Generative Adversarial Networks Emulate Cosmological Models Simulators

(Simulation Emulation)

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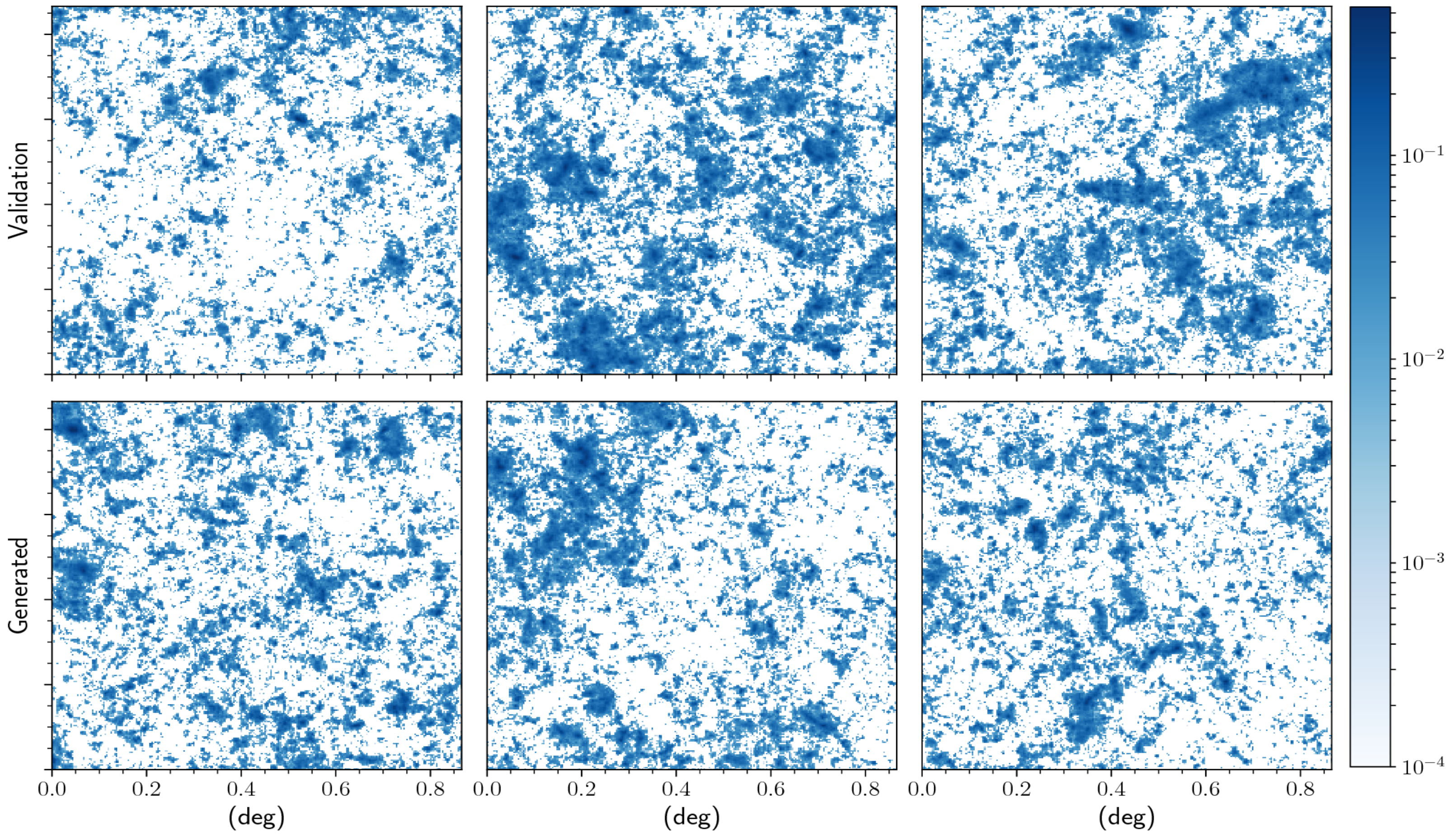
05/16/2017

Cosmo Convergence Maps



Weak lensing convergence maps κ(**ν**) for a ΛCDM cosmological model.

Generative Models

The central problem of generative models is that given a data distribution $\mathbb{P}_{data}$ can one devise a generator G such that the generated distribution

$$\mathbb{P}_{model} = \mathbb{P}_{data}\,?$$

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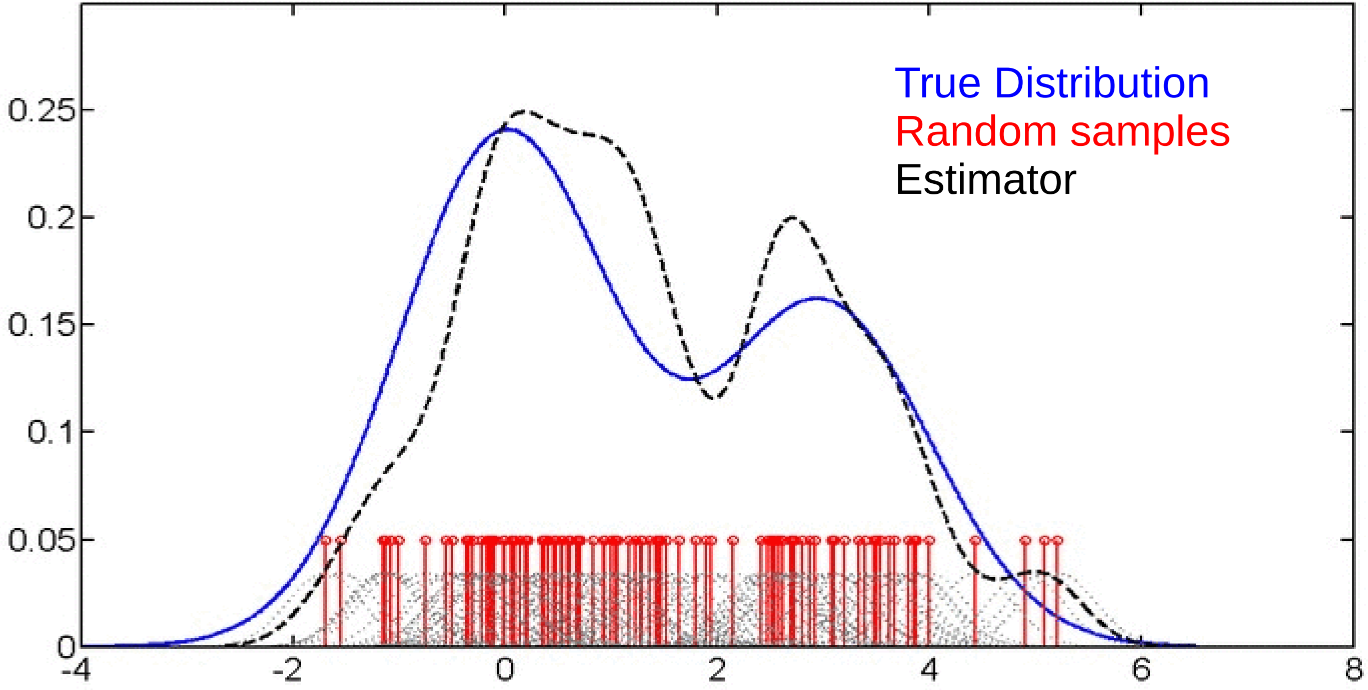
$$\mathbb{P}_{model} = \mathbb{P}_{data} \,?$$

Our information about $\mathbb{P}_{data}$ comes from an independent and identically distributed sample $x_1, x_2, \ldots, x_n$ which is assumed to have the same distribution as $\mathbb{P}_{data}$.

