Applications of deep learning in wide-field cosmological surveys

2nd ASTERICS-OBELICS Workshop
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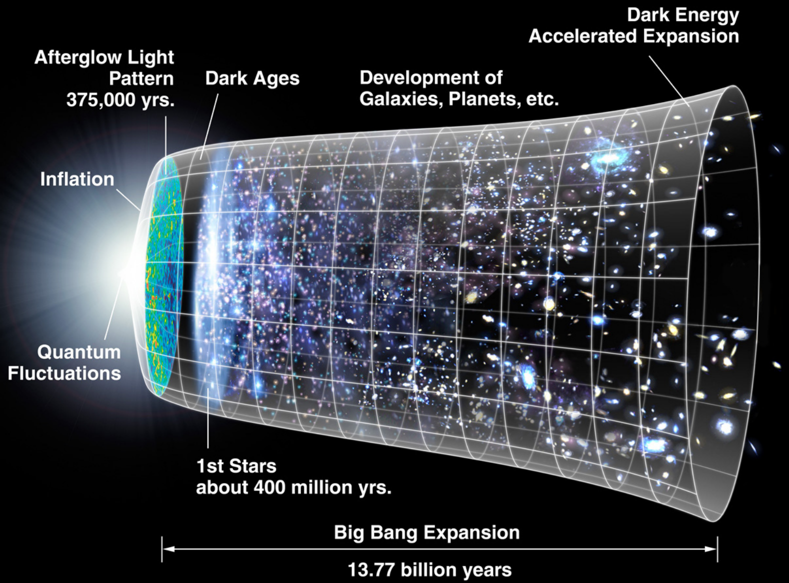
18 October 2017

McWilliams Center for Cosmology
Carnegie Mellon University

Asterics
Astronomy ESFRI & Research Infrastructure Cluster

H2020-Astronomy ESFRI and Research Infrastructure Cluster
(Grant Agreement number: 653477).

the ΛCDM view of the Universe



NASA/WMAP Science Team

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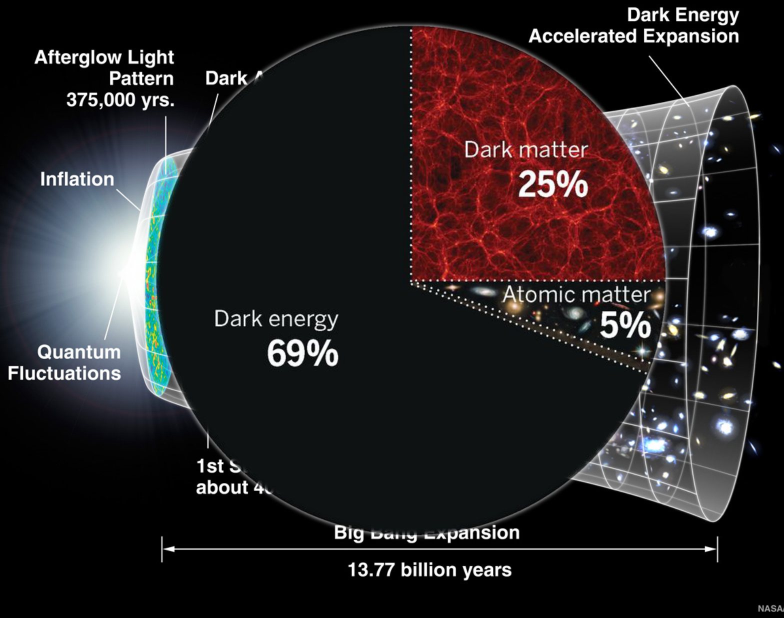
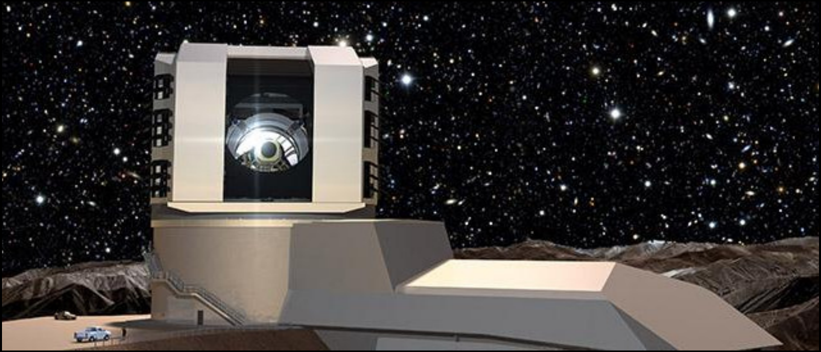


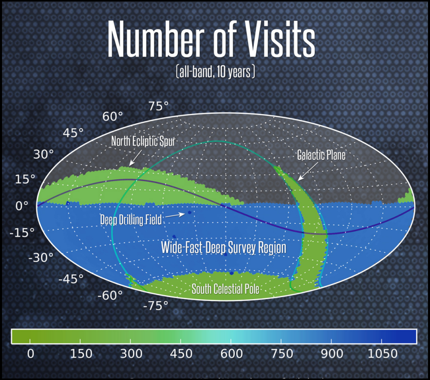
the Large Synoptic Survey Telescope



LSST in a few numbers

- 1000 images each night, each one is 3.2 GB and 40 full moons
  $\Longrightarrow$ 15 TB/night for 10 years
- Covers 18,000 square degrees (40% of the sky)
- Tens of billions of objects, each one observed $\sim$ 1000 times

what does it look like ?



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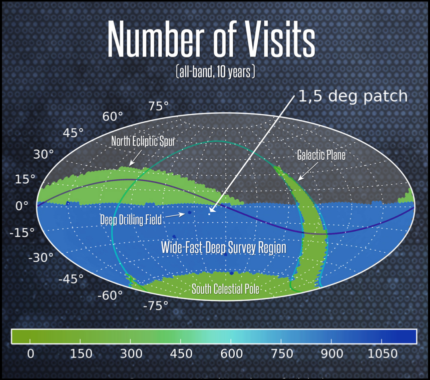

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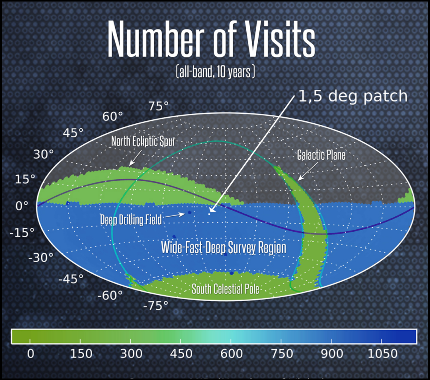

HSC-SPP Data Release 1

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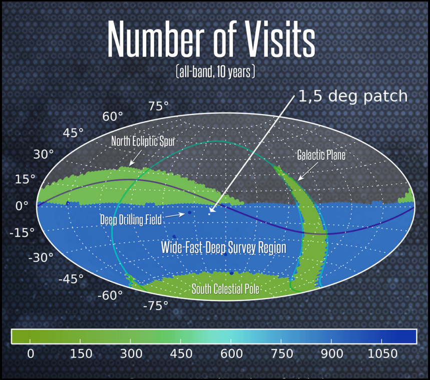

