

# Encoding large scale cosmological structure with Generative Adversarial Networks

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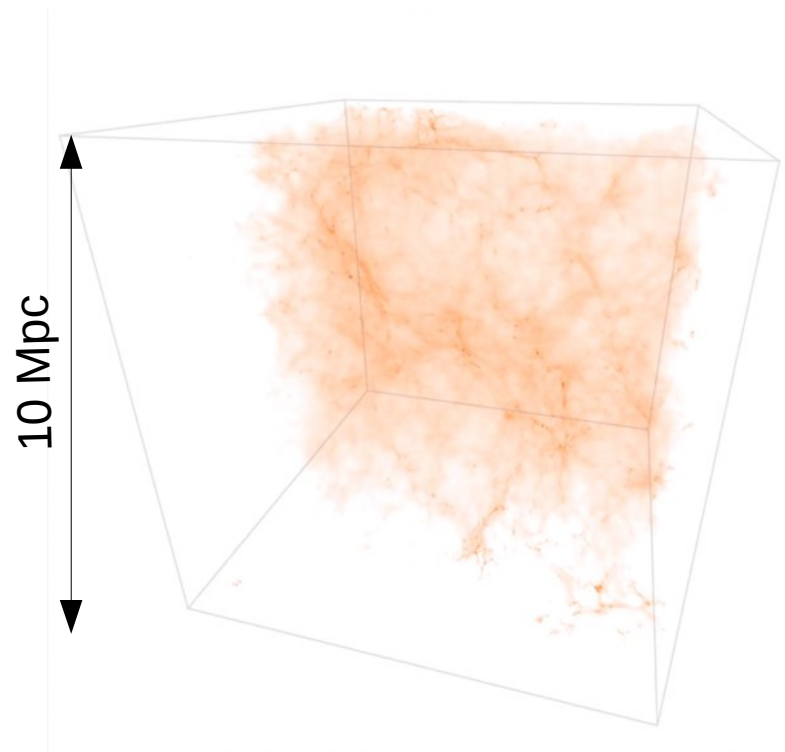
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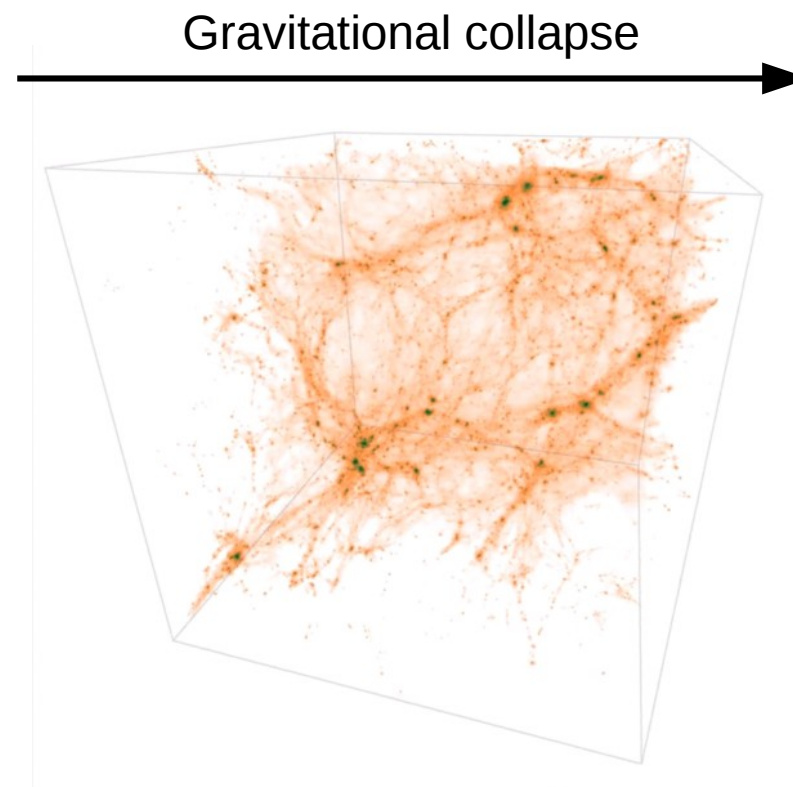
# The Cosmic Web and Large Scale Structures

Initial Conditions :  
quasi-homogeneous  
matter distribution



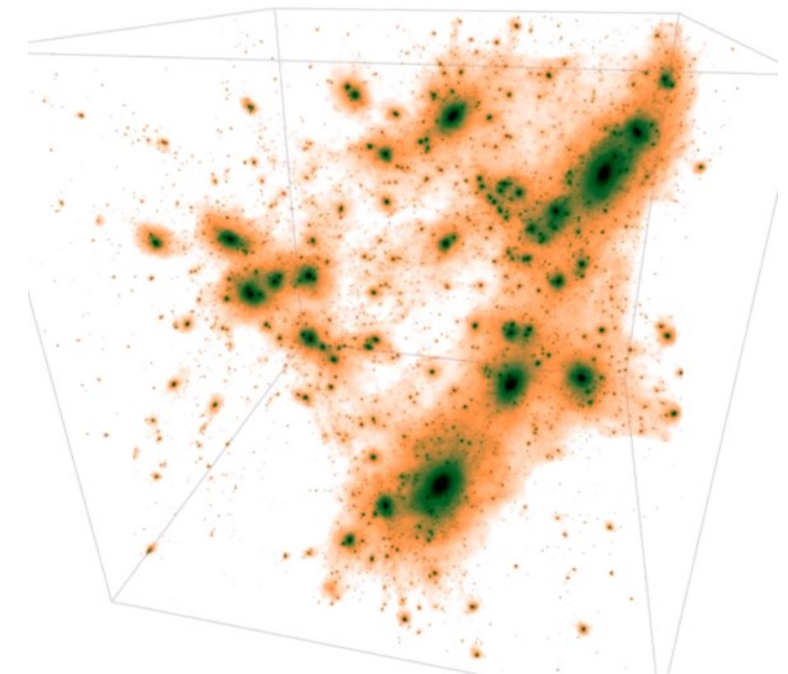
Redshift:  $z = 10$   
Time since  
Big Bang: 0.5 billion years

Structures form through  
gravitational collapse



$z = 5$   
0.9 billion years

Current state :  
virialized overdense  
halos have formed

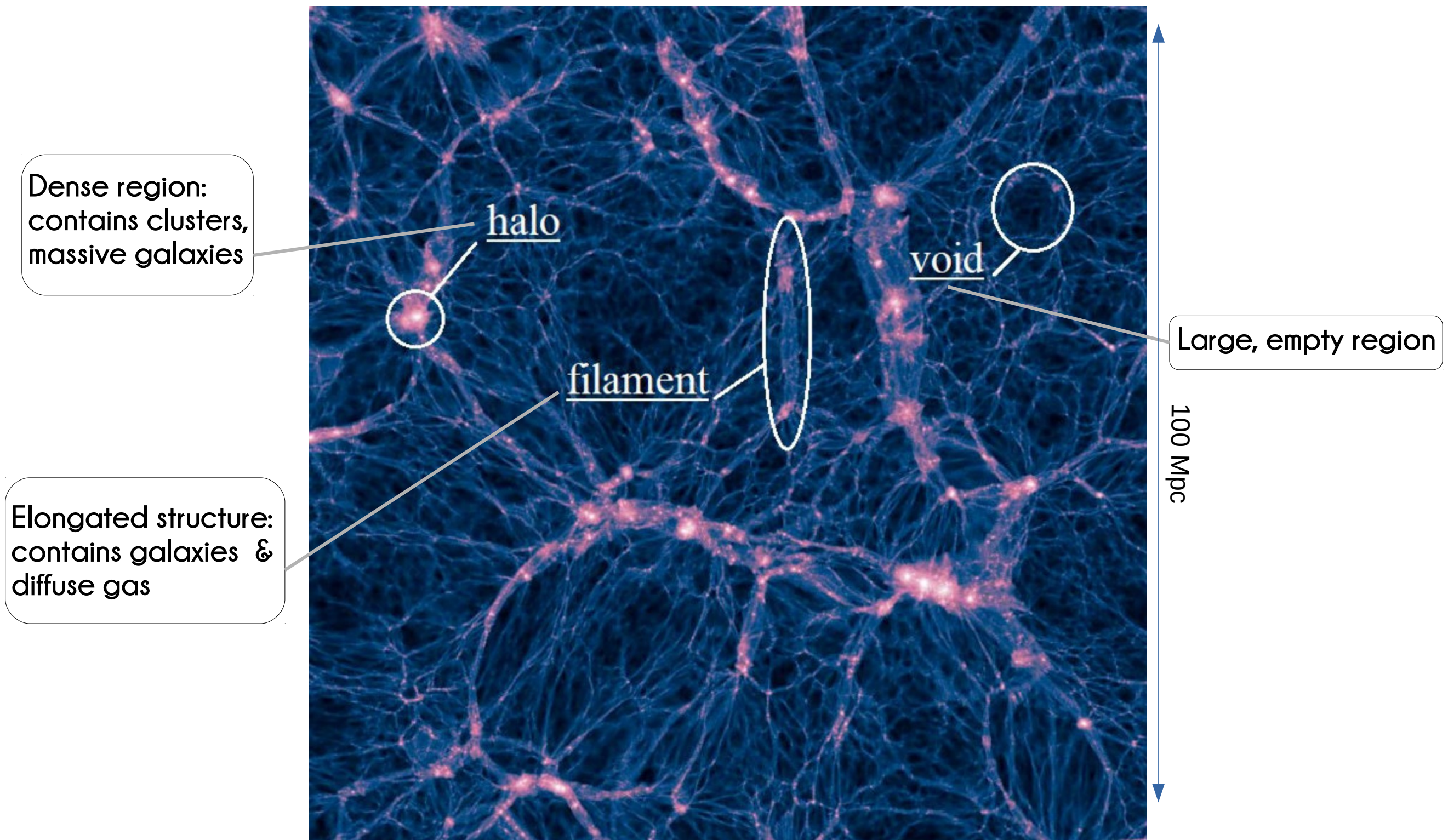


$z = 0$   
13.8 billion years

Illustris Simulations -  $(10 \text{ Mpc})^3$  snapshot Vogelsberger *et al*, 2014



