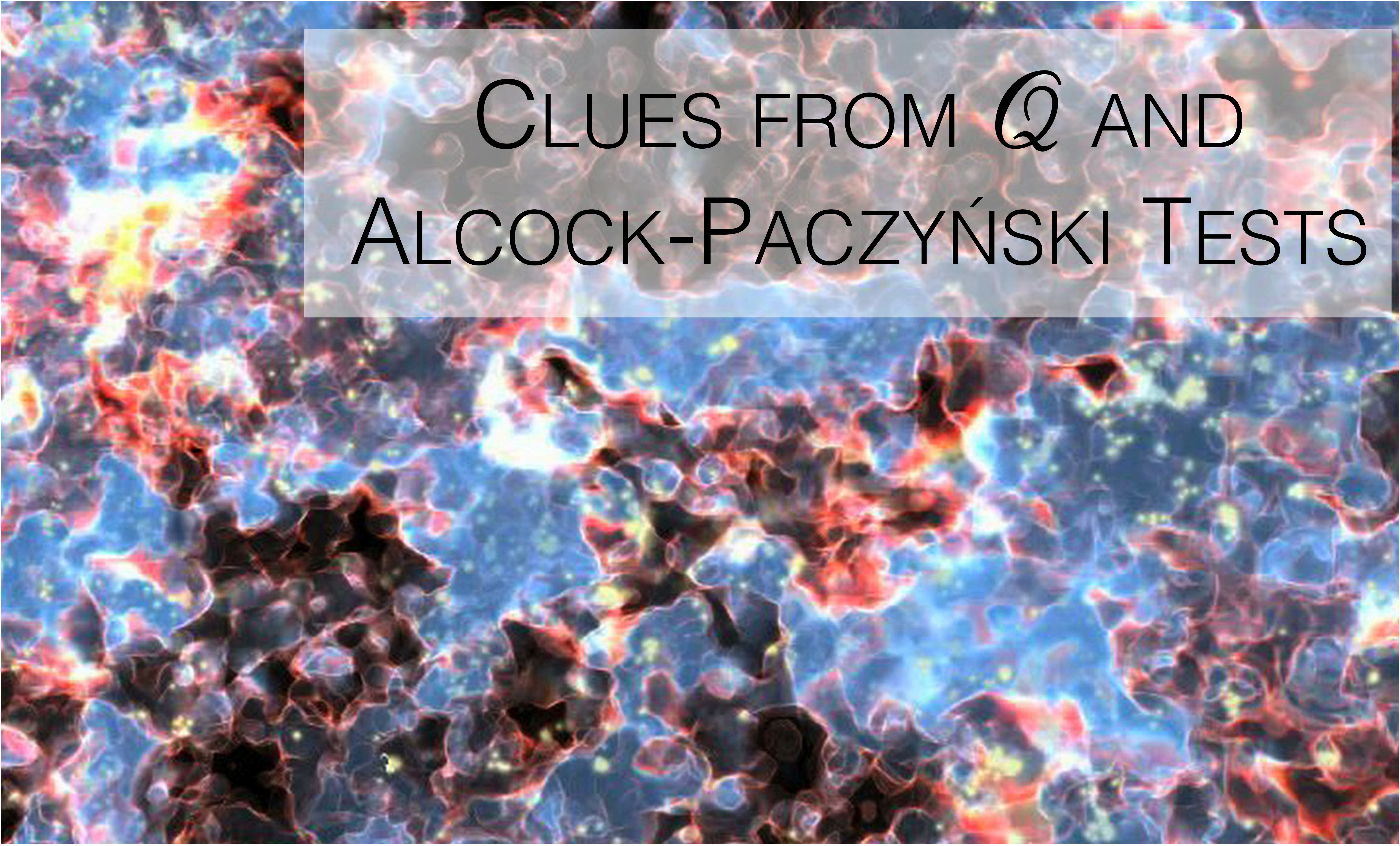
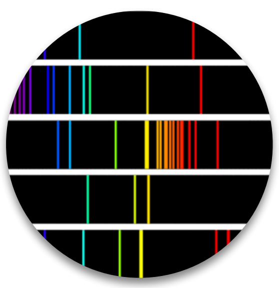
Clues from $\mathcal{Q}$ and Alcock-Paczyński Tests

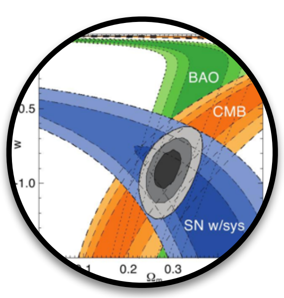


Adrian Liu
McGill University

On today’s agenda



In the era of **multiple spectral lines,** what are some interesting opportunities **beyond “just” cross correlations?**



How can we **look past astrophysics** during cosmic dawn and reionization to place constraints on **fundamental cosmological parameters?**

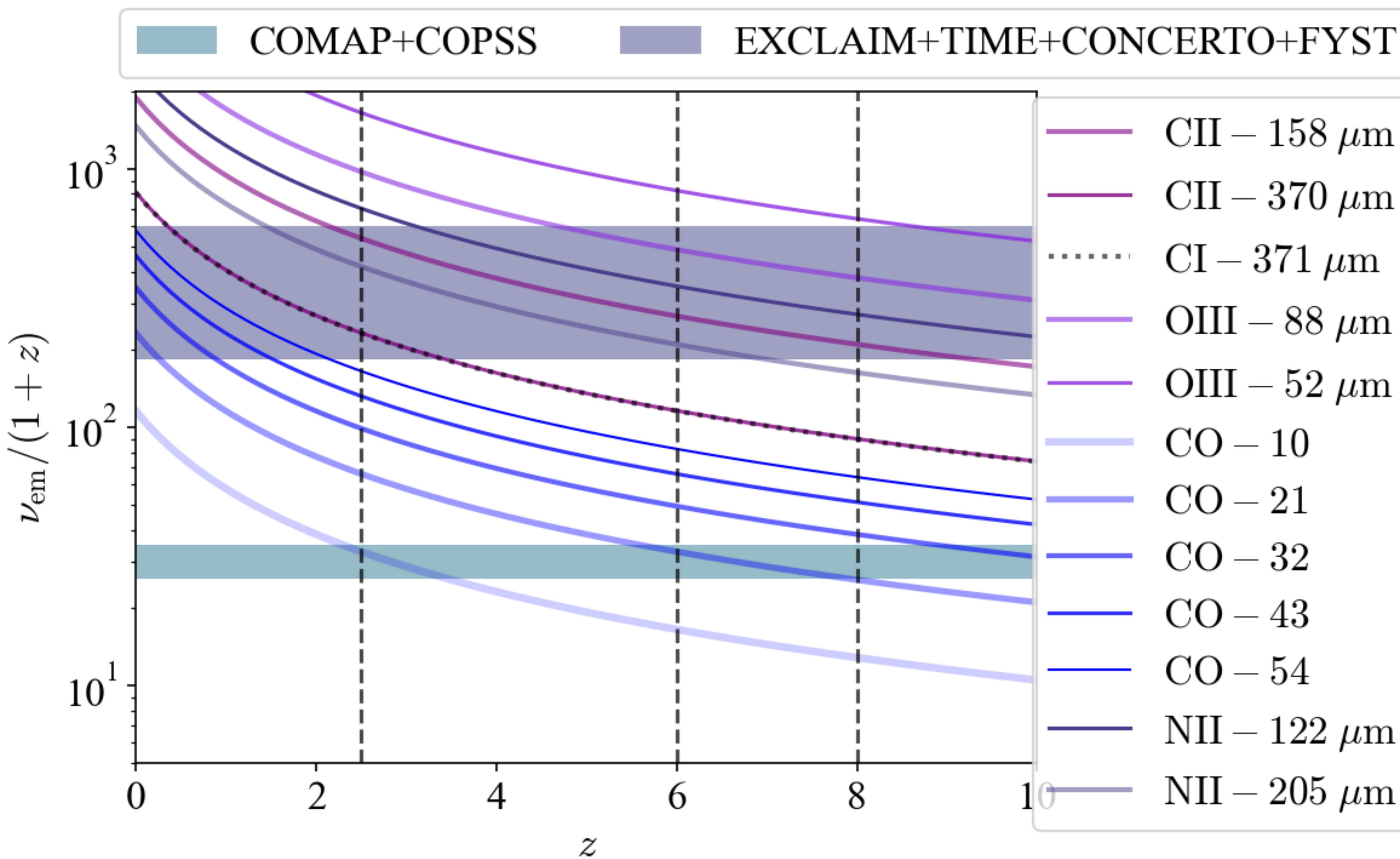
Clues from $\mathcal{Q}$

Sarkar, Iles, **AL** (2025), in prep.

Dr. Debanjan Sarkar
McGill University

Ella Iles
McGill undergrad —> ???

It no longer seems crazy to imagine an era of N lines covering the same redshift…



…and with this prospect comes new opportunities

$$\hat{P}_{aa} \equiv \frac{P_{ab} P_{ac}}{P_{bc}}$$

Beane et al. (2019)

…and with this prospect comes new opportunities

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Do the relevant assumptions (linear bias, strong inter-line correlation) hold?

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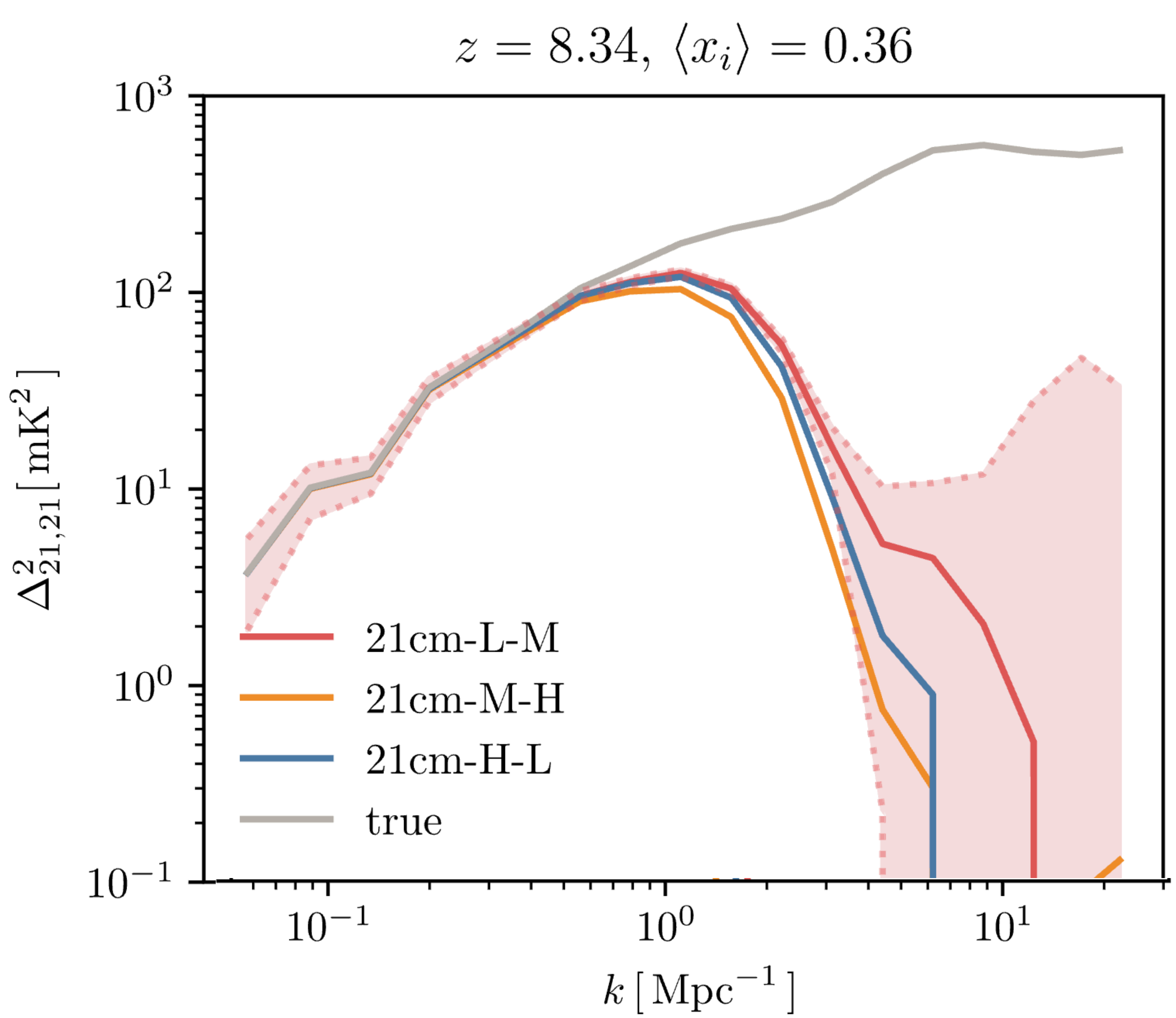


Do the relevant assumptions (linear bias, strong inter-line correlation) hold?

Simulations are ok, but what if we aren't sure about the modelling?

Data-driven way to test the assumptions

$$\mathcal{Q}_{abcd} \equiv \frac{P_{ab}P_{cd}}{P_{ac}P_{bd}}$$

Data-driven way to test the assumptions

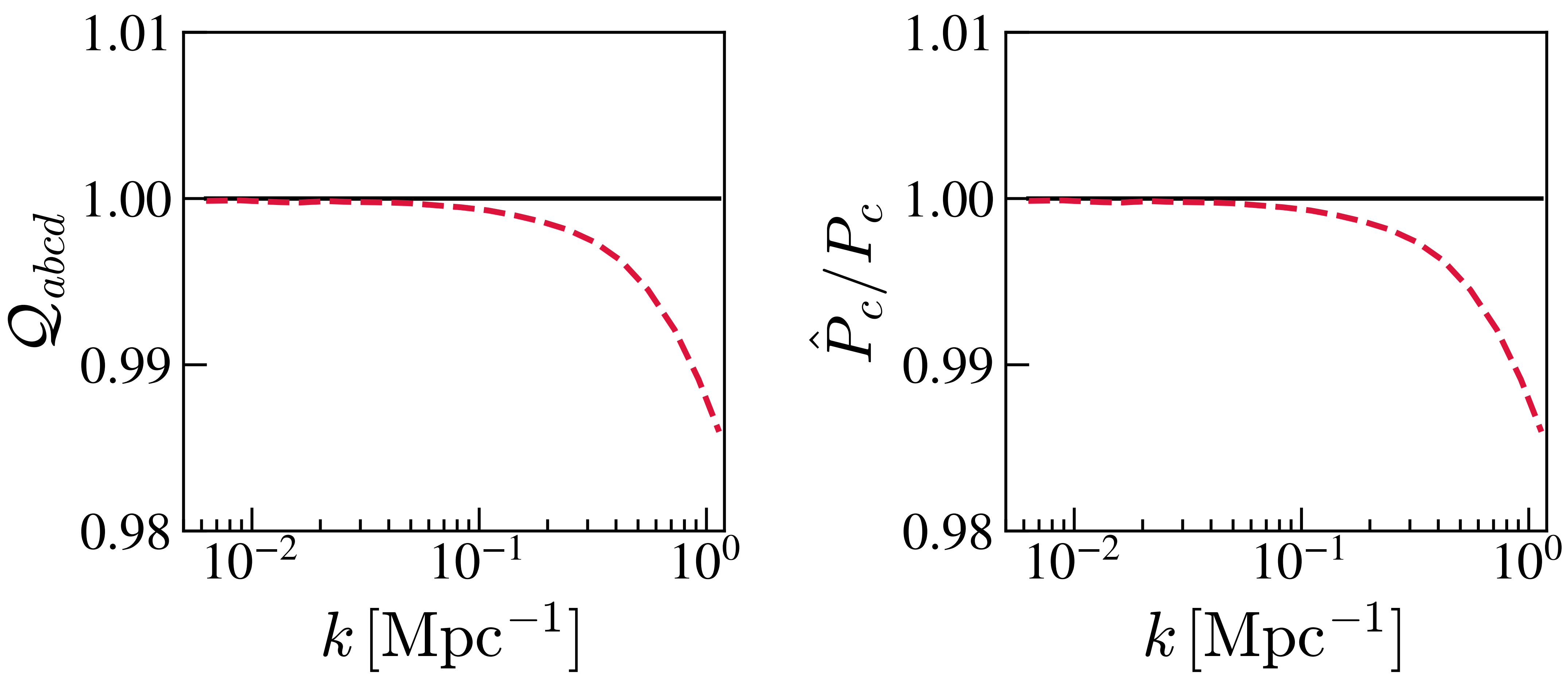
$$\mathcal{Q}_{abcd} \equiv \frac{P_{\cancel{a}\cancel{b}} P_{\cancel{c}\cancel{d}}}{P_{\cancel{a}\cancel{c}} P_{\cancel{b}\cancel{d}}} \rightarrow 1$$ **if** the Beane et al. assumptions hold

Data-driven way to test the assumptions

$$\mathcal{Q}_{abcd} \equiv \frac{P_{\cancel{a}\cancel{b}}P_{\cancel{c}\cancel{d}}}{P_{\cancel{a}\cancel{c}}P_{\cancel{b}\cancel{d}}} \rightarrow 1$$

$\rightarrow 1$ **<u>if</u>** the Beane et al. assumptions hold

(a) [CII] 158 μm, (b) [OIII] 88 μm, (c) [NII] 122 μm, (d) [NII] 205 μm



Under many reasonable scenarios this works.

But when does this fail?