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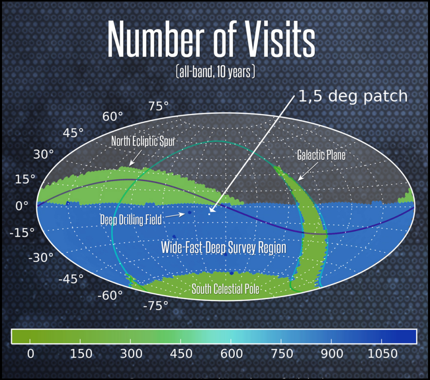

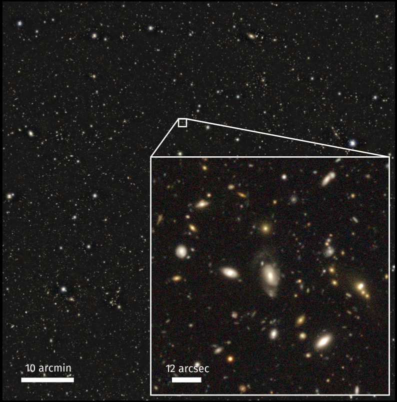

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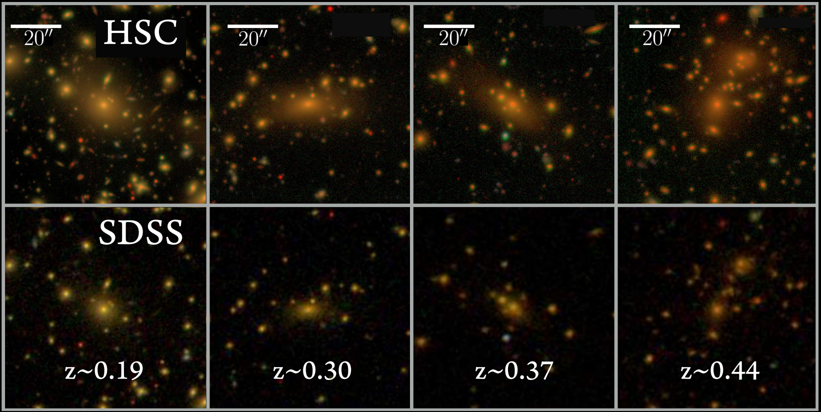

Huang et al. (2017), arXiv:1707.01904

the challenge for modern surveys

$\Longrightarrow$ Modern surveys will provide large volumes of high quality data

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A Blessing

- Unprecedented statistical power
- Great potential for new discoveries

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- Existing methods are reaching their limits (computational cost, accuracy) at every step of the science analysis
- Control of systematic uncertainties becomes paramount

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$\Longrightarrow$ Dire need for novel data analysis techniques to fully realize the potential of modern surveys

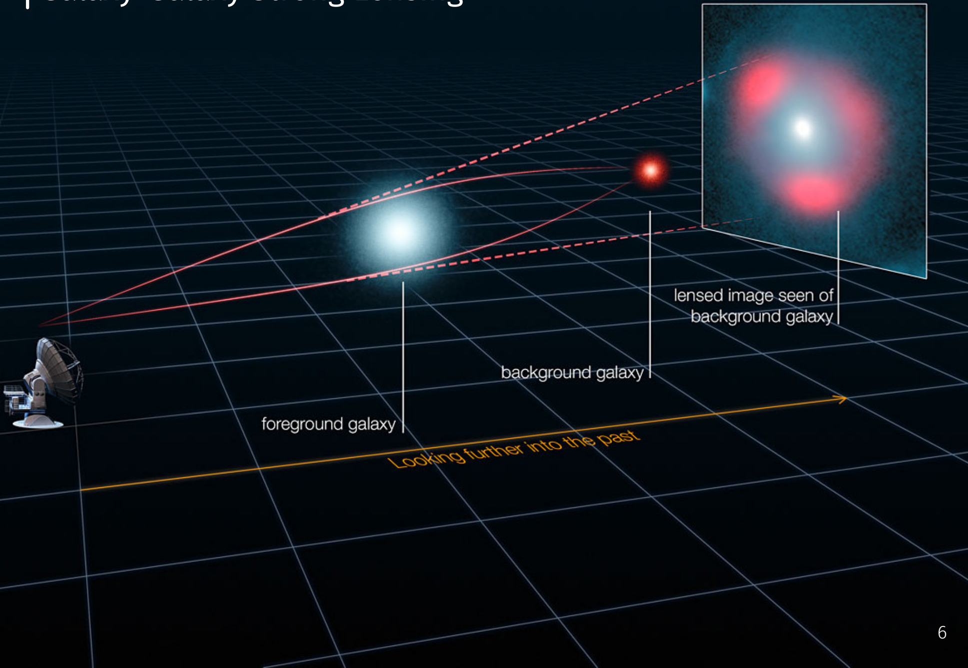
Outline of this talk

1. Finding strong gravitational lenses with Deep Learning
   - Galaxy-Scale strong lensing
   - Finding strong lenses
   - Deep Learning for image classification

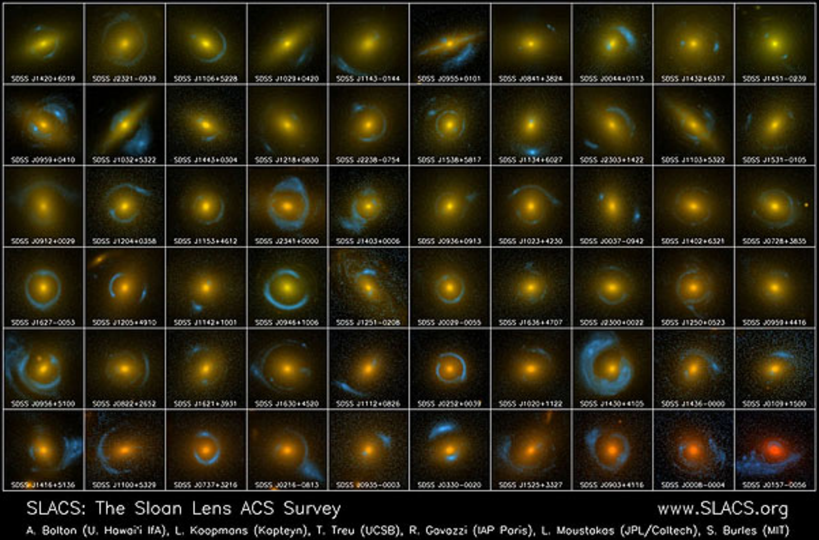
2. Deep Generative Models for weak lensing systematics
   - Weak Gravitational lensing
   - Deep Generative models of galaxy images