Density Estimation



Achieving a high fidelity generation scheme amounts to the construction of a density estimator of the training data.

Generative Adversarial Networks

GANs, Goodfellow et al.arXiv:1406.2661

$$\bar{z} \longrightarrow \boxed{G_\theta} \longrightarrow x_{gen}$$

Generative Adversarial Networks

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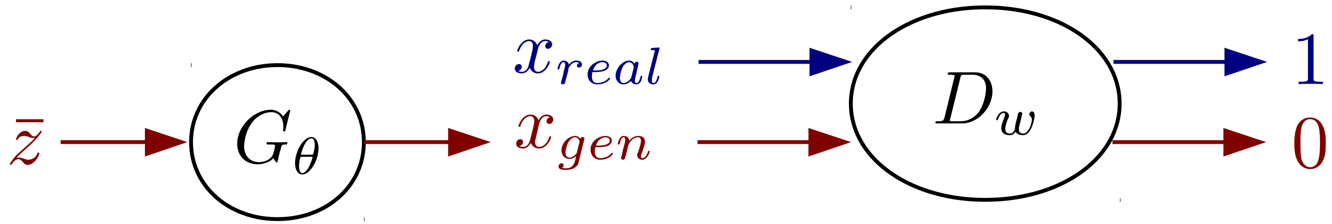
Update discriminator parameters w



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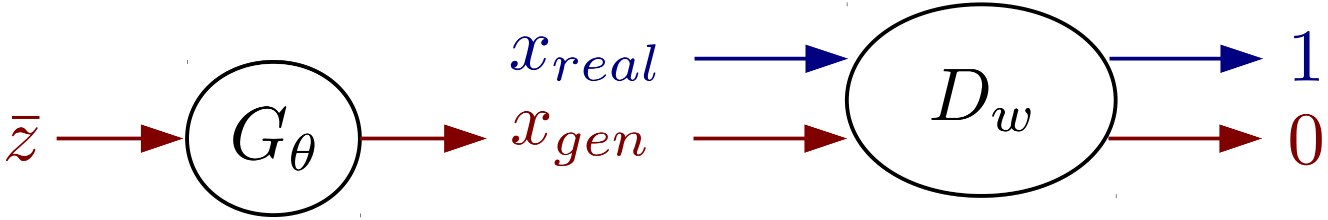

Update generator parameters θ

Generative Adversarial Networks

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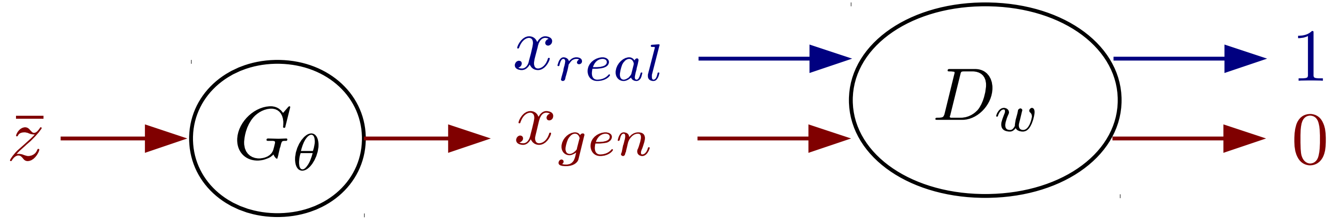
Update discriminator parameters w