Model (`LIMpy`): $L = \alpha\,(\mathrm{SFR})^{\beta}$

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Doesn't matter

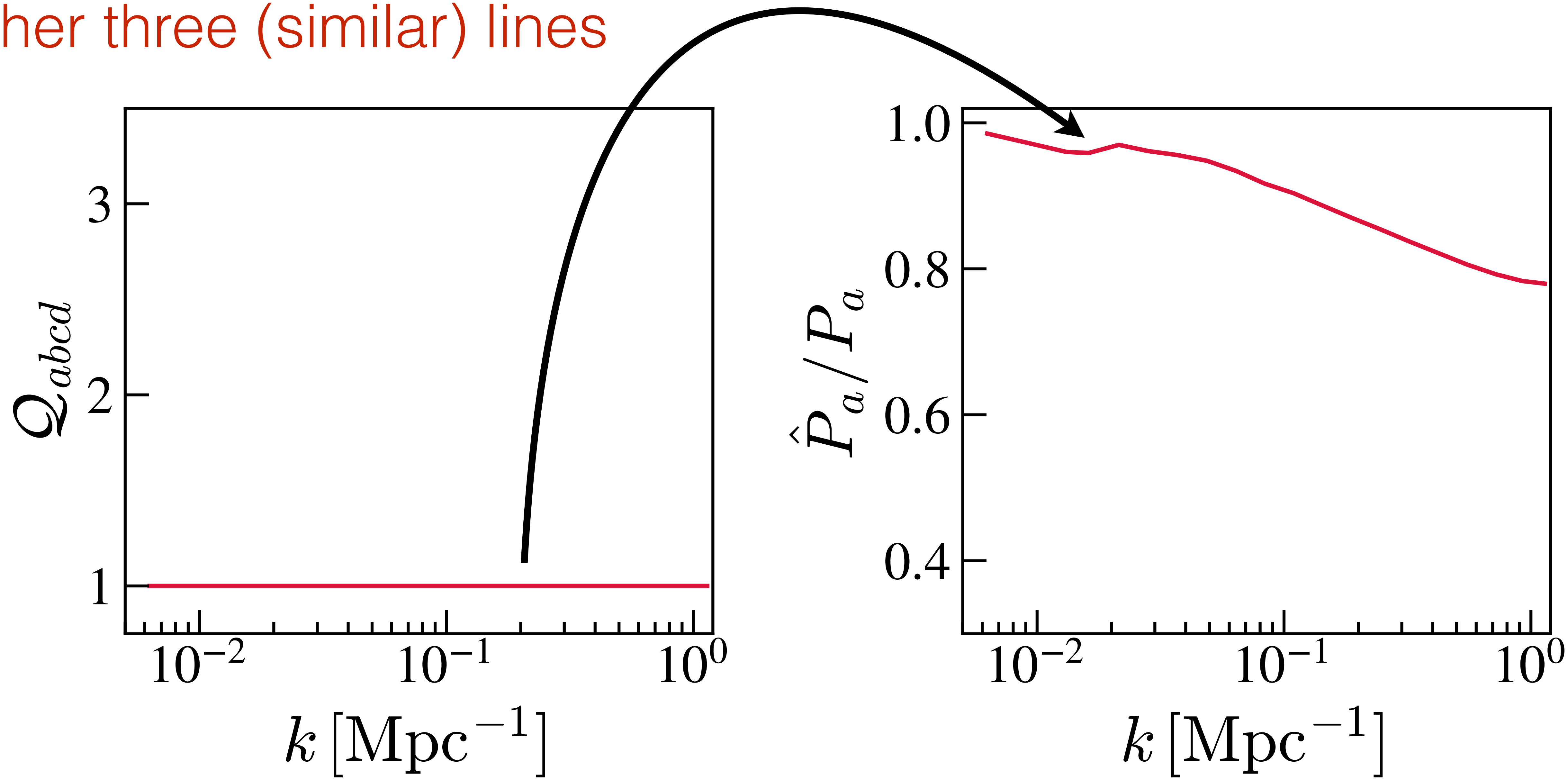
Model ($\texttt{LIMpy}$): $L = \alpha\,(\mathrm{SFR})^{\beta}$

Doesn't matter

Generally, the more similar β, the more $\mathcal{Q} \approx 1$ when it's suppose to be

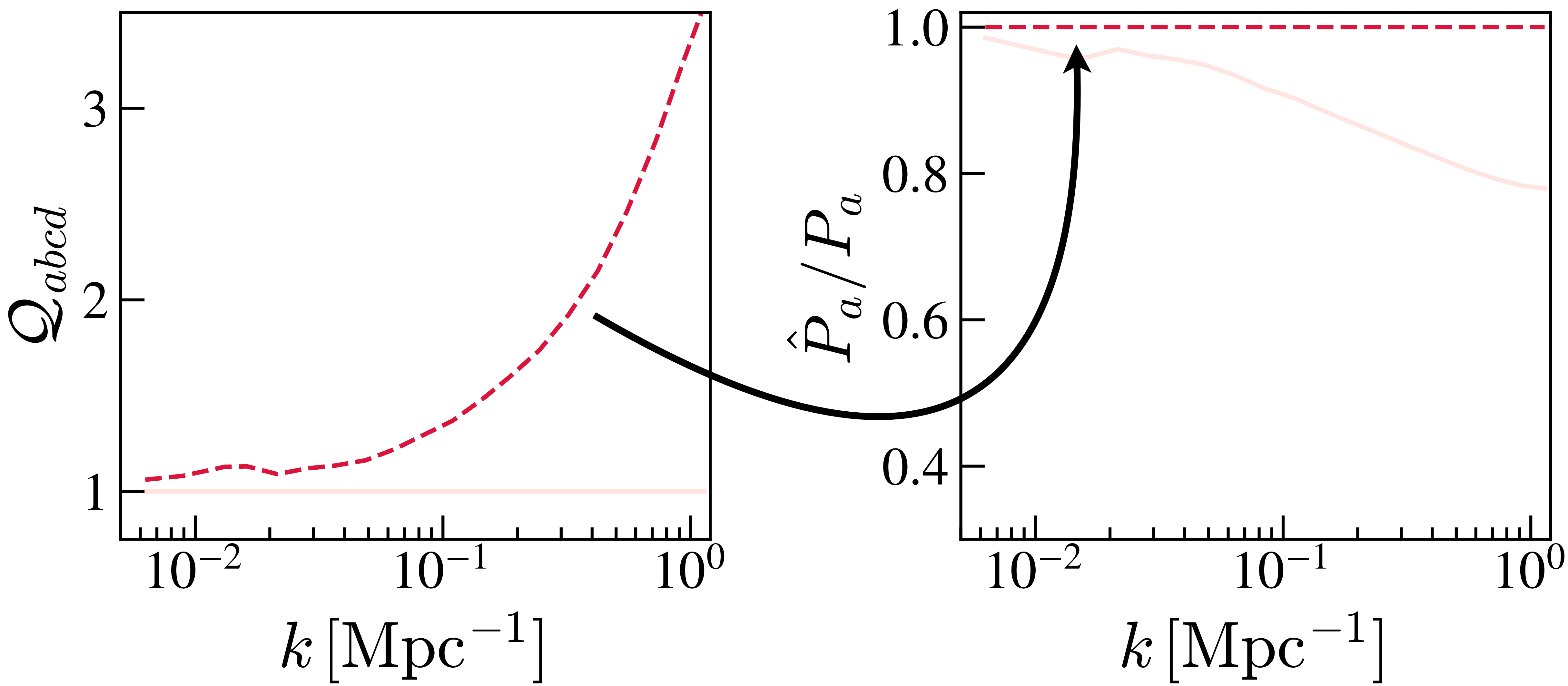
Model (LIMpy): $L = \alpha\,(\mathrm{SFR})^{\beta}$

False negative when the target auto spectrum is very different from the other three (similar) lines

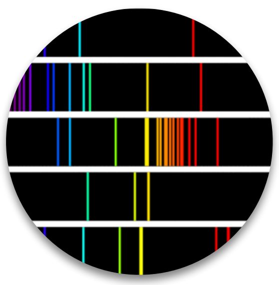


Model (LIMpy): $L = \alpha\,(\mathrm{SFR})^{\beta}$

False positive when the four lines (a,b,c,d) are in two groups (a,b), (c,d) that are internally similar but different from each other

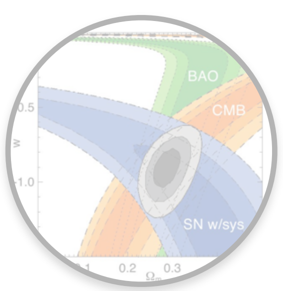


On today's agenda



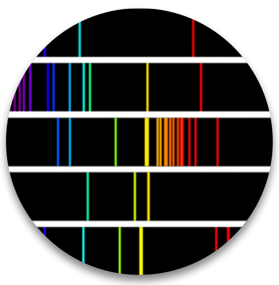
In the era of **multiple spectral lines,** what are some interesting opportunities **beyond "just" cross correlations?**

Ratios of cross-power spectra can be interesting, both for signal estimation and data-driven null tests



How can we **look past astrophysics** during cosmic dawn and reionization to place constraints on **fundamental cosmological parameters?**

On today’s agenda



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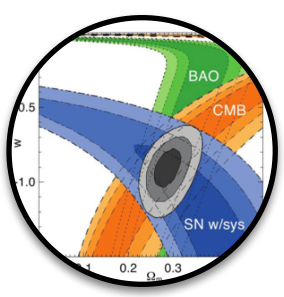


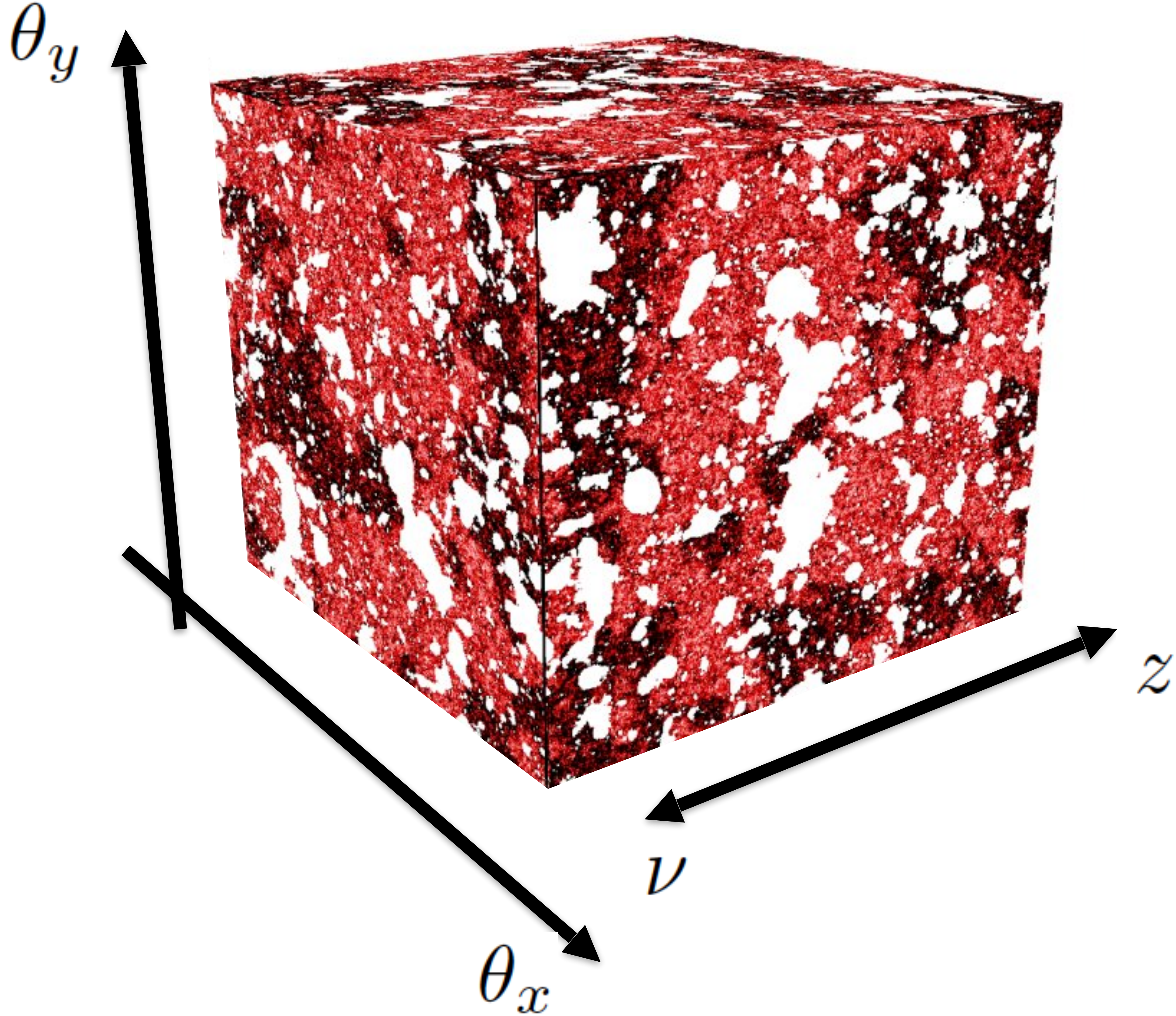
How can we **look past astrophysics** during cosmic dawn and reionization to place constraints on **fundamental cosmological parameters?**

An Alcock-Paczyński Test on Reionization Bubbles for Cosmology

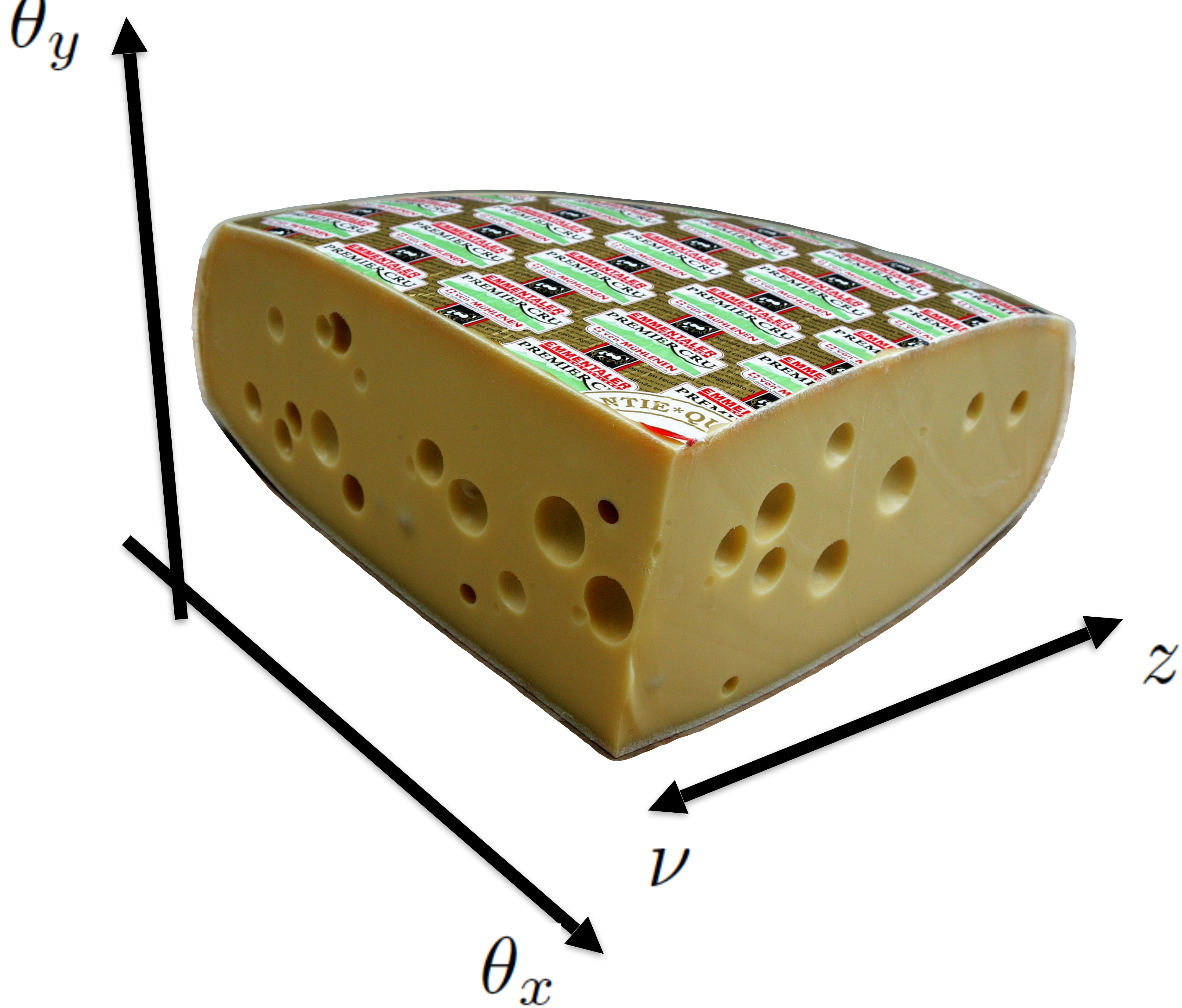
Thélie, Del Balso, Muñoz, **AL** (2025), Phys. Rev. D **111**, 123501

Dr. Emilie Thélie
UT Austin

Franco Del Balso
McGill undergrad —> ???

