Machine Learning, 21cm and further musings

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&

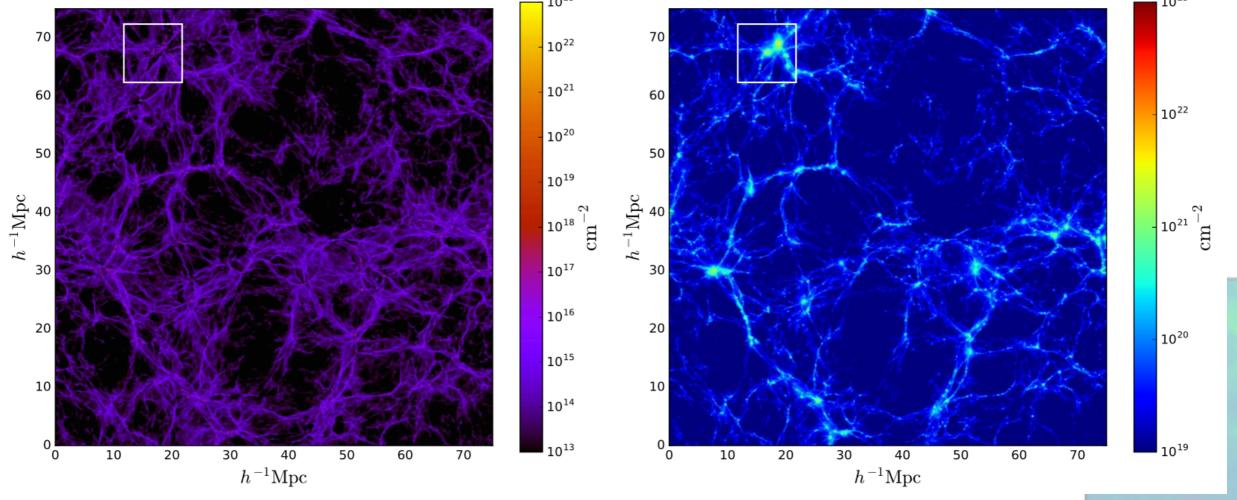
Francesco Villaescusa-Navarro (Flatiron), Siyu He (Flatiron/CMU), Laurence Levasseur (Flatiron)

Intensity mapping workshop, Flatiron Institute, 2019

Generating Neutral Hydrogen map quickly?

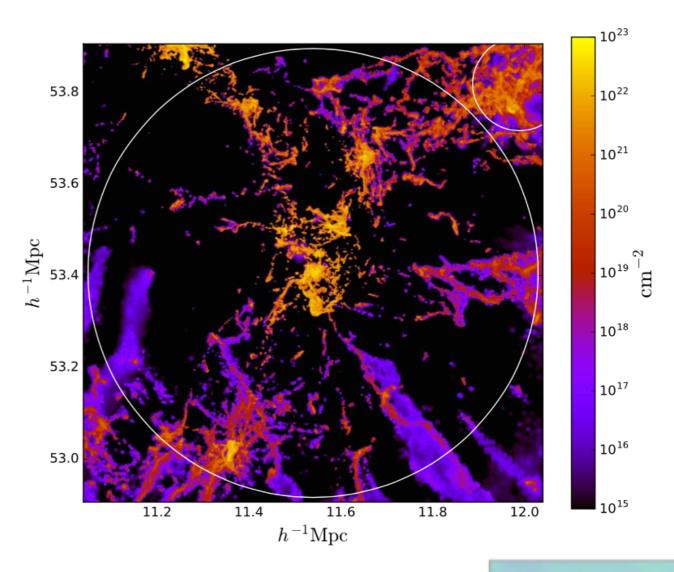
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- (See Francisco and Emmanule's talks)

