Extracting the Full Cosmological Information of Roman

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the *standard* ΛCDM model of cosmology

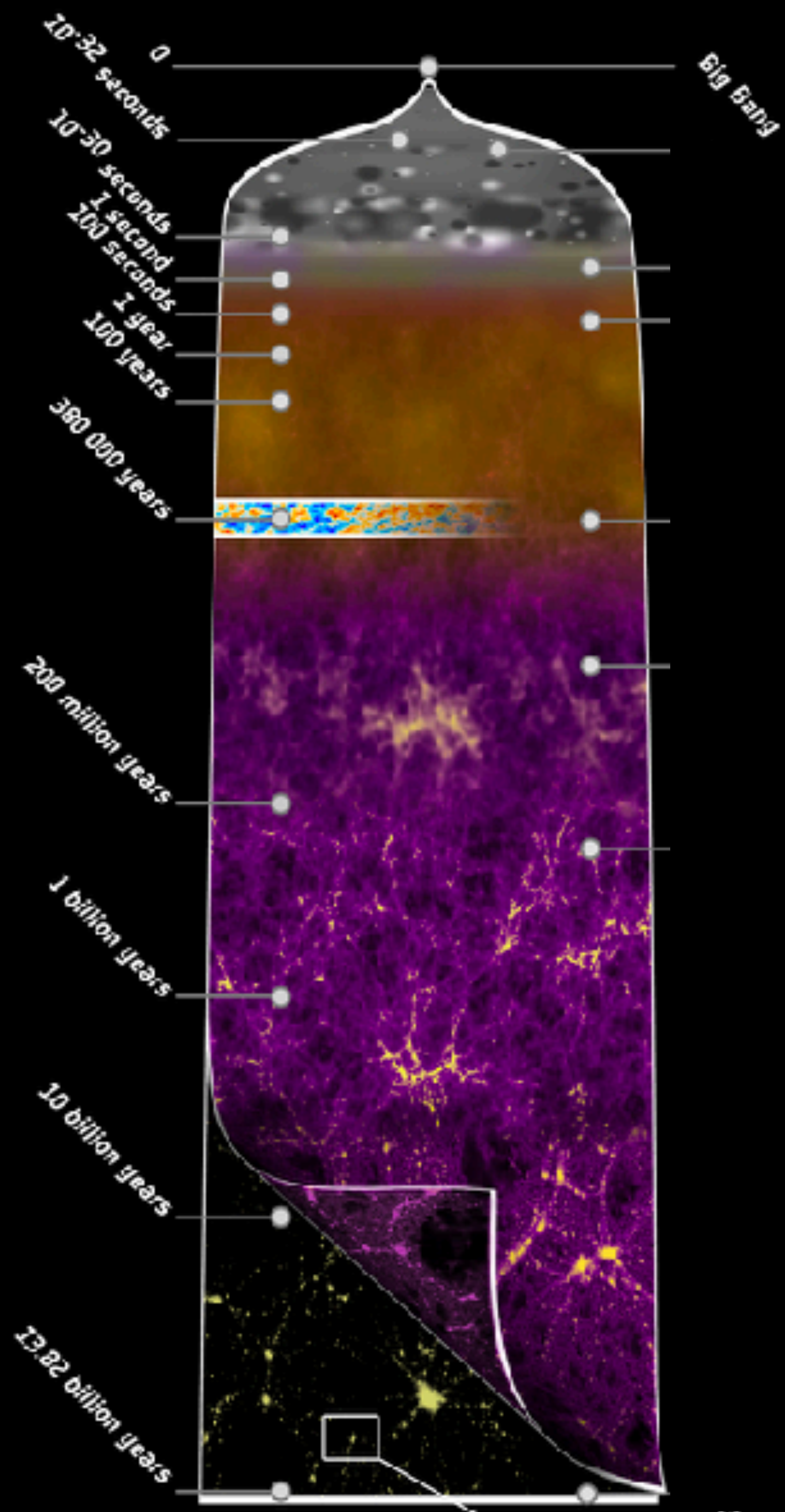
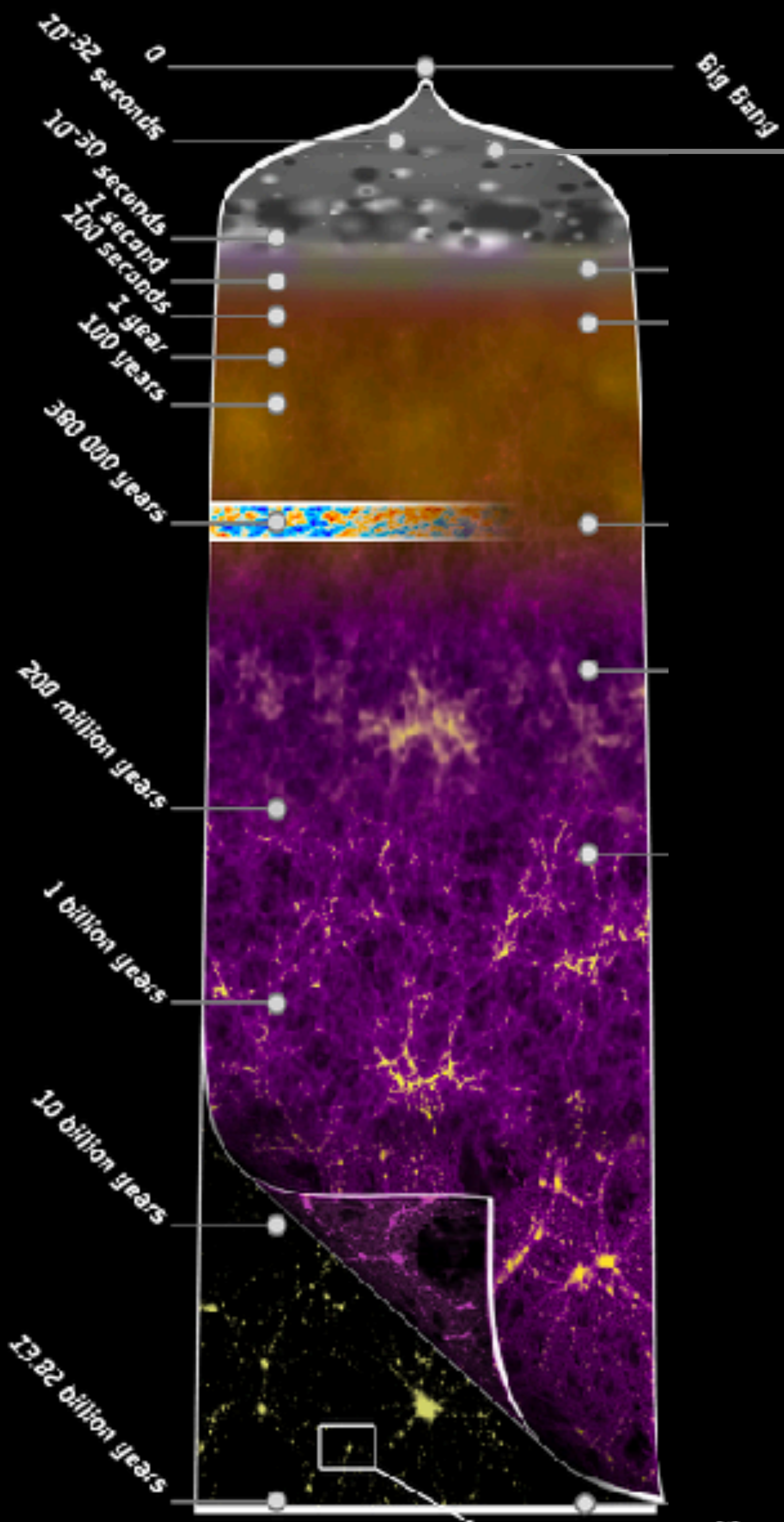


image: NASA

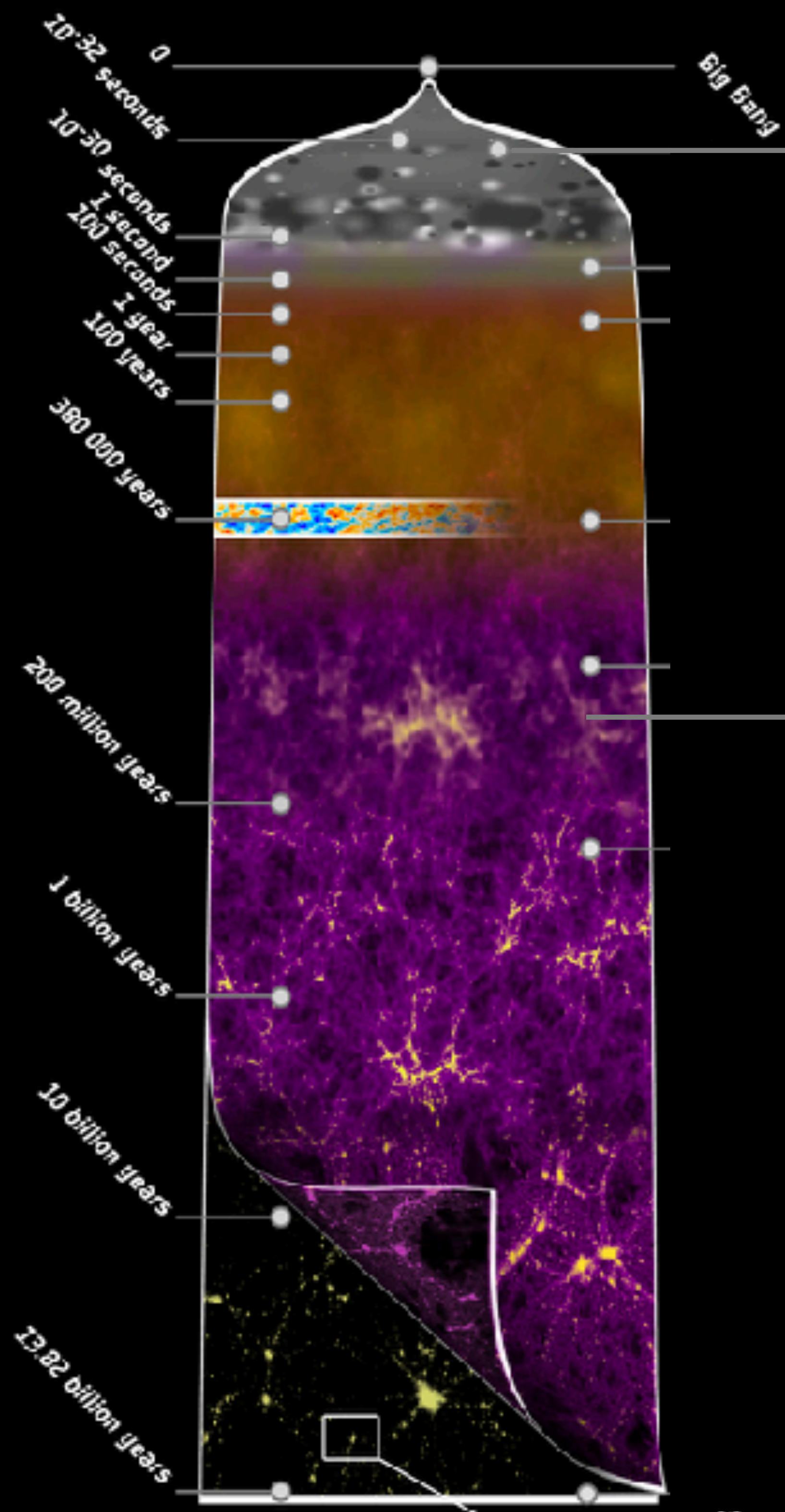
the *standard* ΛCDM model of cosmology



cosmic inflation — *origin of fluctuations*

image: NASA

the *standard* ΛCDM model of cosmology

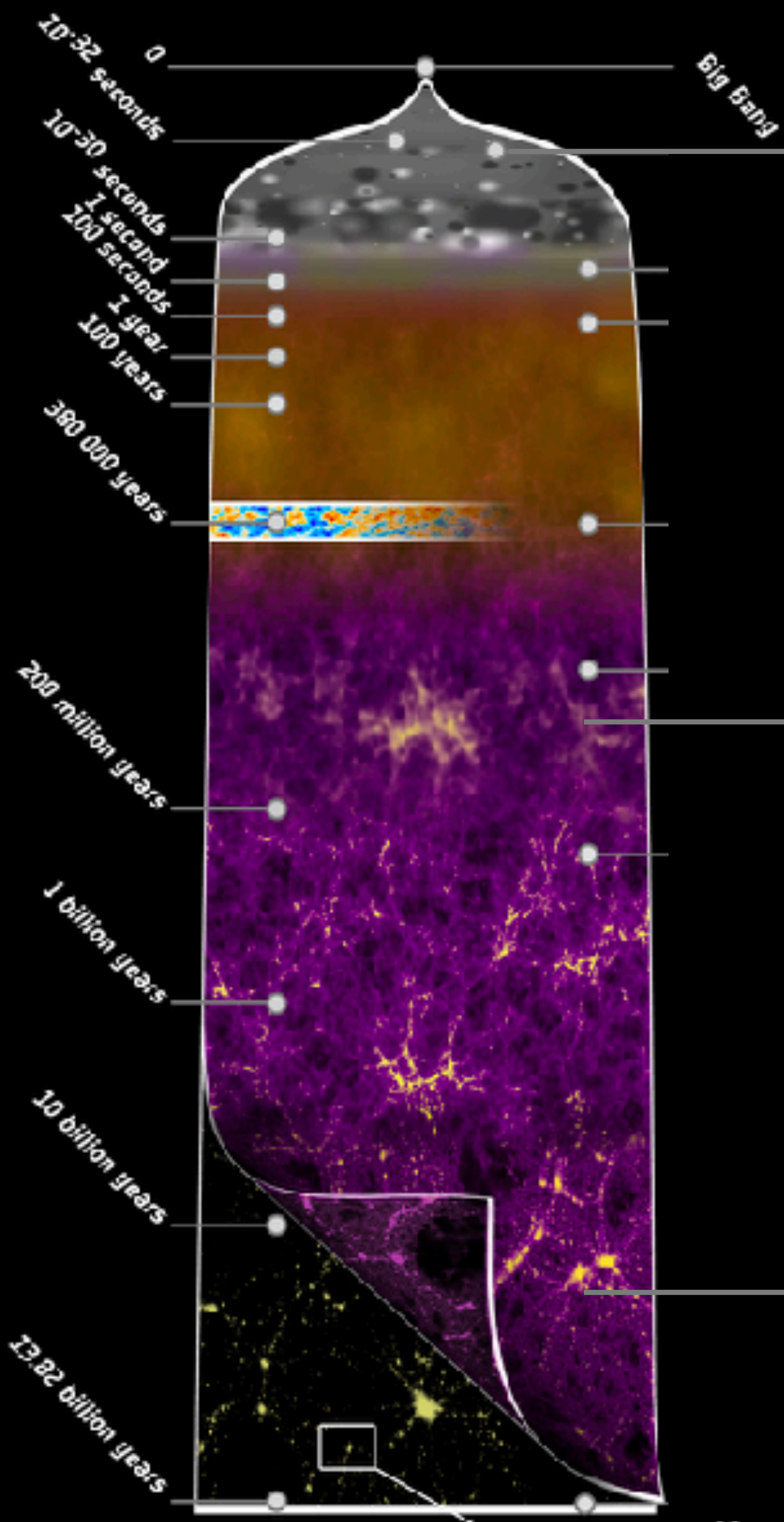


cosmic inflation — *origin of fluctuations*

dark matter — *~85% of matter*

image: NASA

the *standard* ΛCDM model of cosmology



cosmic inflation — *origin of fluctuations*

dark matter — *~85% of matter*

dark energy — *accelerated expansion*

the *standard* ΛCDM model of cosmology is *remarkably successful* at describing current observations

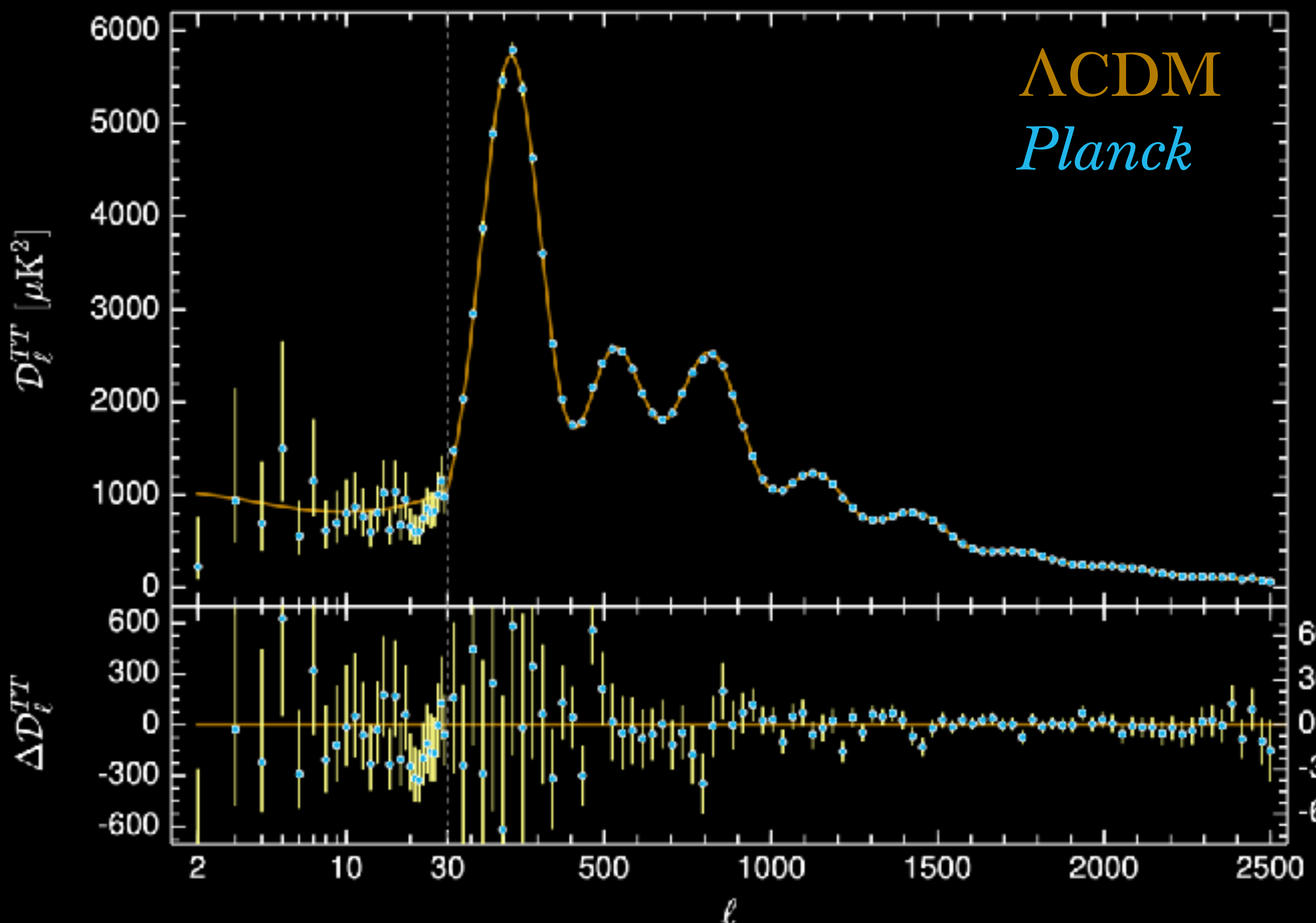
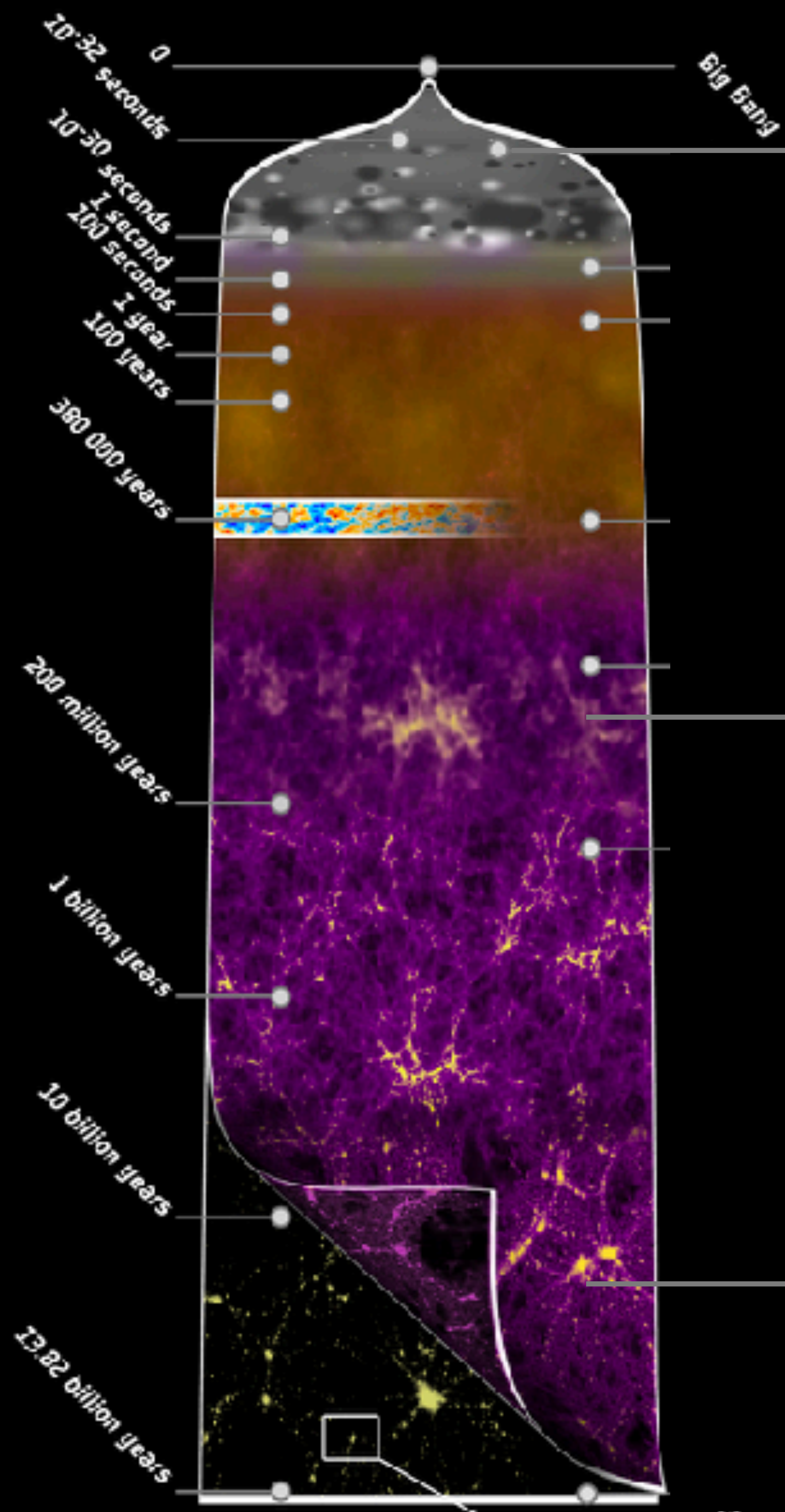


image: Planck

the *standard* ΛCDM model of cosmology



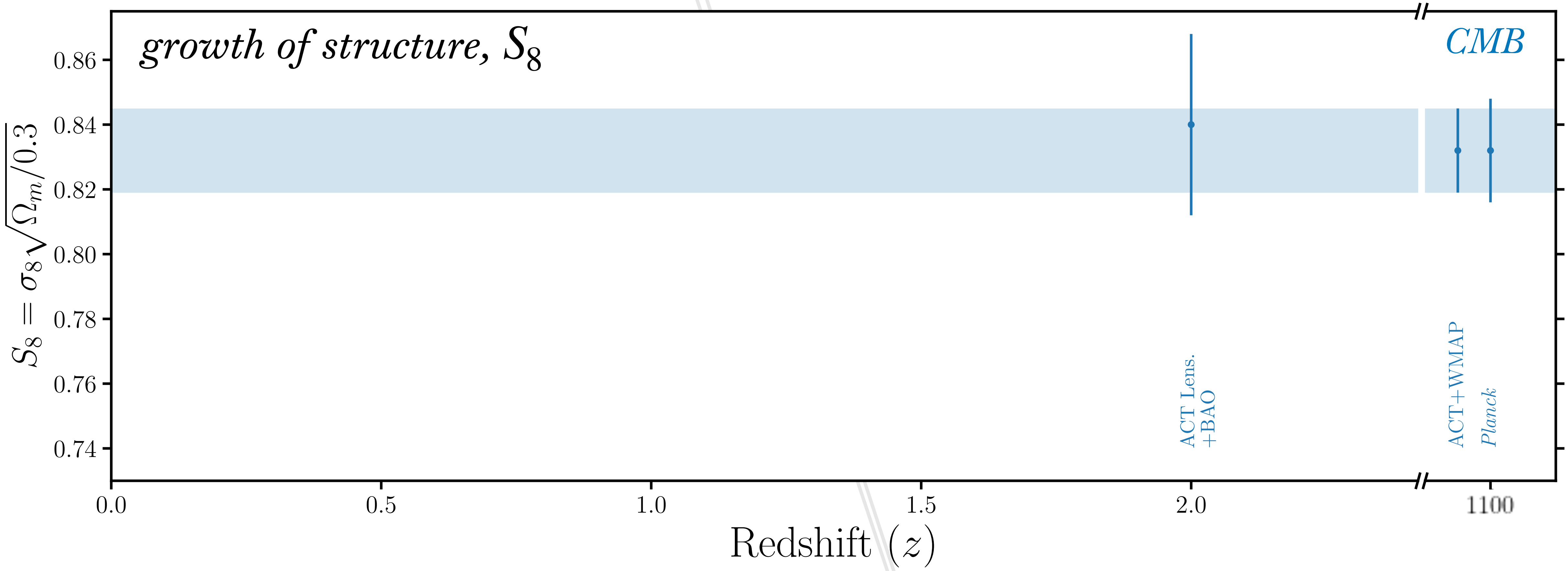
cosmic inflation — ***not understood***

dark matter — ***not understood***

dark energy — ***not understood***

cosmic tensions

cosmic tensions between probes of the early and the late universe



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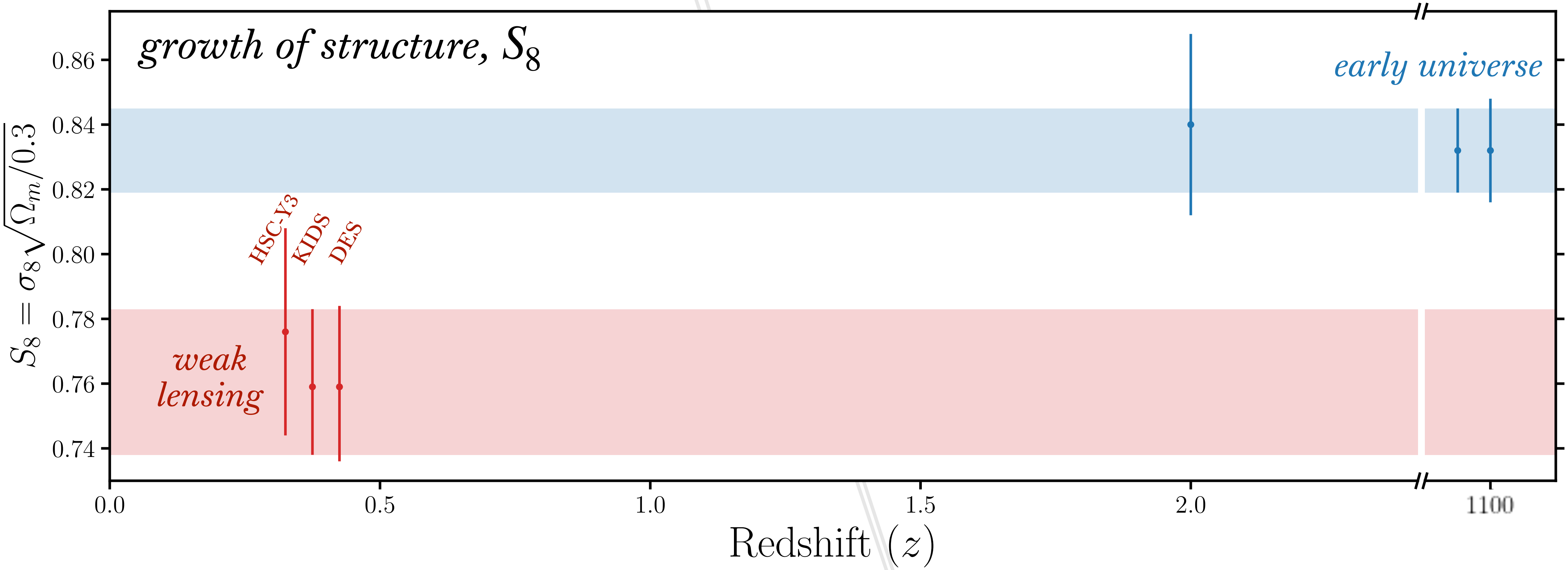

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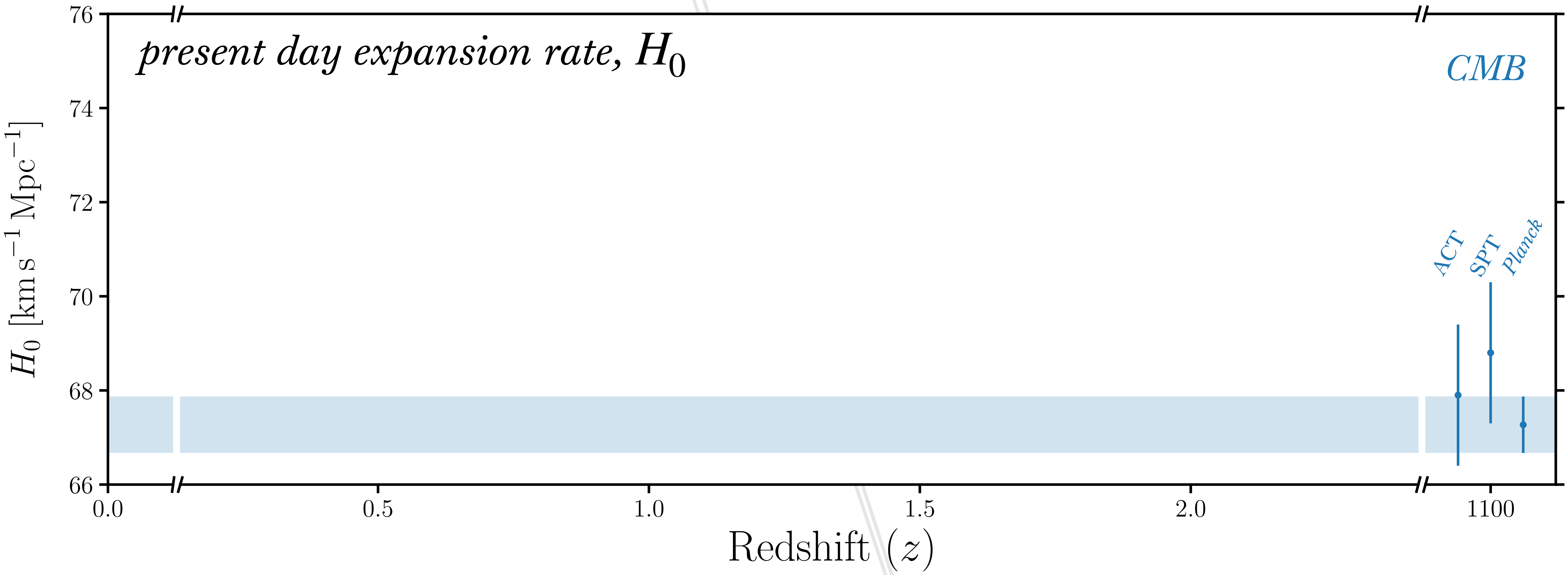

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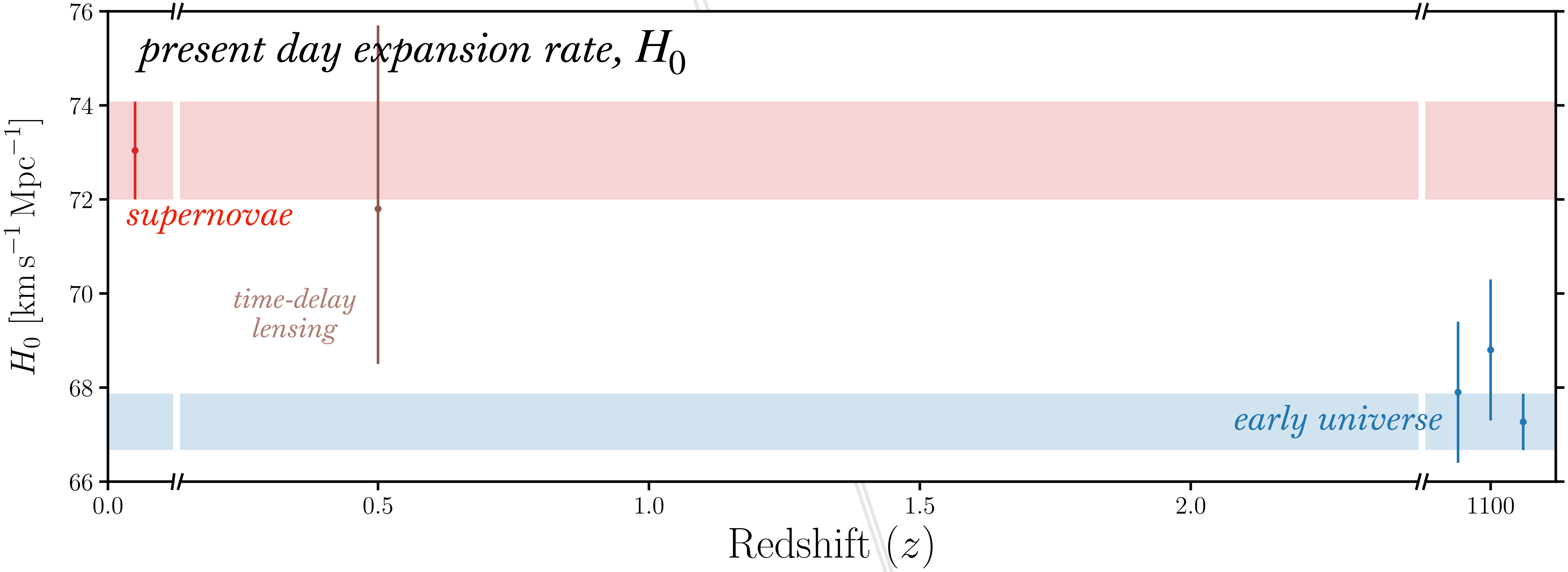

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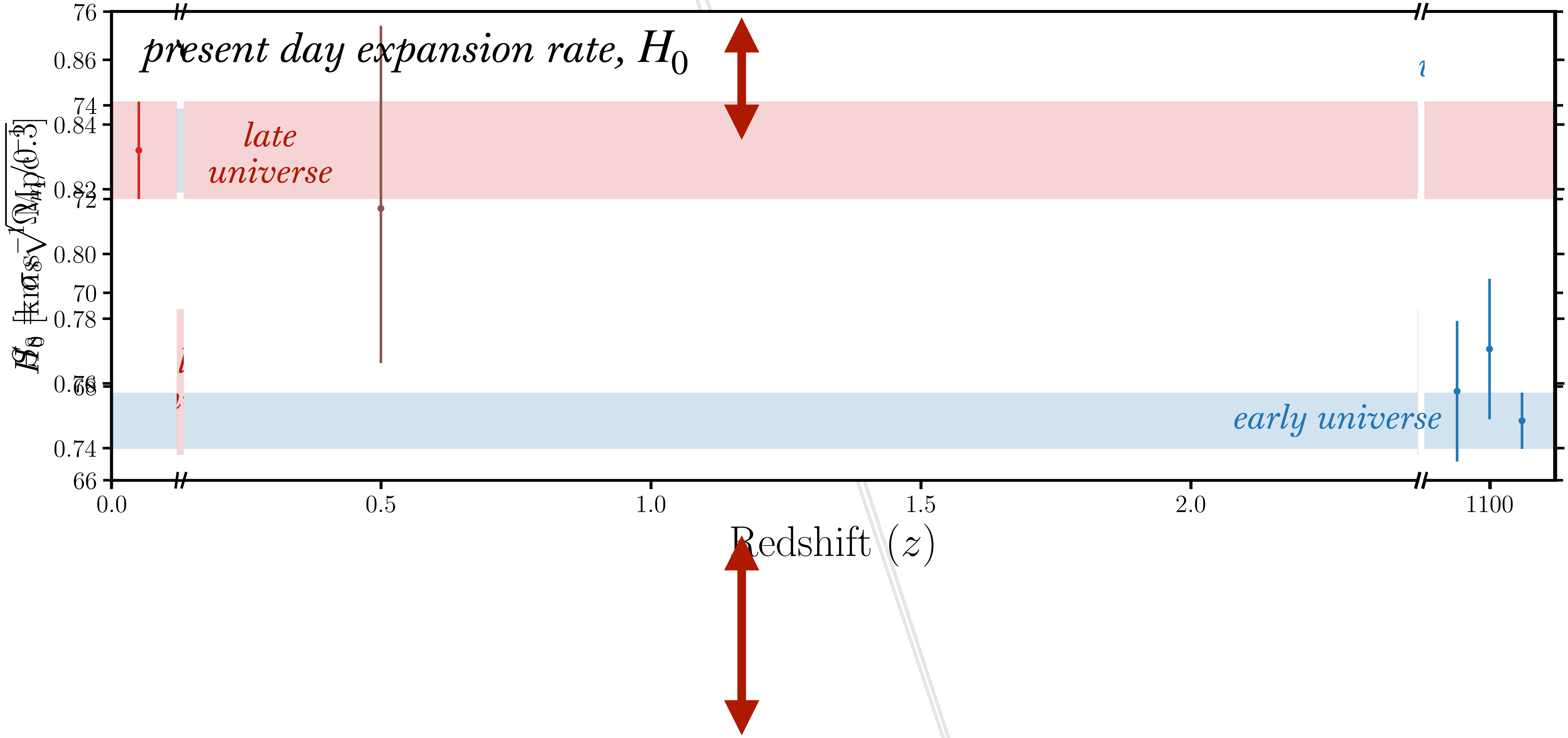


spectroscopic galaxy surveys probe both the growth of structure and the expansion rate

