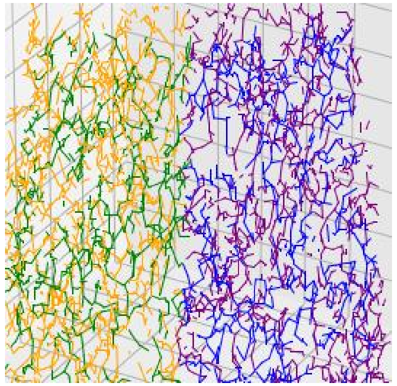
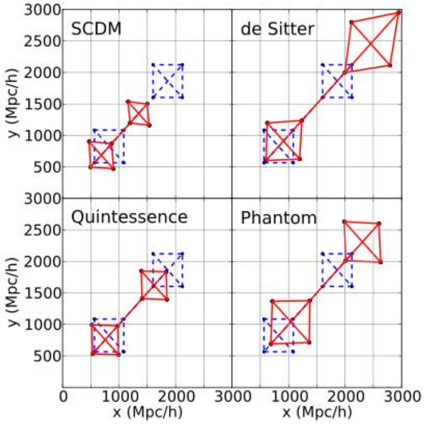
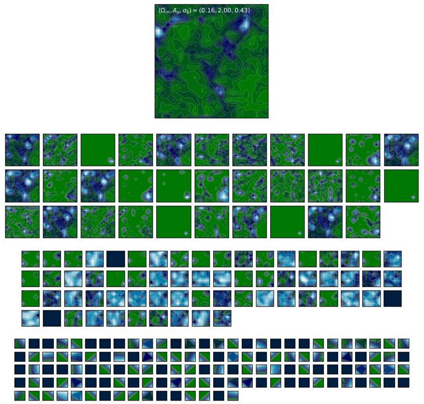
New Methods for Cosmic Large-Scale Structure Analysis