Villaescusa-Navarro et al. 2018



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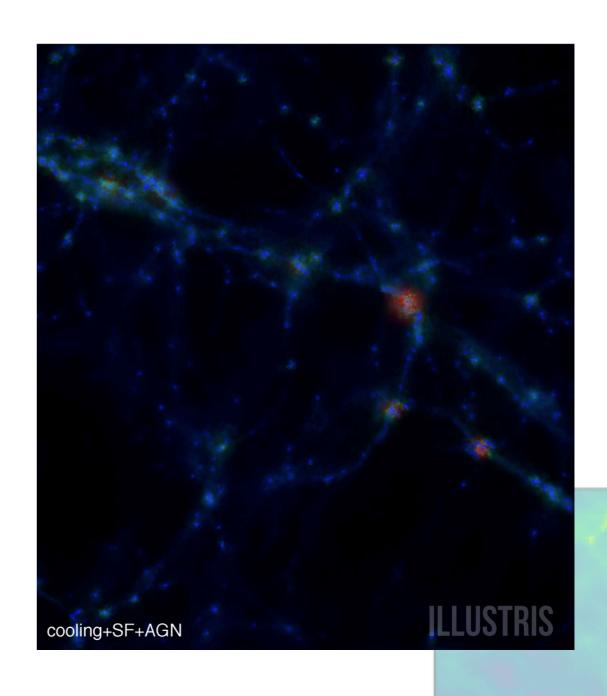
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- Can we generate the small scales (aka the 1-halo term) correctly?
- Assuming we can produce simulations that are "good enough" or observations are "good enough" for small volumes, do we now have enough information to generate lots of 21cm maps correct down to small scales?



Villaescusa-Navarro et al. 2018

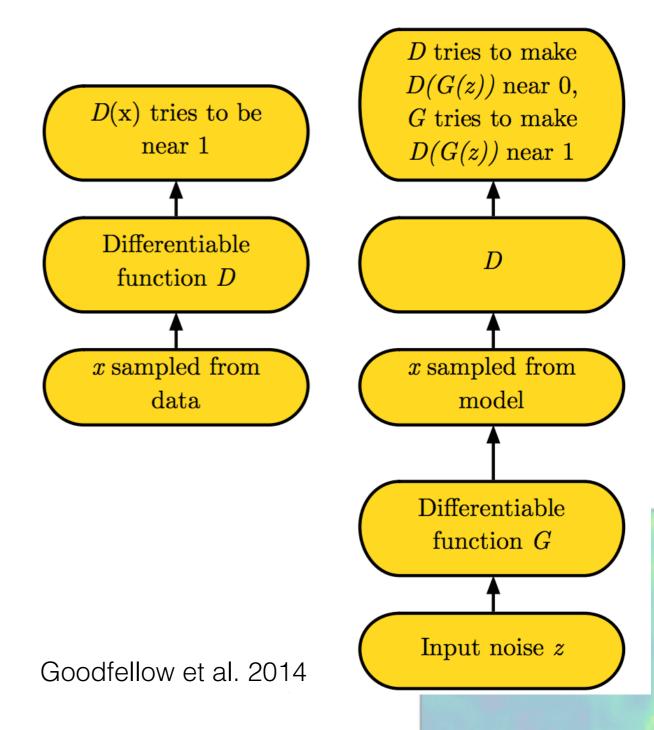
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Introducing our method: Generative Adversarial Network

- We simultaneously train two models:
 - a generative model G that captures the data distribution, and
 - a discriminative model D that estimates the probability that a sample came from the training data rather than G.
- The training procedure for G is to maximize the probability of D making a mistake.
- In the space of arbitrary functions G and D, a unique solution exists, with G recovering the training data distribution and D equal to 1/2

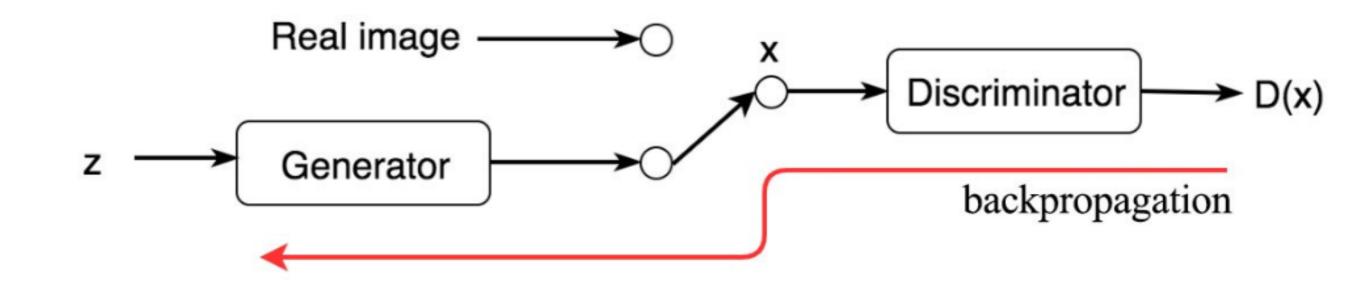


Introducing our method: Generative Adversarial Network

- If you watch Harry Potter:
 Goblet of Fire
- If you ever try to go into a bar when you are too drunk to be allowed in by the bouncer: Try until the bouncer allows you in.