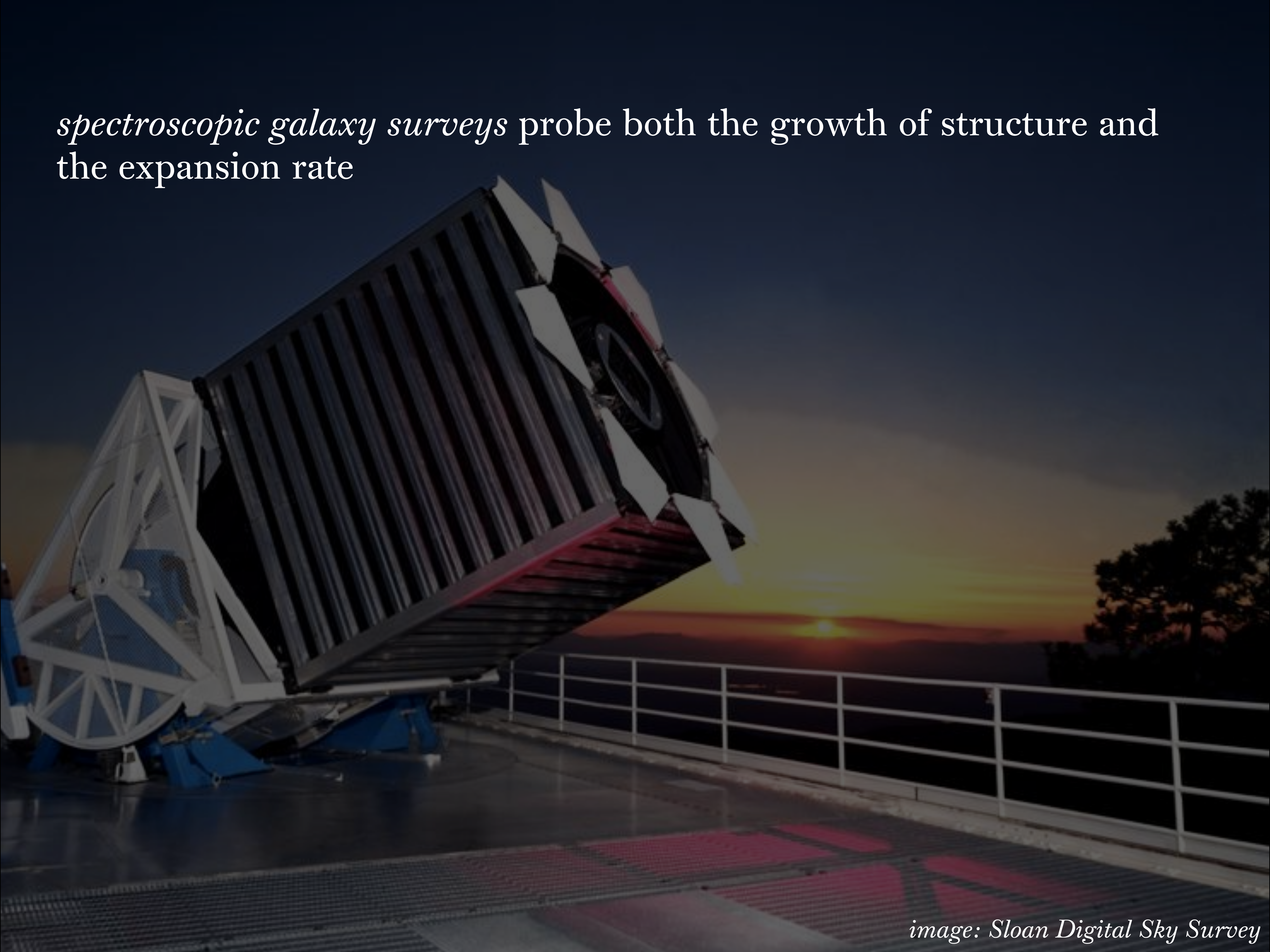
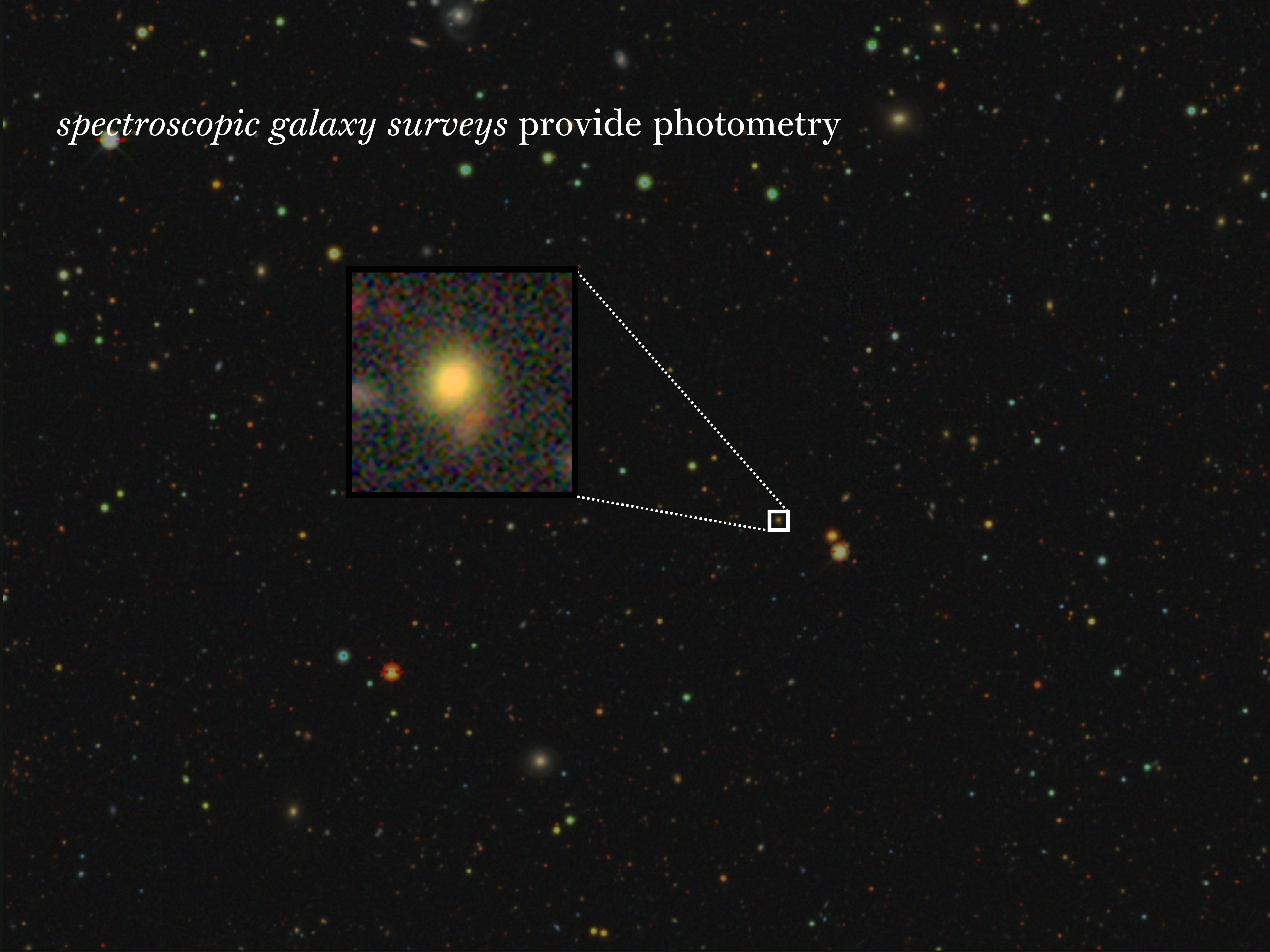
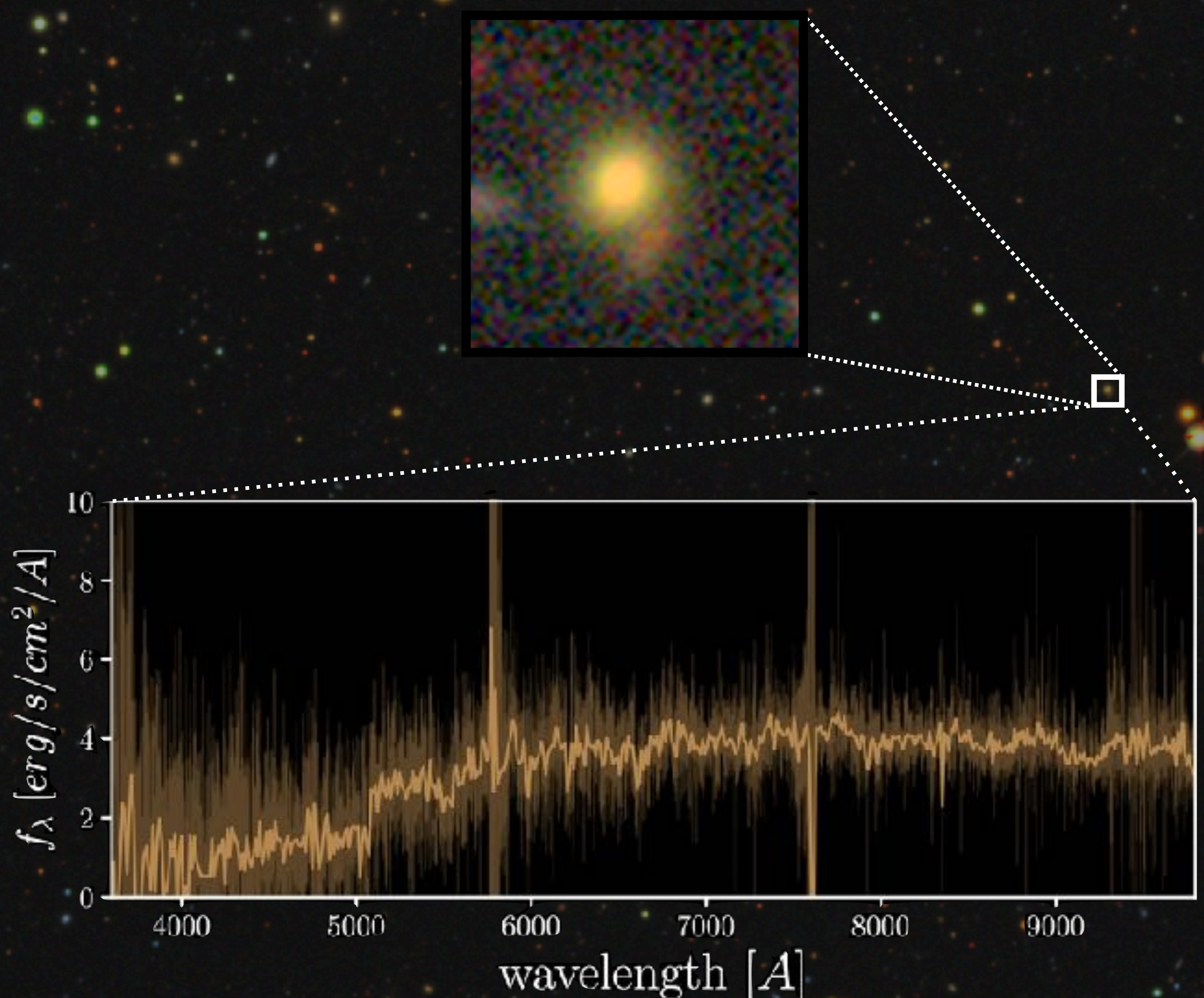


image: Sloan Digital Sky Survey


spectroscopic galaxy surveys provide photometry

spectroscopic galaxy surveys provide photometry and spectra of galaxies



spectroscopic galaxy surveys map the detailed three-dimensional spatial distribution of galaxies

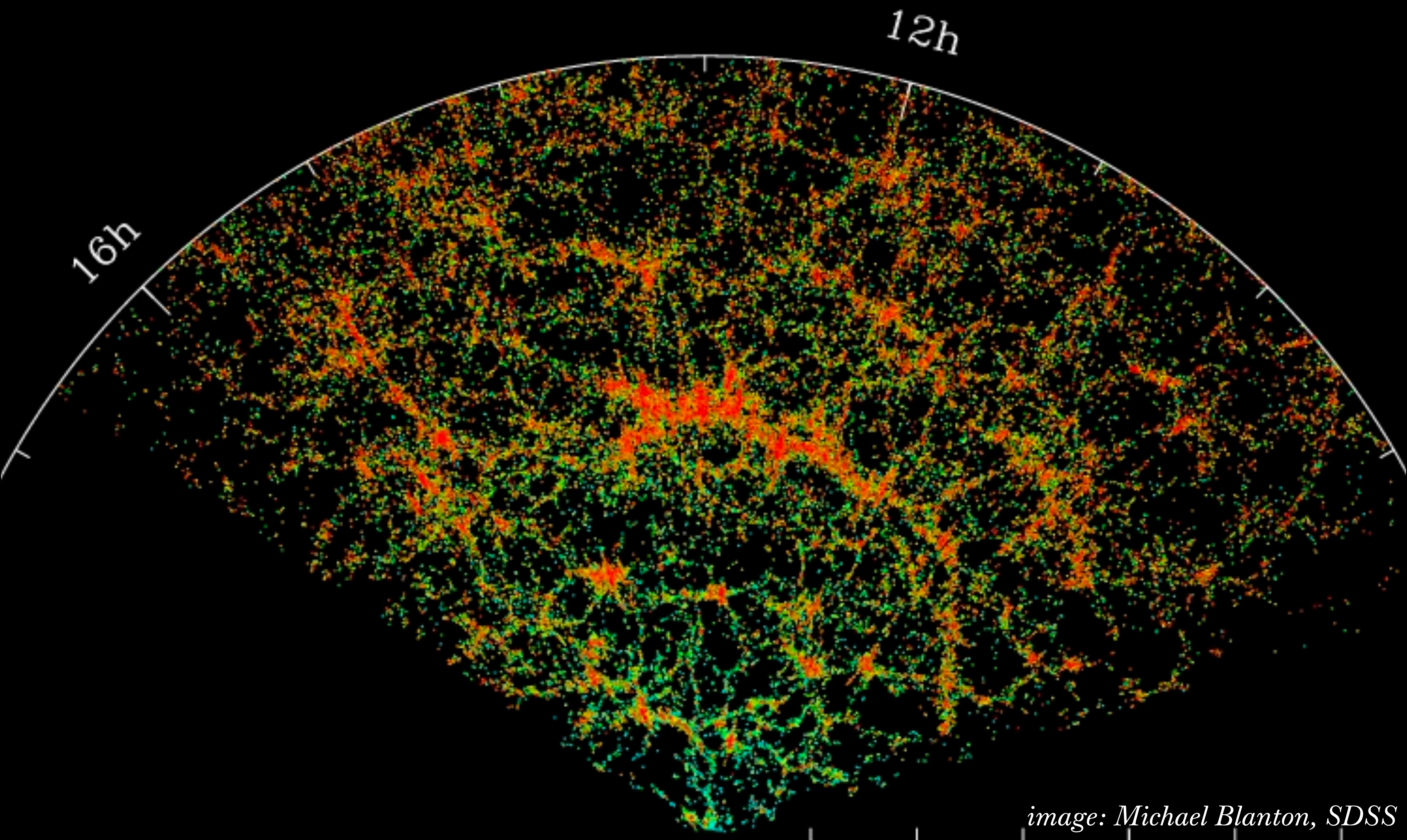


image: Michael Blanton, SDSS

3D distribution of galaxies encodes cosmological information on the **growth of structure** — *redshift-space distortions*

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$$z_{\rm obs} = z_{\rm cosmo} + \frac{v_{\rm pec}}{c}$$

cosmological expansion

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peculiar velocity

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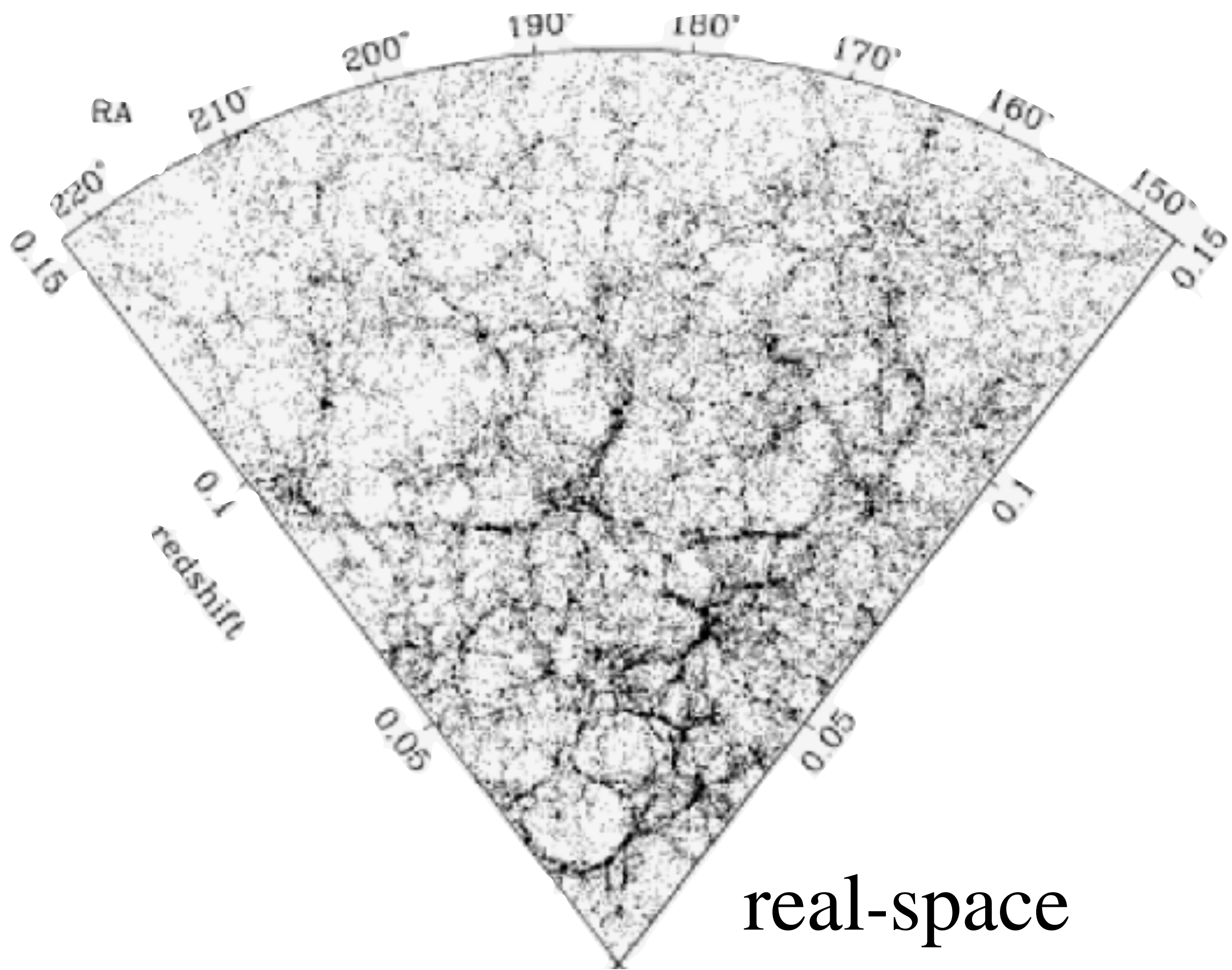

image: Eke et al. (2003)

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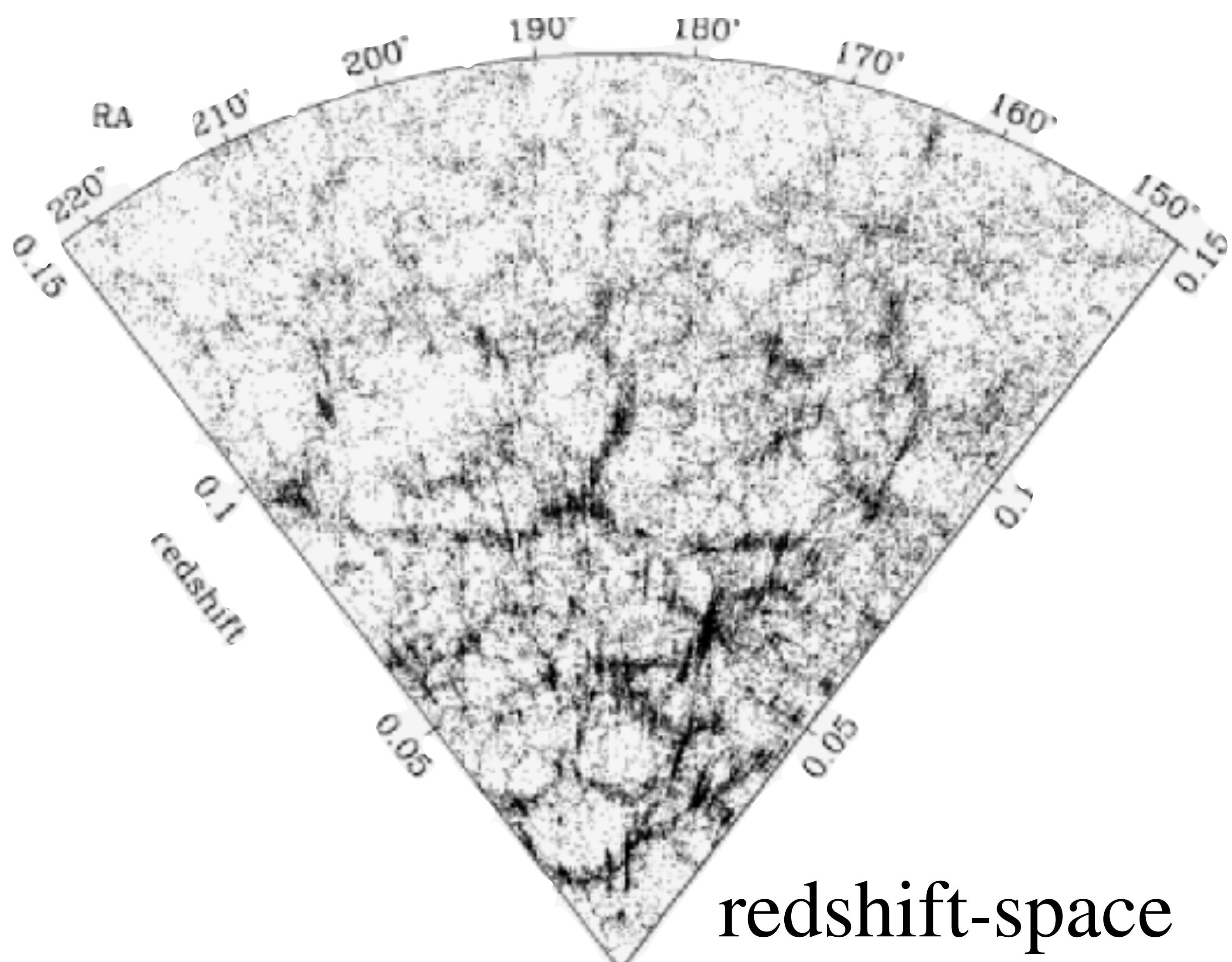

redshift-space

image: Eke et al. (2003)

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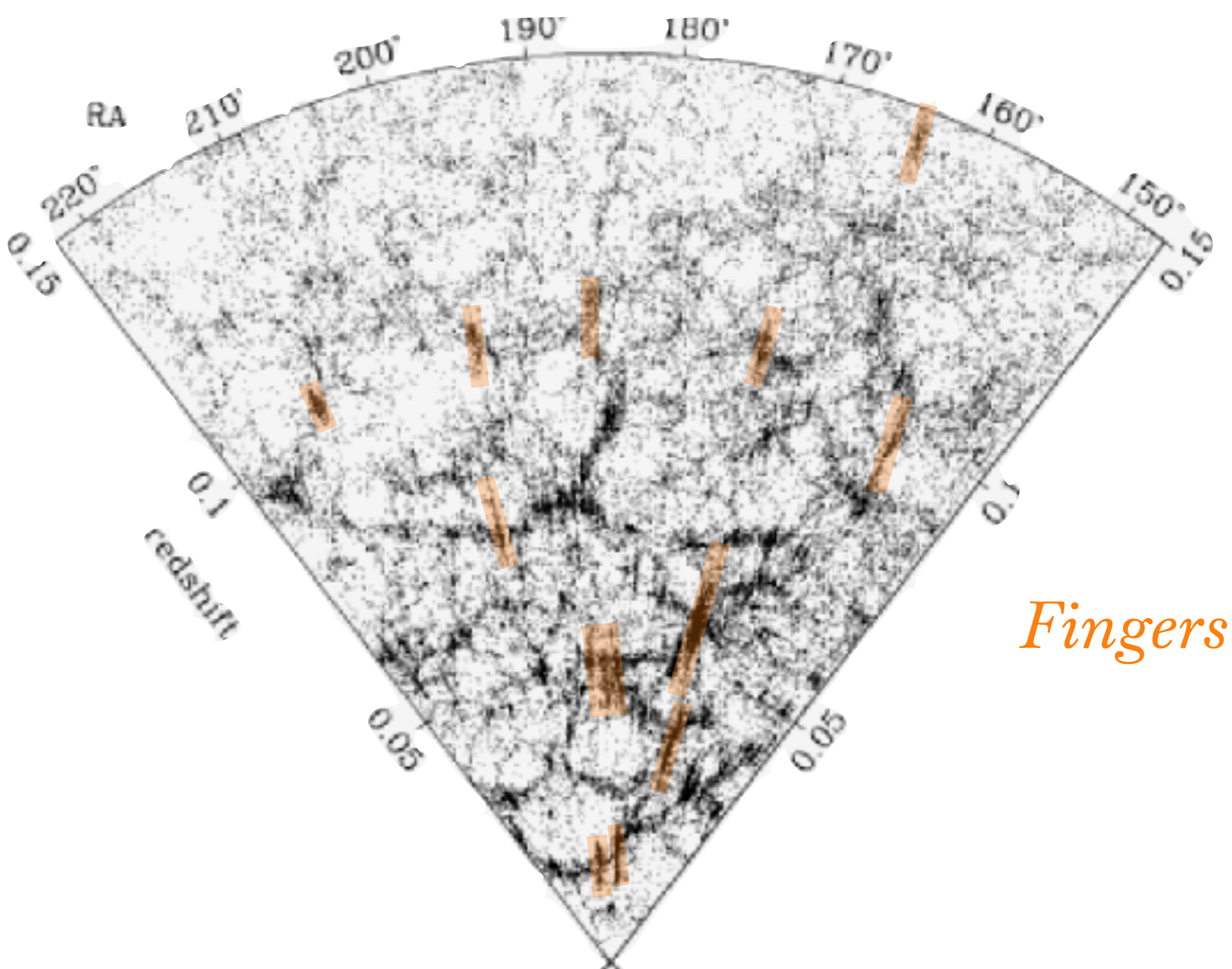

Fingers-of-God

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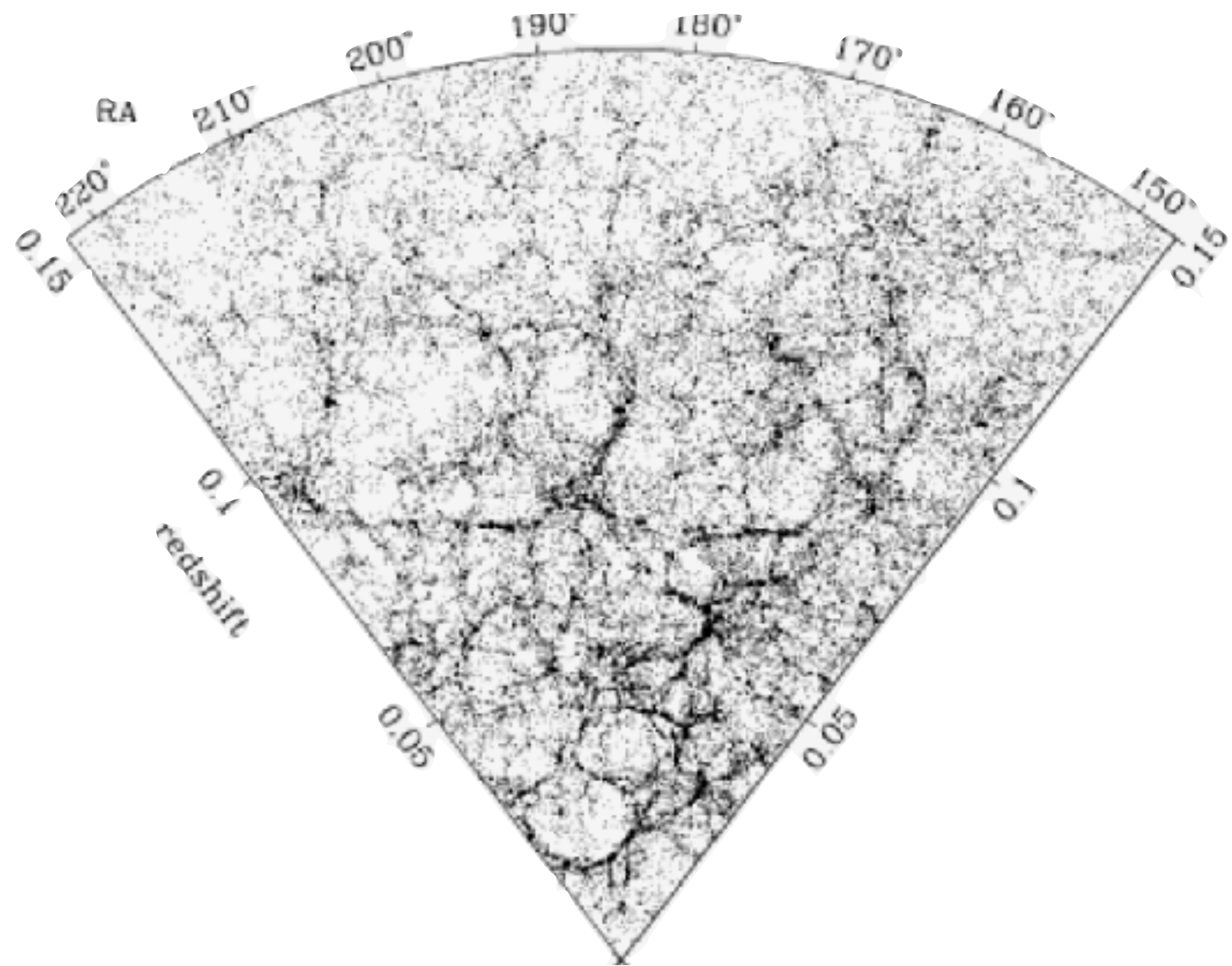

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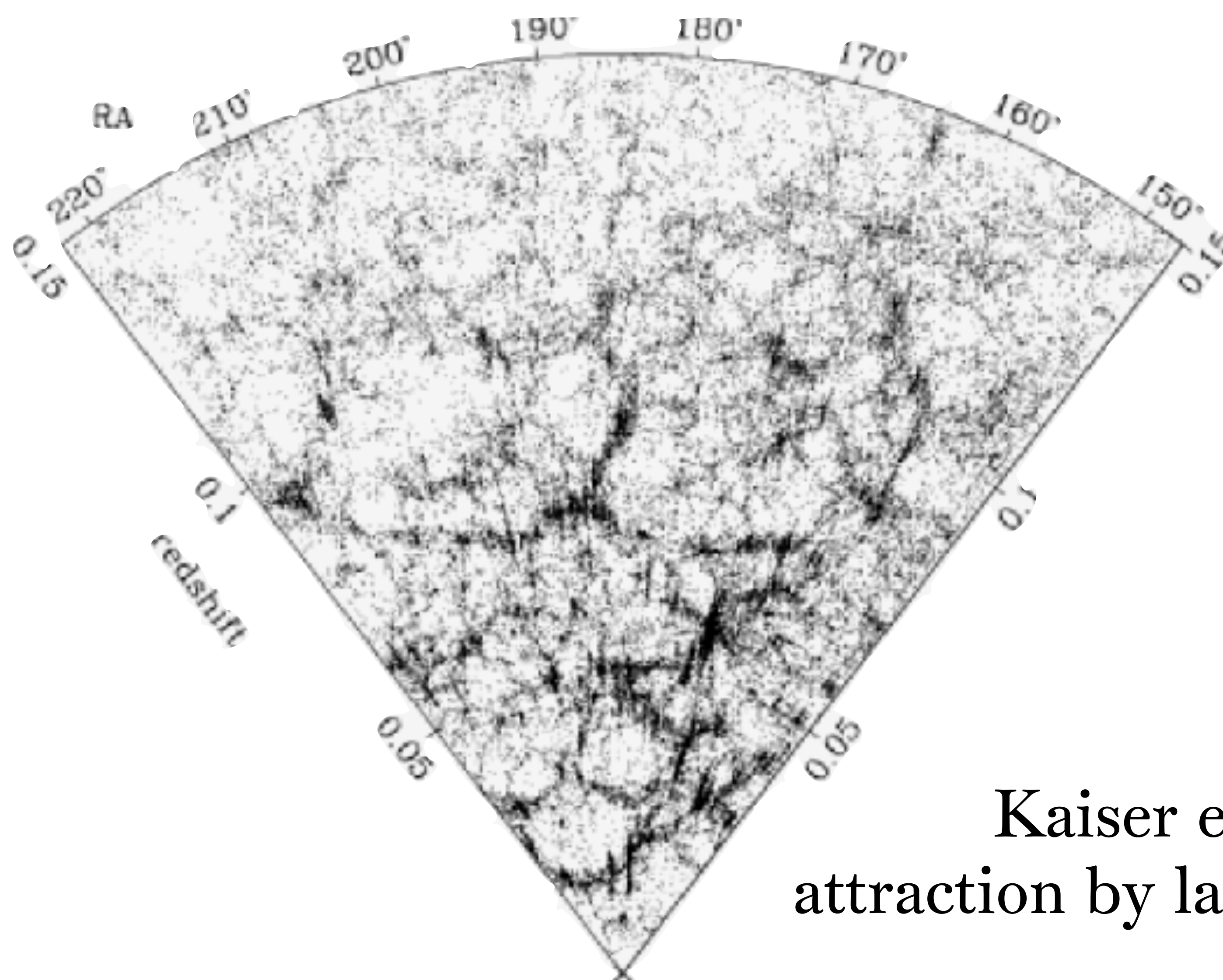


Kaiser effect: gravitational attraction by large-scale structure

3D distribution of galaxies encodes cosmological information on the **growth of structure** — *redshift-space distortions*

galaxy overdensity in redshift-space

$$\delta_g^{(s)}(k)$$

**linear theory*

3D distribution of galaxies encodes cosmological information on the **growth of structure** — *redshift-space distortions*

$$\delta_g^{(s)}(k) = \delta_g(k)$$

galaxy overdensity in real-space

*linear theory

3D distribution of galaxies encodes cosmological information on the **growth of structure** — *redshift-space distortions*

$$\delta_g^{(s)}(k) = \delta_g(k) + f\mu^2\,\delta_m(k)$$

growth rate of structure *matter overdensity*

**linear theory*

3D distribution of galaxies encodes cosmological information on the **growth of structure** — *redshift-space distortions*

$$\delta_g^{(s)}(k) = \delta_g(k) + f\mu^2\,\delta_m(k)$$

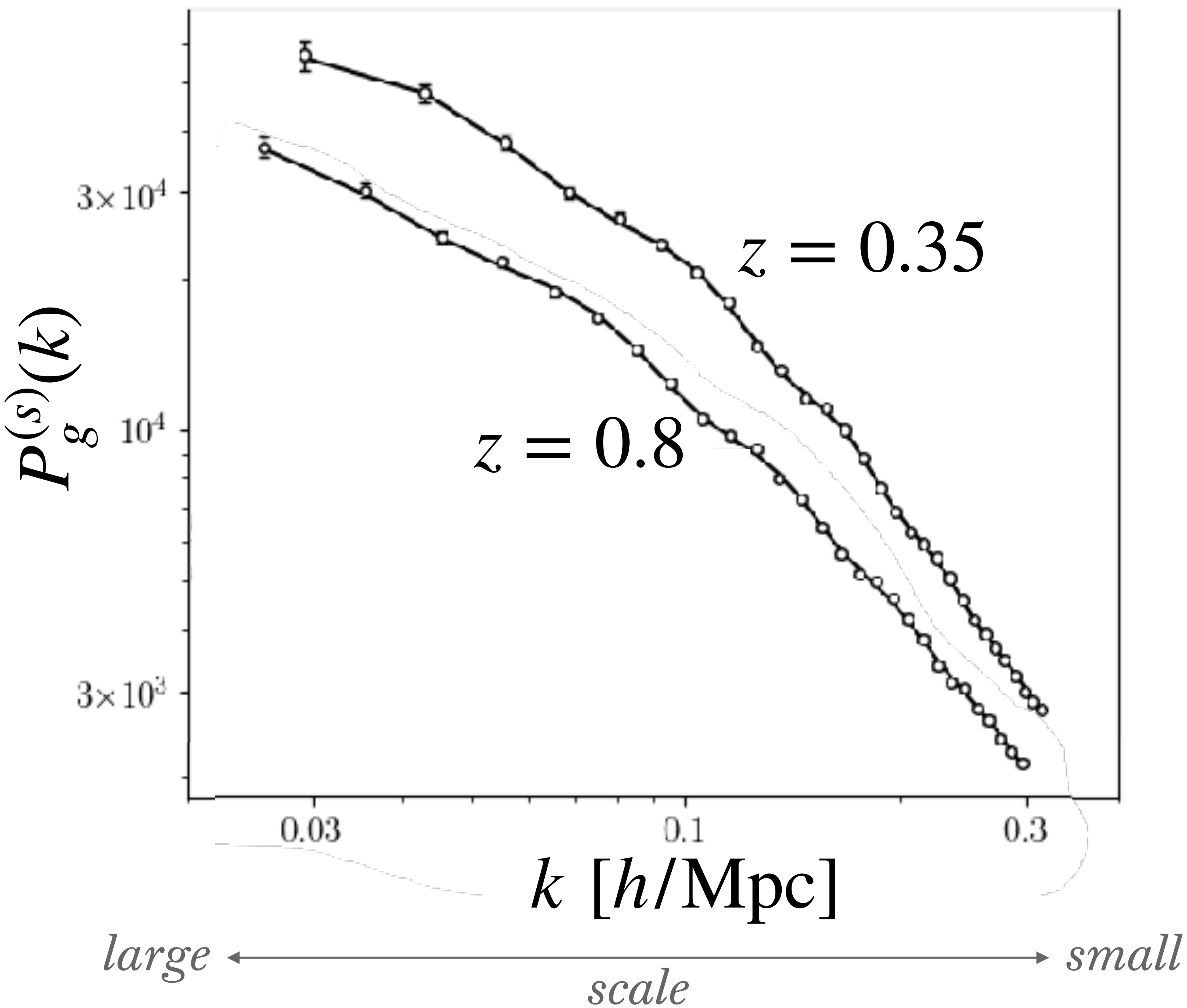
galaxy power spectrum

$$P_g^{(s)}(k) = \langle\, \delta_g^{(s)}(k)\,\delta_g^{(s)}(k')\,\rangle$$

$$= \left(b + f\mu^2\right)^2 P_m(k)$$

**linear theory*

3D distribution of galaxies encodes cosmological information on the **growth of structure** — *redshift-space distortions*