# The Cosmic Web and Large Scale Structures

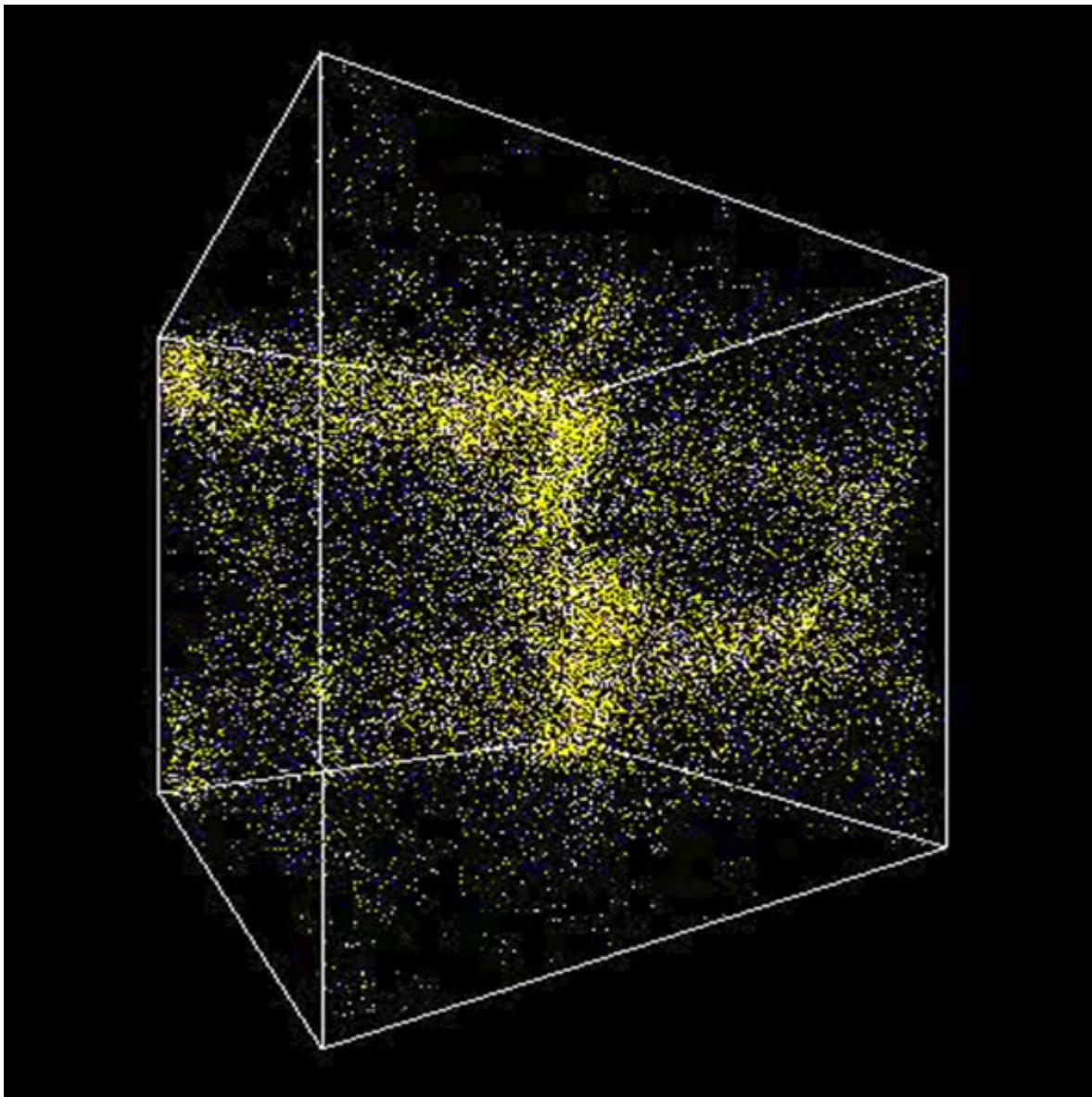


Illustris simulations –  $(100\text{Mpc})^2$  - Vogelsberger *et al*, 2014



# Simulations - a costly necessity

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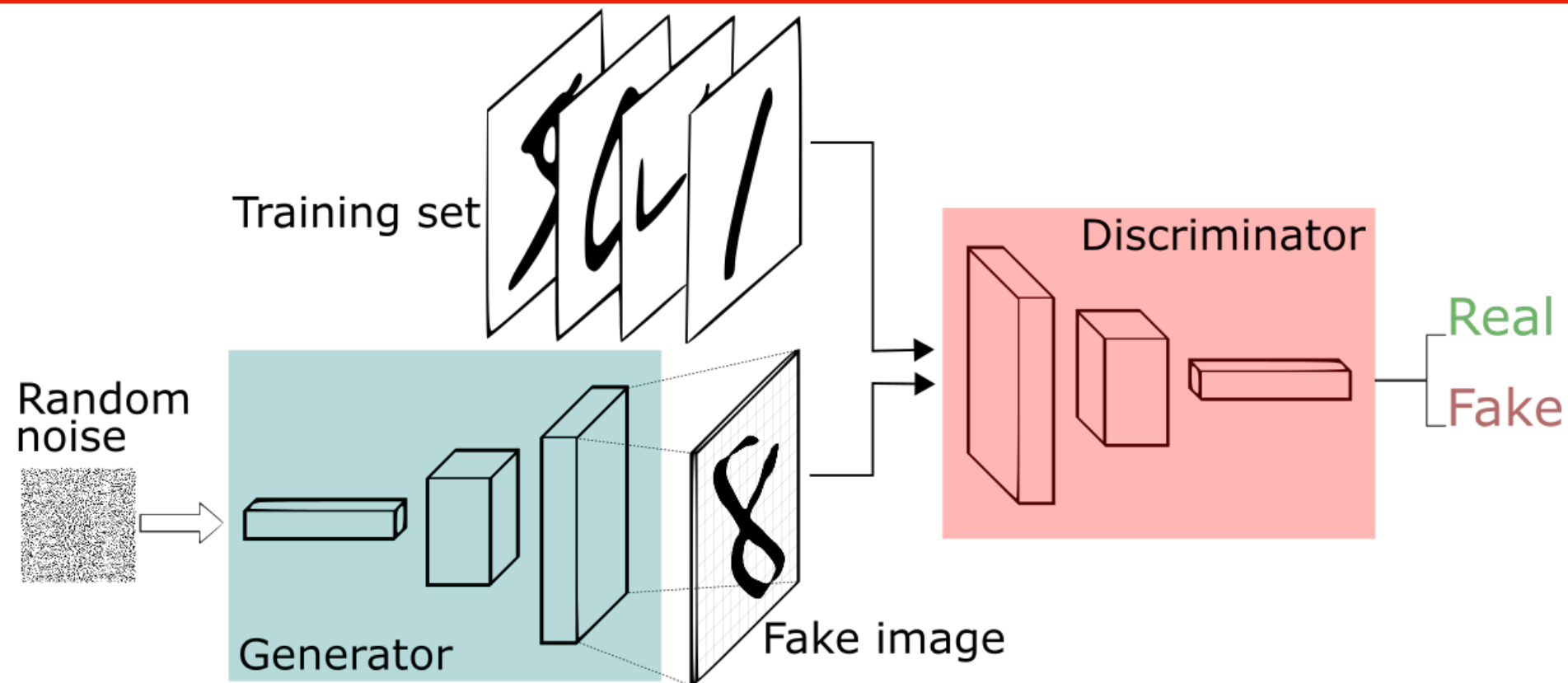
- Simulations → an essential tool to compute the non-linear structuration of matter
- Typically N-body simulations with  $10^6$ - $10^{10}$  particles

A few examples:

- Gravitation only: Millenium, 250 000 CPU hours, 28 days runtime
- Hydrodynamical: Illustris, 19 million CPU hours, 3 months runtime
- Tradeoff between large structures and fine detail

- We build and train a network for fast generation of simulation-like datasets
- We make use of this trained network to construct a simple autoencoder (AE) as a first step towards building a predictive model

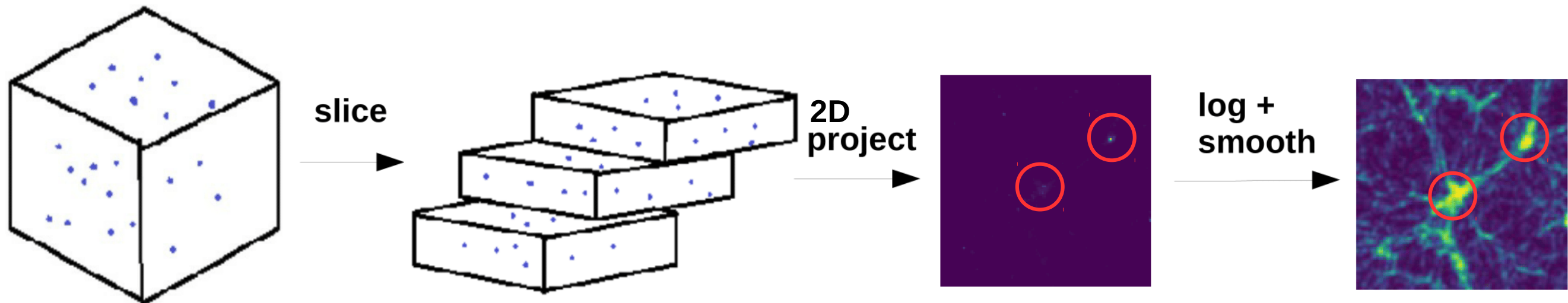
# GANs\* in a nutshell



- GAN : Generative Adversarial Network
- Two competing networks :
  - the **generator**, generates new images
  - the **discriminator**, outputs the certainty (0 to 1) with which it believes an image is from the training set (rather than from the generator)
- A simple loss function!