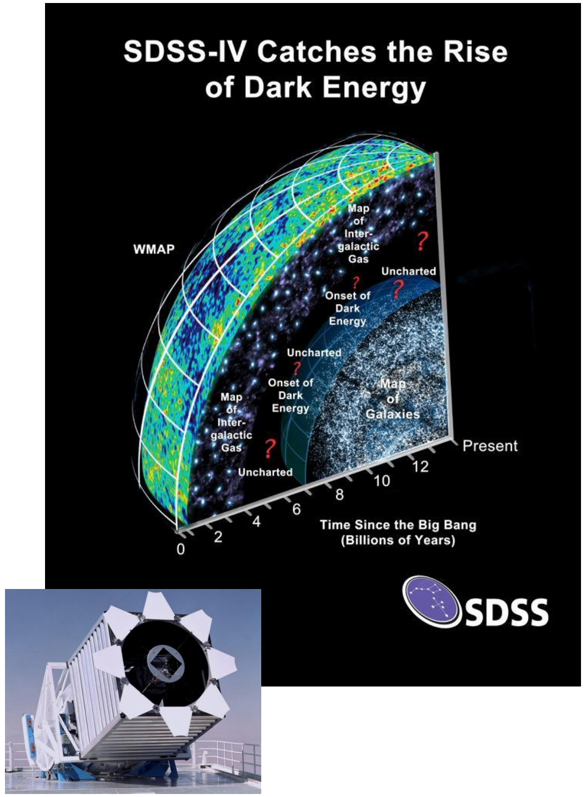




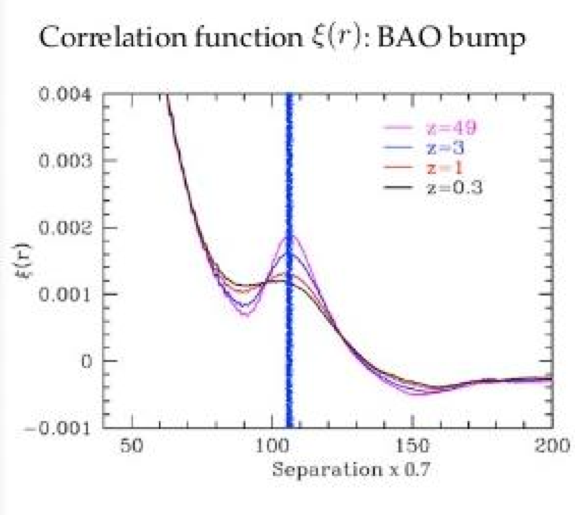
Xiao-Dong Li (李霄栋), from SYSU

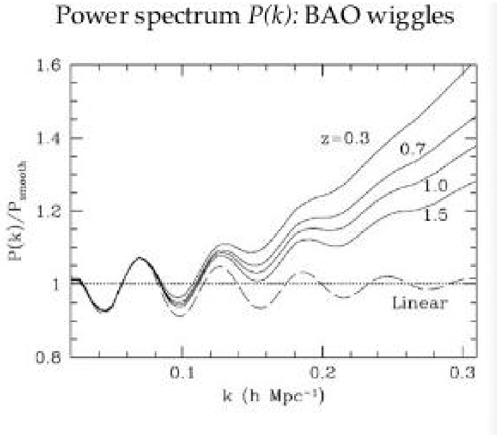
Mar 12, 2020 @ Tsinghua

LSS Cosmology



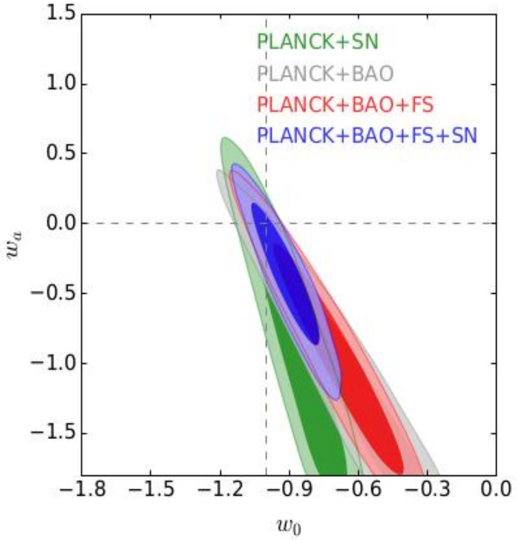
Data





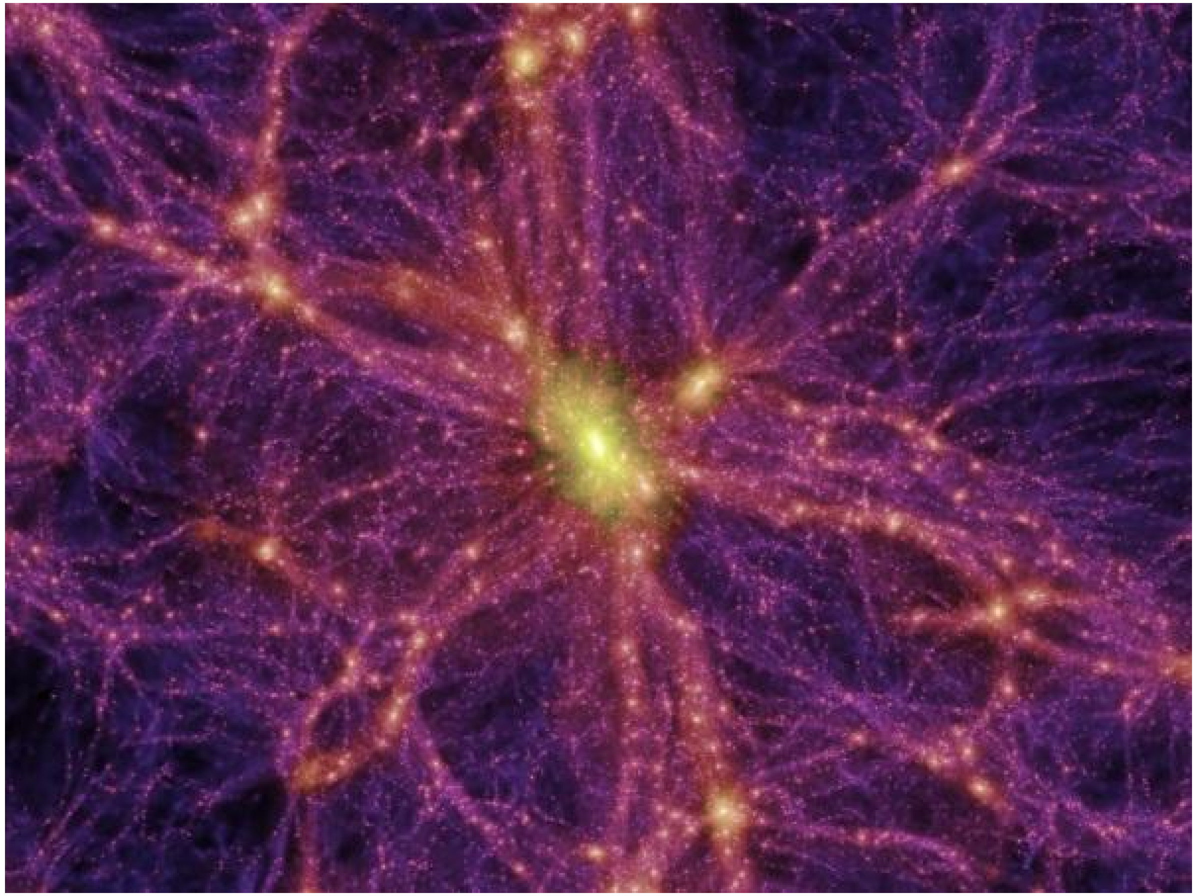
Correlation Function, Power Spectrum

D_A, H, $f\sigma_8$ …



Cosmological Parameters

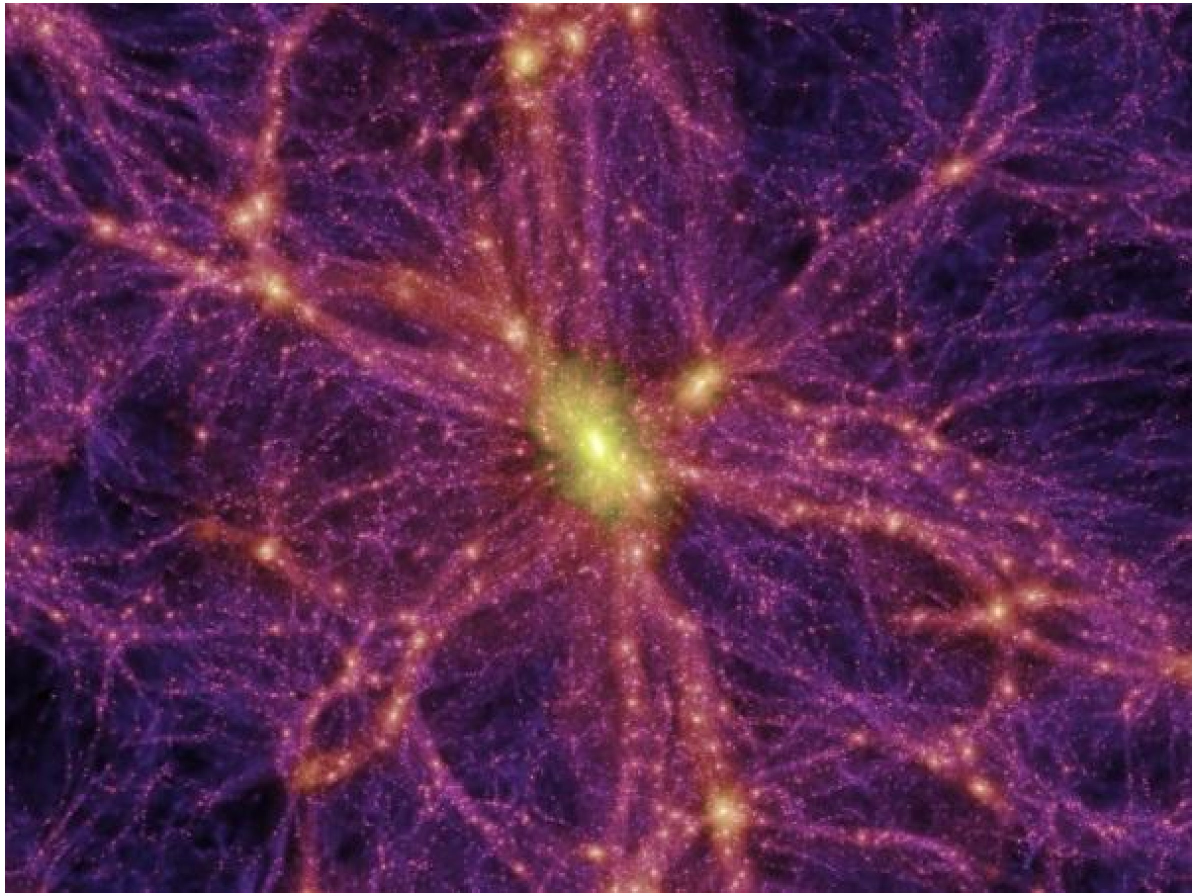
Is that all?



“俺觉得，世界应当更精彩”

I expect more things

Is that all?