Finding strong gravitational lenses with Deep Learning

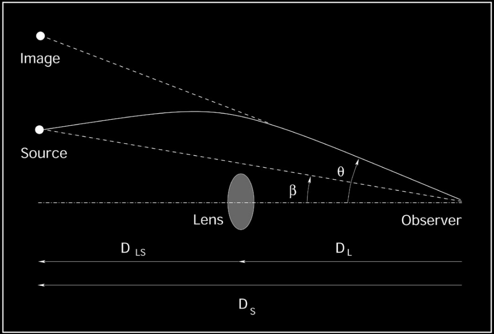
Galaxy-Galaxy Strong Lensing



examples of strong lenses



example of application: gravitational time delays



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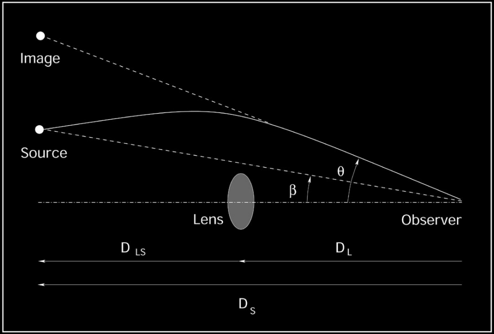
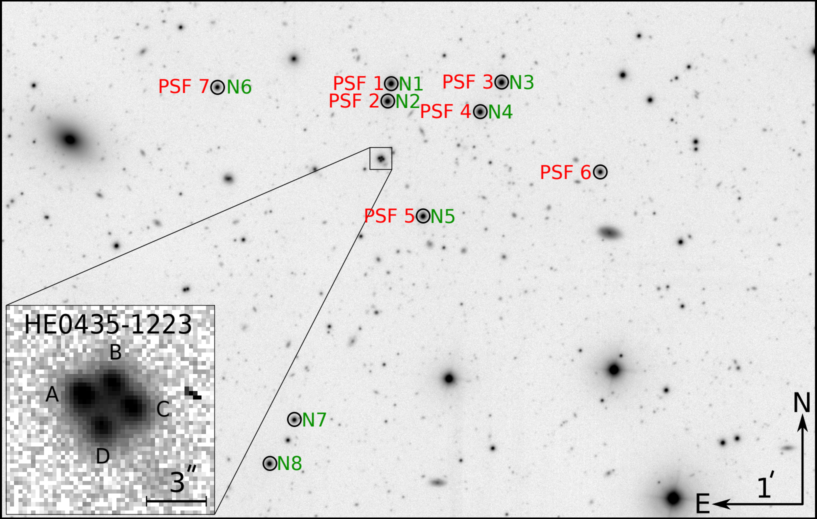


$$\Delta t_{ij} = \frac{1+z_L}{c} \underbrace{\frac{D_L\, D_S}{D_{LS}}}_{\propto H_0^{-1}} \left[\frac{(\boldsymbol{\theta}_i - \boldsymbol{\beta})^2}{2} - \psi(\boldsymbol{\theta}_i) + \frac{(\boldsymbol{\theta}_j - \boldsymbol{\beta})^2}{2} + \psi(\boldsymbol{\theta}_j) \right]$$

time delays of HE0435-1223 (Bonvin et al. 2017)



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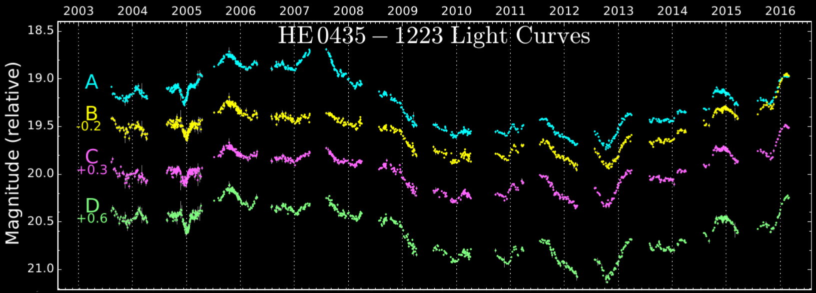

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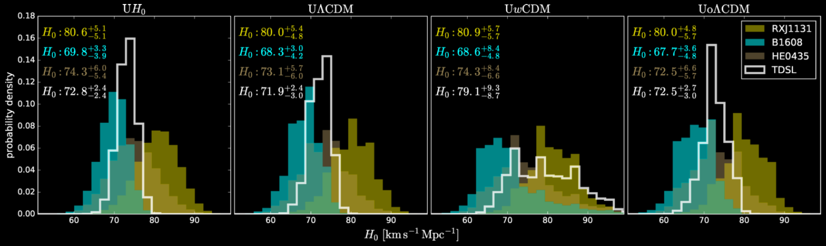

the problem: finding strong lenses

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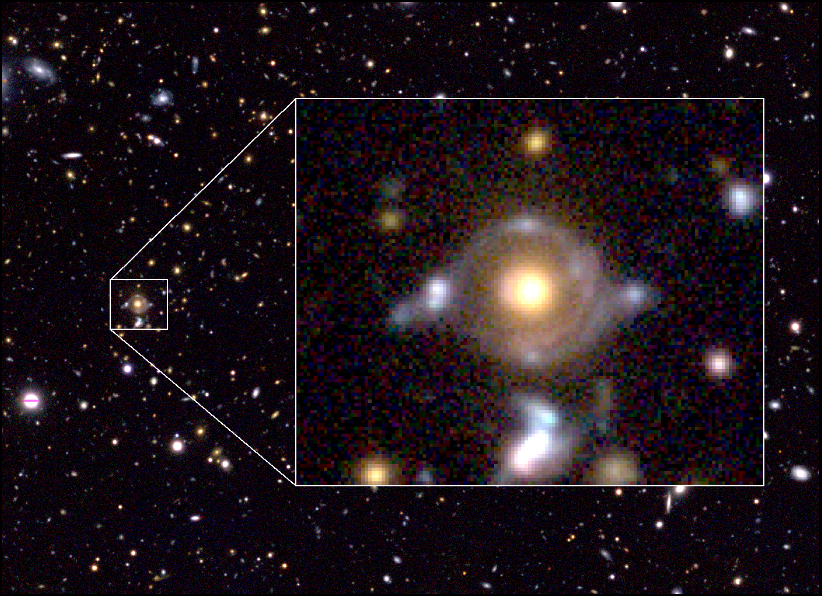
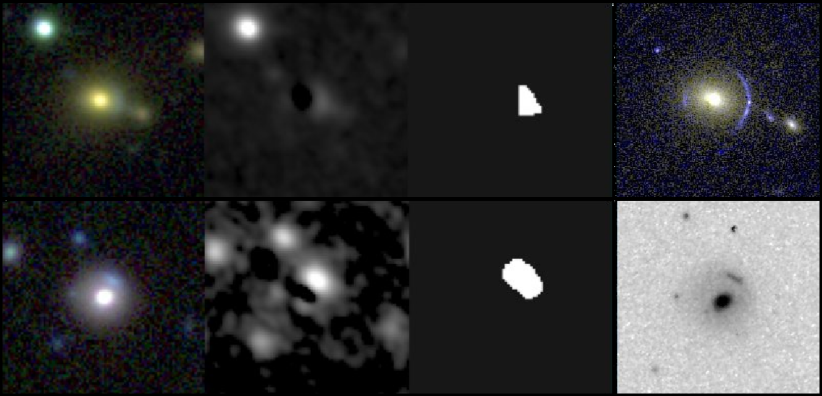