$$L_D = -\frac{1}{2}\mathbb{E}(\log D(I_R) + \log(1 - D(I_G)))$$

## 2 types of datasets : 3D & 2D simulations



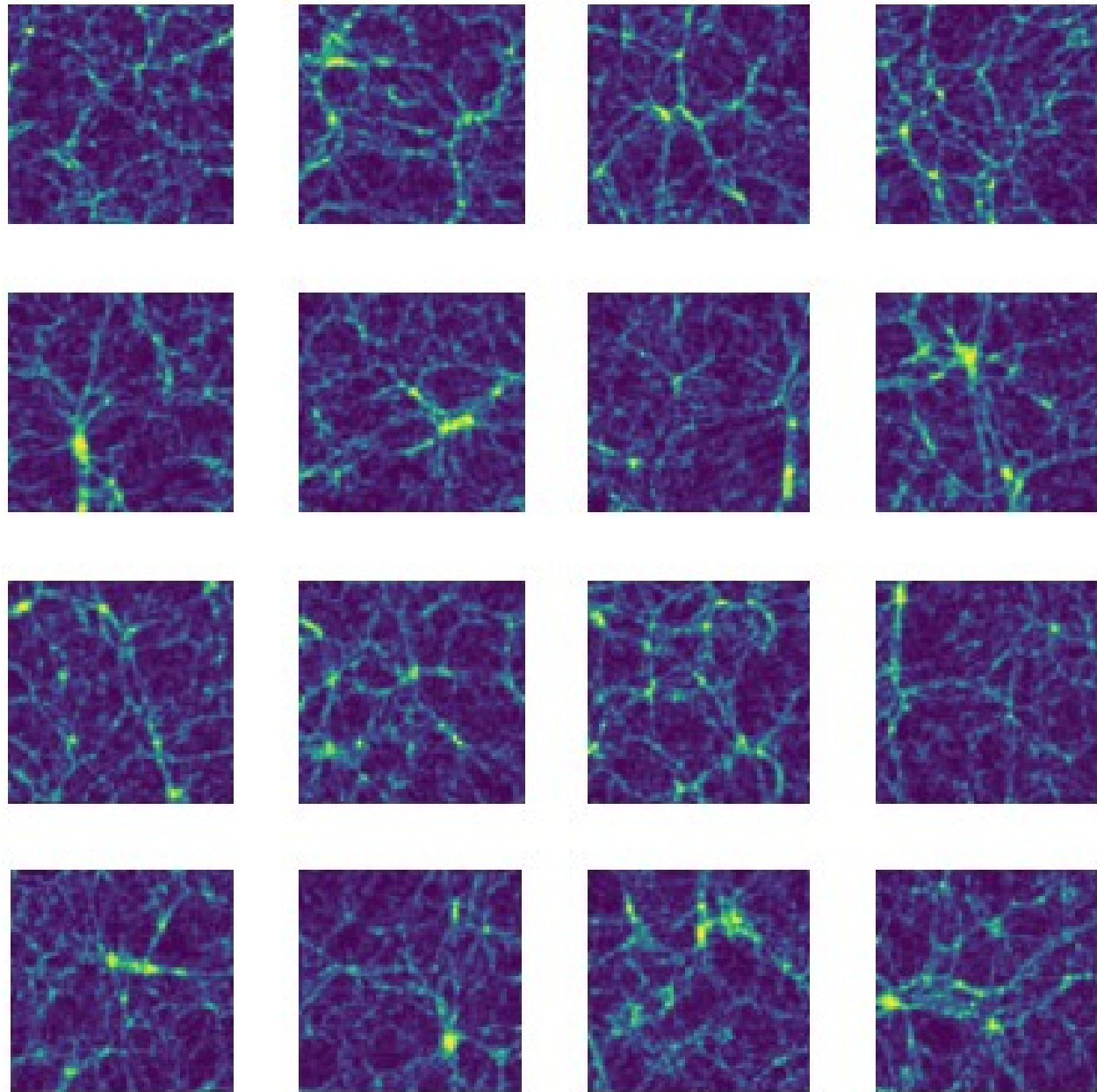
- 3D simulations :
  - Run with **GADGET2**
  - Box size  $(100 \text{ Mpc})^3$ ,  $(512)^3$  particles
  - Snapshot is divided into **slices**, from which we estimate a set of **2D log-density maps** (76 000 images, size  $(50 \text{ Mpc})^2$ ,  $128^2$  pixels ) after augmentation
- 2D simulations :
  - Run with a 2D particle-mesh N-body code \*
  - 1000 simulations, size  $(100 \text{ Mpc})^2$ ,  $512^2$  particles each
  - From them, estimate 2D log-density maps (76 000 images, size  $(50 \text{ Mpc})^2$ ,  $128^2$  pixels ) after augmentation

→ We show GAN results for 3D simulations

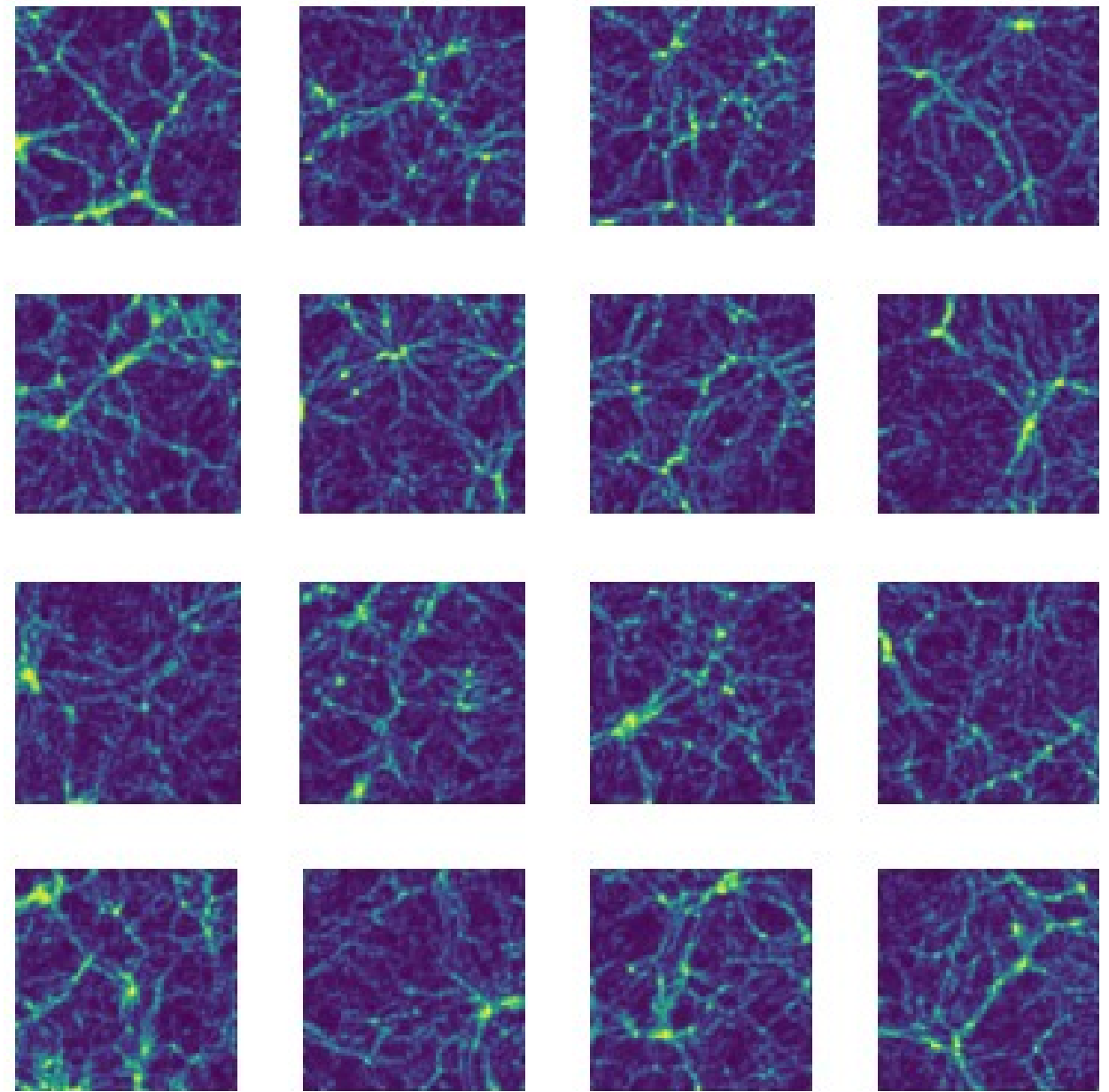
# Results – log density images from 3D simulation slices

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Simulation images (“true”)

