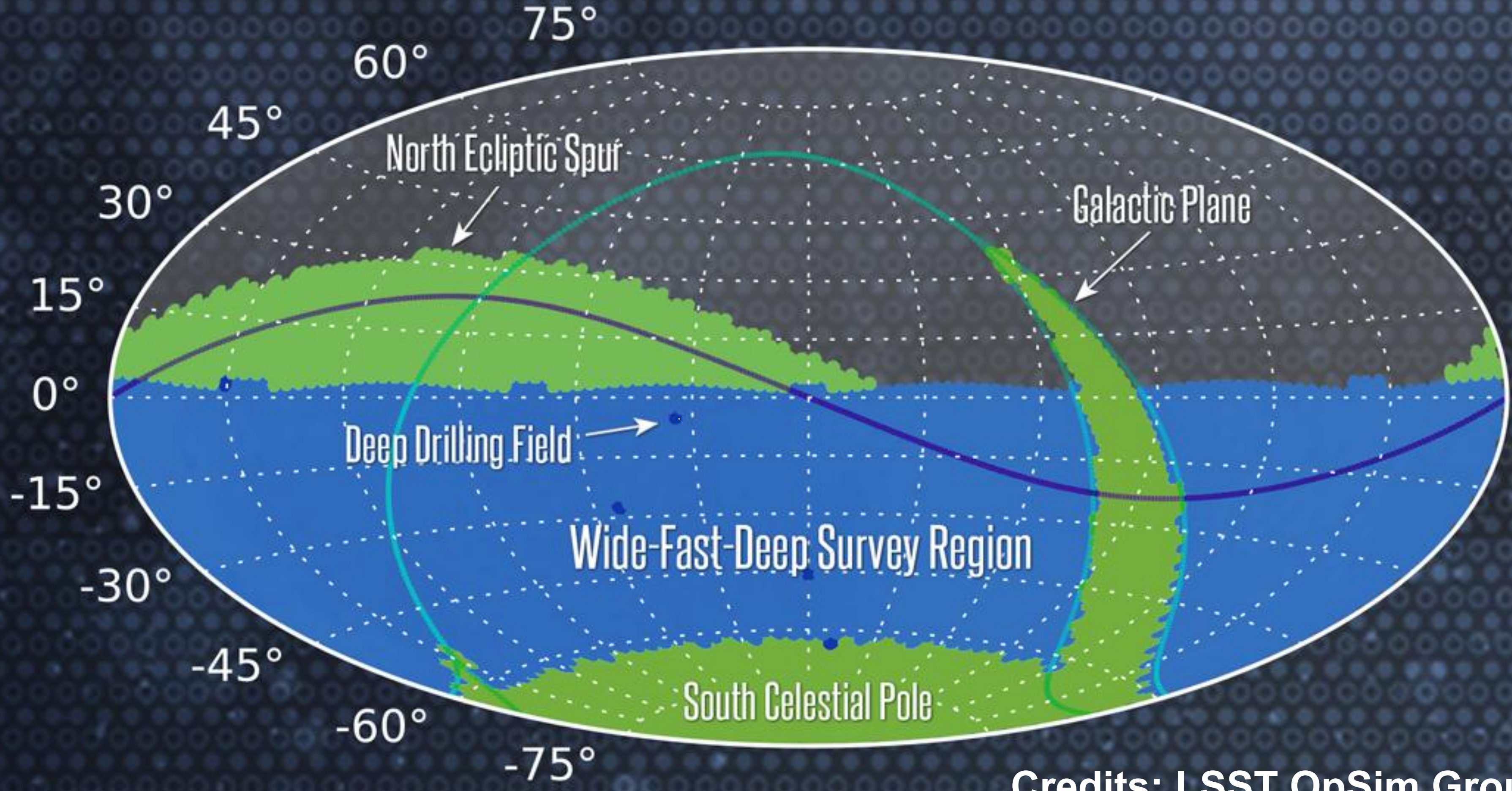


NASA/WMAP Science Team

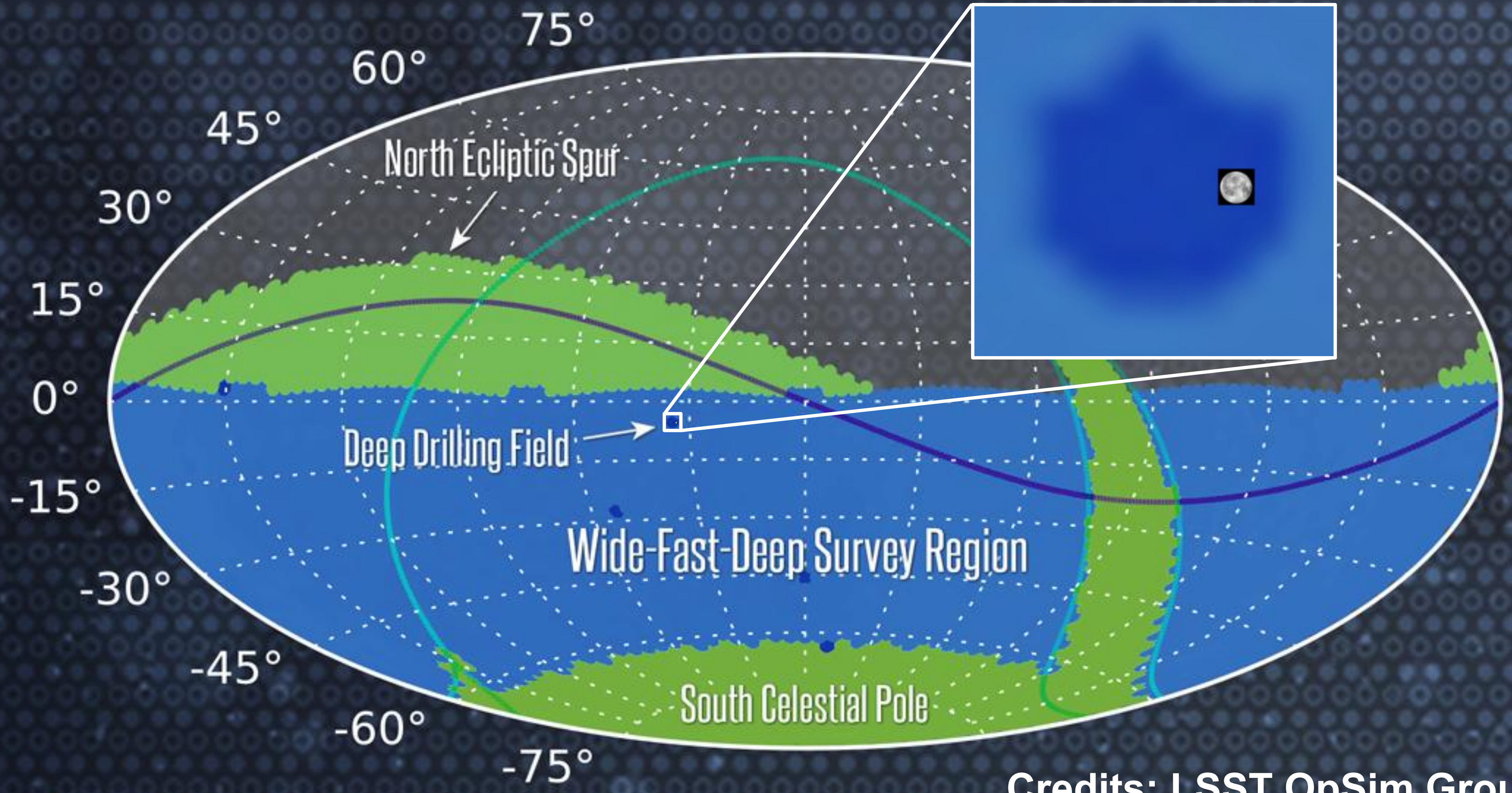
"Looking for needles in a haystack."