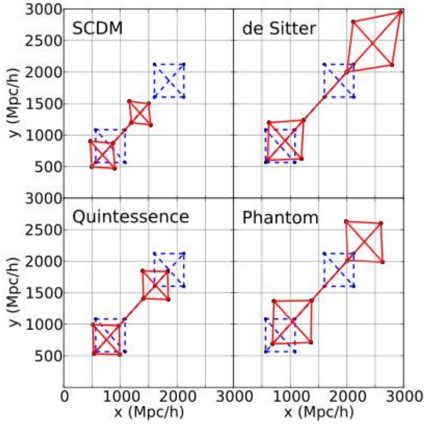


解决小尺度是关键

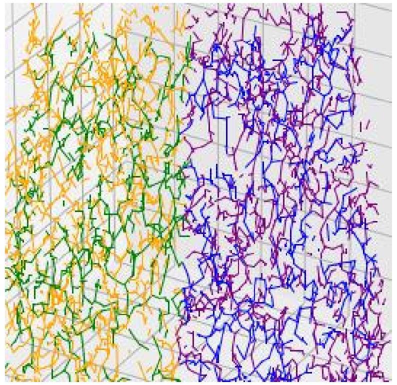
small scale is important

Outline

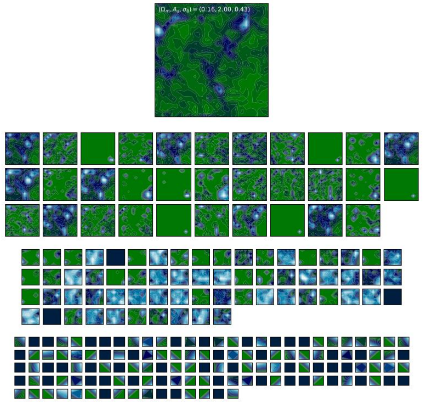
Tomographic AP



Topology



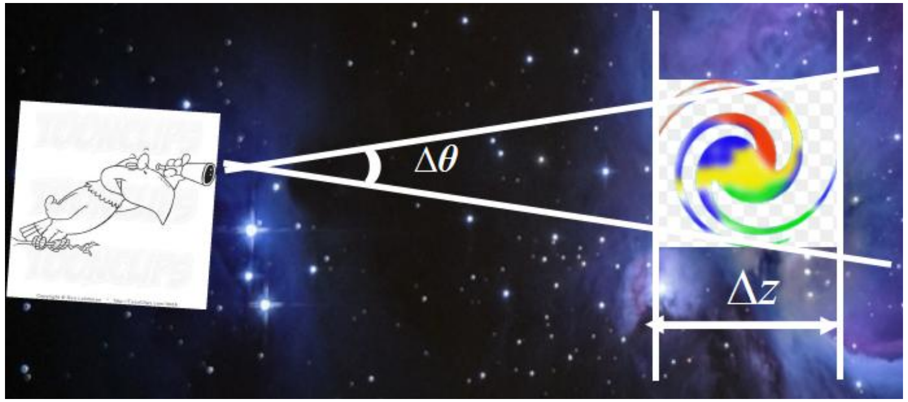
Machine learning



I. Tomographic AP Test

The Alcock-Paczynski test

Alcock & Paczynski, Nature, 1979



We use cosmology to calculate 3d shape

$$\Delta r_{\parallel} = \frac{c}{H(z)} \Delta z$$

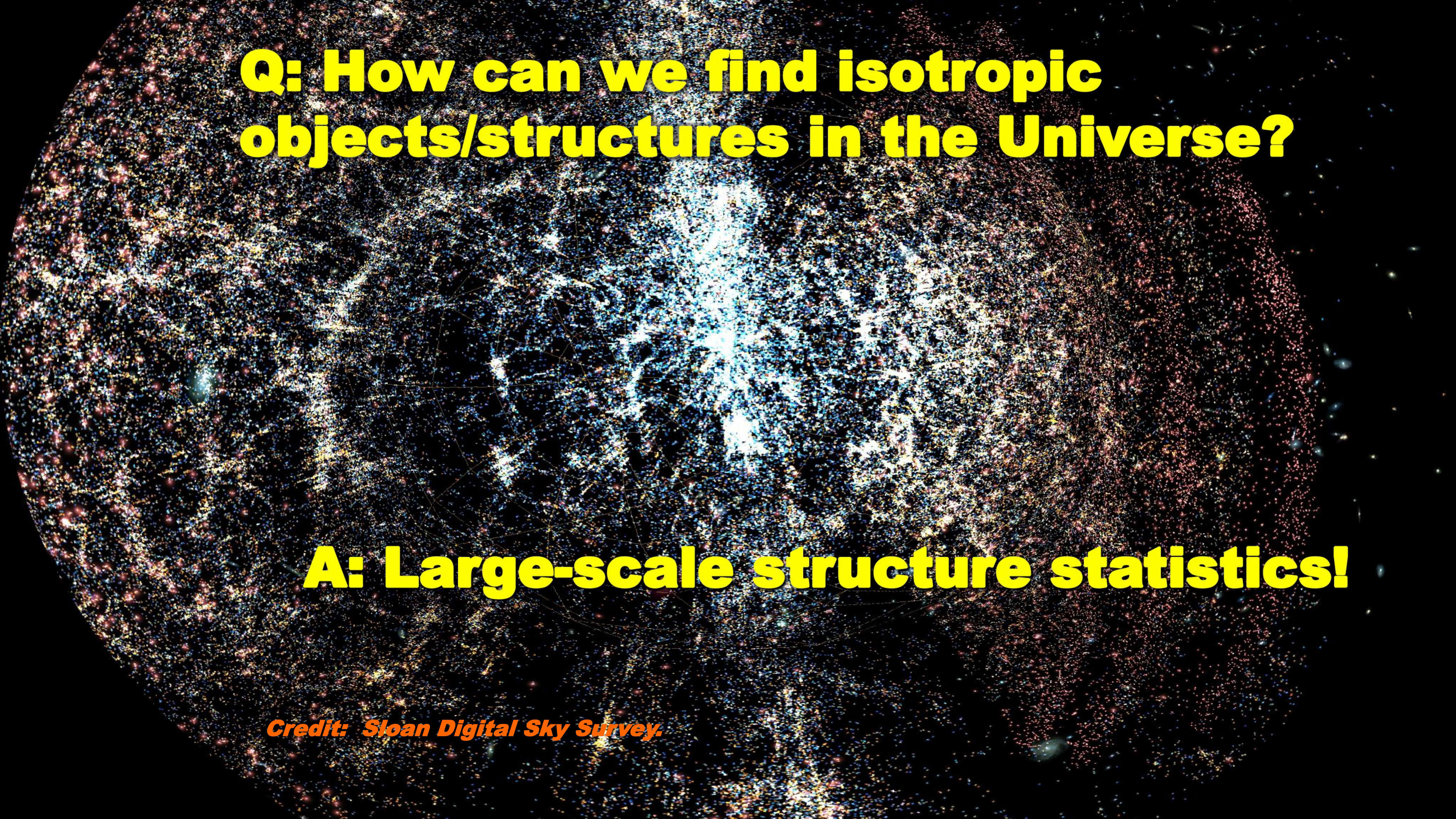
$$\Delta r_{\perp} = (1+z) D_A(z) \Delta\theta$$

$$H(z) = H_0 \sqrt{\Omega_m a^{-3} + (1 - \Omega_m) a^{-3(1+w)}}$$

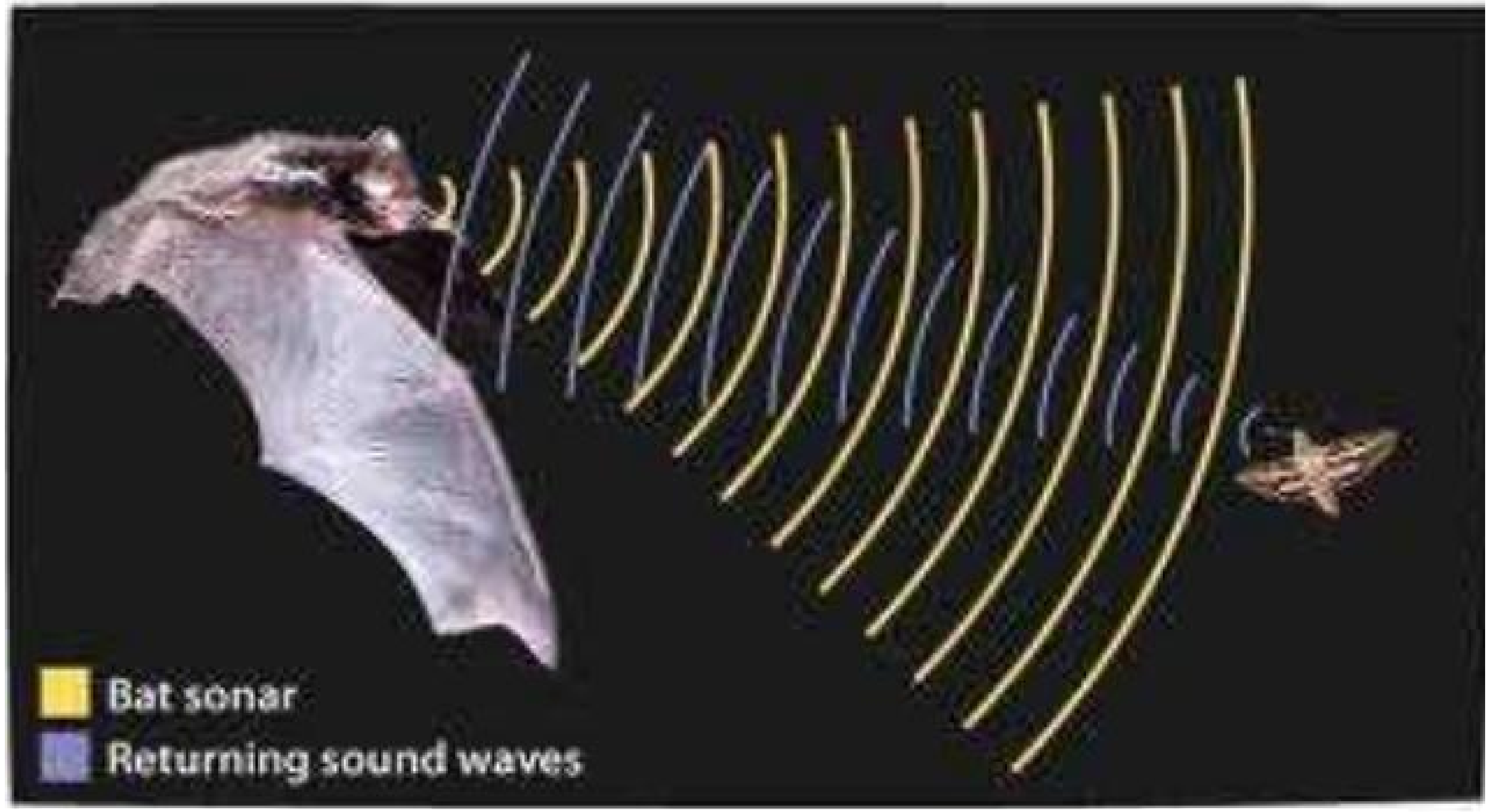
$$D_A(z) = \frac{c}{1+z} r(z) = \frac{c}{1+z} \int_0^z \frac{dz'}{H(z')}$$

