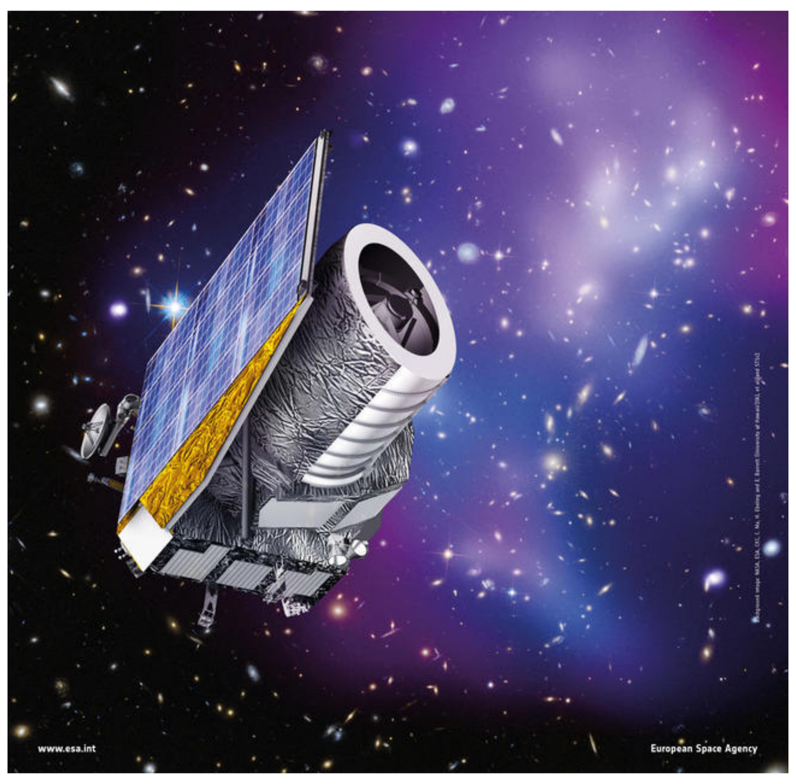
# Galaxy Image Simulation Using Progressive GANs


Mohamad Dia,[1] Elodie Savary,[2] Martin Melchior,[1] Frederic Courbin[2]

[1]FHNW, Switzerland - [2]EPFL, Switzerland


## 1. Euclid Space Mission

- Space-based astronomy and astrophysics telescope:
  - Understand the accelerated expansion of the universe.
  - Investigate dark matter and dark energy.
  - Silicon Carbide1.2m mirror telescope.
  - Extragalactic sky coverage with 15000 square degrees.
  - Visible and near-infrared imaging.
  - Featuring more than 10 billion sources, 10's of Petabytes.



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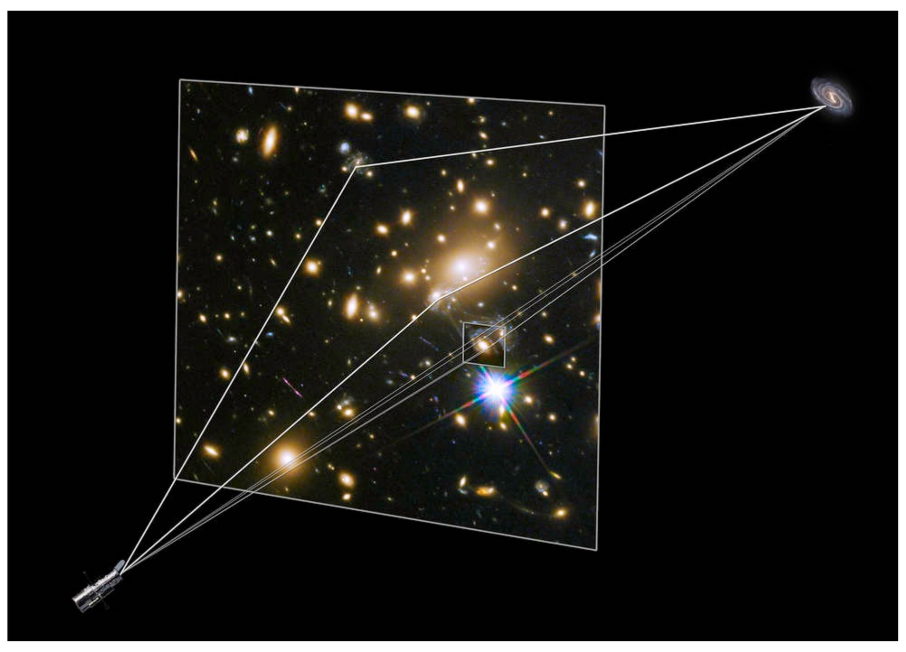
  - Scientific analysis by the Euclid Consortium that includes more than 1400 scientists.
  - Scheduled for launch in June 2022 by ESA.