automated lens searches: RingFinder (Gavazzi et al. 2014)



gri composite $g - \alpha i$ detected areas HST images

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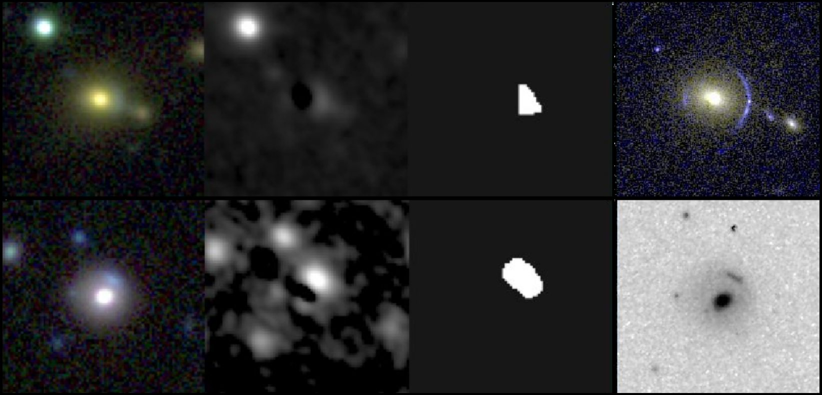
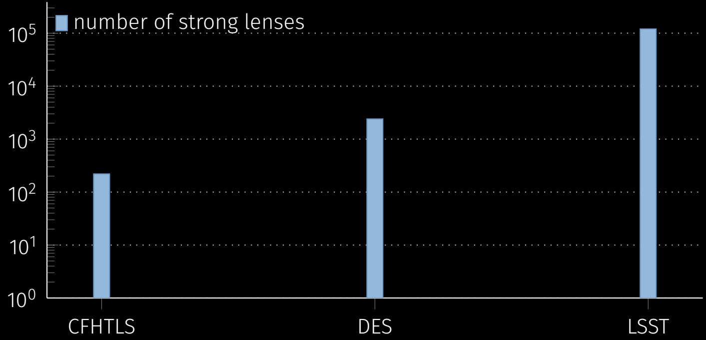


gri composite | $g - \alpha i$ | detected areas | HST images

Visual inspection time required
$\sim$ 30 person-minutes / deg^2

extrapolation to future surveys



Gavazzi et al. (2014), Collett (2015)

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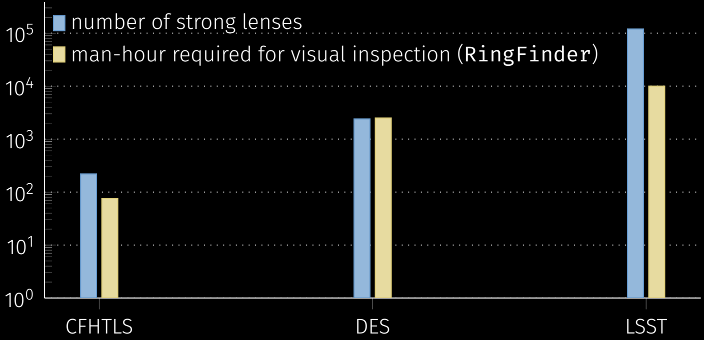

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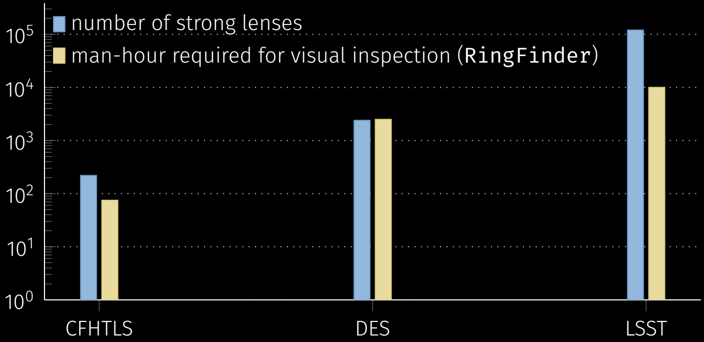
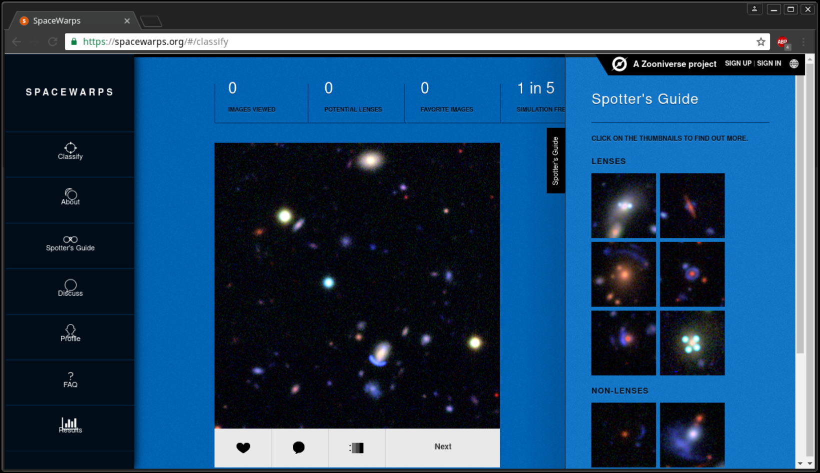


Gavazzi et al. (2014), Collett (2015)

$\Longrightarrow$ LSST would require an estimated 10^4 man-hours.

citizen science, the crowd-sourcing approach



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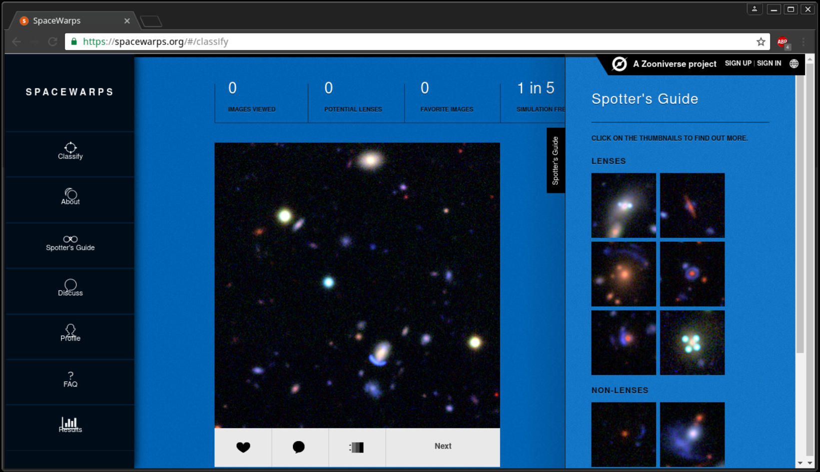

$\Longrightarrow$ Classifying all of LSST would take a few weeks with a crowd of 10^6 volunteers

Deep Learning to the rescue

in the news lately...

- Self-driving Uber takes the road in Pittsburgh (Sept. 2016)

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$\Longrightarrow$ technological revolution brought about by the advancement of deep learning

how did this happen ?