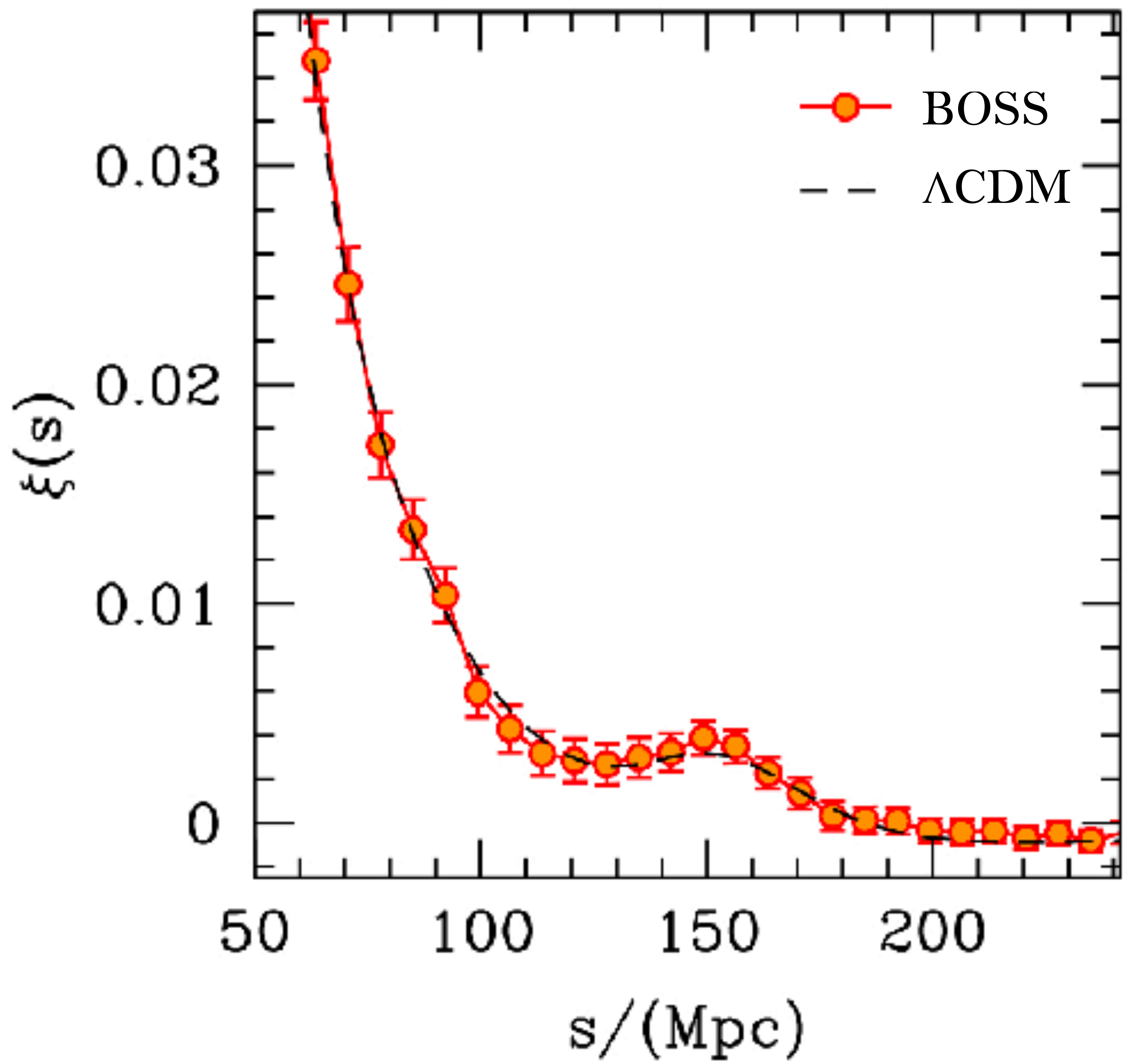


SDSS — Beutler et al.(2017), Gil-Marín et al.(2020)

3D distribution of galaxies encodes cosmological information on the **expansion history** from Baryon Acoustic Oscillations (BAO)

video: Scott Wiessinger, Ashley Balzer

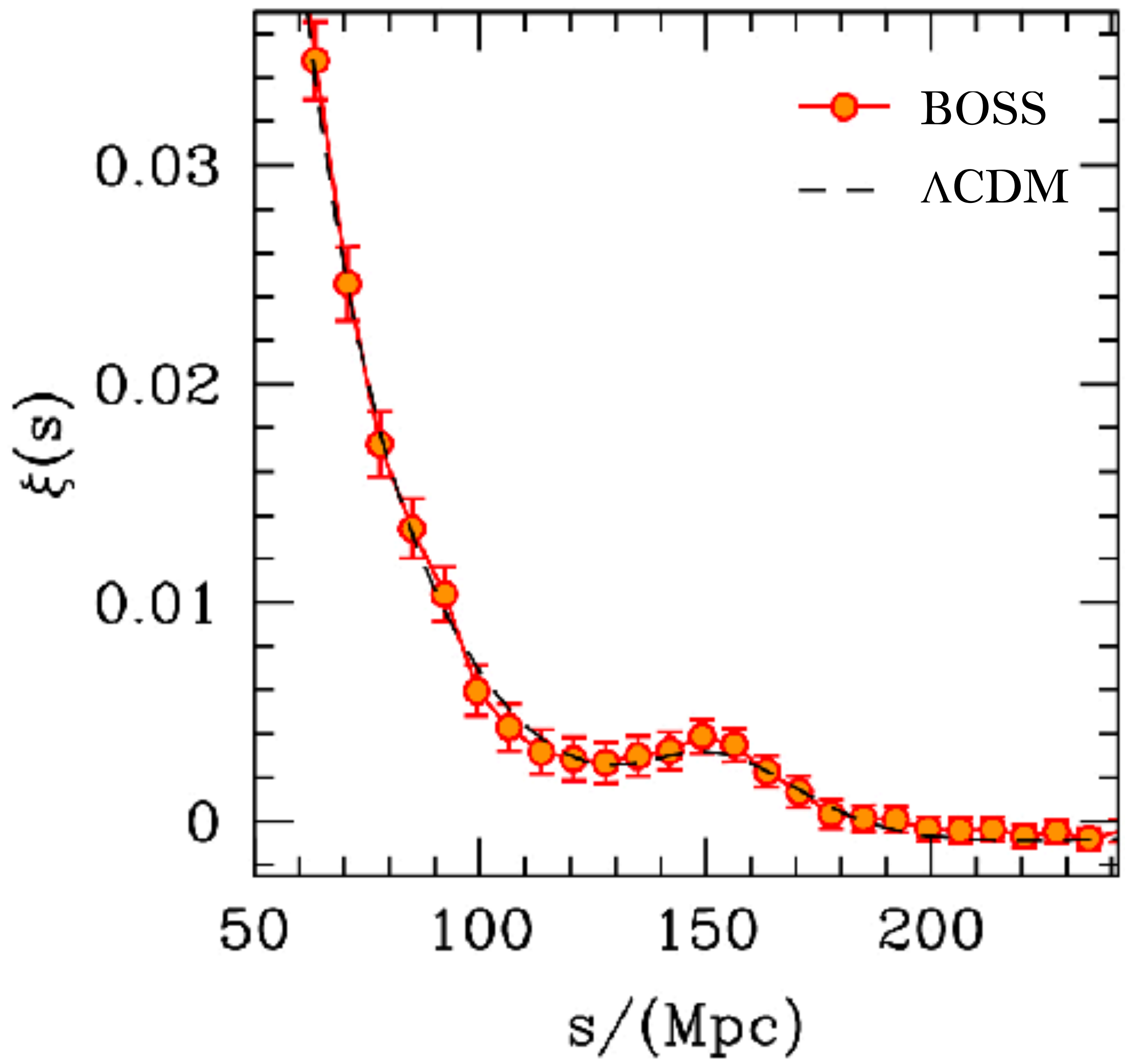
3D distribution of galaxies encodes cosmological information on the **expansion history** from Baryon Acoustic Oscillations (BAO)



2pt correlation function $\xi \equiv$ Fourier transform of P_g

BOSS — Sanchez et al. (2013)

3D distribution of galaxies encodes cosmological information on the **expansion history** from Baryon Acoustic Oscillations (BAO)



standard ruler

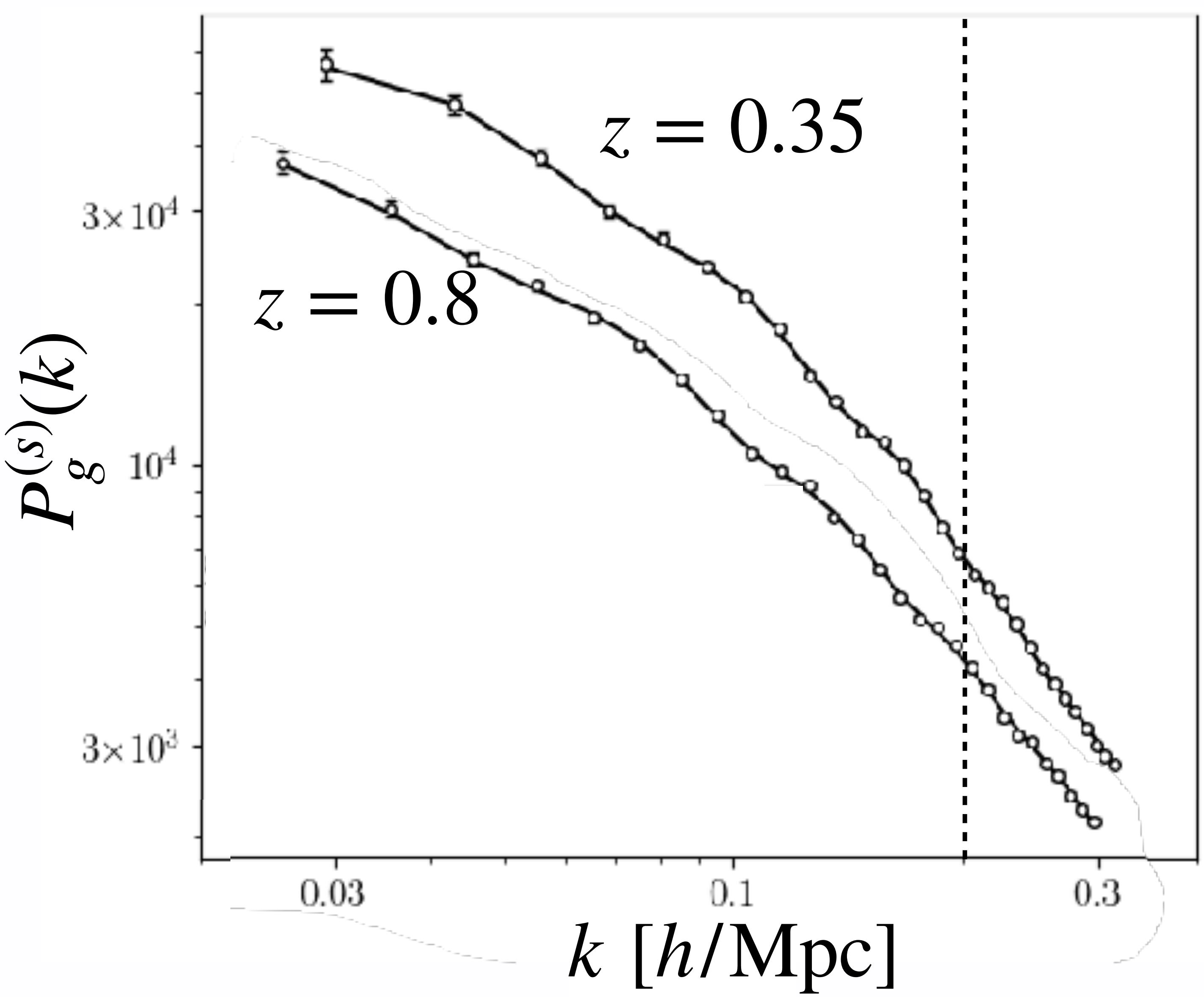
$$\theta = \frac{r_s}{d_A}$$

BOSS — Sanchez et al. (2013)

3D galaxy distribution encodes cosmological information on the **growth** and **expansion history** of the Universe


current analyses
galaxy surveys

current galaxy clustering analyses only use the **power spectrum** on large **linear scales**



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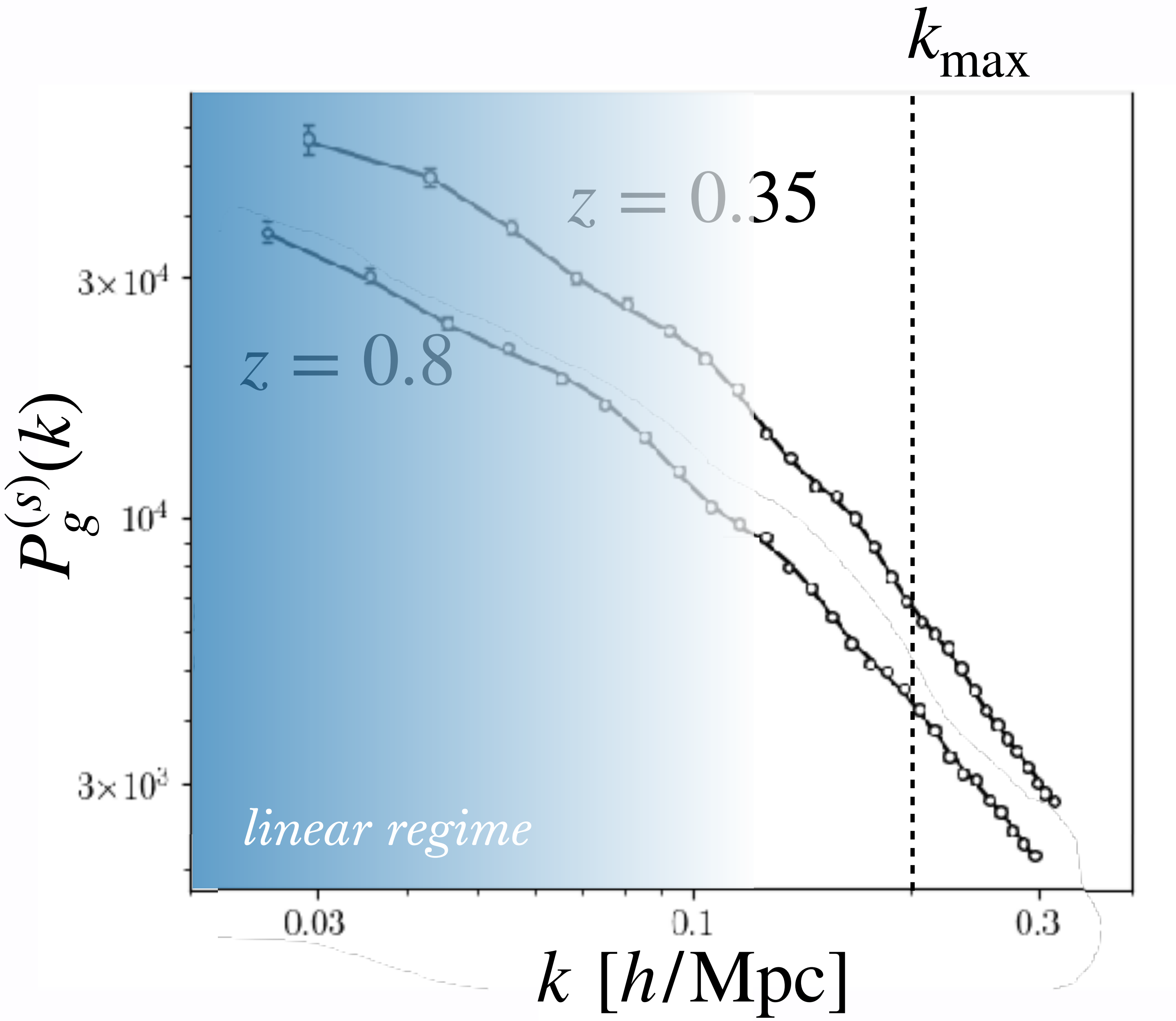

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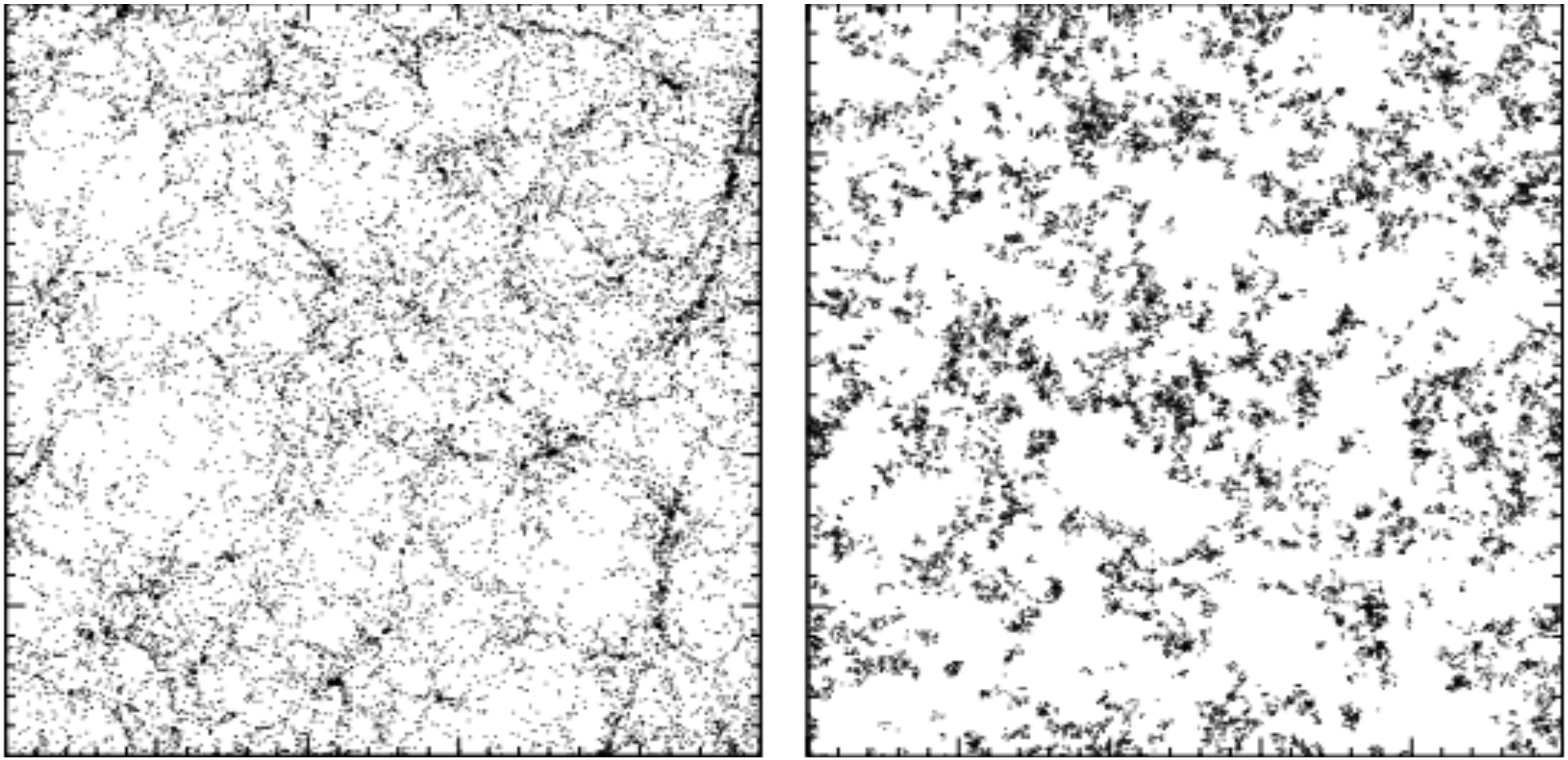
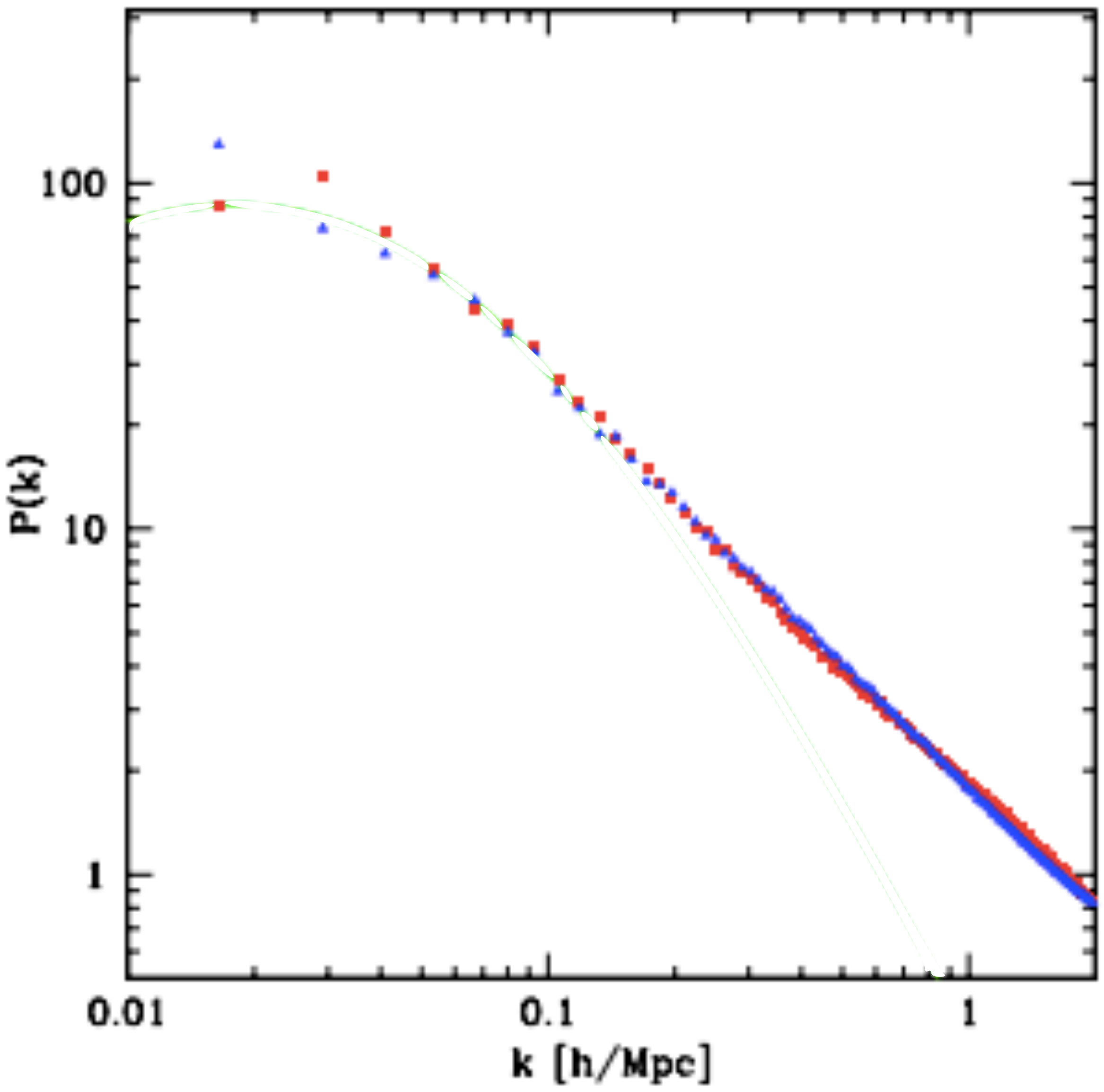


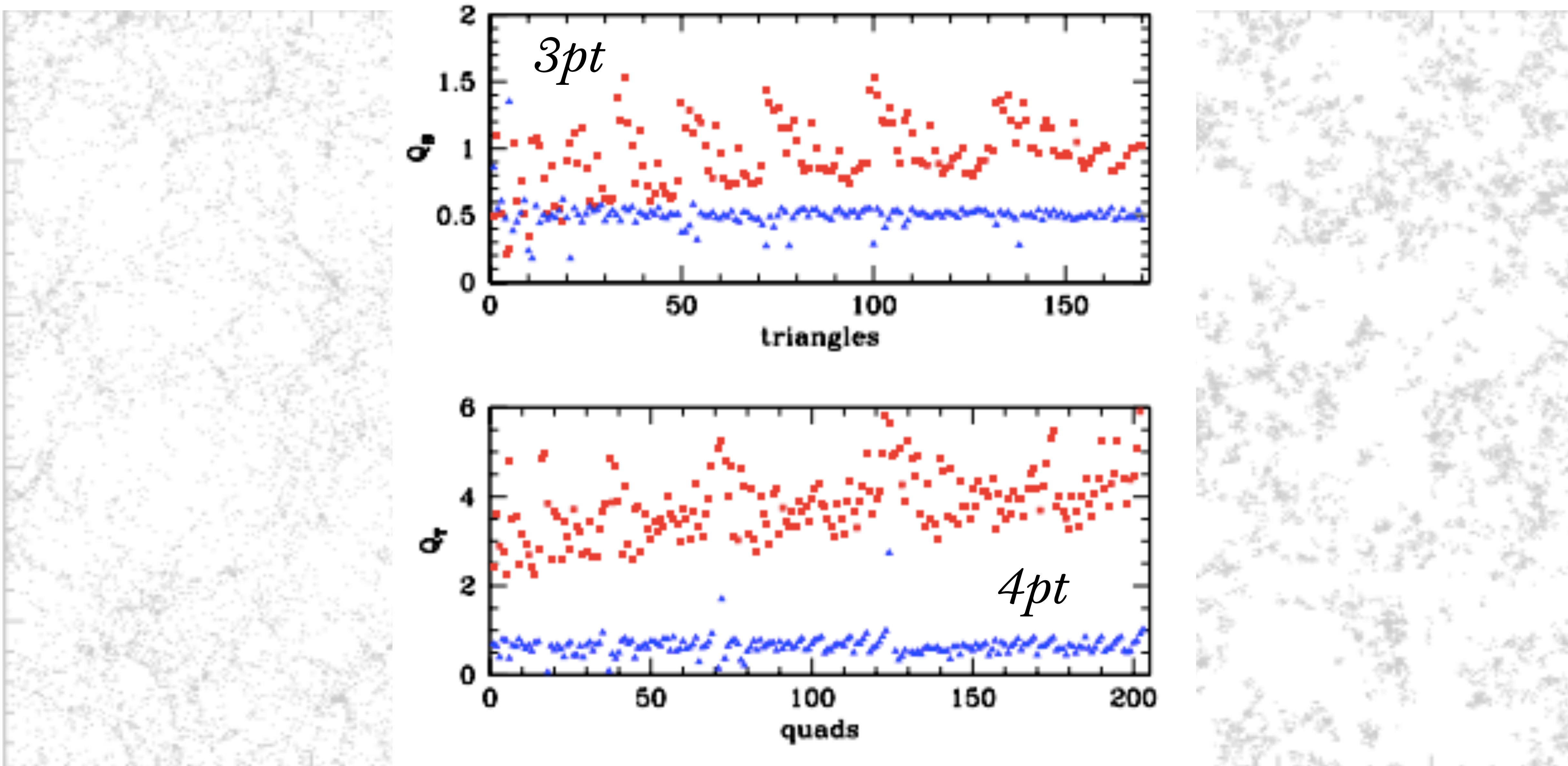
Sefusatti et al.(2005)

these two distributions have the *same* power spectrum



Sefusatti et al.(2005)

these two distributions have the *same power spectrum* but very different *higher-order clustering*



Sefusatti et al.(2005)

how much cosmological information is available *beyond the power spectrum*?

Quijote

82,000 full N-body simulations

*Villaescusa-Navarro, **Hahn** et al. (2019)*

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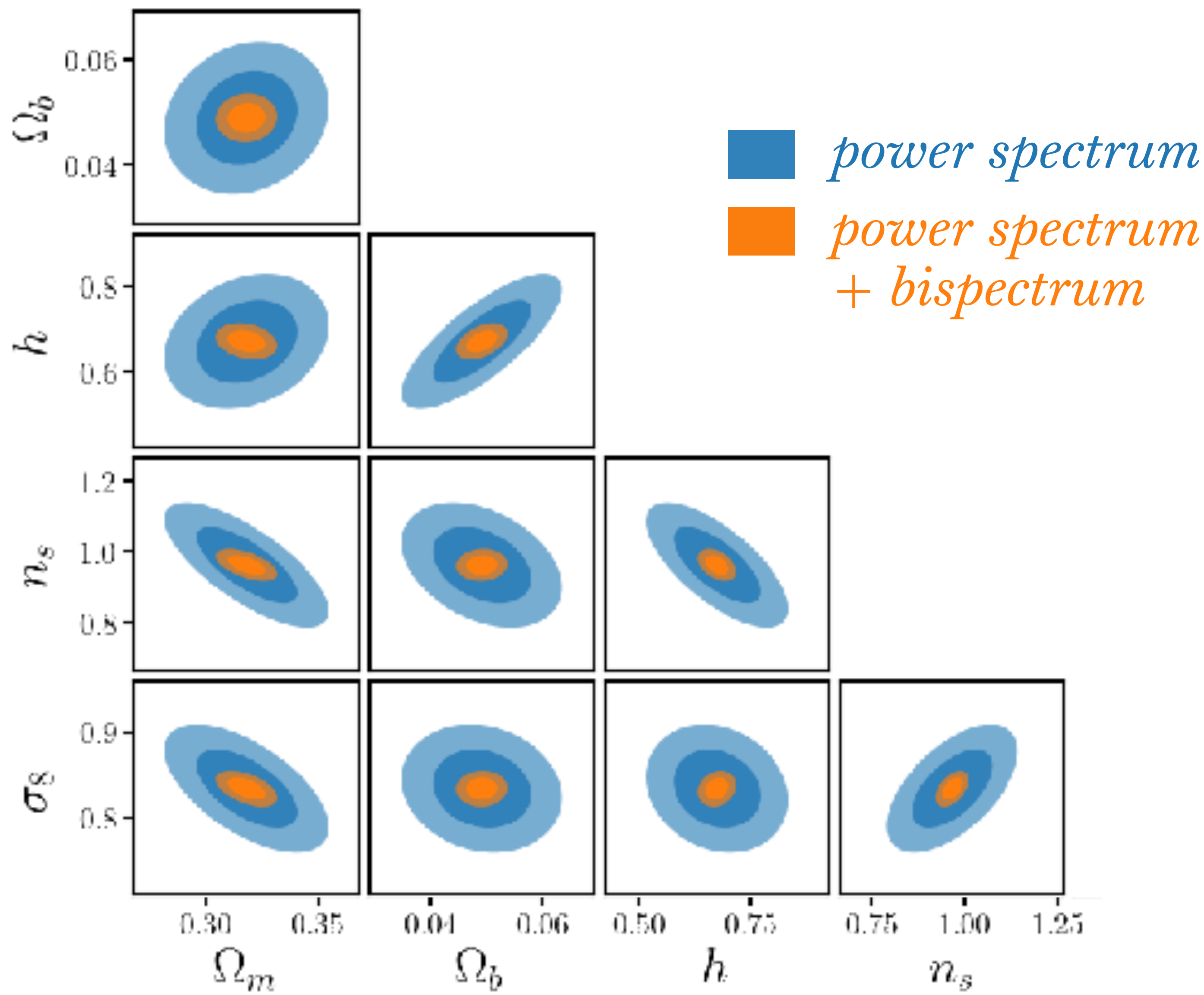
molino

75,000 simulated galaxy catalogs

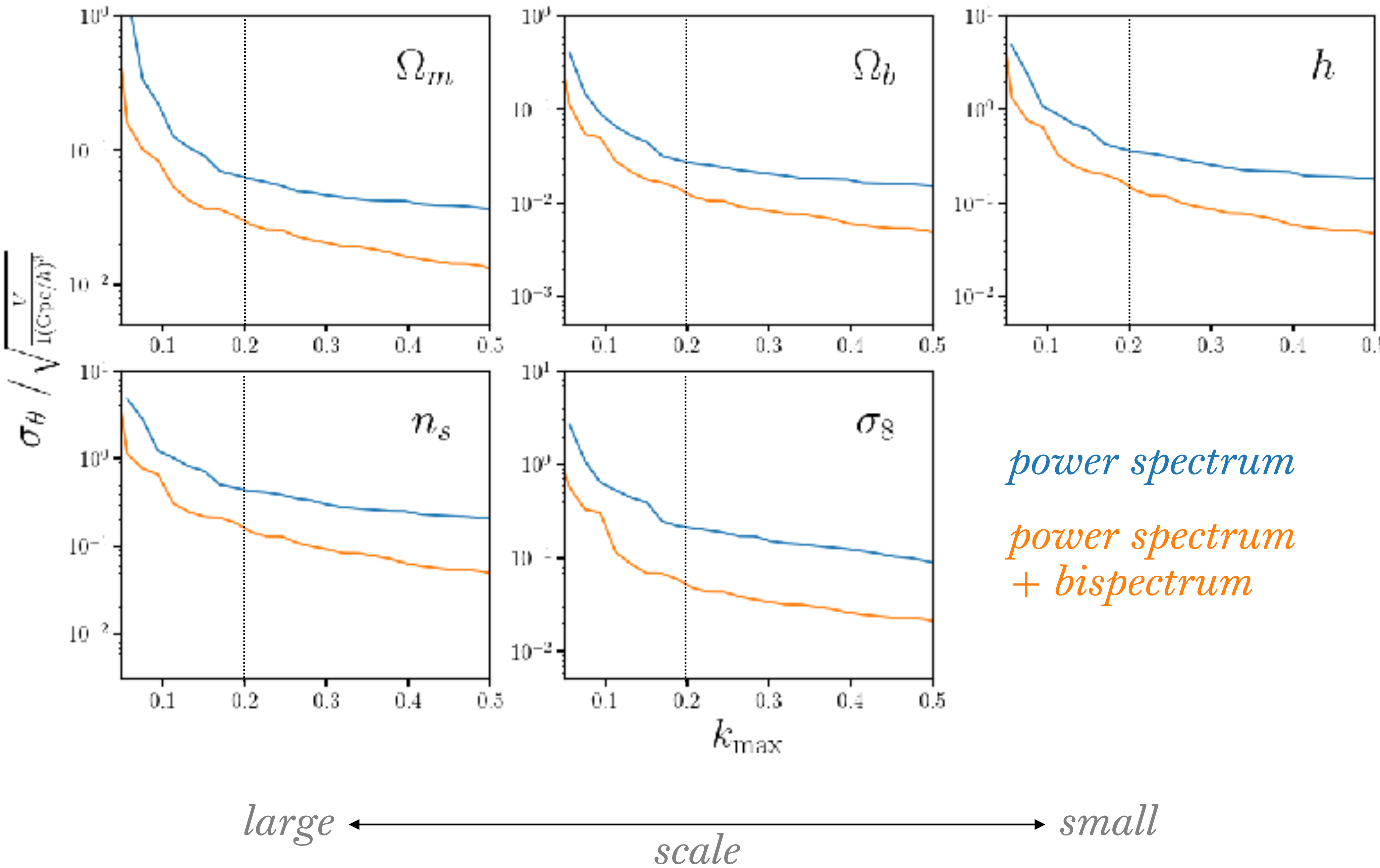
***Hahn** & Villaescusa-Navarro (2021)*



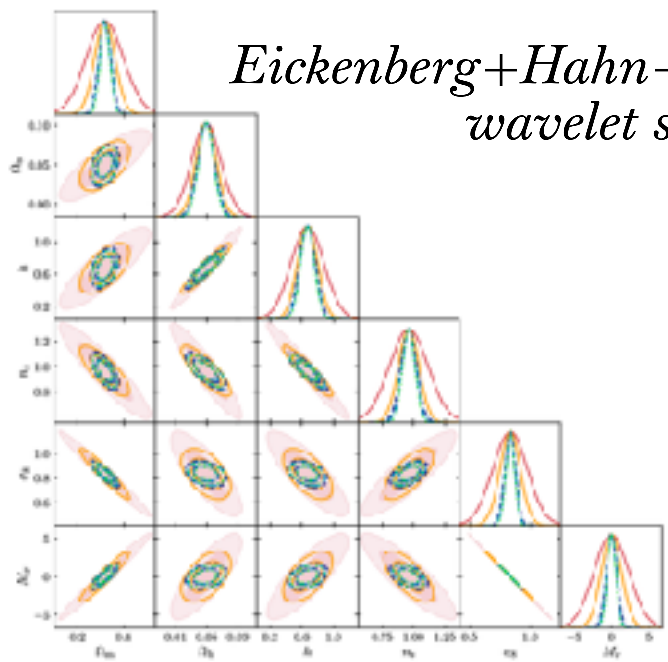
with the bispectrum we can constrain the ΛCDM parameters $(\Omega_m, \Omega_b, h, n_s, \sigma_8)$ $\gtrsim$ **3 × tighter** than the power spectrum alone

Hahn et al. (2020)
Hahn & Villaescusa-Navarro (2021)

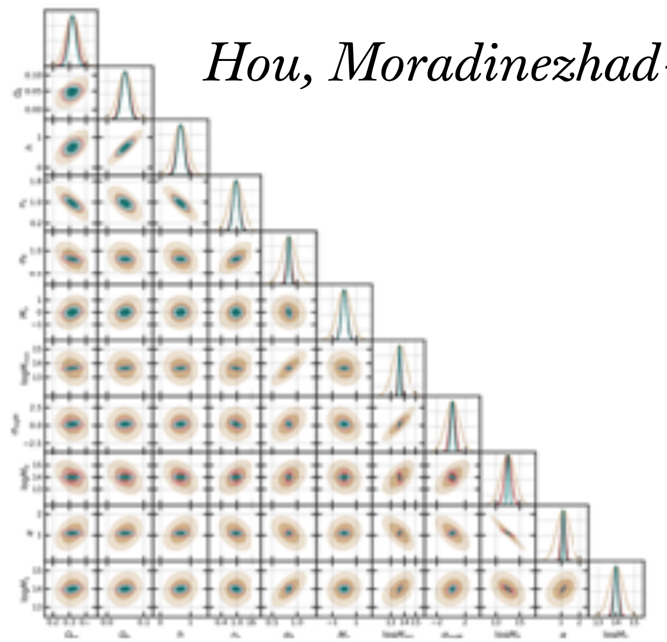
significant cosmological information on *non-linear scales*



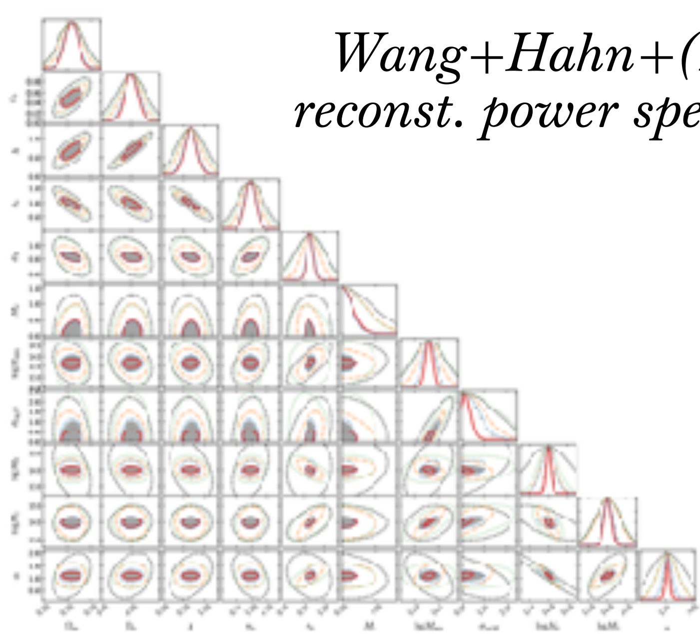
many promising clustering statistics beyond the power spectrum — *e.g.*



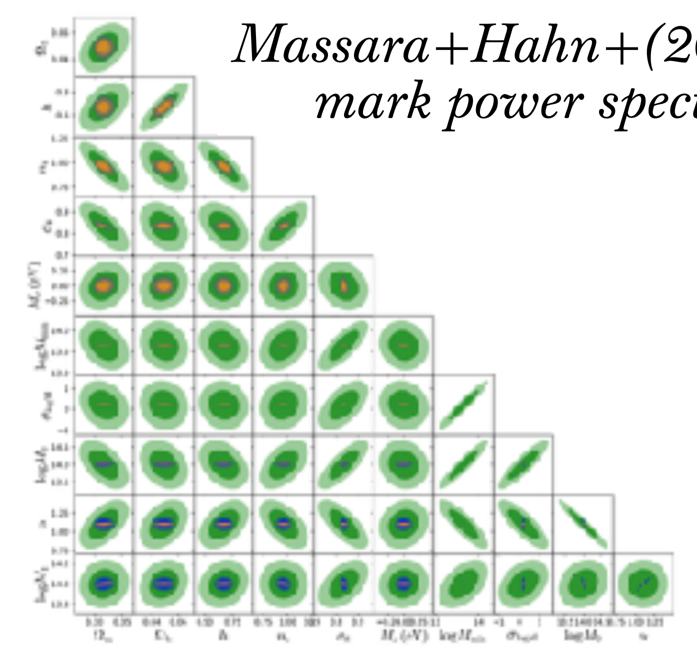
Eickenberg+Hahn+(2022)
wavelet statistics