In other words...



Why GAN?



(CelebA)



Sample Generator (Karras et al, 2017)

Image generation by GAN in last 4 years



(Brundage et al, 2018)

Improving resolution: super-resolution using GANs

bicubic (21.59dB/0.6423)



SRResNet (23.53dB/0.7832)



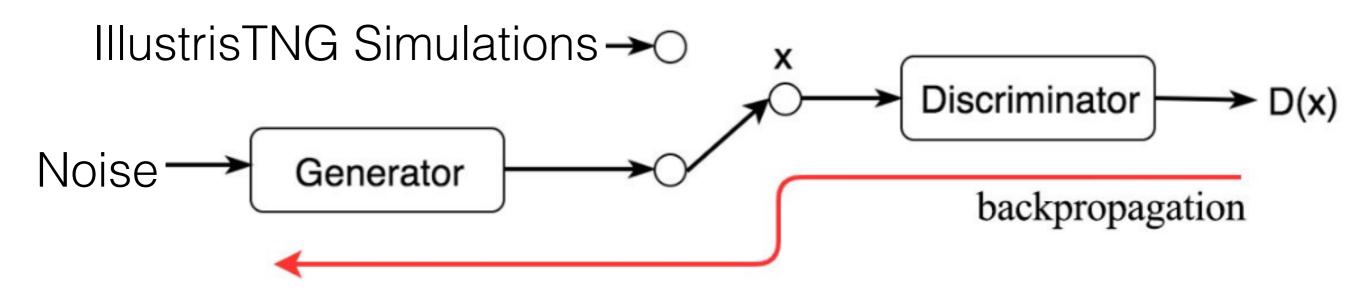
SRGAN (21.15dB/0.6868)



original



Generating neutral hydrogen using GANs?



Many different types of GANs and other methods

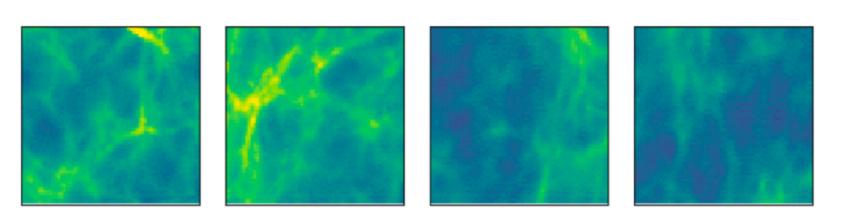
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- DCGANs
- MMDGANs
- Wasserstein GANs
- Conditional GANs

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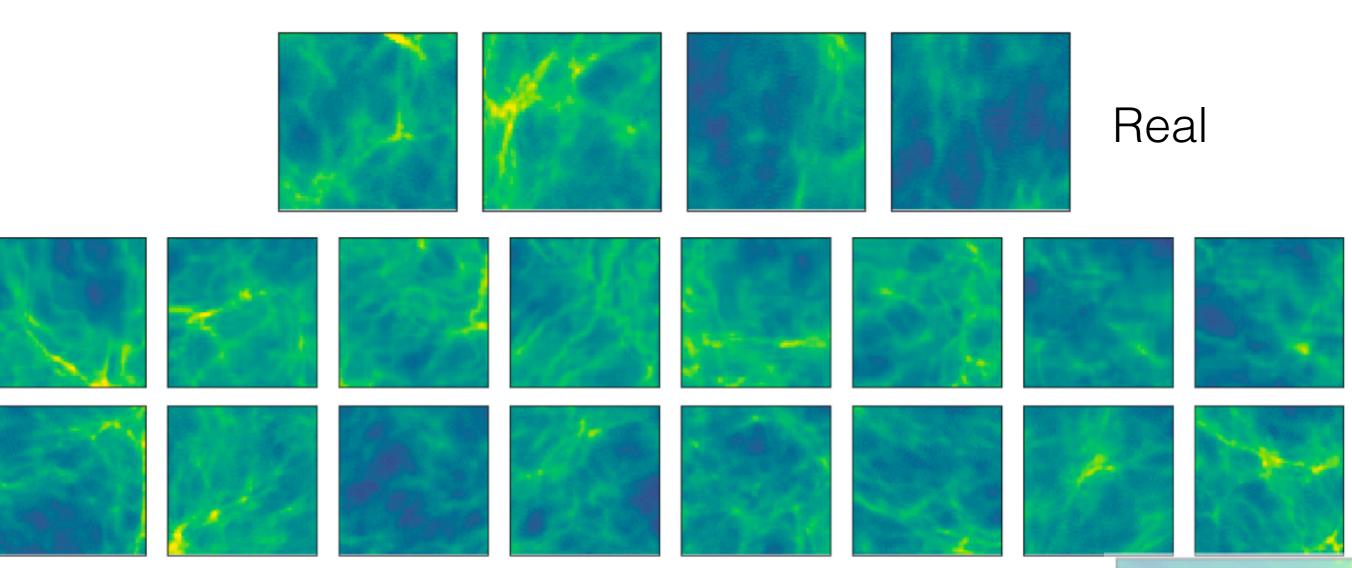
Venture a guess?