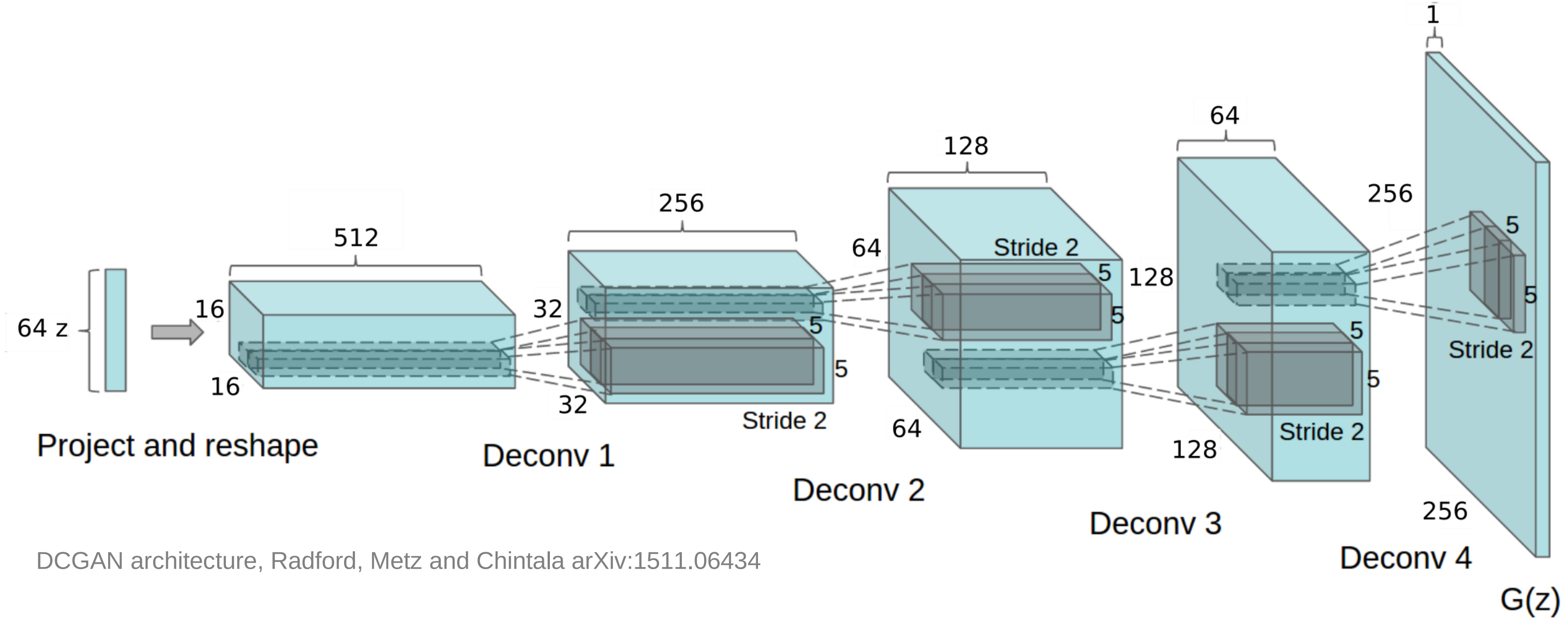


Update generator parameters θ

$$\bar{z} \sim [\mathcal{N}_0(0,1), \ldots, \mathcal{N}_{63}(0,1)]$$

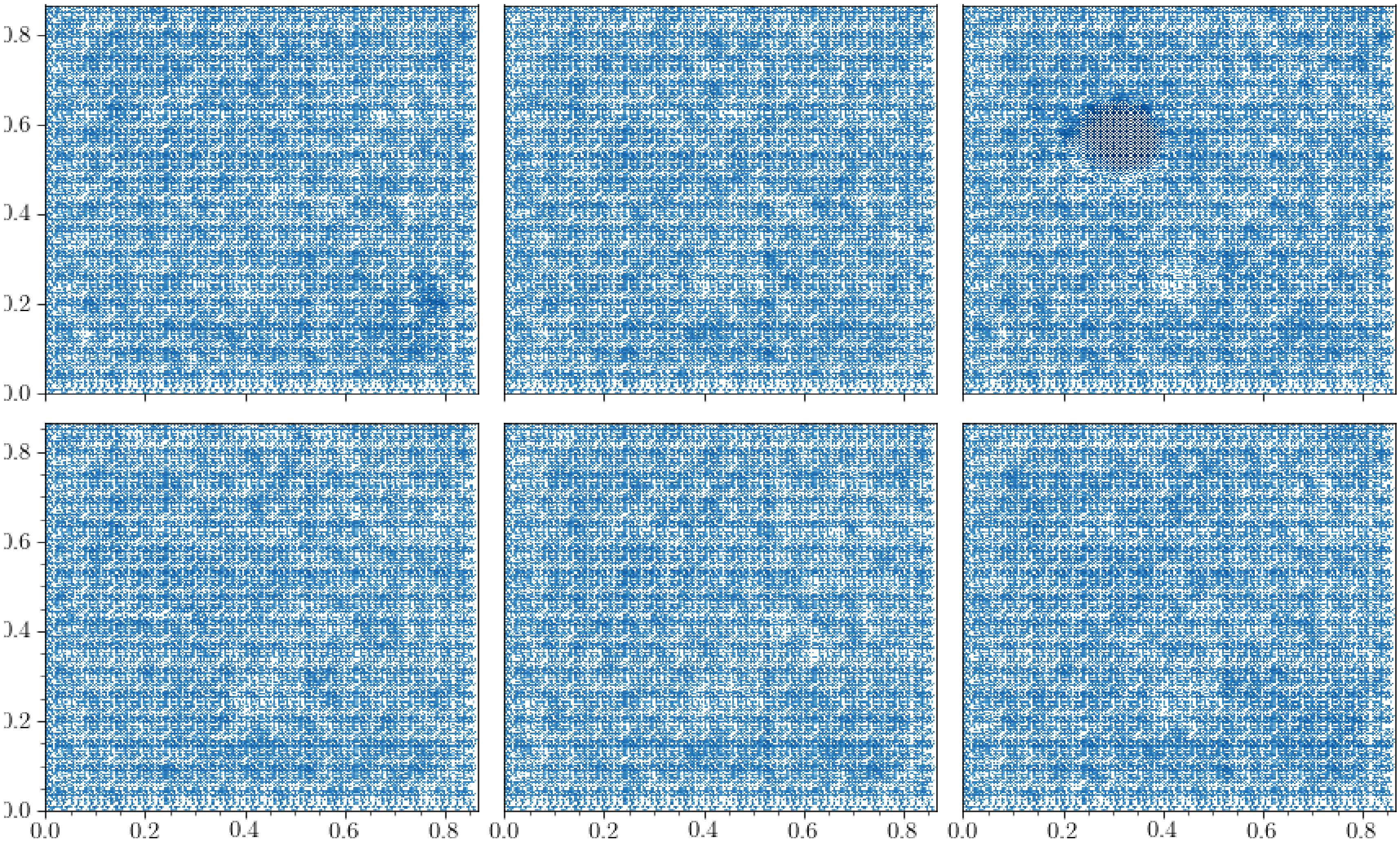
$$G_\theta : \bar{z} \rightarrow x \; \epsilon \; \mathbb{R}^{256\times 256}$$

Deep Convolutional Generative Adversarial Networks (DCGAN)



DCGAN architecture, Radford, Metz and Chintala arXiv:1511.06434

Generative Adversarial Networks



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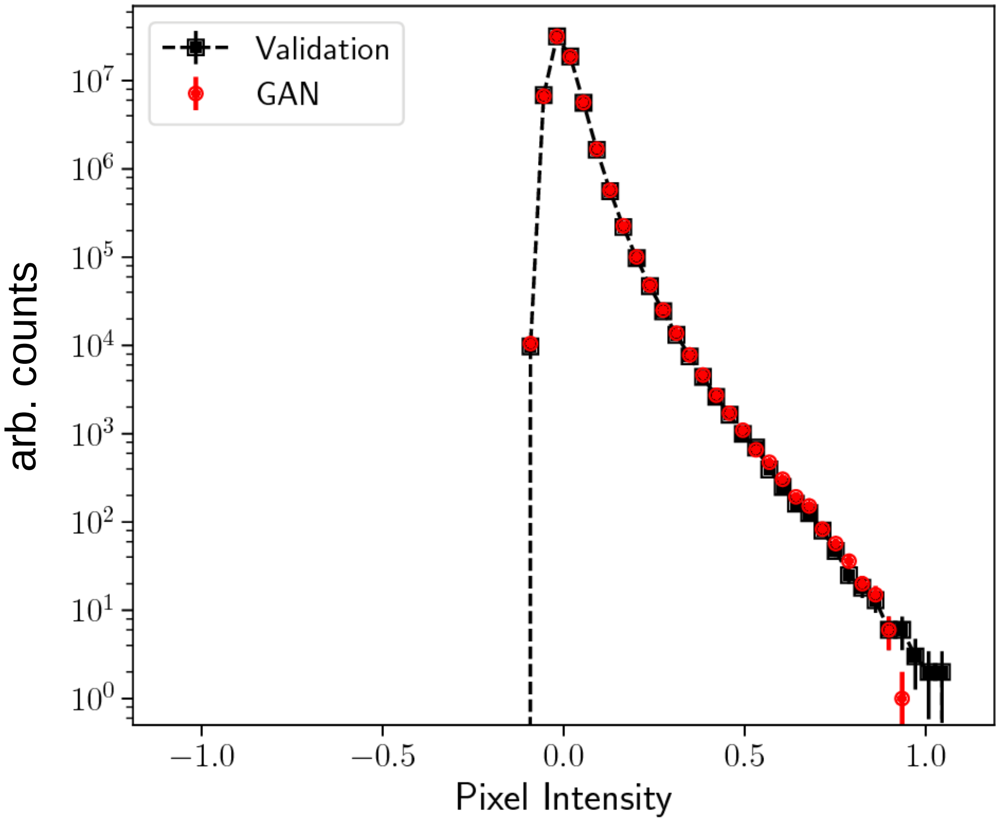
Evaluation of Generative Models

We think that when it comes to practical applications of generative models, such as in the case of emulating scientific data, the criterion to evaluate generative models is to study their ability to reproduce the statistics which we can measure on the original dataset.