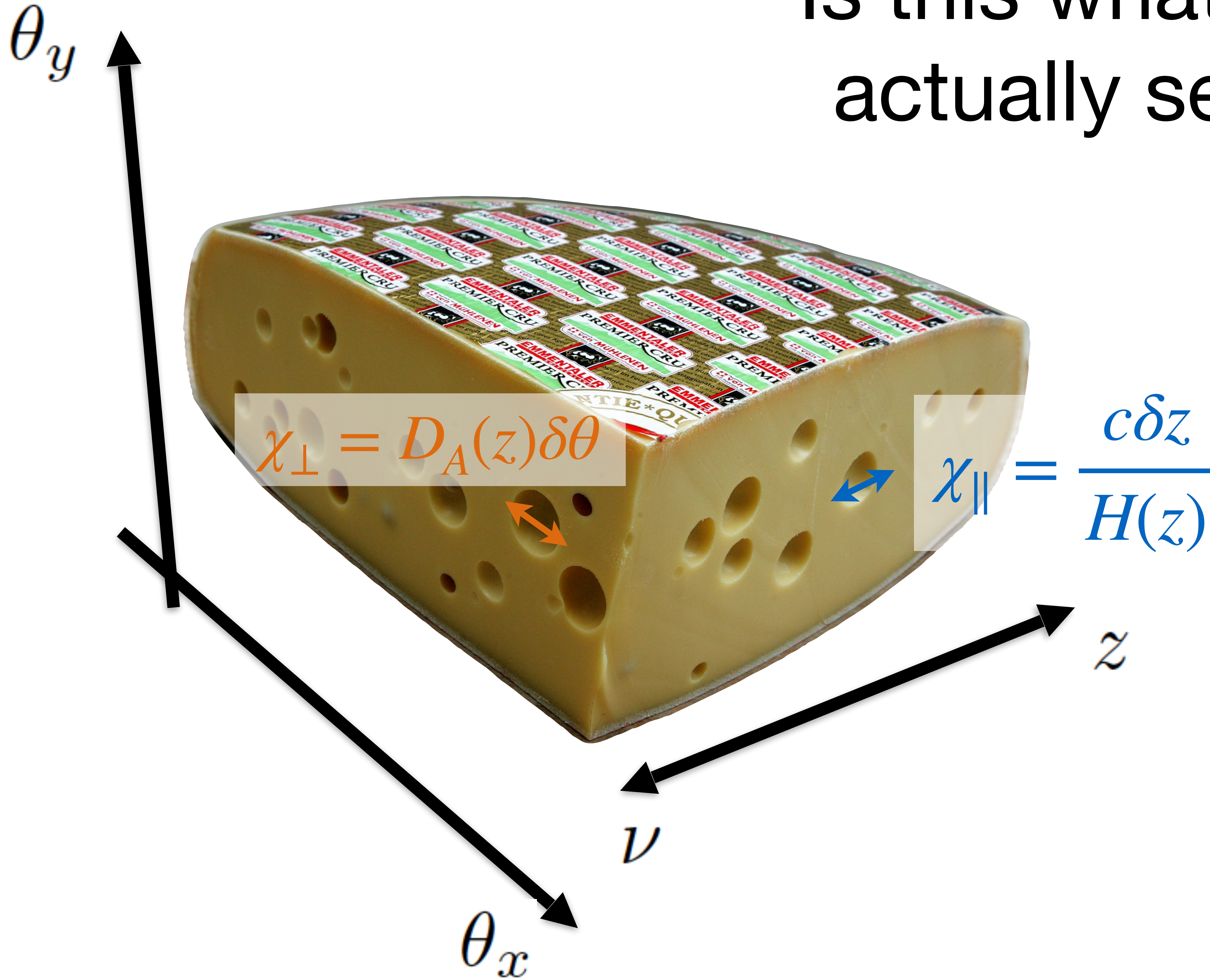


θ_y
z
ν
θ_x



θ_y
EMMENTALER
PREMIER CRU
z
ν
θ_x

Is this what we actually see?



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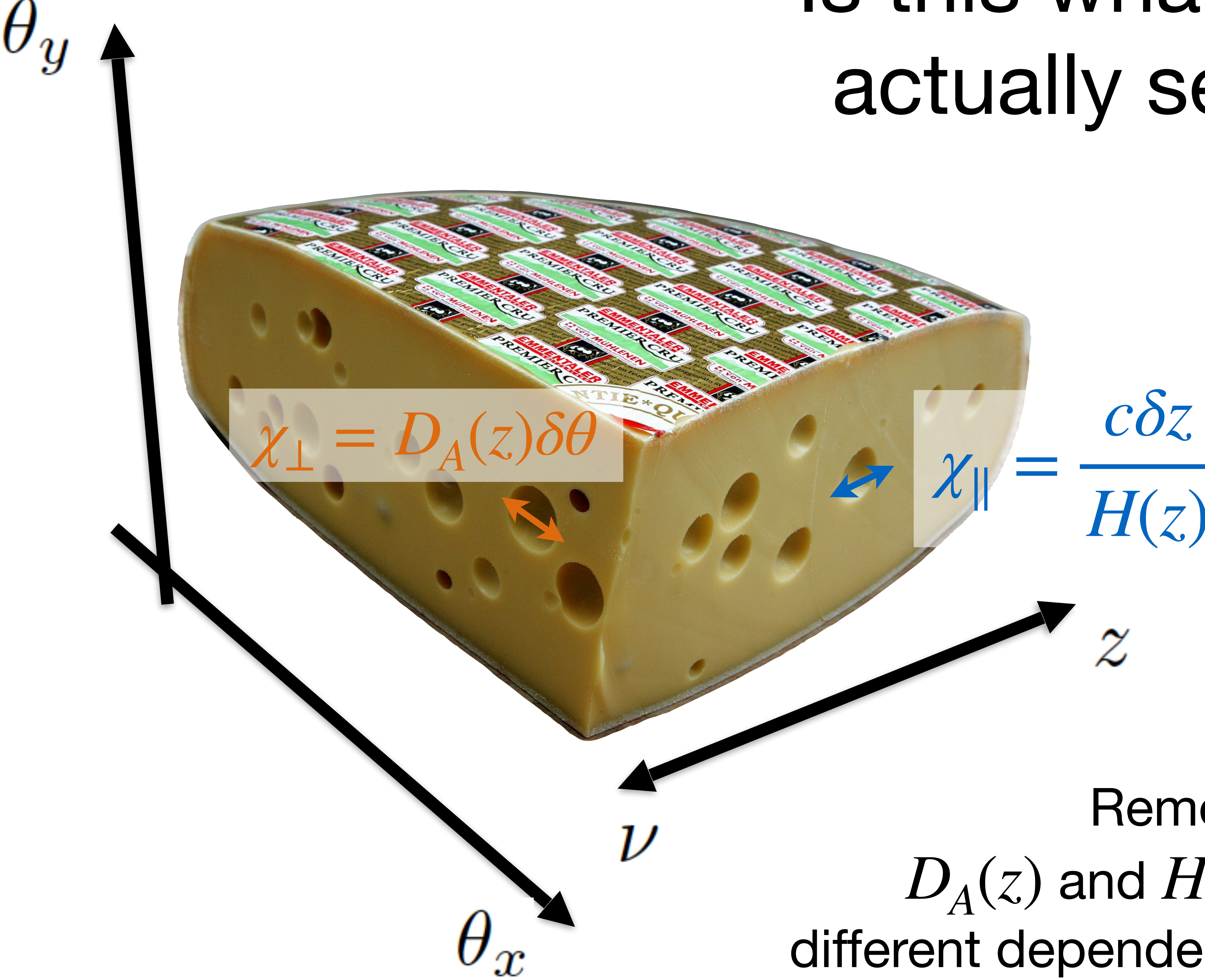
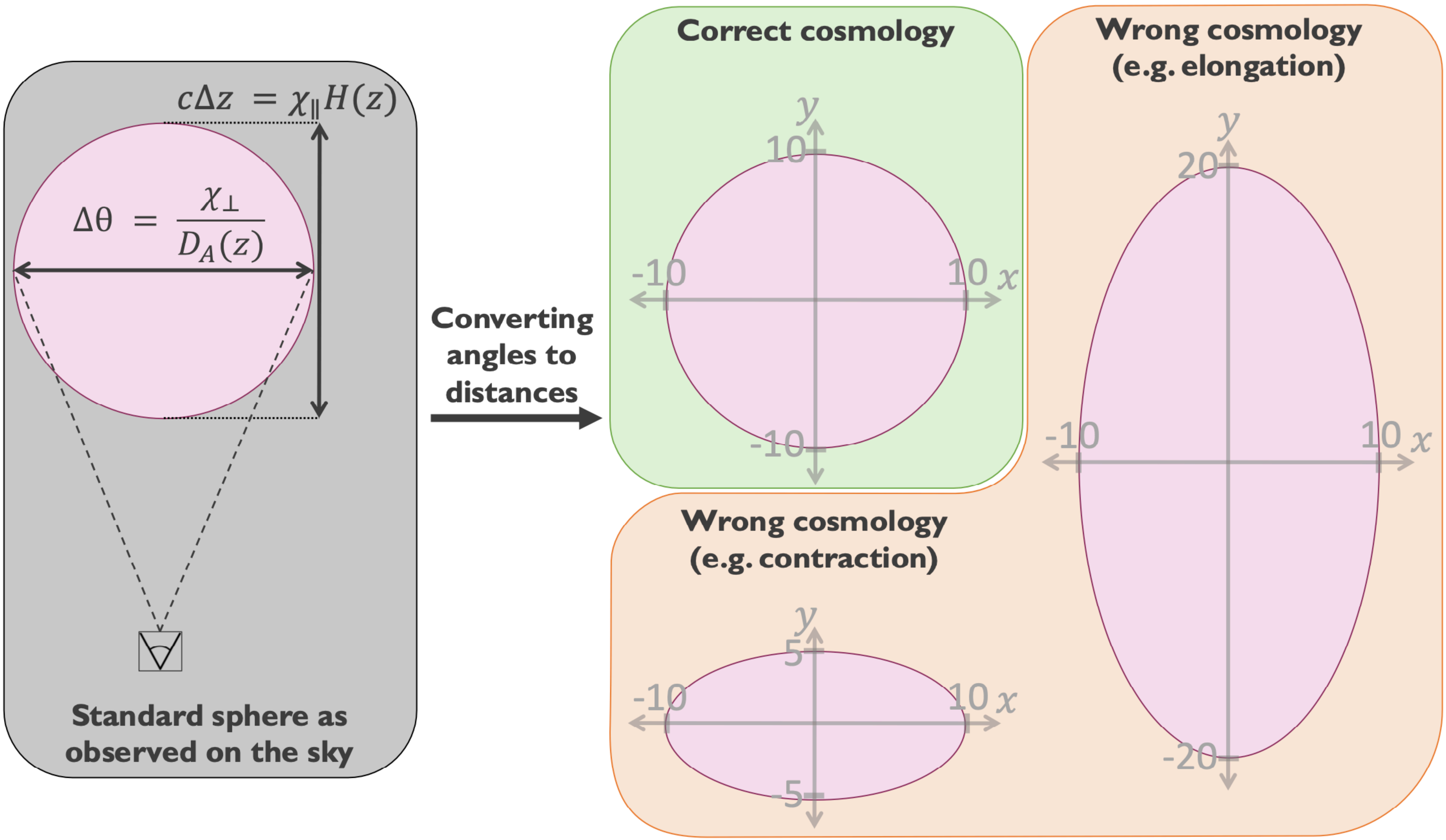


Remember…
$D_A(z)$ and $H(z)$ have different dependencies on cosmological parameters

Converting angles and redshifts to comoving distances requires cosmological assumptions

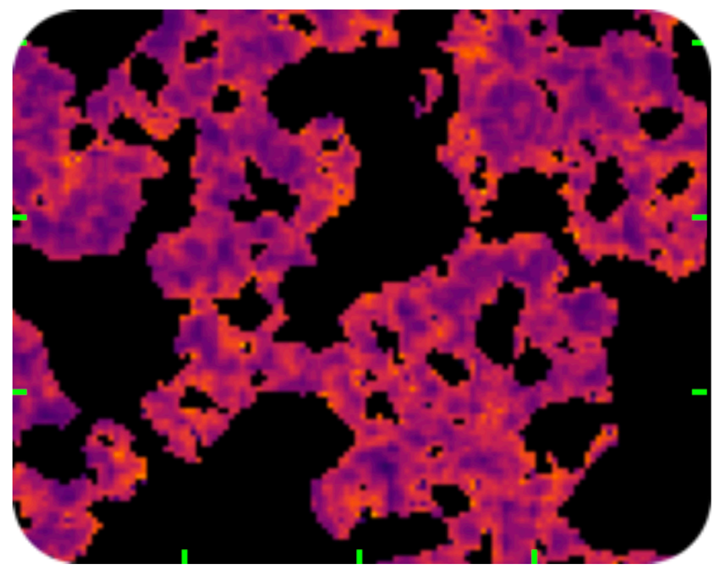


Standard spheres

will only appear spherical if we have a correct cosmological mapping between observer coordinates and theory coordinates, which means we can work in reverse and

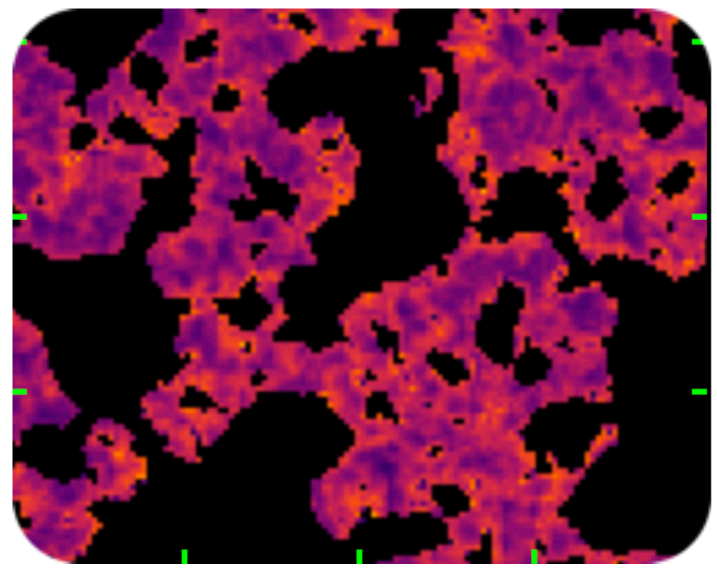
constrain cosmological parameters by testing for sphericity

An actual reionization model

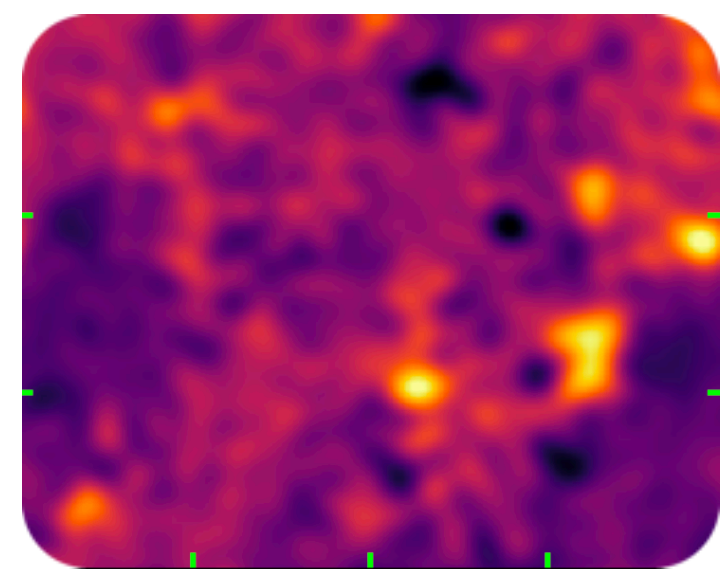


We don’t have standard spheres!

An actual reionization model



After foreground filtering



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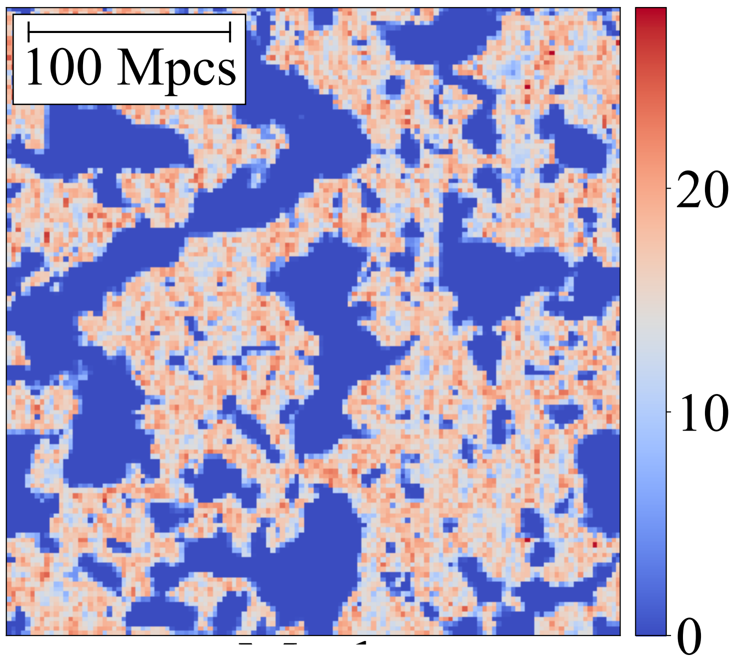
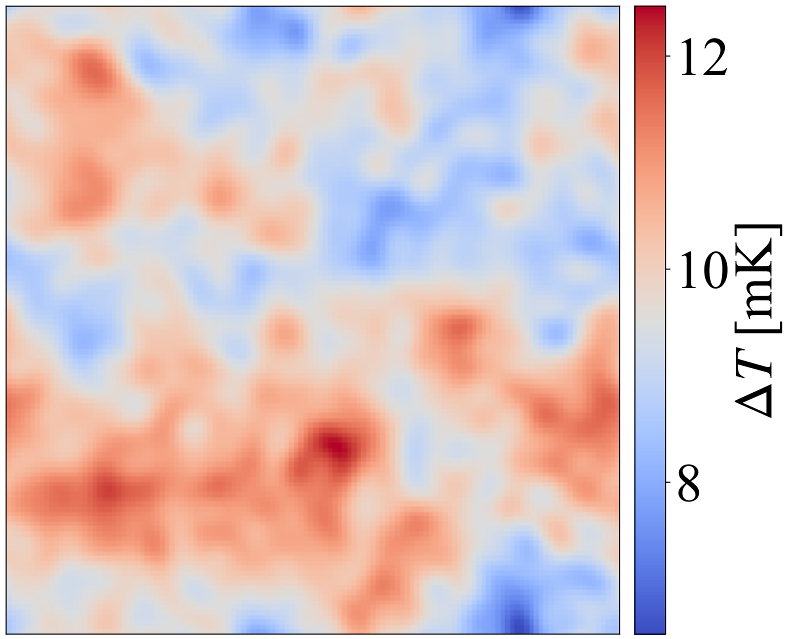
Filtering the data can get rid of contaminants, but **destroy lots of information**….