Real



Which row is the real data? Which row is the generated data?

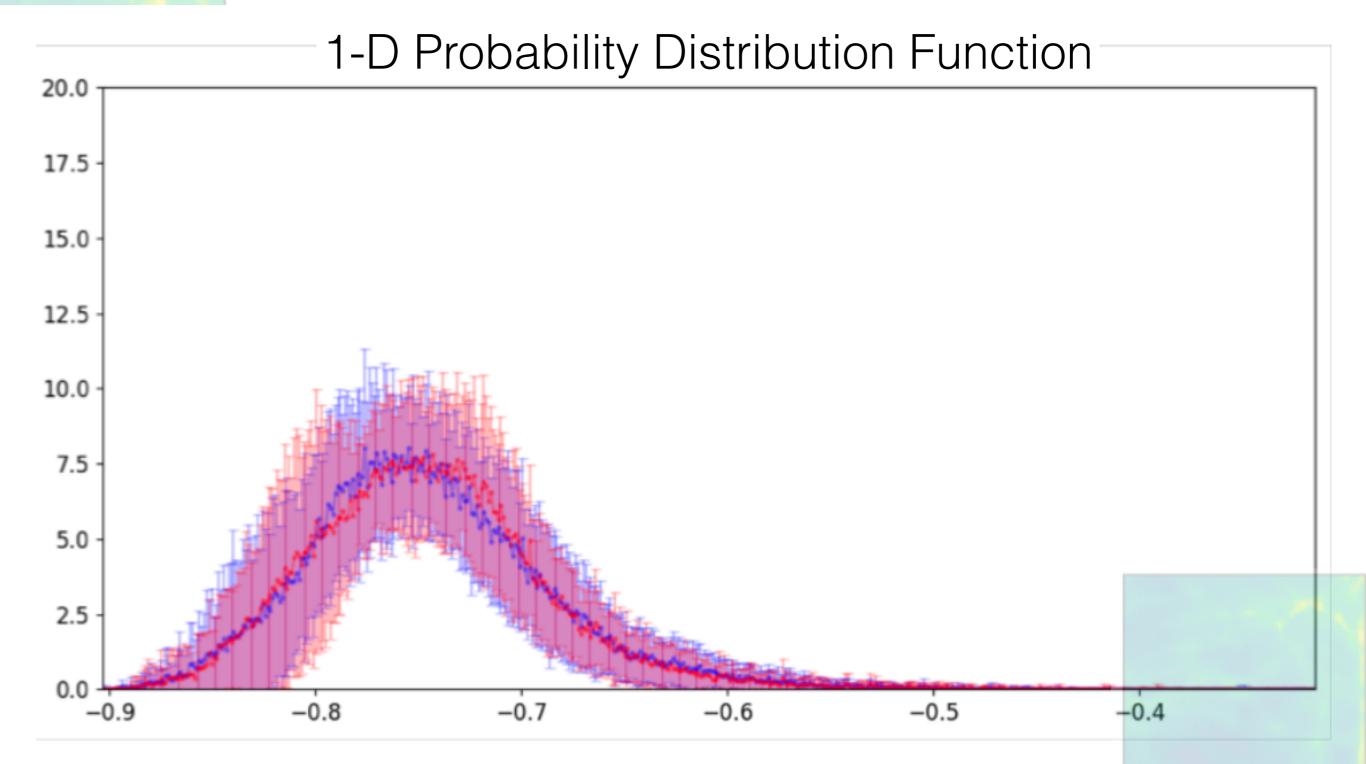
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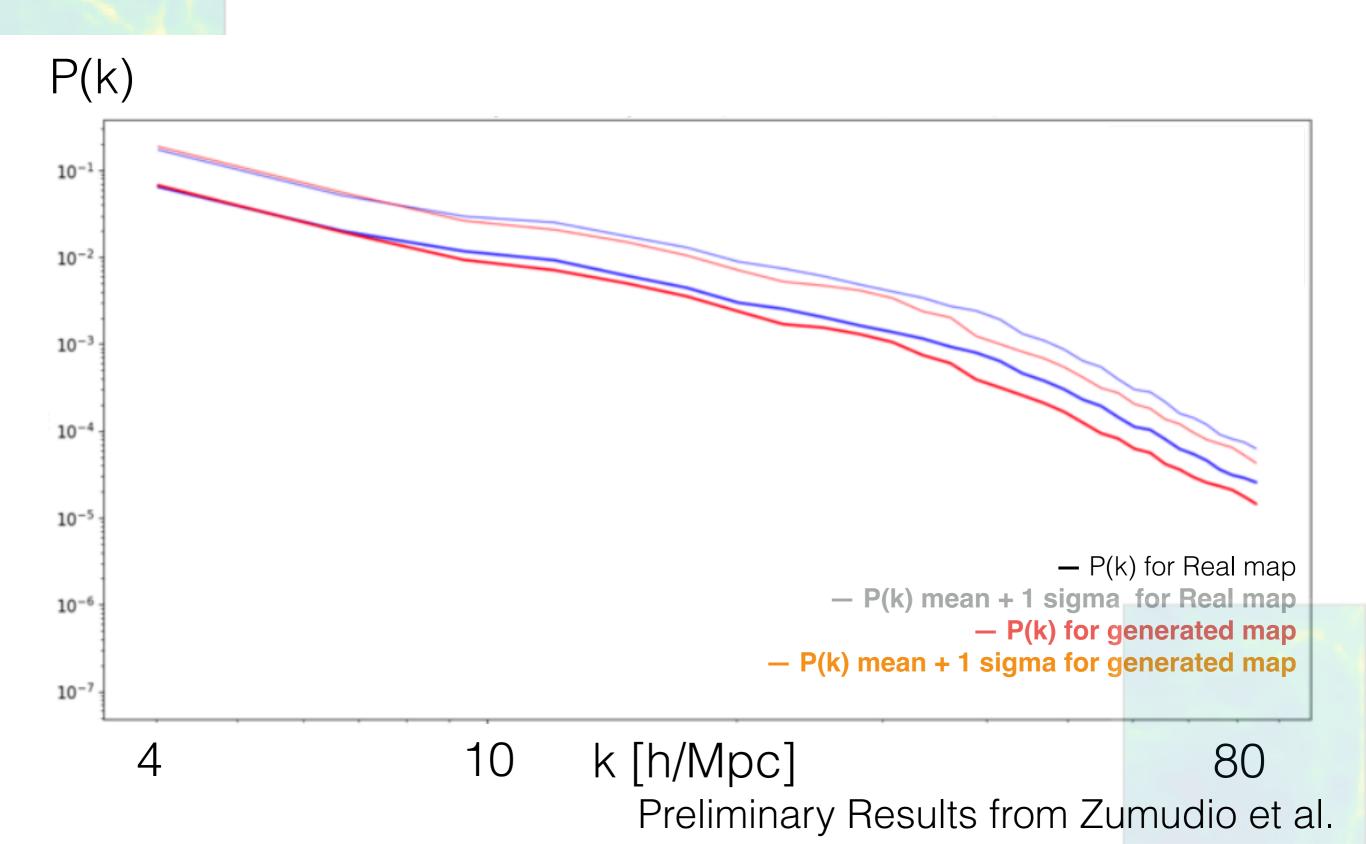
Preliminary Results from Zumudio et al.

Statistics of the generated maps



Preliminary Results from Zumudio et al.

Power-spectrum comparison



Looking forward and other musings

- Check how well the method does at bi-spectrum level
- Use this method to "in-paint" the 1-halo term using sCOLA (Tassev, Eisenstein et al., 2015)
- Can generate 21cm maps with correct 1-halo terms and large scale effects quickly (O(minutes))
- What other applications of ML in 21cm that can be interesting?

Other possible applications

- Foreground removals?
 - Talk to Lachlan Lancaster, Paco and Laurence
- Direct cosmological or astrophysical parameter estimation?
 - See Ravanbakhsh et al. 2016
- Picking out "bad data" such as RFI?
- Other ideas?