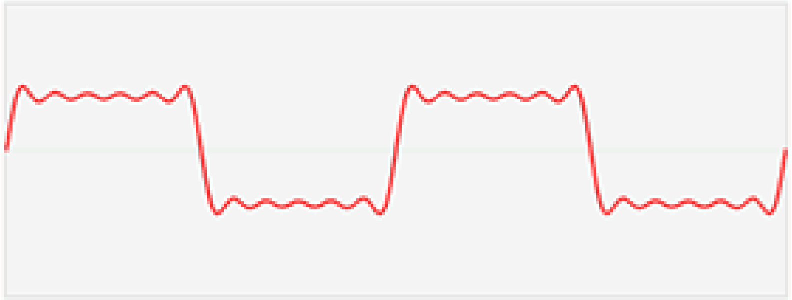
Convergence Maps First Order Statistics



Kolmogorov-Smirnov two tailed test yields p-value >0.999

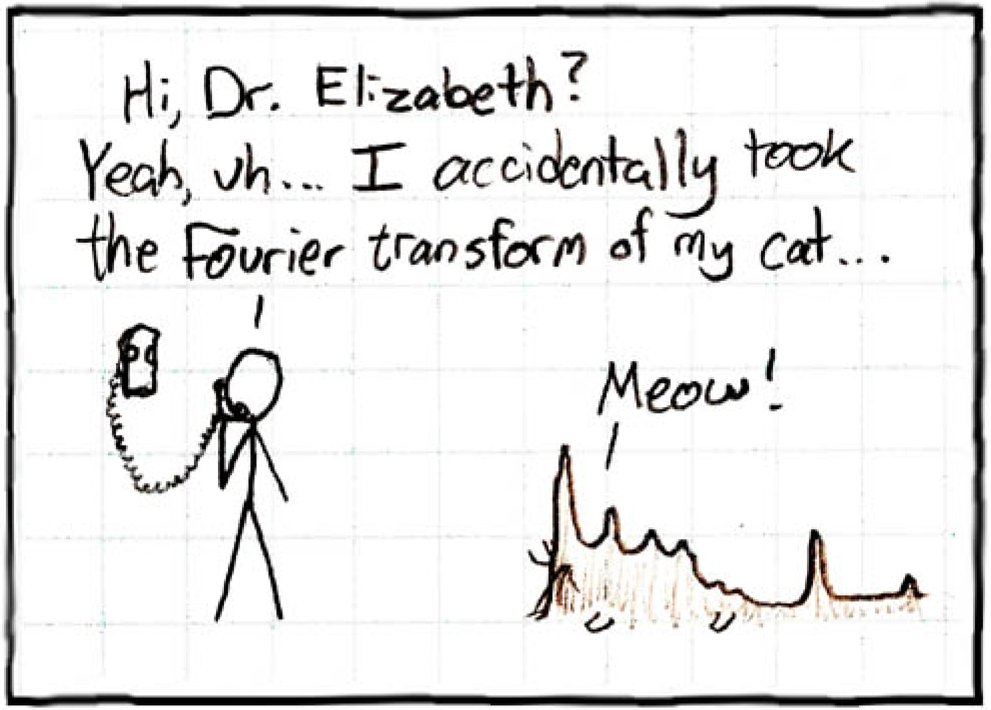
Fourier Spectral Analysis

quora.com/Whats-the-use-of-Fast-Fourier-Transform



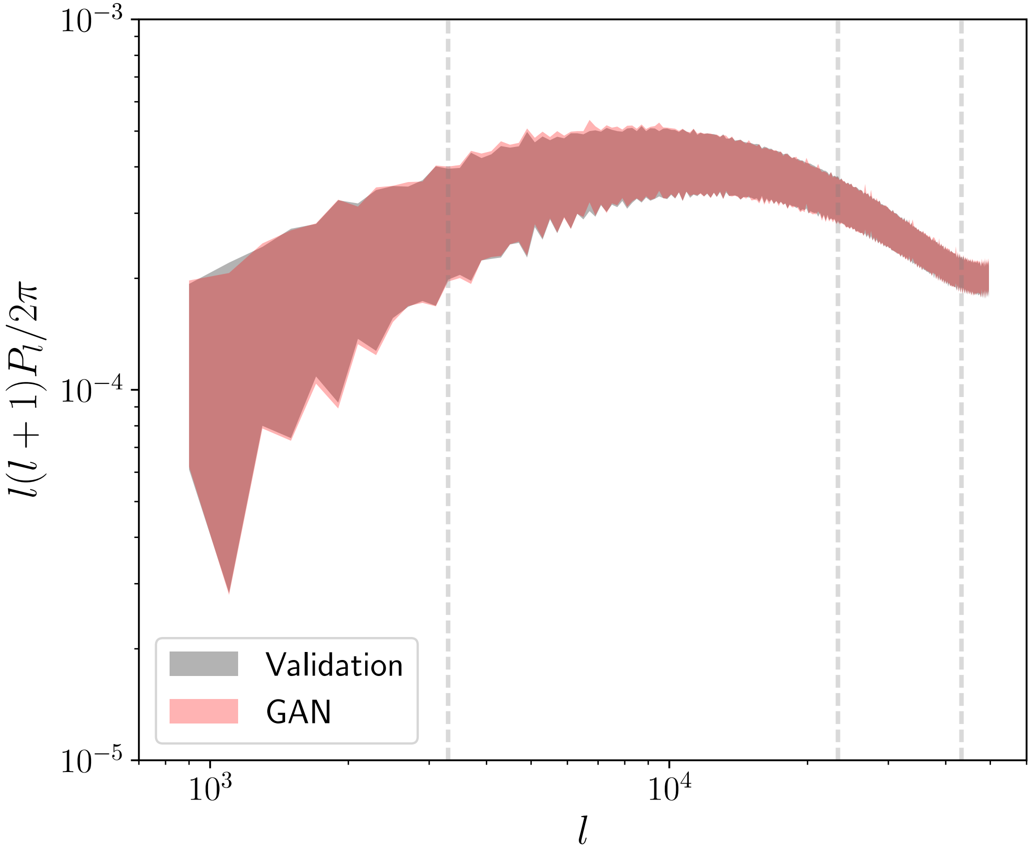
Fourier Spectral Analysis

https://xkcd.com/26/



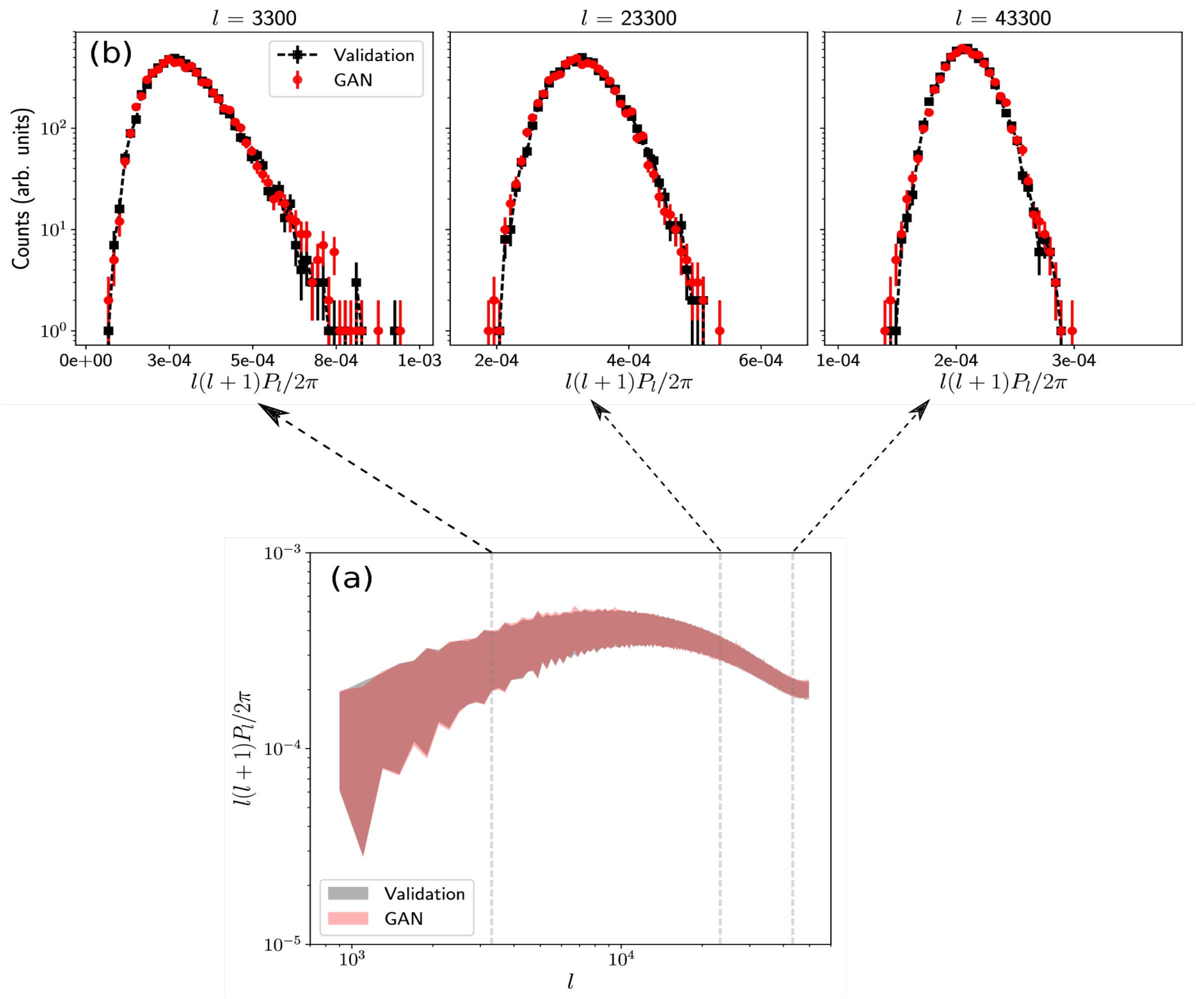
Fourier Spectral Analysis: Power Spectrum

$$\langle \tilde{\kappa}(l)\tilde{\kappa}^*(l')\rangle = (2\pi)^2\delta_D(l-l')P_\kappa(l)$$