In case of using wrong cosmology....

Shape distortion due to wrong H, D_A :

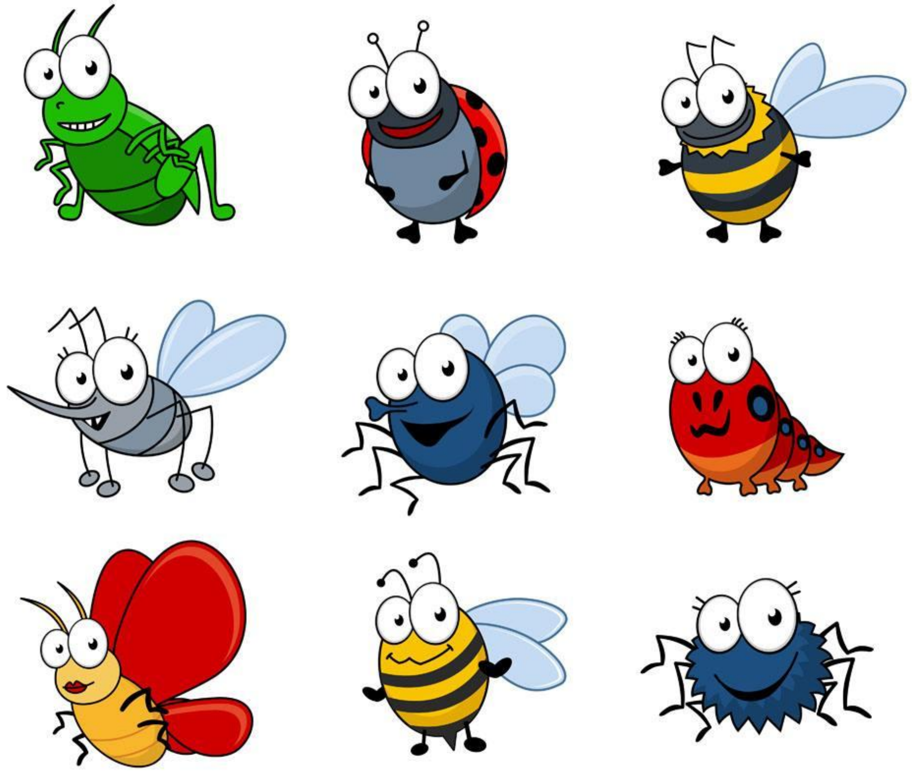


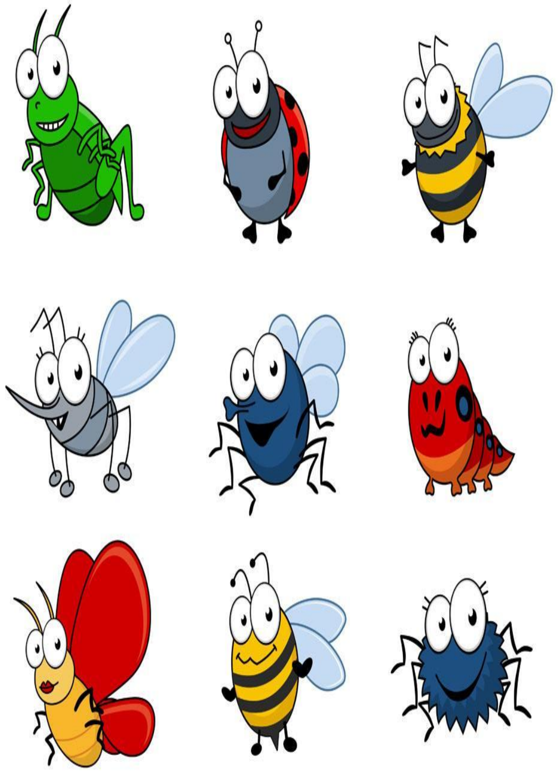
Credit: Sloan Digital Sky Survey.



- The bat can identify an object by the sound of the echo.

The bat's brain converts the received sound into 3d positions.