## 2. Gravitational Lensing

- Relativistic curvature in space-time due to the presence of matter.



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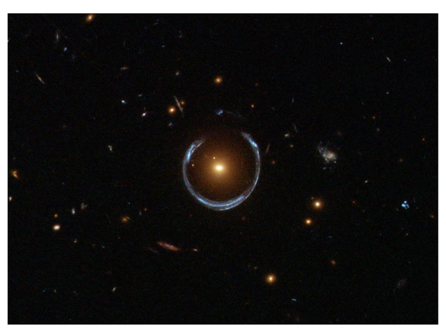
  - Deflection of light coming from distant galaxy (source) by the massive intermediate object (lens).
  - The lensing effect varies with the distance, alignment, mass, and shape of the source and lens.

- Strong gravitational lensing:
  - Duplicate images, arcs, Eistein rings.



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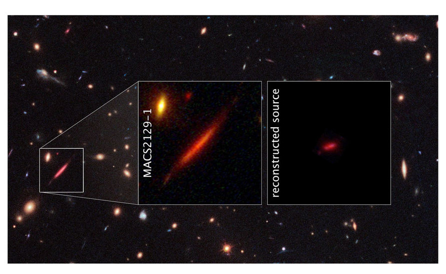
- Weak gravitational lensing:
  - Shear (tangential stretch) and convergence (magnification).



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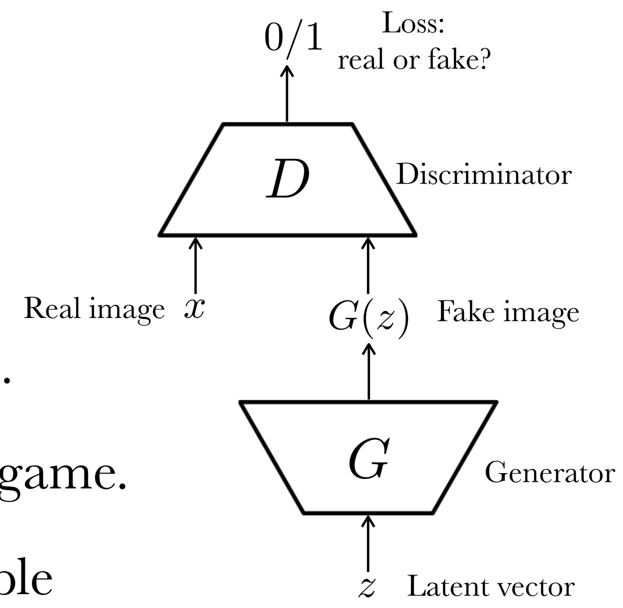
## 3. Simulated Images of Galaxies

- Calibration and bias detection for shape measurement algorithms (weak lensing) require simulated images with known ground truth lensing.
- Training neural network classifiers (e.g. CNN) to detect strong lenses requires simulated images in order to mitigate class imbalance in the current datasets and avoid false-positive type of error.
- Model-driven v.s. data-driven simulation:
  - Fitting an analytic/parametric profiles using simple model is not able to generate complex morphologies.
  - Generative networks from machine learning can learn the data distribution and generate more realistic images (e.g. VAE, GAN).