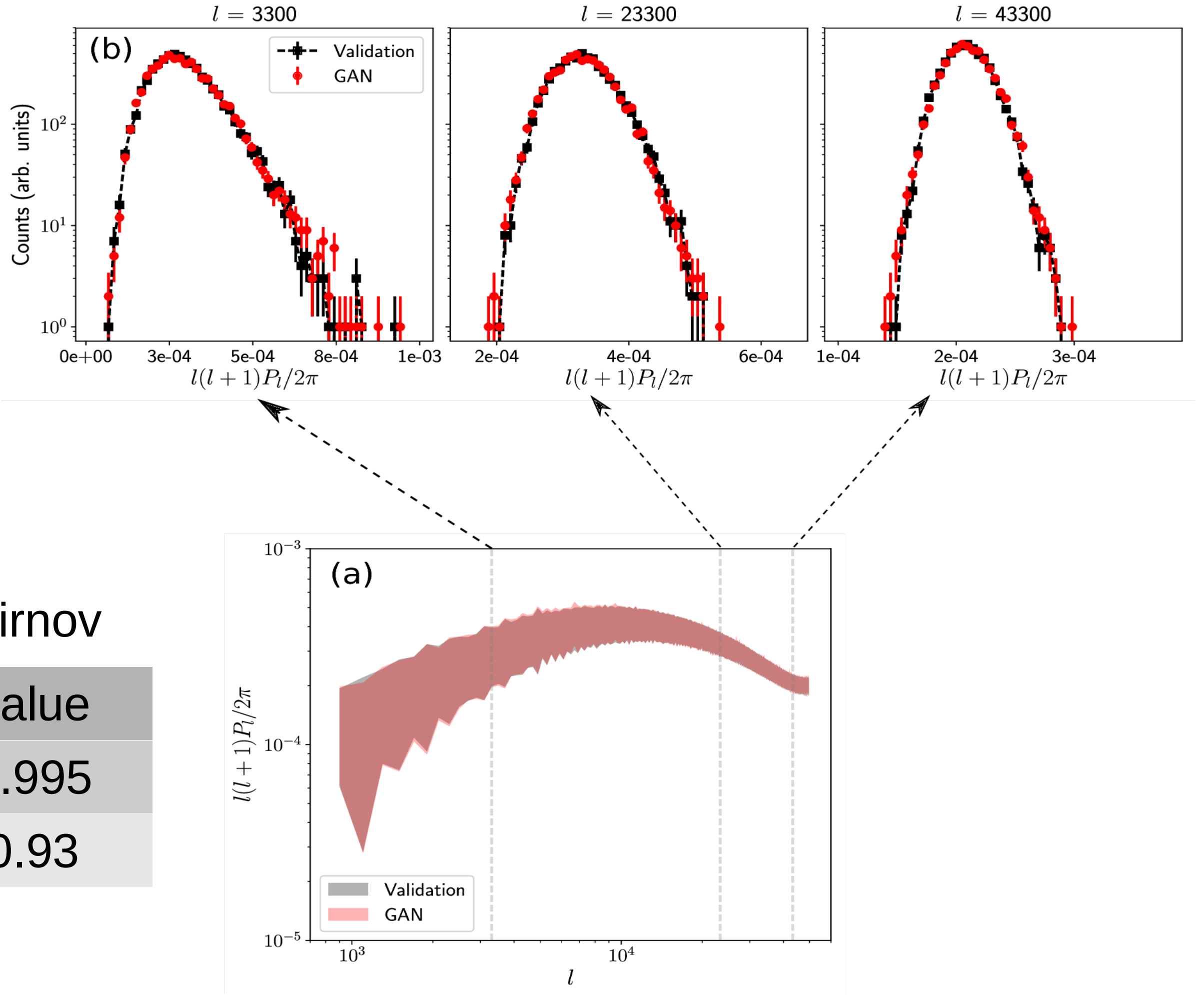


Bands are $\mu(l) \pm \sigma(l)$

Fourier Spectral Analysis: Power Spectrum



Fourier Spectral Analysis: Power Spectrum



Kolmogorov-Smirnov

# moments	p-value
242	> 0.995
6	> 0.93

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Non-Gaussian Corrections

The power spectrum captures the Gaussian structures in the images. However, gravity produces non-Gaussian structures