Original



Filtered

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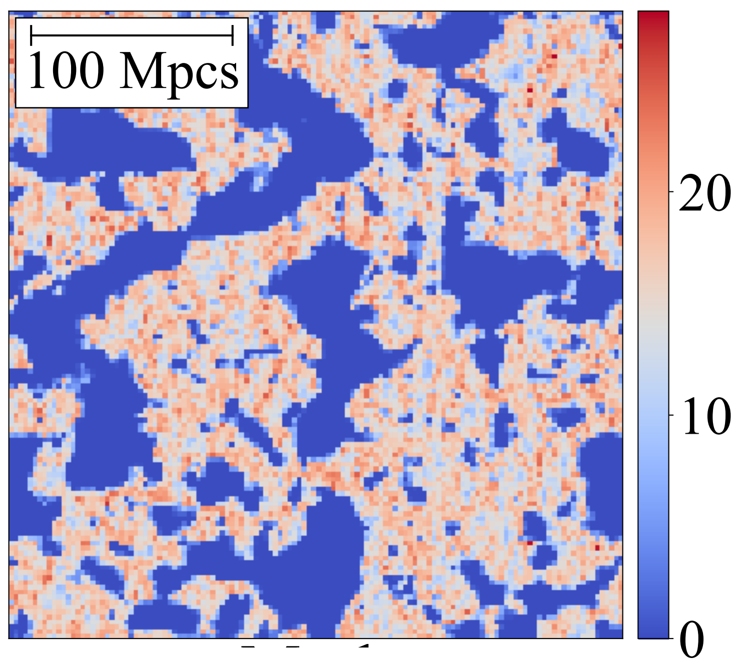
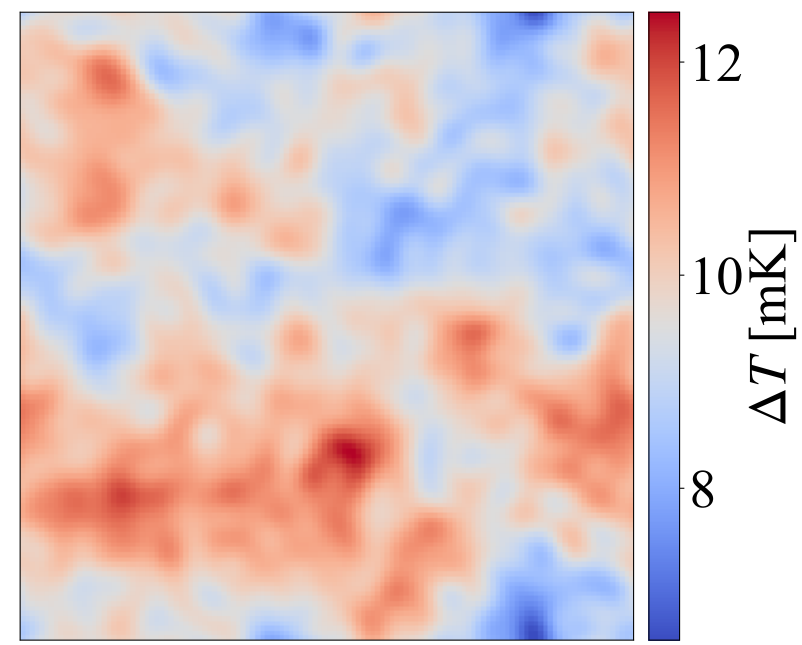
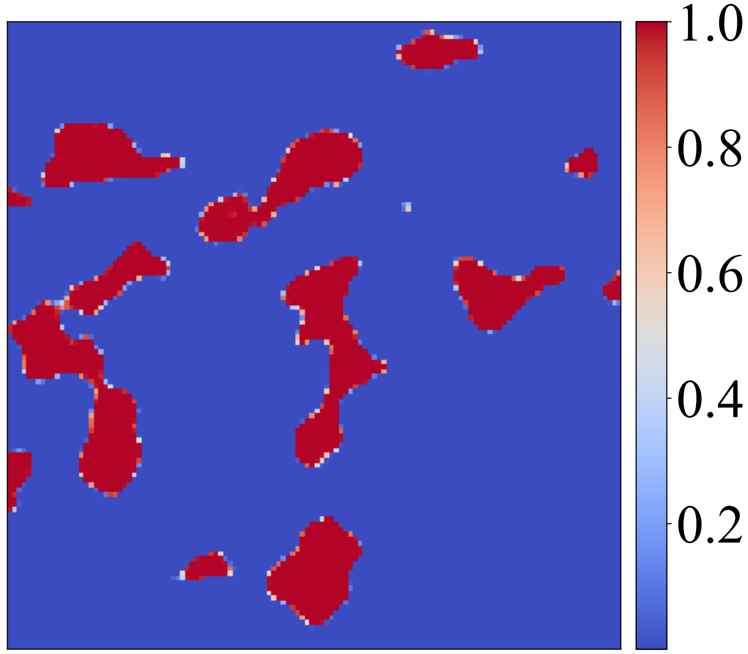


Original



Filtered

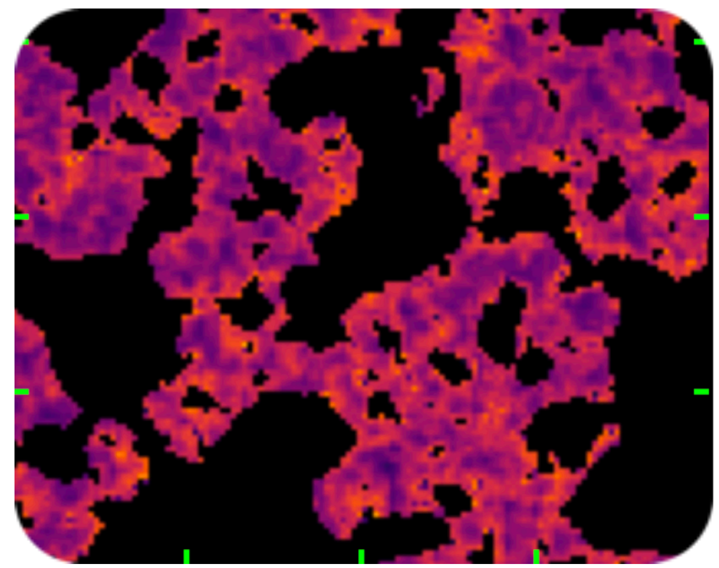


Predicted ionization

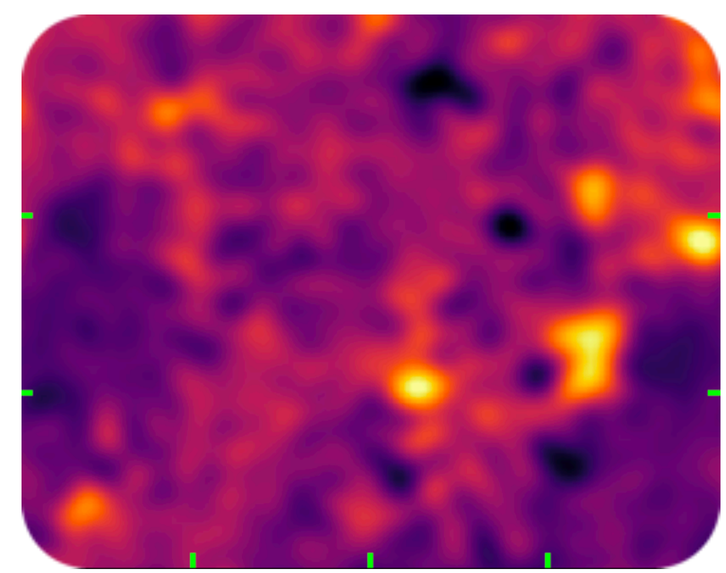
….but perhaps **machine learning** can save the day!

- Gagnon-Hartman, Cui, Kennedy, **AL**, Ravanbakhsh (2021) MNRAS **504**, 4716
- Kennedy, Colaço Carr, Gagnon-Hartman, **AL**, Mirocha, Cui (2024) MNRAS **529**, 3684

An actual reionization model

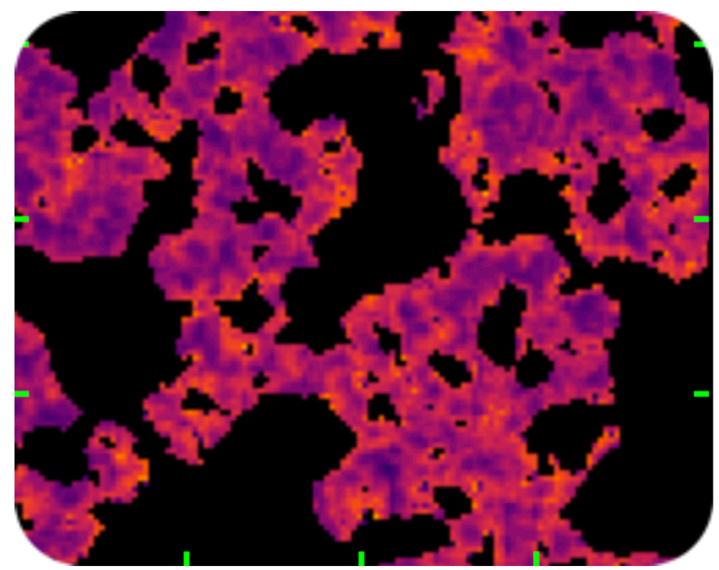


After foreground filtering

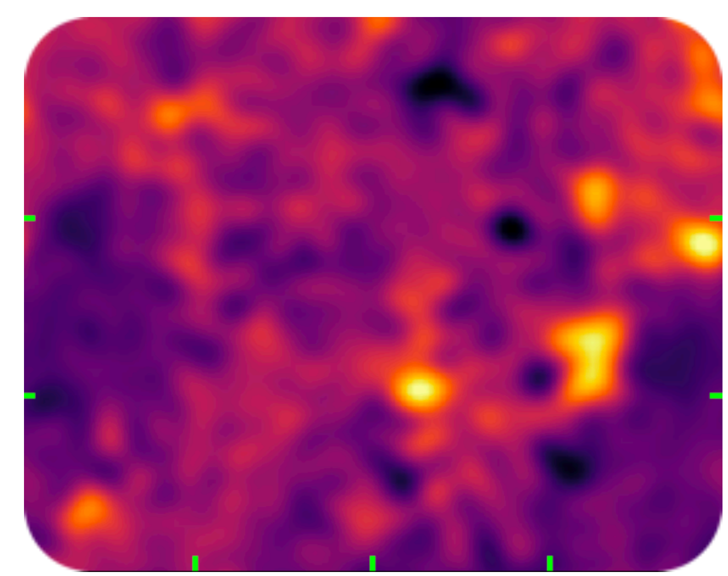


We don’t have standard spheres!

An actual reionization model



After foreground filtering

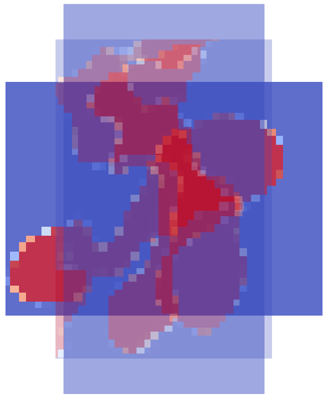


ML reconstruction of ionized bubbles

We don’t have standard spheres!

Individual bubbles are definitely not spherical…

…but our Universe has no preferred direction, so the weird shapes will be randomly oriented and **stacks** of bubbles should be statistically spherical