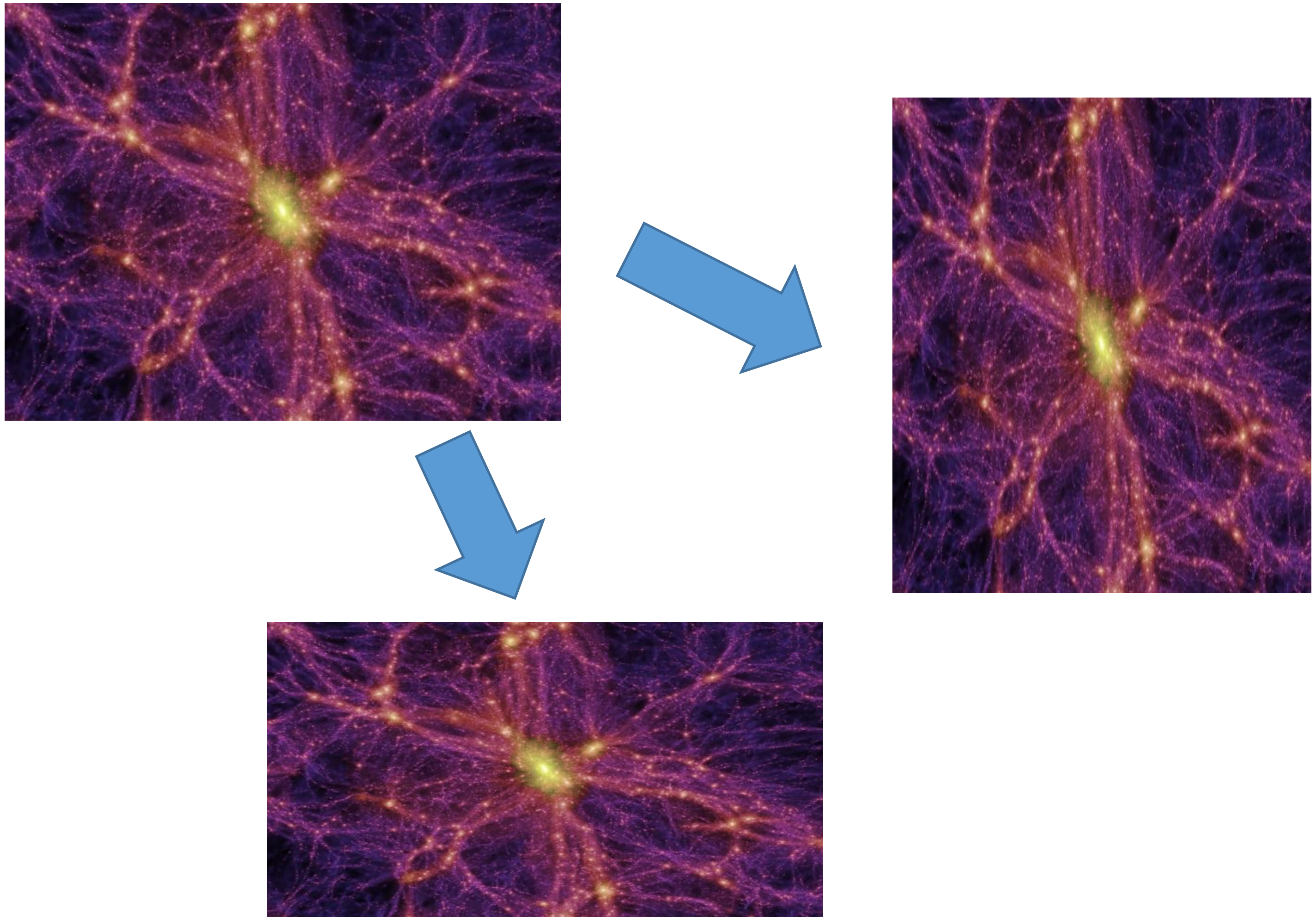




If you see this, something wrong with your brain

AP is very simple (easy modeling)

happens on all scales (including non-linear!)



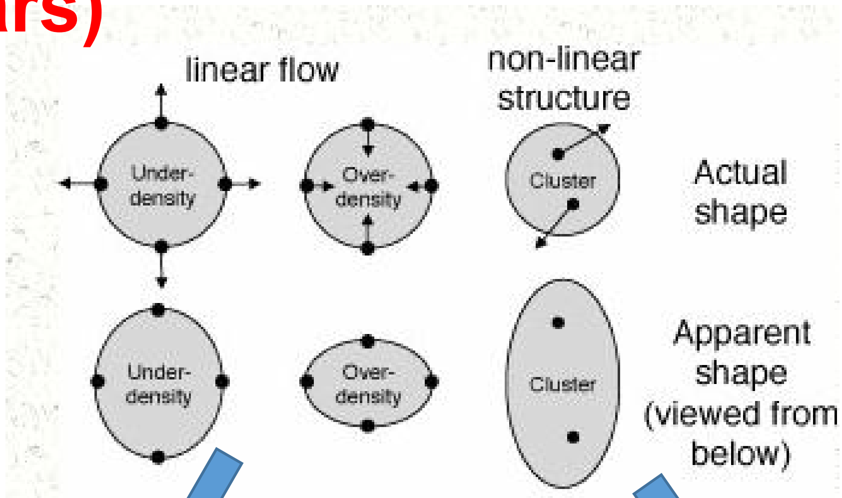
Spread out

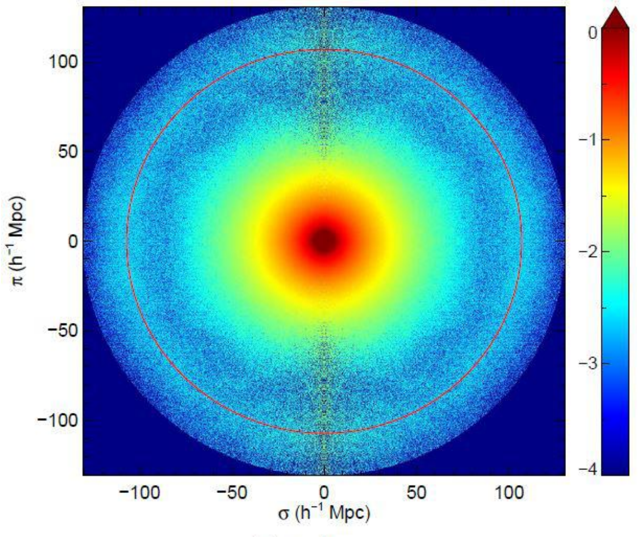
But life is not so simple…

Difficulty: RSD!

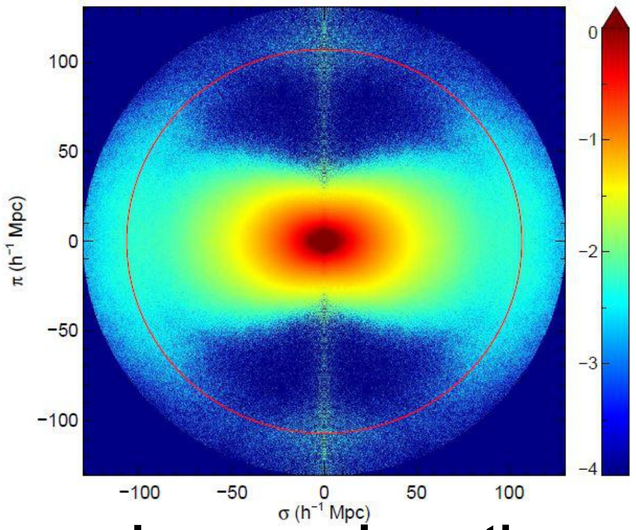
(no good solution for many years)

Anisotropy from peculiar motion

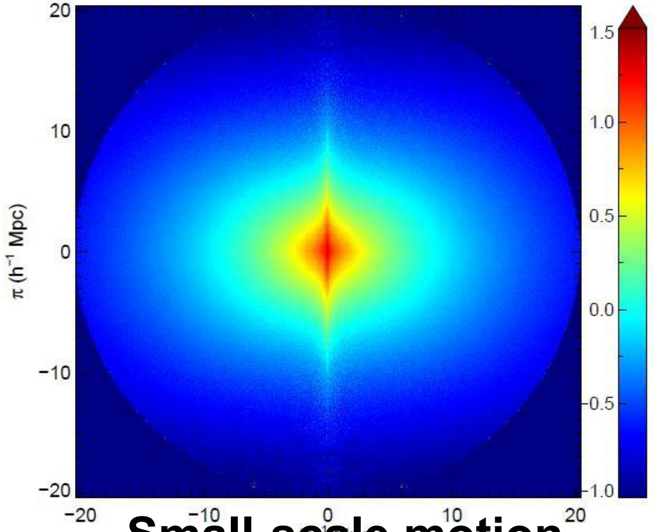




No RSD



Large-scale motion (Kaiser effect)



Small-scale motion (FOG effect)