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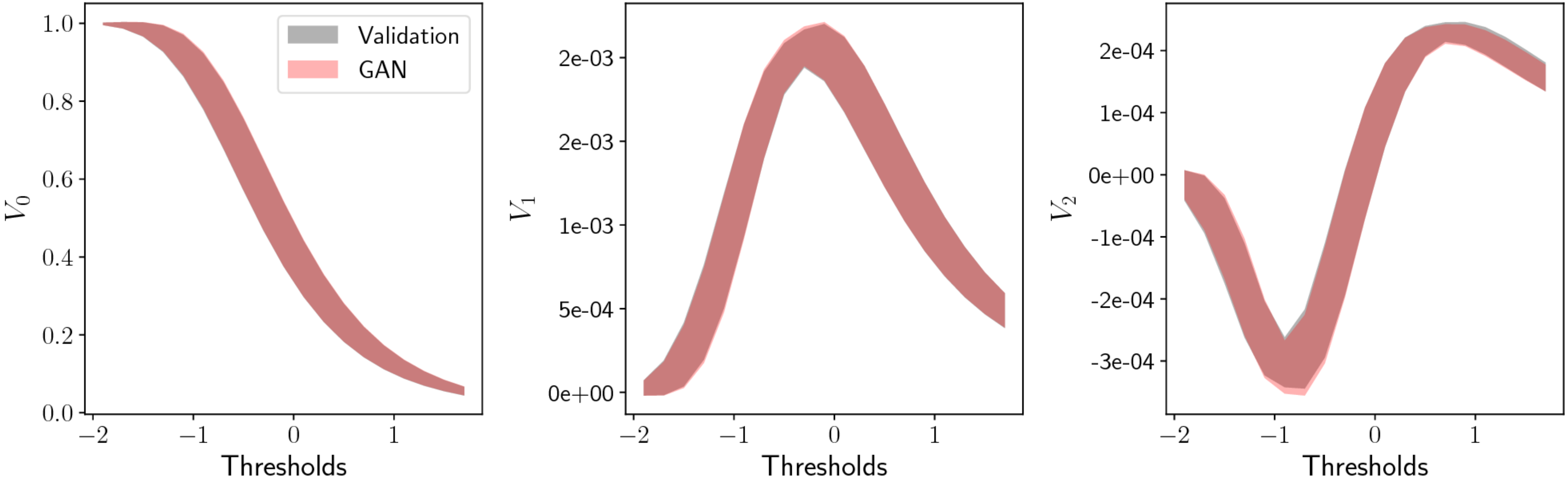
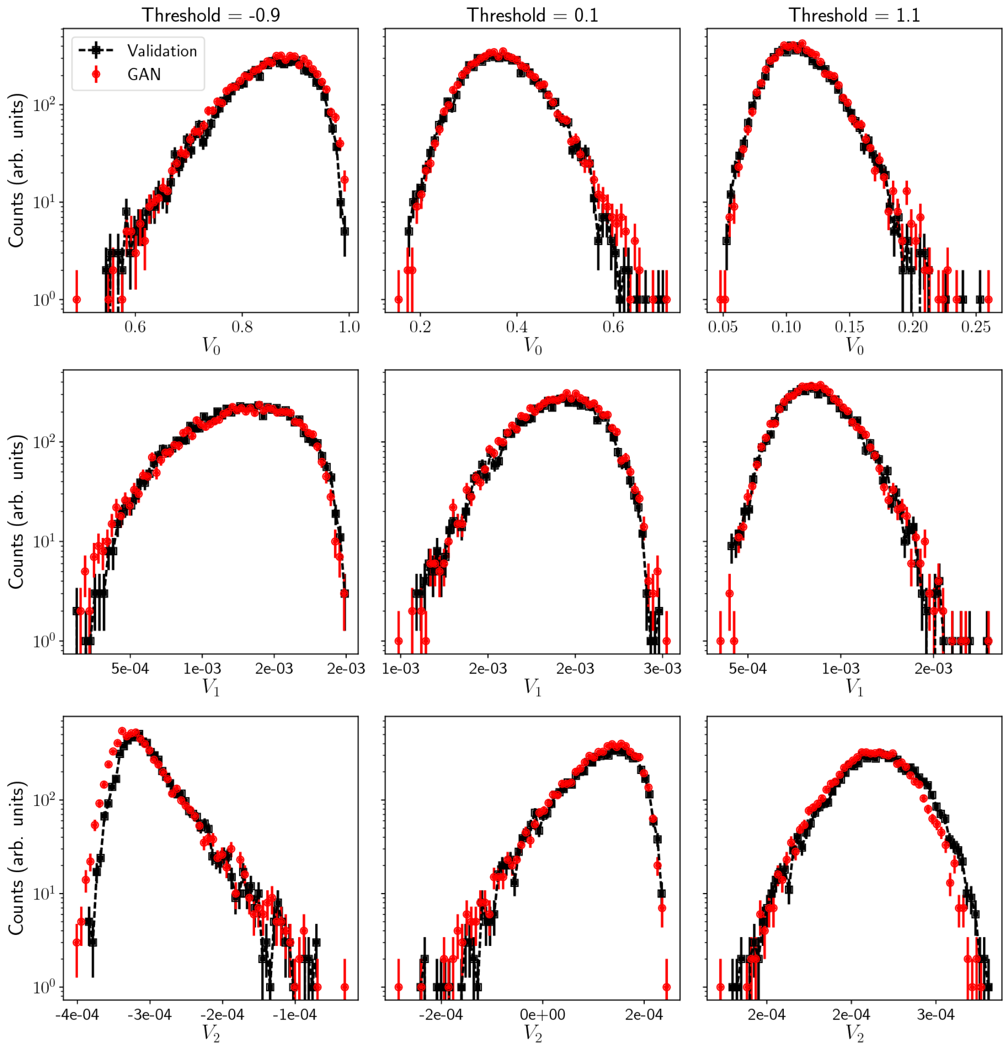


The three Minkowski Functionals are sensitive to the higher order correlations.

Non-Gaussian Corrections



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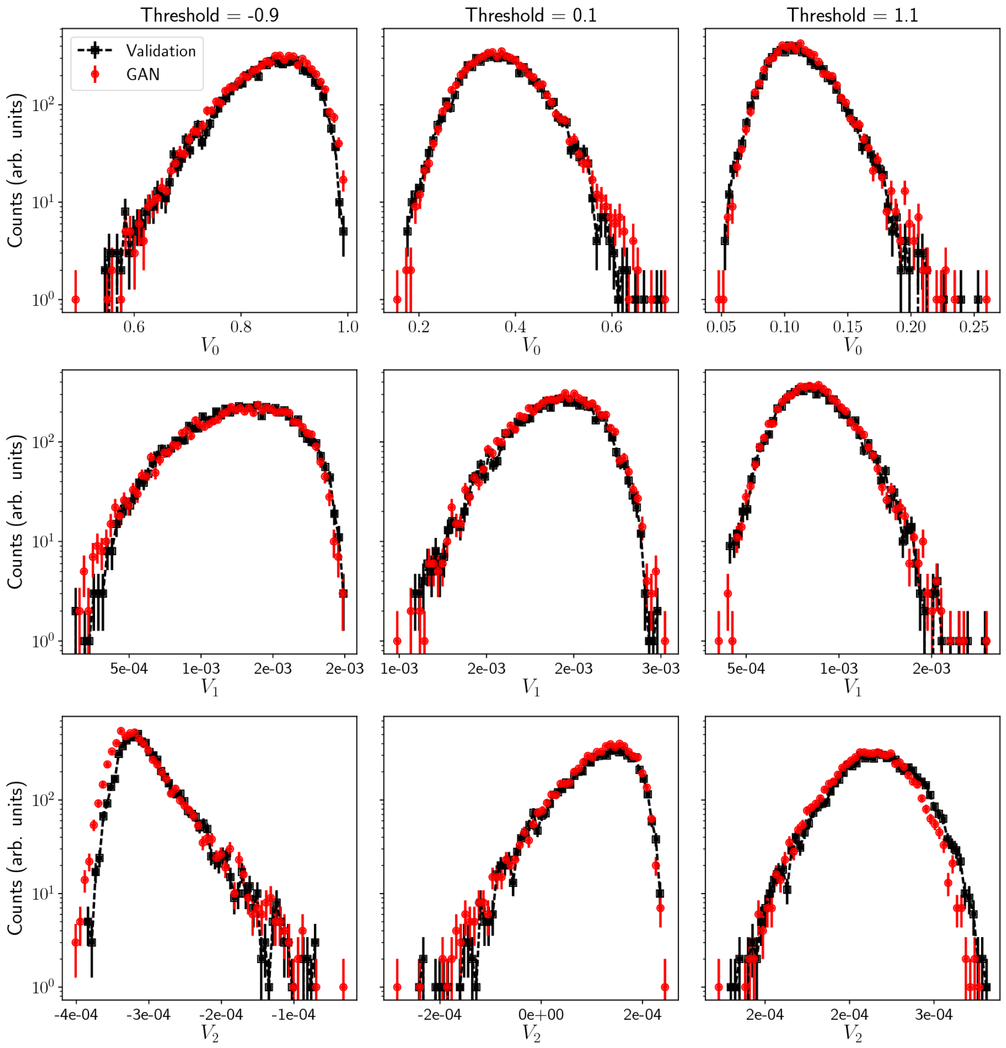
Non-Gaussian Corrections



Kolmogorv-Smirnov

# thresholds	p-value
34	>0.999
16	>0.97
6	>0.6
1	0.32

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Generative Models for Emulating Scientific Data

Model parameters

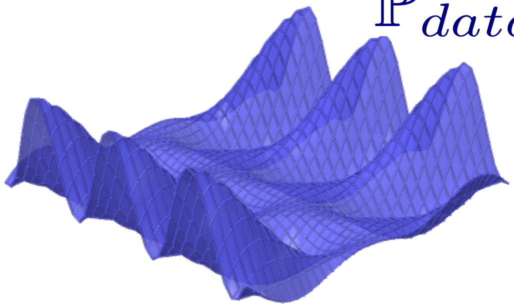
$$\begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \vdots \\ \sigma_m \end{bmatrix}$$

Physical Model

$$S(\bar{\sigma}, r)$$

Data of interest,
images or otherwise.