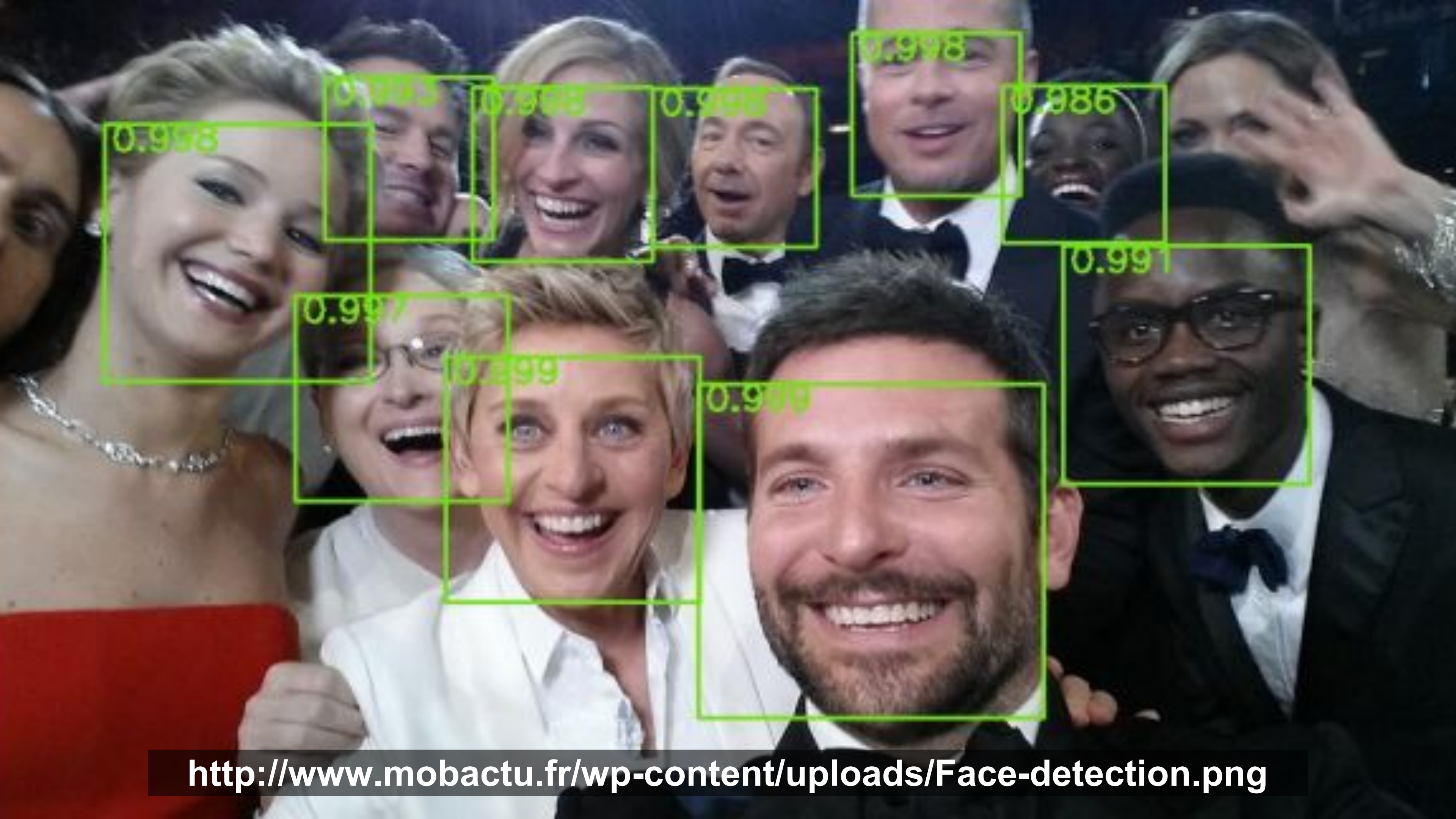
Credit: Modified from Omar Almaini



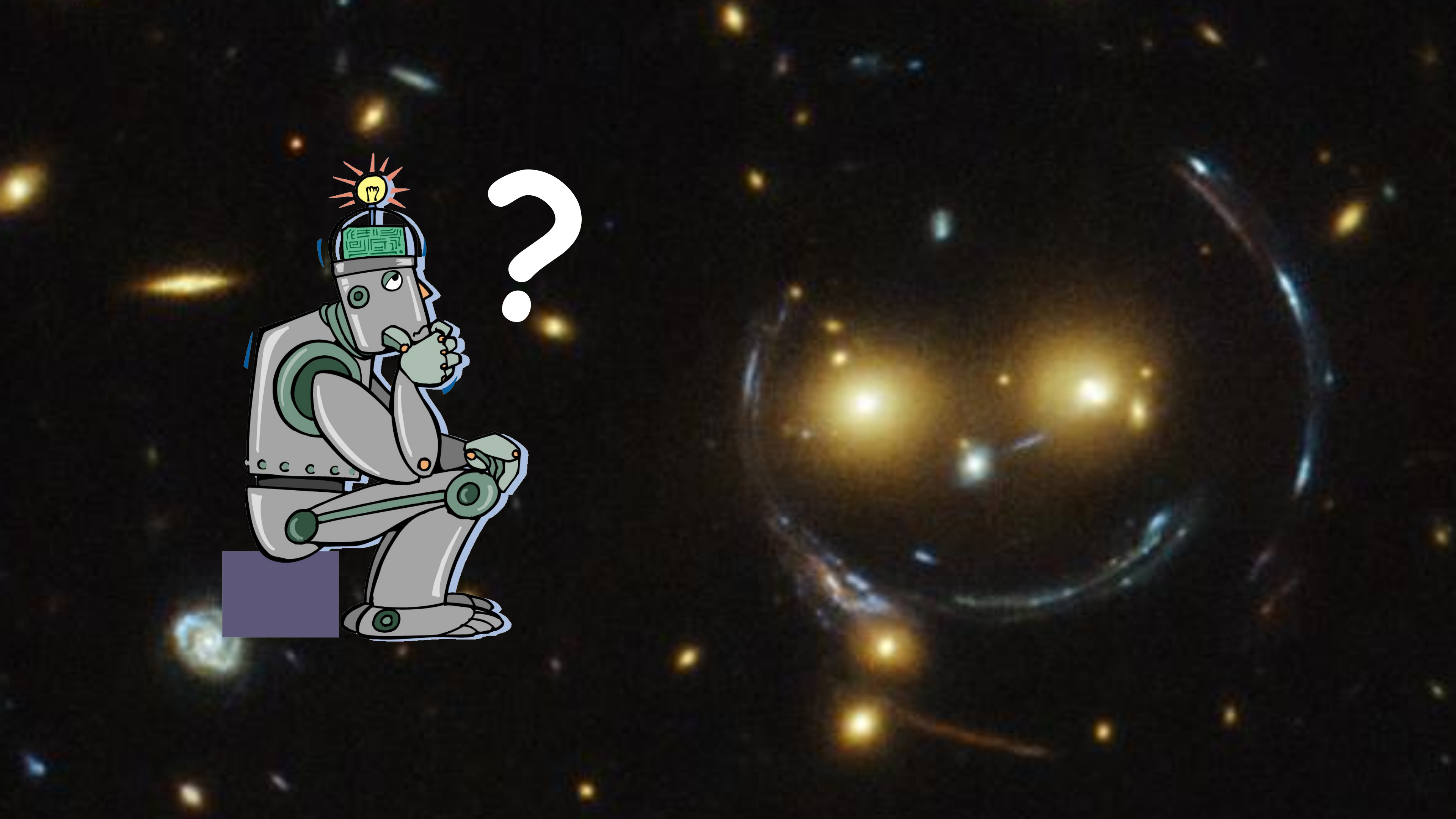
Credits: LSST OpSim Group



Credits: LSST OpSim Group

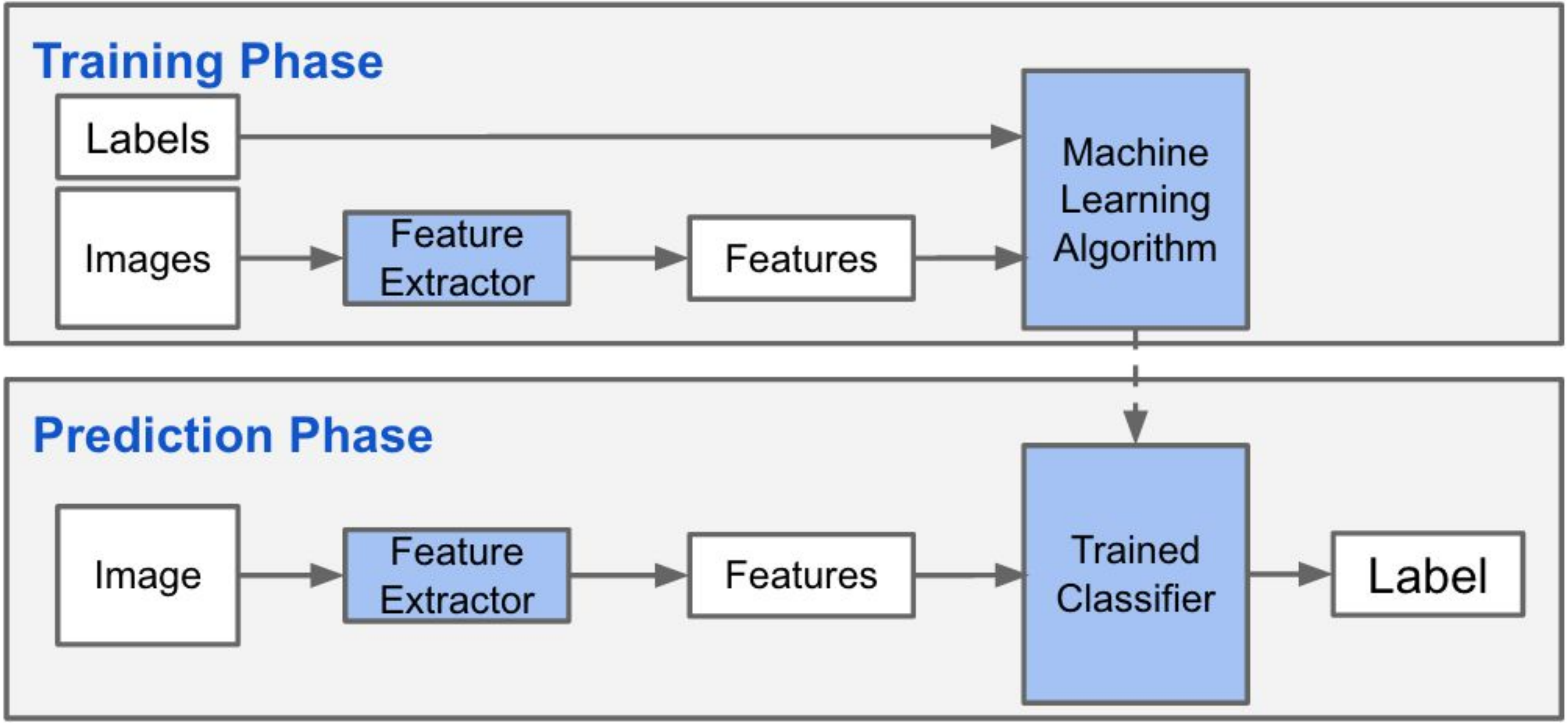


http://www.mobactu.fr/wp-content/uploads/Face-detection.png

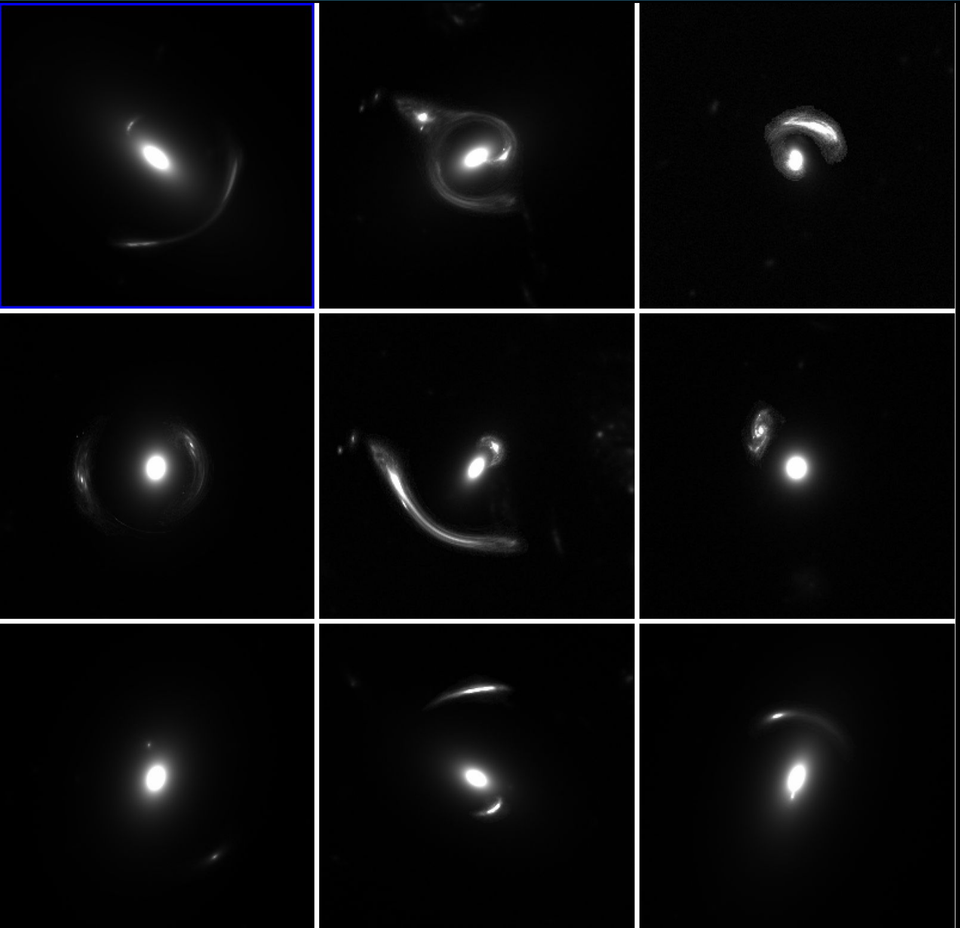


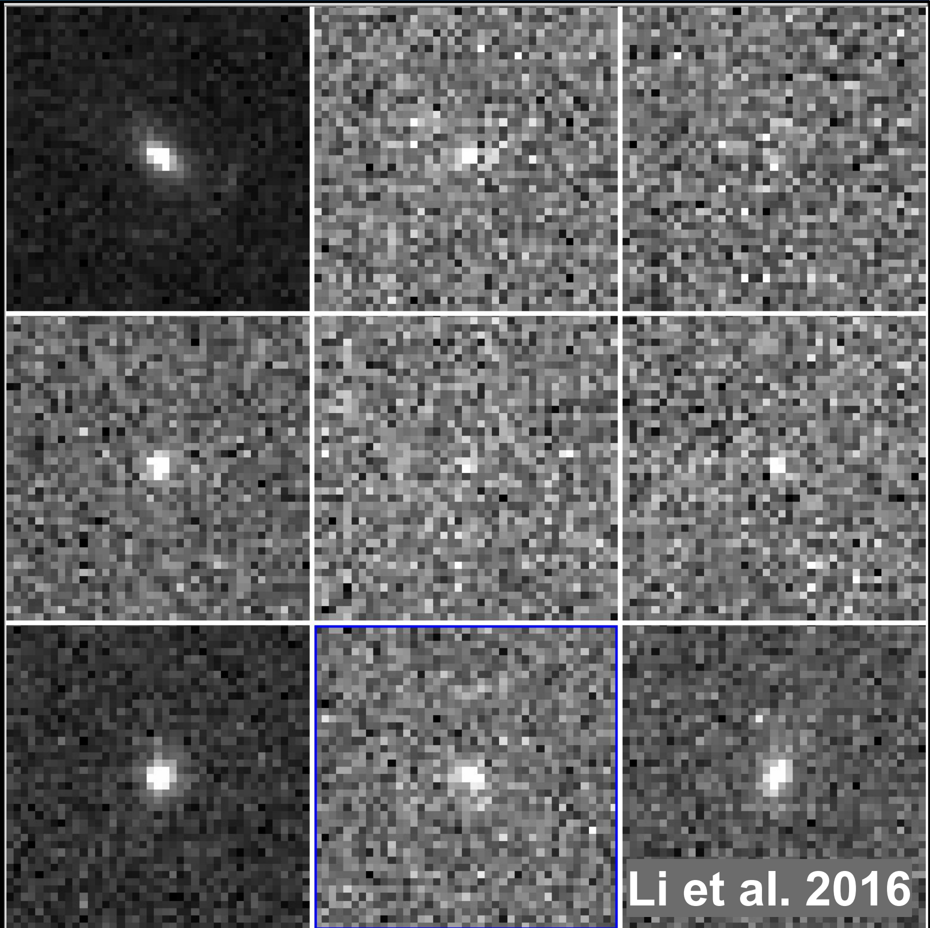
- Introduction
- **Machine Learning and Strong Lensing**
  - *Machine Learning and Lens-finding*
  - *Machine Learning and Lens-modelling*
- Beyond Machine Learning
- Summary and Future Work

Machine Learning and Lens-finding

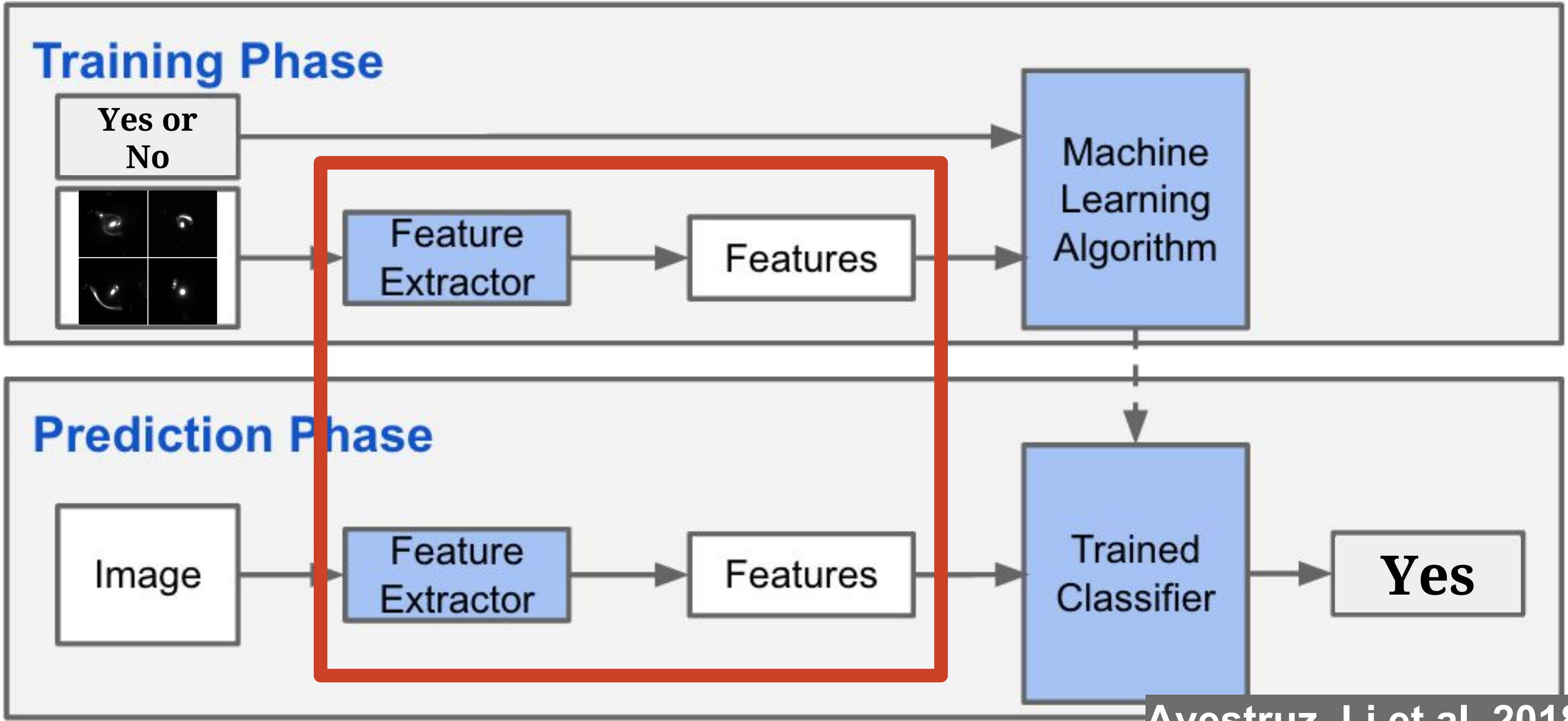


Simulations of Galaxy-galaxy Strong Lensing





Supervised Machine Learning



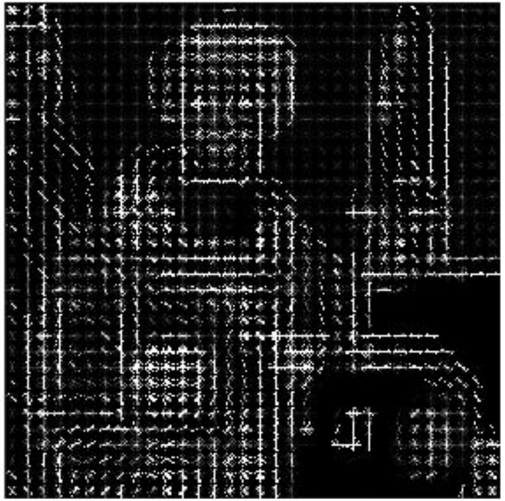
Avestruz, Li et al. 2018

Feature Extraction

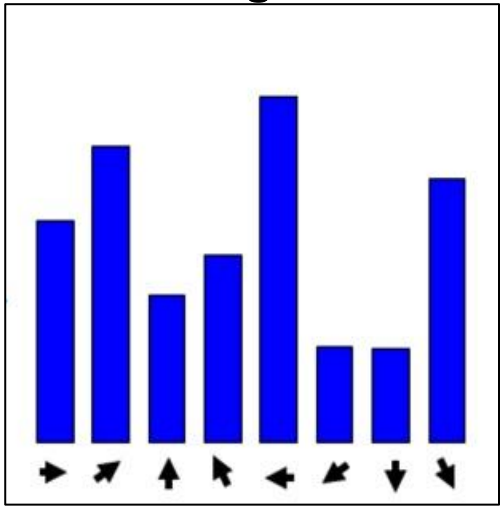
Histogram of Oriented Gradients (HOG)