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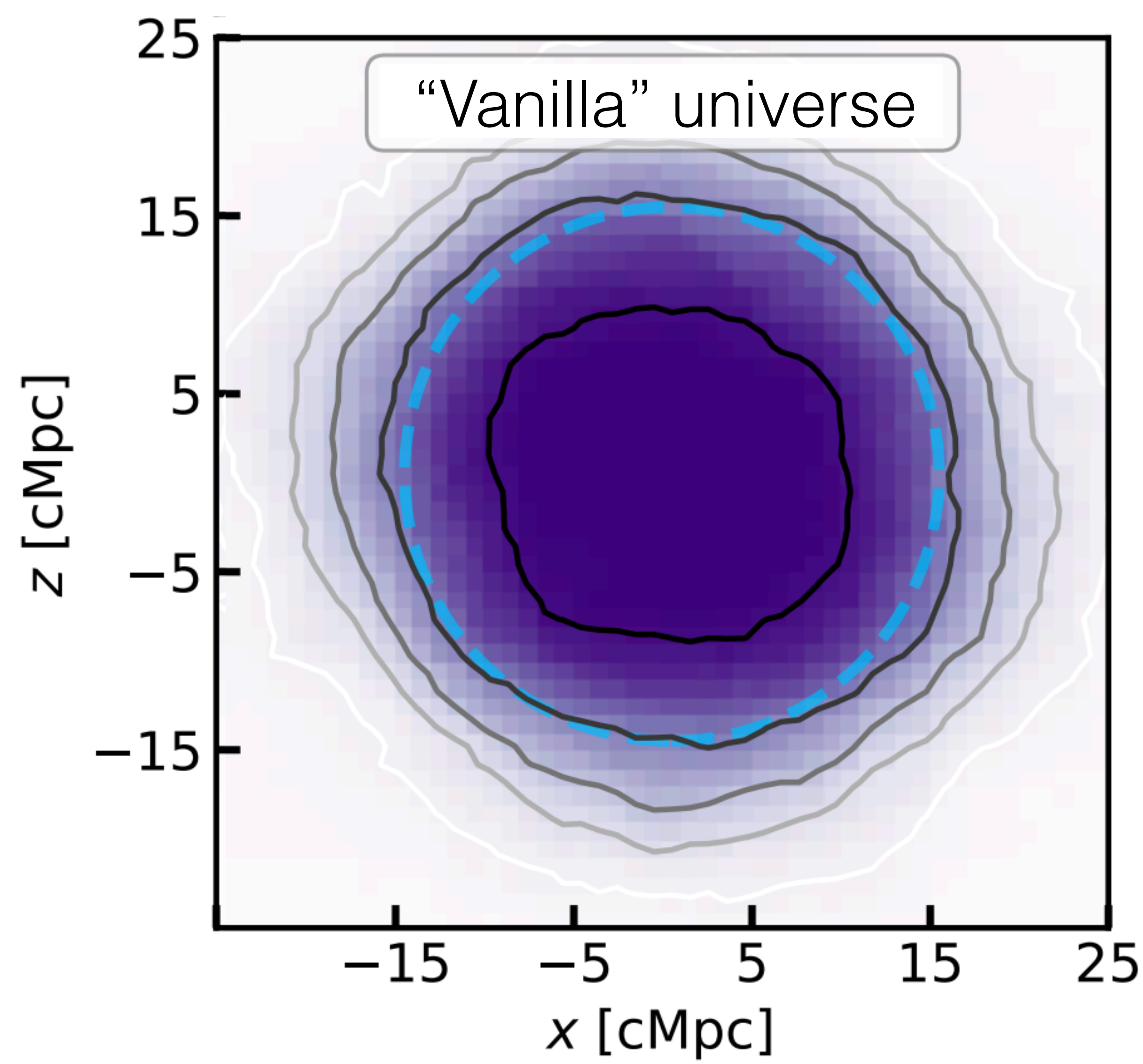
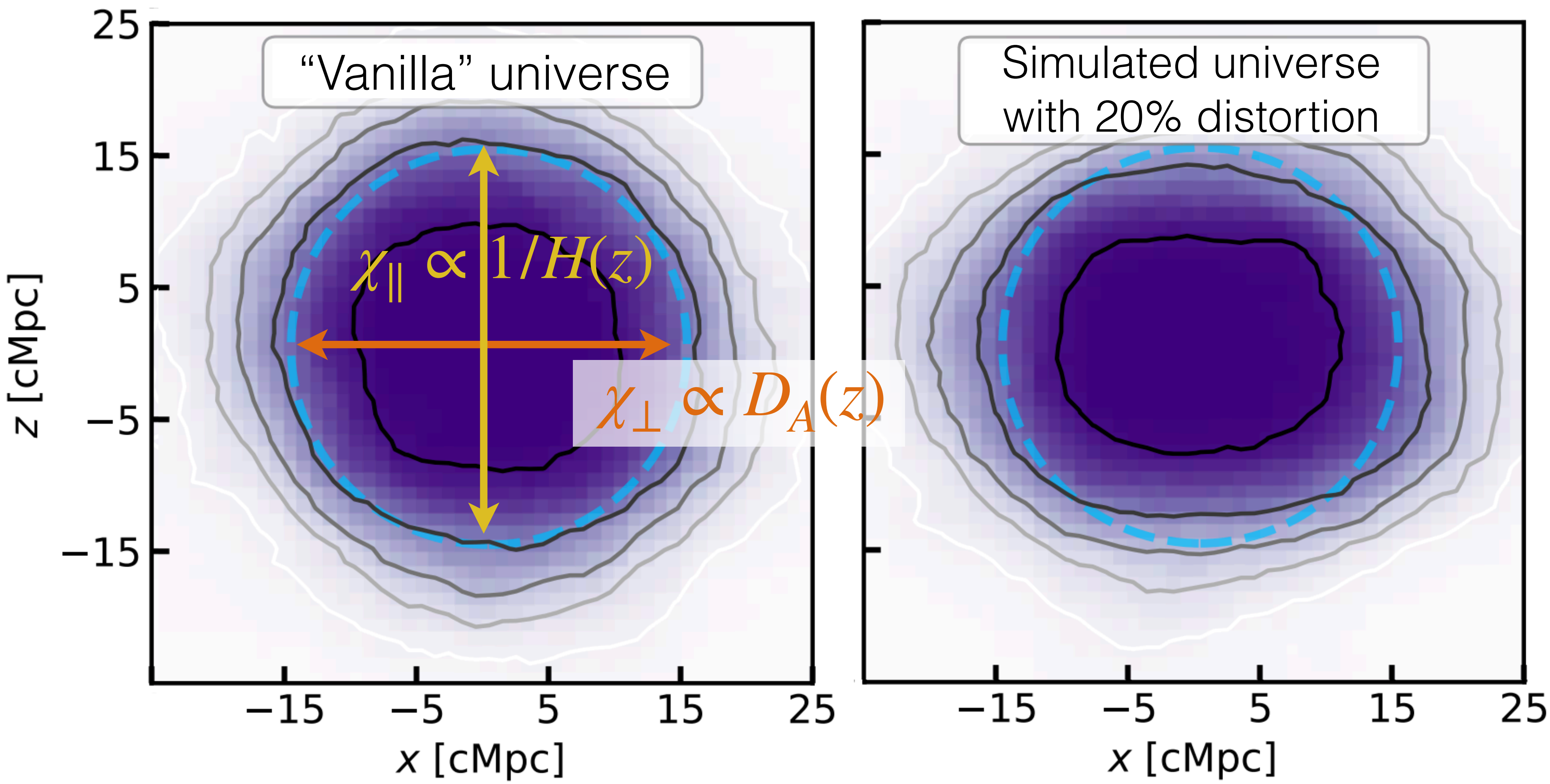
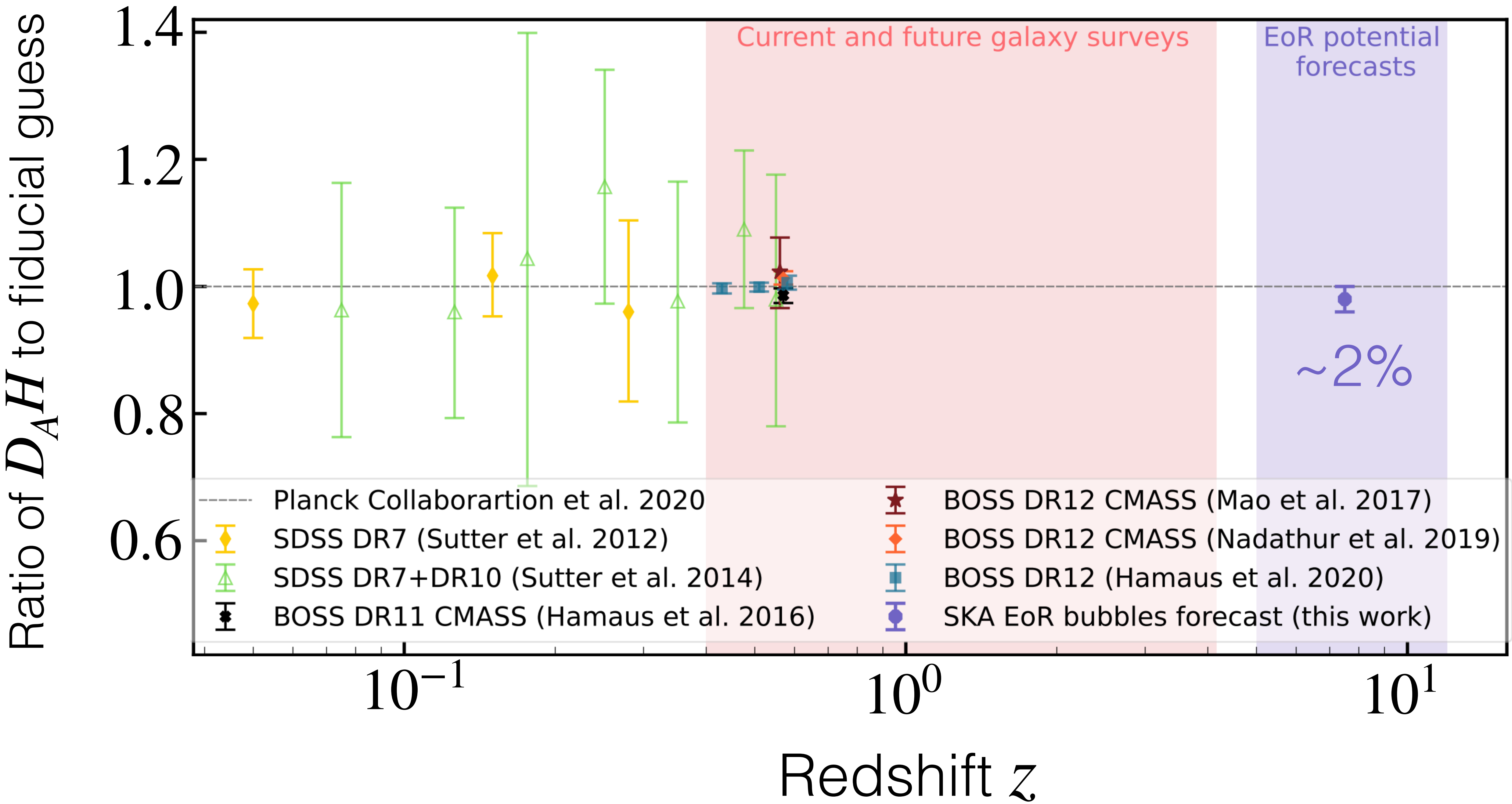


Measuring the sphericity (or lack thereof) constrains the parameter combination

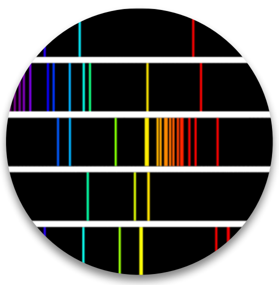
$$\chi_\perp / \chi_{||} \propto D_A H$$





Current and future galaxy surveys
EoR potential forecasts
~2%
Ratio of $D_A H$ to fiducial guess
Redshift z
1.4
1.2
1.0
0.8
0.6
10^{-1}
10^{0}
10^{1}
Planck Collaborartion et al. 2020
SDSS DR7 (Sutter et al. 2012)
SDSS DR7+DR10 (Sutter et al. 2014)
BOSS DR11 CMASS (Hamaus et al. 2016)
BOSS DR12 CMASS (Mao et al. 2017)
BOSS DR12 CMASS (Nadathur et al. 2019)
BOSS DR12 (Hamaus et al. 2020)
SKA EoR bubbles forecast (this work)

On today's agenda



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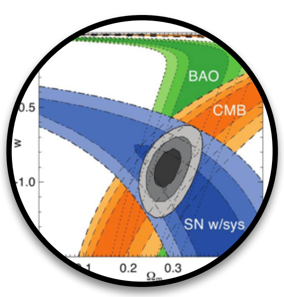


How can we **look past astrophysics** during cosmic dawn and reionization to place constraints on **fundamental cosmological parameters?**

Use ML to recover bubbles that can be stacked. Stacks will only appear spherical if our cosmological parameter (and therefore distance measures) are correct

Backup Slides

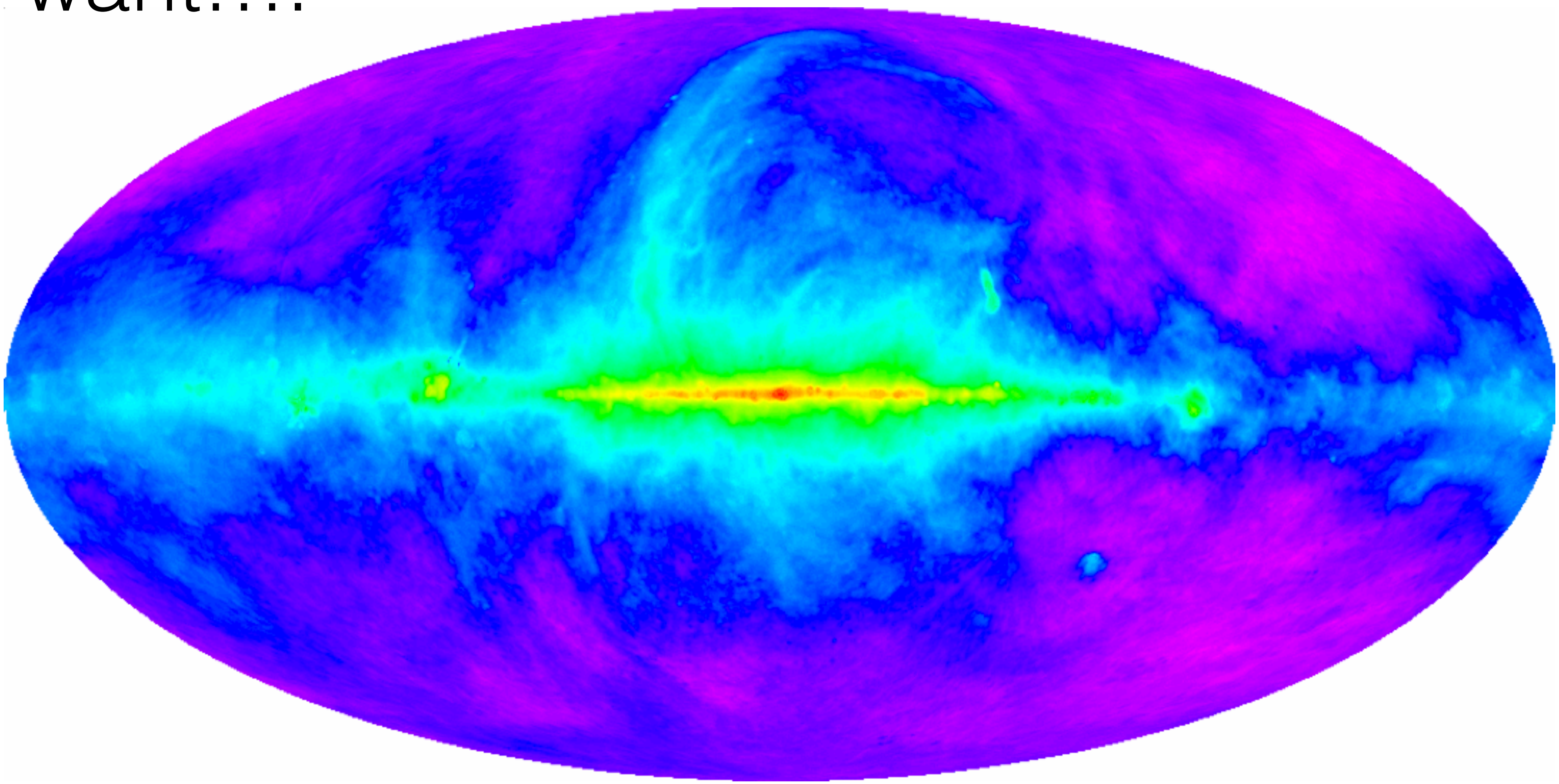
Wedge

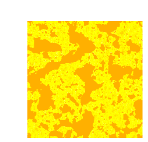
The strongest observational effect is that our measurements are strongly contaminated by

foreground emission

that is $\sim 10^4$ to 10^5 times brighter than the cosmological signal

A huge portion is not what you want….



….and just a tiny portion is what you're interested in 

Filtering in Fourier space may be a solution…

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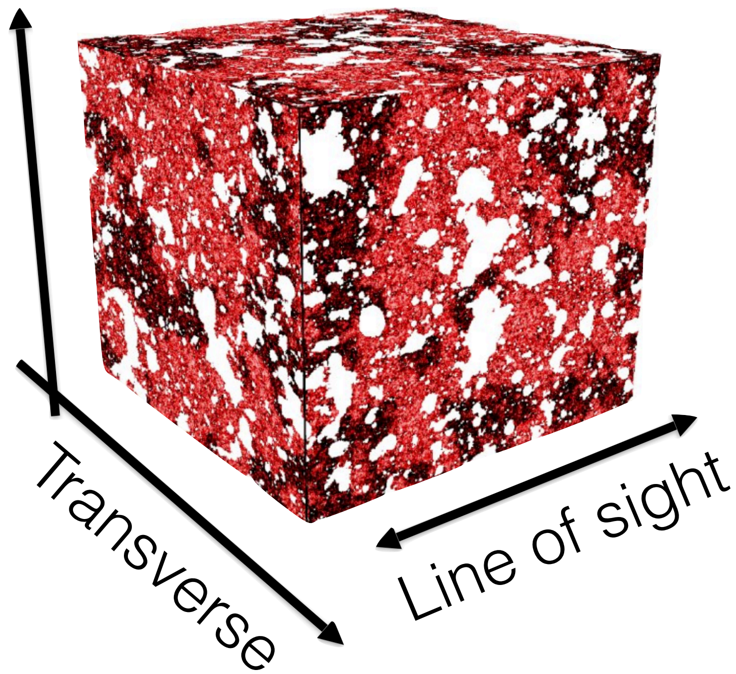
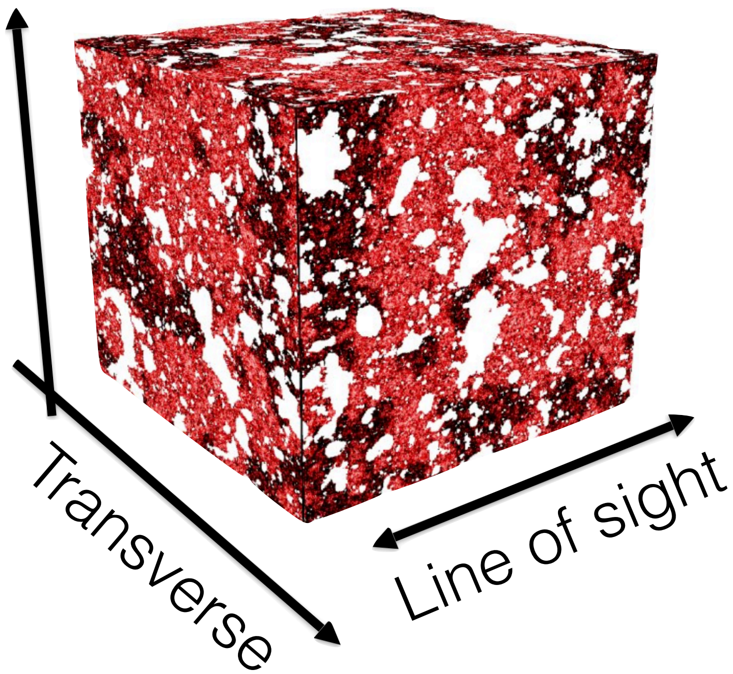
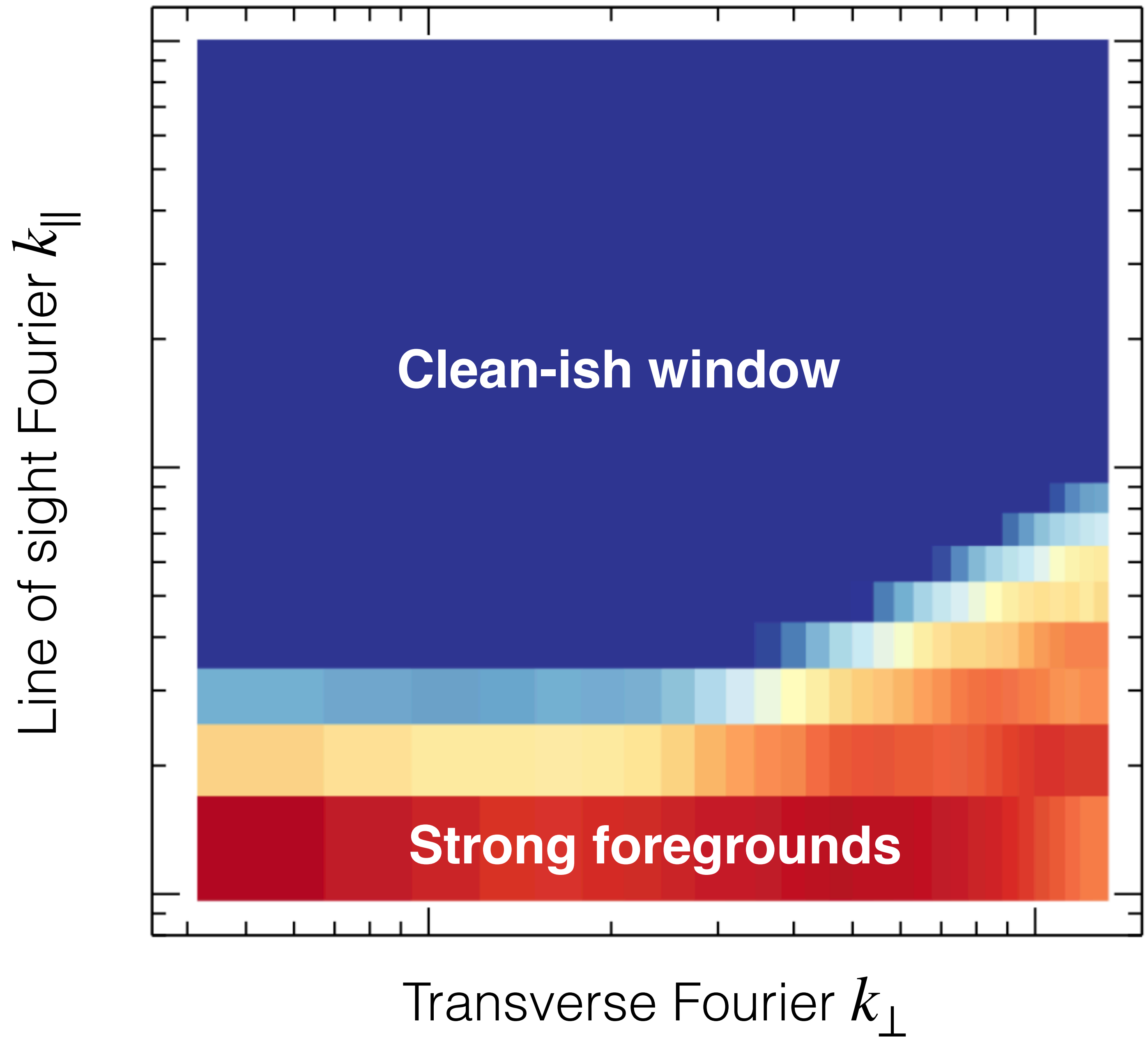
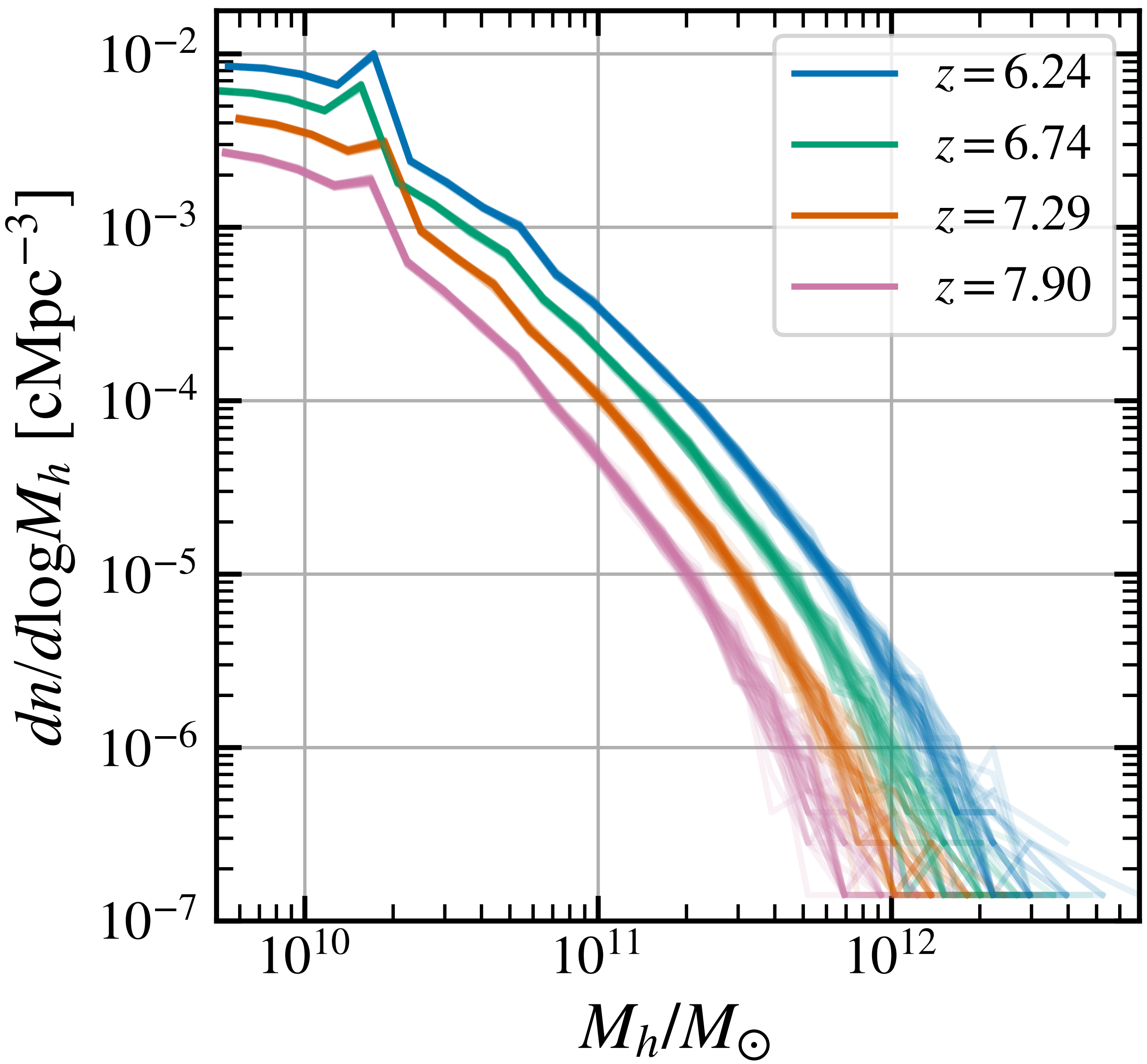