Difficulty: Contamination from RSD

Strong
（5-10 times larger than AP）

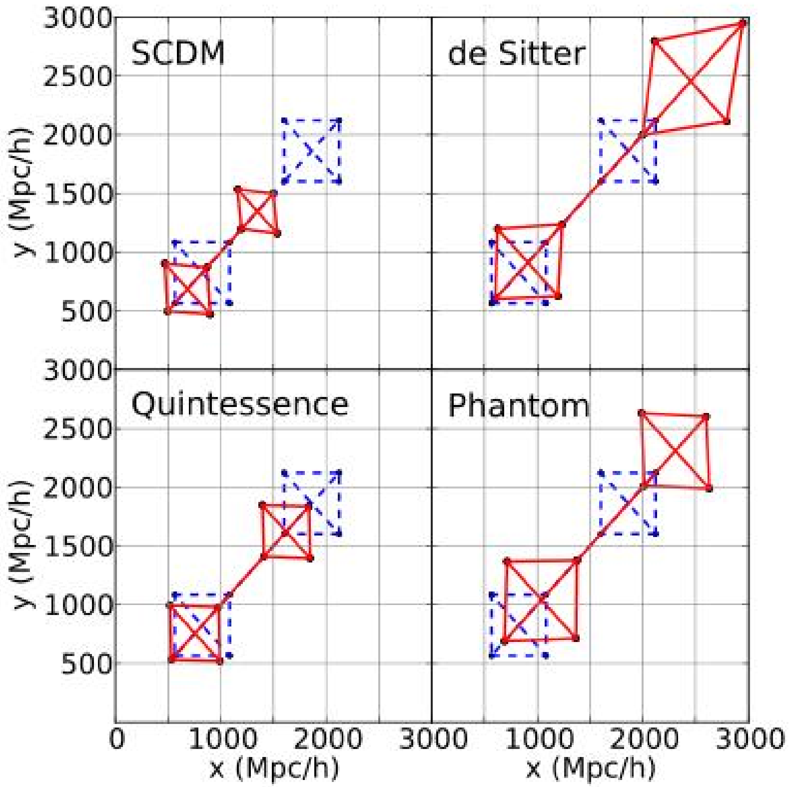
Non-linear, very headache

I want him disappears

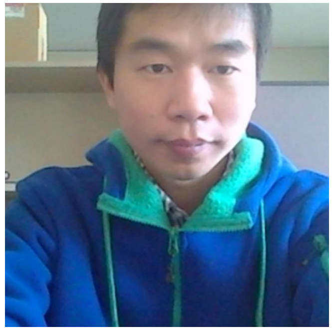
Distinguish AP from RSD?

Li et al, 2014, ApJ, with Prof. Changbom Park @ KIAS

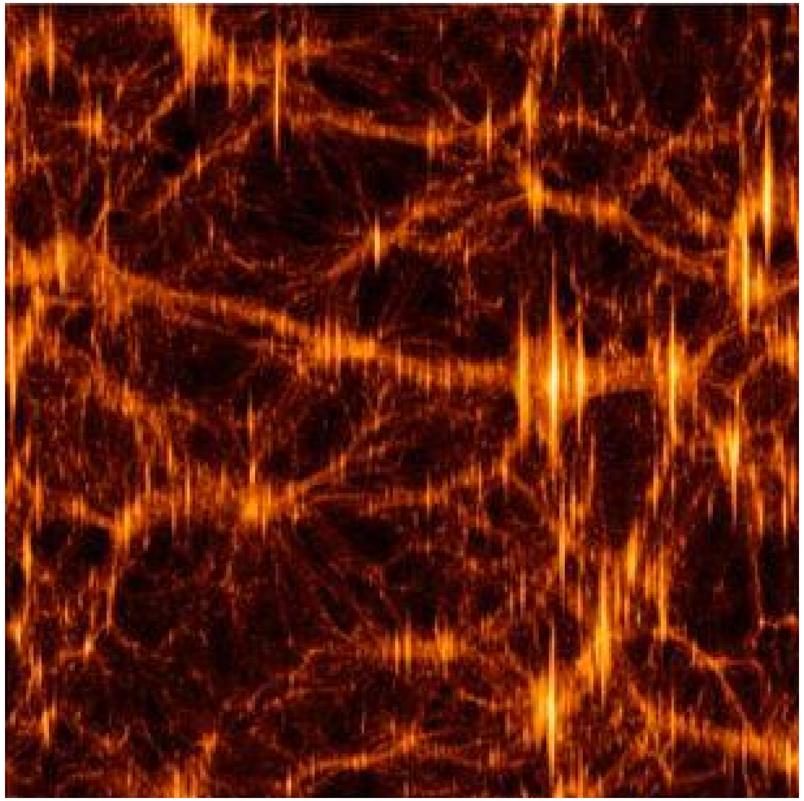
AP in Ω_m=0.26 ΛCDM



I found a hard-working ~~slave~~ postdoc



Well, thank you



AP: significant redshift evolution

RSD: evolves less with redshift

Statistical Quantification via 2PCF

Li, Park, Sabiu, et al. 2015, MNRAS

$$\xi_{\Delta s}(\mu) \equiv \int_{s_{\rm min}}^{s_{\rm max}} \xi(s,\mu)\ ds.$$

$$\hat{\xi}_{\Delta s}(\mu) \equiv \frac{\xi_{\Delta s}(\mu)}{\int_0^{\mu_{\rm max}} \xi_{\Delta s}(\mu)\ d\mu}.$$

Integration scale

6-40 Mpc/h

μ = cos θ
θ = angle between galaxy pairs and LOS

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Test on N-body

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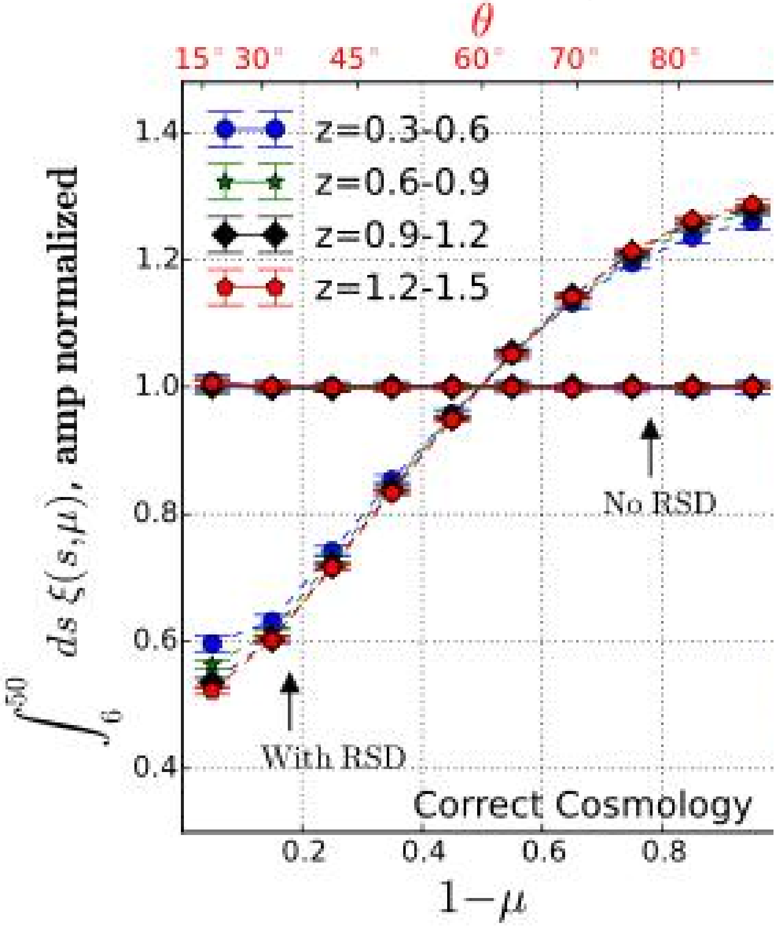

