

Using GAN for fast event generation

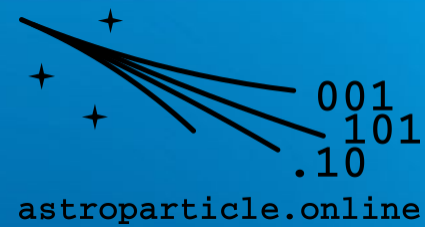
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The problem

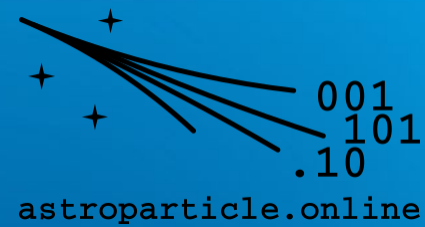


- Develop fast event generator for astroparticle physics application area, for example IACT.

Mathematically:

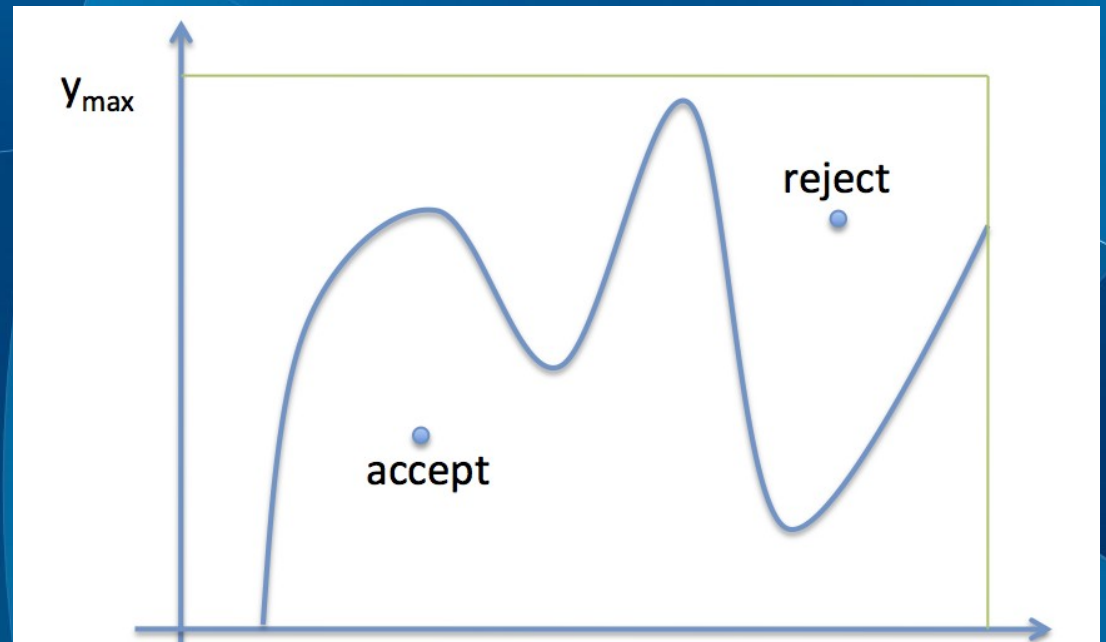
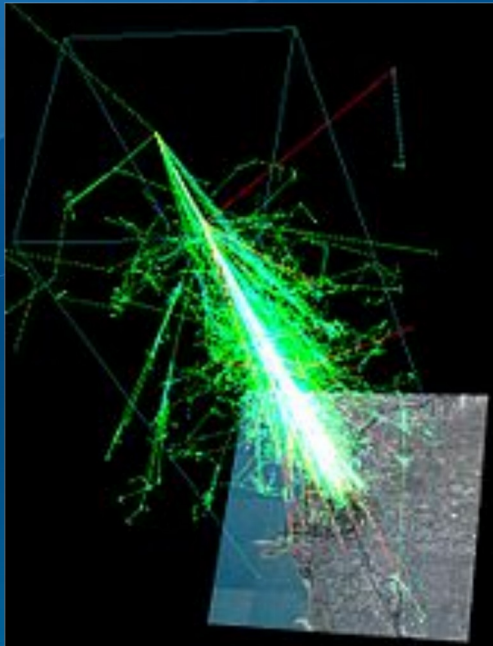
- Let us x is a random variable with probability density $P(x)$
- How to generate sample $\{x_1, x_2, \dots\}$ that has the same probability density?