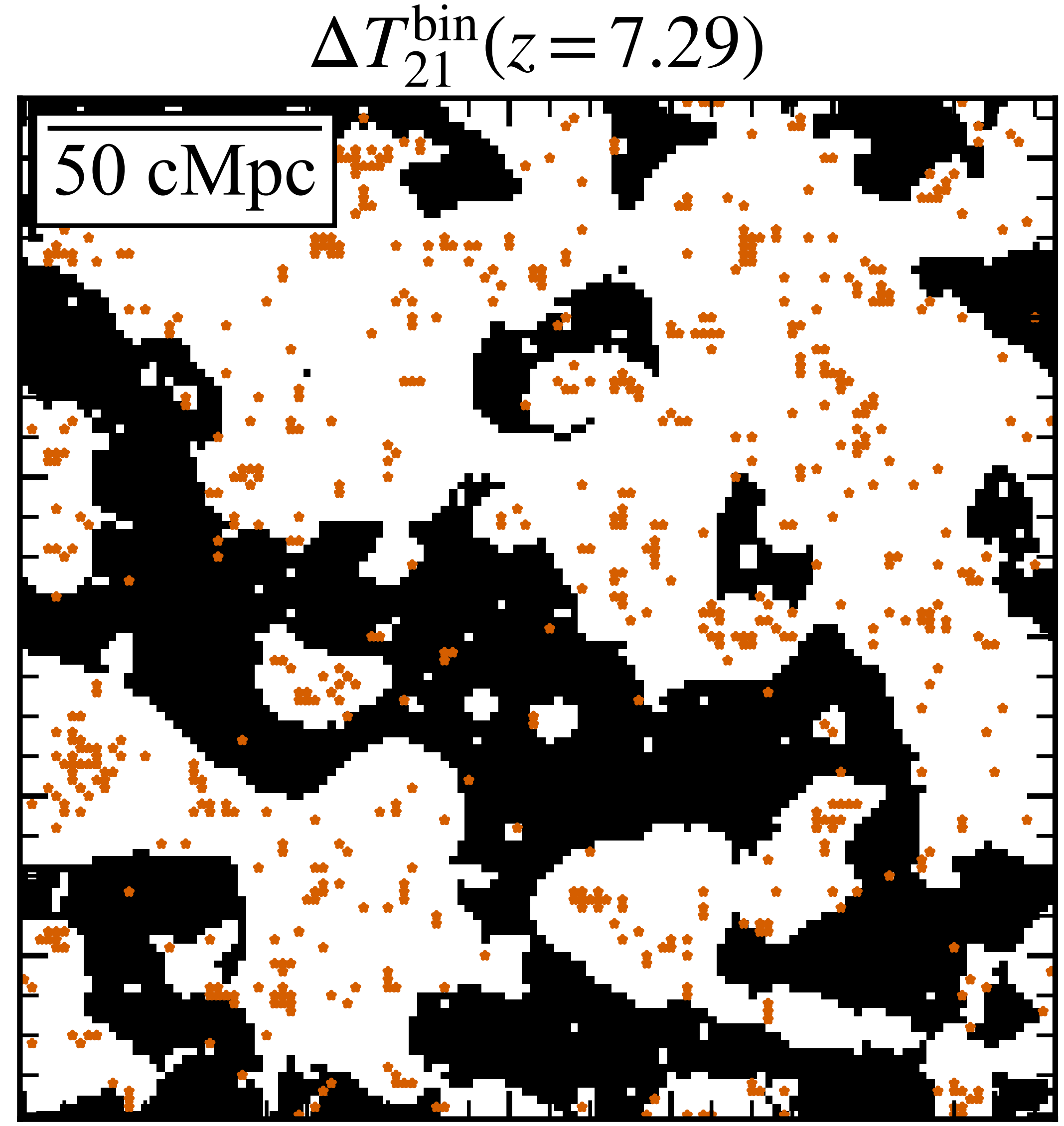
Filtering in Fourier space may be a solution…





ML

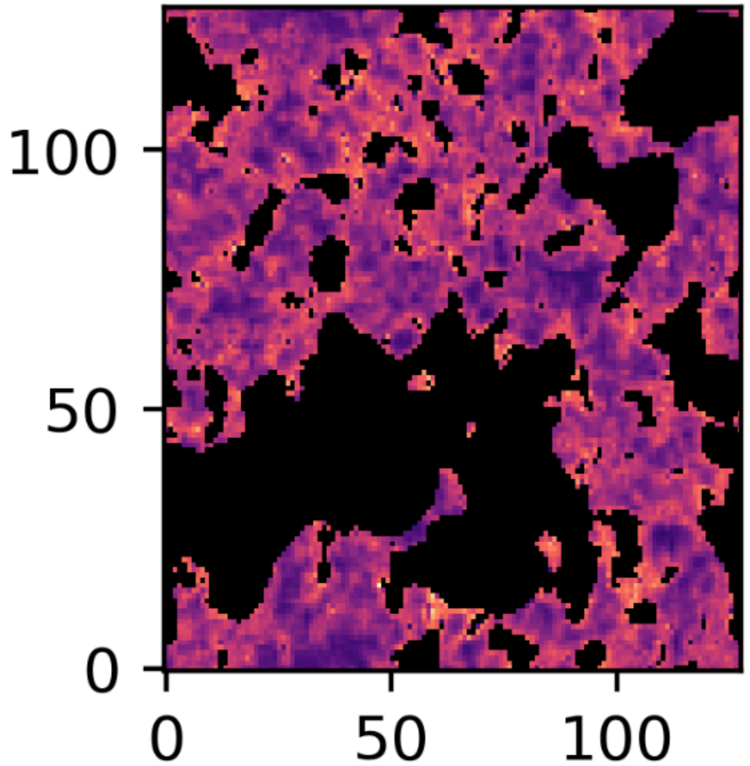




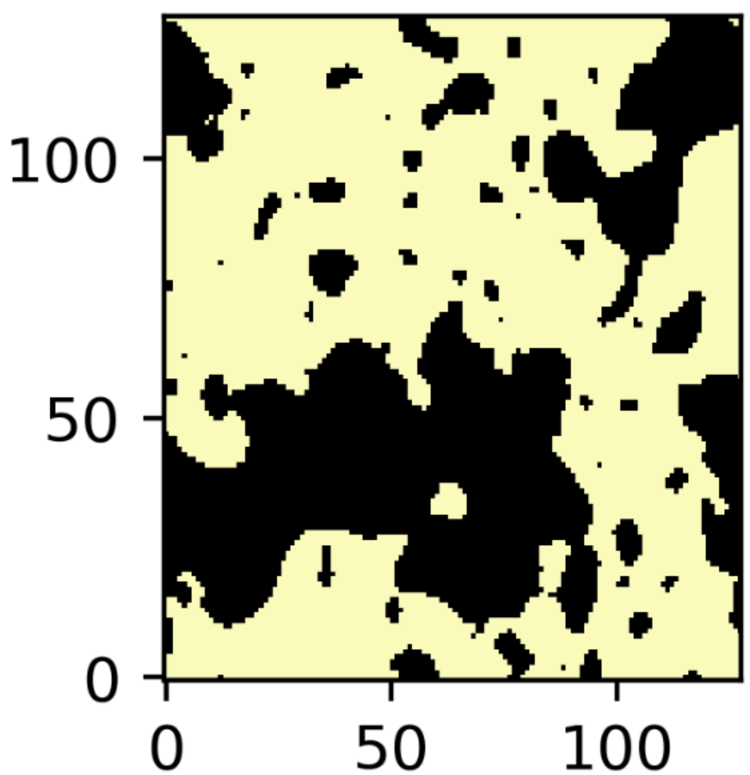
These maps can be used as a guide map for galaxies!

Kennedy, Carr, Gagnon-Hartman, **AL** et al. (2024)
MNRAS **529**, 3684

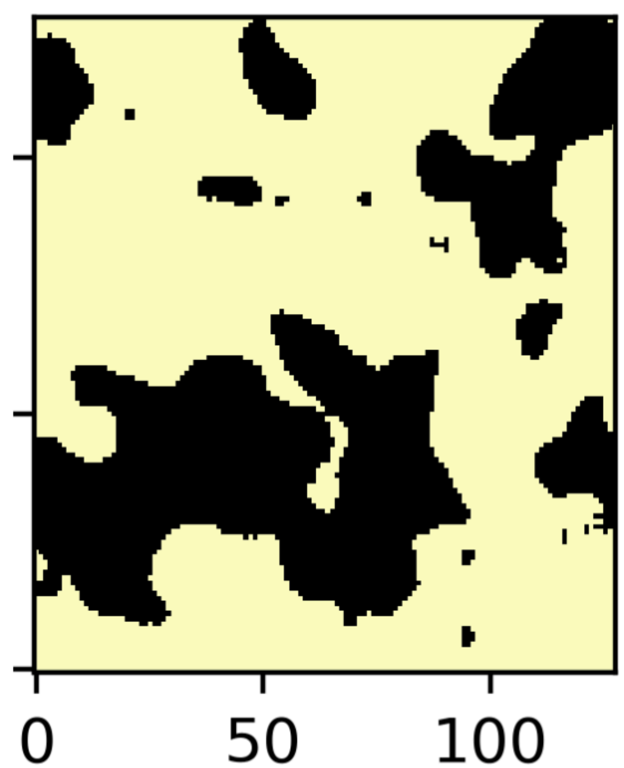
Jacob Kennedy
Former McGill undergrad



Or if we have already found the galaxies, we can improve the reconstruction of bubbles!



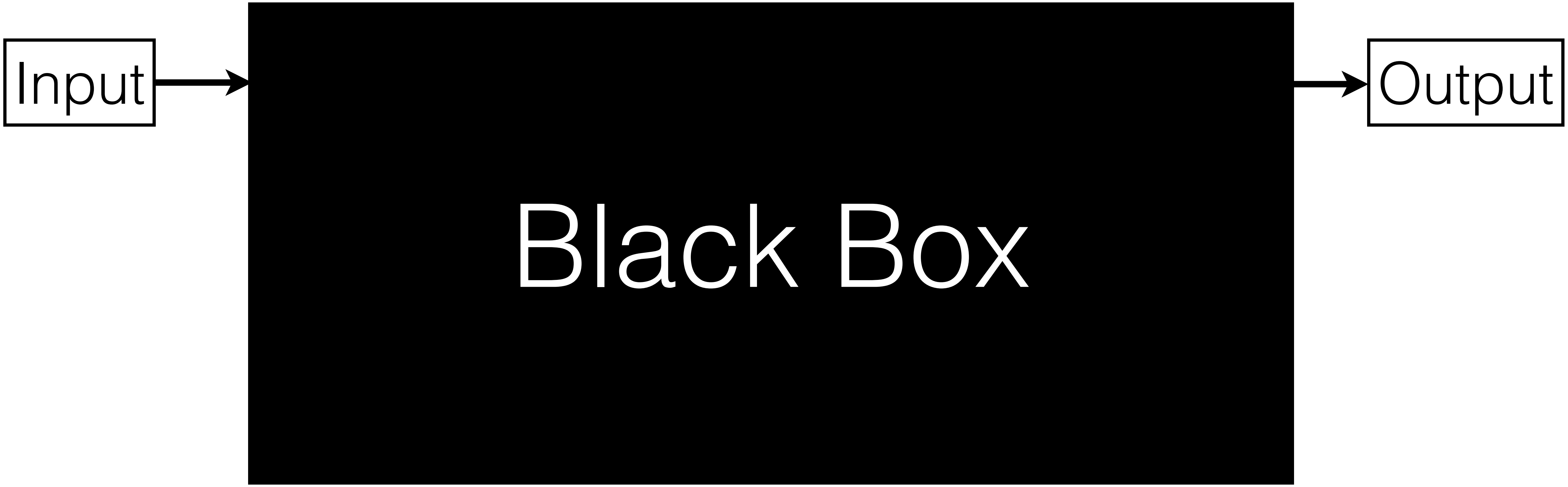
With the help of galaxies



Without using galaxies

Franco del Balso

How can this possibly even work?!