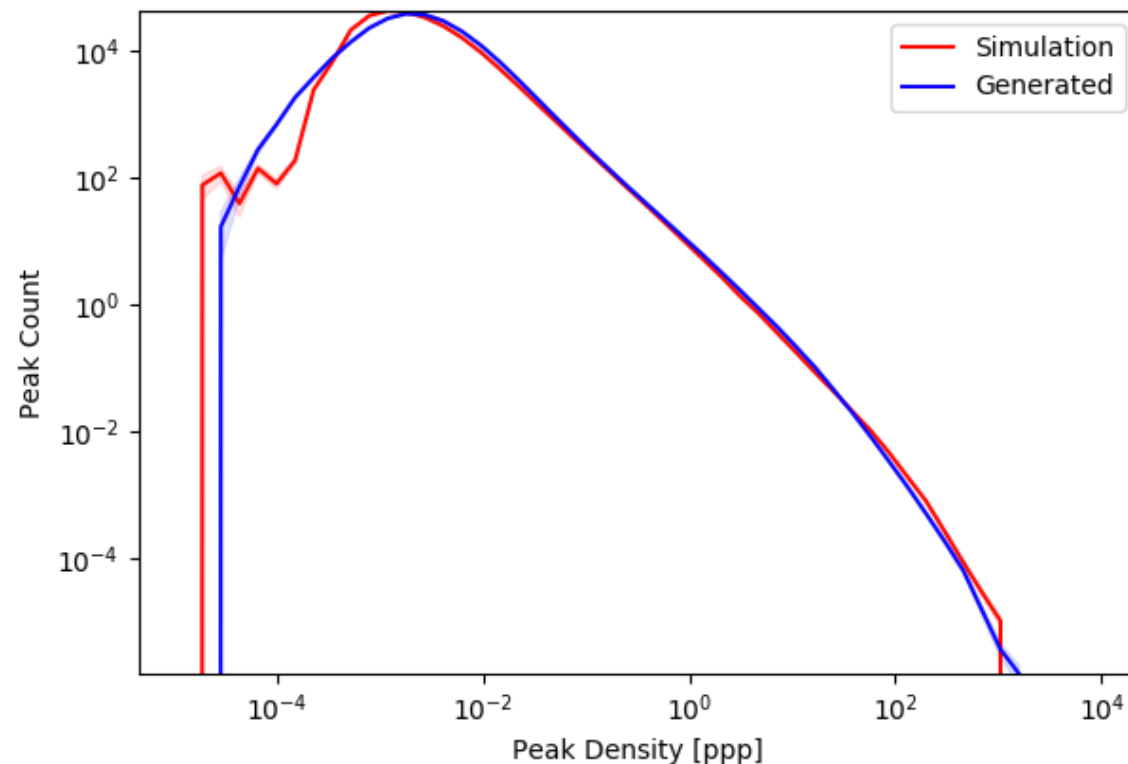
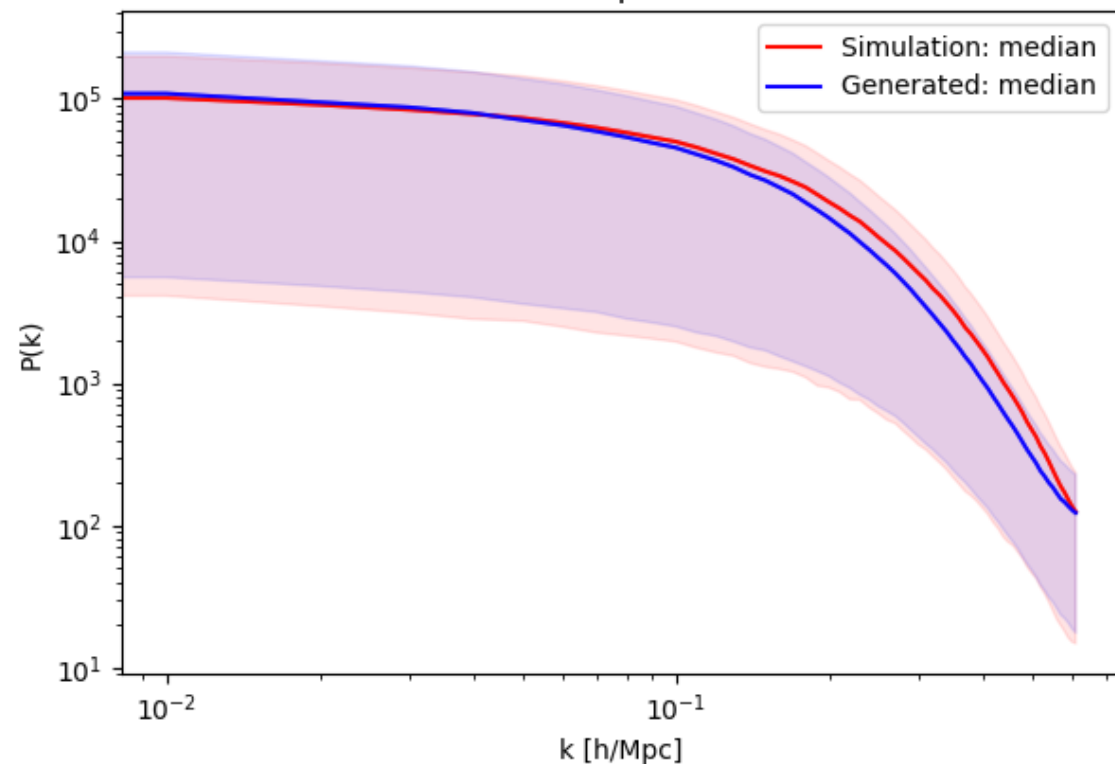
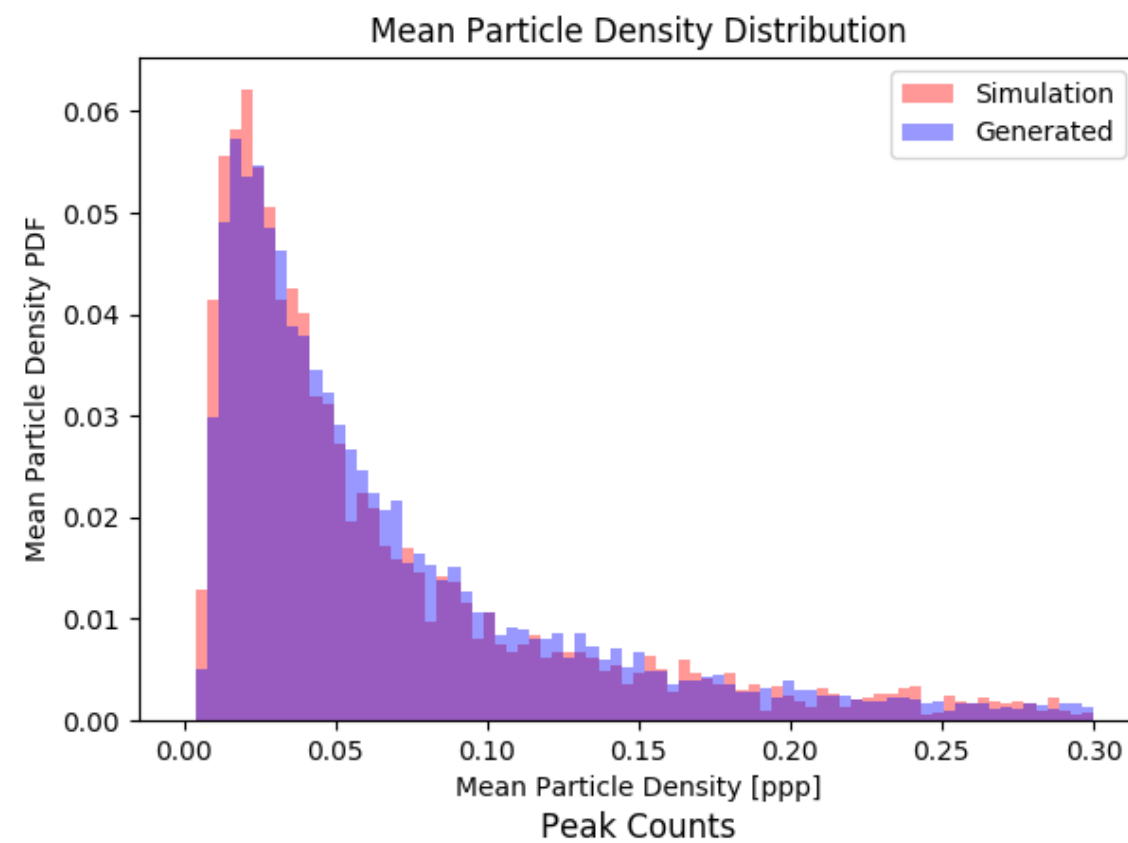
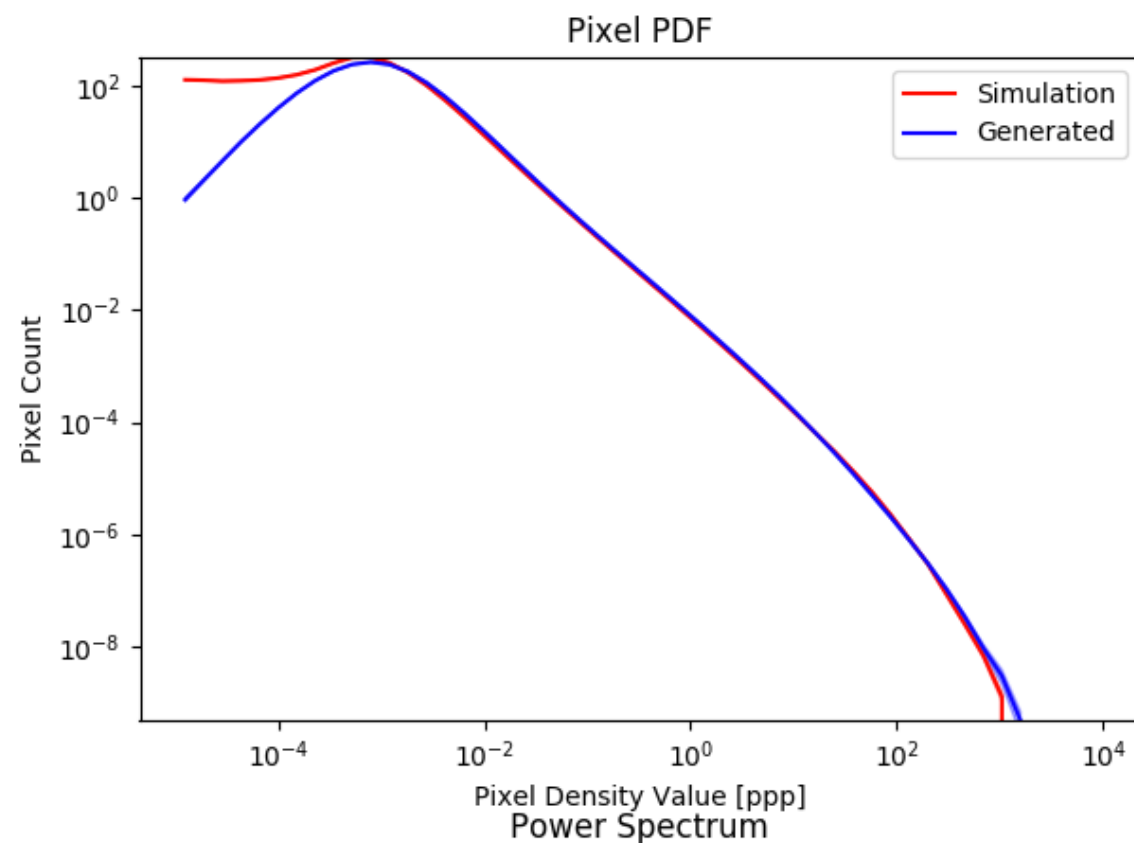


GAN images (“fake”)