Training deep networks is difficult

Until $\sim$2010, networks were limited to a few layers because of vanishing gradients.

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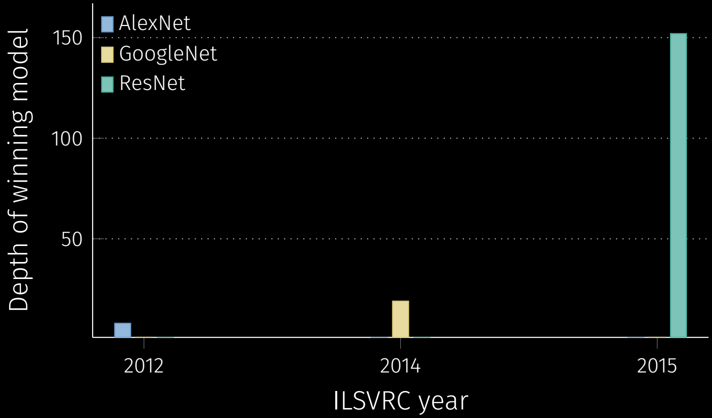

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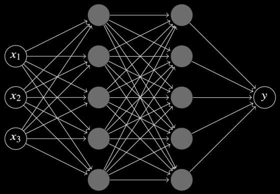
$\Longrightarrow$ State-of-the-art models outperform humans for image detection/classification

Convolutional Neural Network



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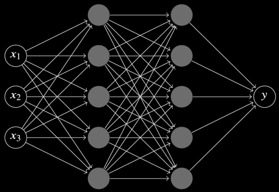

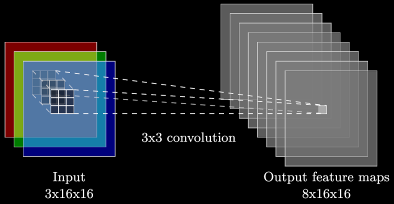

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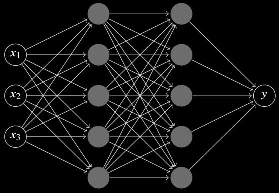
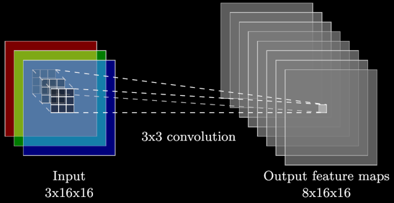
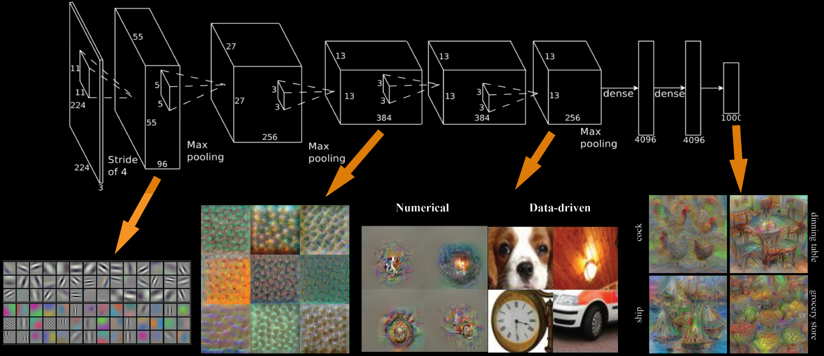






Conv 1: Edge+Blob Conv 3: Texture Conv 5: Object Parts Fc8: Object Classes

residual learning

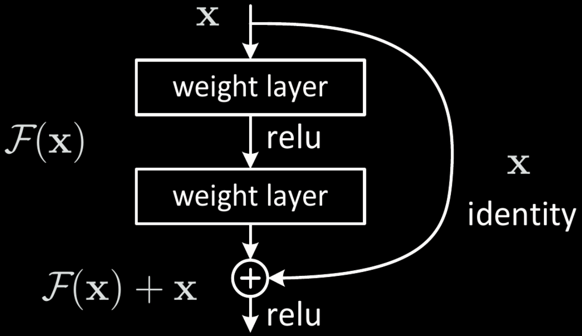
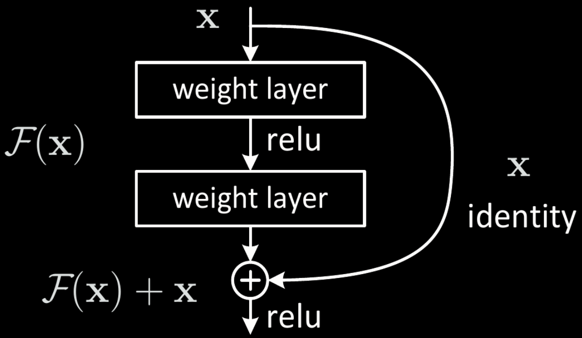


Image credit: He et al. (2015)

- Learning the difference to the identity (He et al. 2015)

residual learning



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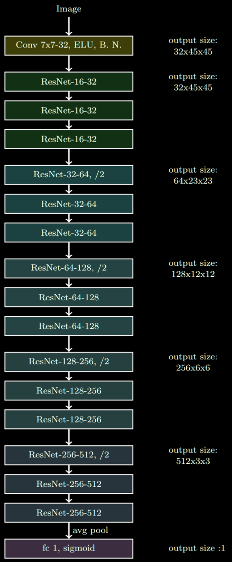
- Learning the difference to the identity (He et al. 2015)
- Easier to initialize and to train in deep architectures ($>$ 1000 layers)

CMU DeepLens: deep residual learning for strong lens finding



- Deep residual network (46 layers) with pre-activated bottleneck residual units

model architecture

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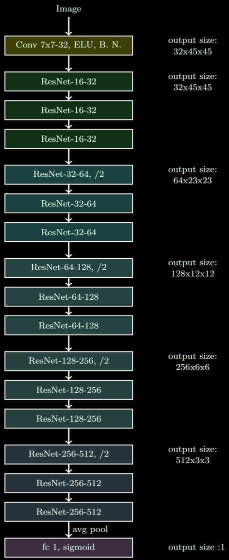

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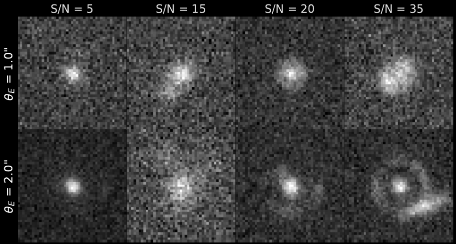

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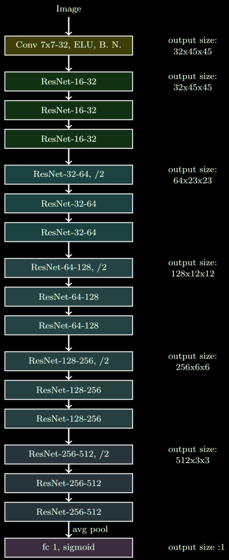