Input Image

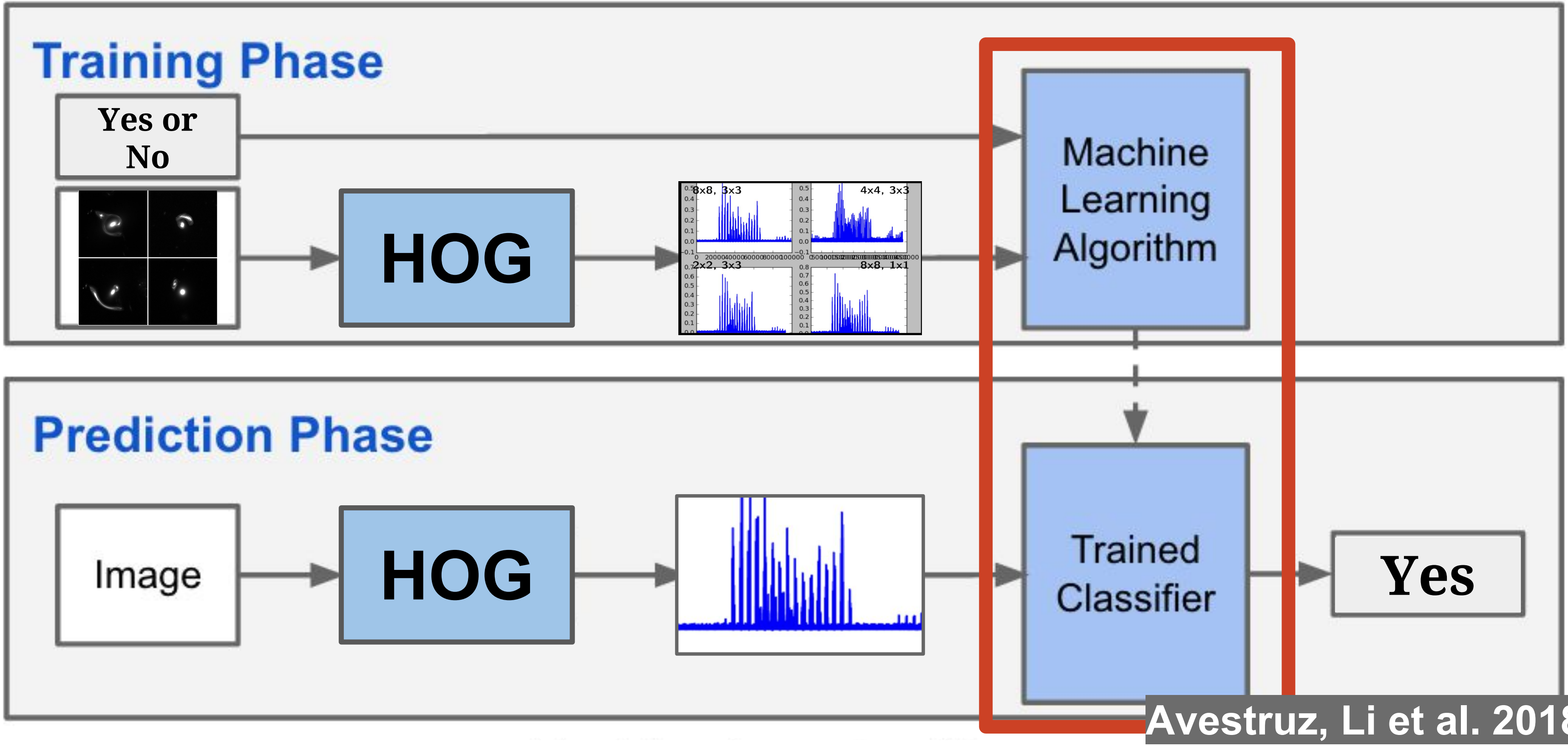
Oriented Gradients



Histogram



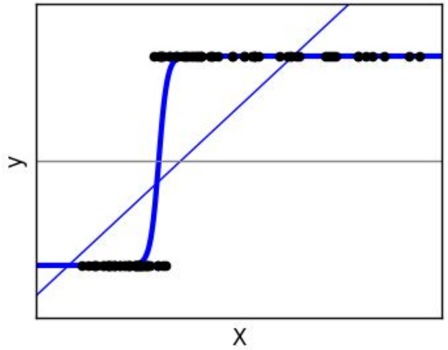
Supervised Machine Learning

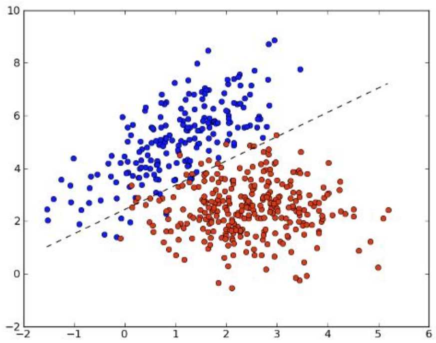


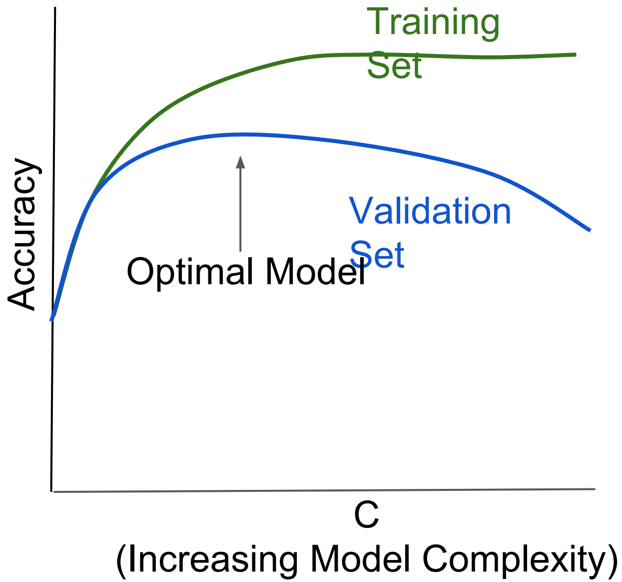
Avestruz, Li et al. 2018

Machine Learning Algorithms

Supervised Learning
Logistic Regression



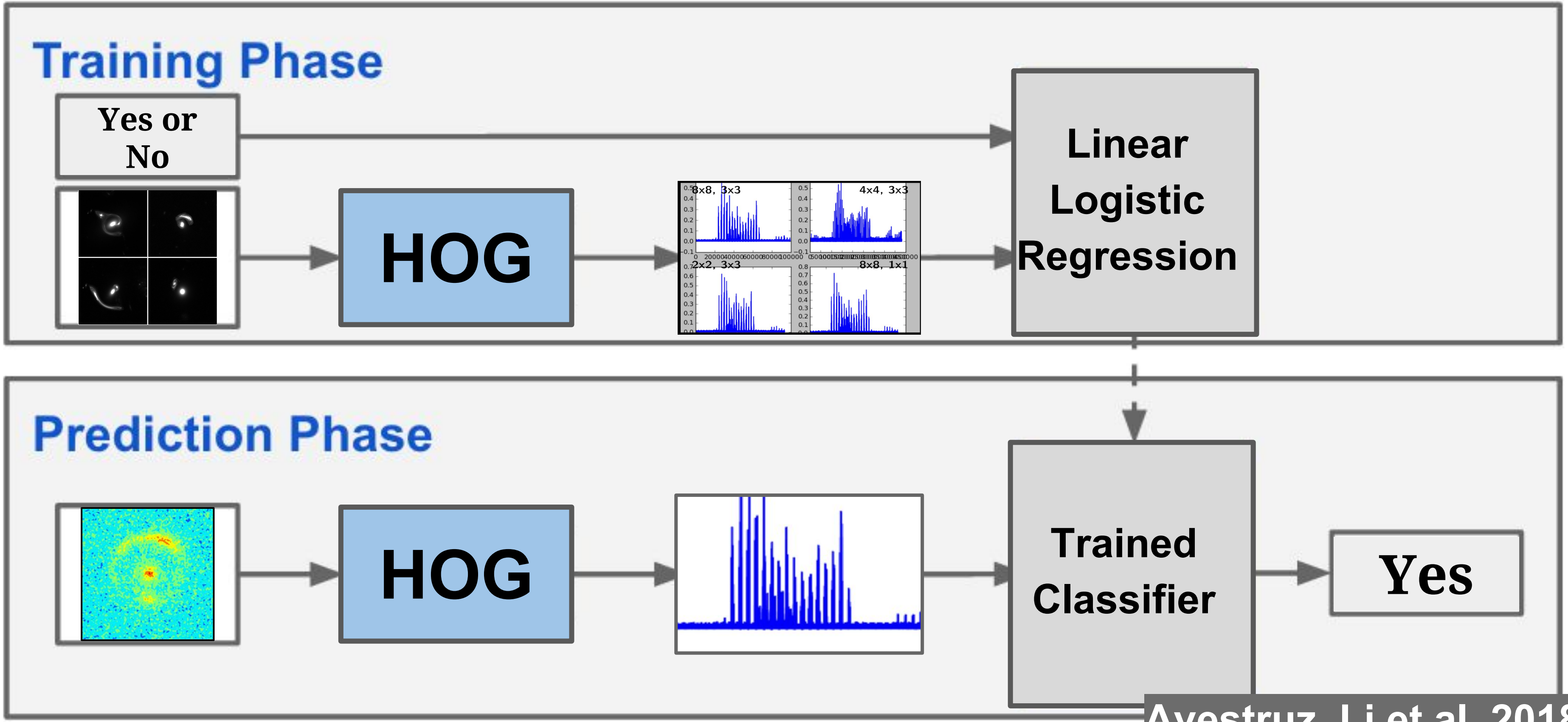




Source: http://stats.stackexchange.com

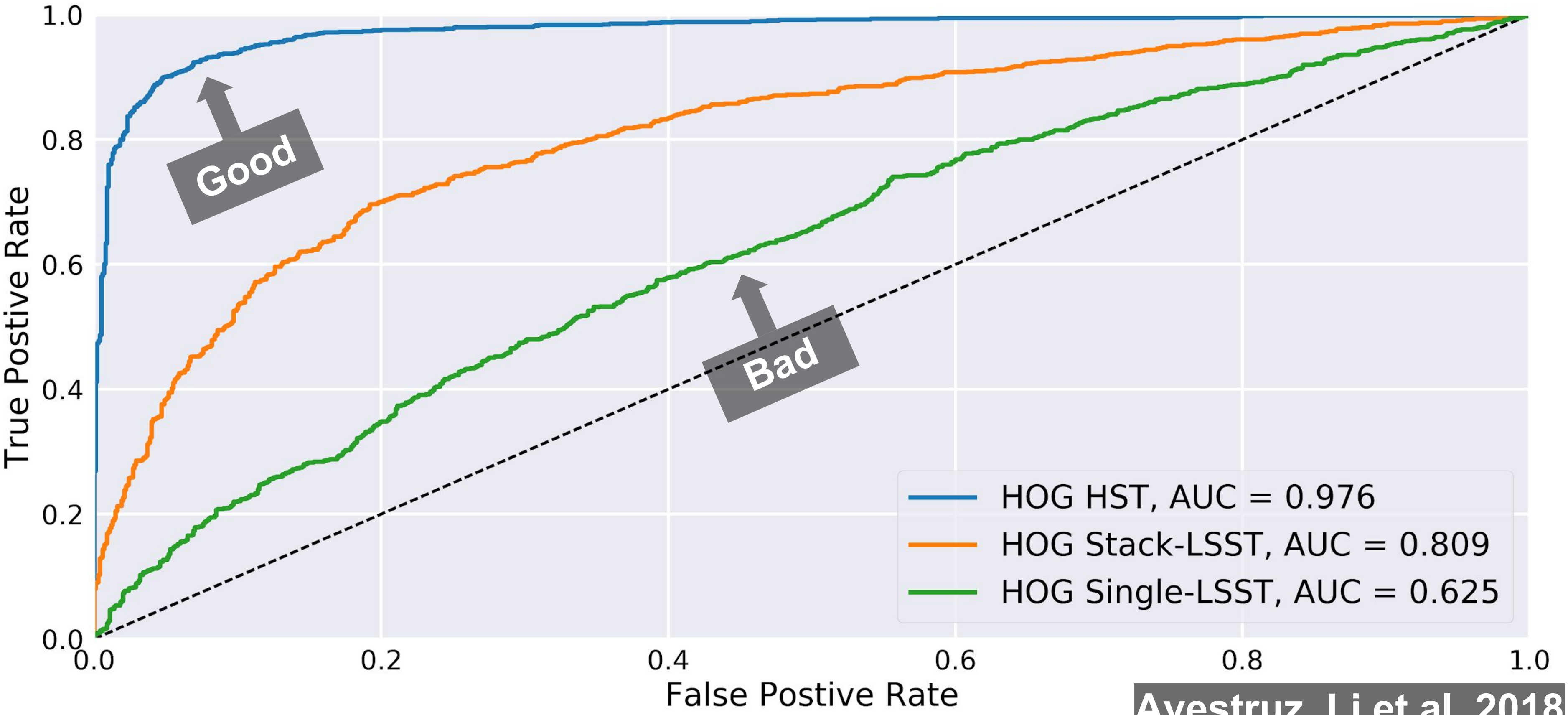
Model must be regularized to prevent over-fitting. Cross validation on a separate test set is used to decide the optimal amount of regularization.

Supervised Machine Learning



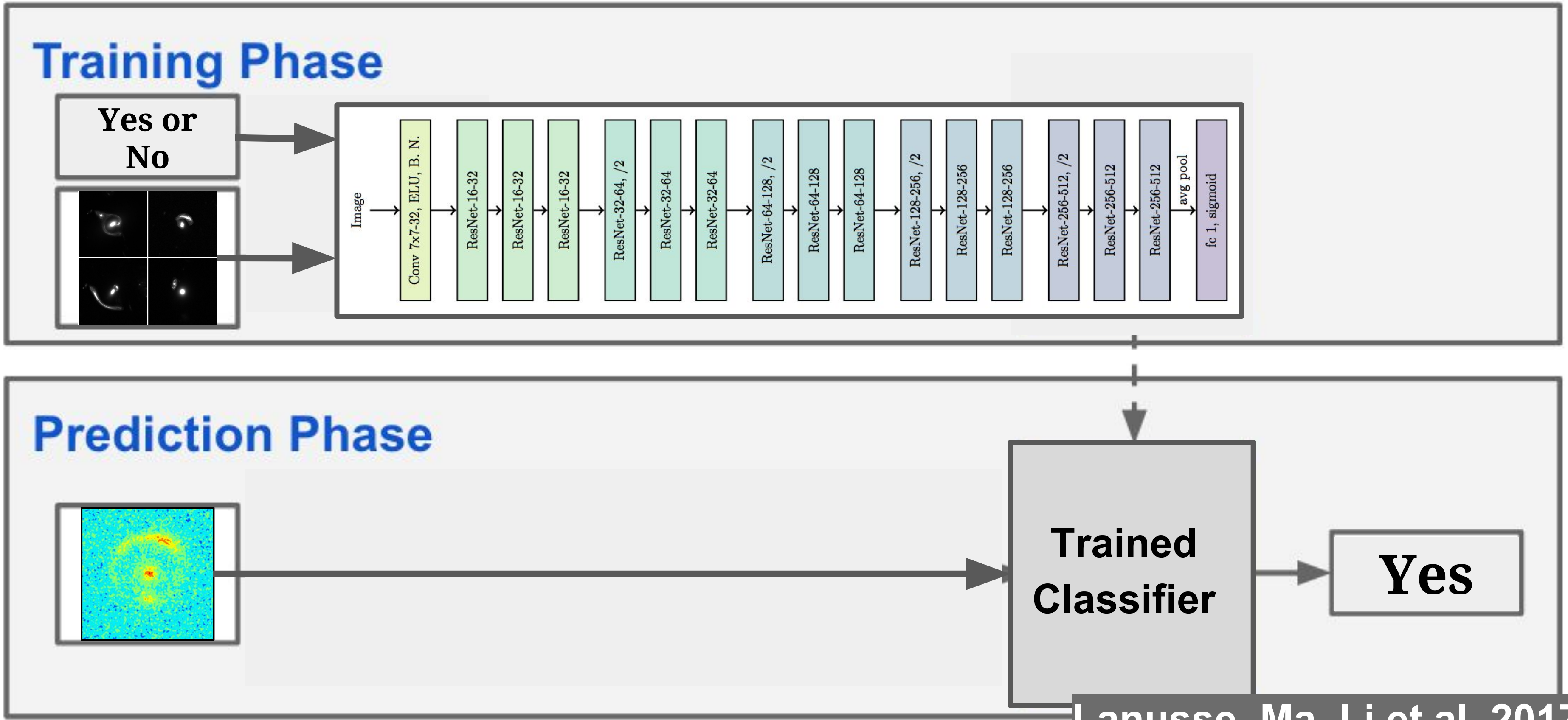
Avestruz, Li et al. 2018

Receiver Operating Characteristic Curves



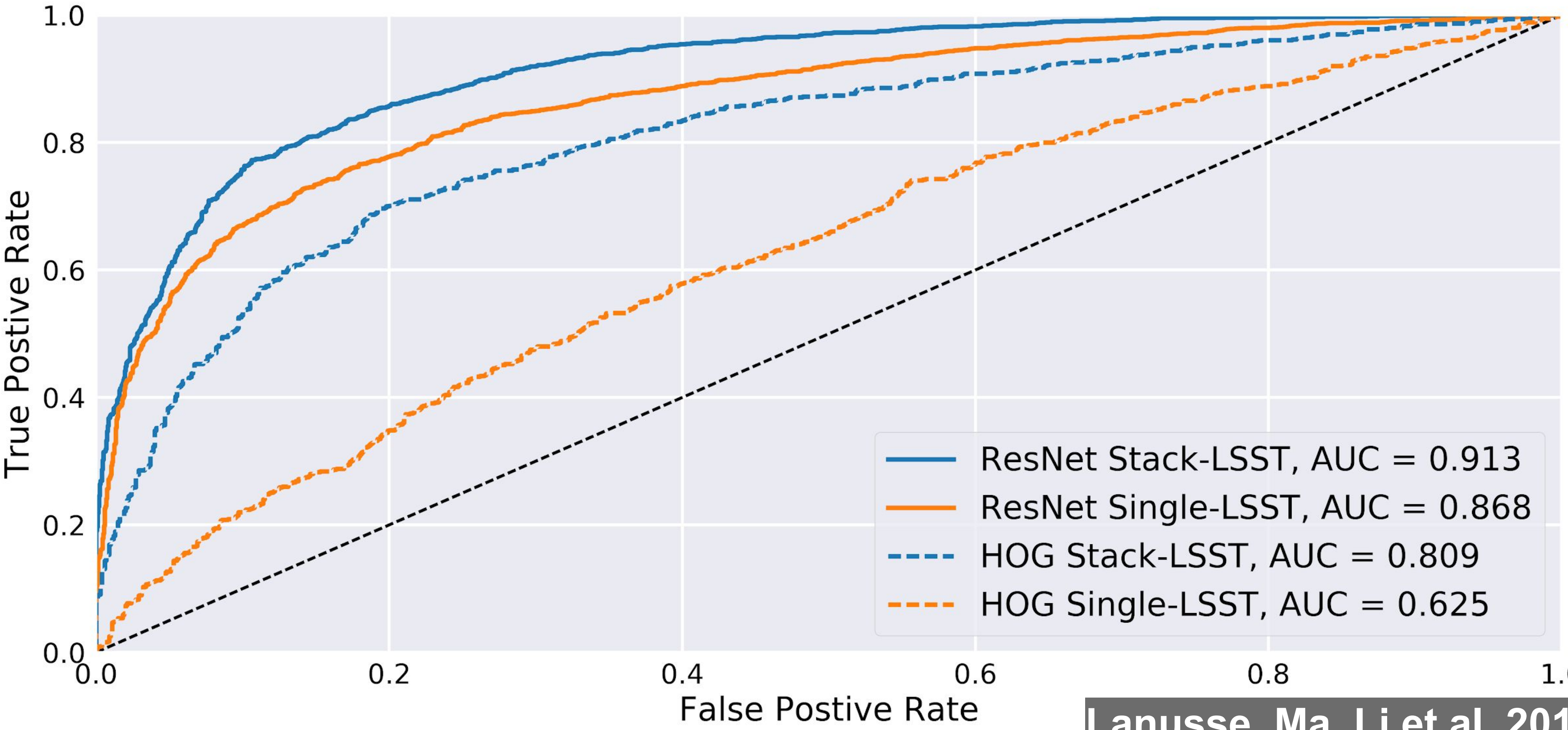
Avestruz, Li et al. 2018

Supervised Machine Learning (DL)