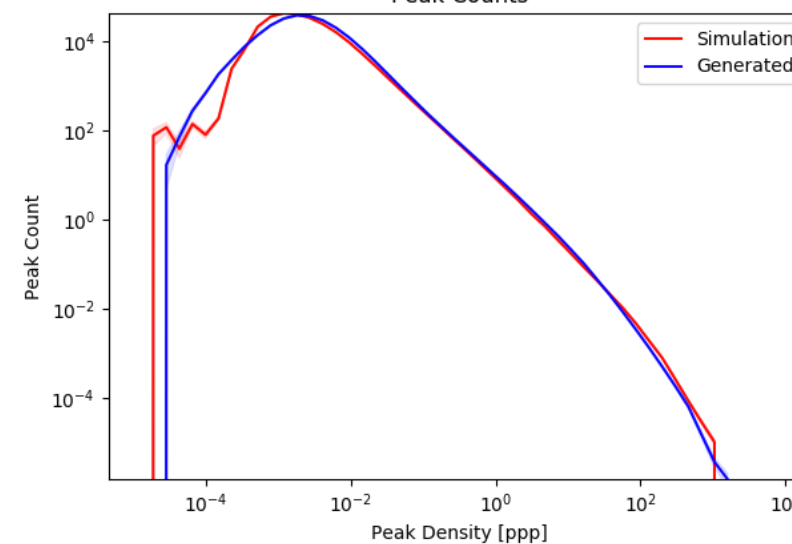
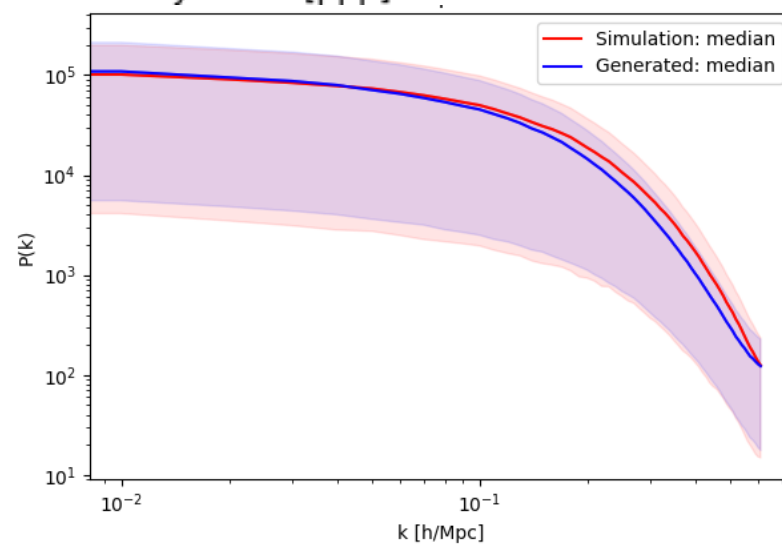
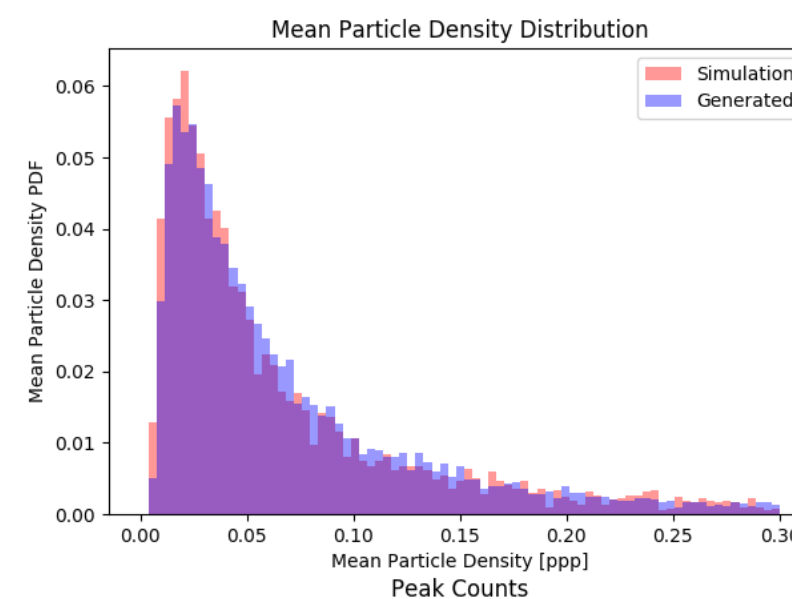
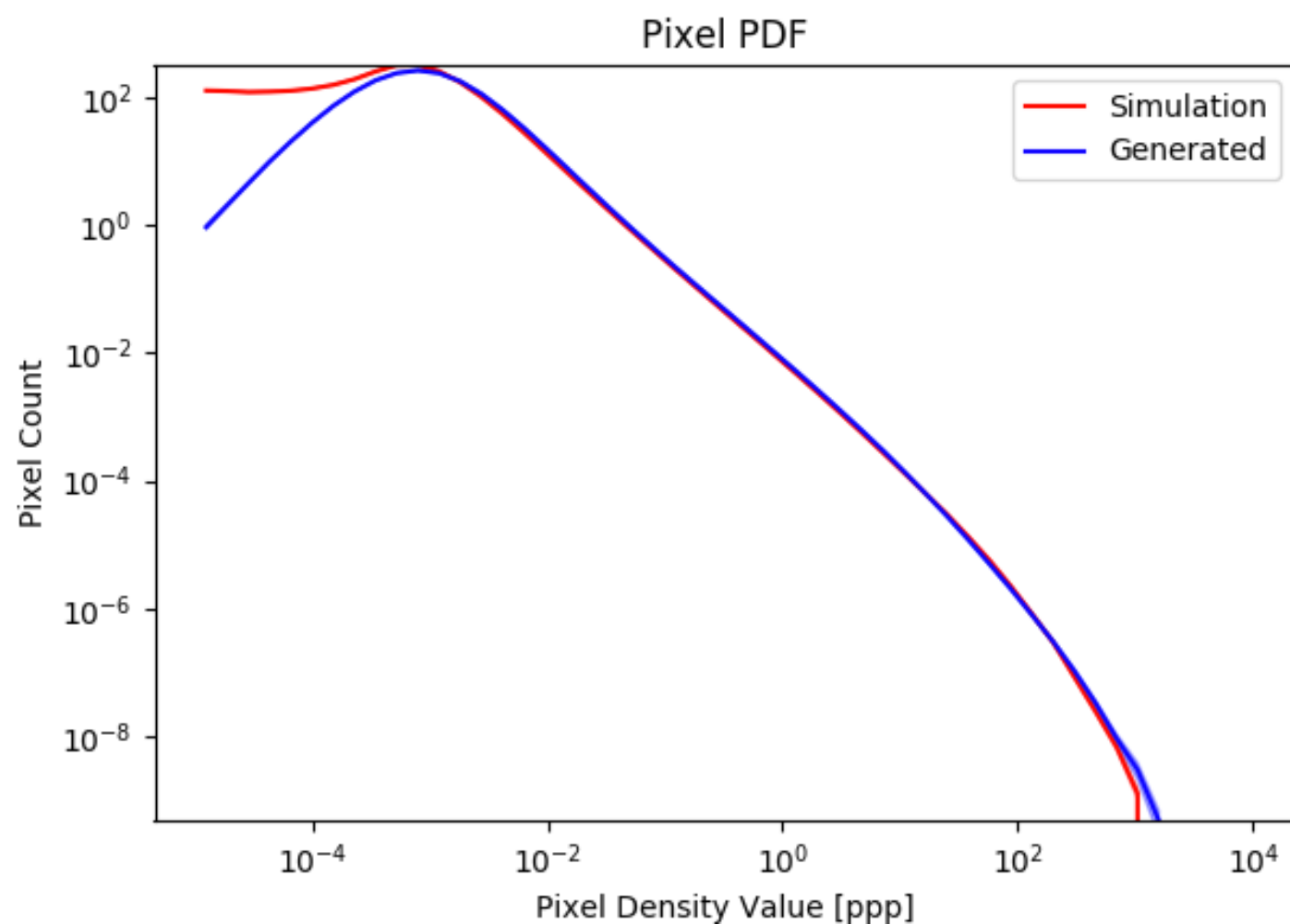




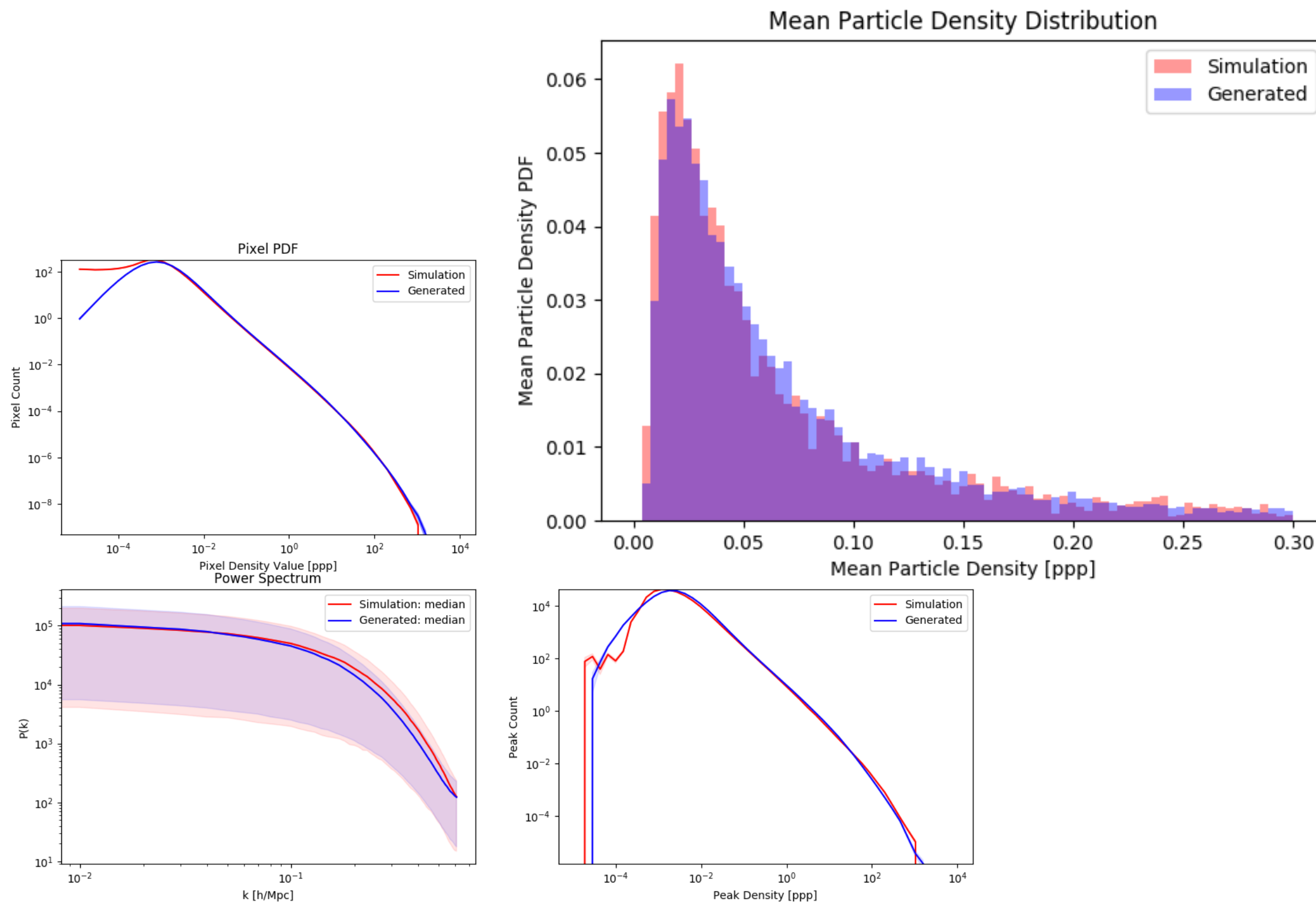
# Comparing simulated images & generated images