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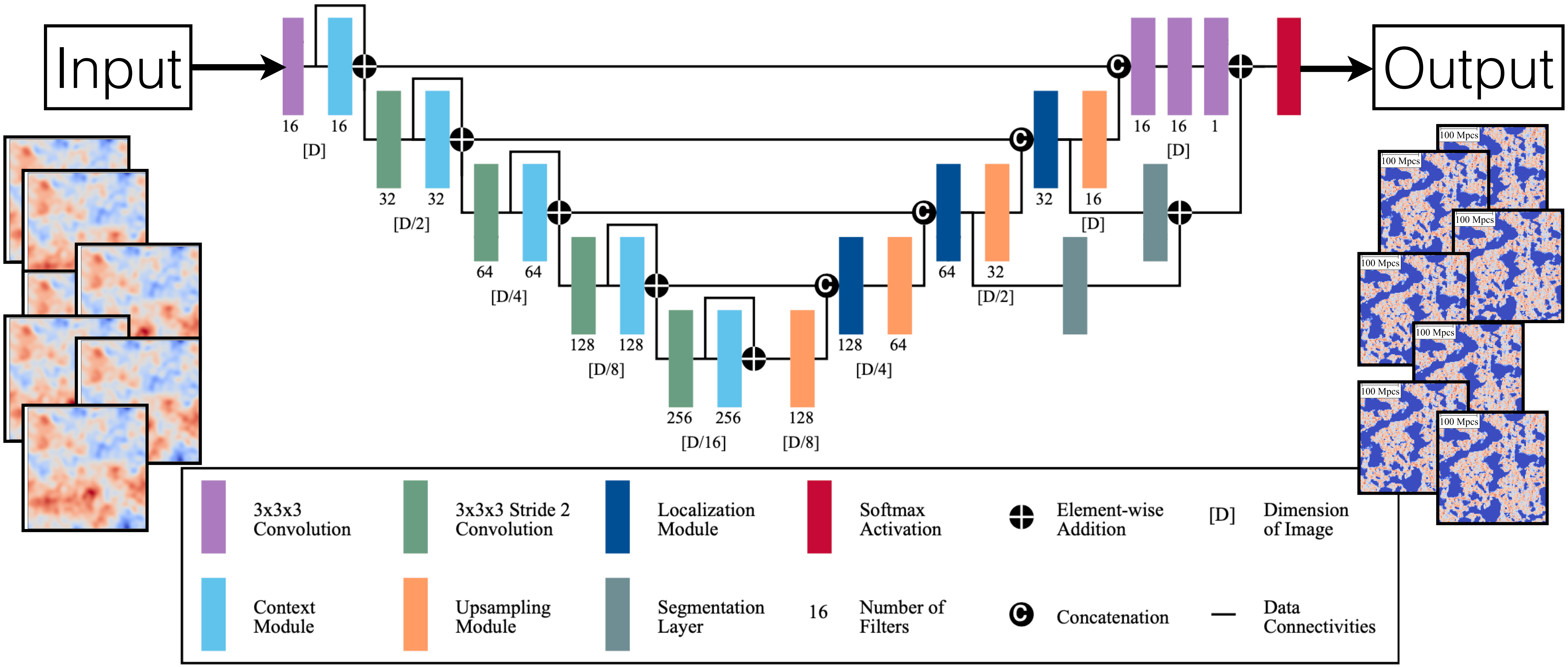

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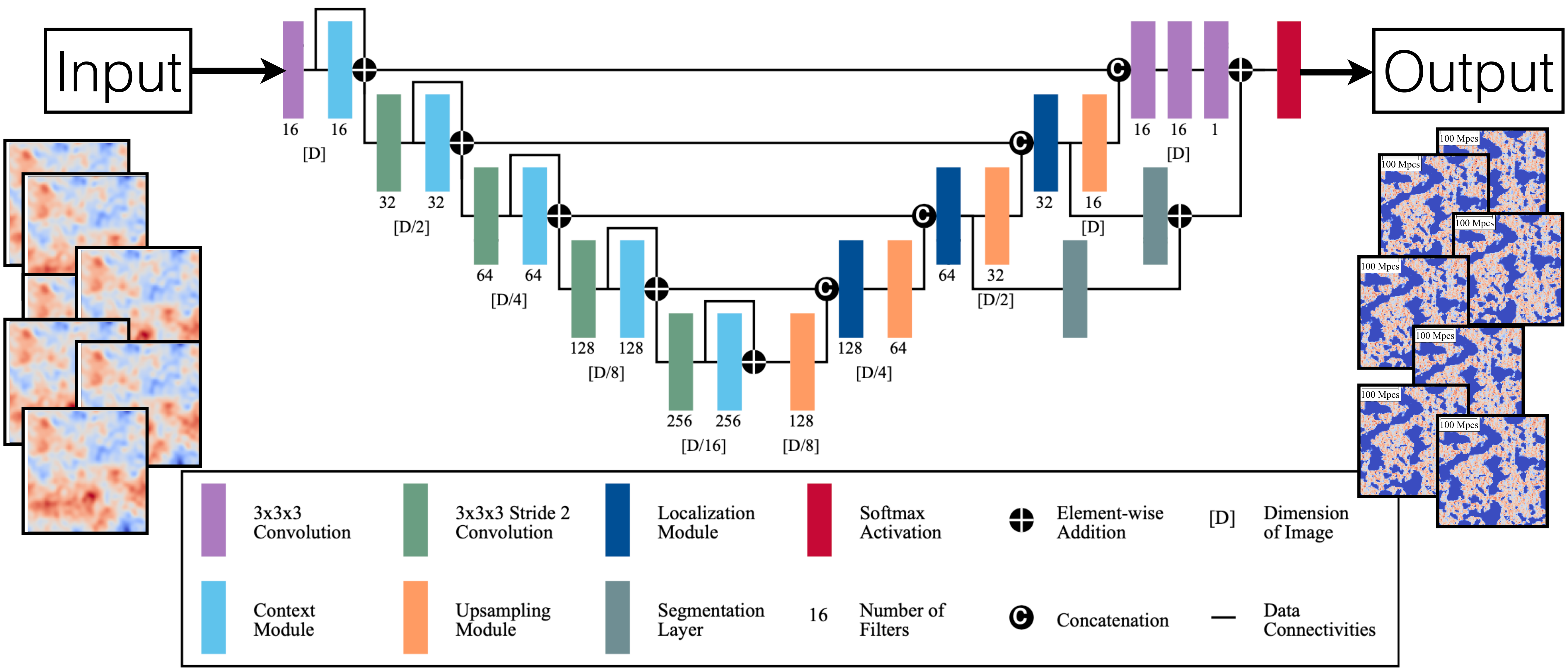
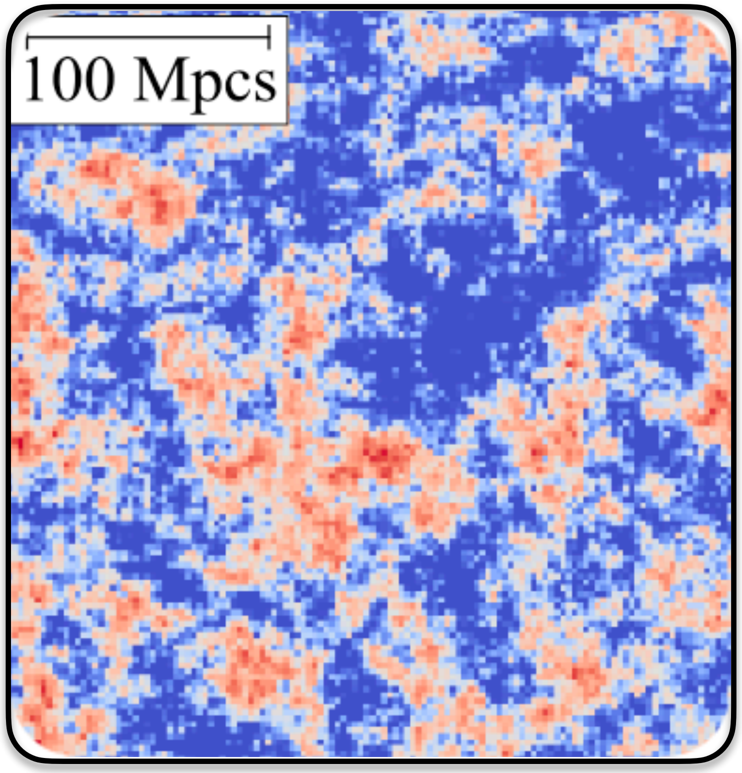
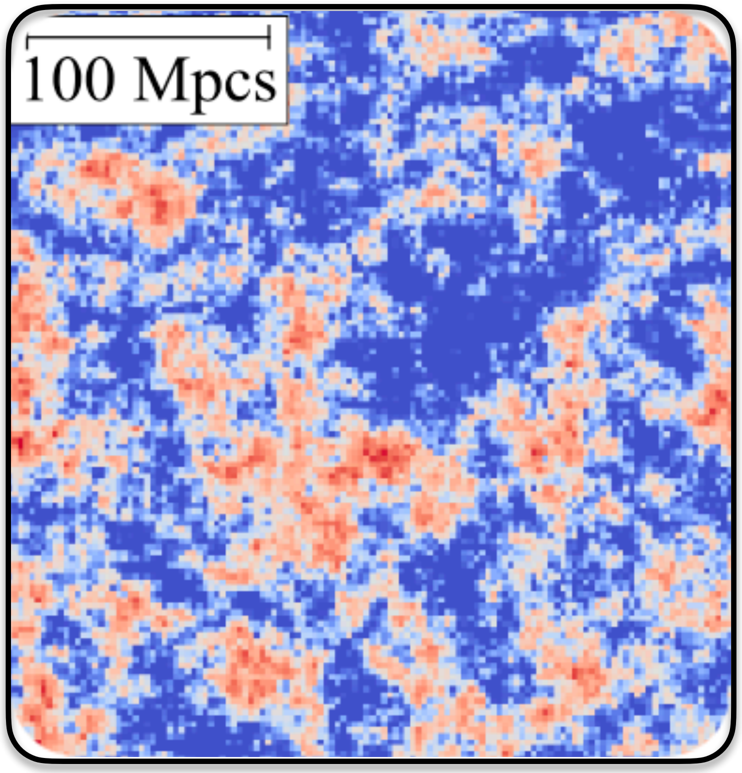


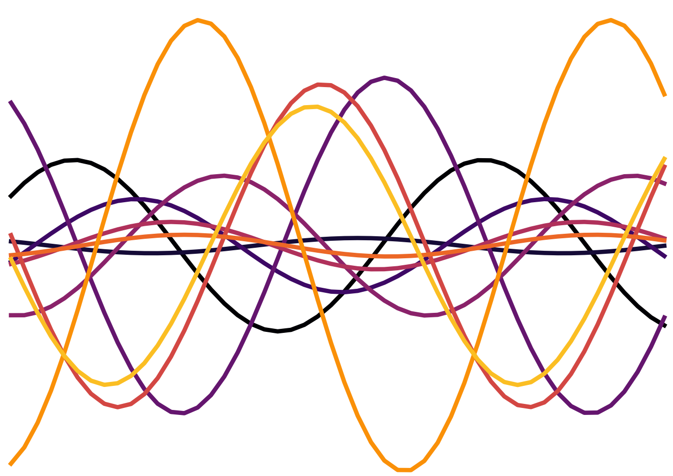
Machine learning isn't magic. It can't get information that isn't there.