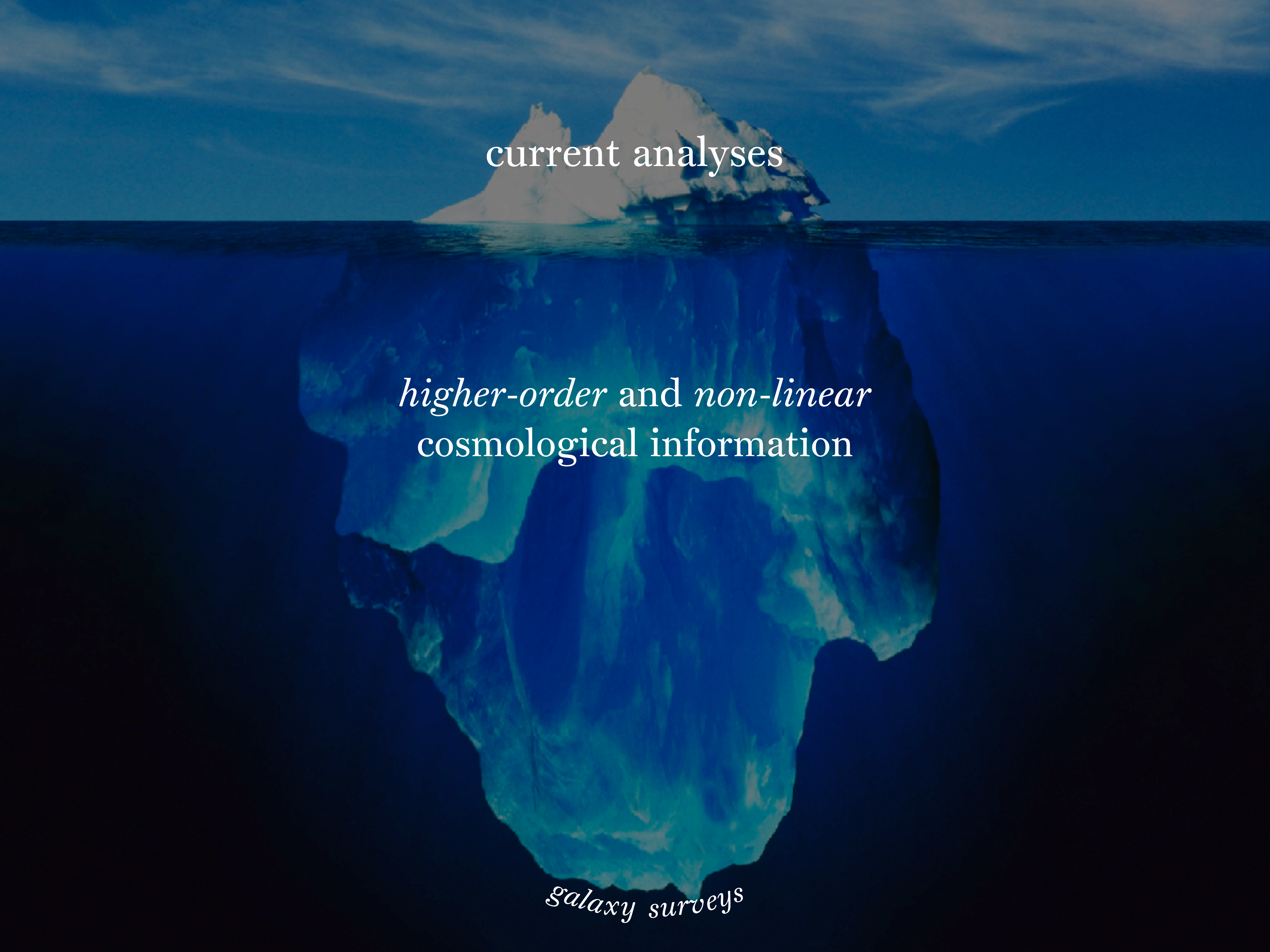
Hou, Moradinezhad+Hahn+(2022)
skew spectra



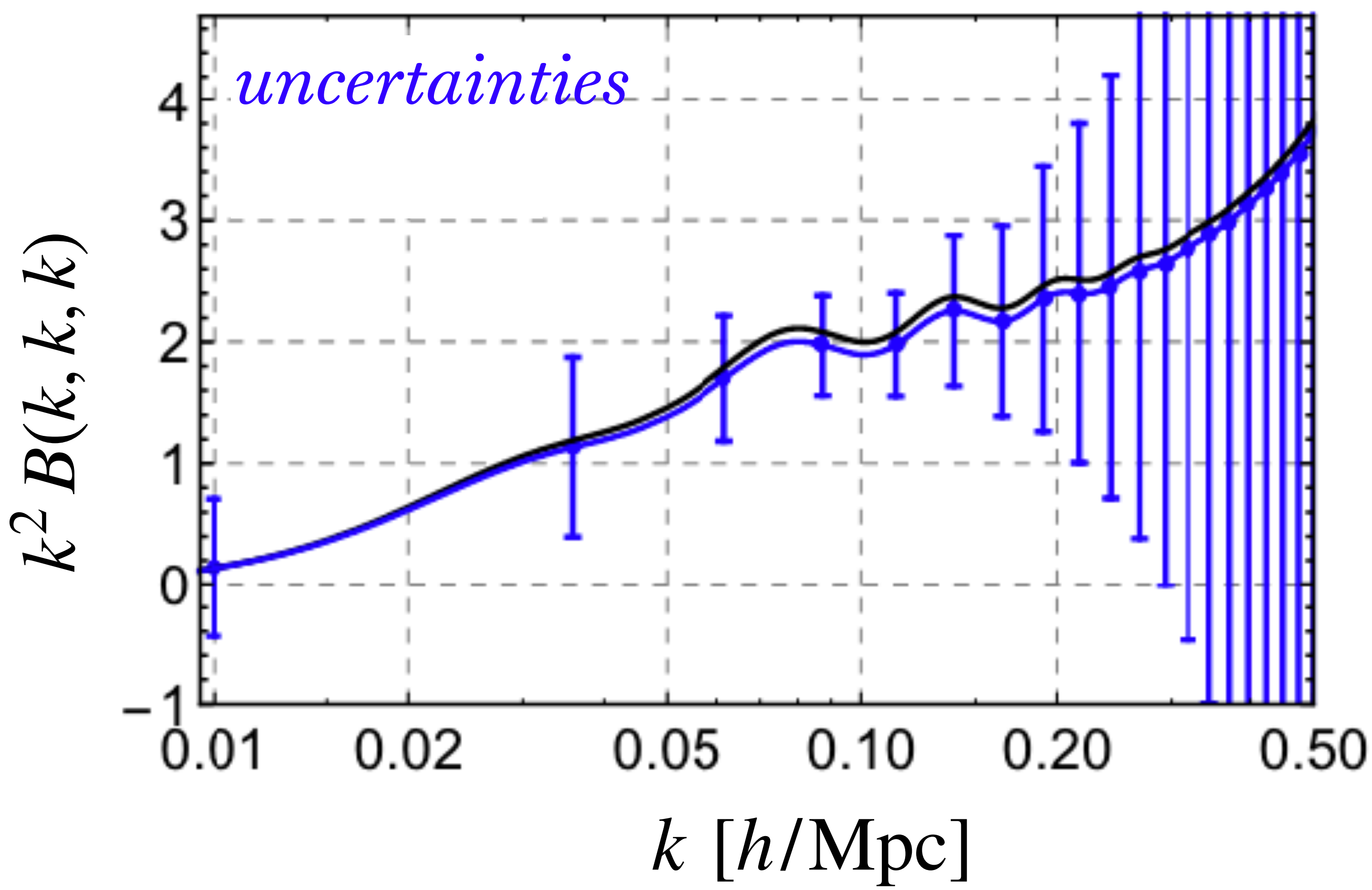
Wang+Hahn+(2024)
reconst. power spectrum



Massara+Hahn+(2022)
mark power spectrum


current analyses
higher-order and *non-linear*
cosmological information
galaxy surveys

challenges: analytic models of galaxy clustering are *inaccurate* on non-linear scales $k_{\text{max}} \gtrsim 0.2\, h/\text{Mpc}$



Chudaykin & Ivanov (2019)

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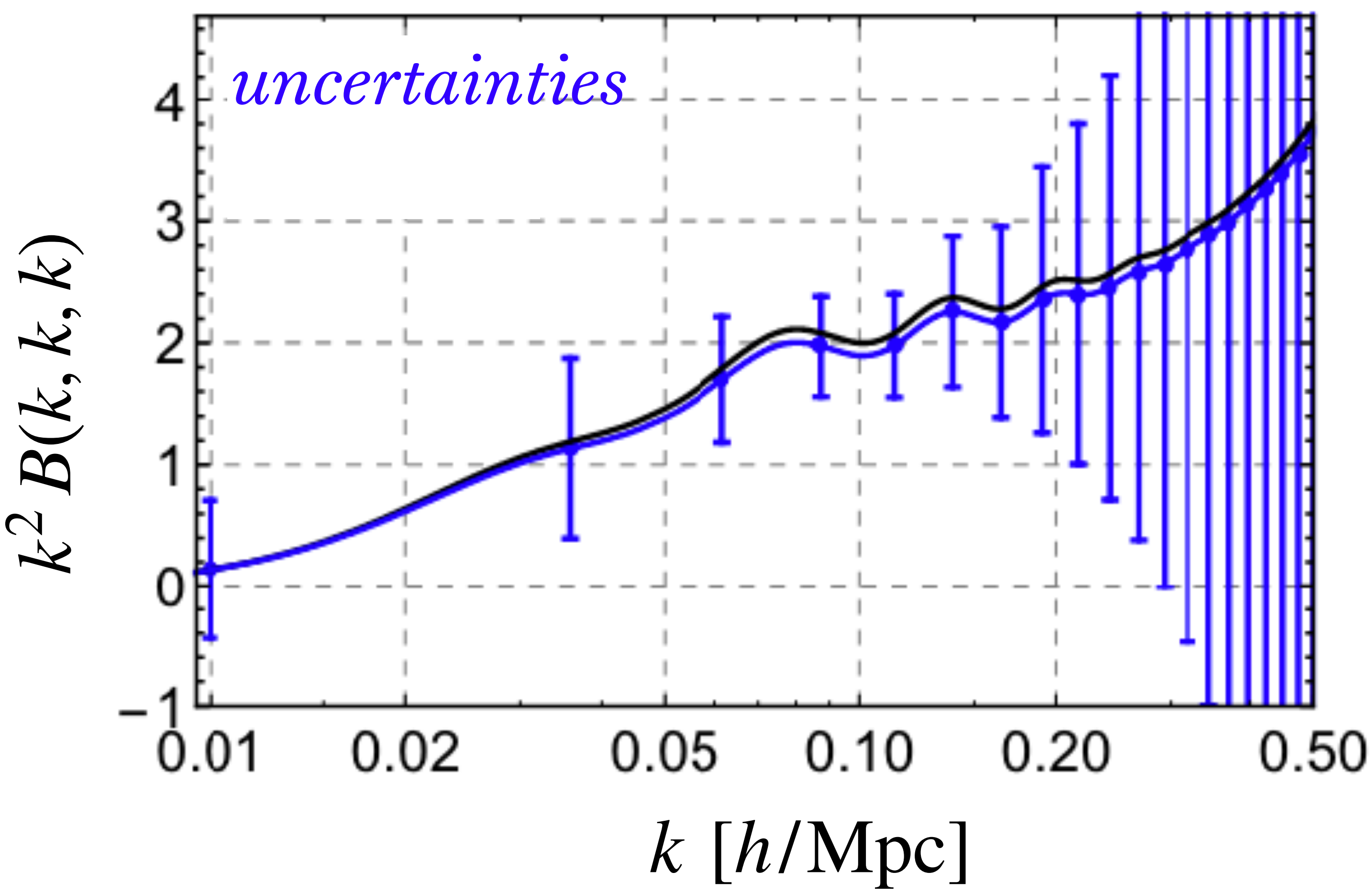
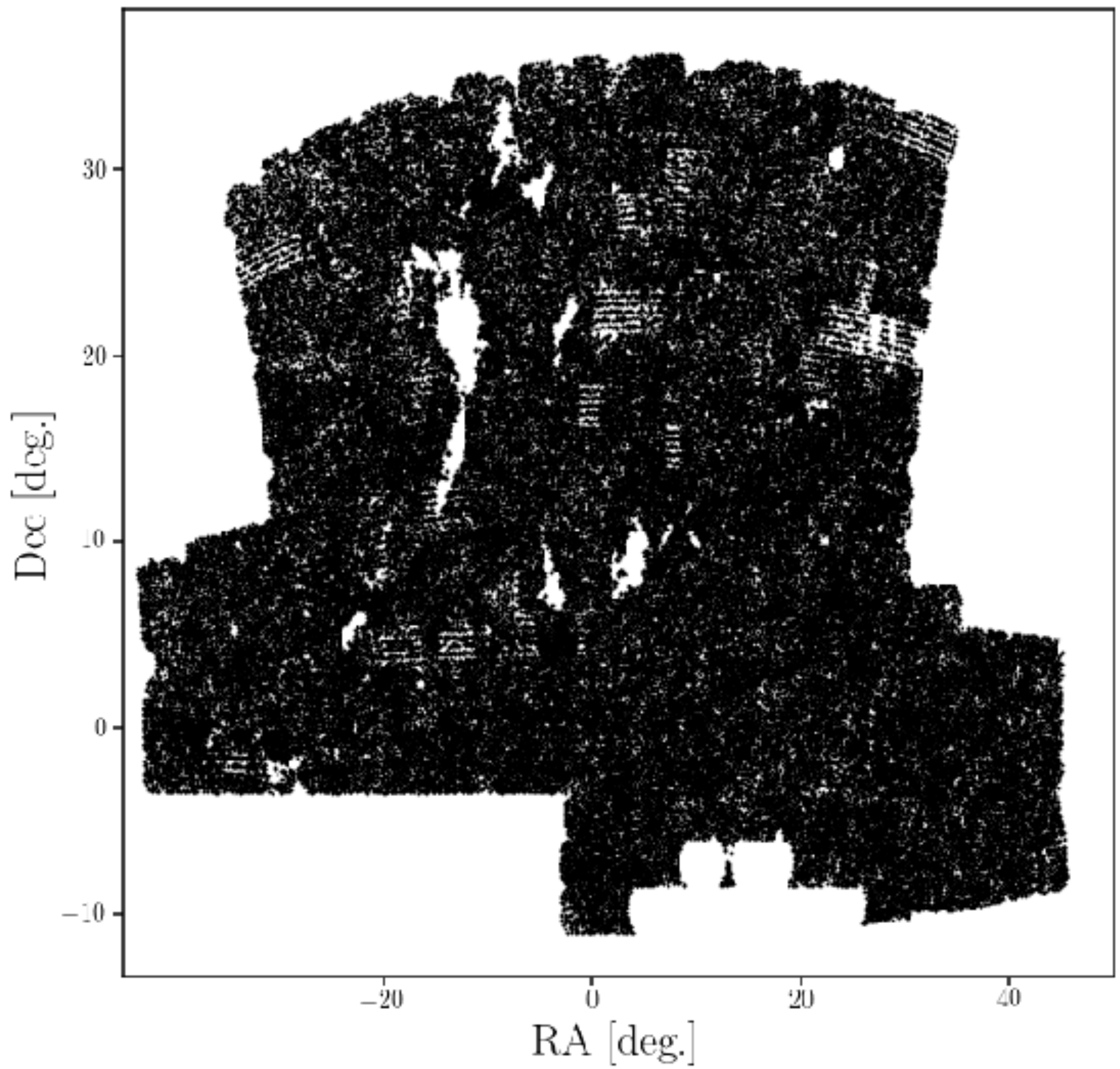


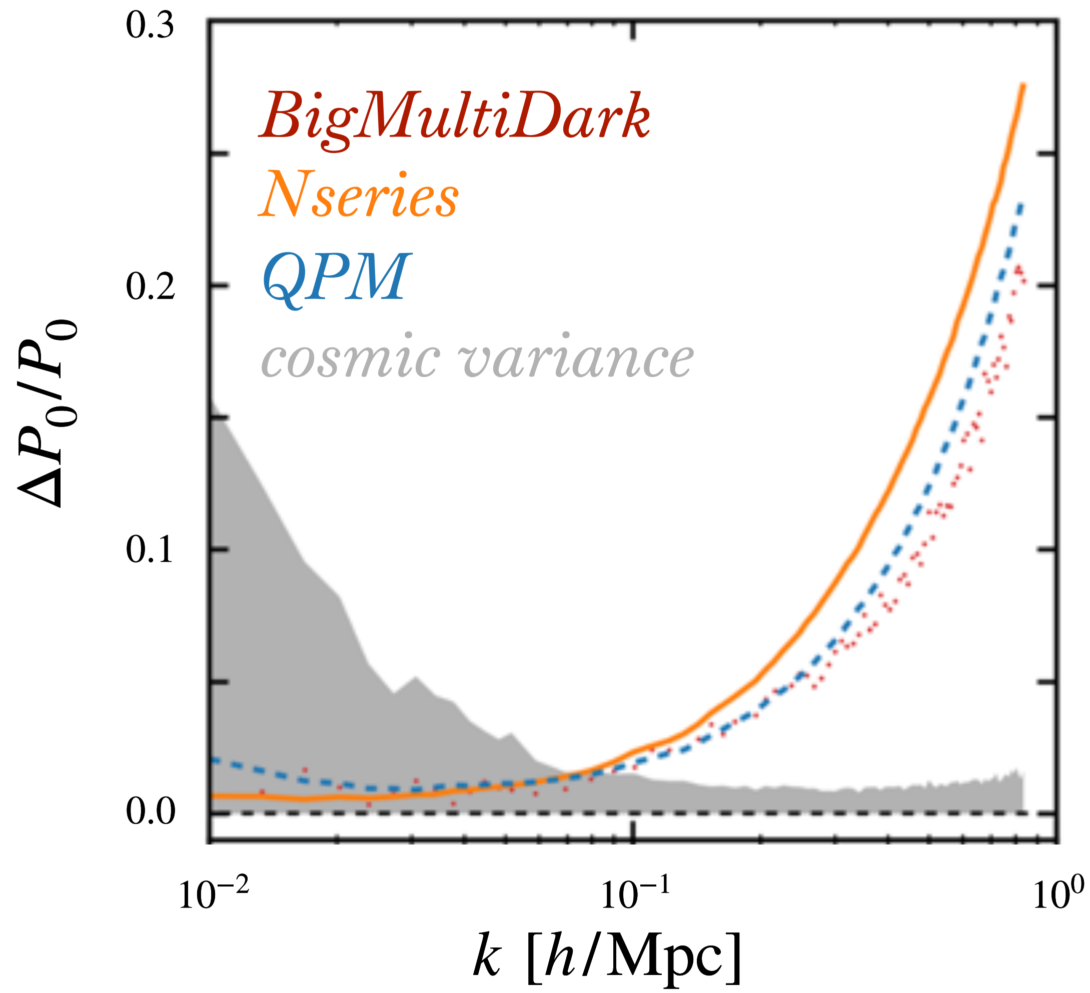
no analytic models available for — *e.g. wavelet statistics, k^{th}-nearest neighbor, minimum spanning tree…*

challenges: observations are *messy*



SDSS-III: BOSS CMASS Southern Galactic Cap

challenges: observations are *messy* — *e.g.* fiber collisions strongly affect small scale clustering



no correction scheme currently available for higher-order statistics

current challenges for clustering using higher-order statistics on non-linear scales

1. modeling *non-linear* scales

2. modeling clustering statistics *beyond* P_ℓ

3. observational *systematics*

current challenges can be addressed with a **simulation-based approach**

1. modeling *non-linear* scales

N-body simulations can accurately model small scales

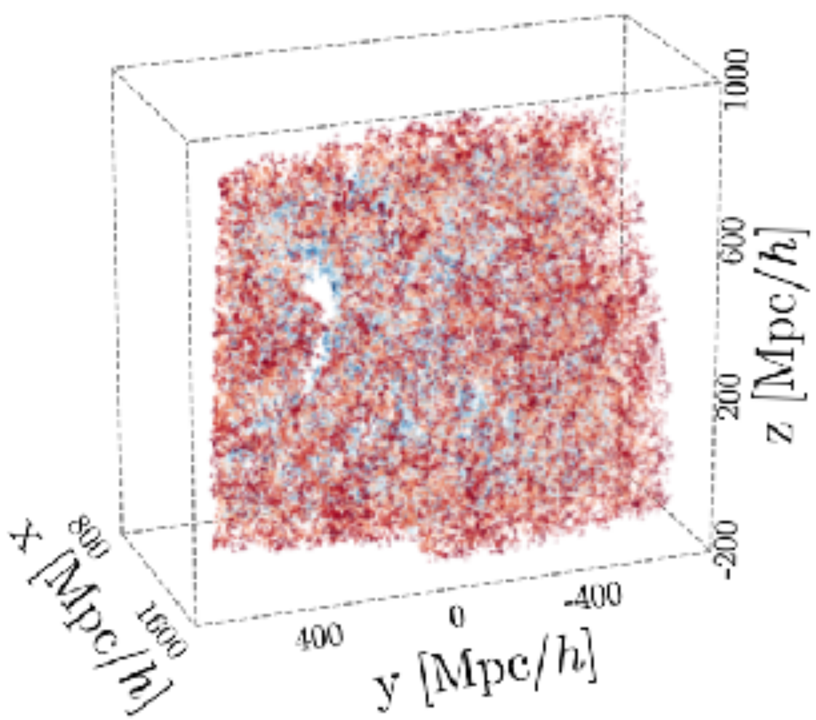
2. modeling clustering statistics *beyond* P_ℓ

we can use any statistic that can be measured in observations

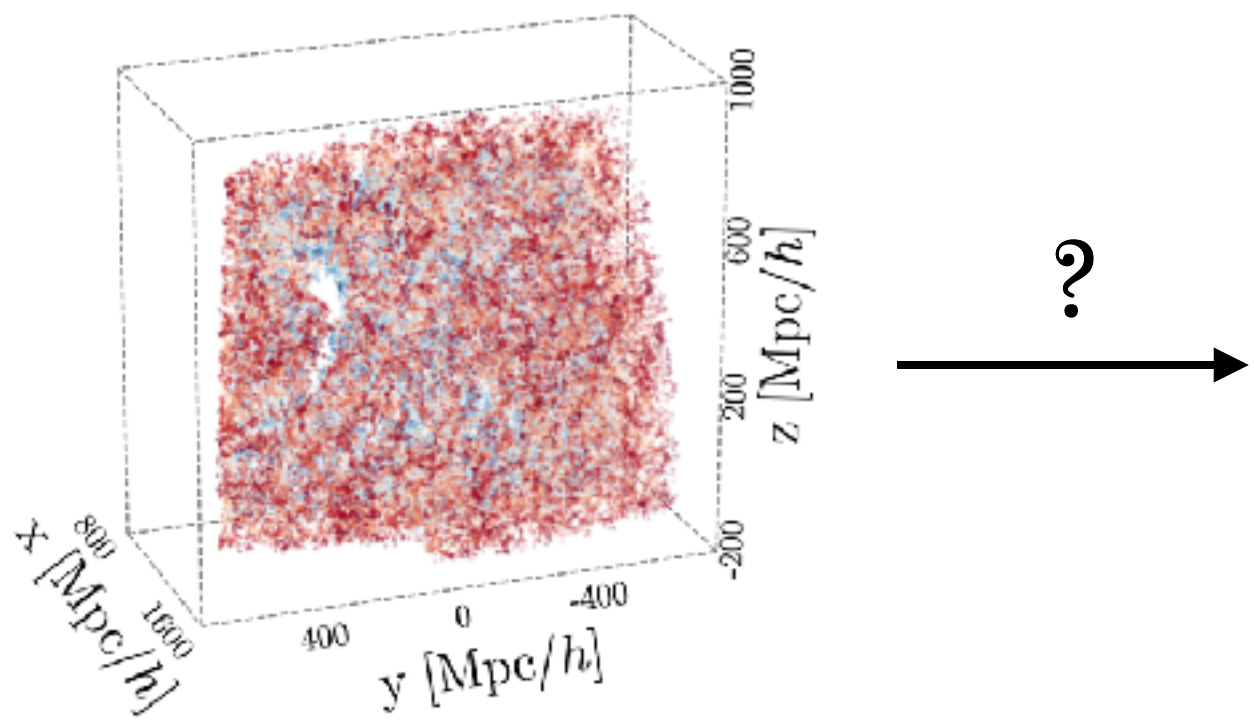
3. observational *systematics*

we already have forward models of geometry, fiber collisions, etc

image: Quijote

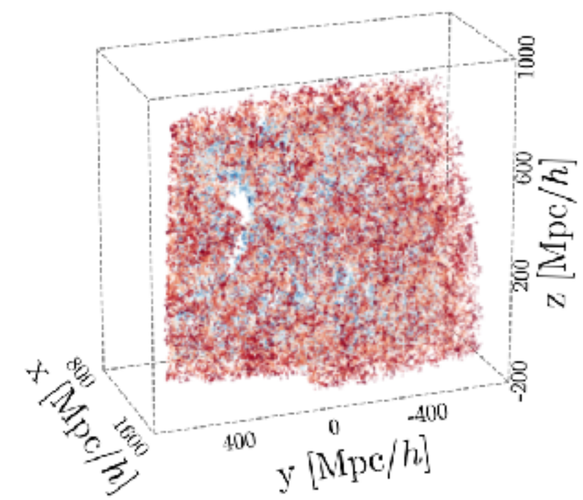


1000
600
200
-200
z [Mpc/h]
400
0
-400
y [Mpc/h]
800
1600
x [Mpc/h]



$$\theta = \left\{ \begin{matrix} \Omega_m, \Omega_b, h \\ n_s, \sigma_8 \end{matrix} \right\}$$

$$p\left(\begin{matrix} \Omega_m, \Omega_b, h \\ n_s, \sigma_8 \end{matrix} \;\middle|\; \right.$$

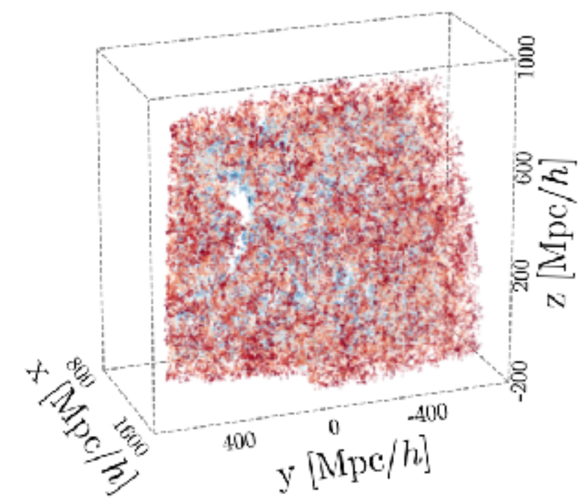


$$\left. \right)$$

ΛCDM *parameters*

galaxy distribution

$$p\left(\begin{matrix} \Omega_m, \Omega_b, h \\ n_s, \sigma_8 \end{matrix} \;\middle|\; \right.$$



$$)$$

using **simulation-based inference**

what is **simulation-based inference**?

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some stochastic forward model/simulator

$$\mathbf{X}' \sim F(\theta')$$

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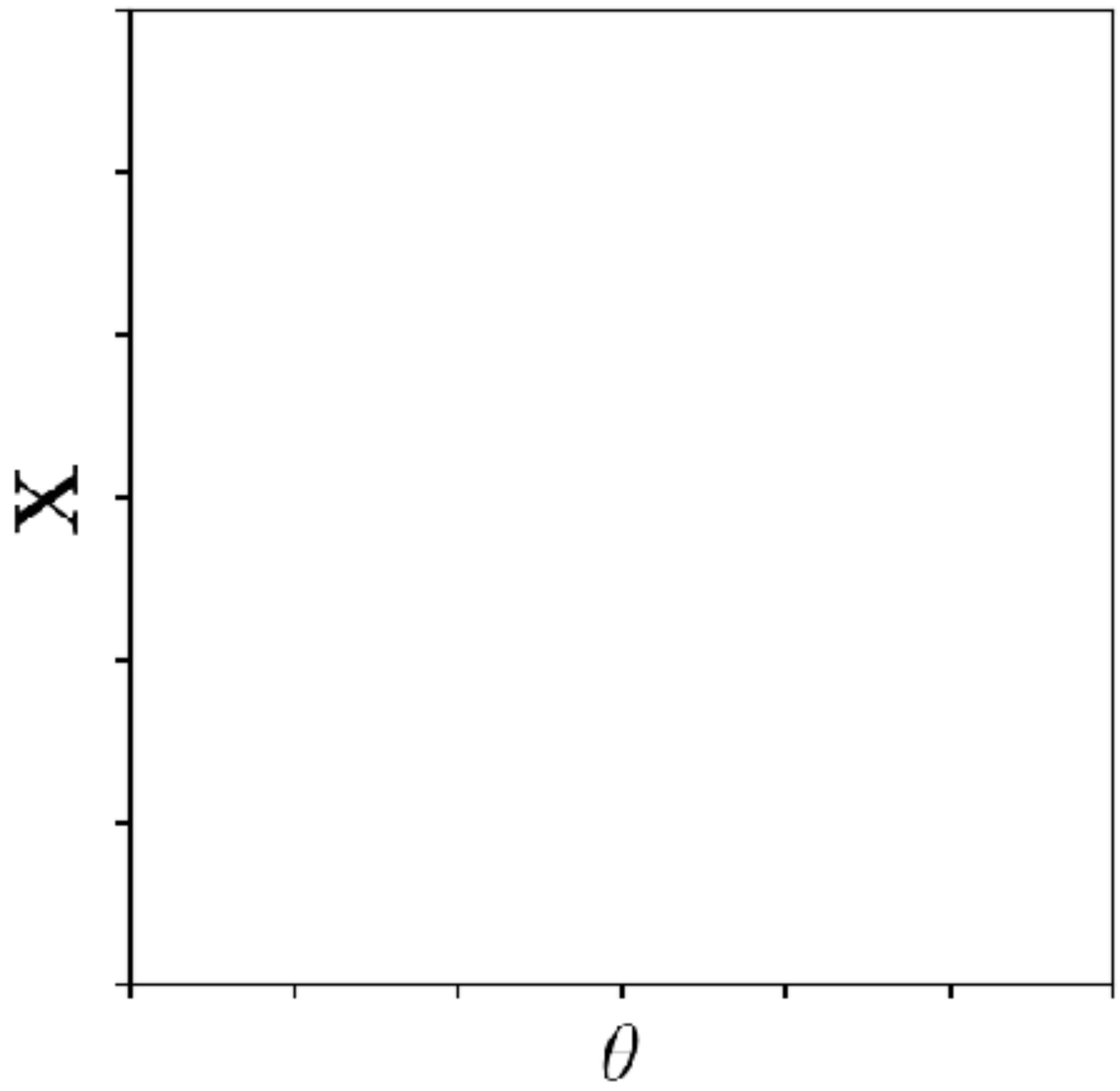

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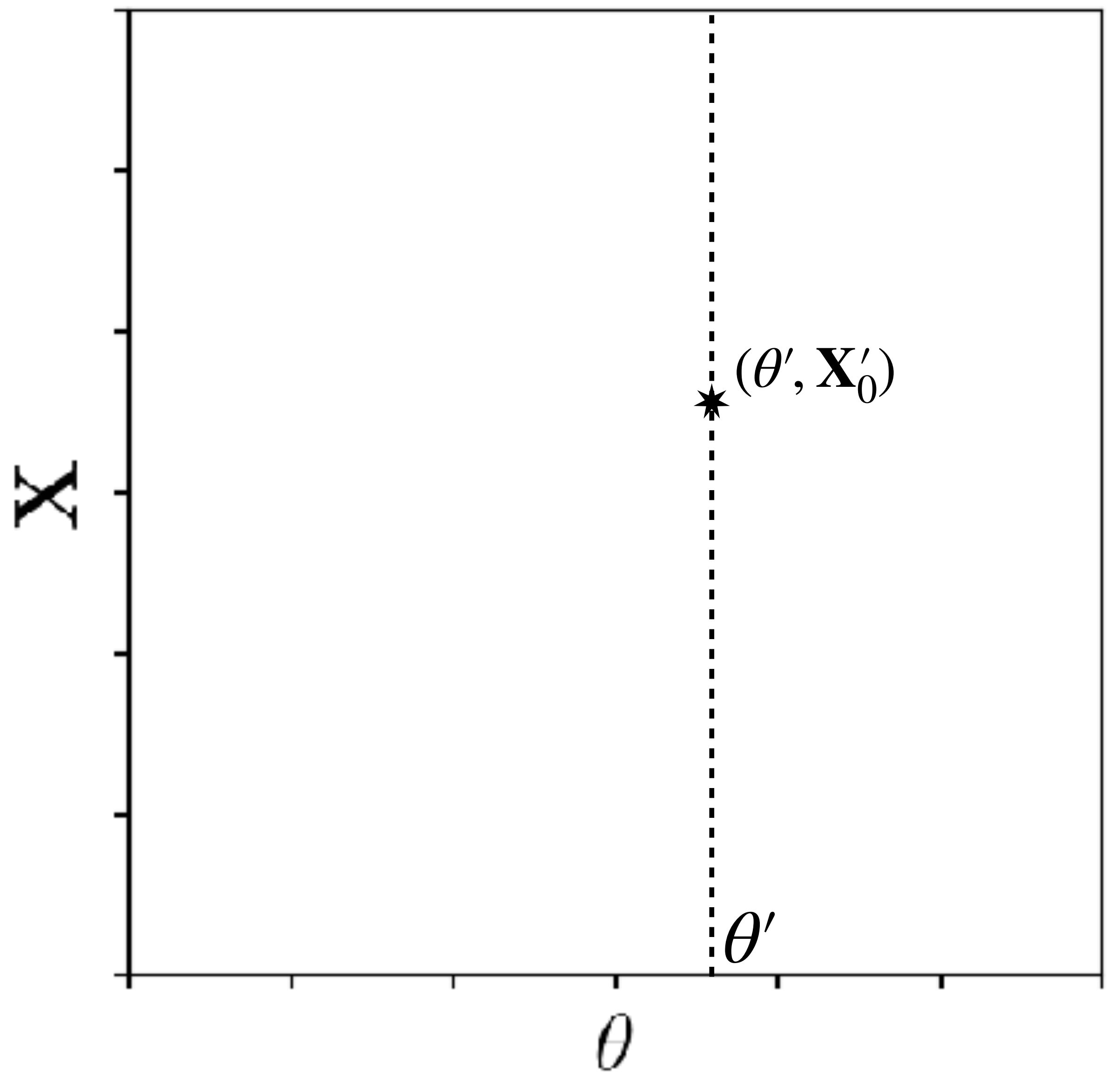

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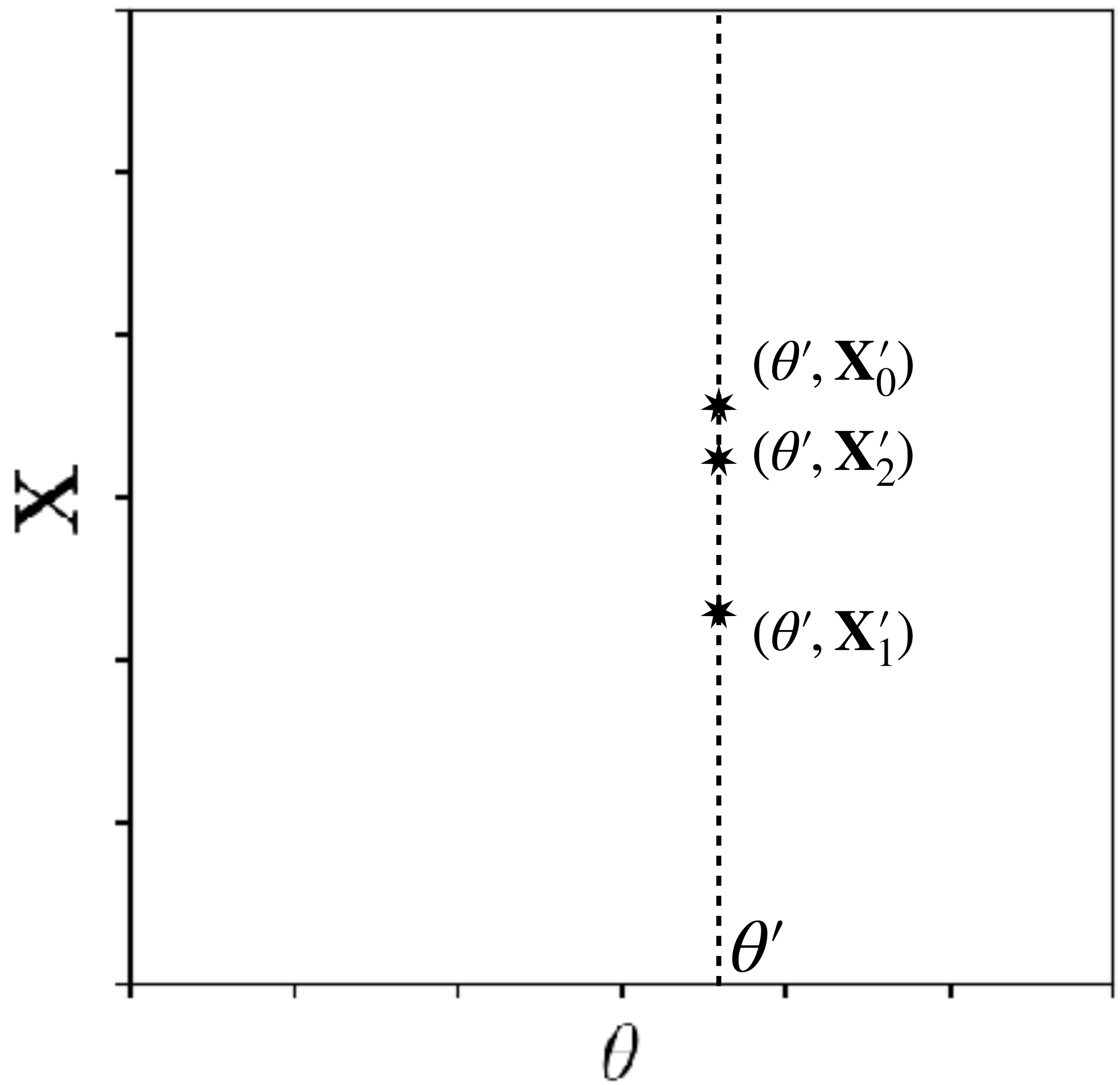