# Comparing simulated images & generated images

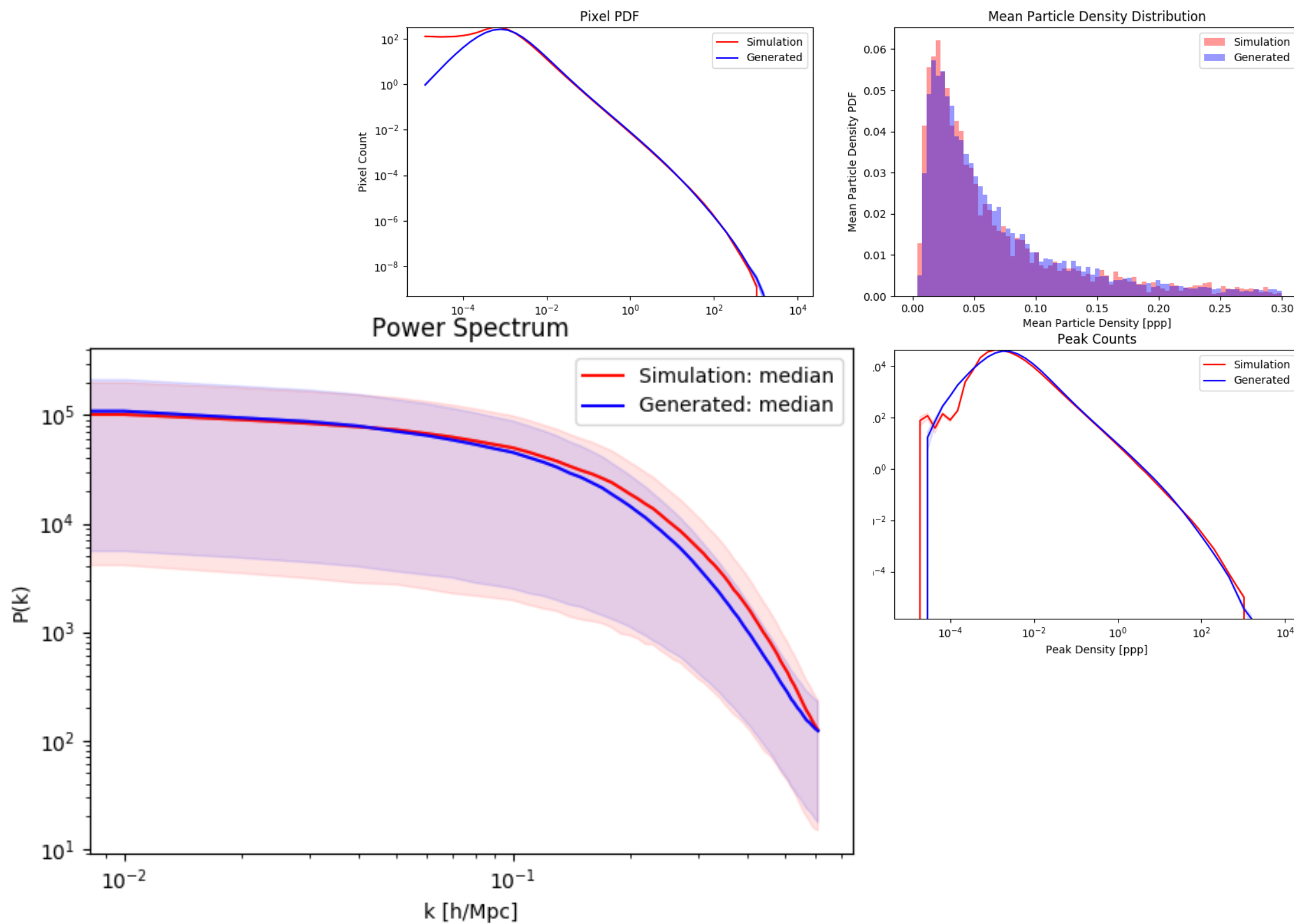


# Comparing simulated images & generated images

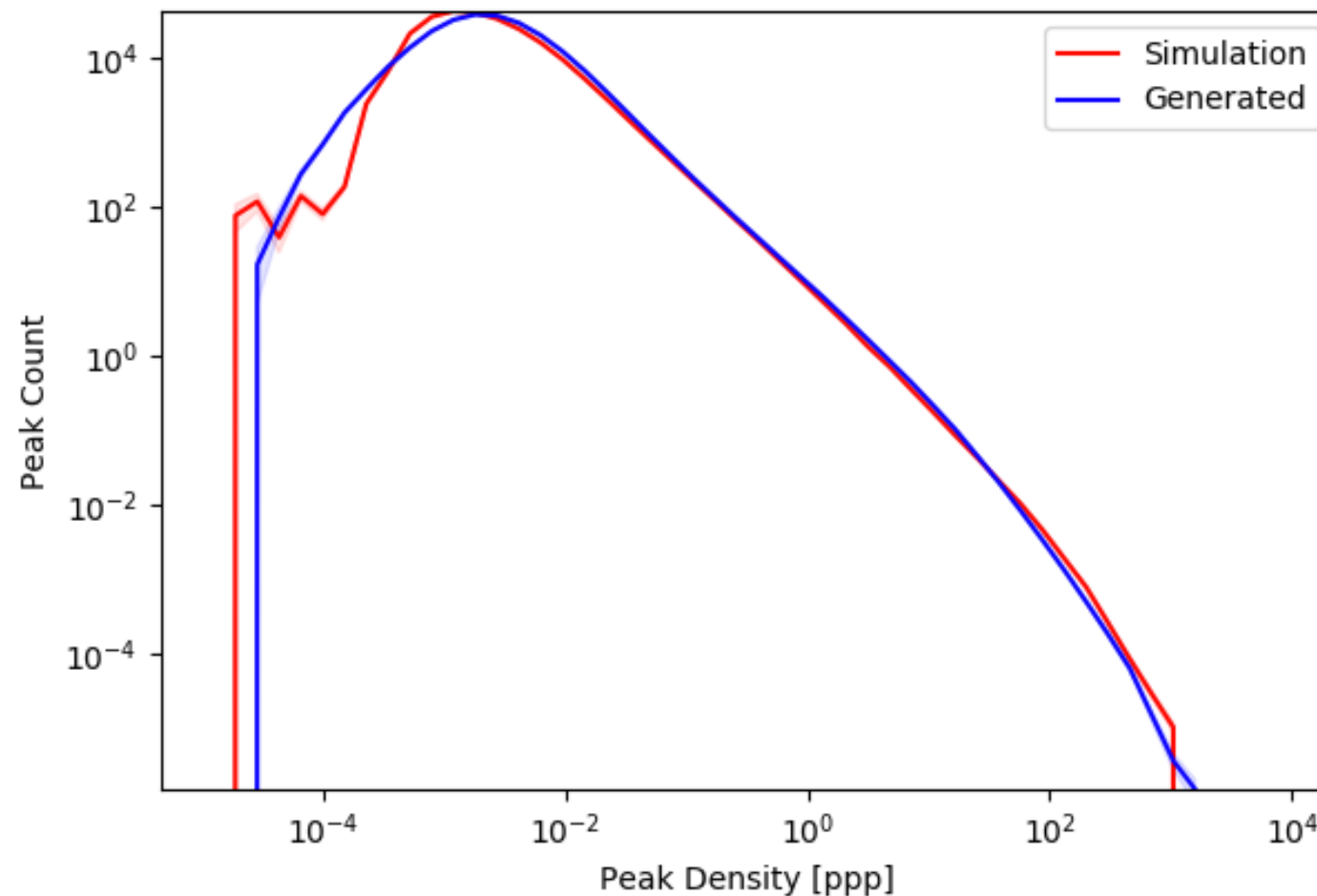
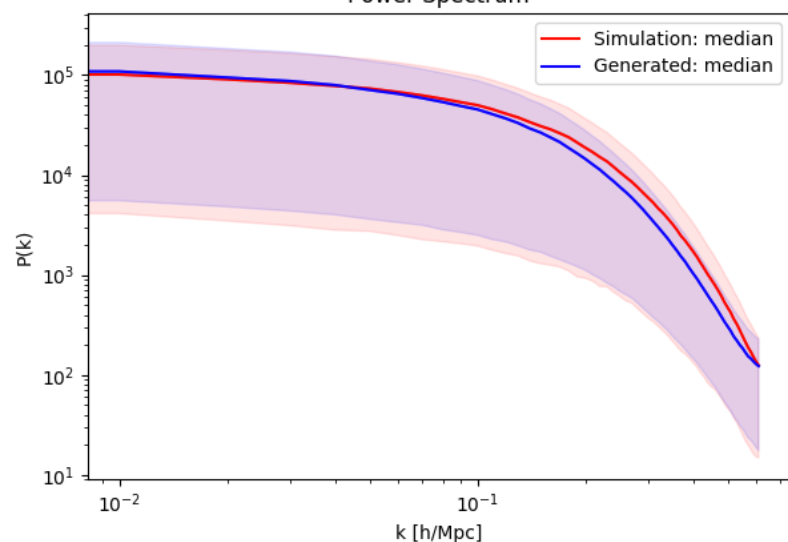
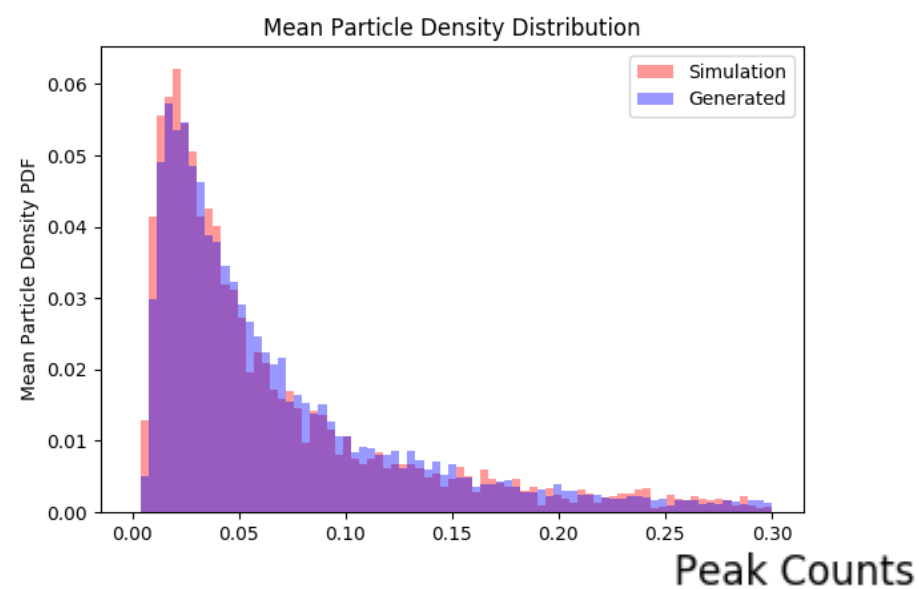
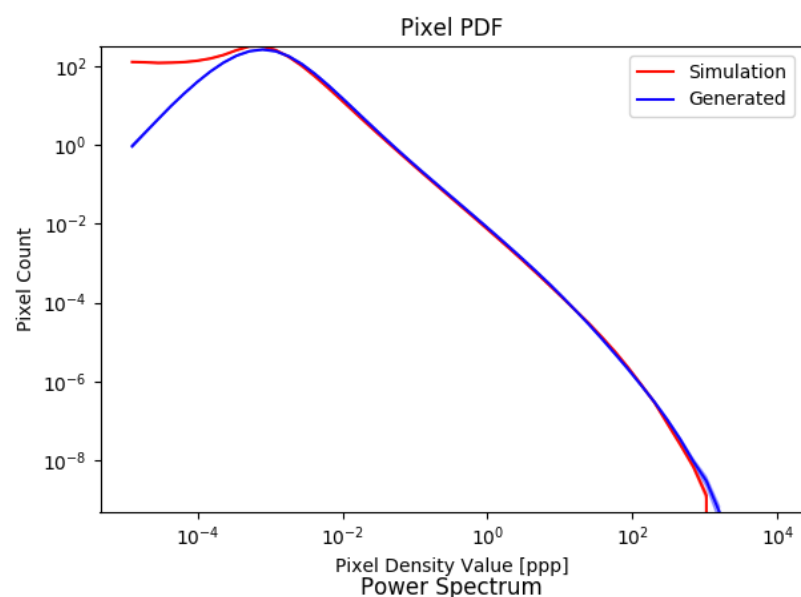