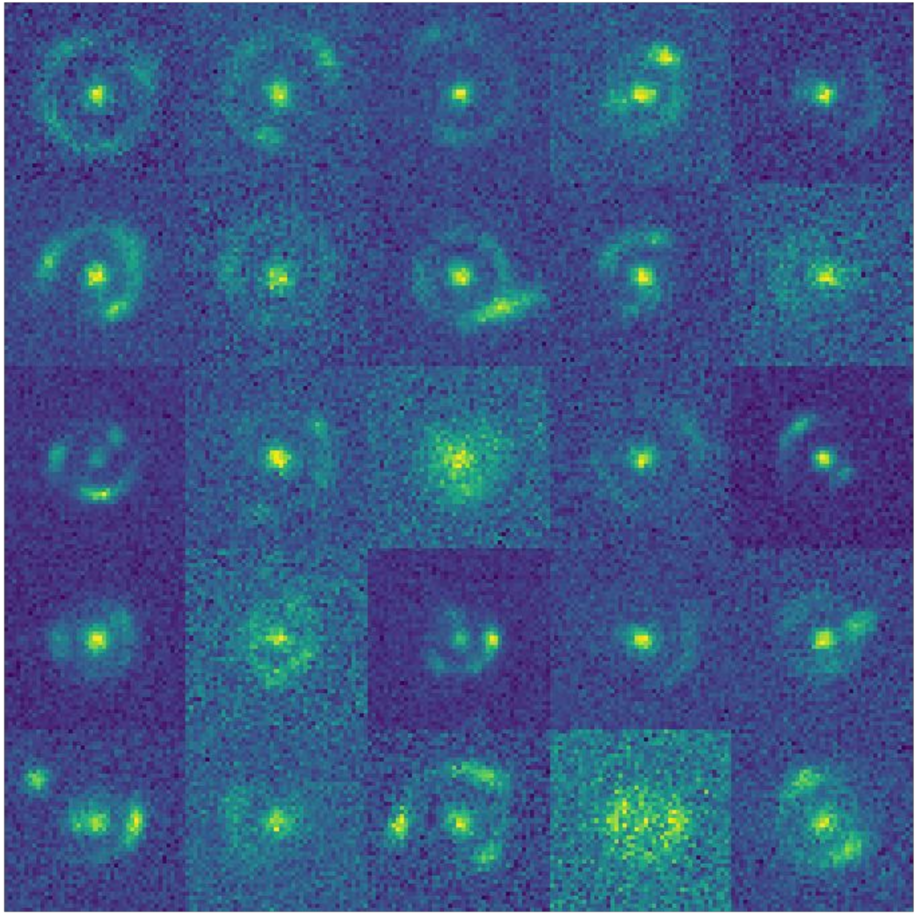
Lanusse, Ma, Li et al. 2017

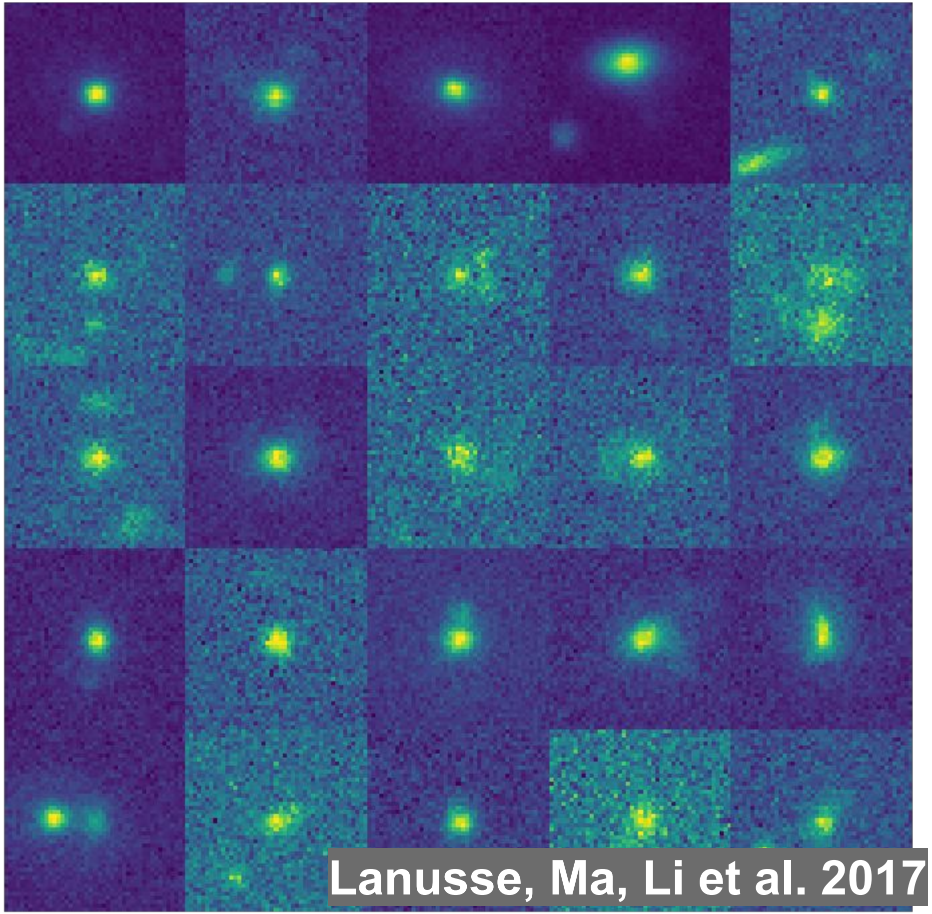
R.O.C Curves (DeepLens vs HOG)



Lanusse, Ma, Li et al. 2017

Detected Images in LSST Mocks



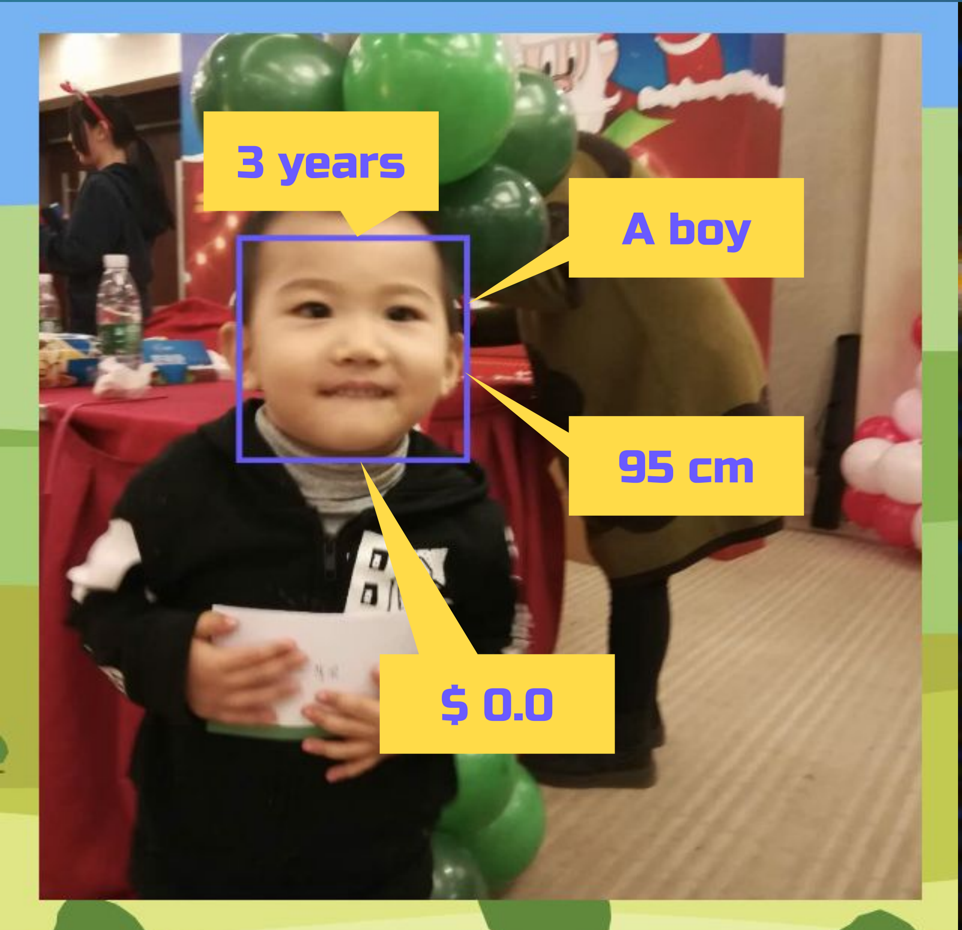


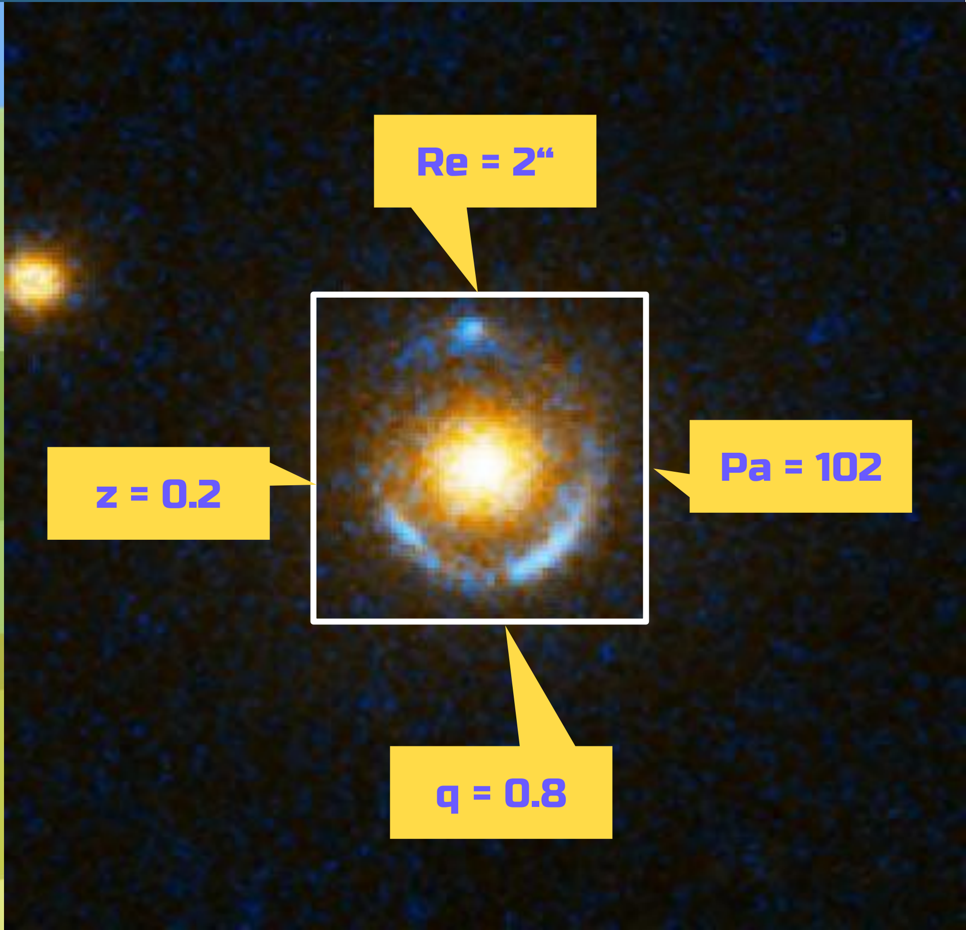
Sorted by area under the ROC curve

##		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 [illegible]	[illegible]

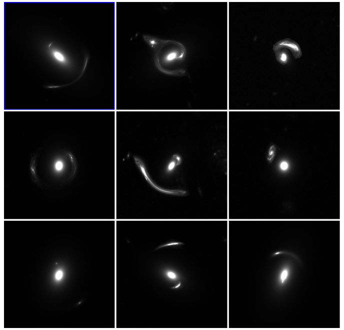
Metcalf et al. 2018

Machine Learning and Lens Modelling

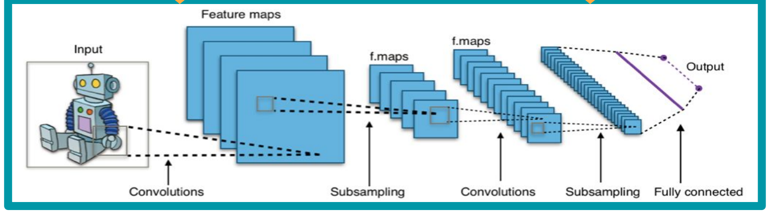


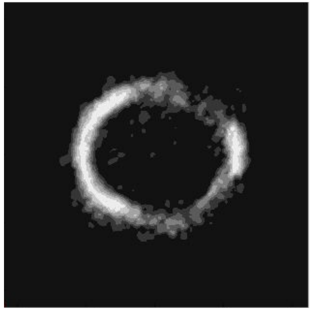


Machine Learning and Lens Modelling

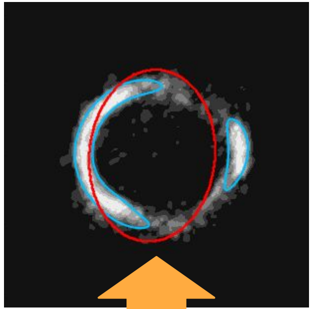


- RE
- Ell
- Phi
- ….

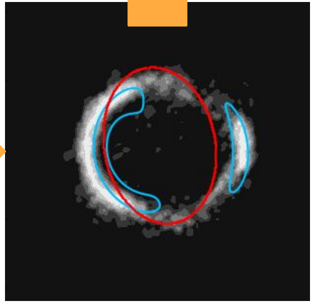




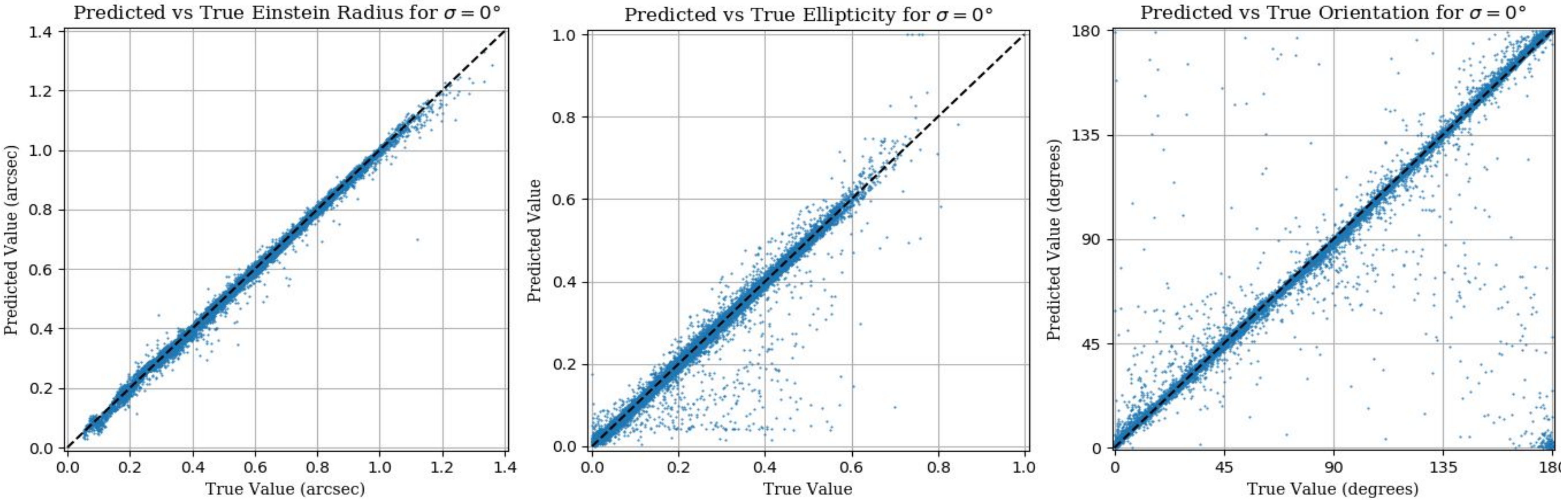
- RE
- Ell
- Phi
- ….



Optimization



Predictions vs True Values



More details in James' Talk tomorrow.