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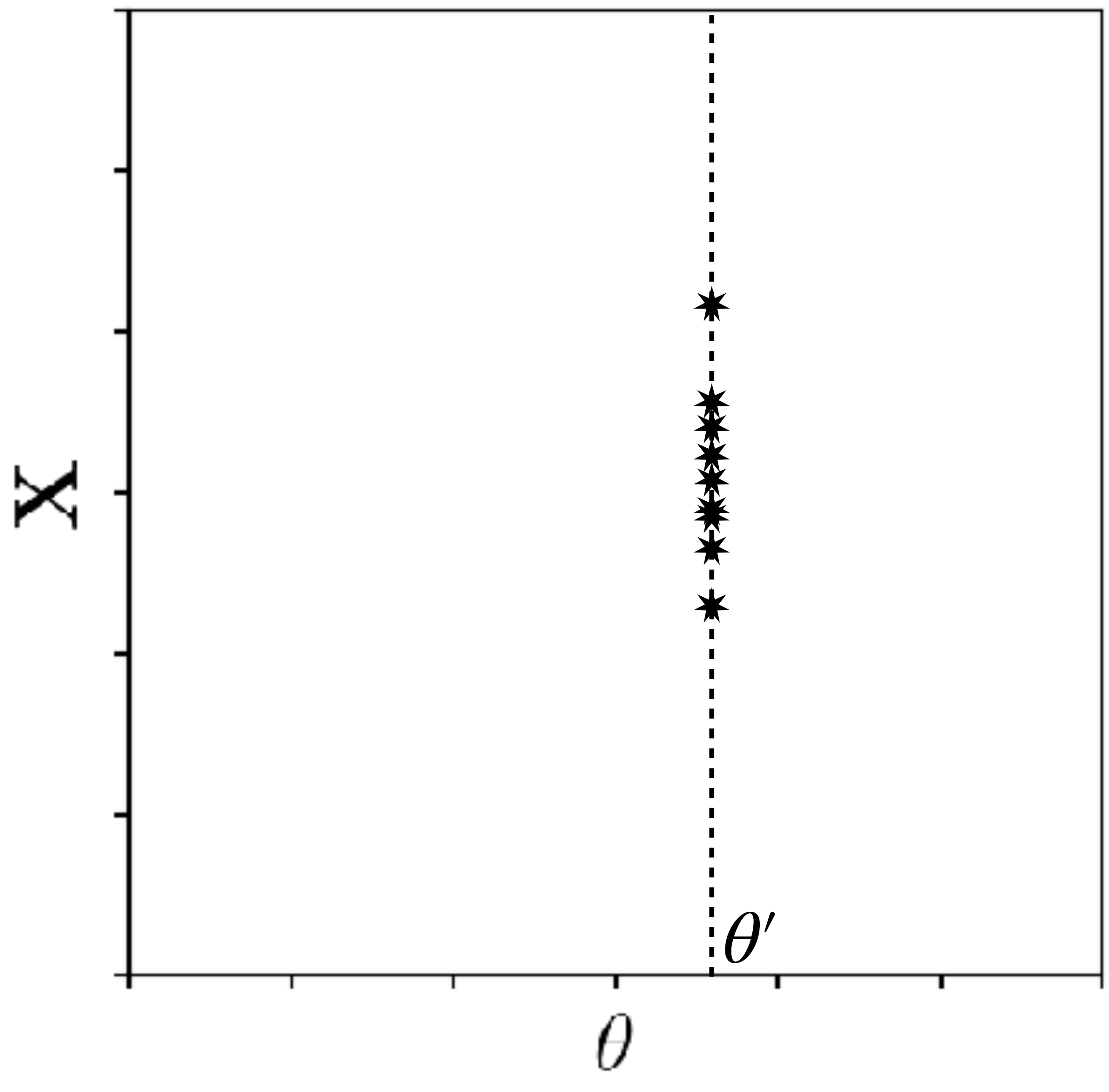
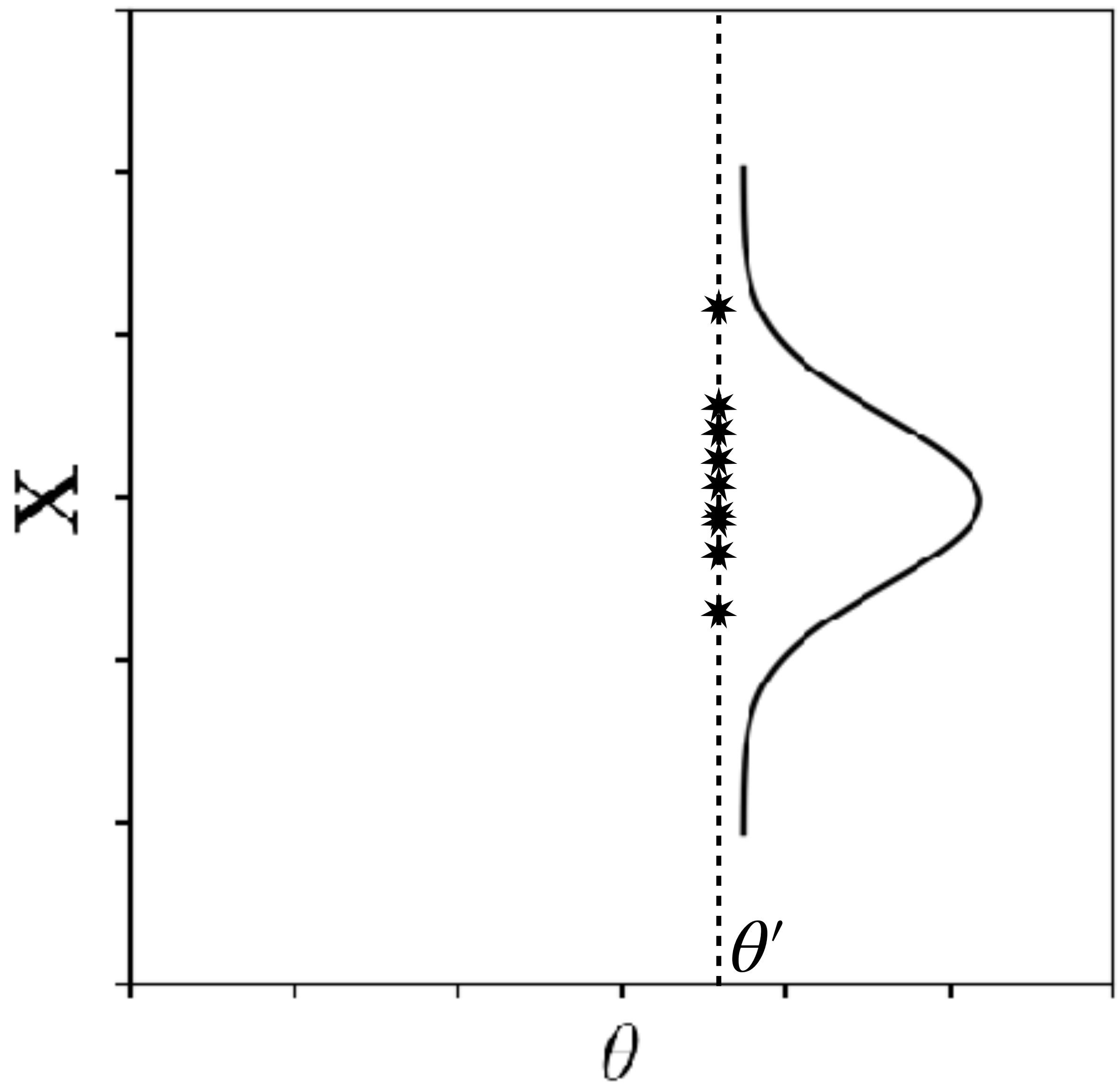


what is **simulation-based inference**?

the forward model/simulator implicitly defines our likelihood

$$\mathbf{X}' \sim F(\theta') \quad \equiv \quad \mathbf{X}' \sim p(\mathbf{X} \,|\, \theta')$$



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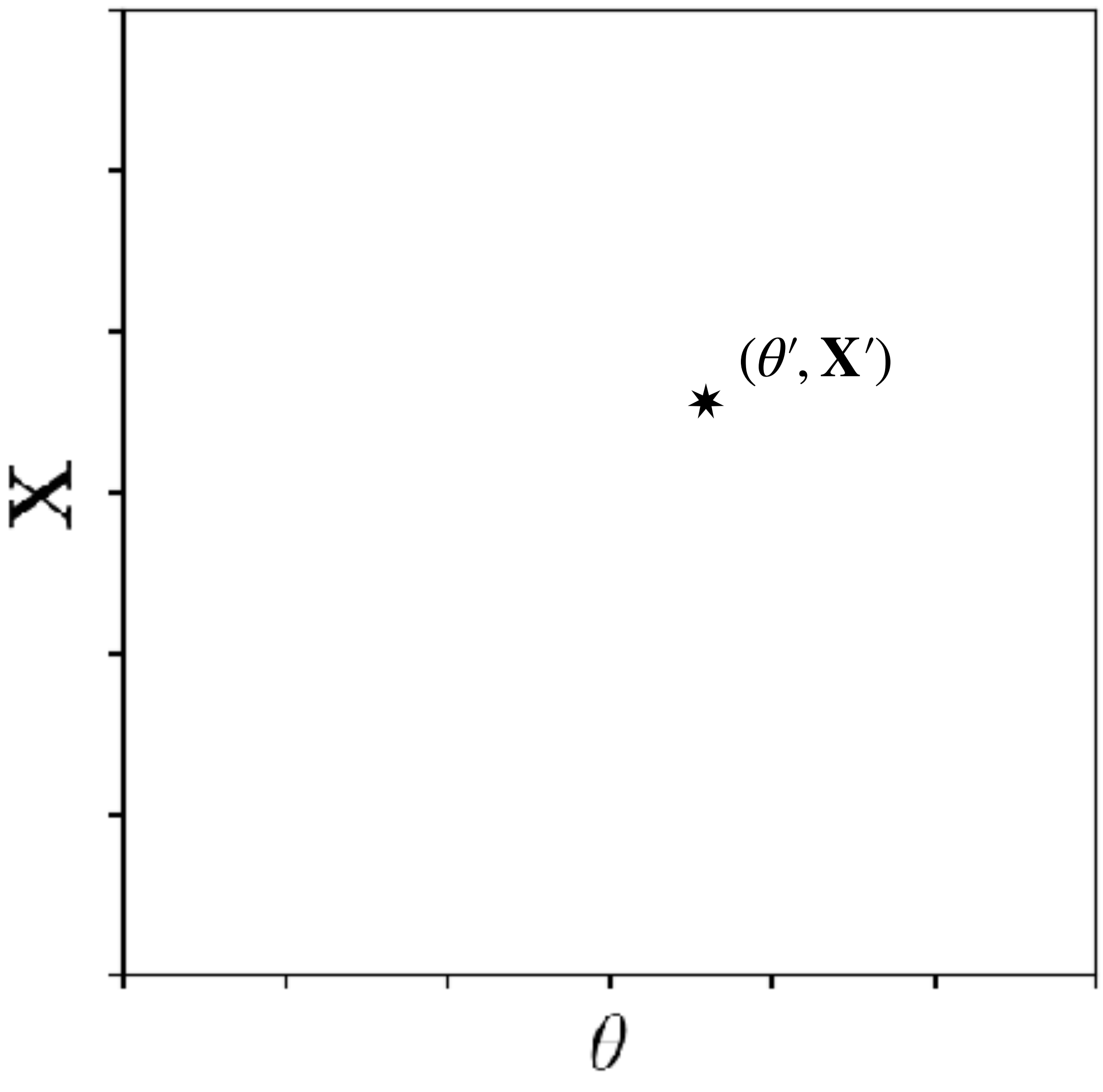
1. sample the prior

$$\theta' \sim p(\theta)$$

2. run simulator

$$\mathbf{X}' \sim F(\theta')$$



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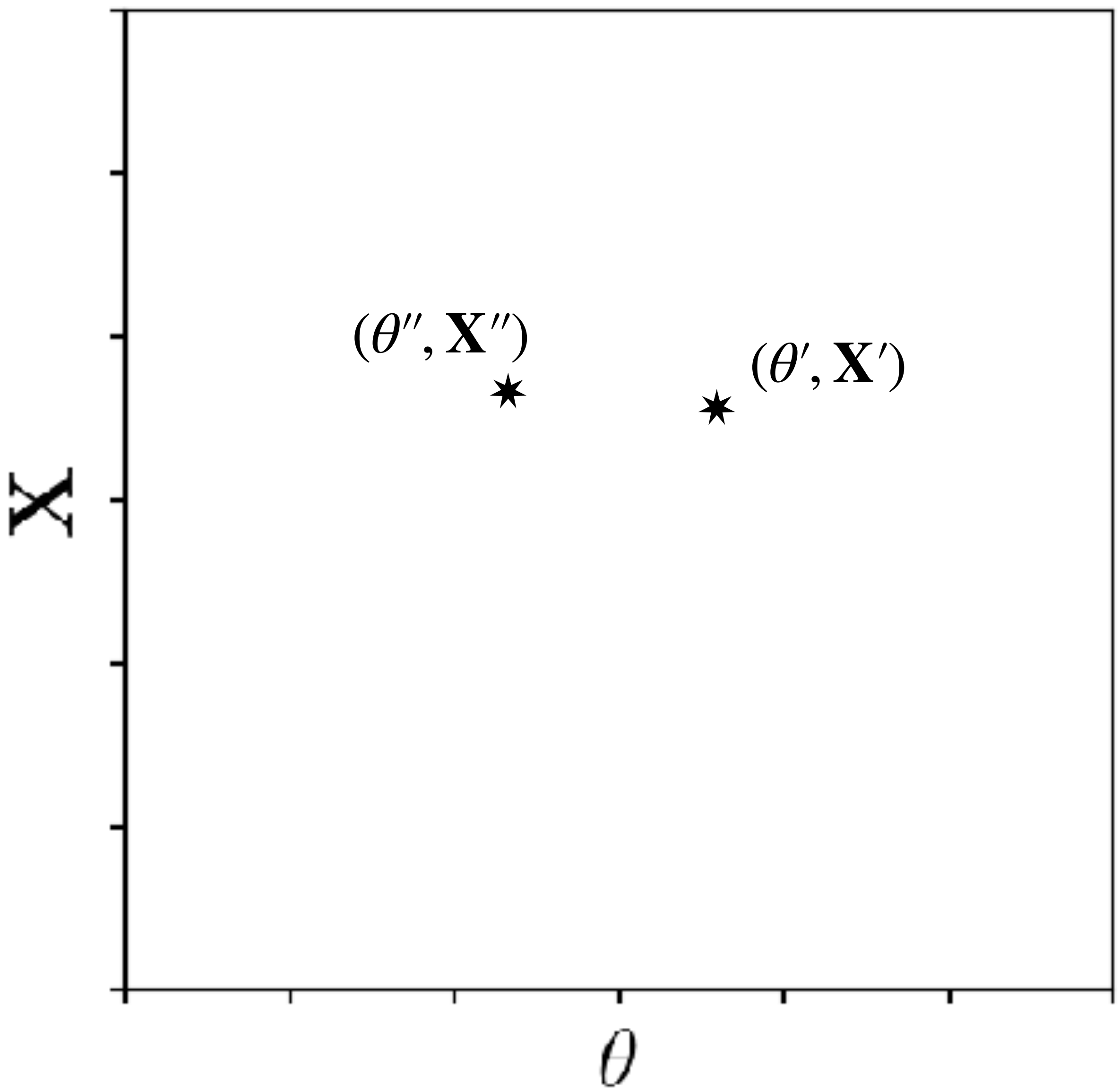

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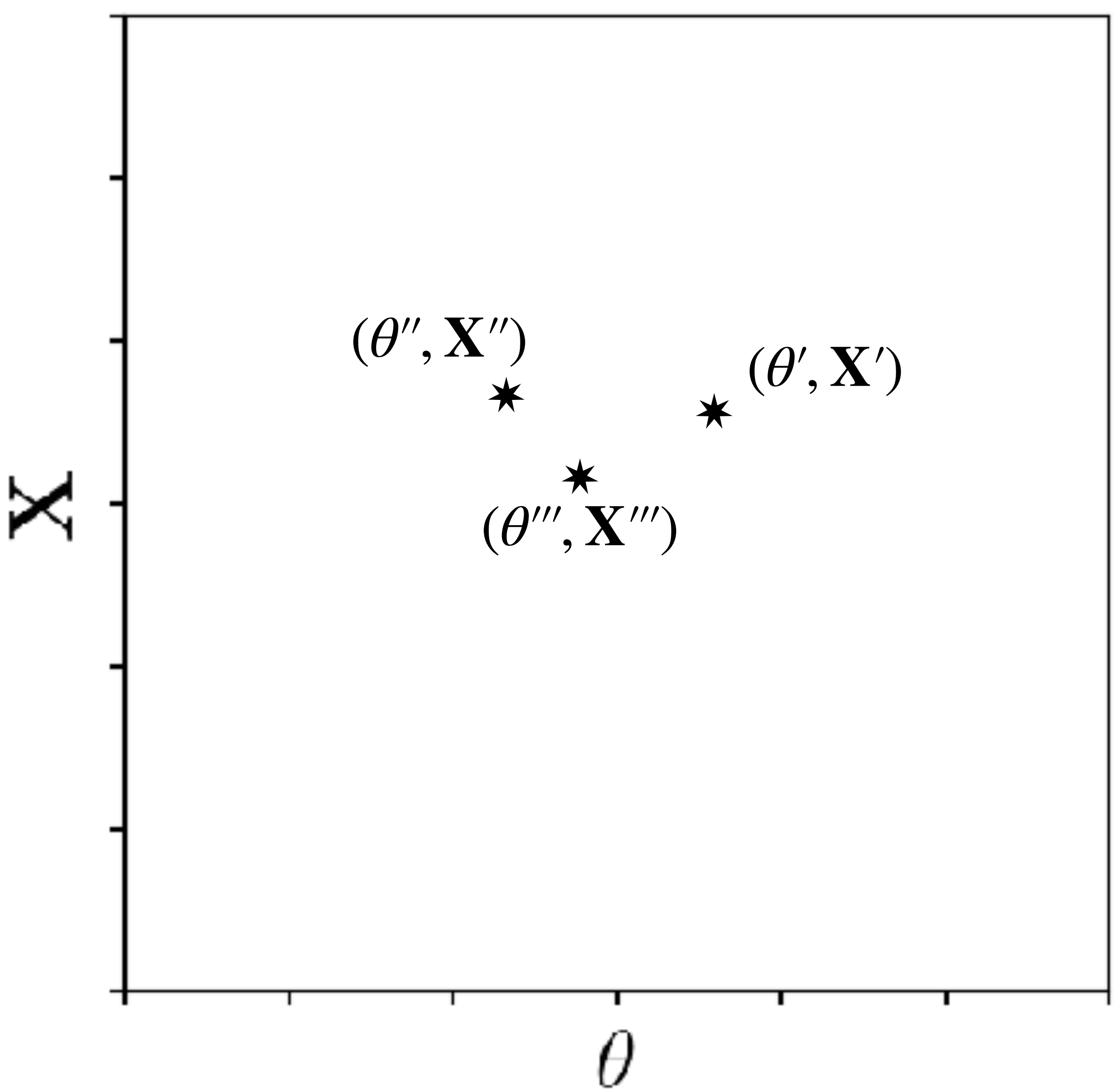


what is **simulation-based inference**?

the forward model/simulator implicitly defines our likelihood

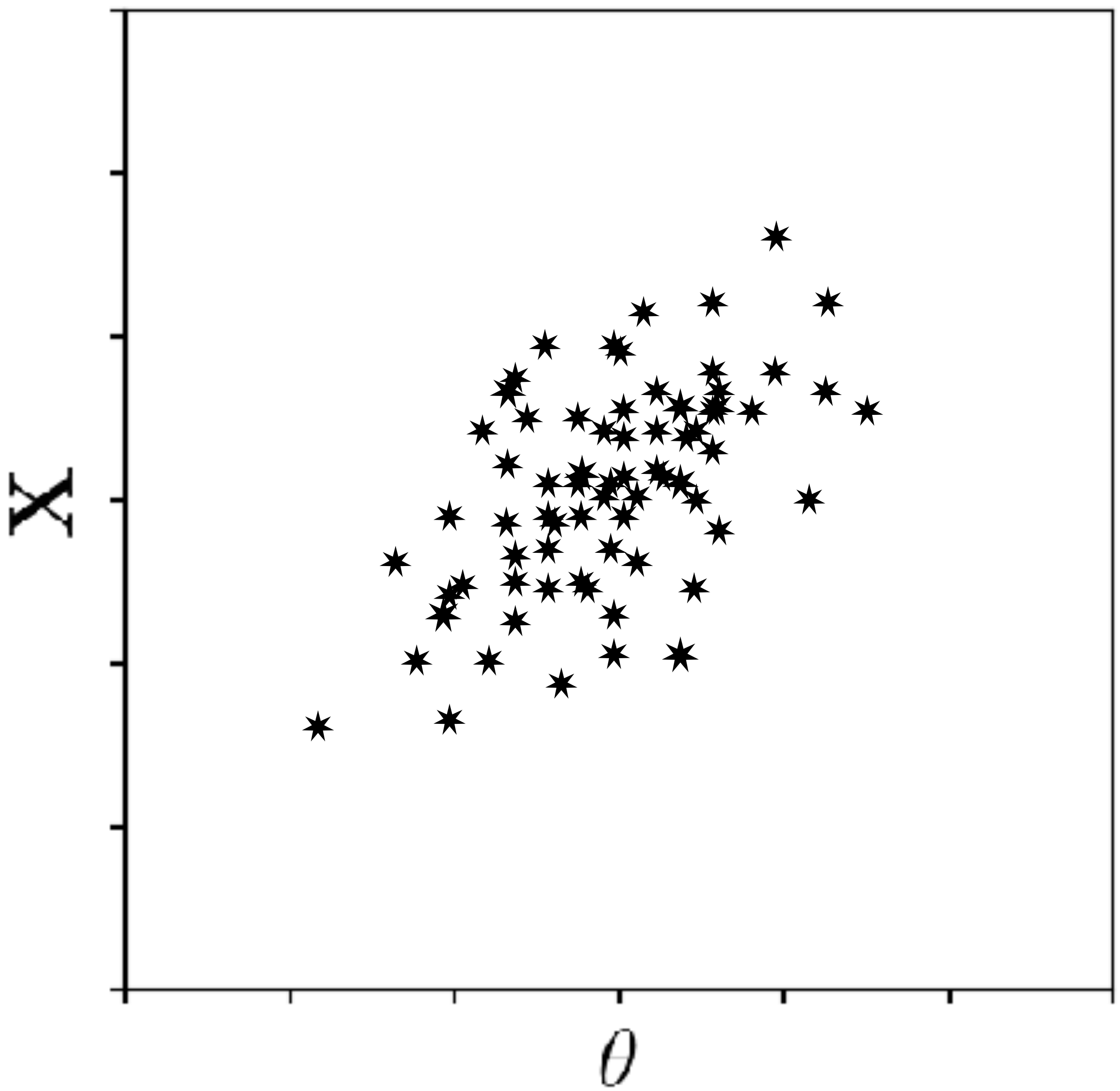
$$\mathbf{X}' \sim F(\theta') \quad \equiv \quad \mathbf{X}' \sim p(\mathbf{X} \mid \theta')$$

1. sample the prior

$$\theta' \sim p(\theta)$$

2. run simulator

$$\mathbf{X}' \sim F(\theta')$$



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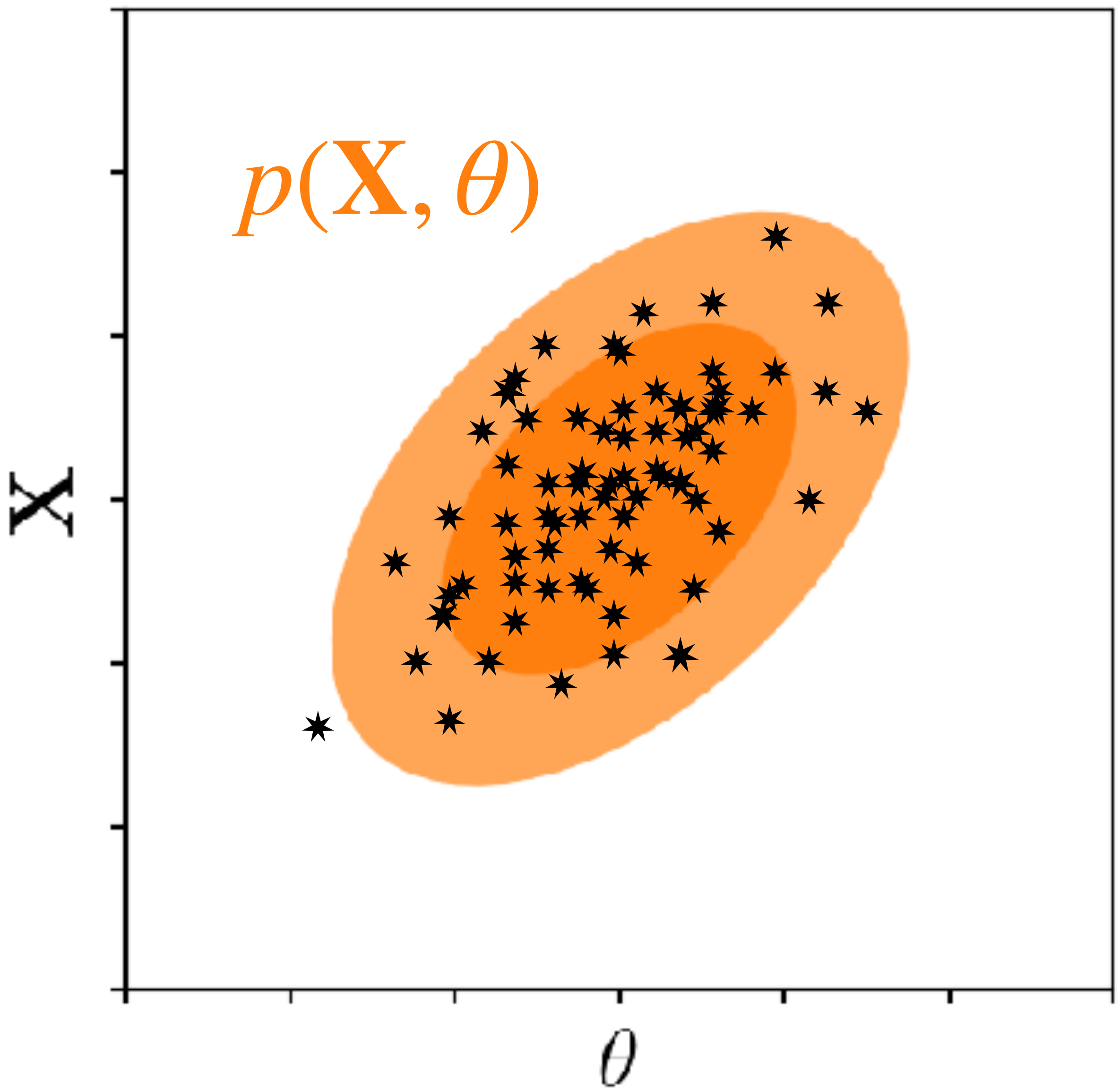

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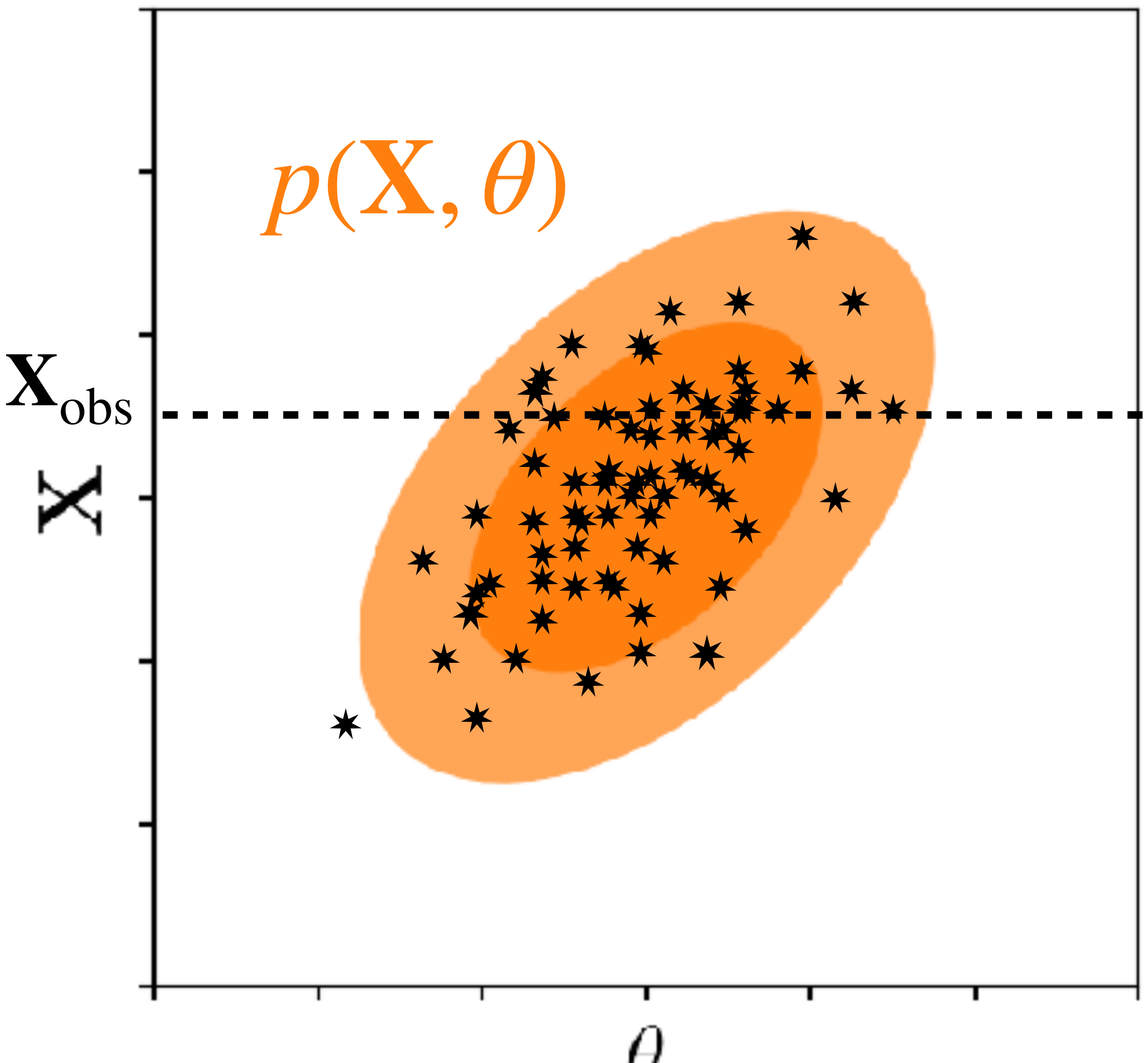

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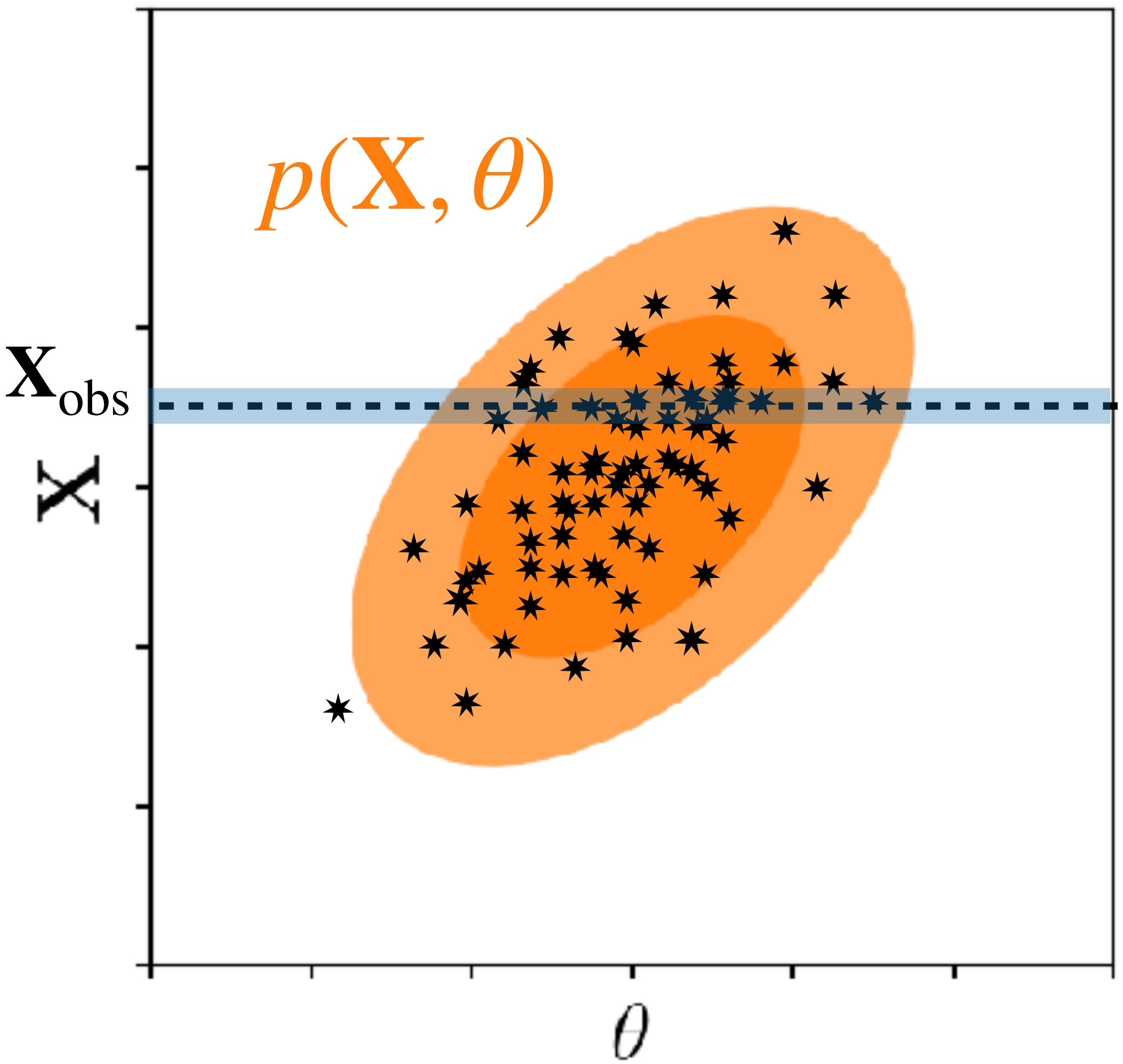
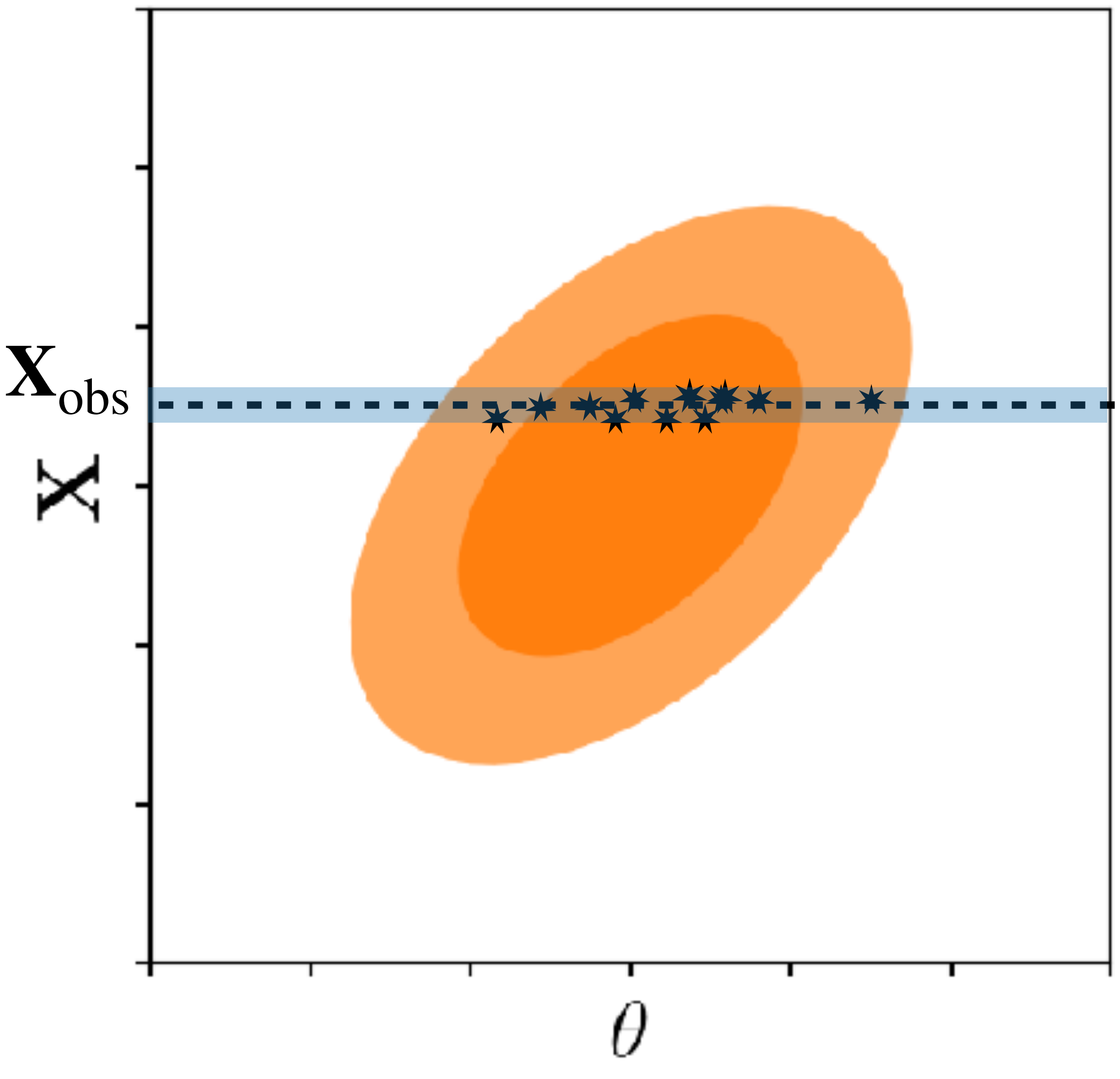
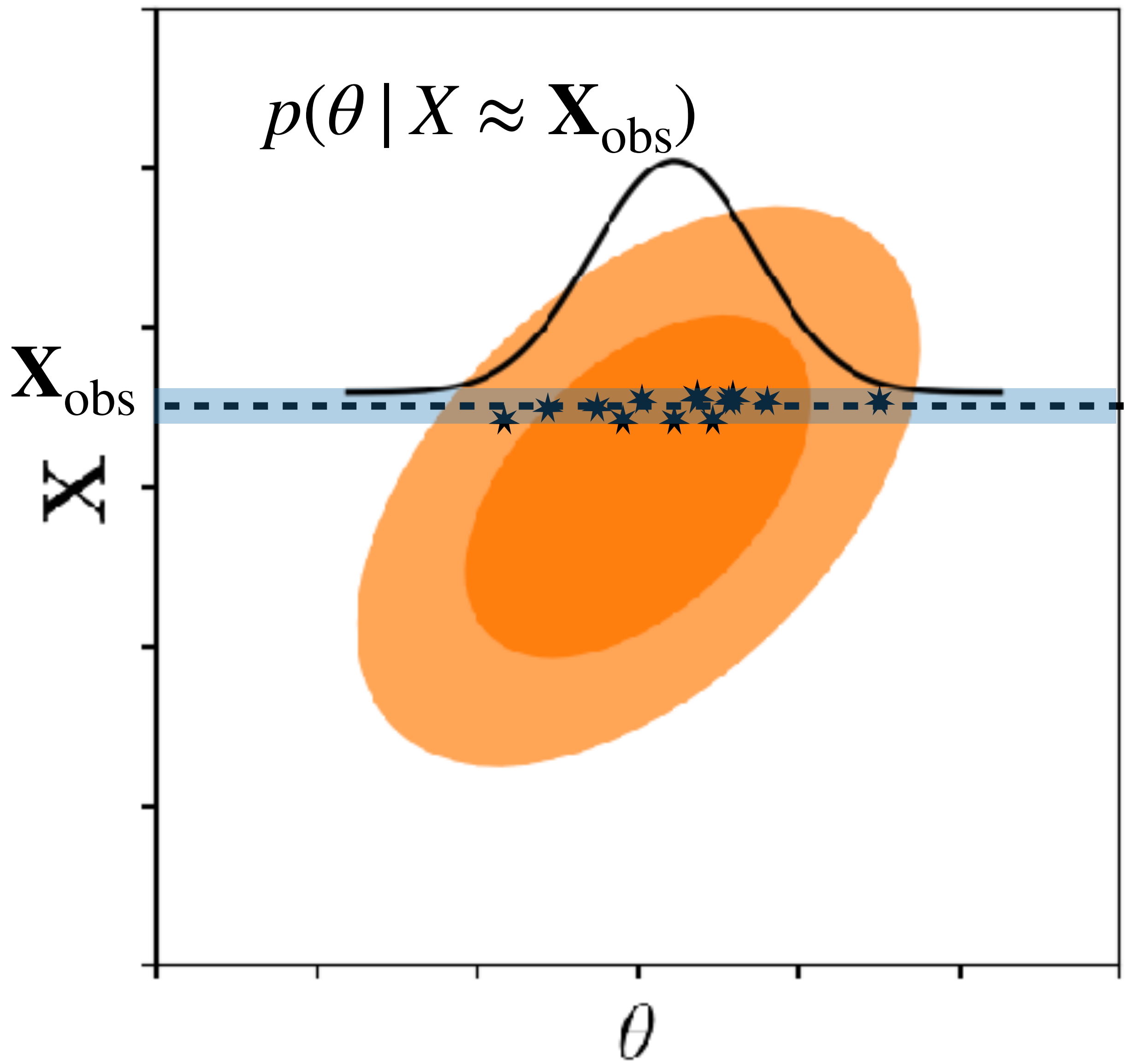


what is **simulation-based inference**?