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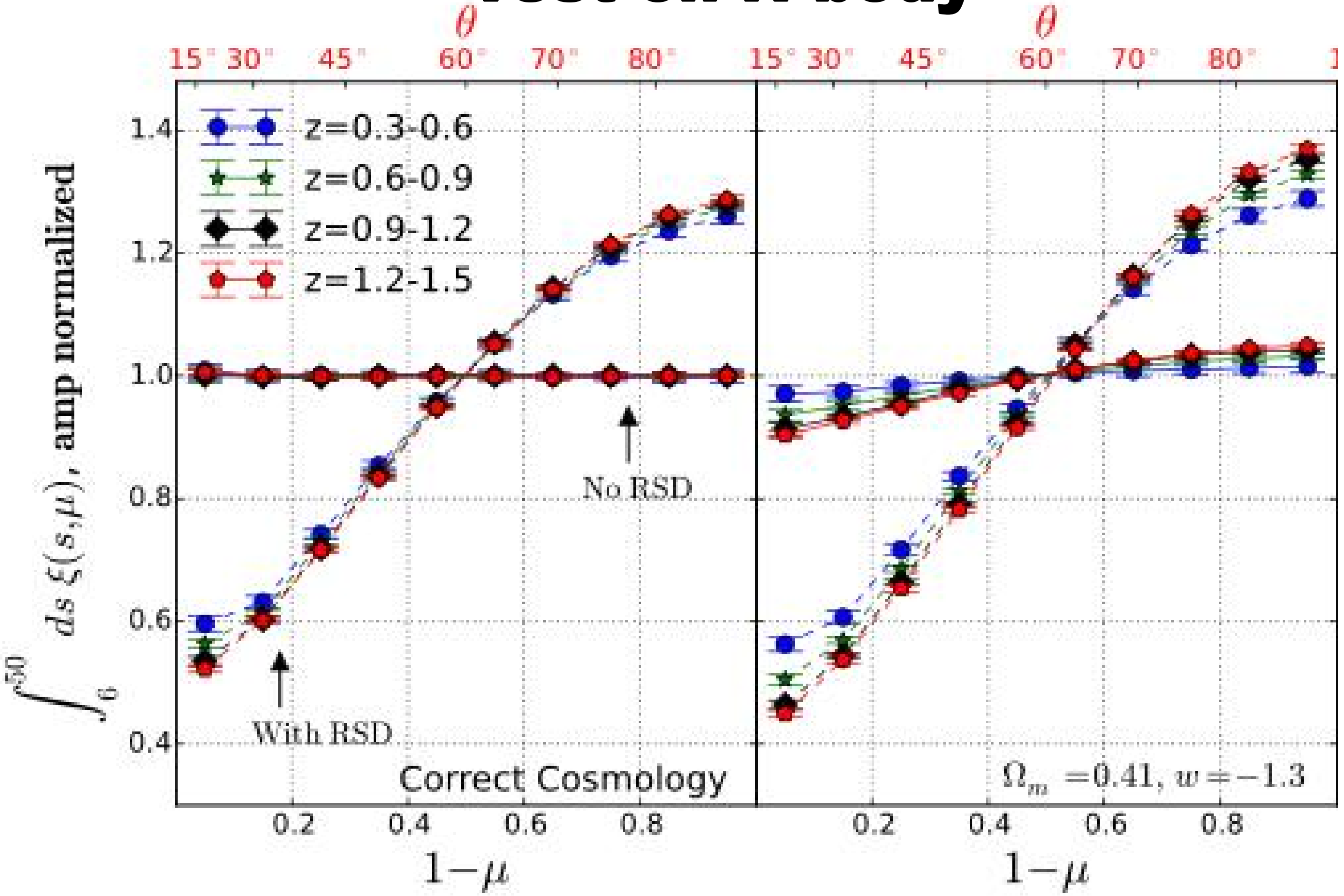
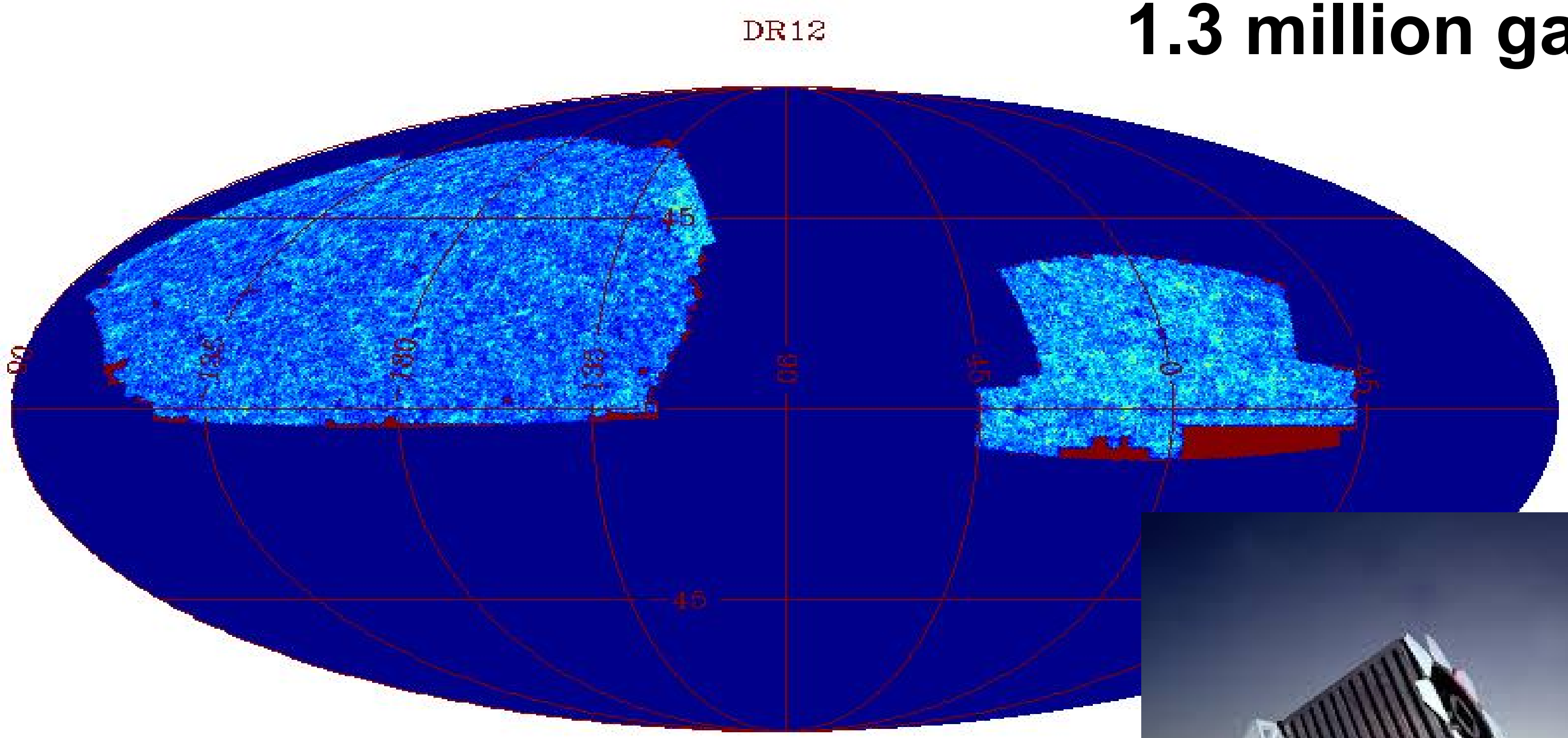