Pearson et al. in progress

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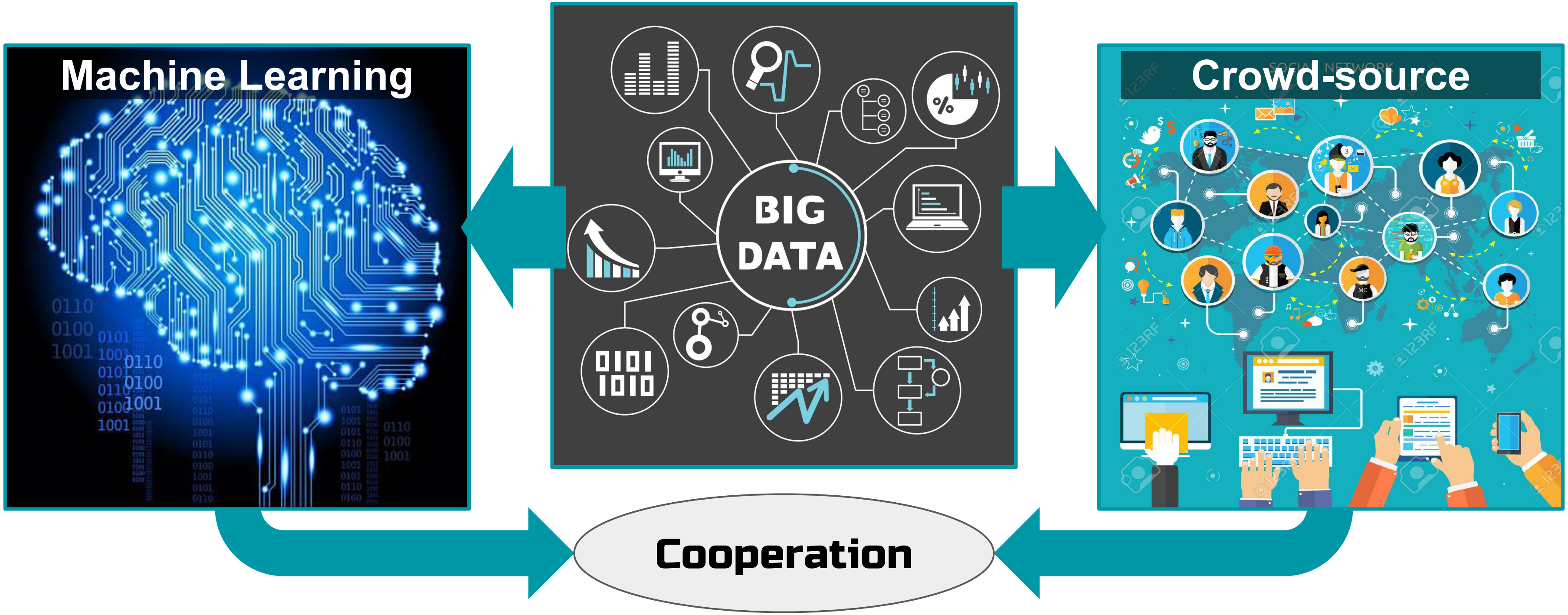
- Machine Learning and Strong Lensing
- **Beyond Machine Learning**

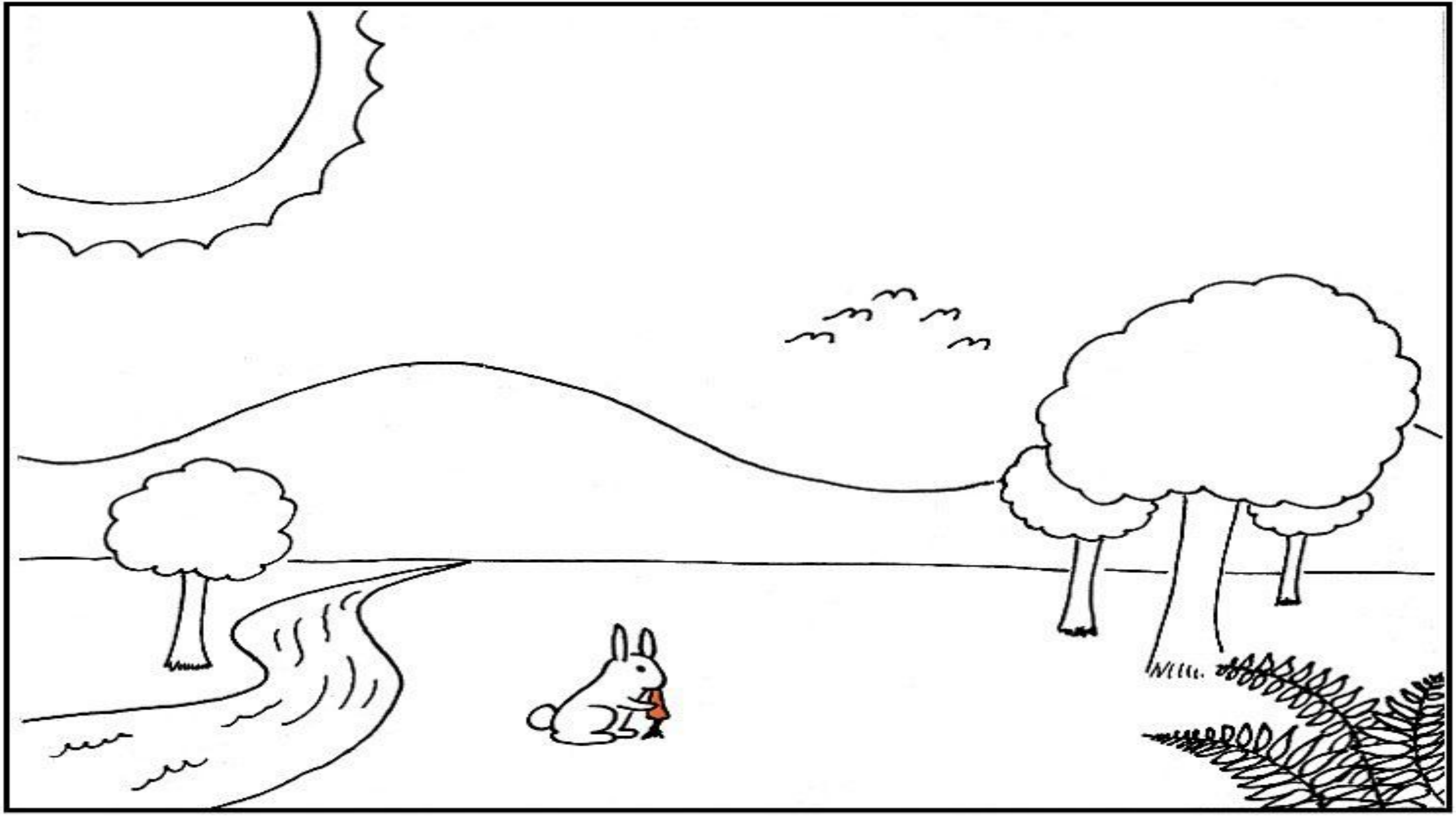
  Crowd-sourcing and Lens-finding

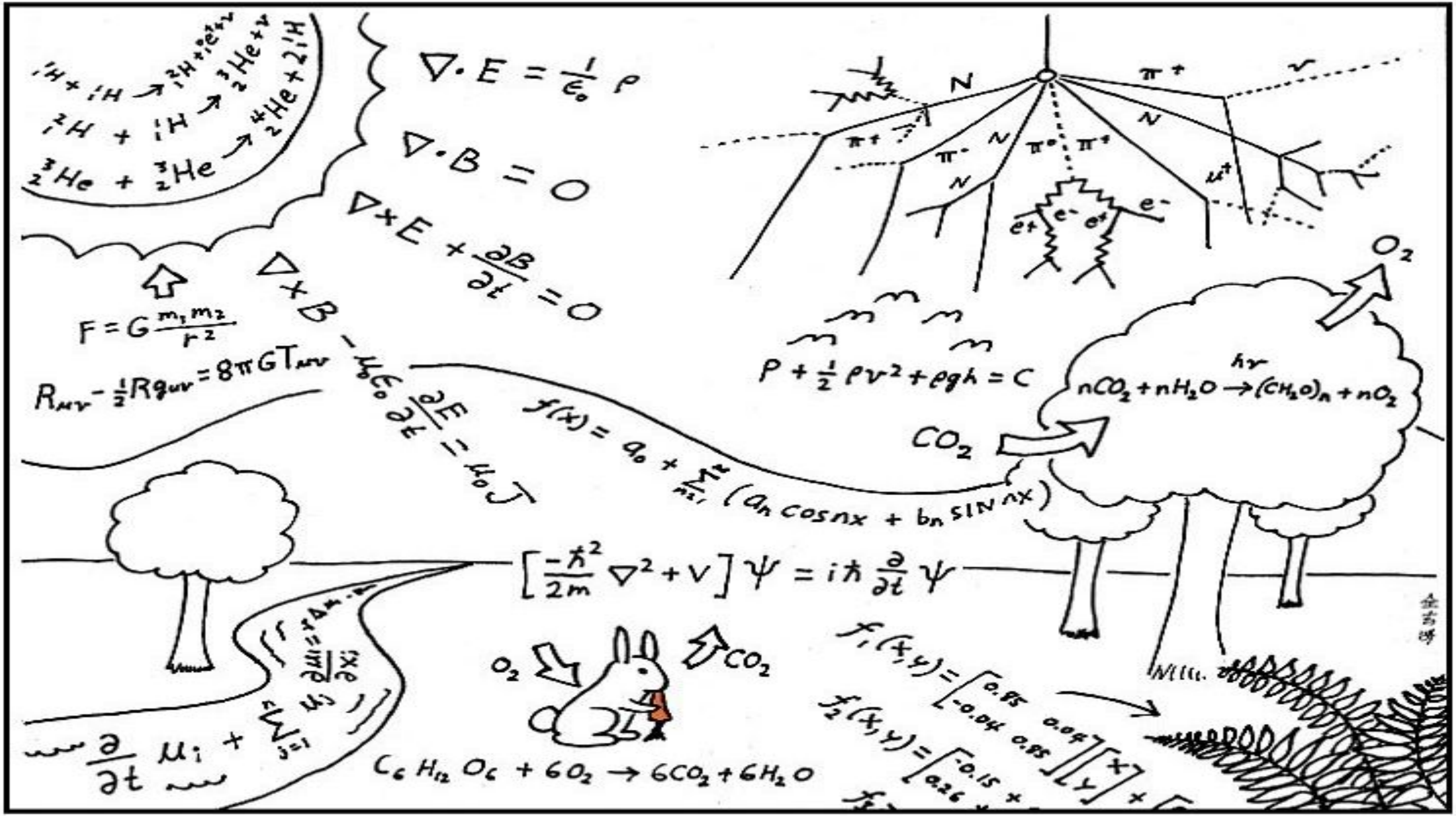
  Crowd-sourcing and Lens-modelling
- Summary and Future Work