$\mathbb{P}_{data}$



Generative Models for Emulating Scientific Data

Random seed(s)
r

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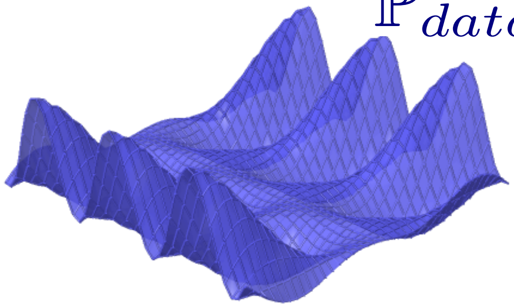

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Physical Model

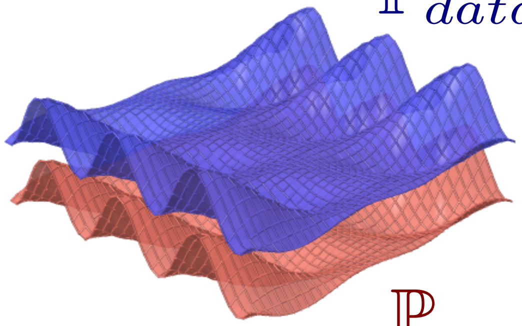
$$S(\bar{\sigma}, r)$$

Generative Model

$$G(z)$$

Random vector
$z \sim \text{prior}$

$\mathbb{P}_{data}$



$\mathbb{P}_{model}$

How close can it get?

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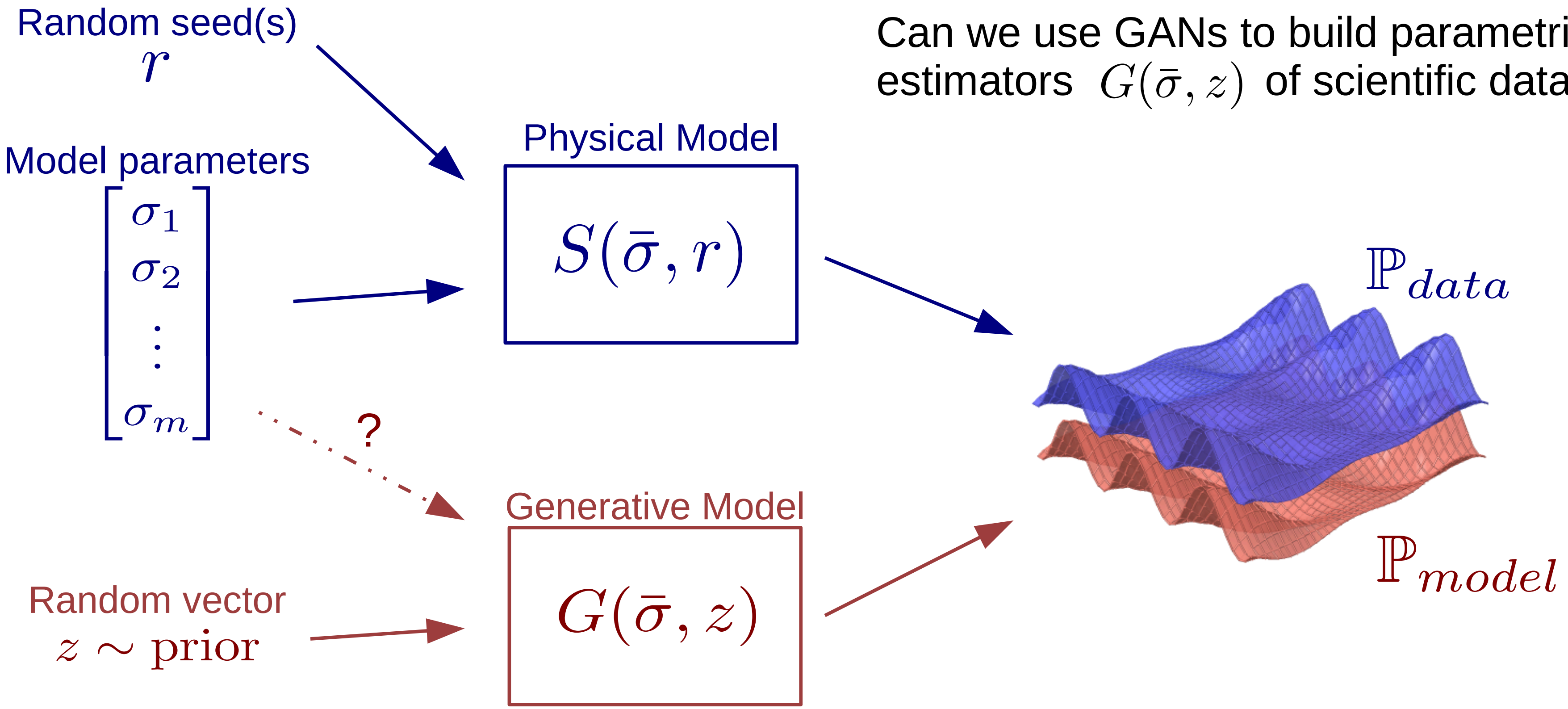
Generative Models for Emulating Scientific Data

Can we use GANs to build parametric density estimators $G(\bar{\sigma}, z)$ of scientific data?



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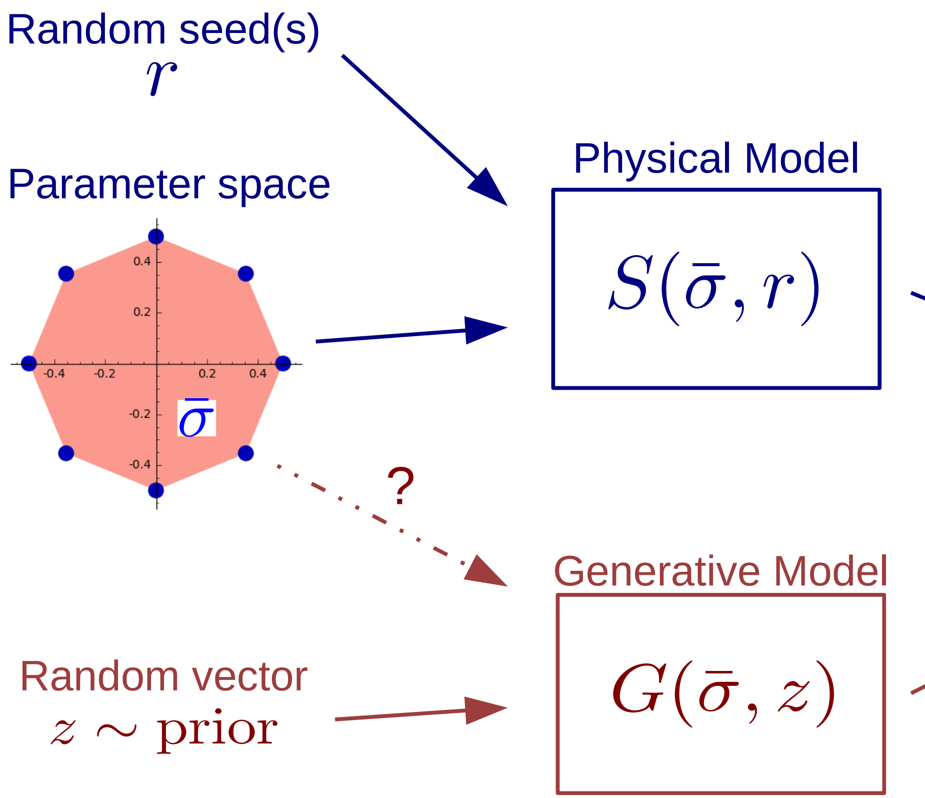