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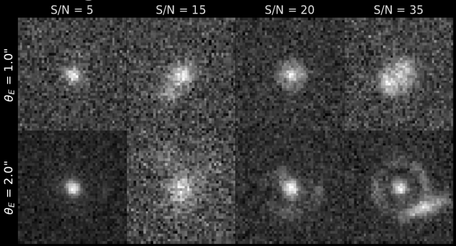
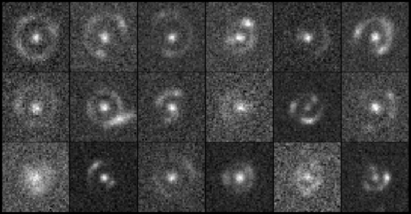
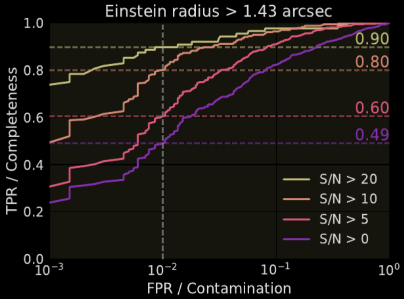


- Classification of 45x45 images in 350 μs $\implies$ 9 hours to classify a sample of 10^8 lens candidates on a single GPU (Nvidia Titan X)

performance on simulations



Highest probability lenses



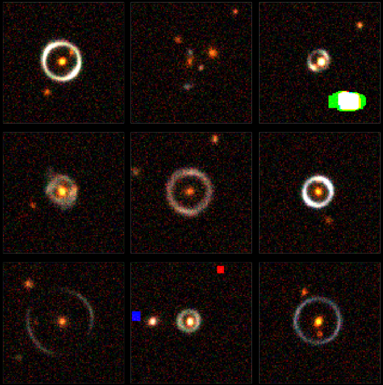
$$\text{True Positive Rate} = \frac{TP}{TP + FN}$$

$$\text{False Positive Rate} = \frac{FP}{FP + TN}$$

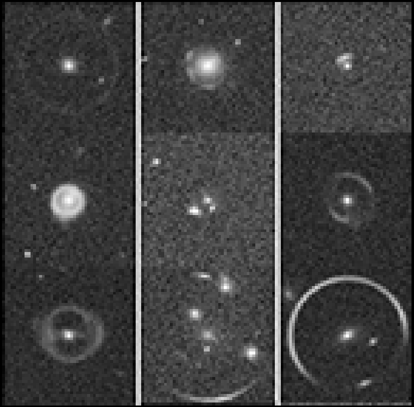
- TP: True Positives
- FN: False Negatives

- FP: False Positives
- TN: True Negatives

Euclid strong lens finding challenge

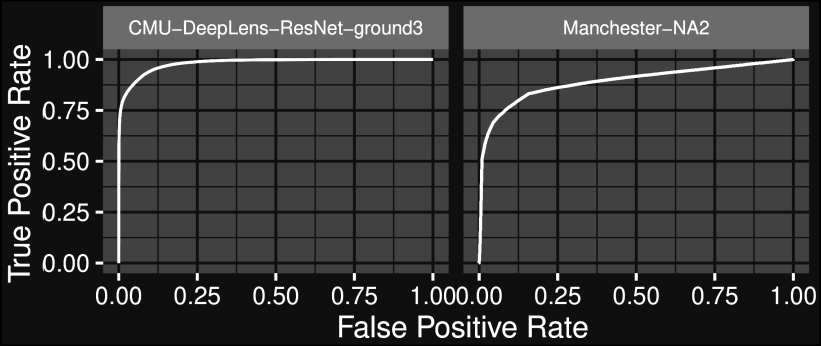


Ground based simulations



Space based simulations

Euclid strong lens finding challenge



- `CMU DeepLens` wins over 24 other methods (including other CNN methods) in space and ground challenge.
- Significantly outperforms human classification accuracy.

outlook for LSST

- Automated lens finder faster and more reliable than human volunteers

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- Rethink the pipeline infrastructure if there is no need for visual inspection

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- Deep Learning model is only as good as its training data
  $\Longrightarrow$ Need realistic simulations

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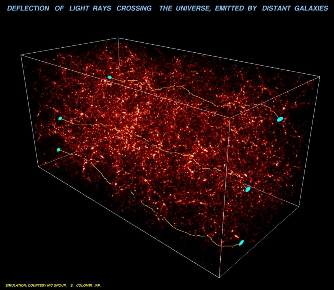
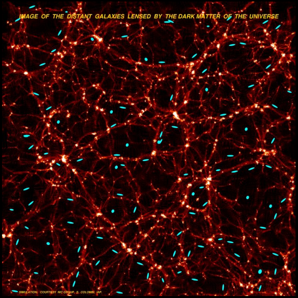
Honorable mentions:

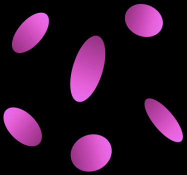
- Classification of time series using Deep Recurrent Neural networks
- Estimation of galaxy redshifts from multi-band images with residual networks

Deep Generative Models for weak lensing systematics

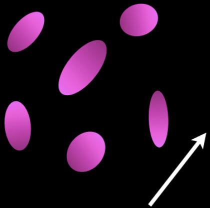
weak gravitational lensing







Galaxies randomly distributed

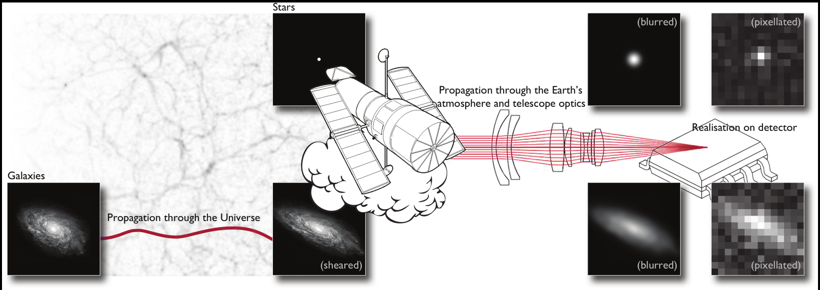


Slight alignment

$\epsilon = \epsilon_i + \gamma$ with $< \epsilon_i >= 0$

$\Longrightarrow \quad < \epsilon >= \gamma$

a very delicate measurement



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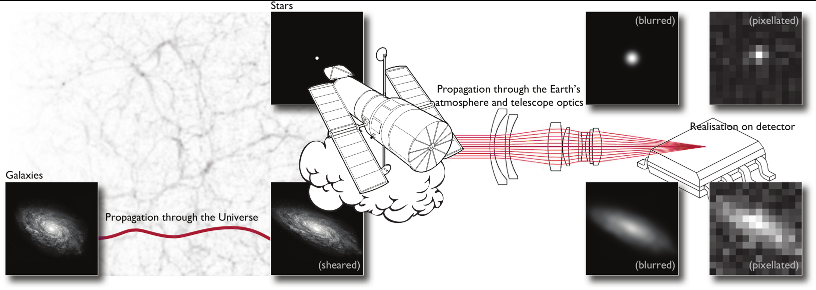