The University of Nottingham

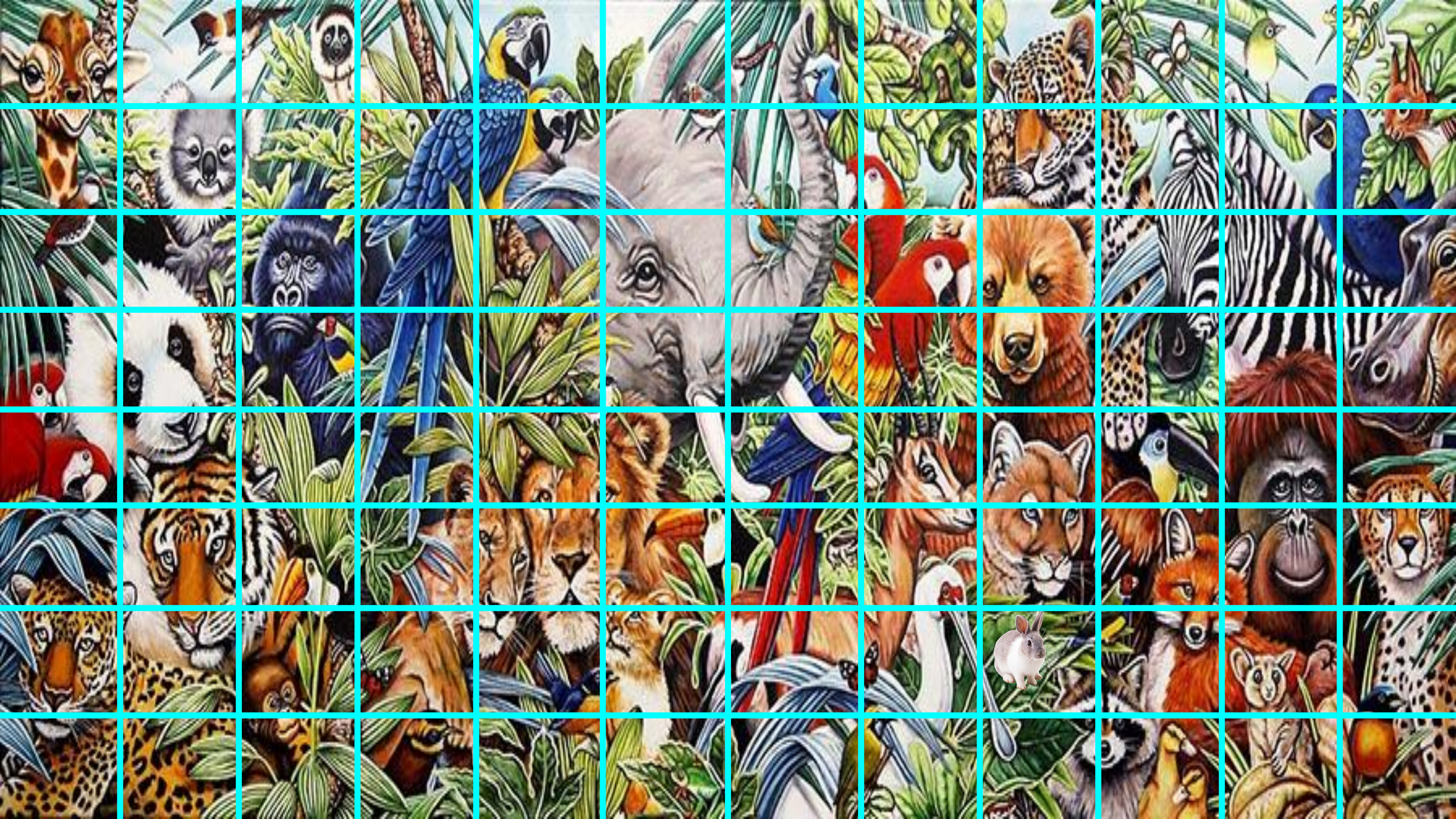
Machine Learning and Crowd-sourcing

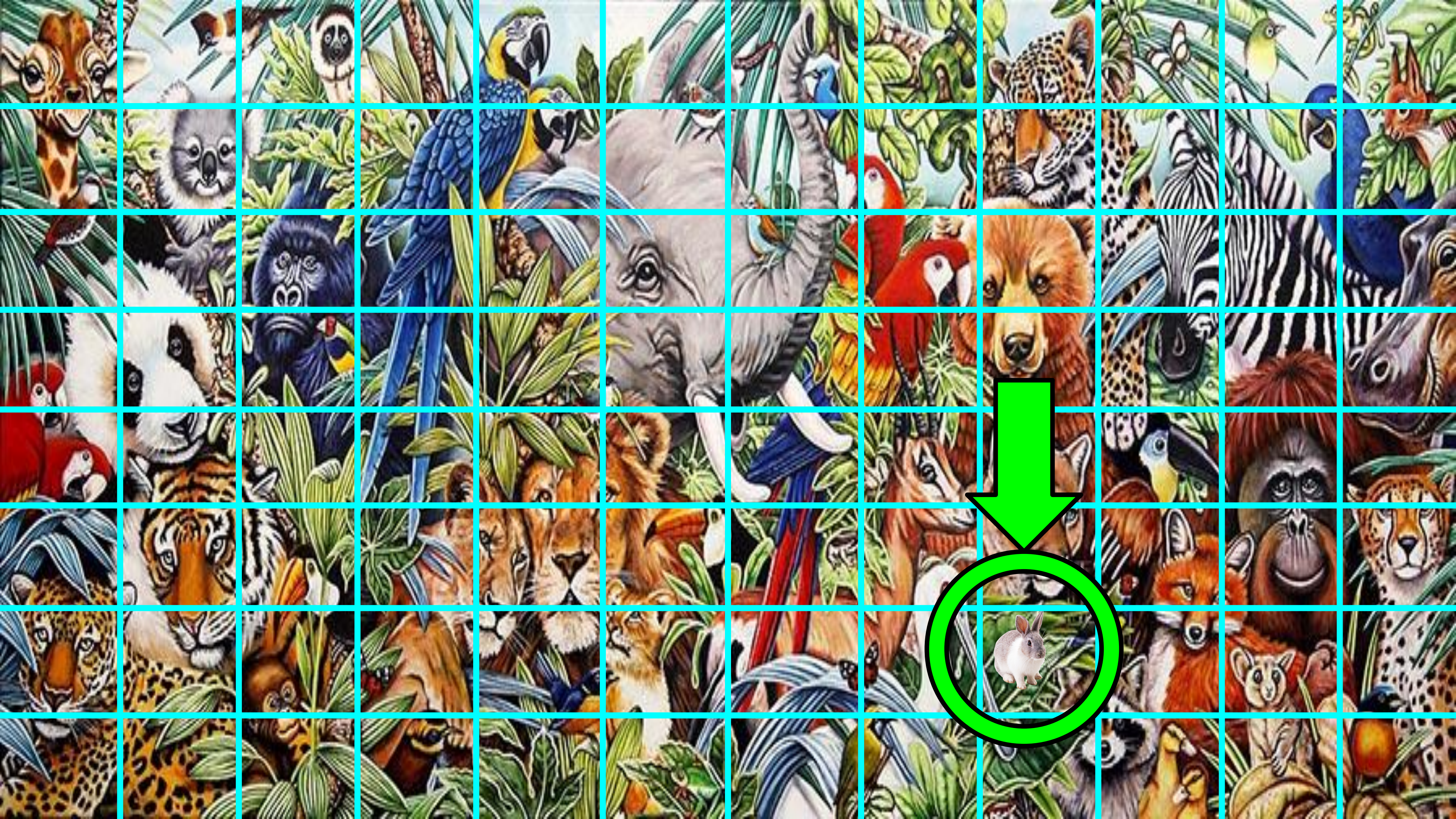






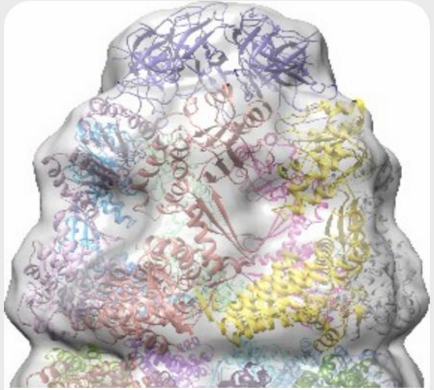
${}^1_1H + {}^1_1H \rightarrow {}^2_1H + {}^0_1e + \nu$
${}^2_1H + {}^1_1H \rightarrow {}^3_2He + \gamma$
${}^3_2He + {}^3_2He \rightarrow {}^4_2He + 2\,{}^1_1H$
$\nabla \cdot E = \frac{1}{\epsilon_0}\rho$
$\nabla \cdot B = 0$
$\nabla \times E + \frac{\partial B}{\partial t} = 0$
$\nabla \times B - \mu_0\epsilon_0 \frac{\partial E}{\partial t} = \mu_0 J$
$F = G\frac{m_1 m_2}{r^2}$
$R_{\mu\nu} - \frac{1}{2}Rg_{\mu\nu} = 8\pi G T_{\mu\nu}$
$f(x) = a_0 + \sum_{n=1}^{\infty}(a_n \cos nx + b_n \sin nx)$
$P + \frac{1}{2}\rho v^2 + \rho g h = C$
$nCO_2 + nH_2O \xrightarrow{h\nu} (CH_2O)_n + nO_2$
O_2
CO_2
N
π^+
π^-
π^0
ν
μ^+
e^-
e^+
$\left[\frac{-\hbar^2}{2m}\nabla^2 + V\right]\psi = i\hbar\frac{\partial}{\partial t}\psi$
$\frac{\partial}{\partial t}u_i + \sum_{j=1}^{n} u_j \frac{\partial u_i}{\partial x_j} = \nu\Delta u_i$
O_2
CO_2
$C_6H_{12}O_6 + 6O_2 \rightarrow 6CO_2 + 6H_2O$
$f_1(x,y) = \begin{bmatrix} 0.85 & 0.04 \\ -0.04 & 0.85 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} +$
$f_2(x,y) = \begin{bmatrix} -0.15 & \\ 0.26 & \end{bmatrix}$



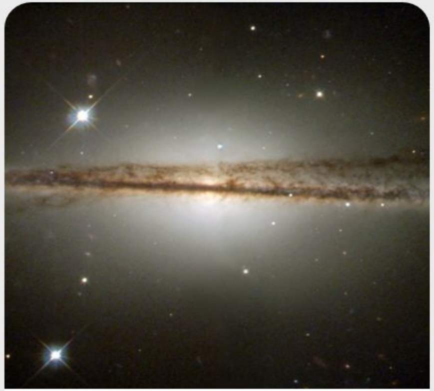


COMPUTER VISION: SERENGETI

WESTERN SHIELD — CAMERA WATCH



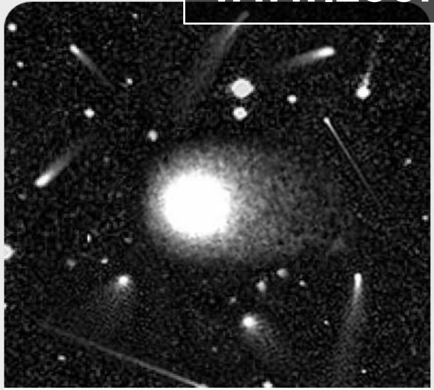
MICROSCOPY MASTERS



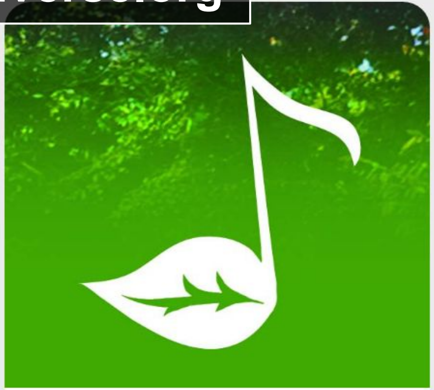
POPPIN' GALAXY

www.zooniverse.org

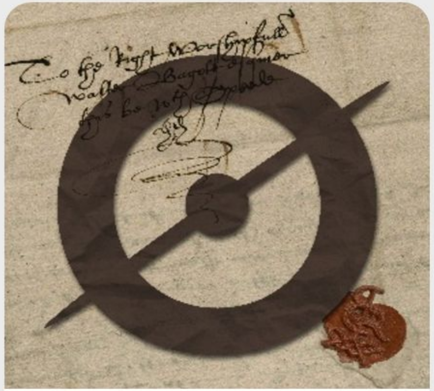
SNAPSHOTS AT SEA



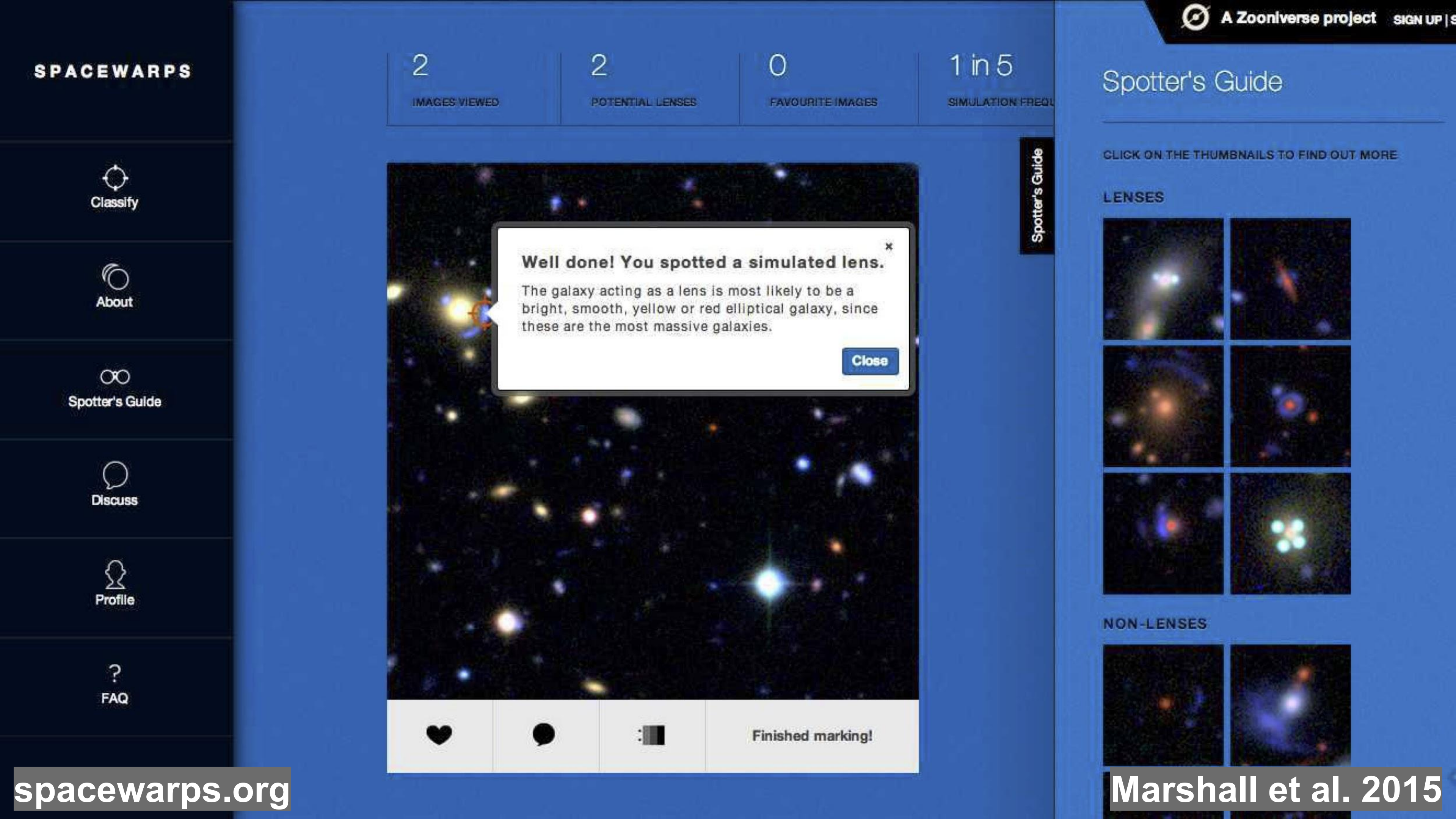
COMET HUNTERS



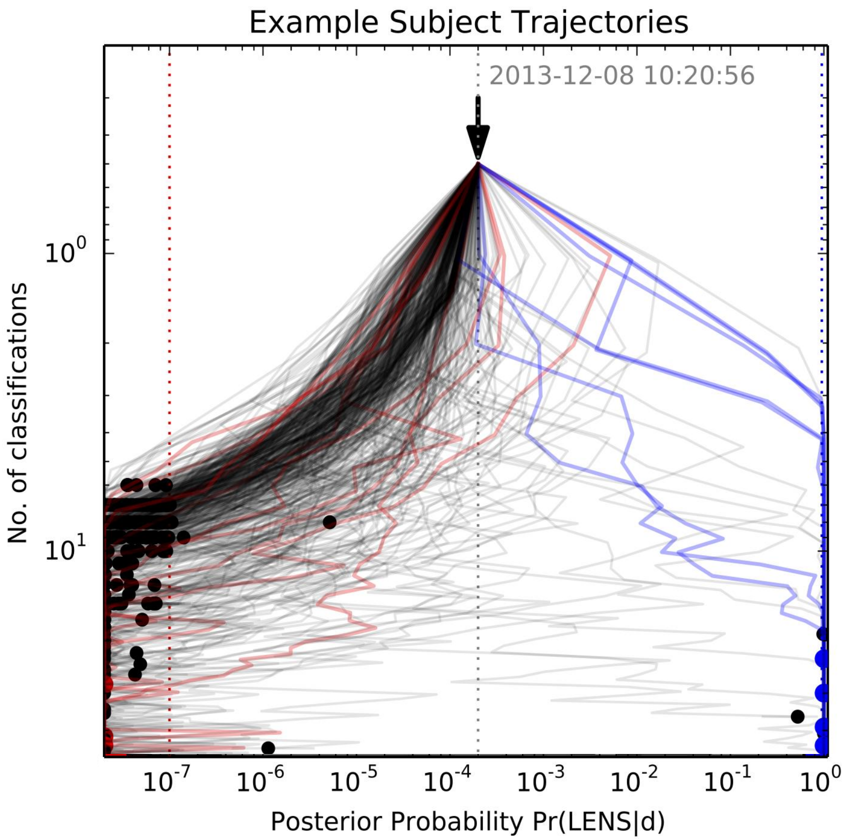
JUNGLE RHYTHMS

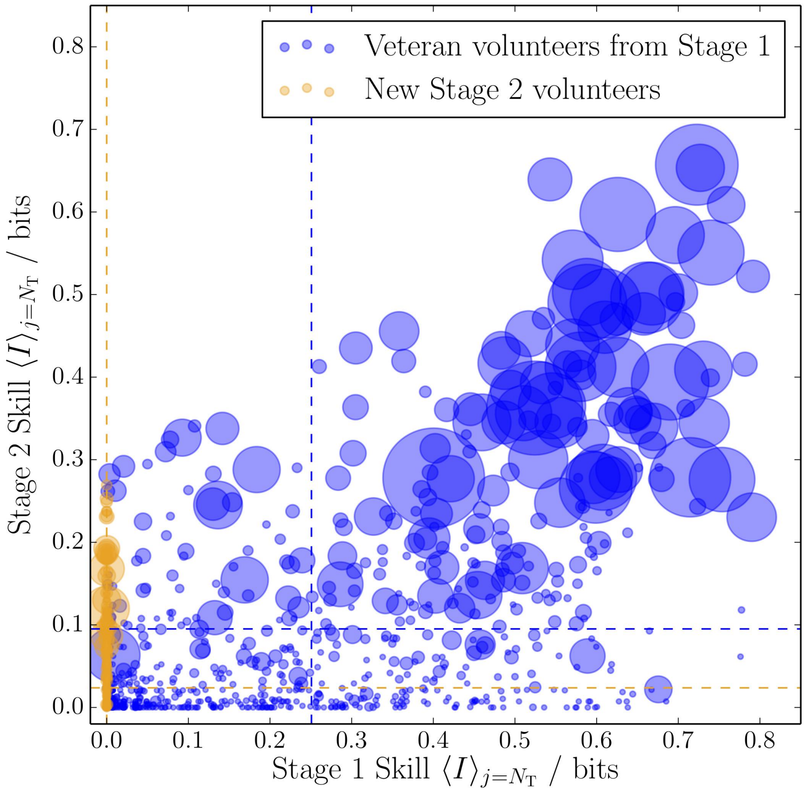


SHAKESPEARE'S WORLD


SPACEWARPS
2
IMAGES VIEWED
2
POTENTIAL LENSES
0
FAVOURITE IMAGES
1 in 5
SIMULATION FREQU
A Zooniverse project
SIGN UP | S
Spotter's Guide
CLICK ON THE THUMBNAILS TO FIND OUT MORE
LENSES
NON-LENSES
Spotter's Guide
Classify
About
Spotter's Guide
Discuss
Profile
?
FAQ
Well done! You spotted a simulated lens.
The galaxy acting as a lens is most likely to be a bright, smooth, yellow or red elliptical galaxy, since these are the most massive galaxies.
Close
Finished marking!
spacewarps.org
Marshall et al. 2015

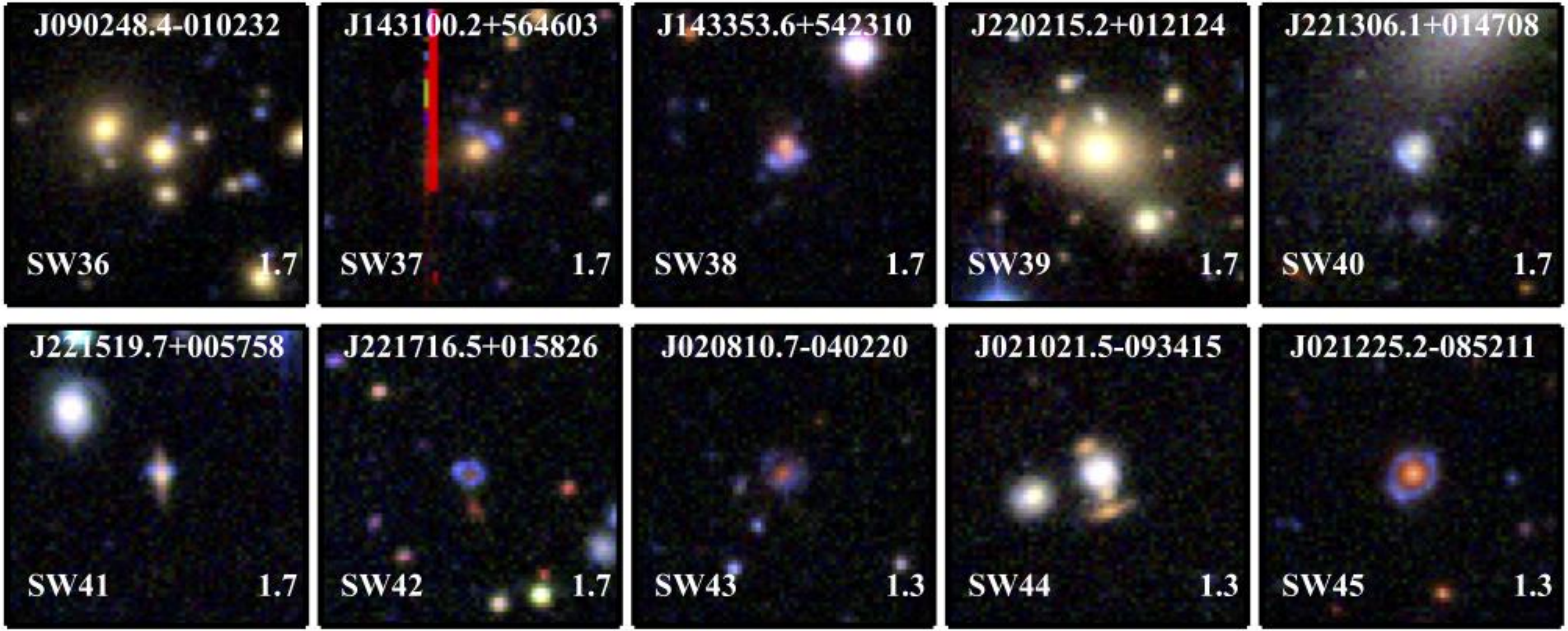
Crowd-sourcing and Lens-finding (CFHTLS)