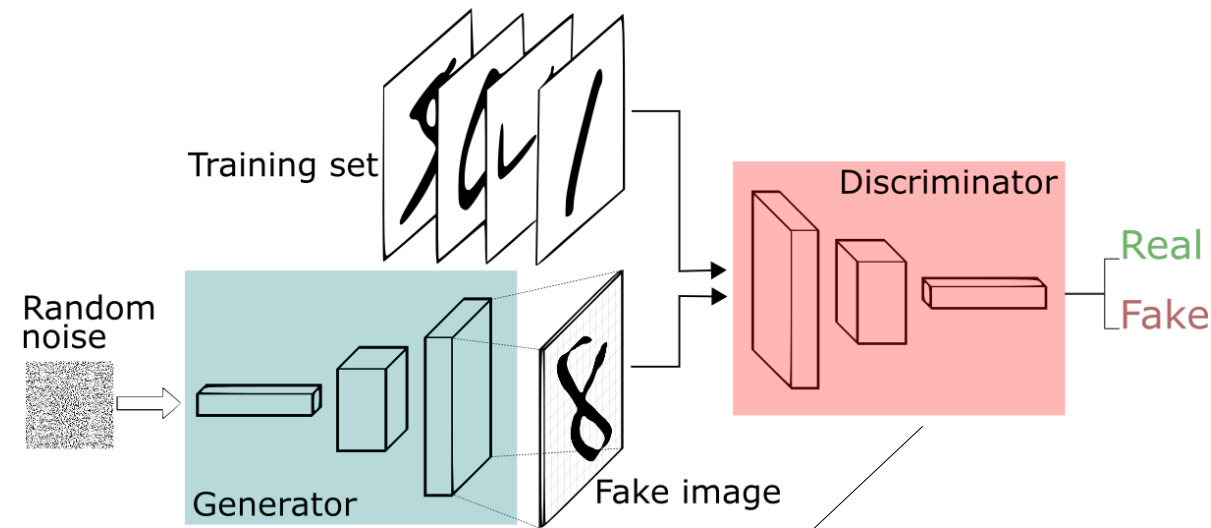
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# Comparing simulated images & generated images

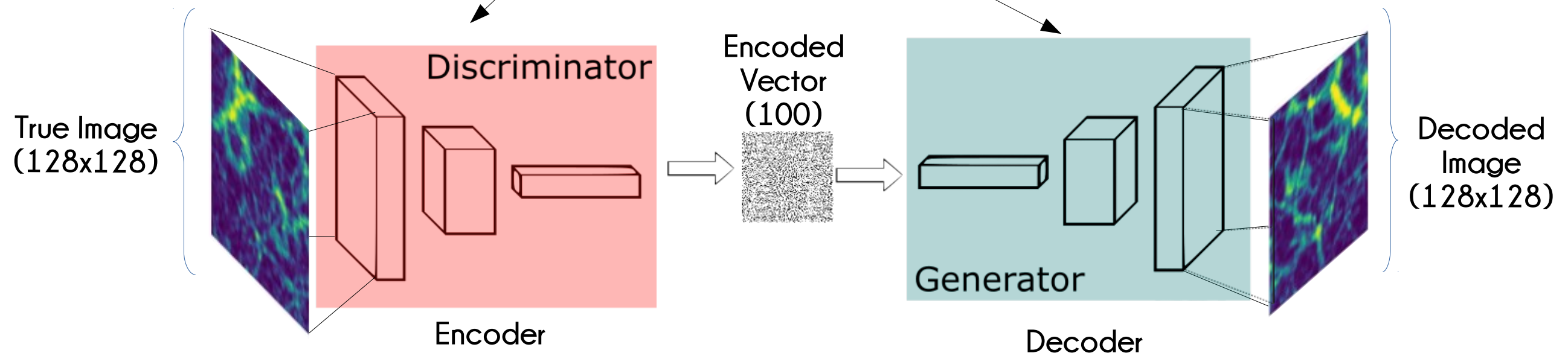


# From GAN to Autoencoder



The **discriminator** breaks down an image to extract its essential information: we keep its structure but **change its weights**

The **generator** intakes a vector and outputs a simulation-like image: we keep it unchanged, **fixing its weights**, to use as a decoder



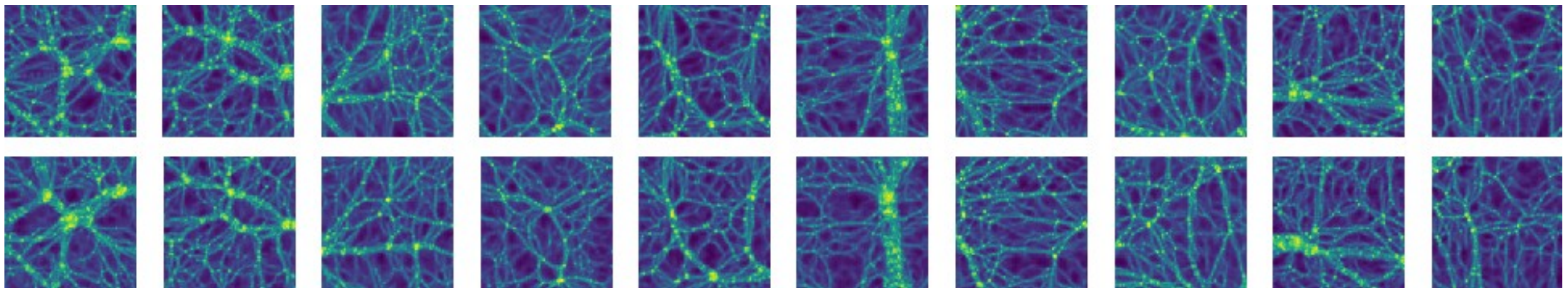


# Autoencoders : visual inspection

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→ We show AE results for 2D simulations

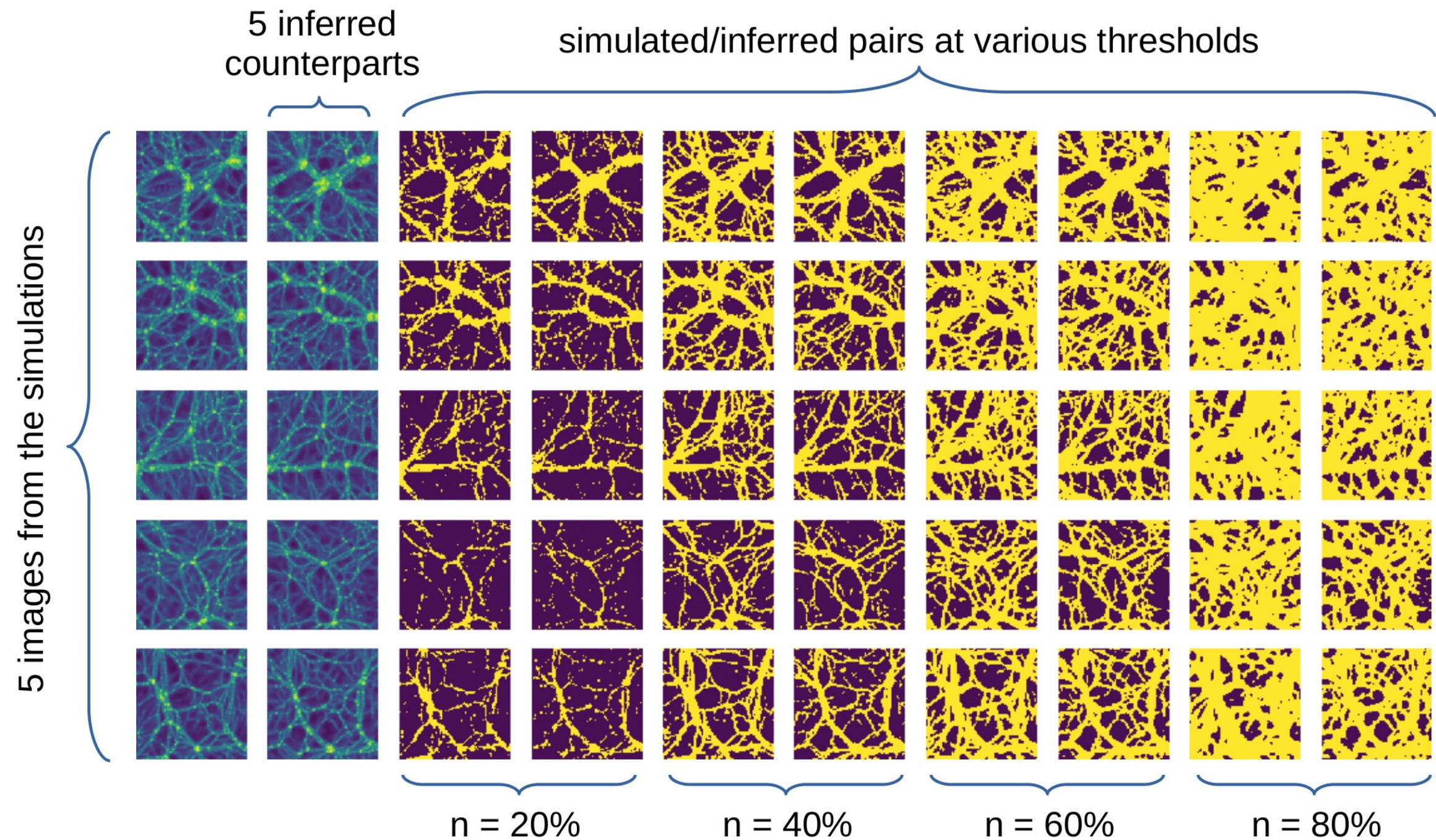
10 “true” images randomly chosen from the simulations