Shape measurement biases

$$< e > \quad = \quad (1+m)\,\gamma + c$$

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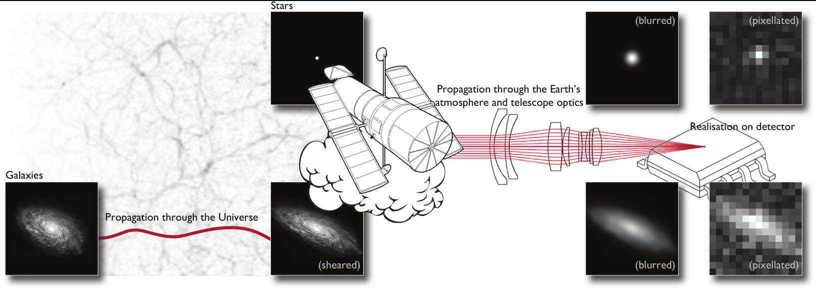

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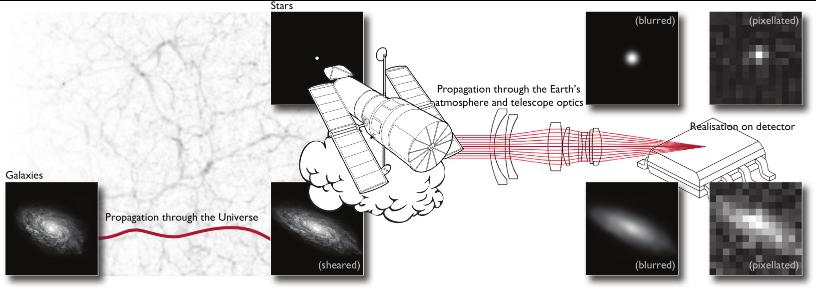

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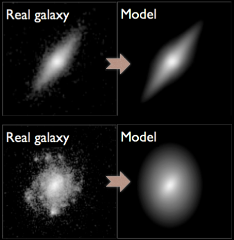
$$< e > \quad = \quad (1 + m)\, \gamma + c$$

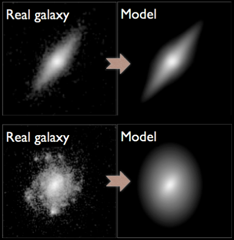
- Can be calibrated on image simulations
- How complex do the simulations need to be ?

impact of galaxy morphology



Mandelbaum et al. (2013)

impact of galaxy morphology



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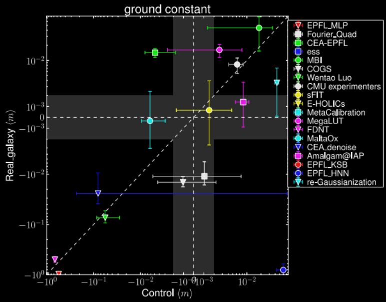

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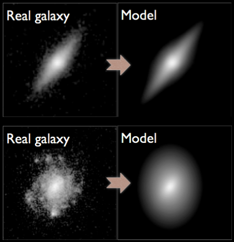

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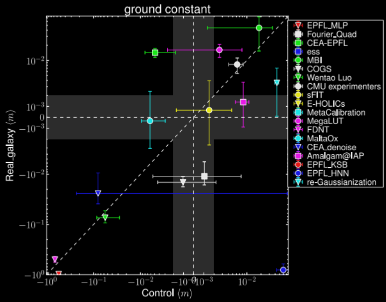

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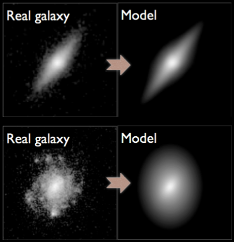
The need for data-driven generative models

There can be two situations:

- Lack or inadequacy of physical model

impact of galaxy morphology



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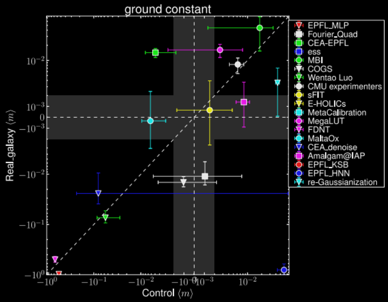

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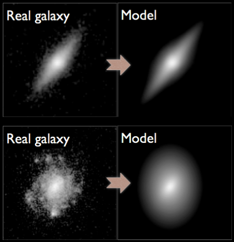
impact of galaxy morphology



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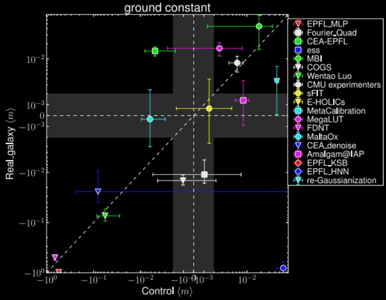

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$\Longrightarrow$ Learn a model for the signal from the data itself

the evolution of deep generative models

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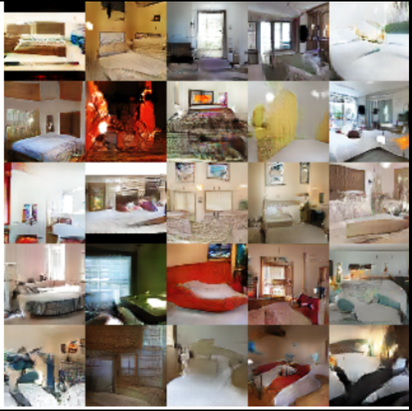
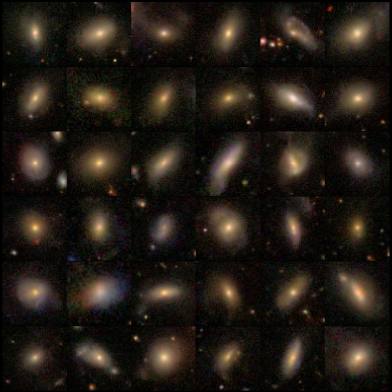
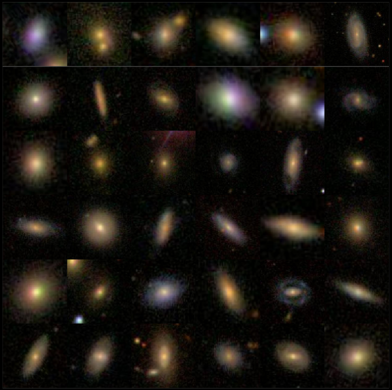


visual Turing test





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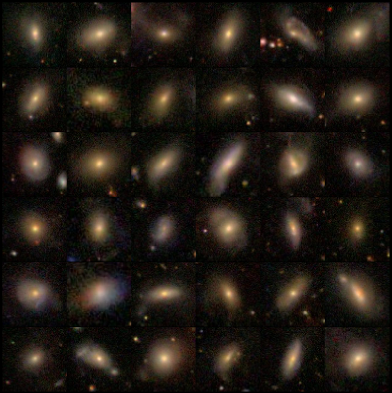
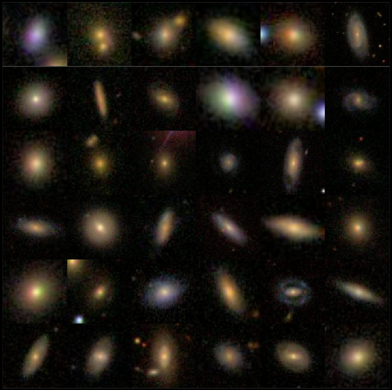
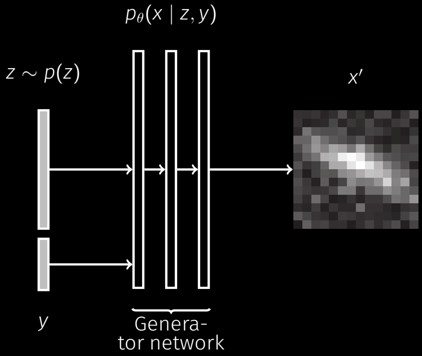