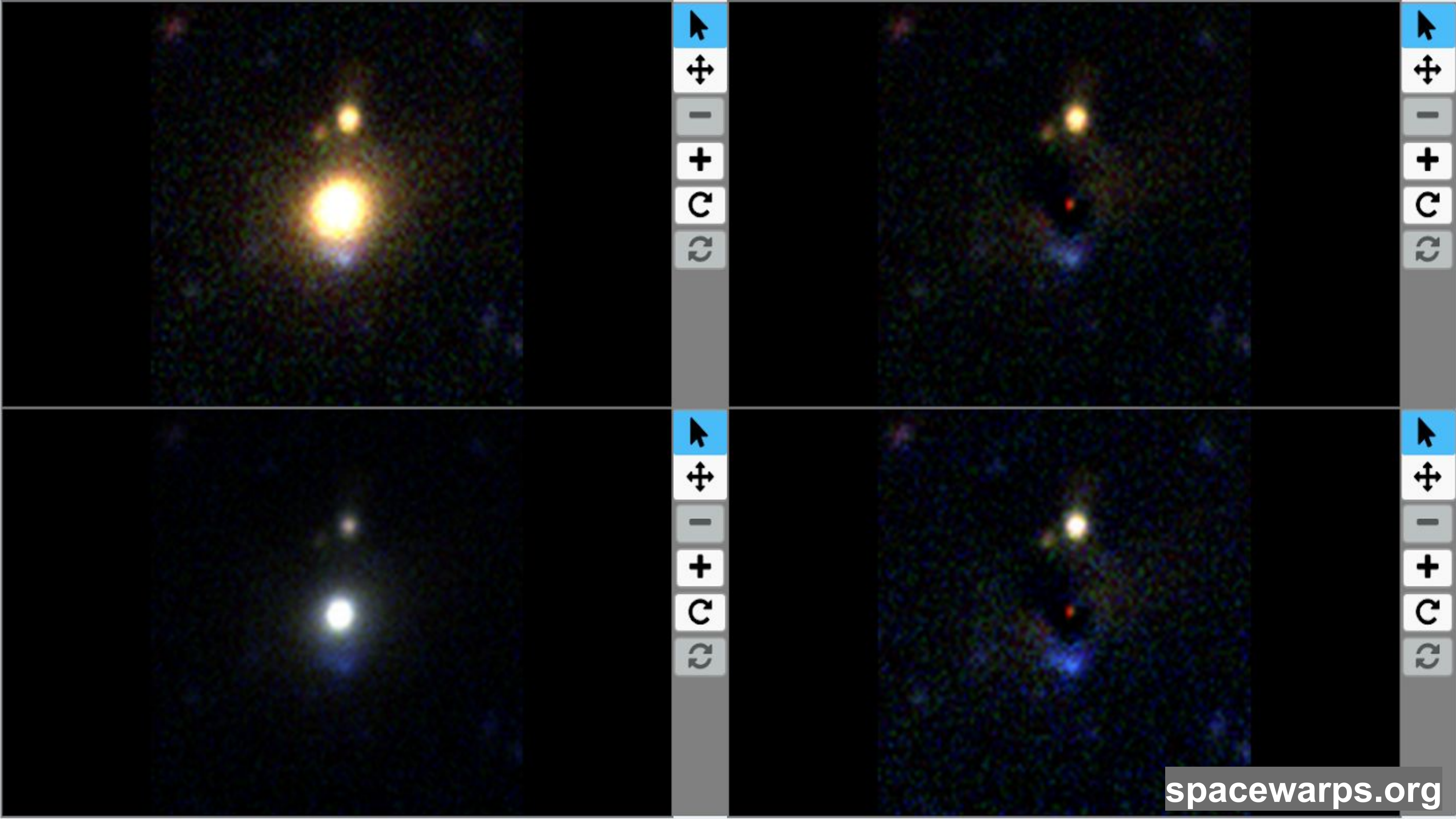
Marshall et al. 2015

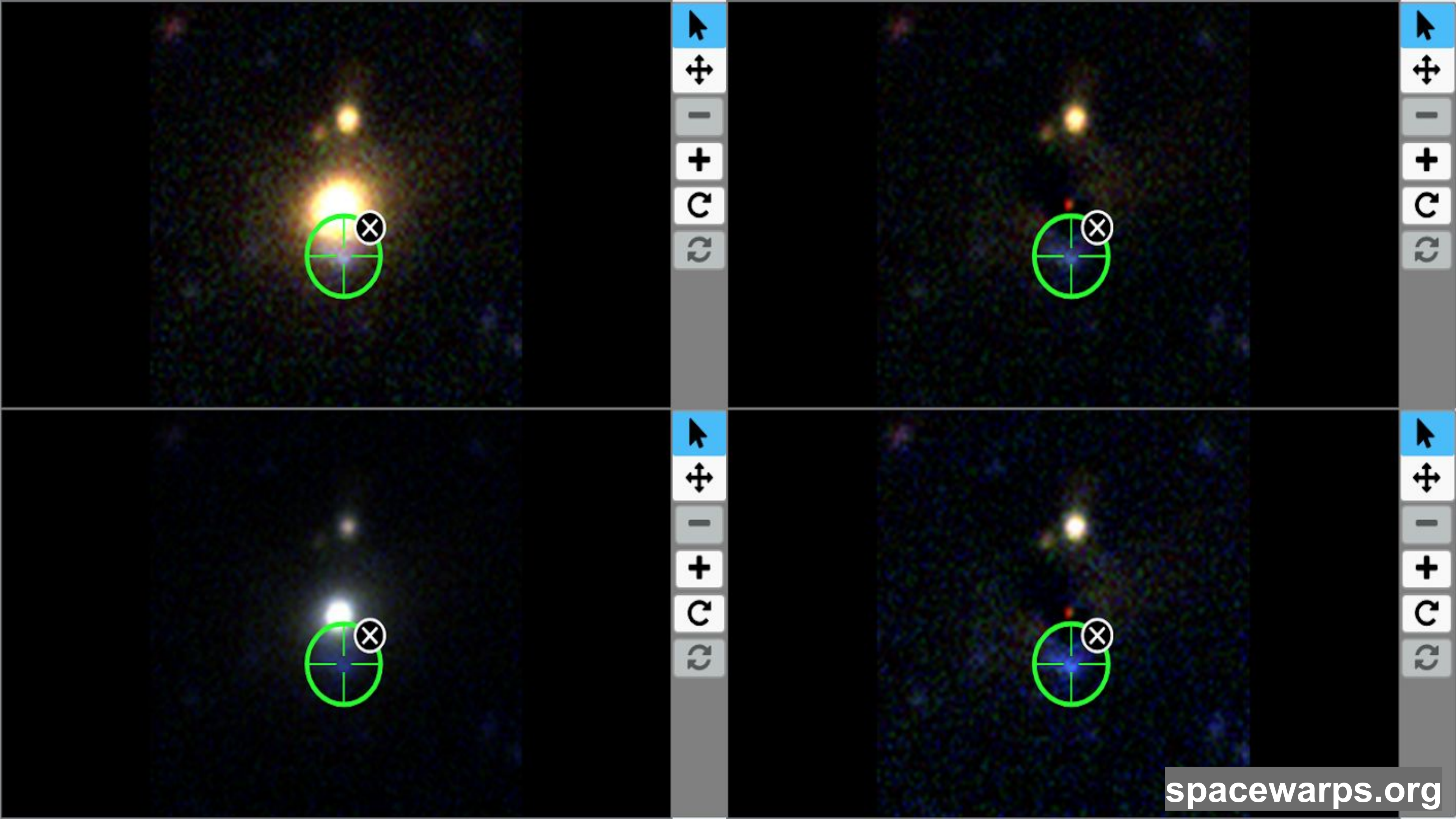
Crowd-sourcing and Lens-finding (CFHTLS)



More et al. 2015

Crowd-sourcing and Lens-finding (DES)


spacewarps.org

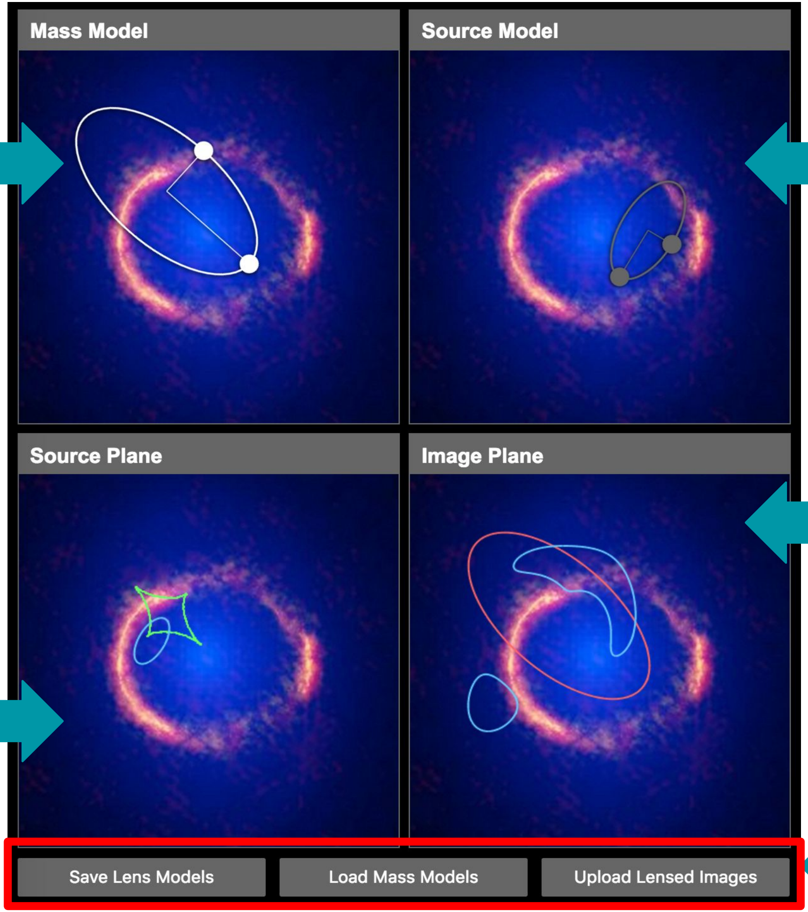

spacewarps.org

Crowd-sourcing and Lens-modelling

Draw an ellipse to model the lens

Javascript
HTML5
CSS3

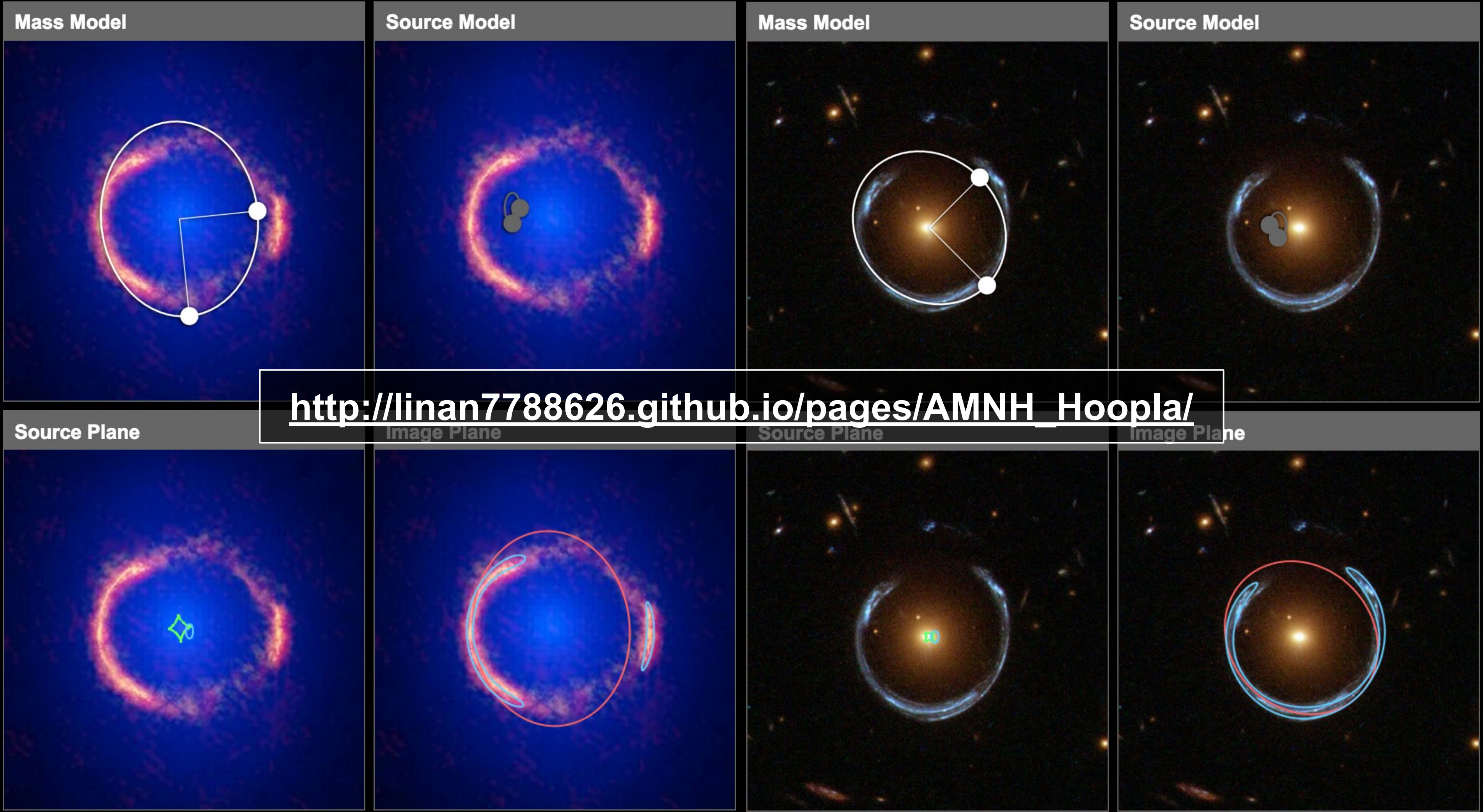
Move the cursor to reconstruct the image



Draw an ellipse to model the source

Predicted images

- Save Models
- Load Models
- Upload Images



http://linan7788626.github.io/pages/AMNH_Hoopla/

- Introduction
- Machine Learning and Strong Lensing
- Beyond Machine Learning
- **Summary and Future Work**

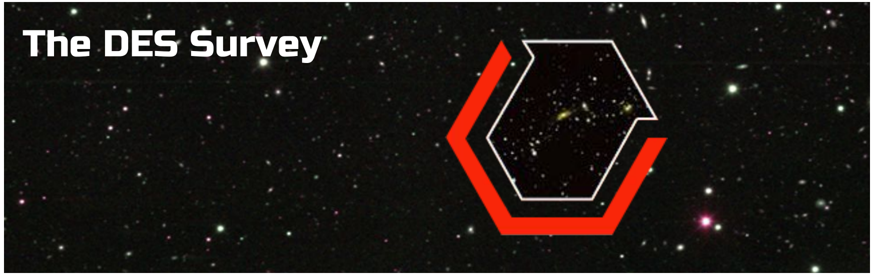
The University of Nottingham

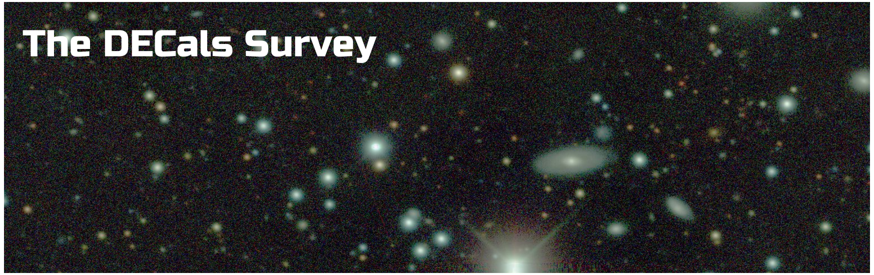
Summary

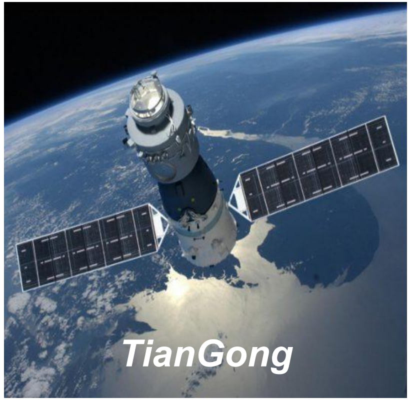
- ❖ Gravitational lensing is useful, but we will encounter some problems in the upcoming Big Data Era, such as identifying and modelling strong gravitational lenses.
- ❖ Deep learning works better than traditional methods and human eyes in the detection of SG lenses. Lens modelling can be improved by utilising deep learning (automatization and higher efficiency).
- ❖ Crowdsourcing is an alternative way to deal with the problems of lens-finding/modelling in the big data era; it is primitive cooperation between humans and machines.
- ❖ The problem mentioned in the introduction can be solved with machine learning or/and Crowdsourcing. More such problems in astrophysics and cosmology will be solved in the same way.