MC generators

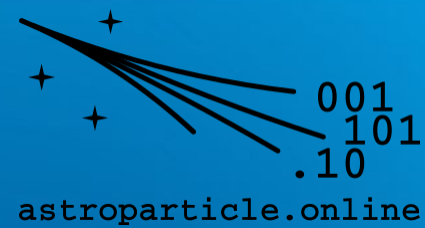


- **Algorithm von Neumann**

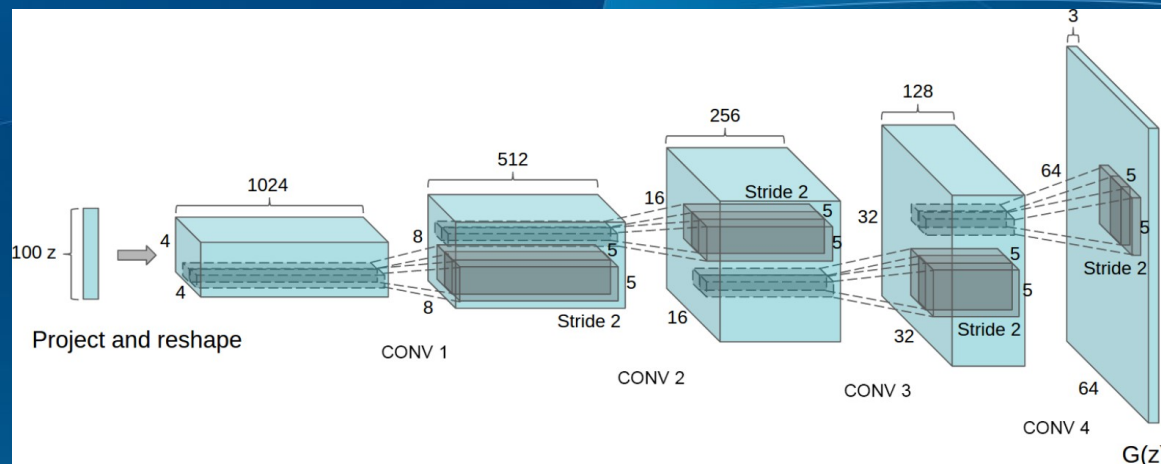
A simple method for generating random points with distribution $P(x)$ was deduced by von Neumann. The idea is extremely simple. In one dimension, if you have a function with known everywhere on a specific domain (i.e. $[x_{\min}, x_{\max}]$) and with a known supremum M over that domain, you can sample from it as follows:



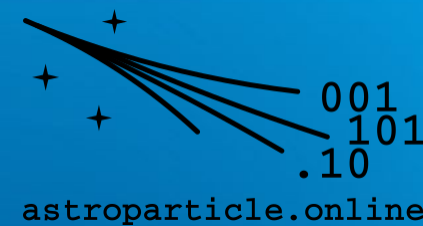
Sample Training



- Sampling procedure
 - Traditionally this is a neural network

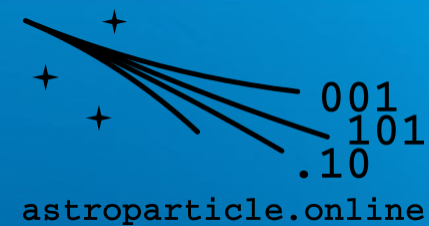


Generator vs probability function

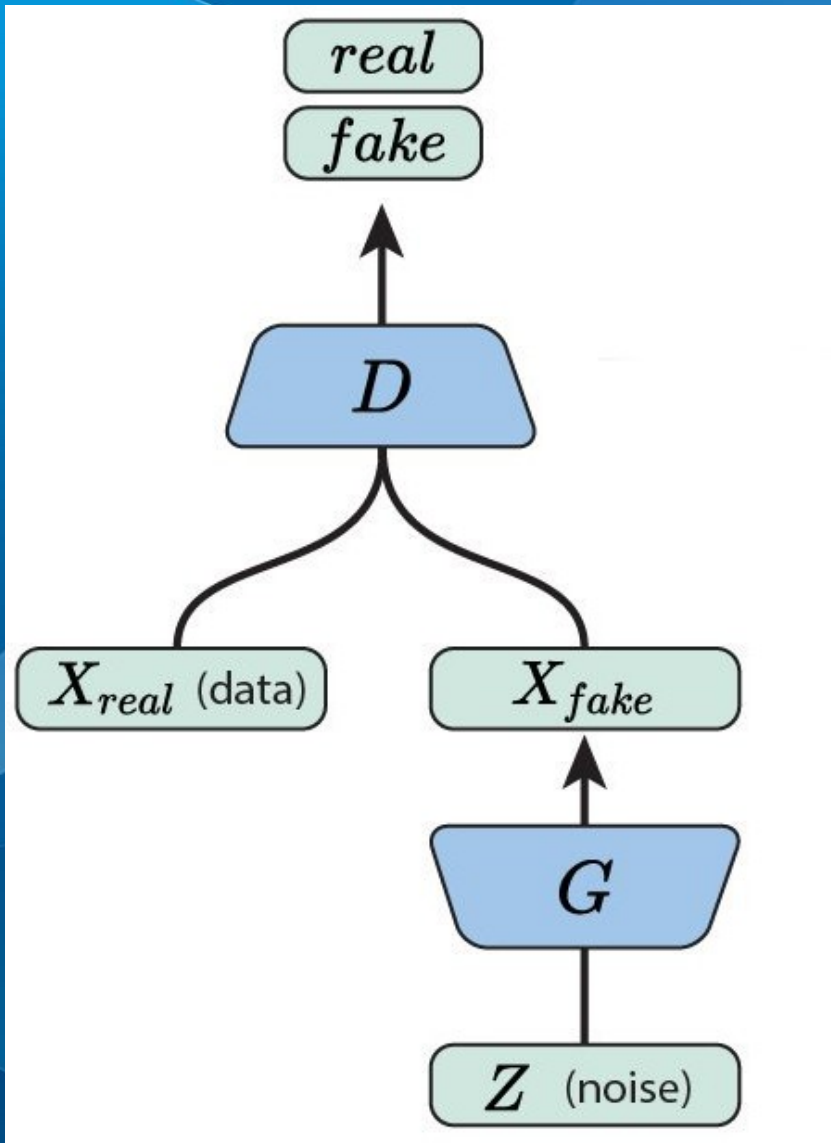
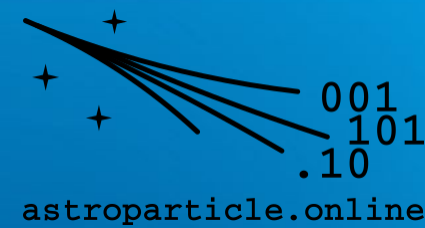


- A probability density function $P(x)$ is hard:
 - normalization is the main issue;
 - sampling might be computationally costly (usually, long MC);
 - CORSIKA: hours and days of works per shower.
- Learning a generator is easier:
 - $x = G(z)$ where:
 - G - a parameterized deterministic function;
 - z - predetermined and easy to sample.