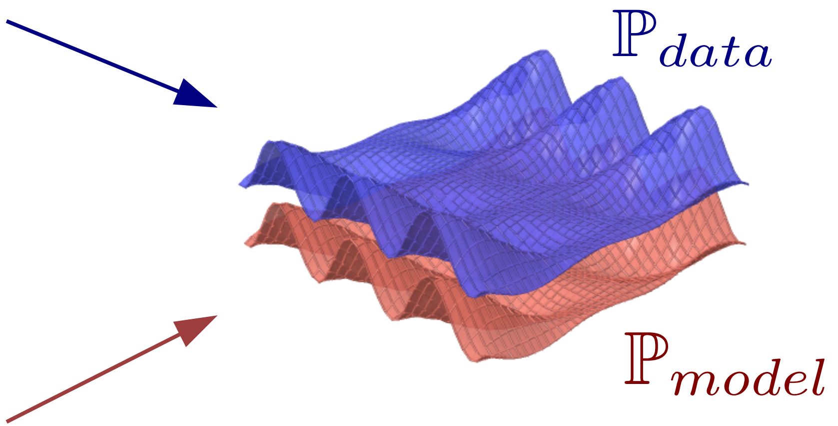

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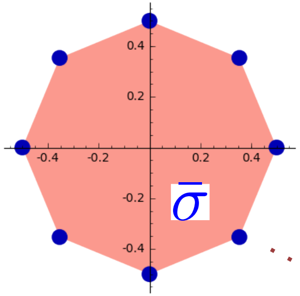
Parameter space



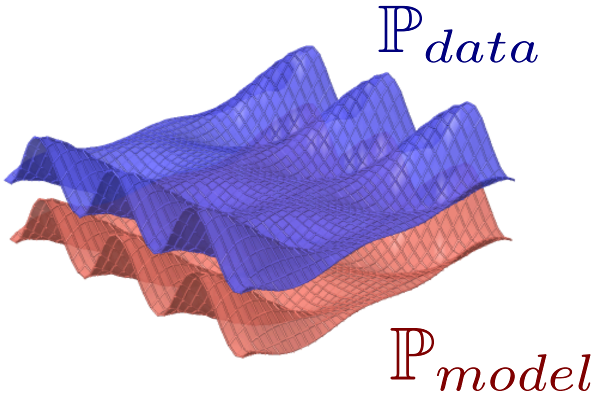
Physical Model

$S(\bar{\sigma}, r)$

Generative Model

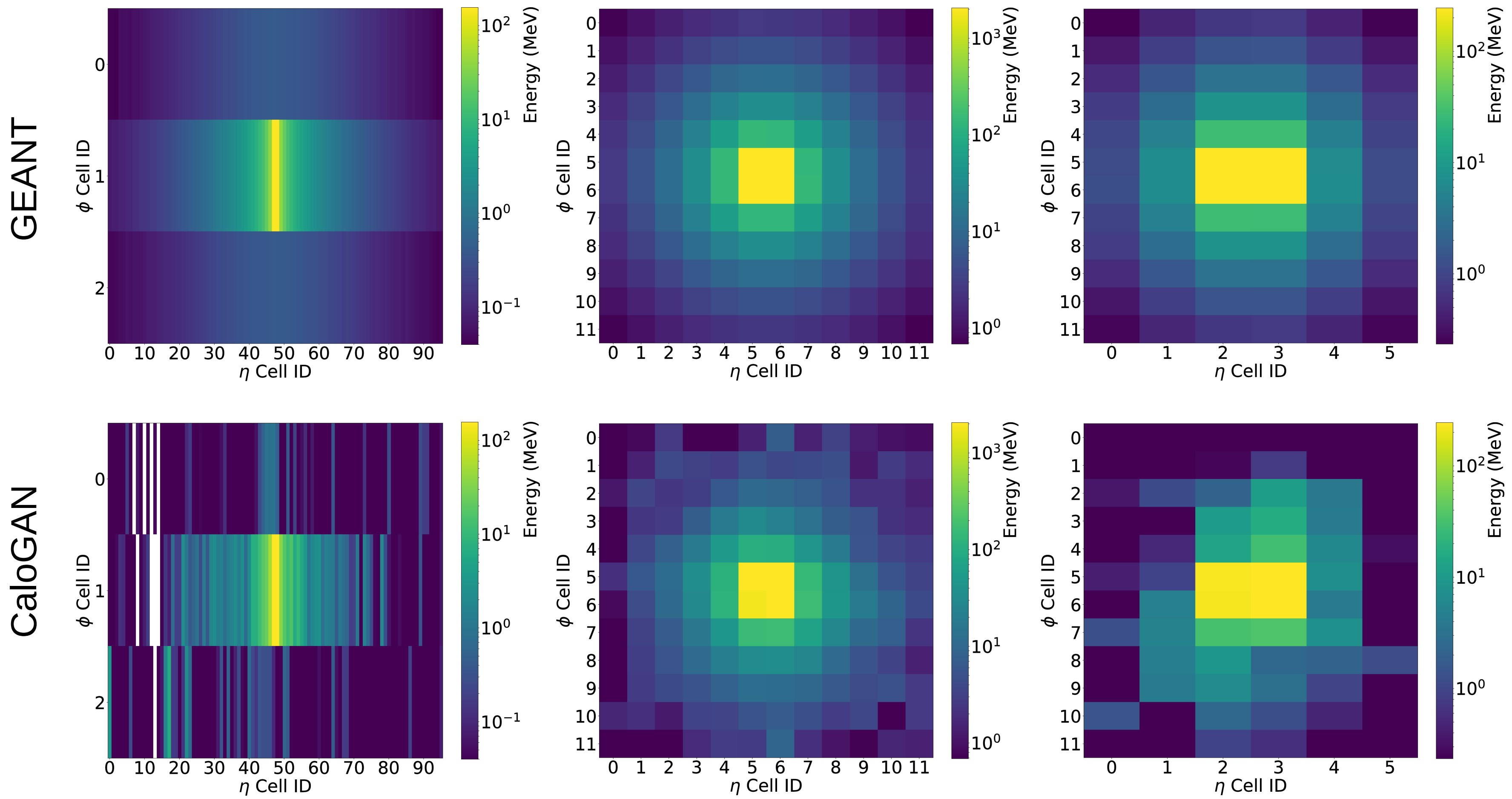
$G(\bar{\sigma}, z)$

Random vector
$z \sim \text{prior}$



Such generators would likely exclude regions in parameter space where the physical model $S(\bar{\sigma}, r)$ exhibits critical behavior.

CaloGAN: Simulating 3D Calorimeter Showers using GANs



Paganini, de Oliveira and Nachman arXiv:1705.02355

Summary and Outlook

- We have shown with statistical confidence that GANs can emulate ΛCDM cosmological model convergence maps
  - Fourier spectrum of generated maps match that of a validation dataset
  - Non-Gaussian structures are discovered and emulated by the generator

- Deep generative models have the potential of creating high-fidelity computationally inexpensive emulators of scientific data.

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- Future lines of work:
  - investigate the ability of GANs to interpolate in the parameter space of physical models.
  - multi dimensional data: 1 & 3D (see CaloGAN), time dependence, “sequential data”
  - using NN interpretation techniques to gain insight in what these networks are learning