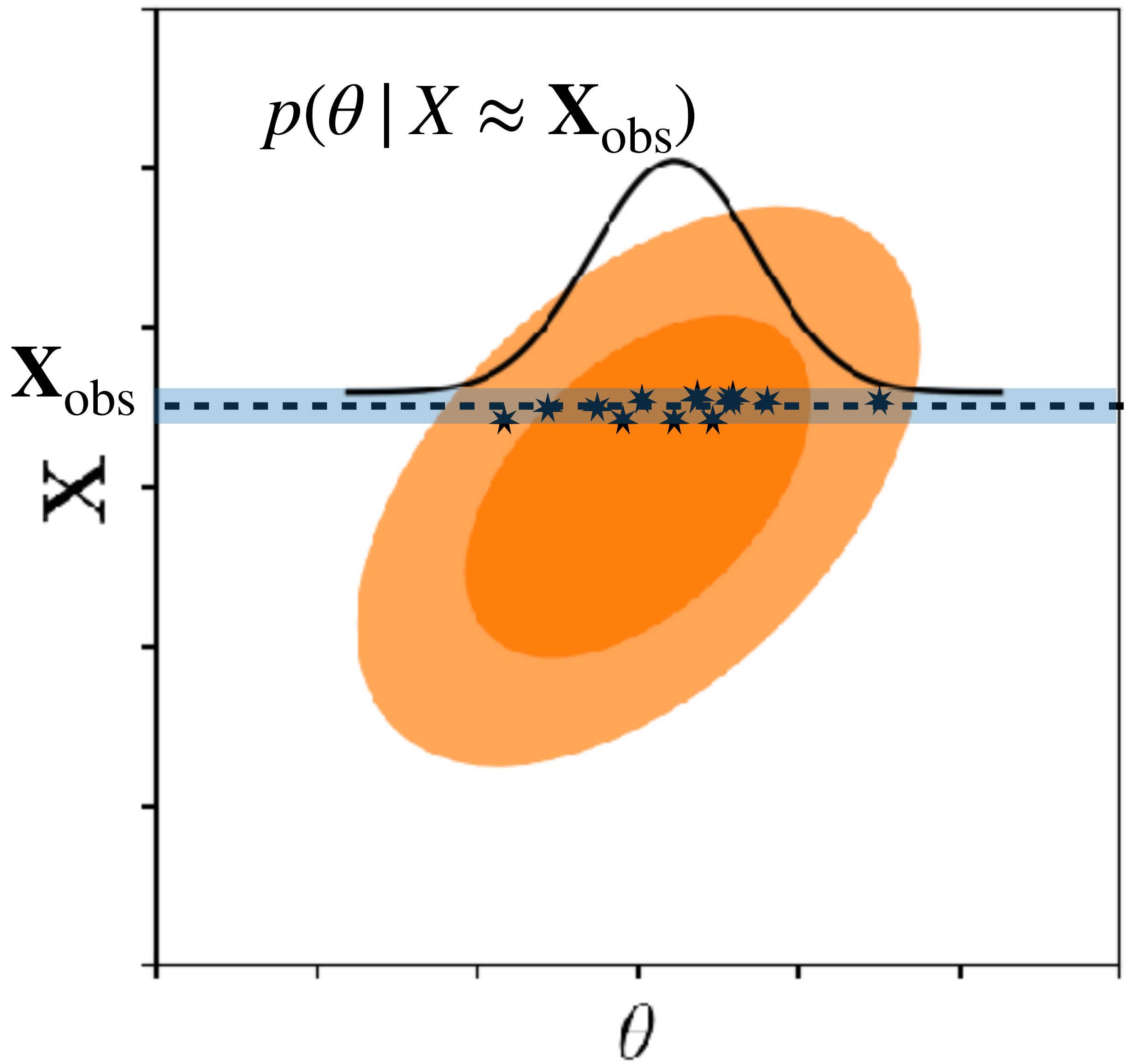
what is **simulation-based inference**?

$$p(\theta \mid \mathbf{X}_{\text{obs}}) \approx p(\theta \mid X \approx \mathbf{X}_{\text{obs}})$$

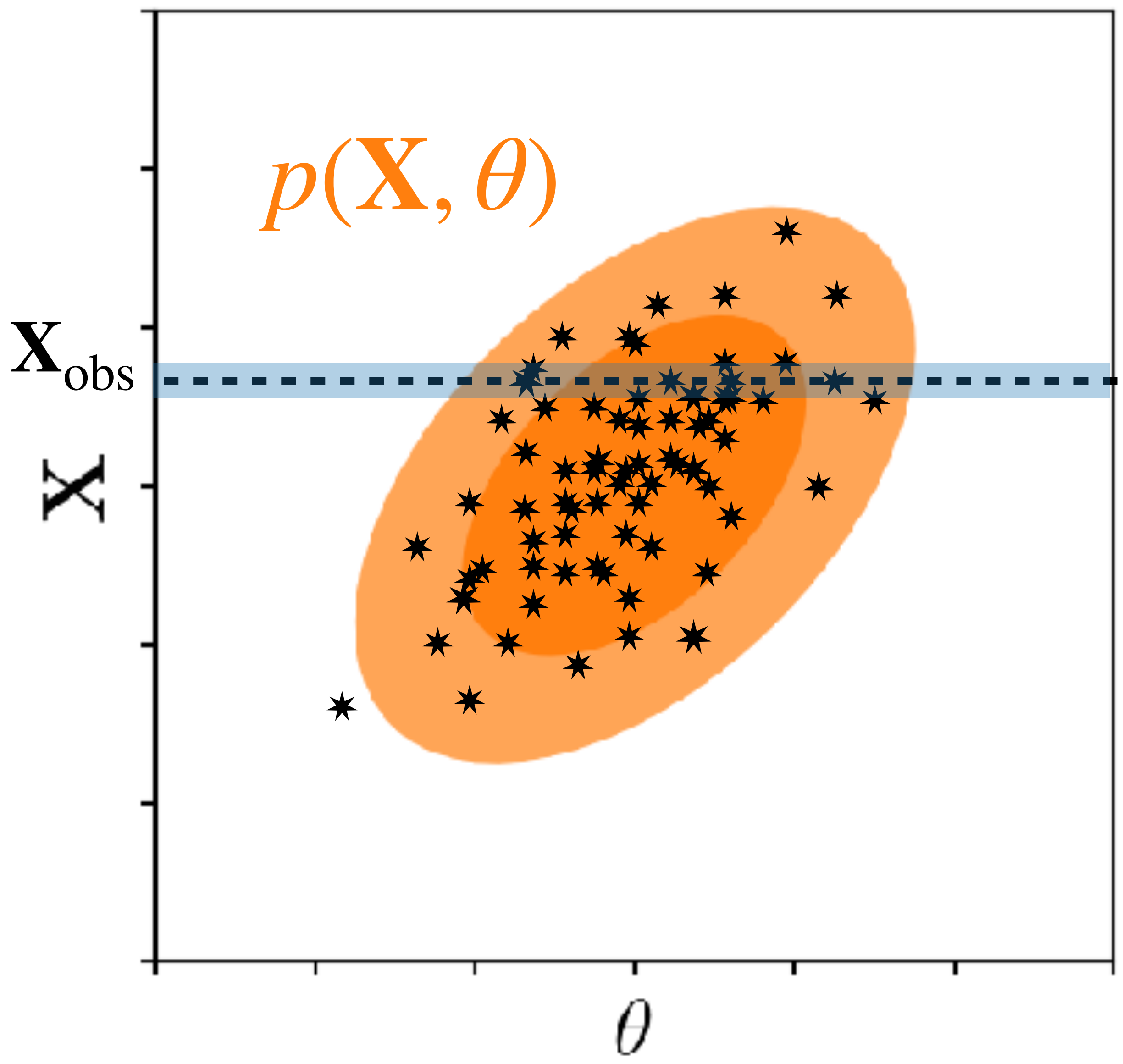


what is **simulation-based inference**?

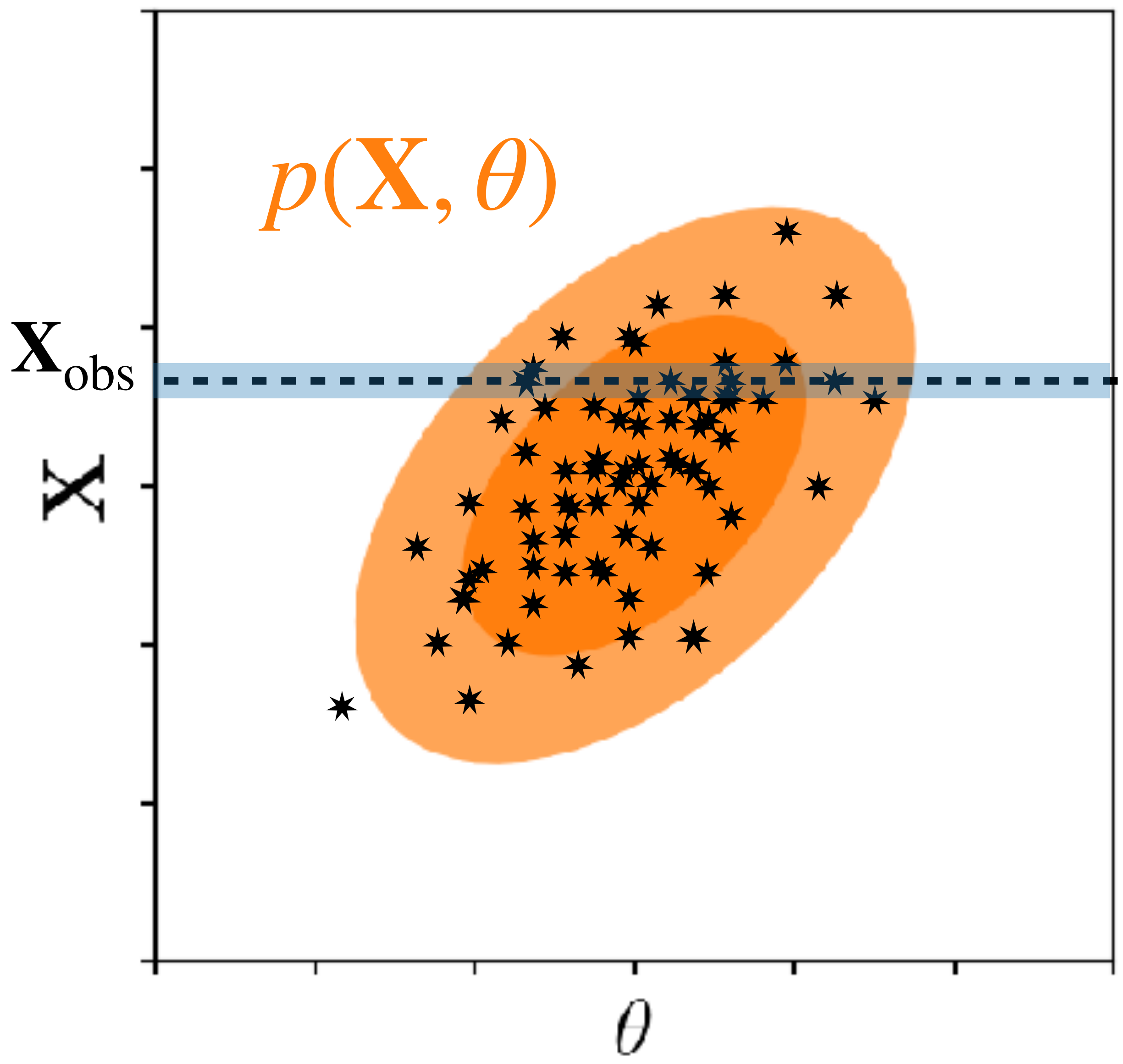
$$p(\theta \,|\, \mathbf{X}_{\text{obs}}) \approx p(\theta \,|\, X \approx \mathbf{X}_{\text{obs}})$$



simulation-based inference *in practice*

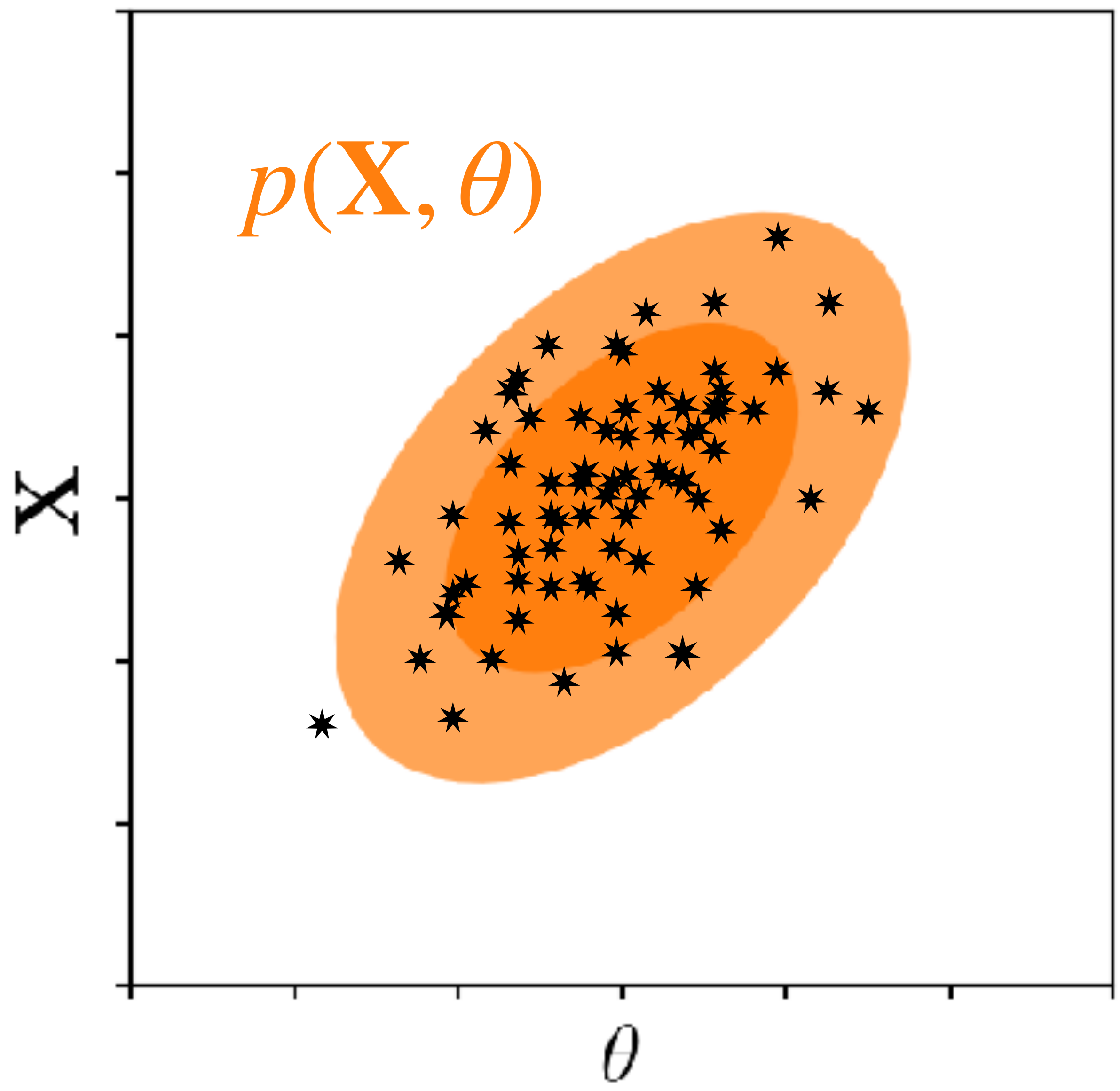


simulation-based inference *in practice*



approximate bayesian computation is often *infeasible*

simulation-based inference *in practice* — density estimation



can we estimate $p(\theta \,|\, \mathbf{X})$ from $\mathbf{X}' \sim F(\theta)$?

$\sim p(\mathbf{X} \,|\, \theta)$

estimate $p(\theta \mid \mathbf{X}) \approx q_\phi(\theta \mid \mathbf{X})$ from $\{(\theta', \mathbf{X}')\} \sim p(\mathbf{X}, \theta)$?

estimate $p(\theta \mid \mathbf{X}) \approx q_\phi(\theta \mid \mathbf{X})$ from $\{(\theta', \mathbf{X}')\} \sim p(\mathbf{X}, \theta)$?

some model q with free parameters ϕ

**Gaussian Mixture Models,*
Independent Component Analysis, neural density estimators…

$$\text{estimate } p(\theta \mid \mathbf{X}) \approx q_\phi(\theta \mid \mathbf{X}) \qquad \text{from } \{(\theta', \mathbf{X}')\} \sim p(\mathbf{X}, \theta) \text{ ?}$$

we can determine ϕ by

$$\min_\phi \; D_{\mathrm{KL}}(\, p(\theta \mid \mathbf{X})\, p(\mathbf{X}) \;\|\; q_\phi(\theta \mid \mathbf{X})\, p(\mathbf{X})\,)$$

Kullback-Leibler divergence (a.k.a. relative entropy) estimate $p(\theta \,|\, \mathbf{X}) \approx q_\phi(\theta \,|\, \mathbf{X})$ from $\{(\theta', \mathbf{X}')\} \sim p(\mathbf{X}, \theta)$?

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$$\min_\phi \; D_{\mathrm{KL}}(\, p(\theta \,|\, \mathbf{X})\, p(\mathbf{X}) \;\|\; q_\phi(\theta \,|\, \mathbf{X})\, p(\mathbf{X})\,)$$

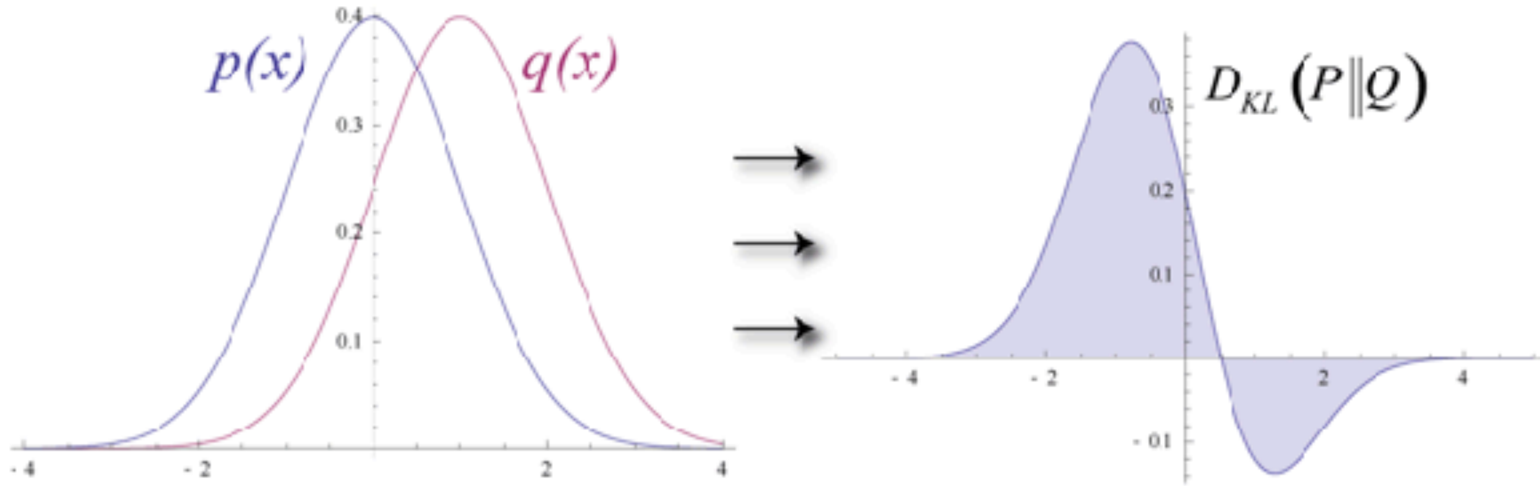

image: wikipedia

estimate $p(\theta \,|\, \mathbf{X}) \approx q_\phi(\theta \,|\, \mathbf{X})$ from $\{(\theta', \mathbf{X}')\} \sim p(\mathbf{X}, \theta)$?

we can determine ϕ by

$$\min_\phi \; D_{\mathrm{KL}}(\, p(\theta \,|\, \mathbf{X})\, p(\mathbf{X}) \;\|\; q_\phi(\theta \,|\, \mathbf{X})\, p(\mathbf{X})\,)$$

$$= \min_\phi \; \int p(\theta \,|\, \mathbf{X})\, p(\mathbf{X}) \;\log \frac{p(\theta \,|\, \mathbf{X})\, p(\mathbf{X})}{q_\phi(\theta \,|\, \mathbf{X})\, p(\mathbf{X})}$$

Kullback-Leibler divergence (a.k.a. relative entropy)

estimate $p(\theta \mid \mathbf{X}) \approx q_\phi(\theta \mid \mathbf{X})$ from $\{(\theta', \mathbf{X}')\} \sim p(\mathbf{X}, \theta)$?

we can determine ϕ *by*

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$$= \min_\phi \int \underbrace{p(\theta \mid \mathbf{X})\, p(\mathbf{X})}^{p(\mathbf{X}, \theta)} \log \frac{p(\theta \mid \mathbf{X})\, p(\mathbf{X})}{q_\phi(\theta \mid \mathbf{X})\, p(\mathbf{X})}$$

$$\text{estimate } p(\theta \,|\, \mathbf{X}) \approx q_\phi(\theta \,|\, \mathbf{X}) \qquad \text{from } \{(\theta', \mathbf{X}')\} \sim p(\mathbf{X}, \theta) \text{ ?}$$

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$$\approx \min_\phi \sum_{(\mathbf{X}', \theta') \sim p(\mathbf{X}, \theta)} \log \frac{p(\theta' \,|\, \mathbf{X}')}{q_\phi(\theta' \,|\, \mathbf{X}')}$$

estimate $p(\theta \mid \mathbf{X}) \approx q_\phi(\theta \mid \mathbf{X})$ from $\{(\theta', \mathbf{X}')\} \sim p(\mathbf{X}, \theta)$?

we can determine ϕ by

$$\min_\phi \; D_{\mathrm{KL}}(\, p(\theta \mid \mathbf{X})\, p(\mathbf{X}) \;\|\; q_\phi(\theta \mid \mathbf{X})\, p(\mathbf{X})\,)$$

$$= \min_\phi \int p(\theta \mid \mathbf{X})\, p(\mathbf{X}) \; \log \frac{p(\theta \mid \mathbf{X})\, p(\mathbf{X})}{q_\phi(\theta \mid \mathbf{X})\, p(\mathbf{X})}$$

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estimate $p(\theta \mid \mathbf{X}) \approx q_\phi(\theta \mid \mathbf{X})$ from $\{(\theta', \mathbf{X}')\} \sim p(\mathbf{X}, \theta)$?

we can determine ϕ *by*

$$\min_\phi \; D_{\mathrm{KL}}(\, p(\theta \mid \mathbf{X})\, p(\mathbf{X}) \;\|\; q_\phi(\theta \mid \mathbf{X})\, p(\mathbf{X})\,)$$

$$= \min_\phi \int p(\theta \mid \mathbf{X})\, p(\mathbf{X}) \; \log \frac{p(\theta \mid \mathbf{X})\, p(\mathbf{X})}{q_\phi(\theta \mid \mathbf{X})\, p(\mathbf{X})}$$

$$\approx \min_\phi \sum_{(\mathbf{X}',\theta') \sim p(\mathbf{X},\theta)} \log \frac{p(\theta' \mid \mathbf{X}')}{q_\phi(\theta' \mid \mathbf{X}')}$$

$$= \min_\phi \sum_{(\mathbf{X}',\theta') \sim p(\mathbf{X},\theta)} - \log \; q_\phi(\theta' \mid \mathbf{X}')$$

$$\text{estimate } p(\theta \mid \mathbf{X}) \approx q_\phi(\theta \mid \mathbf{X}) \qquad \text{from } \{(\theta', \mathbf{X}')\} \sim p(\mathbf{X}, \theta) \text{ ?}$$

we can determine ϕ *by*

$$\min_\phi \; D_{\mathrm{KL}}(\, p(\theta \mid \mathbf{X})\, p(\mathbf{X}) \;\|\; q_\phi(\theta \mid \mathbf{X})\, p(\mathbf{X})\,)$$

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$$= \max_\phi \; \sum_{(\mathbf{X}', \theta') \sim p(\mathbf{X}, \theta)} \log \; q_\phi(\theta' \mid \mathbf{X}')$$

estimate $p(\theta \mid \mathbf{X}) \approx q_\phi(\theta \mid \mathbf{X})$ from $\{(\theta', \mathbf{X}')\} \sim p(\mathbf{X}, \theta)$?

we can determine ϕ by

$q_\phi(\theta \mid \mathbf{X})$ is guaranteed to converge to $p(\theta \mid \mathbf{X})$ if

q_ϕ is flexibly expressive

$N \to \infty$ samples from $p(\mathbf{X}, \theta)$

successful optimization

$$= \max_\phi \sum_{(\mathbf{X}', \theta') \sim p(\mathbf{X}, \theta)} \log q_\phi(\theta' \mid \mathbf{X}')$$

normalizing flows: generative models that are easy to evaluate and flexibly expressive

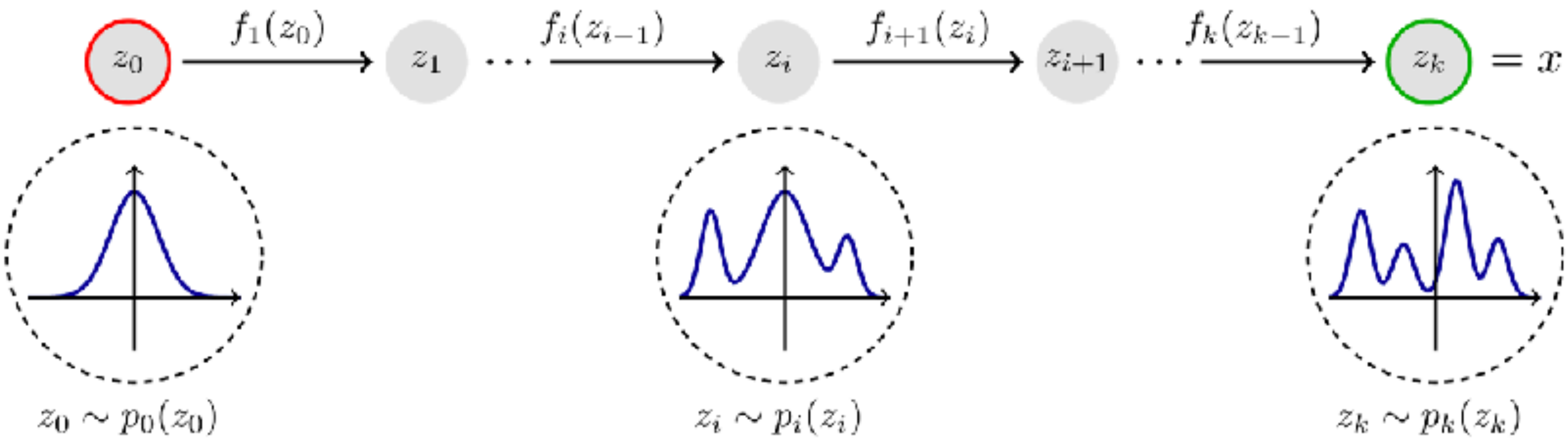
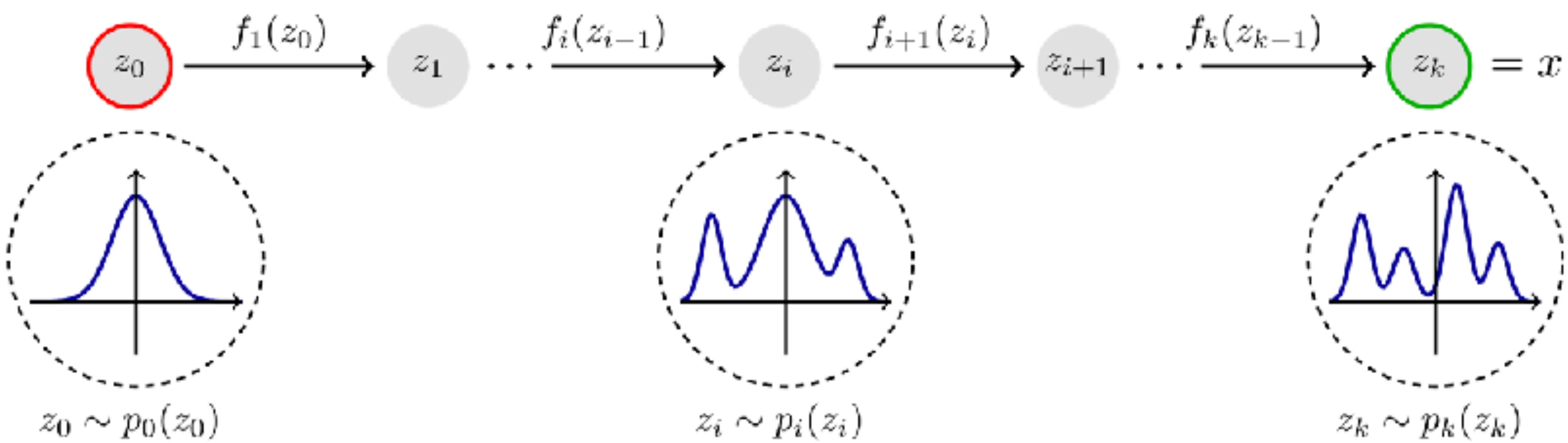


image: Janosh Riebesell

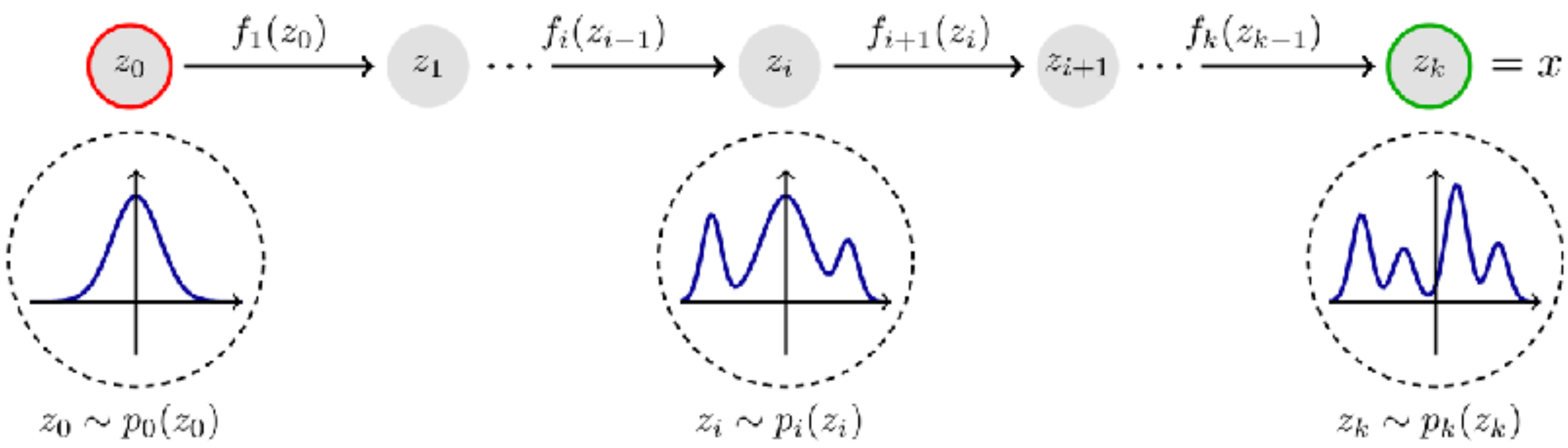
normalizing flows: generative models that are easy to evaluate and flexibly expressive



$z_i = f_i(z_{i-1})$ are invertible and differentiable transformations

$$p(z_i) = p(z_{i-1}) \left| \det \left(\frac{\partial f_i^{-1}}{\partial z_i} \right) \right|$$

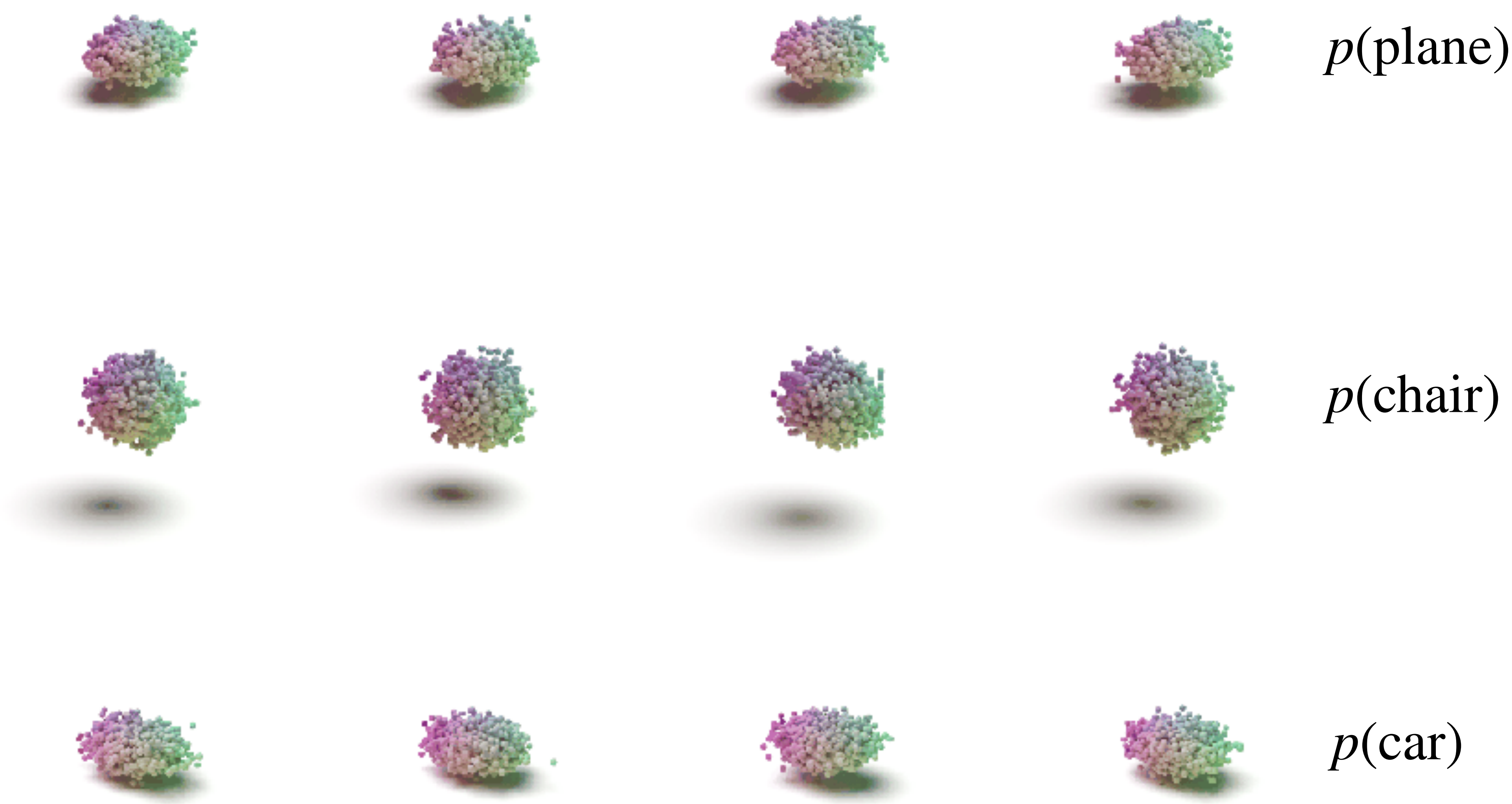
normalizing flows: generative models that are easy to evaluate and flexibly expressive



$z_i = f_i(z_{i-1})$ are invertible and differentiable transformations

$f = f_1 \circ f_2 \ldots \circ f_{k-1} \circ f_k$ is also invertible and differentiable

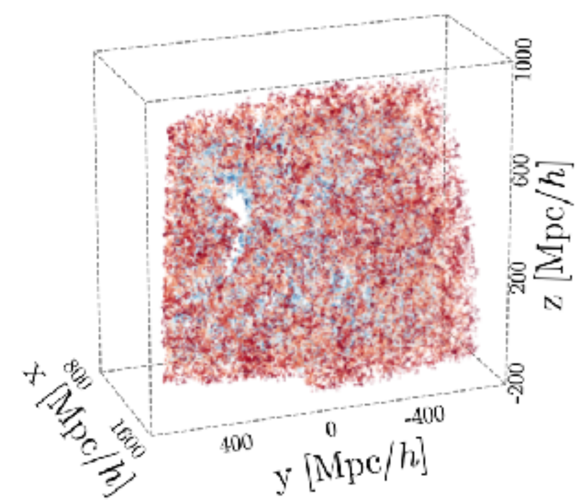
normalizing flows: generative models that are easy to evaluate and flexibly expressive