Generative adversarial networks

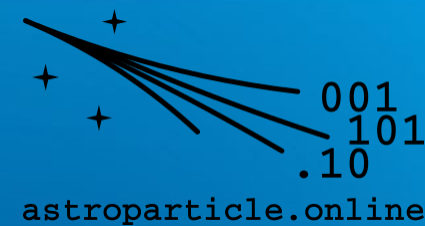


Generative adversarial networks



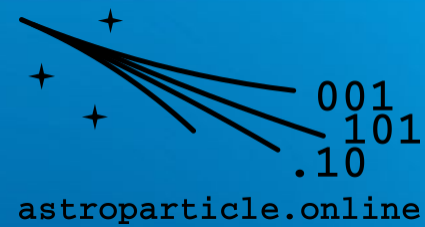
- The discriminator tried to distinguish between fake (generated) and real data
- Input data either generated or from the real dataset
- The generator turns the input noise into fake data to try and fool discriminator
- Input noise

Adversarial training



- Generator is trained to maximize goodness of produced samples.
- GAN defines goodness of a generator via a classifier D :
 - learns to discriminate X against X' ;
 - if quality is close to a random guess:
 X' is similar to X ;
 - if quality is high: G should be improved.

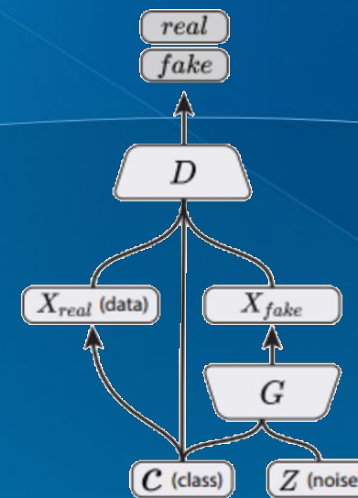
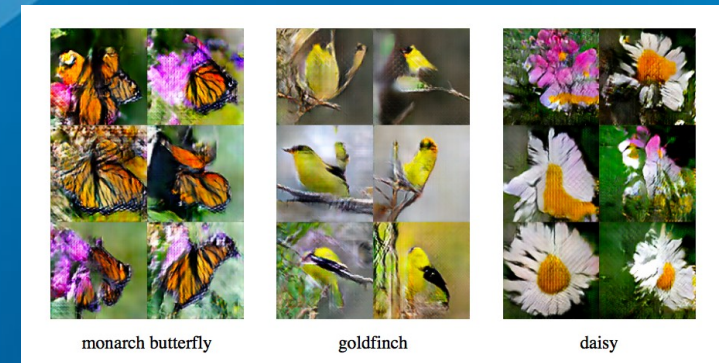
Discriminator



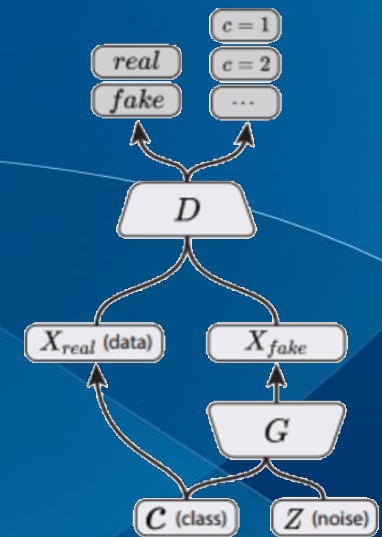
- Usually called adversary or critic
- Traditionally, also a neural network
- Discriminator defines goodness of generated samples:
 - rich set of methods for classification;
 - easy to identify important properties of good generator and use inside discriminator;
 - produces interpretable quality metric.