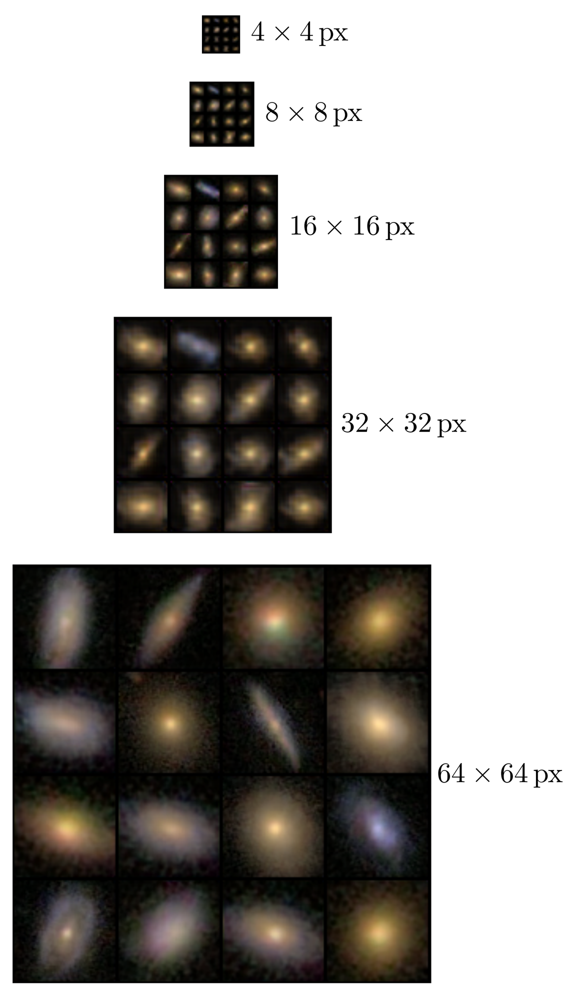
## 4. Generative Adversarial Networks

- Two competing neural networks:
  - Generator samples simulated (fake) images from random latent space.
  - Discriminator plays the role of adaptive loss.
  - Joint optimization in a two-player minimax game.
  - Standard version is hard to train with unstable behaviour, convergence issues, mode collapse, etc…




## 5. Progressive Training and Wasserstein Loss

- Progressive increase of the resolution:
  - Start with low resolution (easy to train) and keep on growing both networks (G & D) by adding layers synchronously and smoothly.
  - Convolutional layers with mirror design.
  - More stable and faster training.
  - Wasserstein distance with gradient penalty to mitigate vanishing gradient.
  - Weight scaling and pixel-wise normalization to avoid unhealthy competition between G and D.




| Generator | Output Dimensions |
|---|---|
| Latent Space | |
| Input latent vector | $1 \times 1 \times 256$ |
| Conv $4 \times 4$ | $4 \times 4 \times 256$ |
| Conv $3 \times 3$ | $4 \times 4 \times 256$ |
| $1^{st}$ Progress | |
| Conv $3 \times 3$ | $8 \times 8 \times 128$ |
| Conv $3 \times 3$ | $8 \times 8 \times 128$ |
| $2^{nd}$ Progress | |
| Conv $3 \times 3$ | $16 \times 16 \times 64$ |
| Conv $3 \times 3$ | $16 \times 16 \times 64$ |
| $3^{rd}$ Progress | |
| Conv $3 \times 3$ | $32 \times 32 \times 32$ |
| Conv $3 \times 3$ | $32 \times 32 \times 32$ |
| $4^{th}$ Progress | |
| Conv $3 \times 3$ | $64 \times 64 \times 16$ |
| Conv $3 \times 3$ | $64 \times 64 \times 16$ |
| RGB Extraction | |
| Conv $1 \times 1$ | $64 \times 64 \times 3$ |

| Discriminator | Output Dimensions |
|---|---|
| RGB Reading | |
| Input image | $64 \times 64 \times 3$ |
| Conv $1 \times 1$ | $64 \times 64 \times 16$ |
| $4^{th}$ Progress | |
| Conv $3 \times 3$ | $64 \times 64 \times 16$ |
| Conv $3 \times 3$ | $64 \times 64 \times 32$ |
| $3^{rd}$ Progress | |
| Conv $3 \times 3$ | $32 \times 32 \times 32$ |
| Conv $3 \times 3$ | $32 \times 32 \times 64$ |
| $2^{nd}$ Progress | |
| Conv $3 \times 3$ | $16 \times 16 \times 64$ |
| Conv $3 \times 3$ | $16 \times 16 \times 128$ |
| $1^{st}$ Progress | |
| Conv $3 \times 3$ | $8 \times 8 \times 128$ |
| Conv $3 \times 3$ | $8 \times 8 \times 256$ |
| Cost Calculation | |
| Conv $3 \times 3$ | $4 \times 4 \times 256$ |
| Conv $4 \times 4$ | $1 \times 1 \times 256$ |
| Conv $1 \times 1$ | $1 \times 1 \times 1$ |

## 6. Extensions

- Exploiting side information in a supervised or semi-supervised fashion:
  - Use class labels when available through class conditioning.
  - Feed class labels to both G and D (conditional generation and conditional discrimination).
  - Feed class labels only to G (conditional generation) and use D for classification (discrimination with auxiliary classification).
  - Improve the image quality and increase the diversity.
  - Control the generation task.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