Yang et al.(2019) PointFlow

normalizing flows: generative models that are easy to evaluate and flexibly expressive

$$p\left(\begin{matrix}\Omega_m, \Omega_b, h \\ n_s, \sigma_8\end{matrix} \;\middle|\; \right.$$



$$\left. \vphantom{\begin{matrix}a\\b\end{matrix}} \right)$$

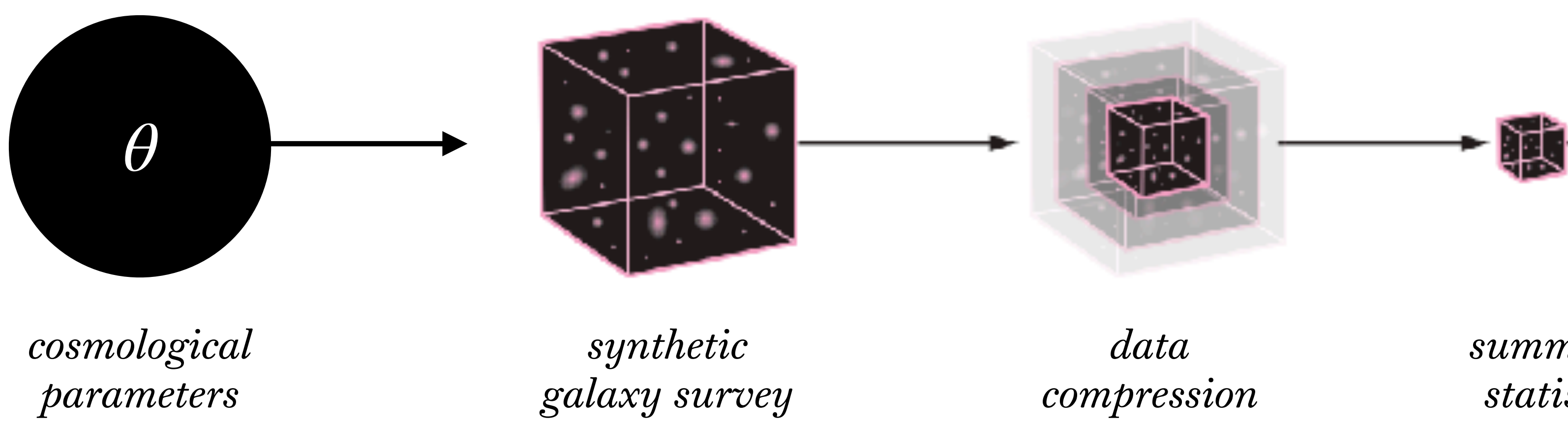
ΛCDM *parameters* — *observed galaxy distribution*

SimBIG

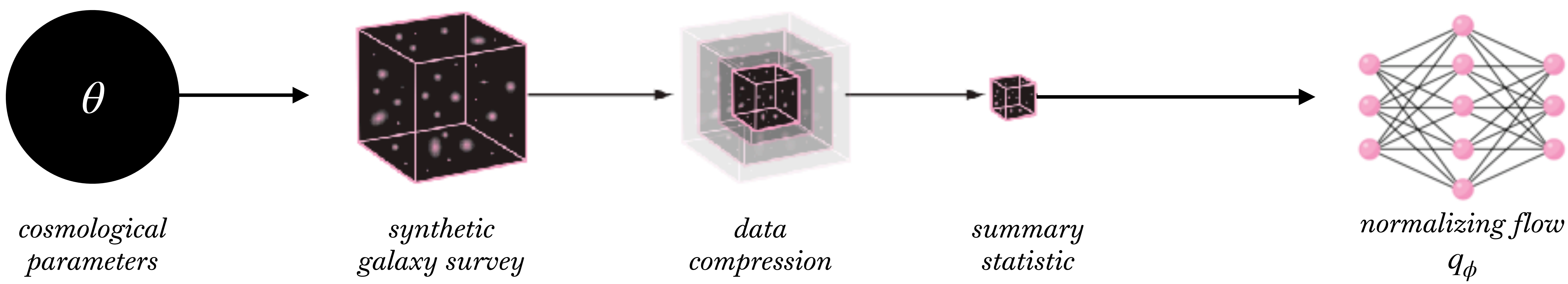
Simulation-**B**ased **I**nference of **G**alaxies

https://changhoonhahn.github.io/simbig/

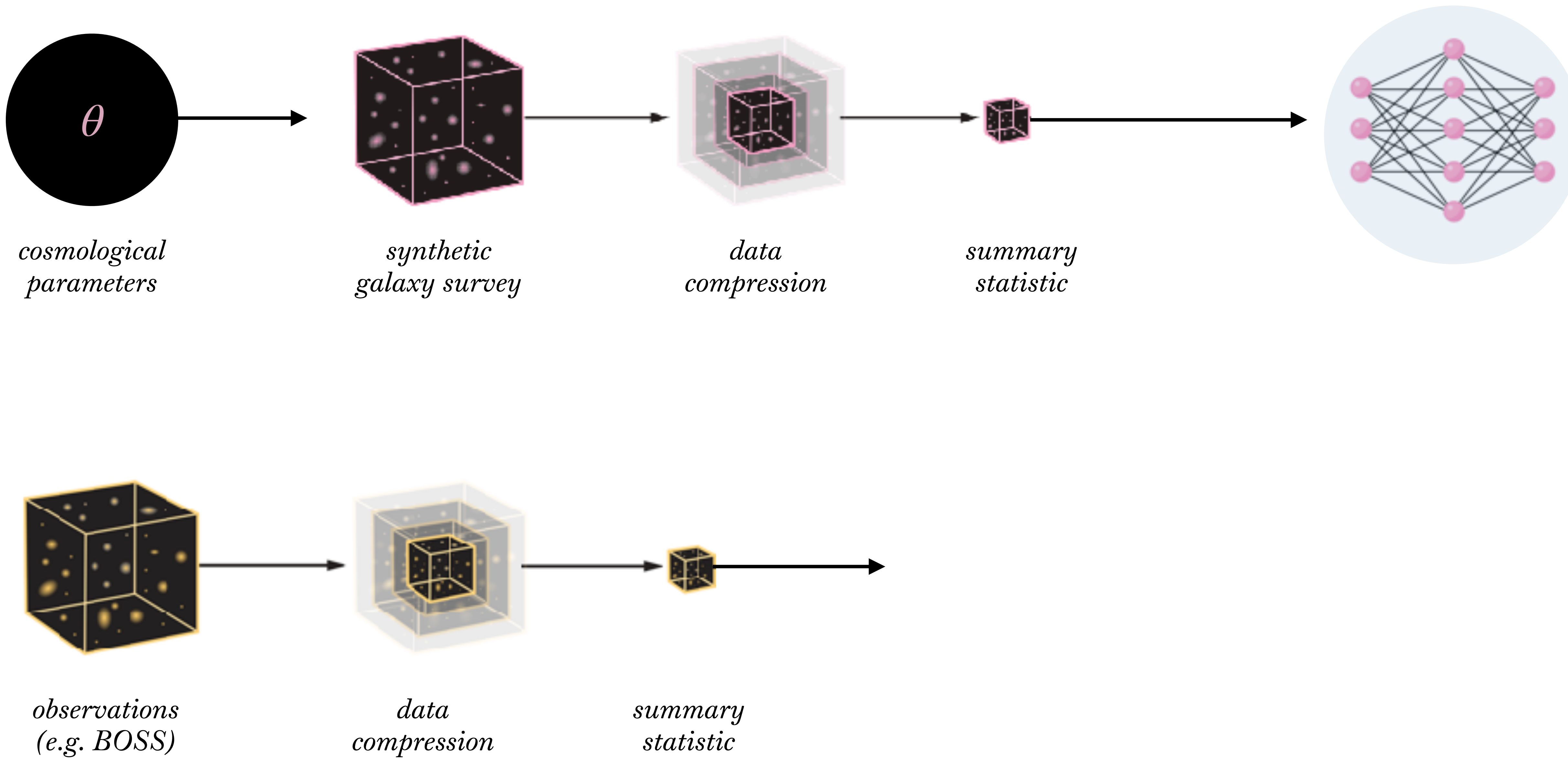
SIMBIG — 1. *generating training data of synthetic observations*



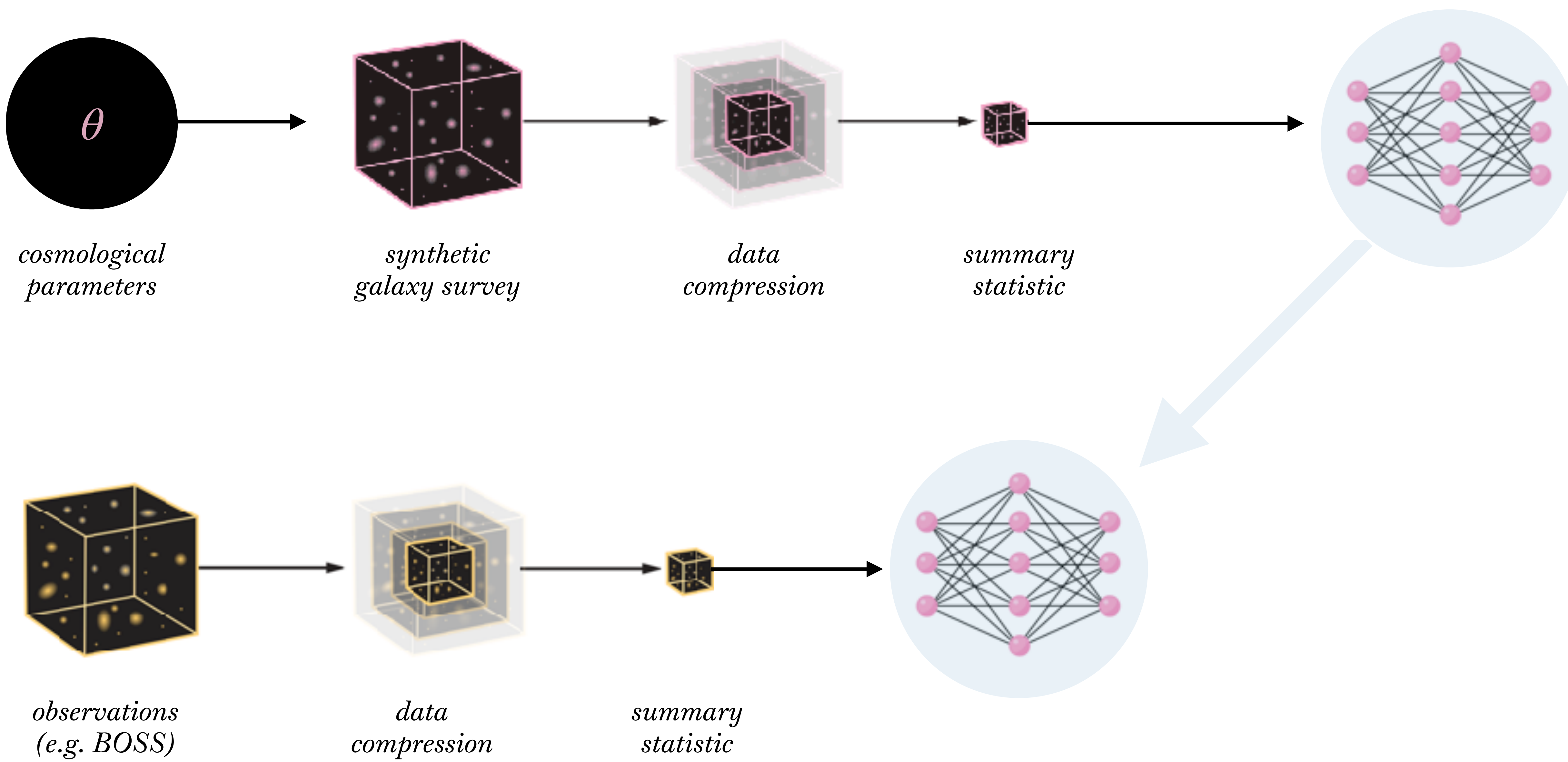
SimBIG — 2. *training the normalizing flow*



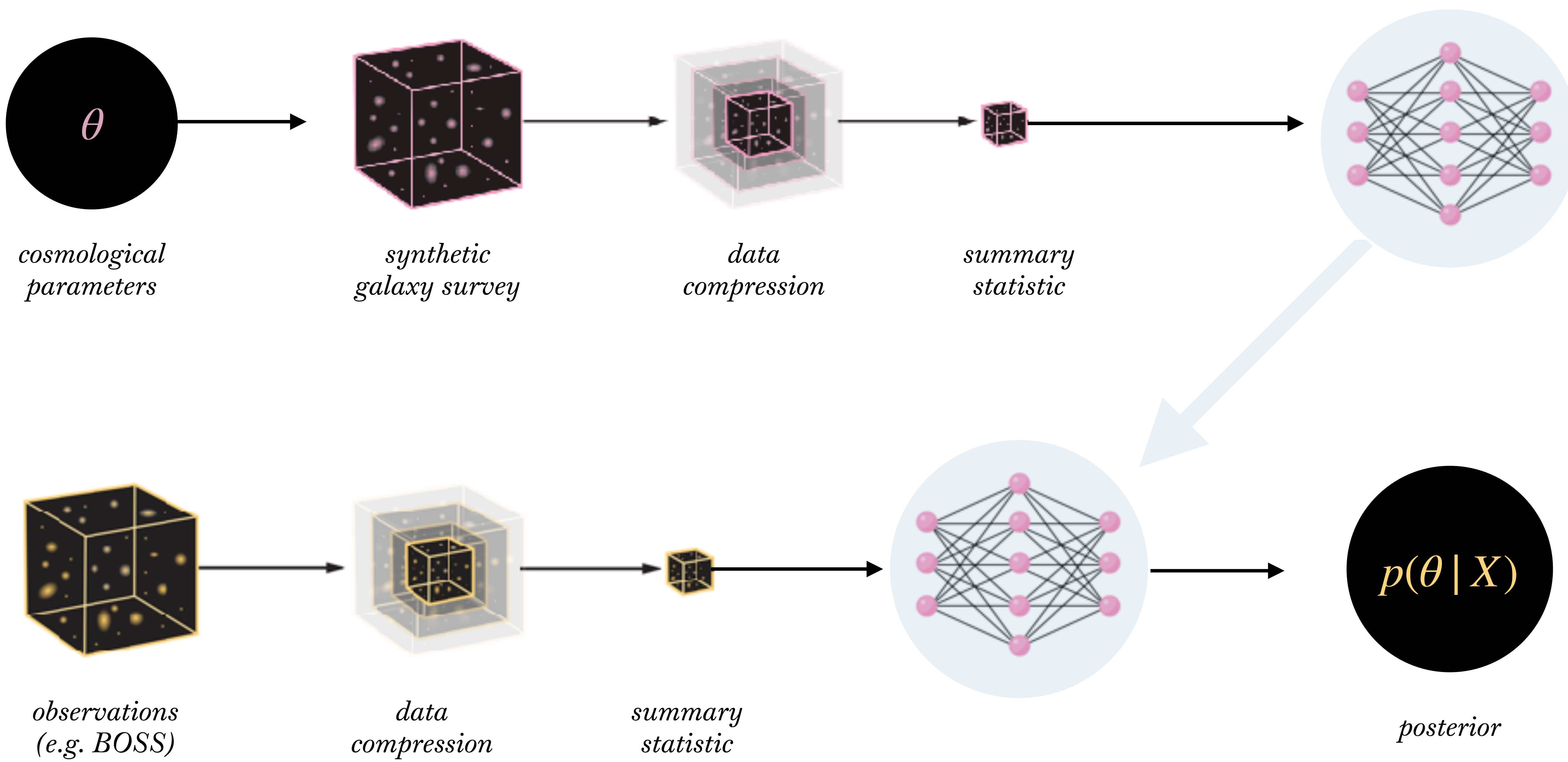
SIMBIG — 3. inference using real observations



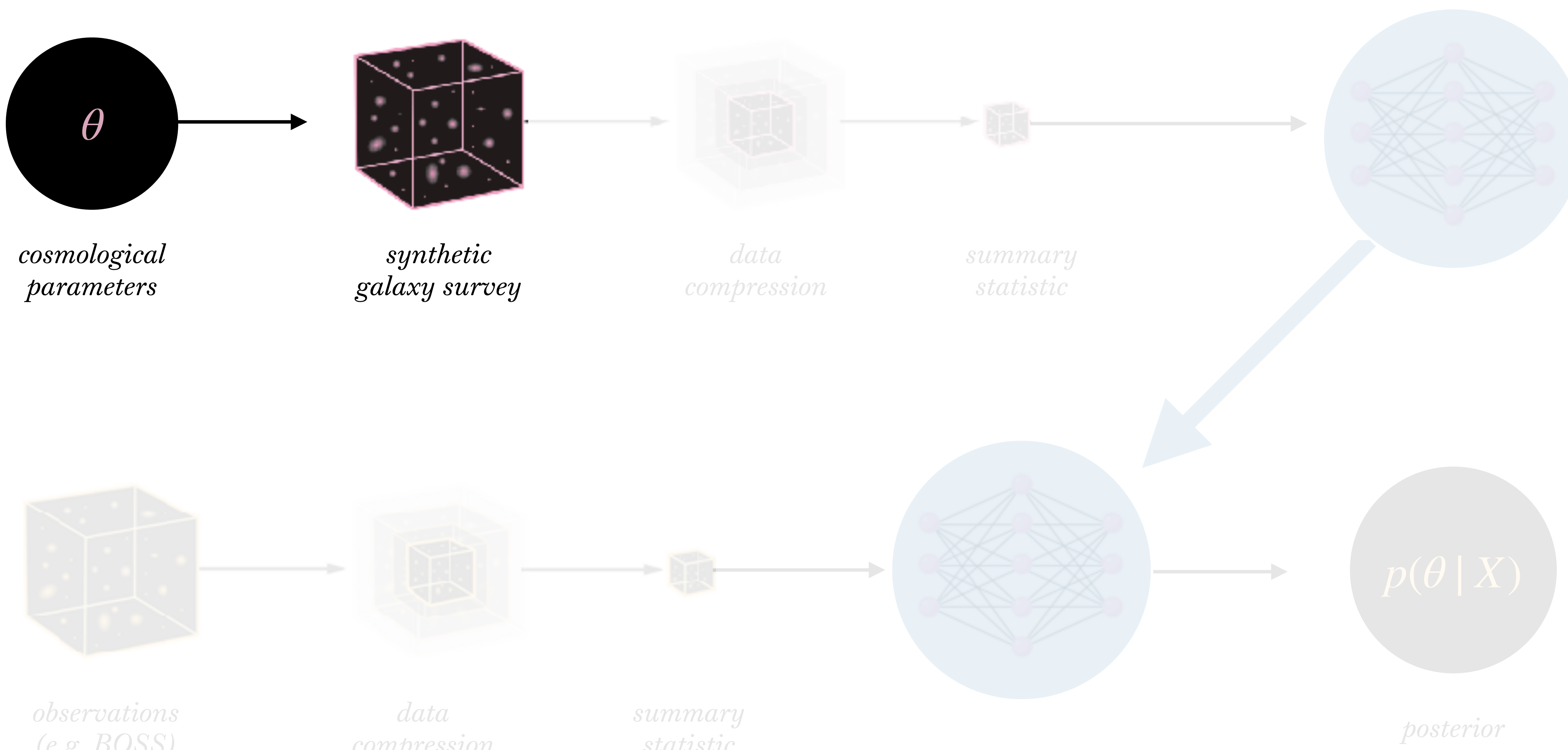
SIMBIG — 3. inference using real observations



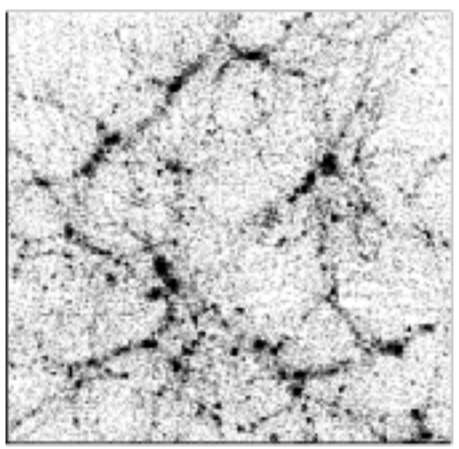
SimBIG — 3. inference using real observations



SimBIG — 3. inference using real observations

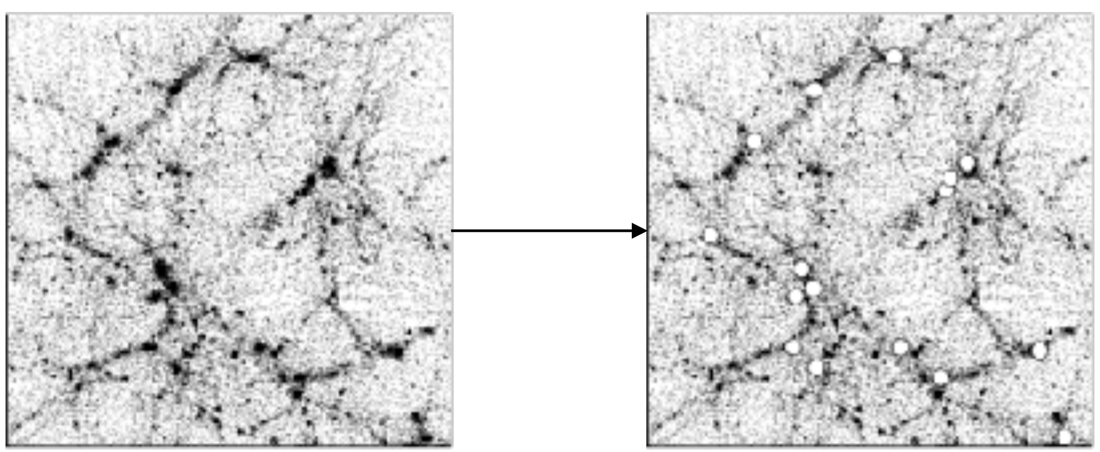


SimBIG **forward model** — SDSS-III: BOSS observations



Quijote high-res
N-body simulations

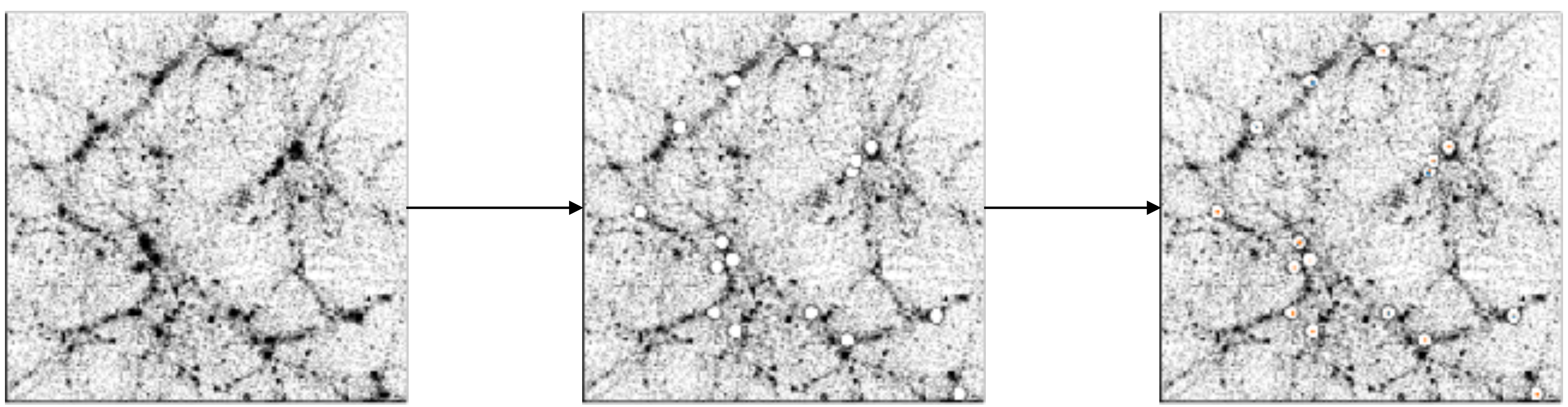
SimBIG **forward model** — SDSS-III: BOSS observations



Quijote high-res
N-body simulations

Rockstar phase-space
halo finder

SIMBIG **forward model** — SDSS-III: BOSS observations

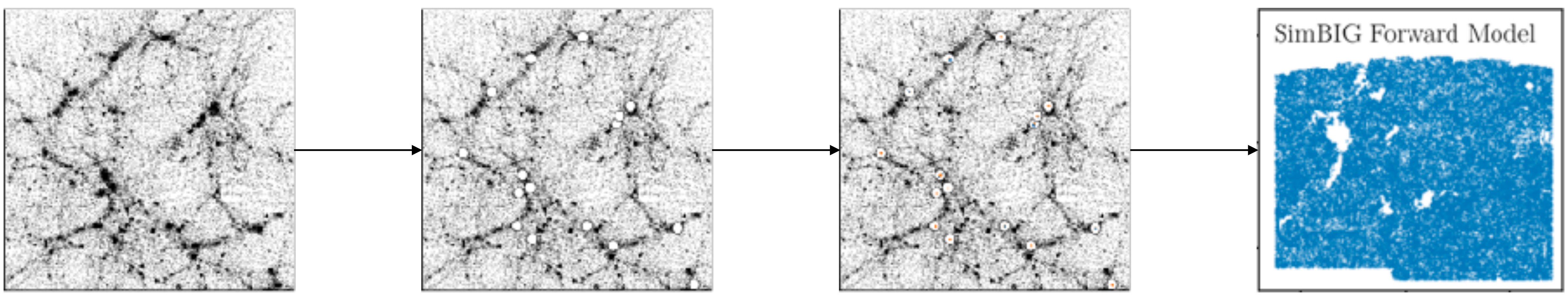


Quijote high-res
N-body simulations

Rockstar phase-space
halo finder

HOD model with *assembly,*
velocity, concentration biases

SimBIG **forward model** — SDSS-III: BOSS observations



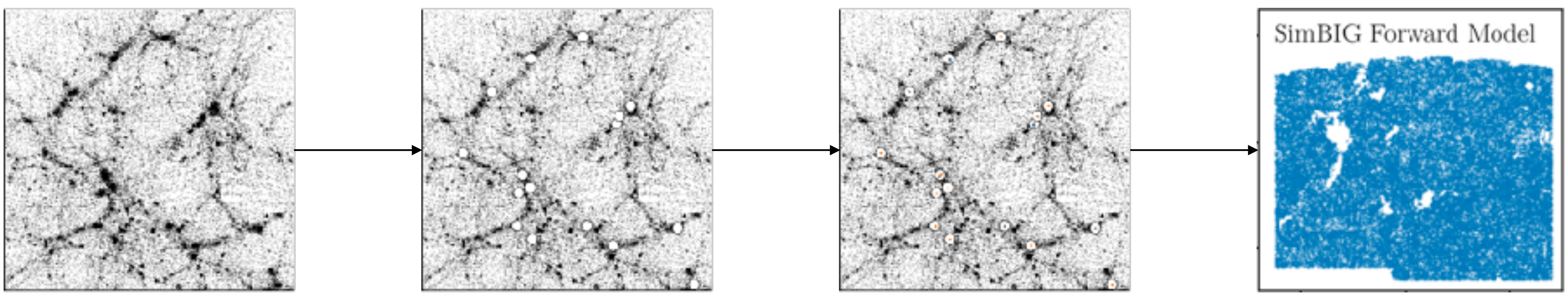
Quijote high-res N-body simulations

Rockstar phase-space halo finder

HOD model with *assembly, velocity, concentration biases*

survey realism: *redshift-space, geometry, mask, fiber collisions*

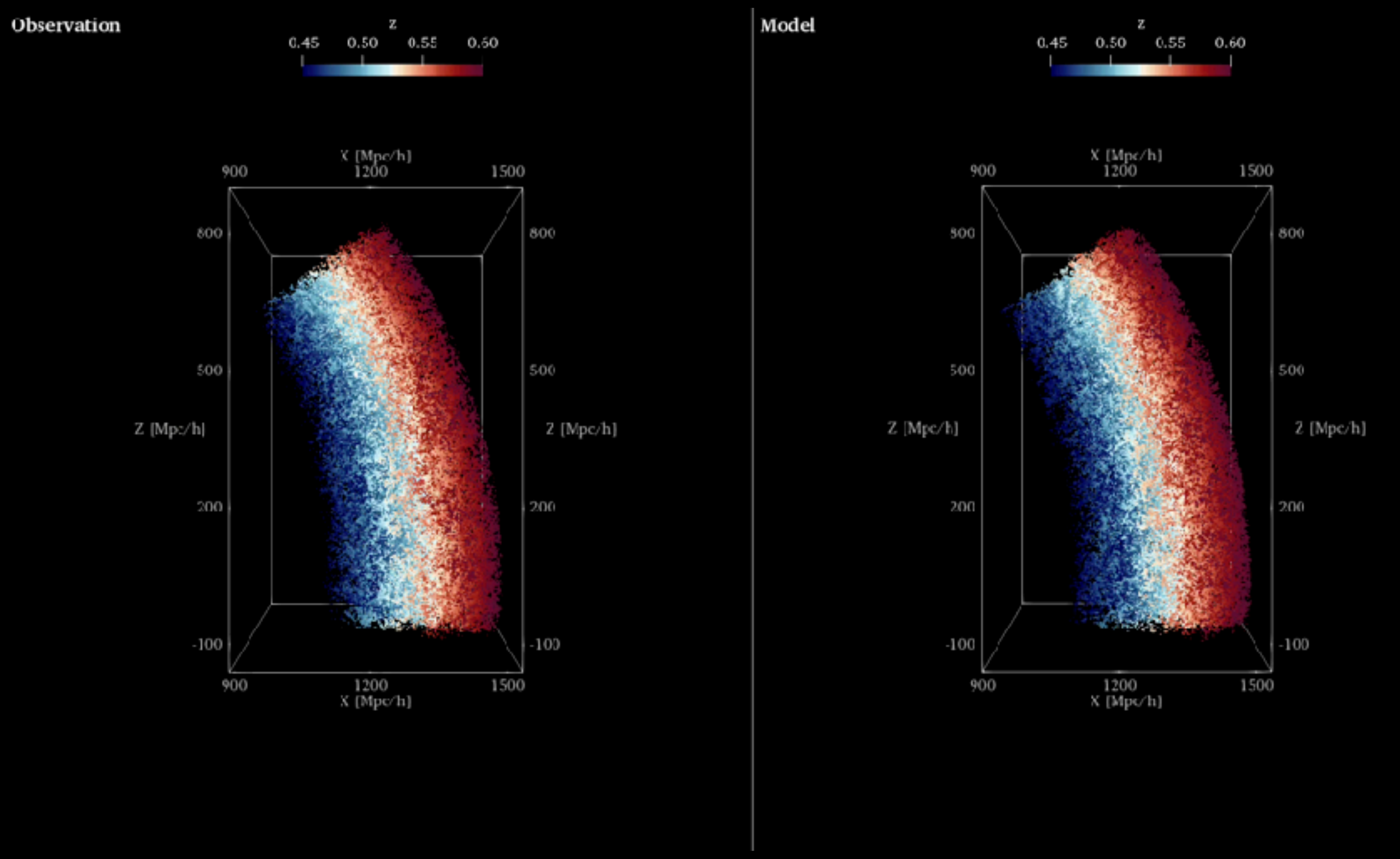
SimBIG **forward model** — SDSS-III: BOSS observations



Quijote high-res N-body simulations | Rockstar phase-space halo finder | HOD model with *assembly, velocity, concentration biases* | survey realism: *redshift-space, geometry, mask, fiber collisions*

20,000 training simulations spanning broad range of cosmologies and HOD parameters

Hahn *et al.(2023c, 2023d)*



Hahn *et al.(2023c, 2023d)*
video: Bruno Régaldo-Saint Blancard

SimBIG: non-linear galaxy power spectrum $P_\ell(k < 0.5\,h/\mathrm{Mpc})$

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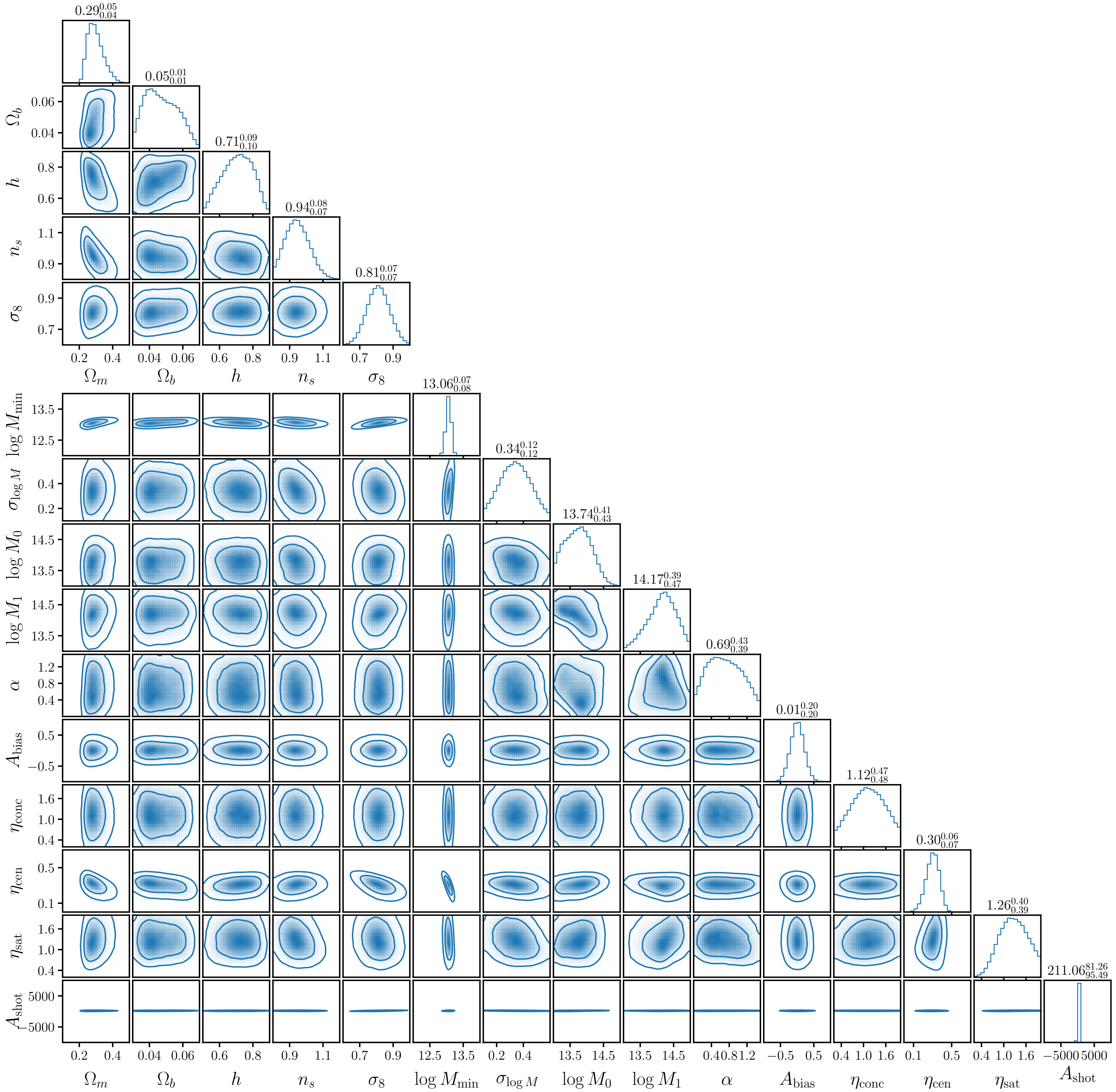
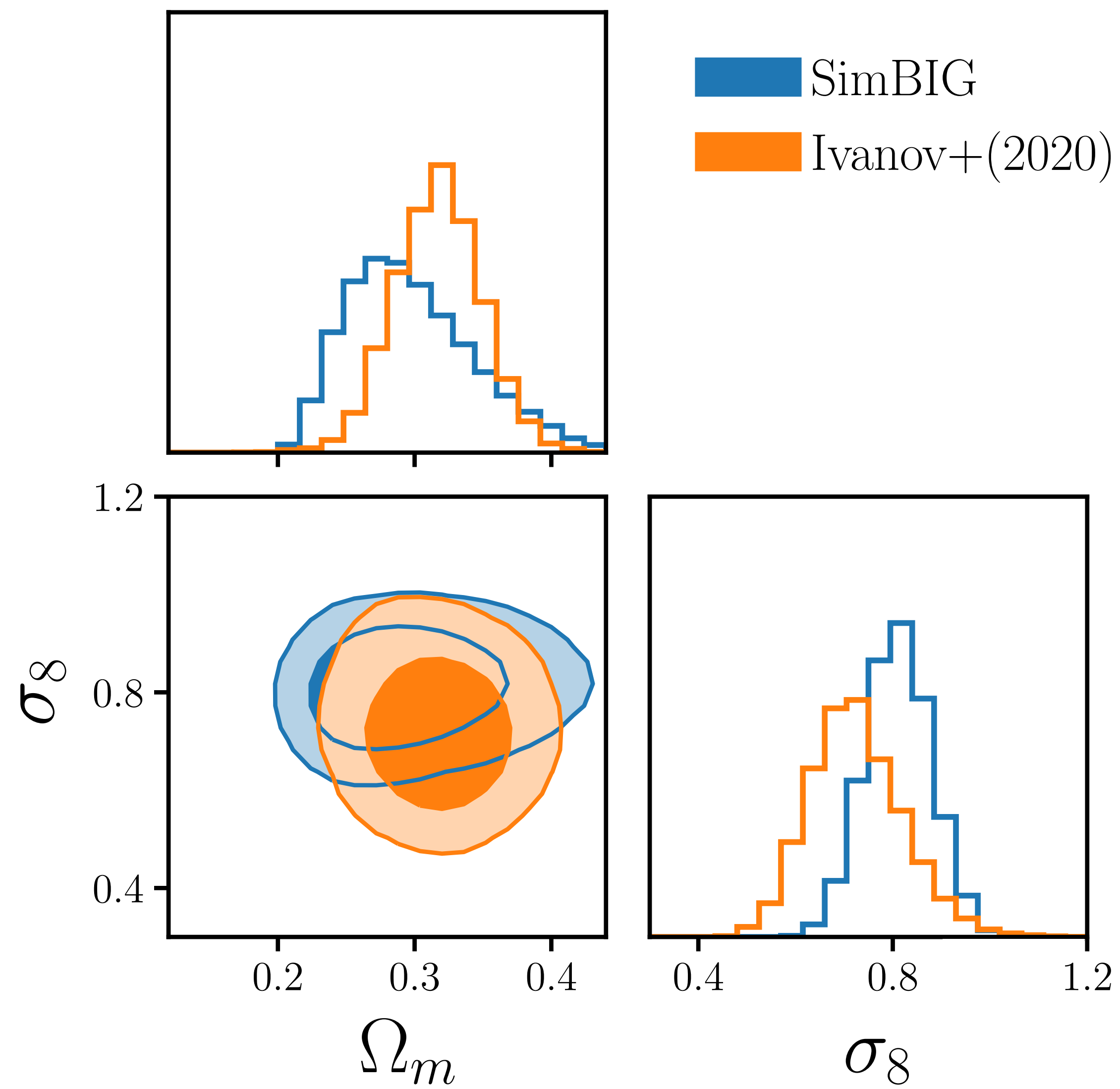