Many GAN flavors

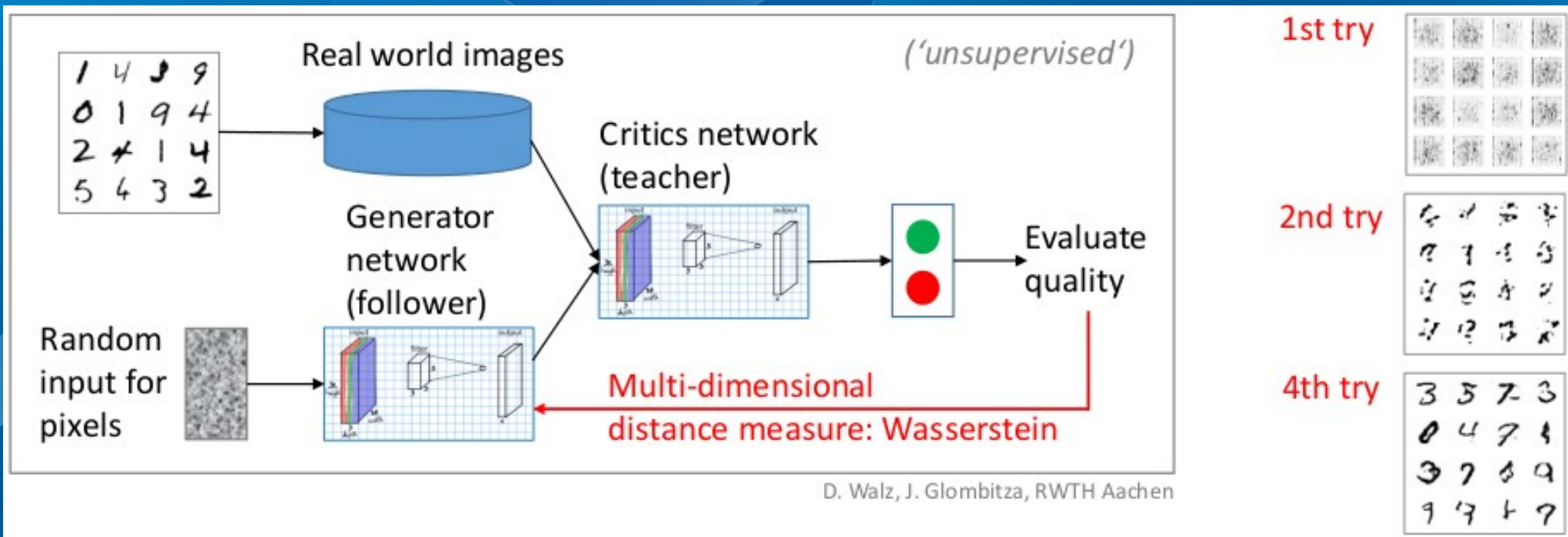
- Original GAN was based on MLP in 2014
- Deep Convolutional GAN in 2015
- Conditional GAN
 - Extended to learn a parameterized generator $p(x|\theta)$;
 - Useful to obtain a single generator object for all θ configurations
 - Interpolate between distribution
- Auxiliary Classifier GAN
 - D can assign a class to the image

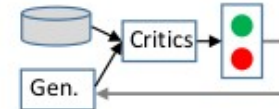


Conditional GAN
(Mitra & Osindero, 2014)



AC-GAN
(PresentWork)