Mock - PixelCNN



Real - SDSS

Conditional Variational AutoEncoder (CVAE)



Ravanbakhsh, Lanusse et al. (2017)

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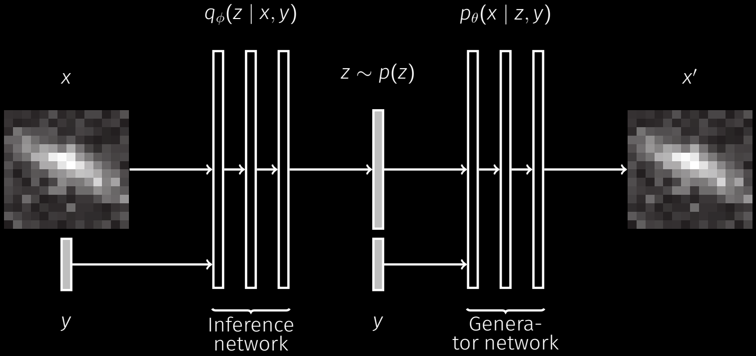

Ravanbakhsh, **Lanusse** et al. (2017)

$$\log(p_\theta(x \mid y)) \geq -\underbrace{\mathbb{D}_{\mathrm{KL}}(q_\phi(z \mid x, y) \| p_\theta(z \mid y))}_{\text{Code regularisation}} + \underbrace{\mathbb{E}_{z \sim q_\phi(\cdot \mid x, y)}[\log p_\theta(x \mid z, y)]}_{\text{Reconstruction error}}$$

modeling galaxy images from the Hubble Space Telescope

Training parameters

- Training set: postage stamps from COSMOS HST/ACS survey
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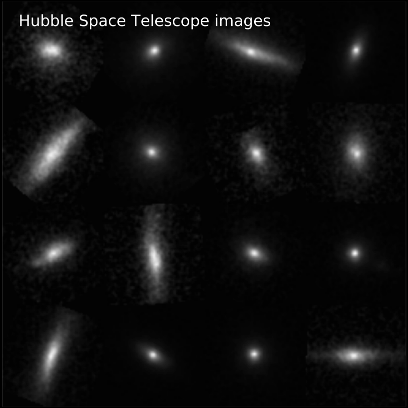
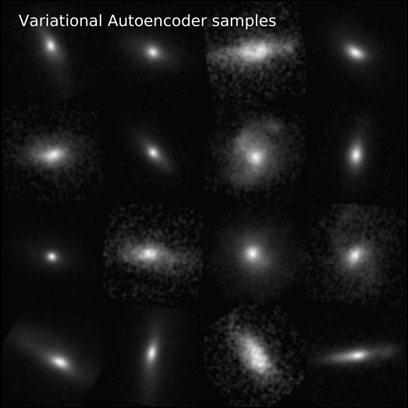
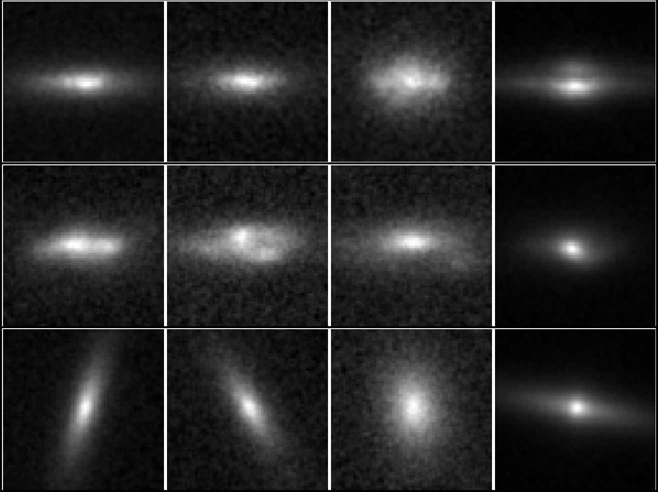


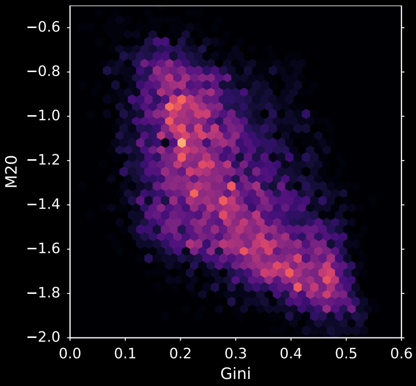


morphological statistics

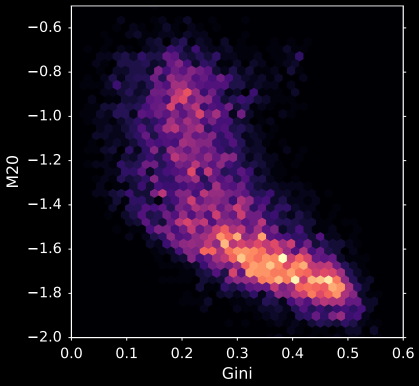


From top to bottom: Real COSMOS galaxies, CVAE samples, Parametric fits

morphological statistics

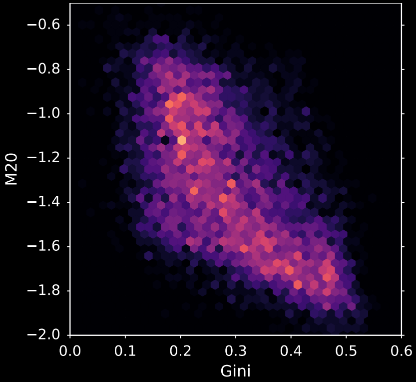


COSMOS images

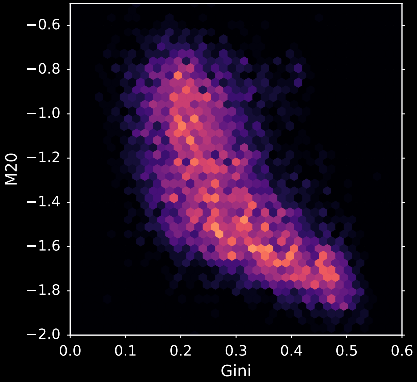


Parametric model

morphological statistics



COSMOS images



CVAE samples

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Honorable mention:

- Modeling galaxy properties in Nbody simulations using deep generative networks on graphs

conclusion

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Acknowledgment

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