Hahn *et al.(2023c);* ***Hahn*** *et al.(2023d) PNAS*

SimBIG: non-linear galaxy power spectrum $P_\ell(k < 0.5\, h/\mathrm{Mpc})$

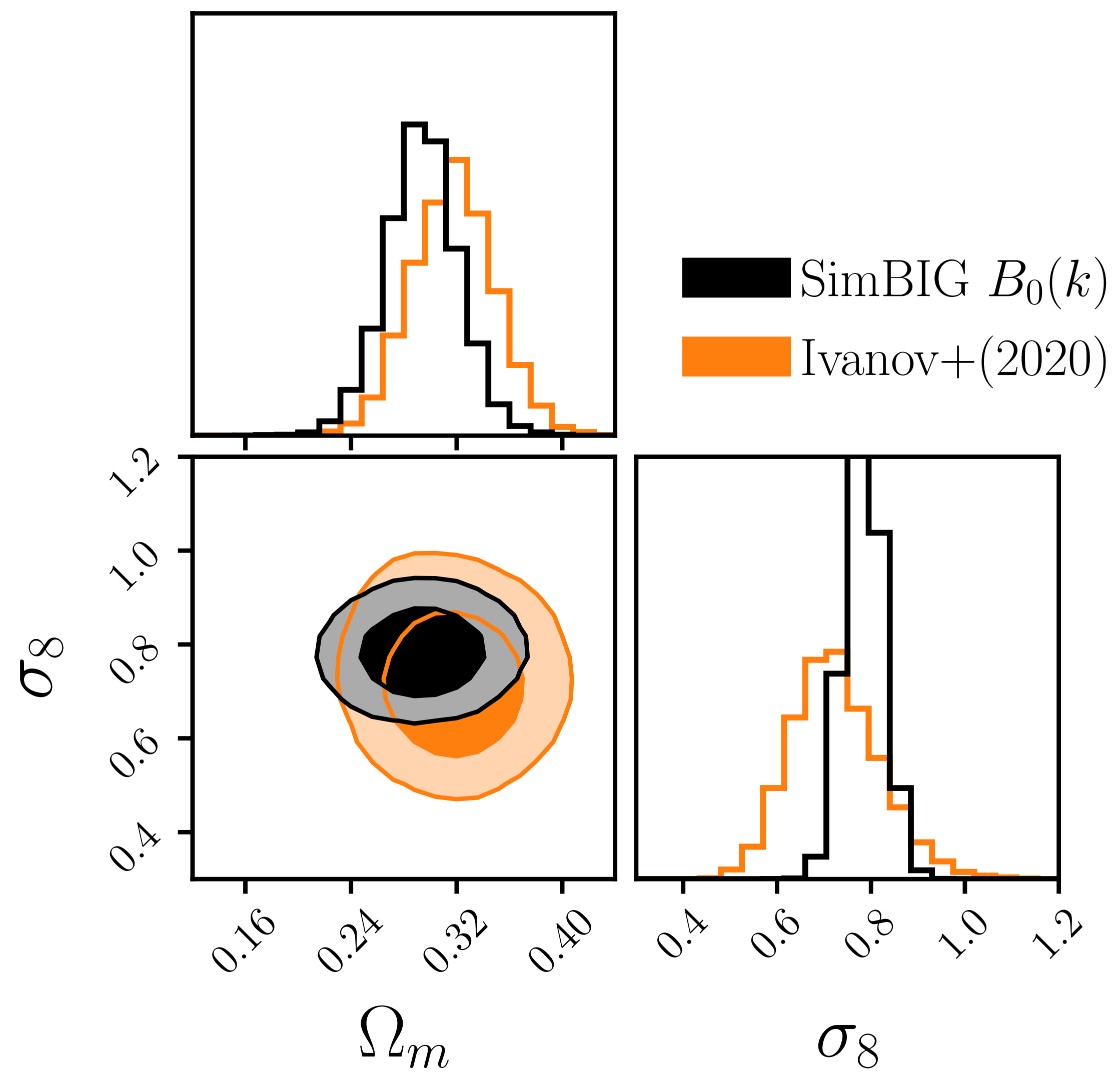


$1.4\times$ *tighter* σ_8 from non-linear scales

Hahn *et al.(2023c);* ***Hahn*** *et al.(2023d) PNAS*

SIMBIG: non-linear galaxy bispectrum $B_0(k_1, k_2, k_3 < 0.5\,h/\mathrm{Mpc})$

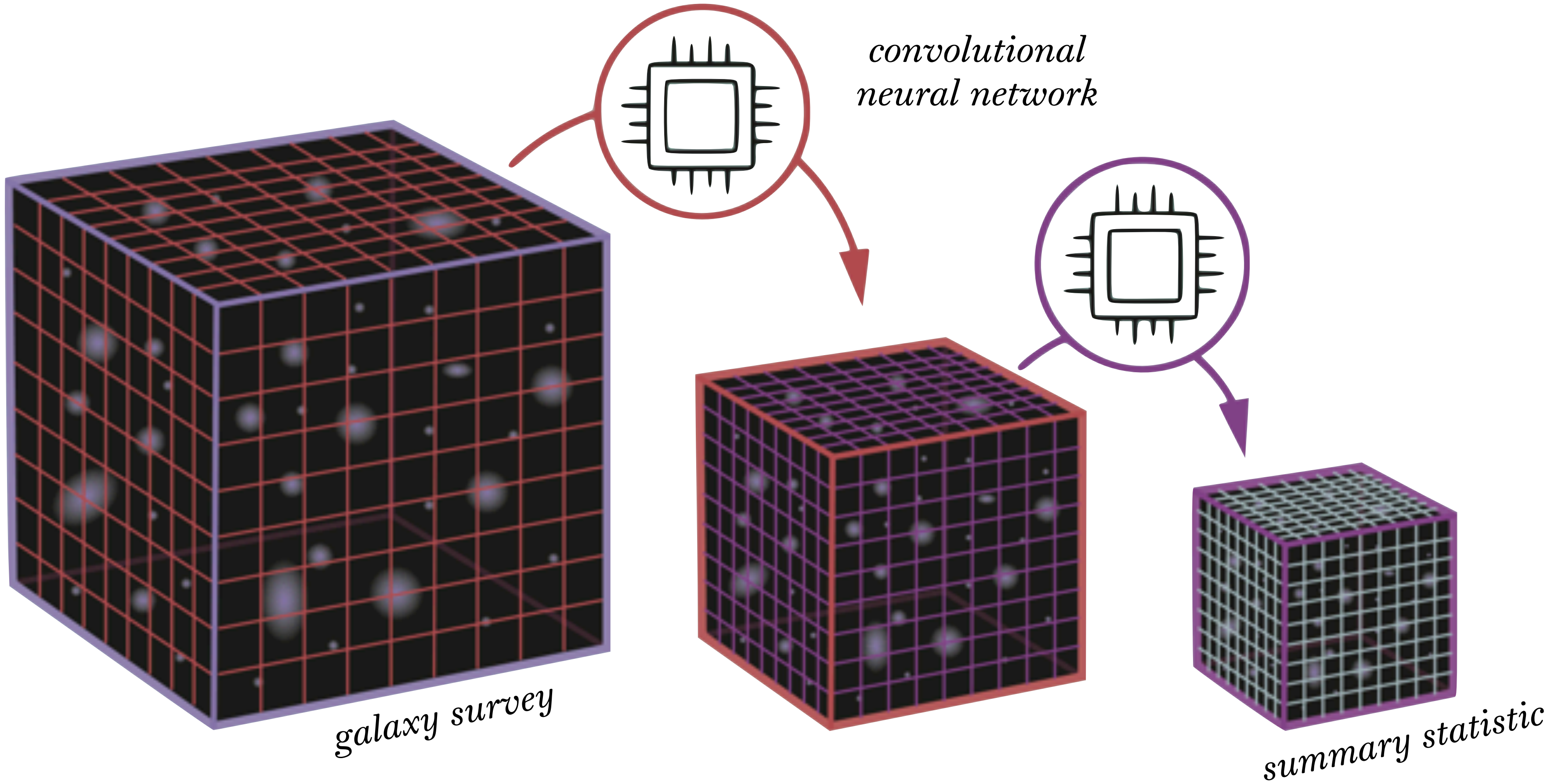
SimBIG: non-linear galaxy bispectrum $B_0(k_1, k_2, k_3 < 0.5\,h/\mathrm{Mpc})$



1.2 and 2.4 $\times$ *tighter* Ω_m and σ_8 from **non-linear** + **higher-order** clustering

Hahn *et al. (2023h)*

SIMBIG: convolutional neural network field-level summary



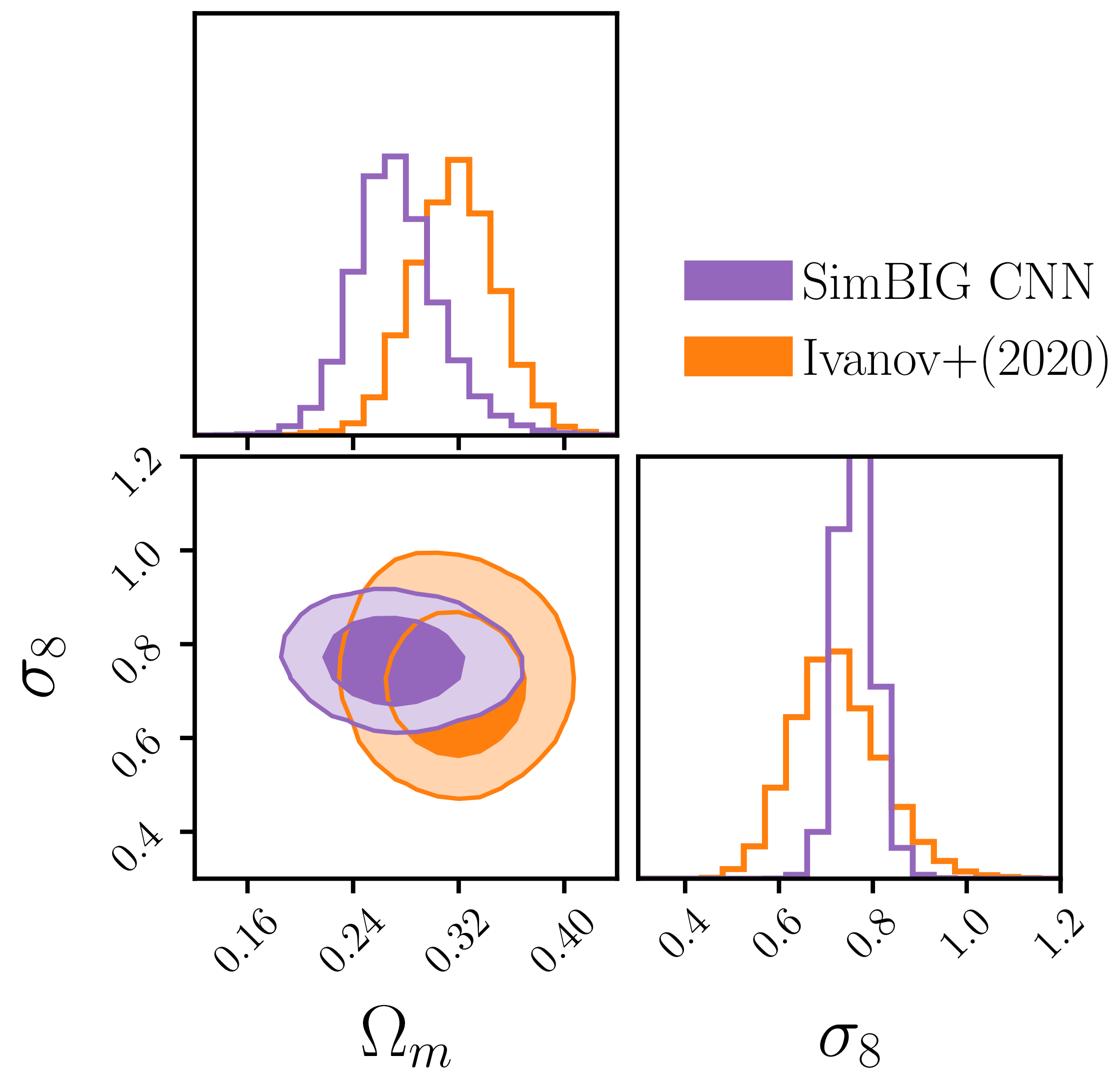
extracting *all* relevant cosmological information in N-pt functions

*Lemos, Parker, **Hahn** et al. (2023)*

SimBIG: convolutional neural network field-level summary

Liam Parker
Princeton Univ.

Pablo Lemos
MILA



extracting *all* relevant cosmological information in N-pt functions

*Parker, Lemos, **Hahn** et al. (2023)*

SIMBIG

wavelet scattering transforms

*Régaldo-Saint Blancard, **Hahn** et al. (2023)*

Bruno Régaldo-Saint Blancard
CCM Flatiron

skew spectra

*Hou, Moradinezhad Dizgah, **Hahn** et al. (2024)*

Jiamin Hou
Univ. of Florida

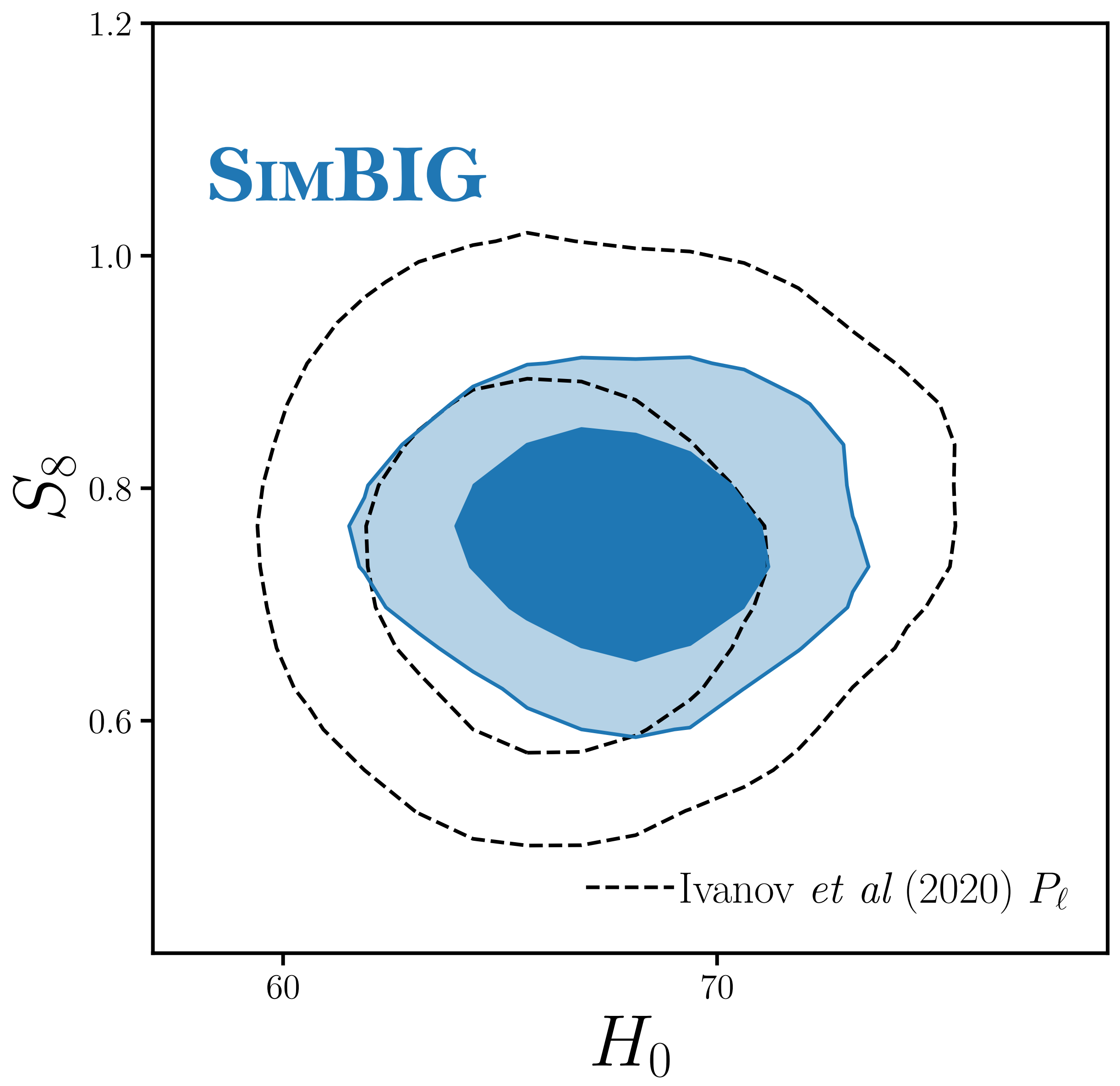
marked powerspectrum

*Massara, **Hahn** et al. (2024)*

Elena Massara
UWaterloo

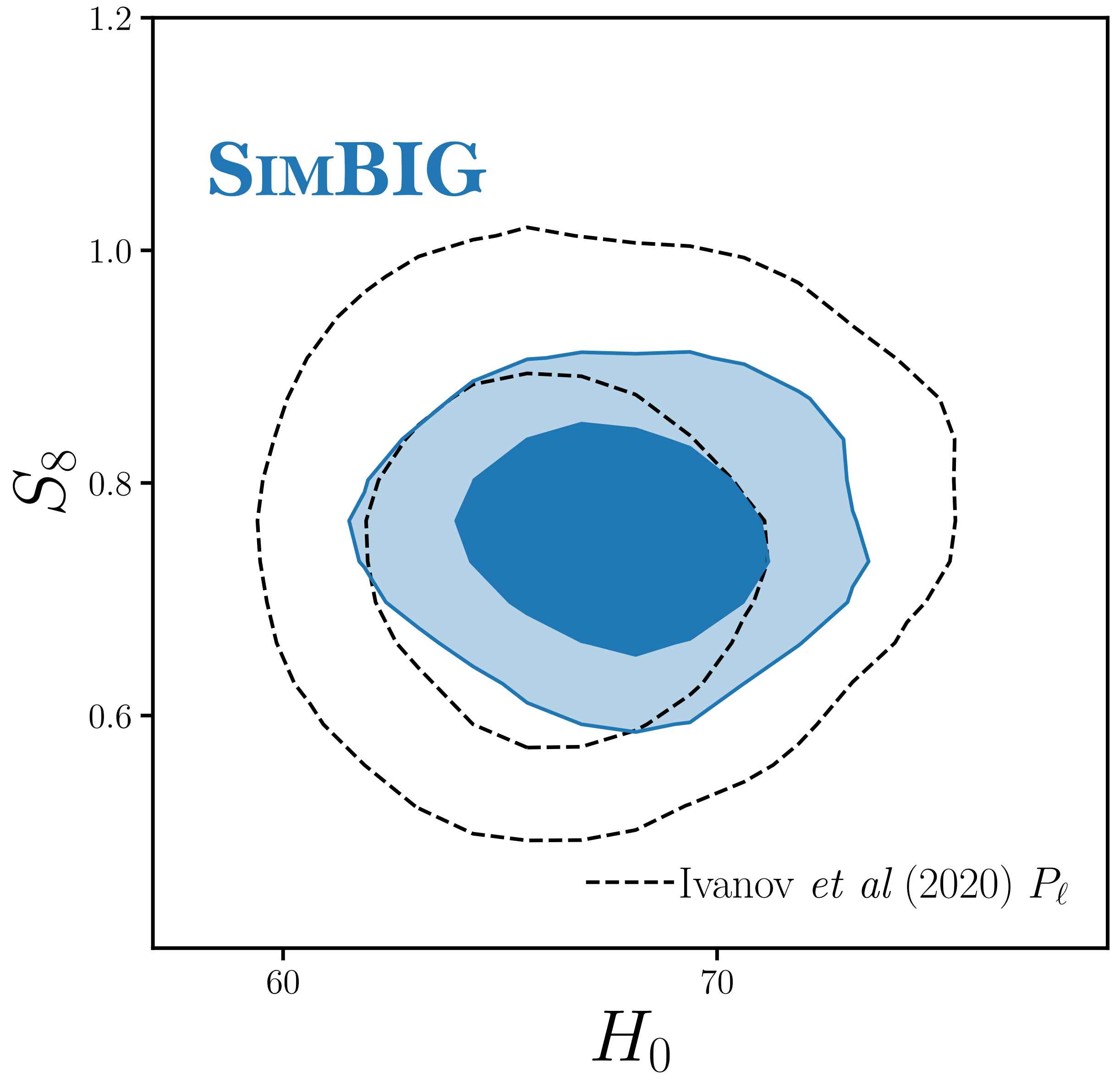
voids, graph neural network, combined … *coming soon*

SimBIG: **~1.9 and 1.5× tighter** S_8 and H_0



Hahn *et al. (2023i)*

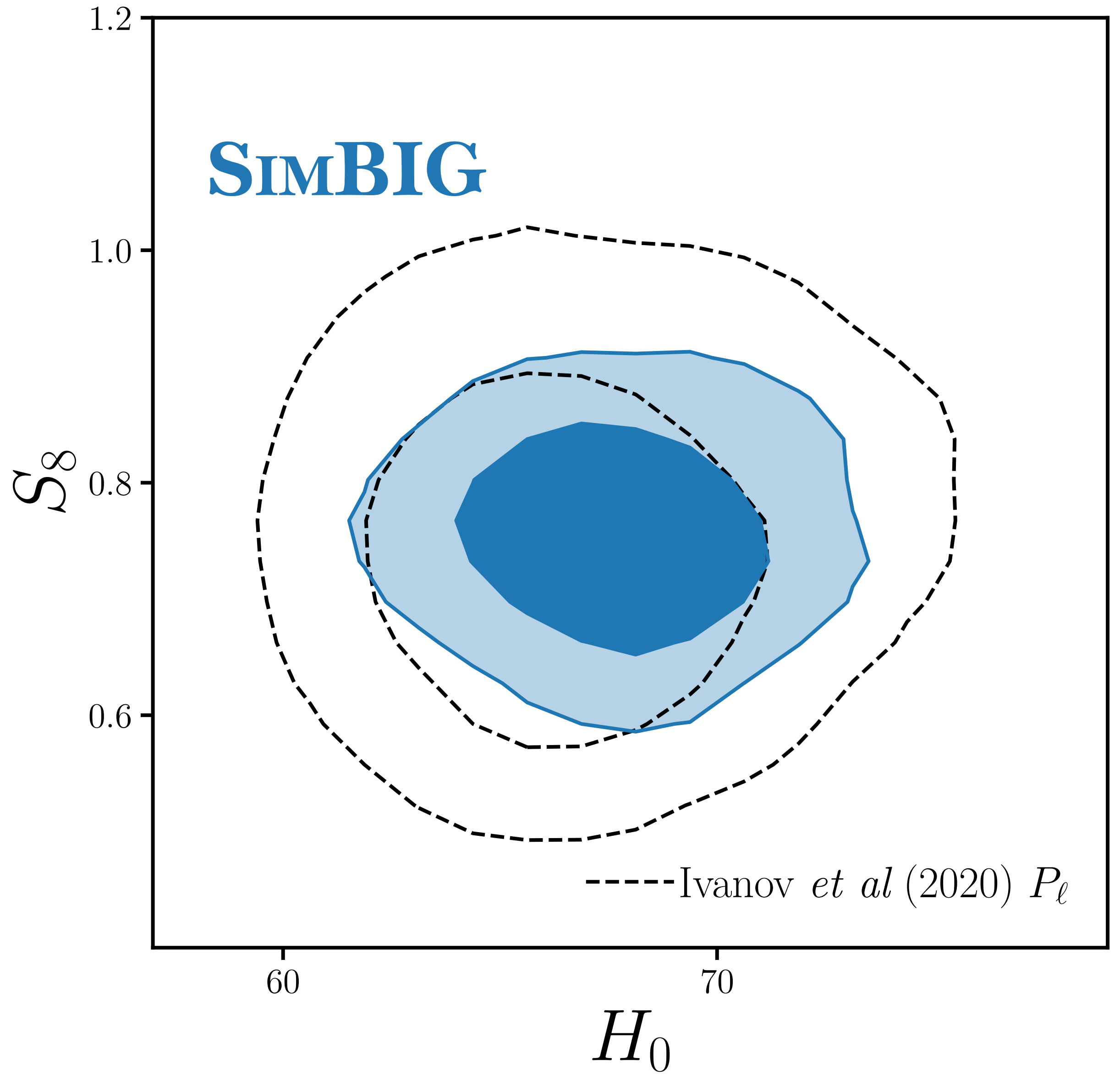
SIMBIG: **~1.9 and 1.5× tighter** S_8 and H_0



production level cosmological constraints — *not a proof-of-concept!*

***Hahn** et al. (2023i)*

SimBIG: **~1.9 and 1.5× tighter** S_8 and H_0



S_8 improvement is equivalent to analyzing a *survey of ~4× larger volume*

Hahn *et al. (2023i)*


~100,000 galaxies at z ~ 0.5
galaxy surveys

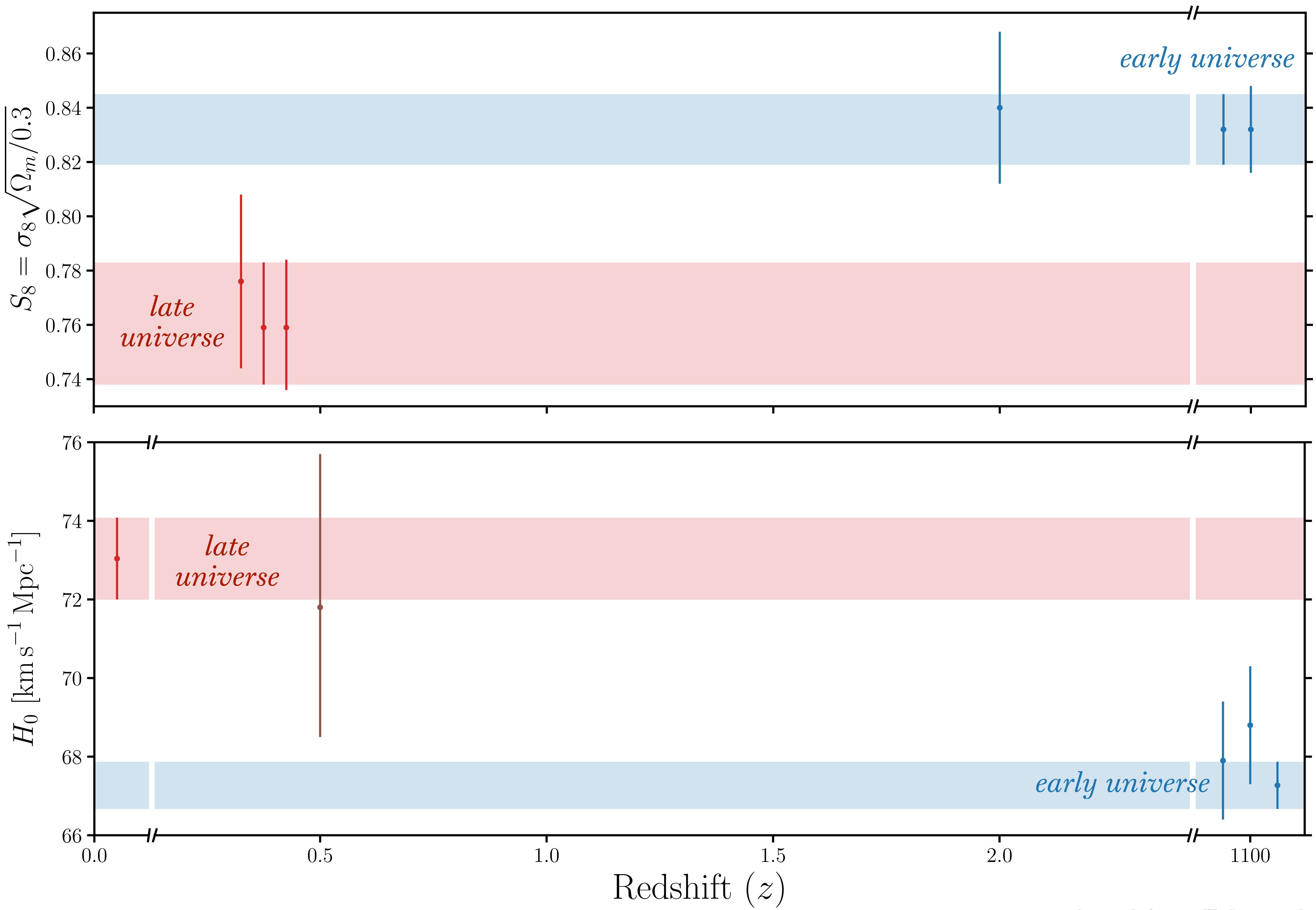

~100,000 *galaxies* at $z \sim 0.5$
galaxy surveys

Roman *High Latitude Spectroscopic Survey*

~10 million Hα Emission-Line Galaxies $1 < z < 2$

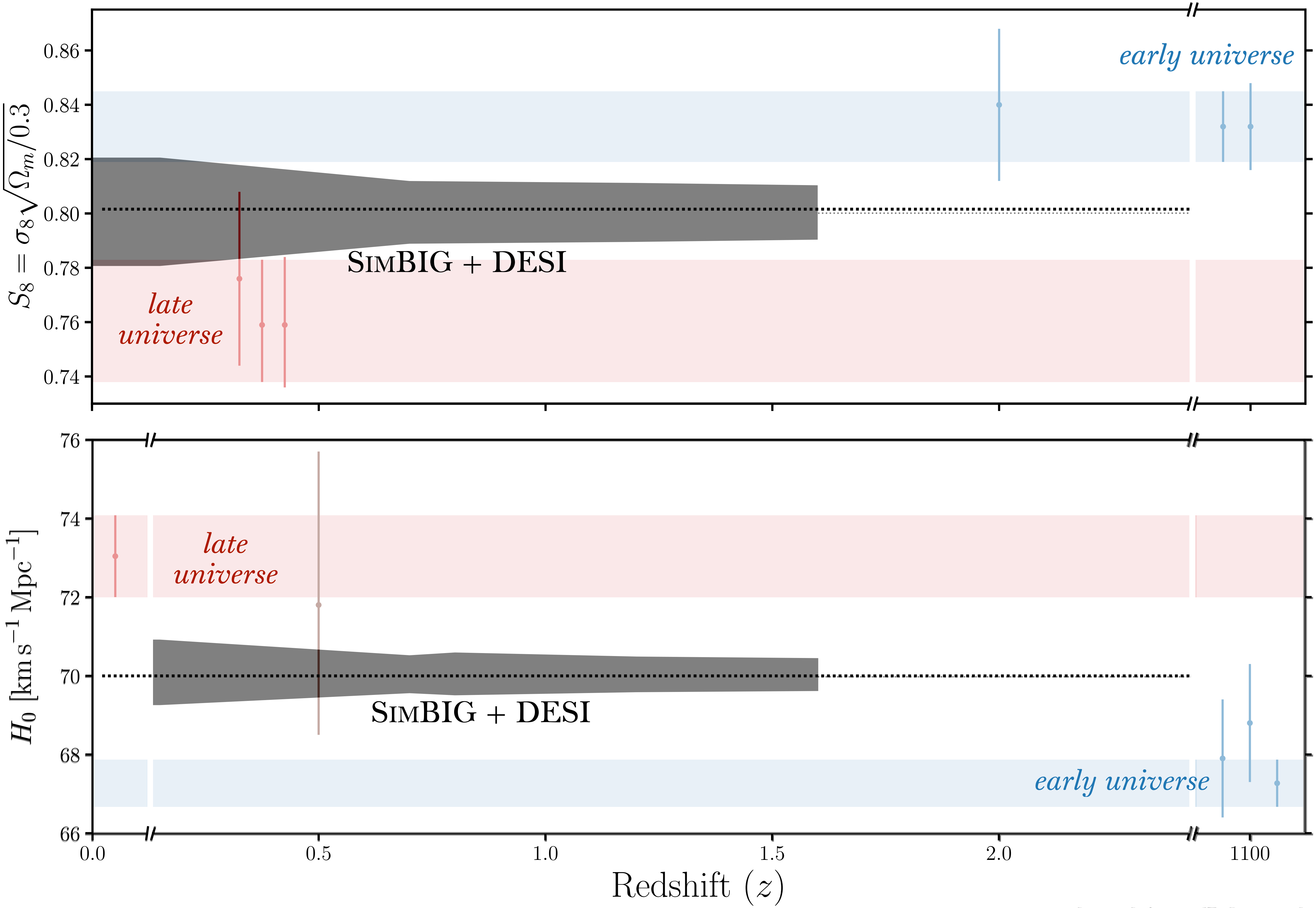
~2 million OIII Emission-Line Galaxies $2 < z < 3$

Wang et al. (2022)



adapted from ***Hahn*** *et al. (2023i)*

SimBIG + DESI and *Roman* will probe *new regimes*



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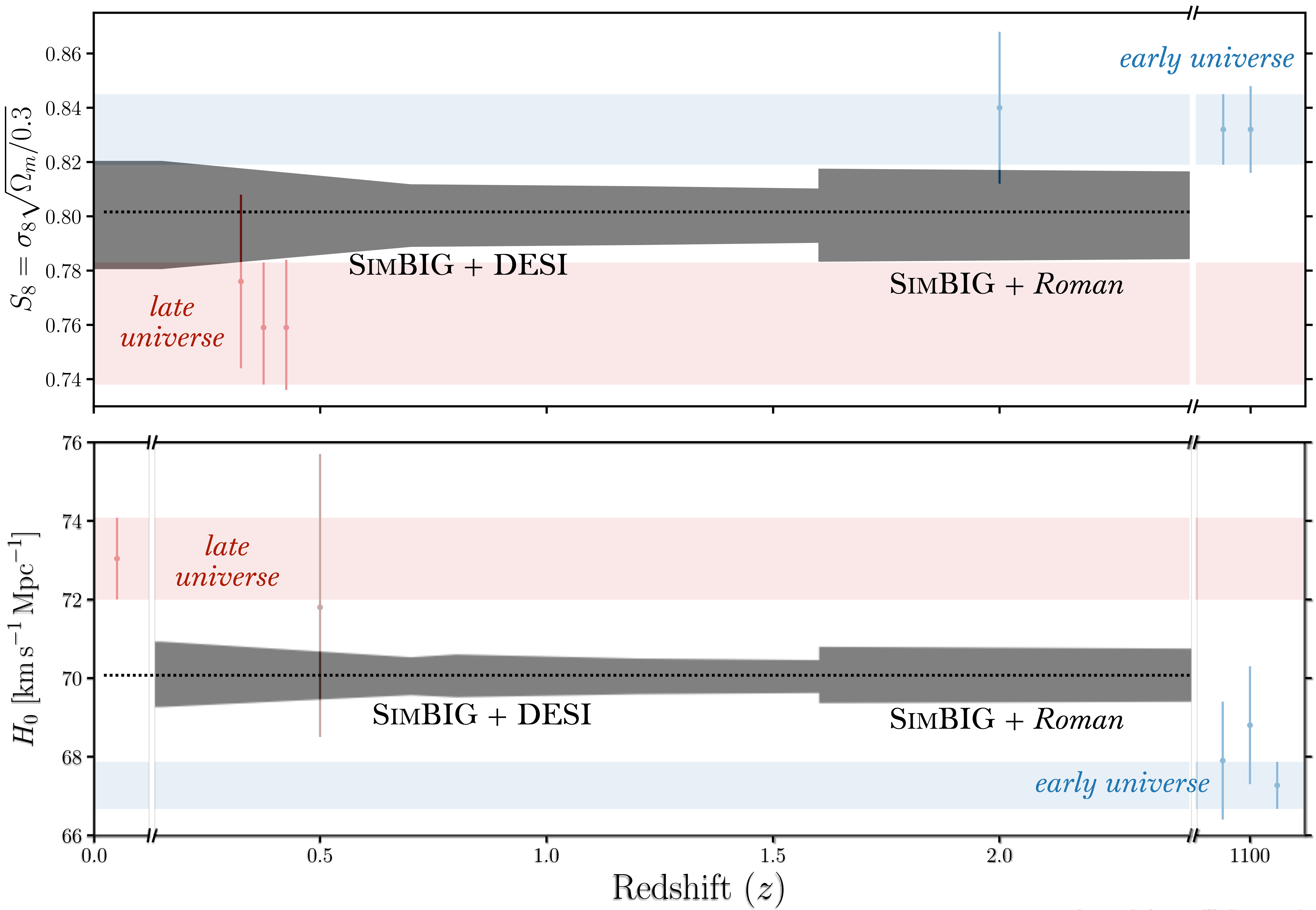

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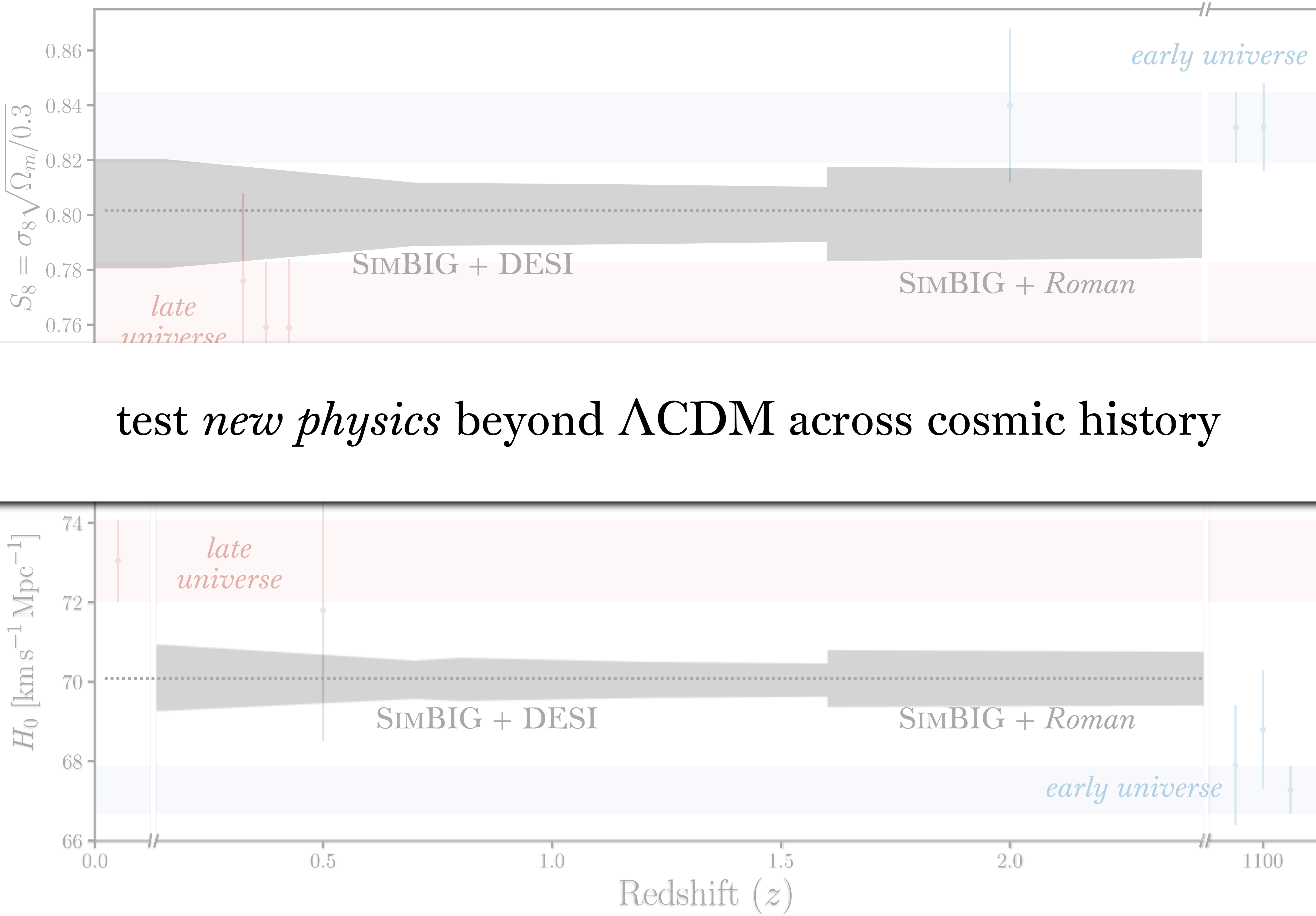

test *new physics* beyond ΛCDM across cosmic history

*adapted from **Hahn** et al. (2023i)*

galaxy surveys encode the *growth* and *expansion histories* of the Universe

ML×Cosmo: SimBIG analyses leverage *non-linear* and *higher-order* galaxy clustering to **double** the cosmological impact of galaxy surveys

Roman with SimBIG will *settle* cosmic tensions and probe *new physics*

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