And their 10 counterparts as inferred by the AE



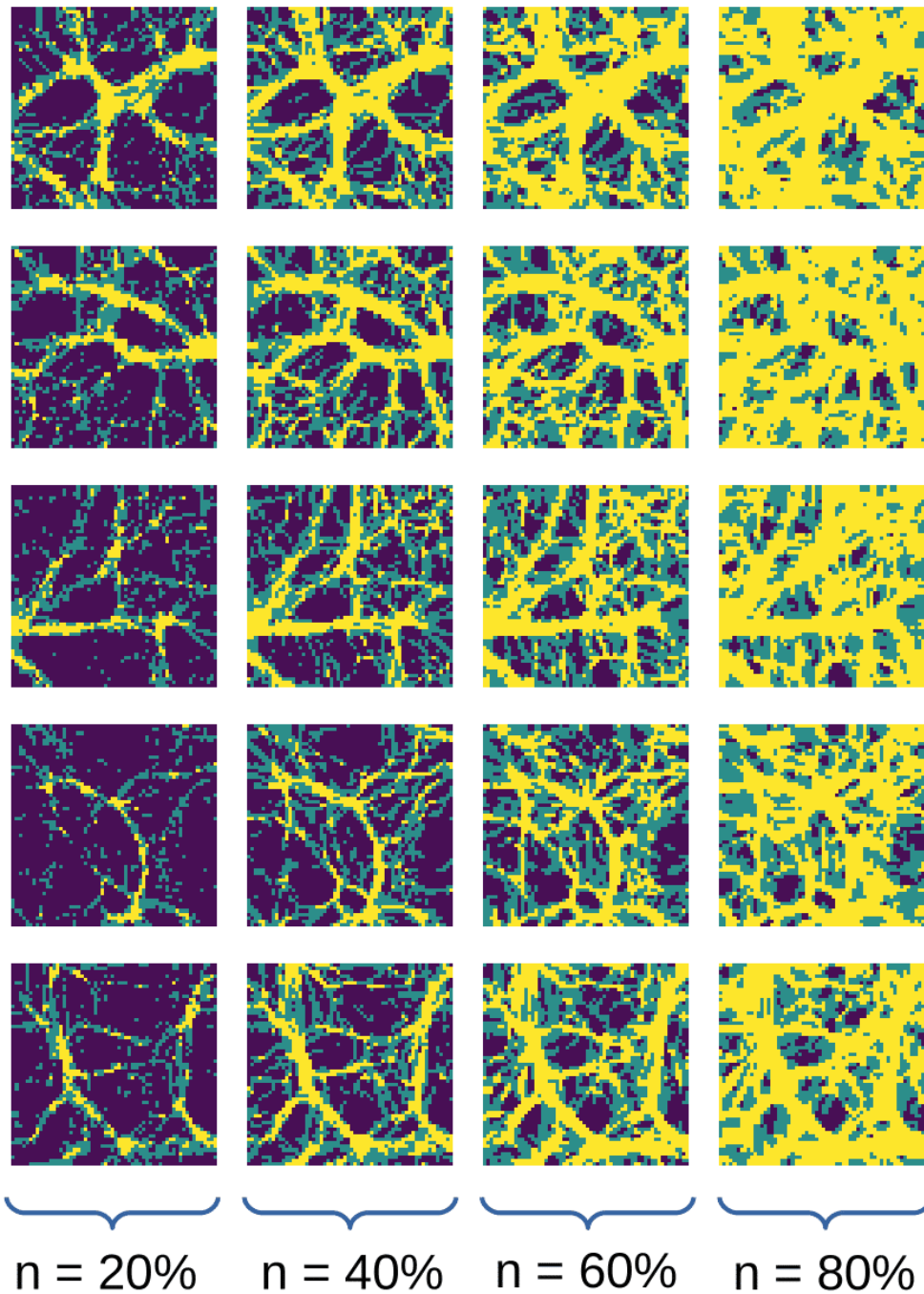
# Image to image comparison



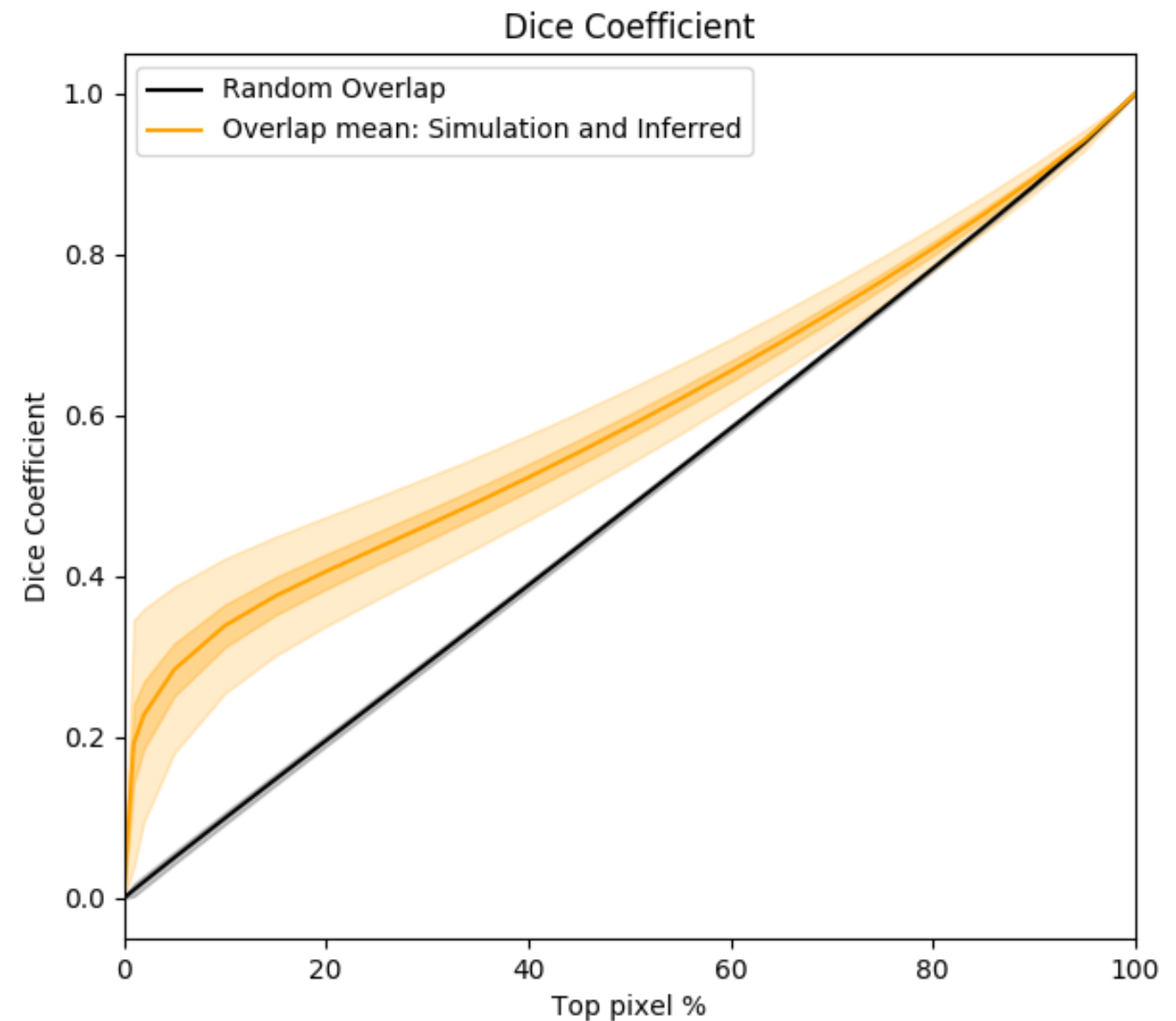


# Image to image comparison

Overlap of the thresholded structures



Yellow: structures overlap    Green : structures differ



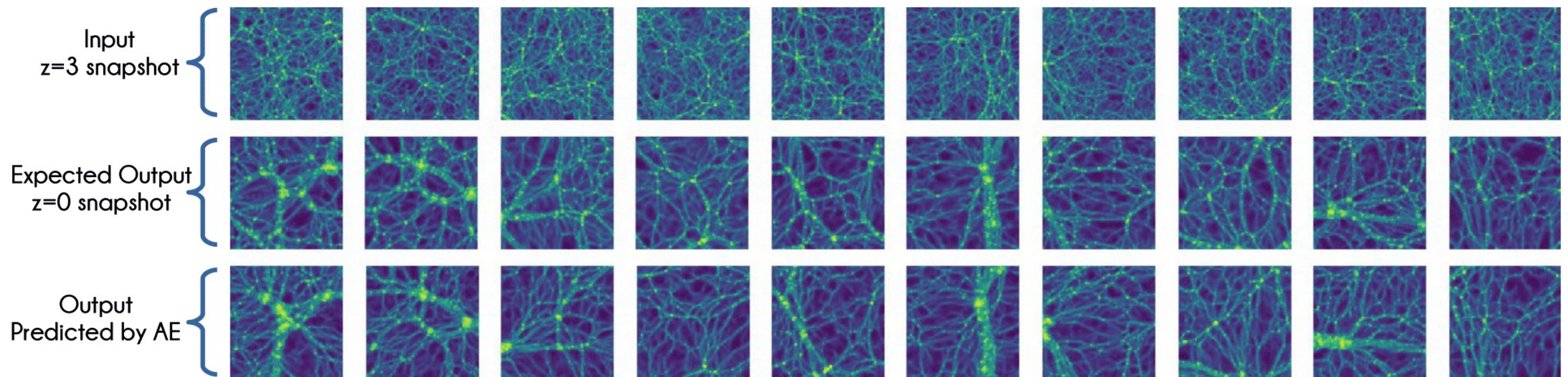


- GANs are a good alternative for fast generation of simulation-like datasets
- We have a working AE that is easy to build from a GAN and provides imperfect but satisfactory results
- We have a series of statistical estimators to quantify agreement between input and output beyond visual inspection → gives a basis of comparison for future work

# Conclusion : Future Work

- Given GANs' great performance in 2D, we can expect this to translate well to 3D
- Using our working AE structure, we can now move on to use it for predictive purposes → encouraging results in 2D simulations already !

Sneak Peek : predicting  $z=0$  images from  $z=3$  inputs (2D simulations, test set results)



**Thank You**