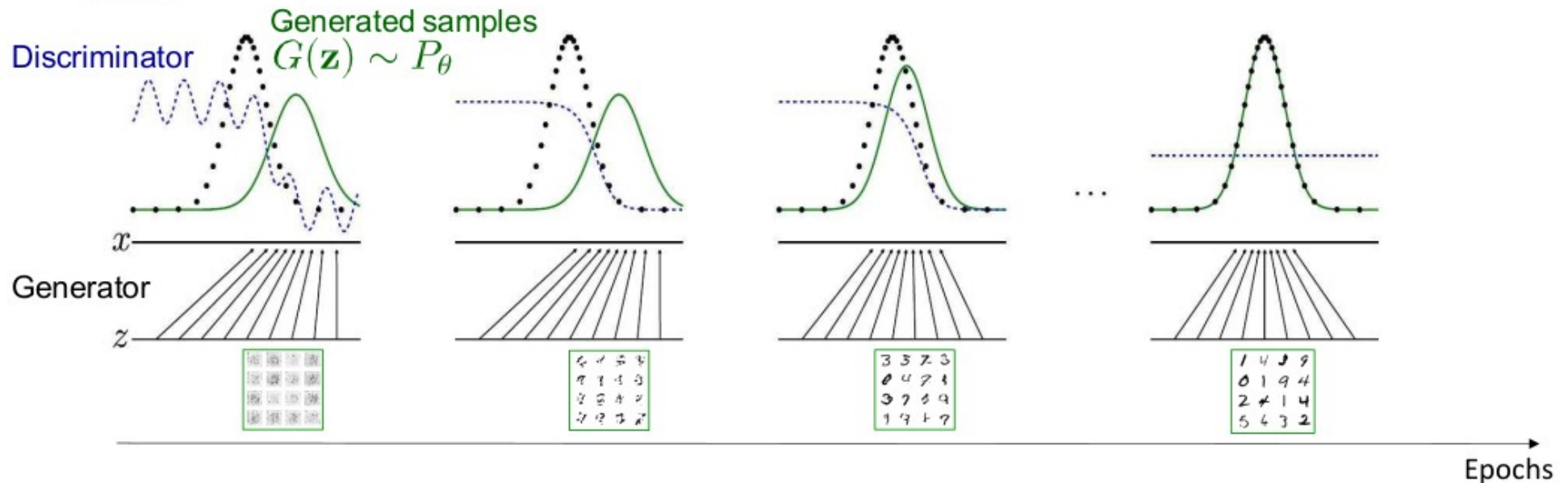




Optimal Evolution of GAN Training

1	4	9	9
0	1	9	4
2	4	1	4
5	4	3	2

 Data samples $x \sim P_r$



Gradient of discriminator guides generator

→ G generates samples which are more likely identified as data

Wasserstein distance

Also known as Earth Mover's distance (EMD)

Ensure smallest cost Expectation value Travel distance

$$D_W(P_r || P_\theta) = \inf_{\gamma \in \Pi(P_r, P_\theta)} \mathbb{E}_{(x,y) \sim \gamma} [\|x - y\|]$$

Transportation plans



Describes **minimal cost** to move distribution P_θ on P_r and vice versa (Cost: mass * distance)

Trick to calculate: Kantorovich-Rubinstein duality

$$D_W \rightarrow \min_{C \in \text{Lip1}} \mathbb{E}_{r \sim P_r} C(r) - \mathbb{E}_{q \sim P_q} C(q)$$

Optimal transport plan:

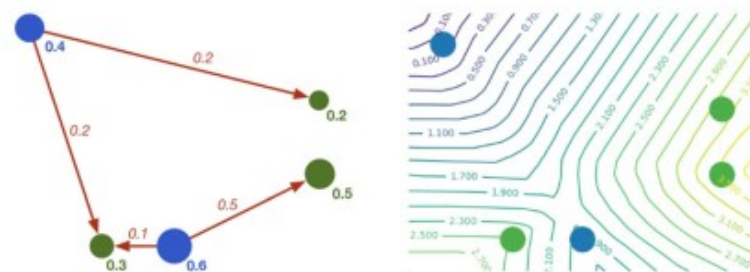
blue dots=earth heaps

green dots=target distribution

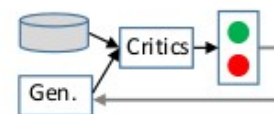
red arrows=optimal transport plan

numbers=amount of mass moved

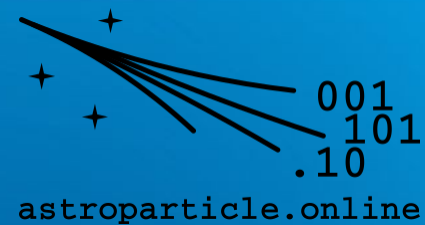
Wasserstein distance=sum over all arrow weights multiplied by path length



Critics: Wasserstein distance = C(green) - C(blue)
Gradients of C parallel to optimal transport paths (red arrows), perpendicular to contour lines.



Conclusion



- It is very important to implement a fast generator for shower simulation
 - Corsika base solution require from hours to few days per one event.
- GAN nets are natural candidates to speedup simulation
 - Rely on the possibility to interpret “events” as “images”
 - First GANs applications to cosmic ray case looks very promising
- 3d GAN is the initial step of a wider plan to do DL based fast simulation within the GeantV project