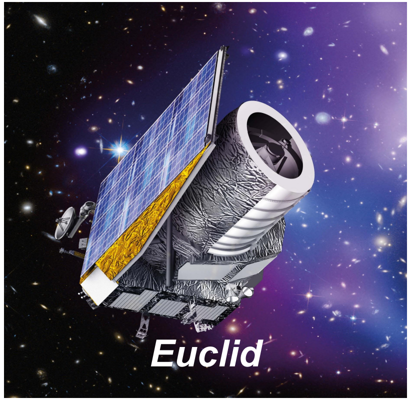
In the Near Future

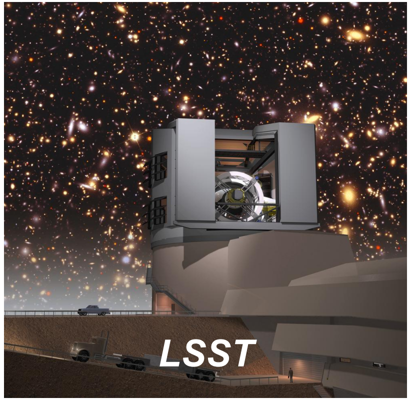
- *Apply the pipelines to the data of large scale sky surveys.*



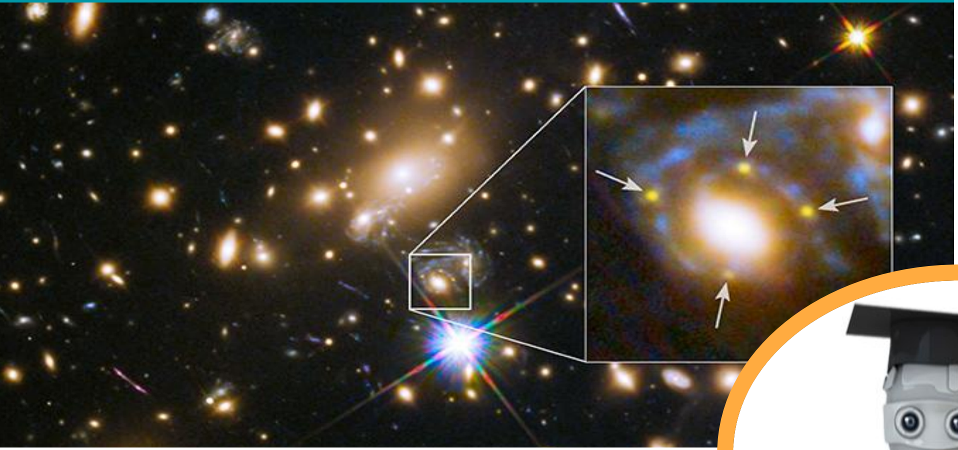




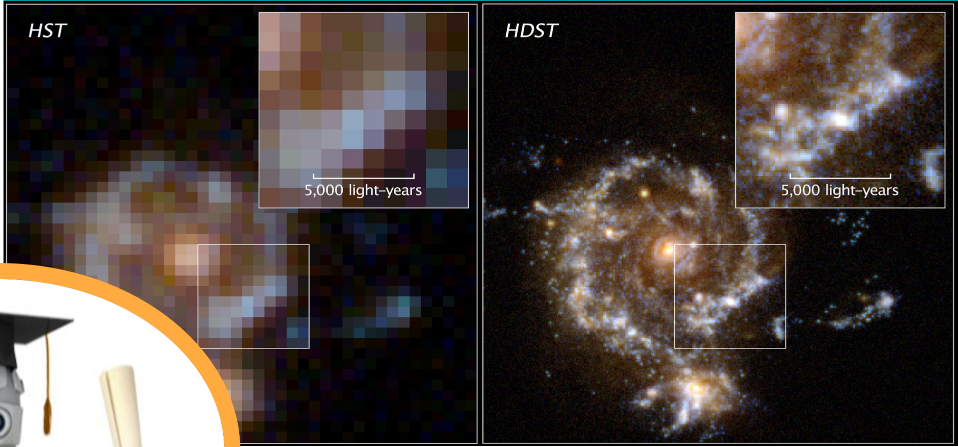




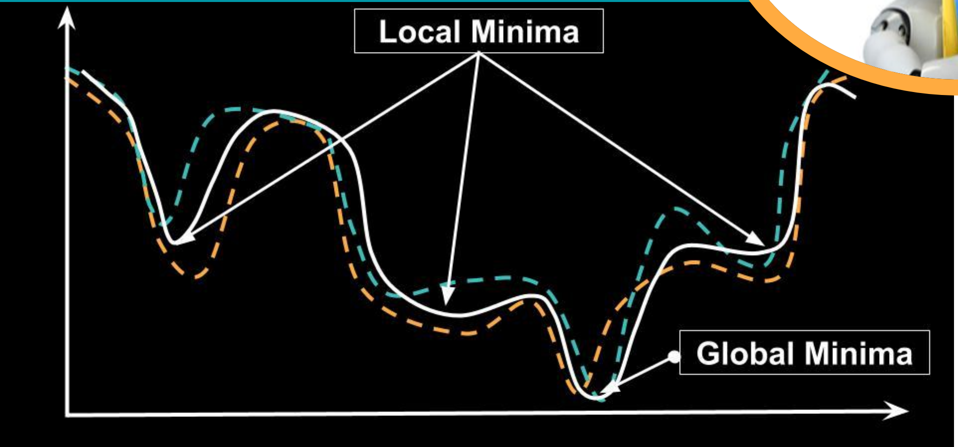
Detecting



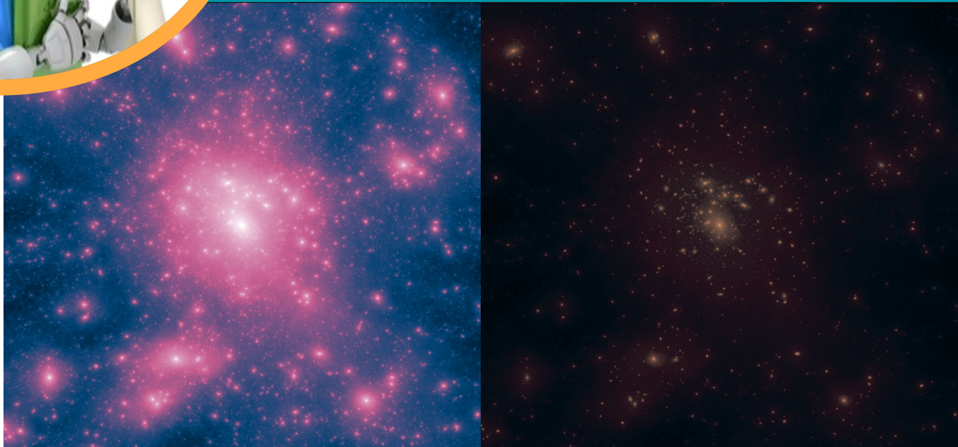
Predicting



Fitting



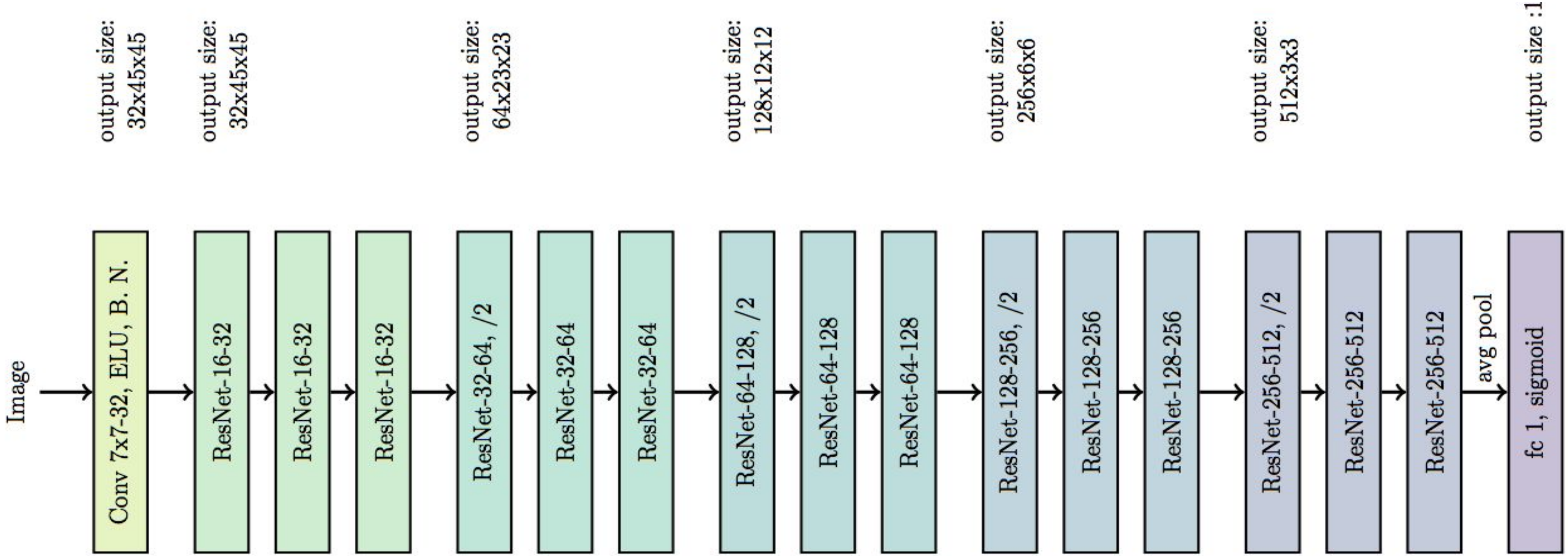
Modelling



Hoopla

CMU-DeepLens

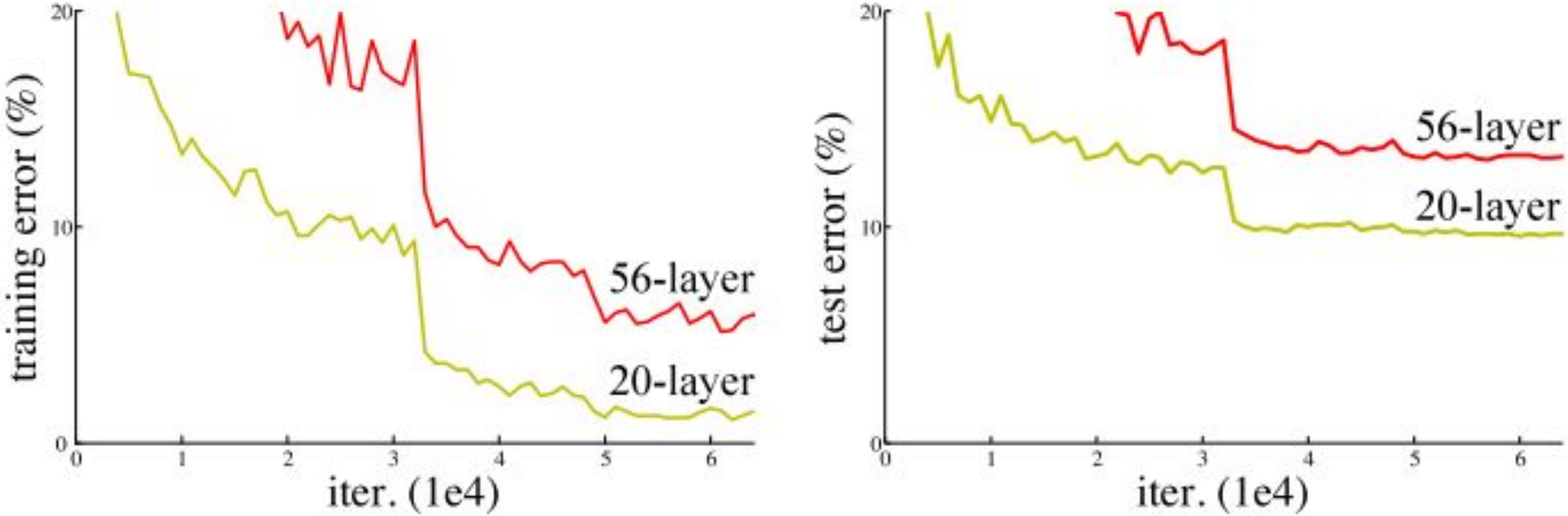
Architecture of CMU DeepLens



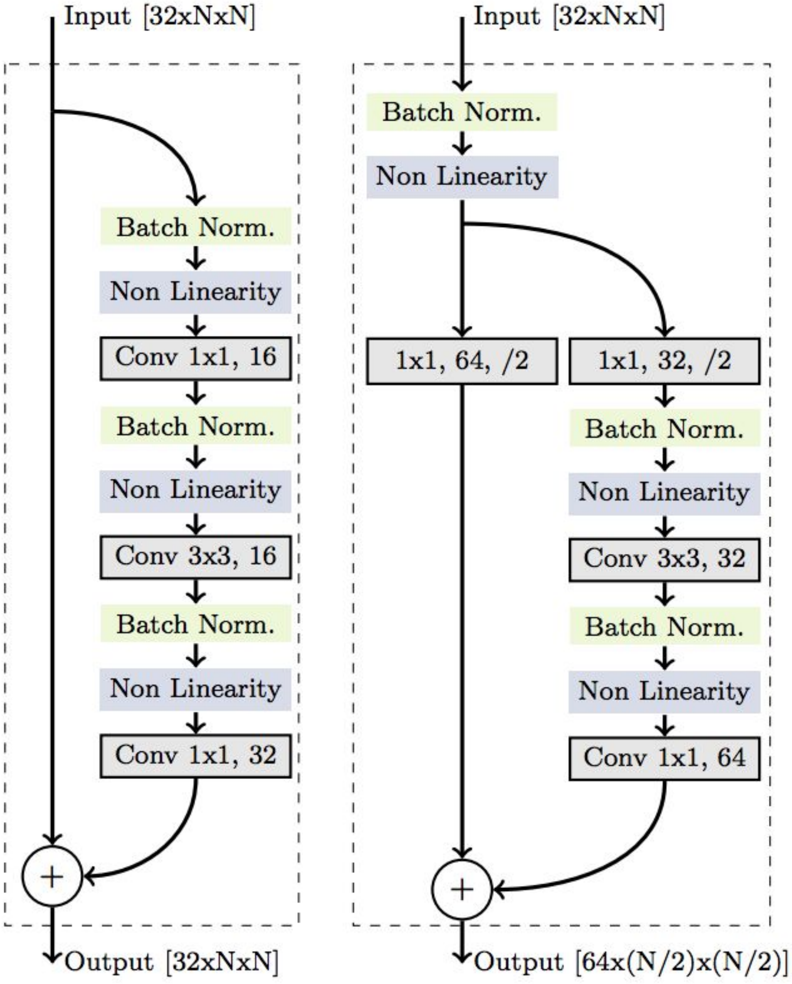
The first block is a single convolutional layer with an ELU activation function and batch normalisation. The last block is a single fully connected layer with a sigmoid activation function, which outputs a probability between 0 and 1.

Lanusse, Ma, Li et al. 2017

The Vanishing Gradient Problem



Increasing network depth leads to worse performance



(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.