Gaussian Fields



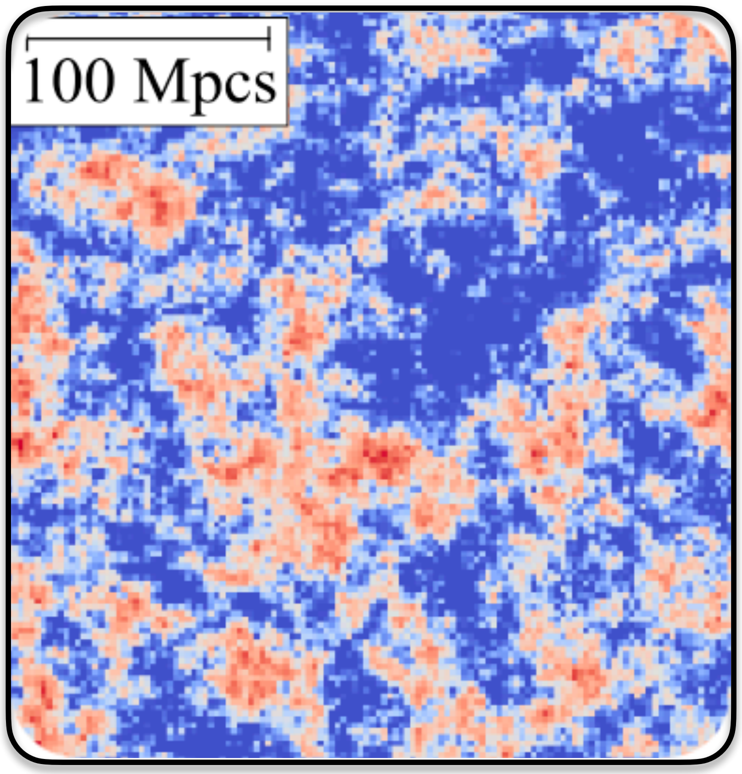
Gaussian Fields

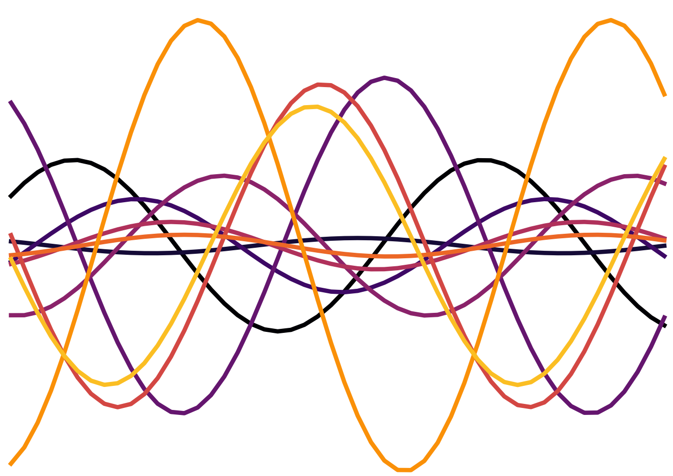




Fourier modes are uncorrelated with one another

Gaussian Fields





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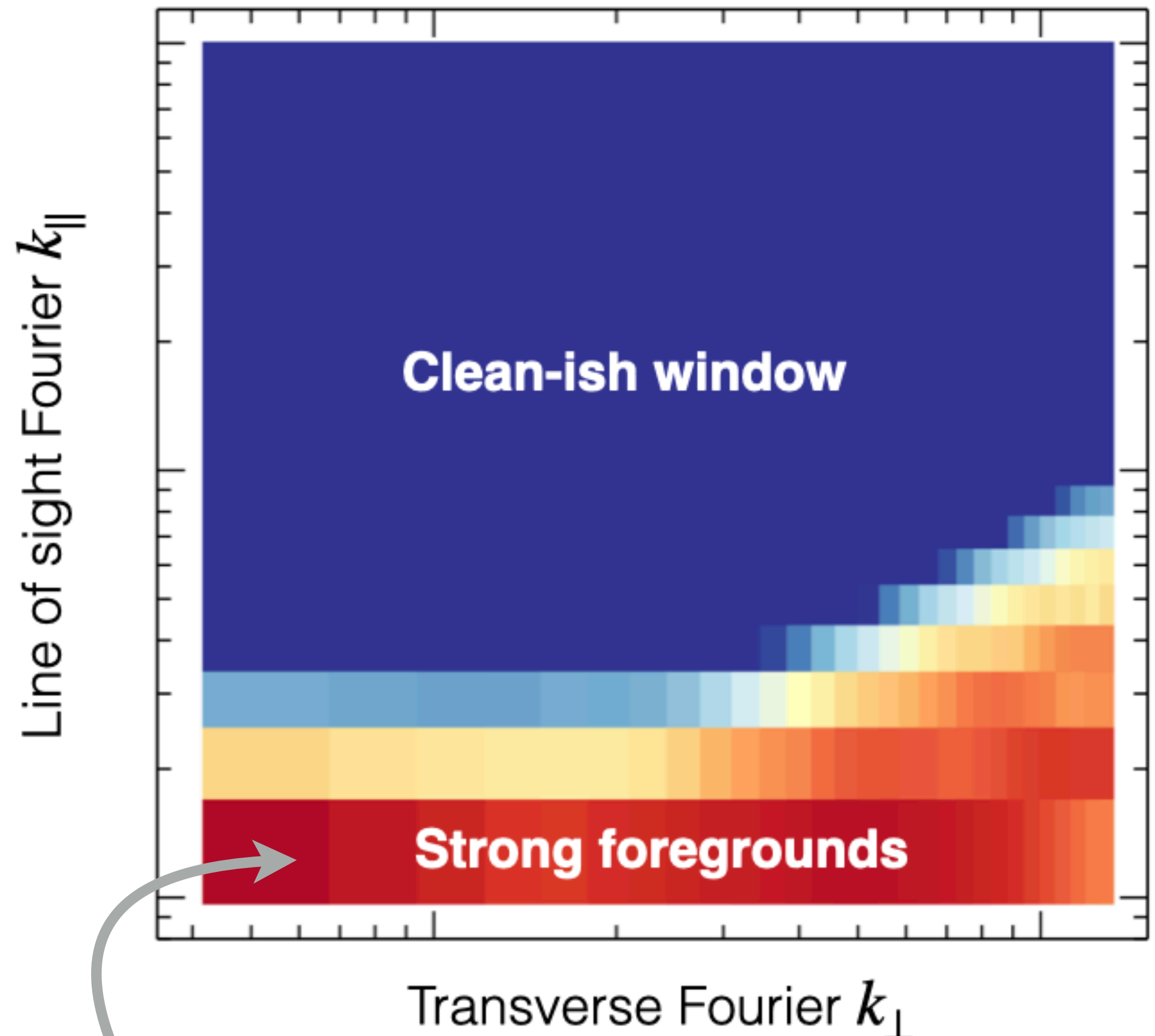
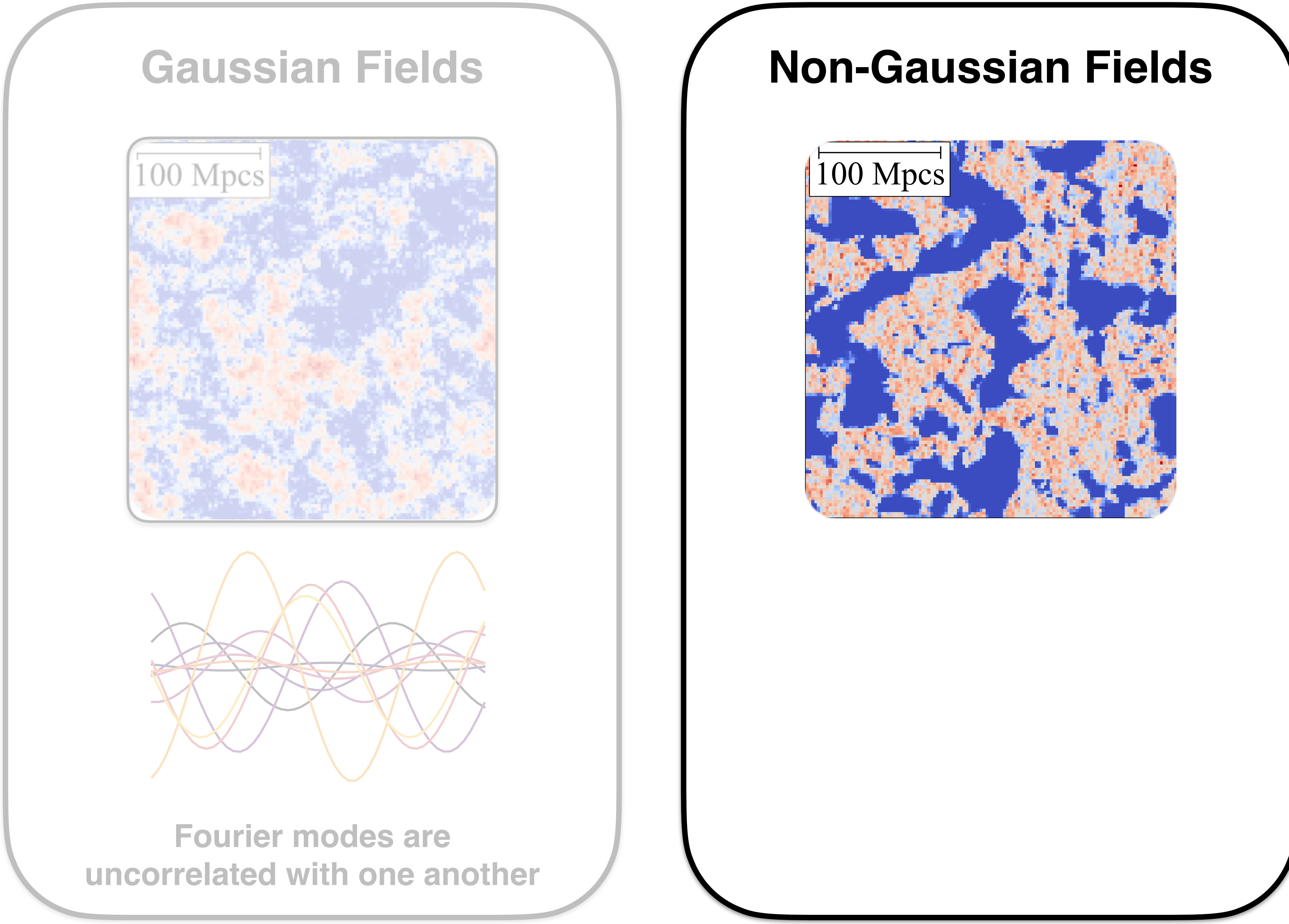
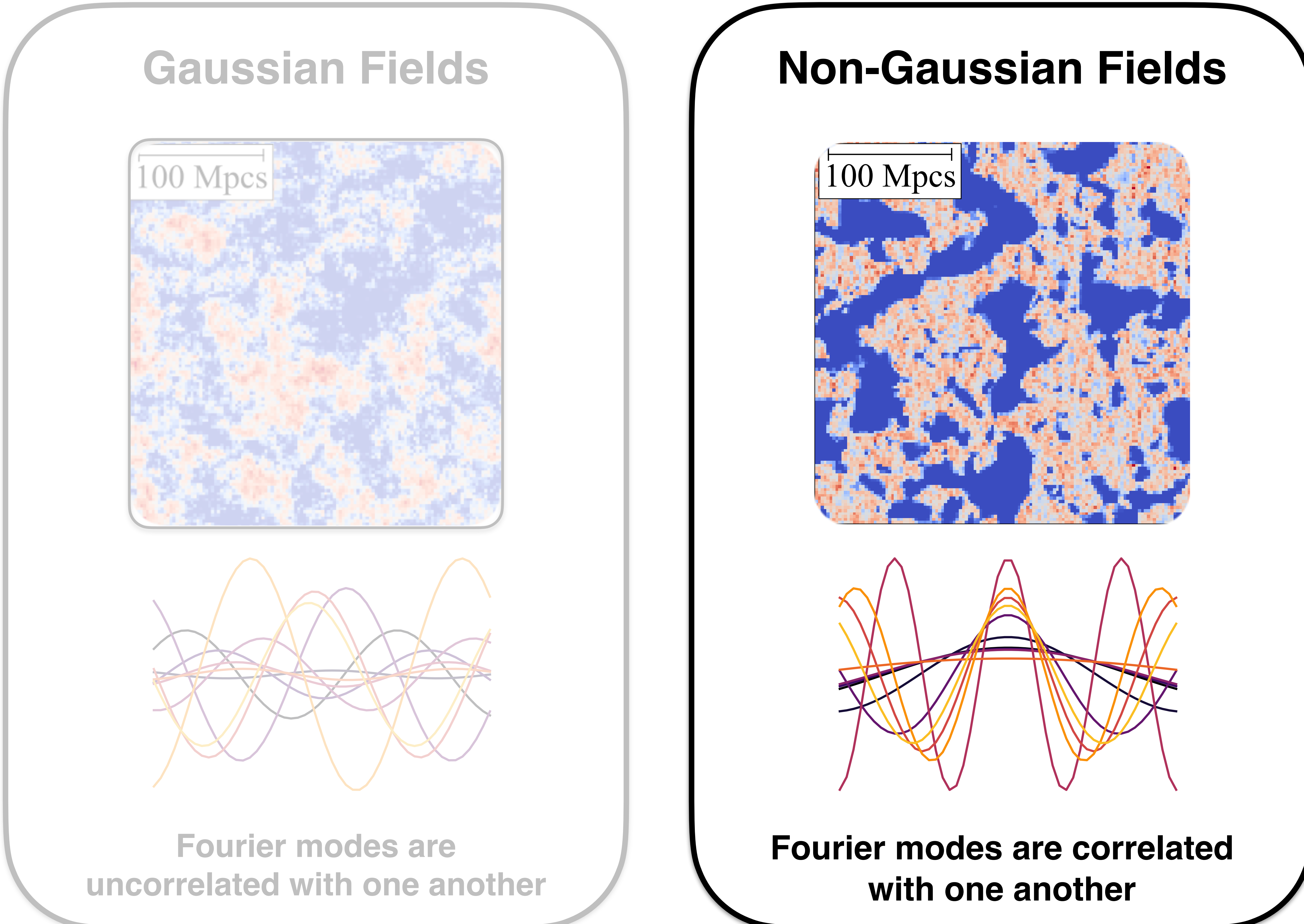
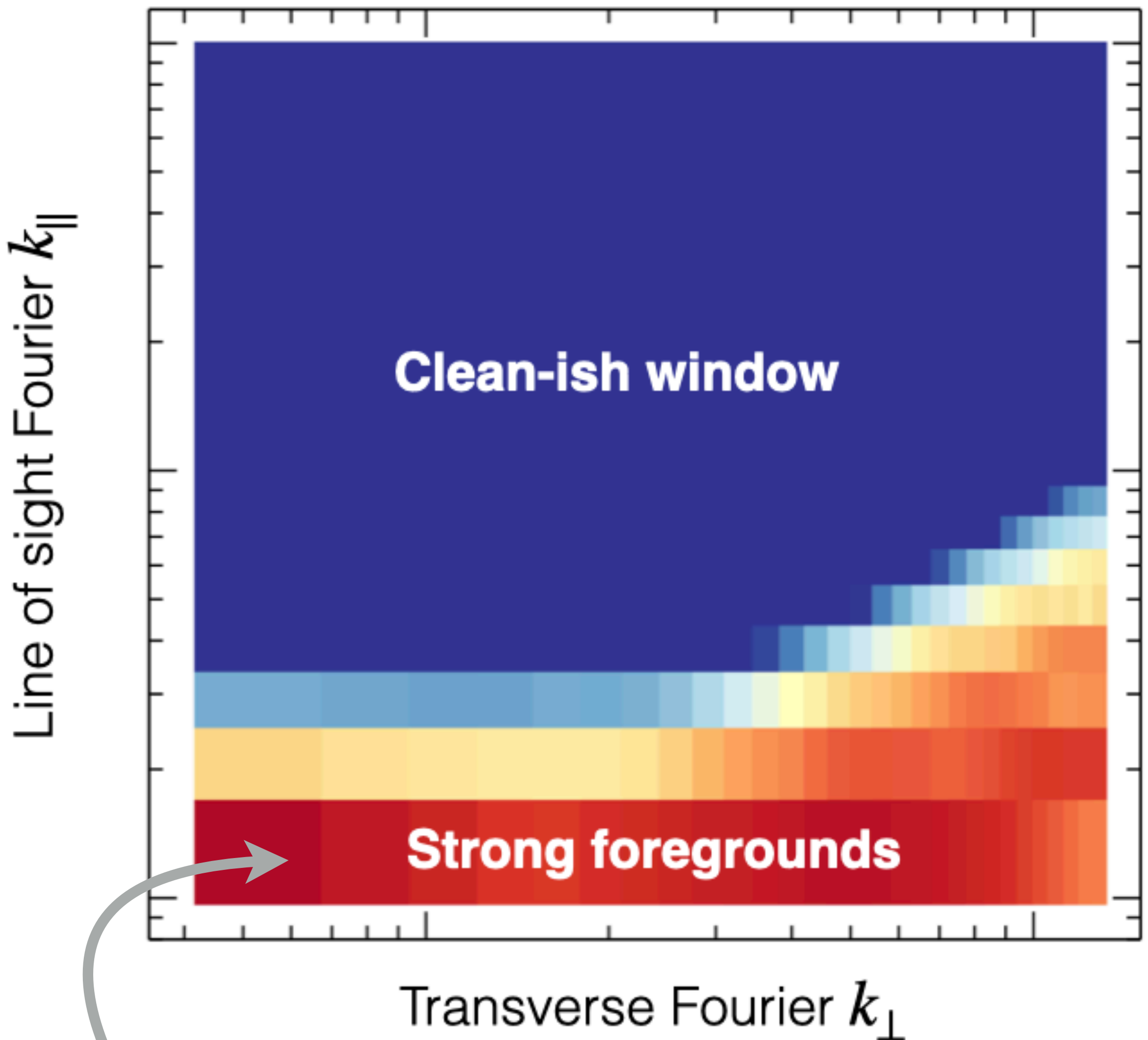


For a Gaussian field, if these modes are filtered out, they are gone forever


Gaussian Fields
100 Mpcs
Fourier modes are uncorrelated with one another
Non-Gaussian Fields
100 Mpcs


Gaussian Fields
100 Mpcs
Fourier modes are uncorrelated with one another
Non-Gaussian Fields
100 Mpcs
Fourier modes are correlated with one another

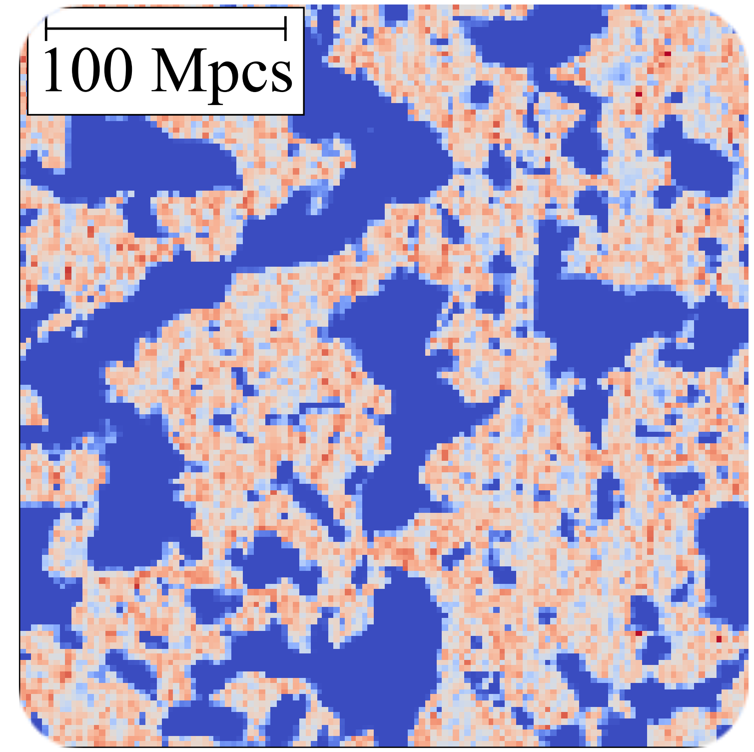
Gaussian Fields

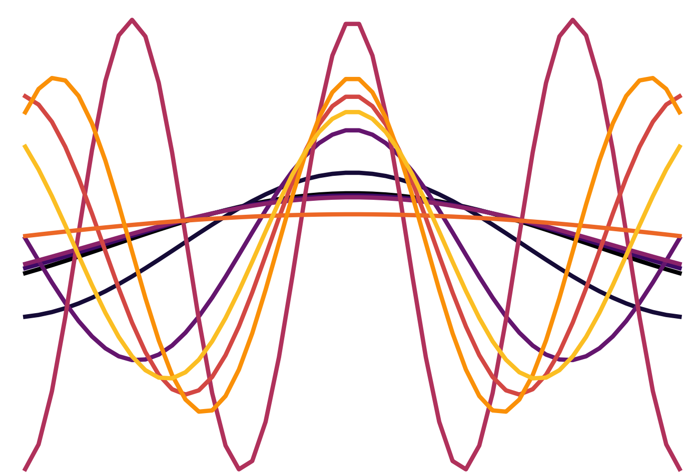


Fourier modes are uncorrelated with one another

For a non-Gaussian field, if these modes are filtered out, there is still some hope for reconstructing them from the measured modes

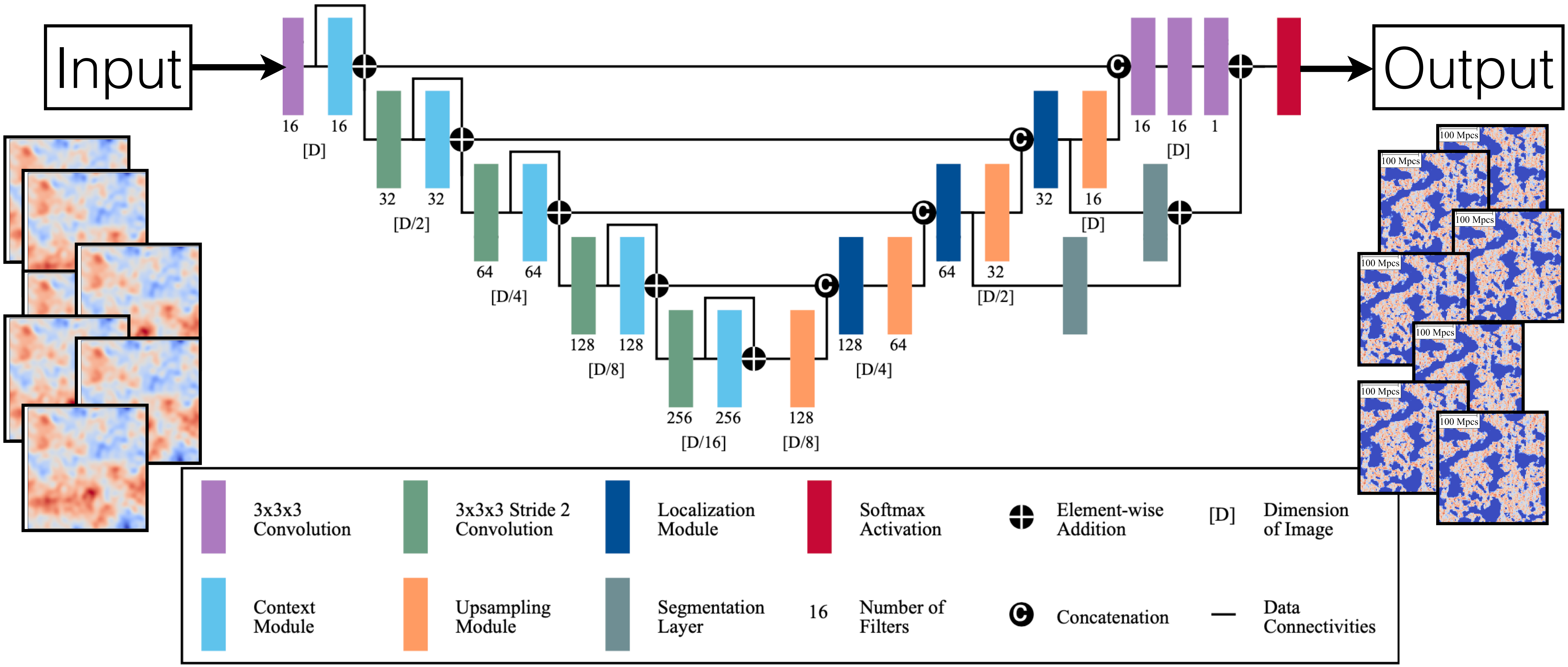
Non-Gaussian Fields





Fourier modes are correlated with one another

How can this possibly even work?!



Machine learning isn't magic. It is using the **non-Gaussianity in the signal** to restore images