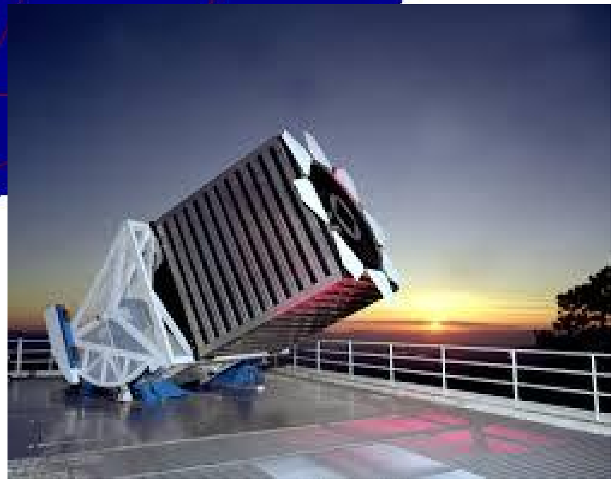
Application to SDSS DR12

Li, Park, Sabiu, et al. 2016, ApJ

1/4 sky, z = 0.15-0.7,
1.3 million galaxies

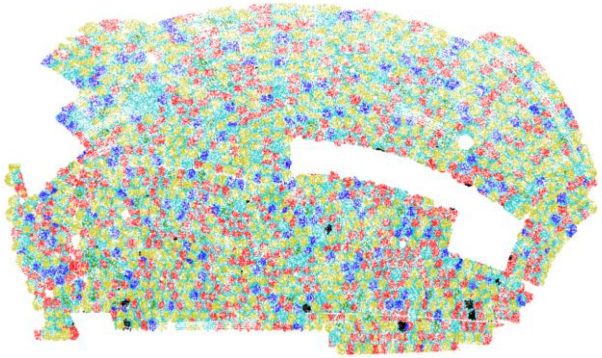


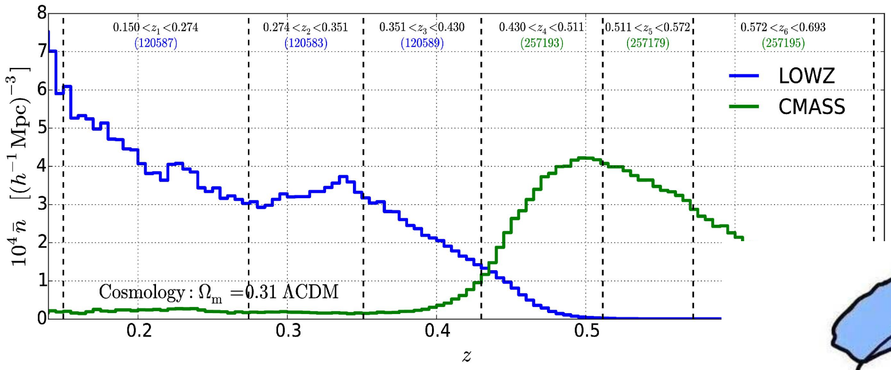
有种的咱就来真的！
A Real fight

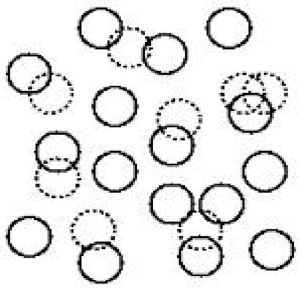


Systematics in real data

1. RSD
2. Galaxy bias
   (affect clustering)
3. Angular variation
4. Radial variation
   (incomplete LF coverage)
5. Fiber collision
   (high-density regions under-sampled)

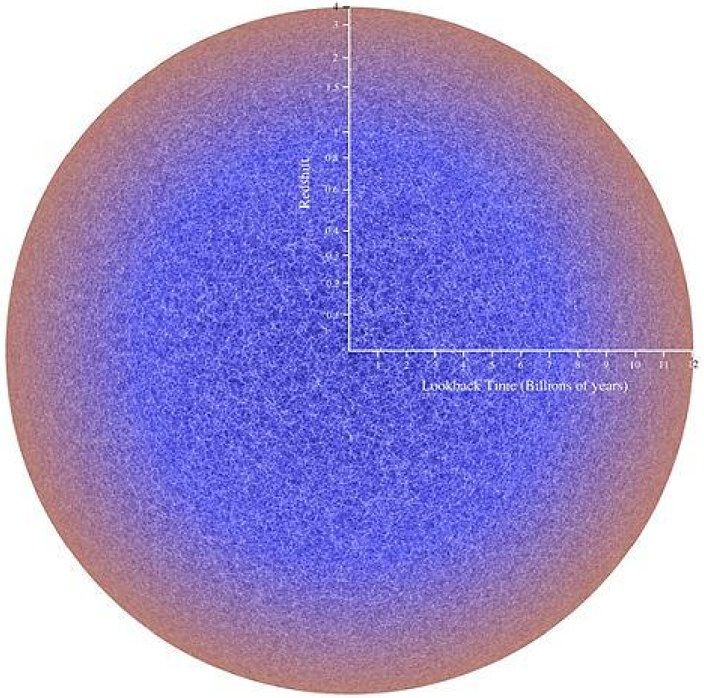


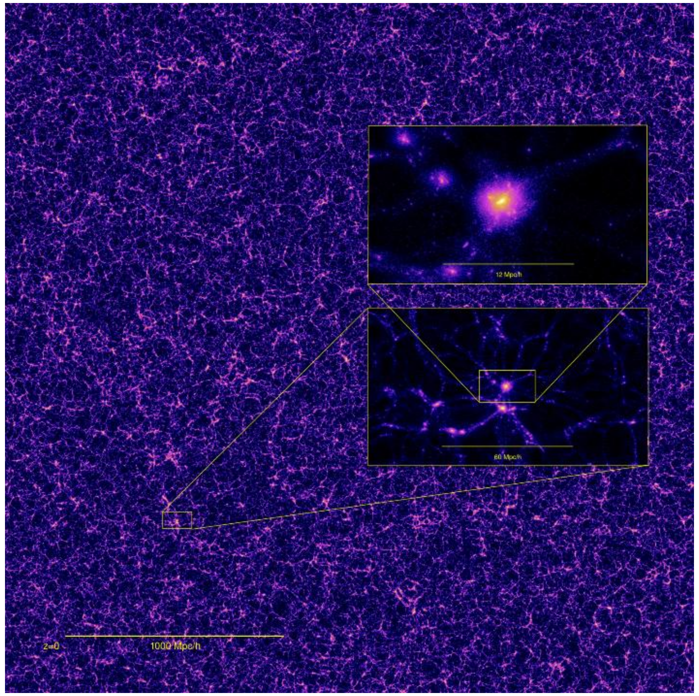




But we can solve them:
Using mocks to simulate everything.

Horizon Run Simulations





HR3 (Kim et al. 2012)

$(10.815\ h^{-1}\ \mathrm{Gpc})^3$

7120^3 particles

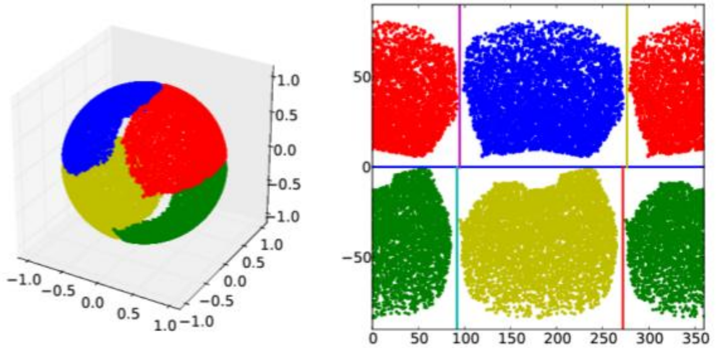
HR4 (Kim et al. 2015)

$(3.15h^{-1}\ \mathrm{Gpc})^3$

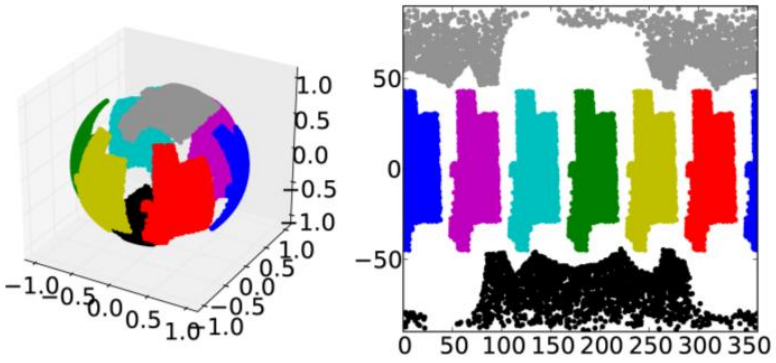
6300^3 particles

Mocks from HR3/HR4

North



South



4 North / 8 South mocks can be made from an all-sky sample.

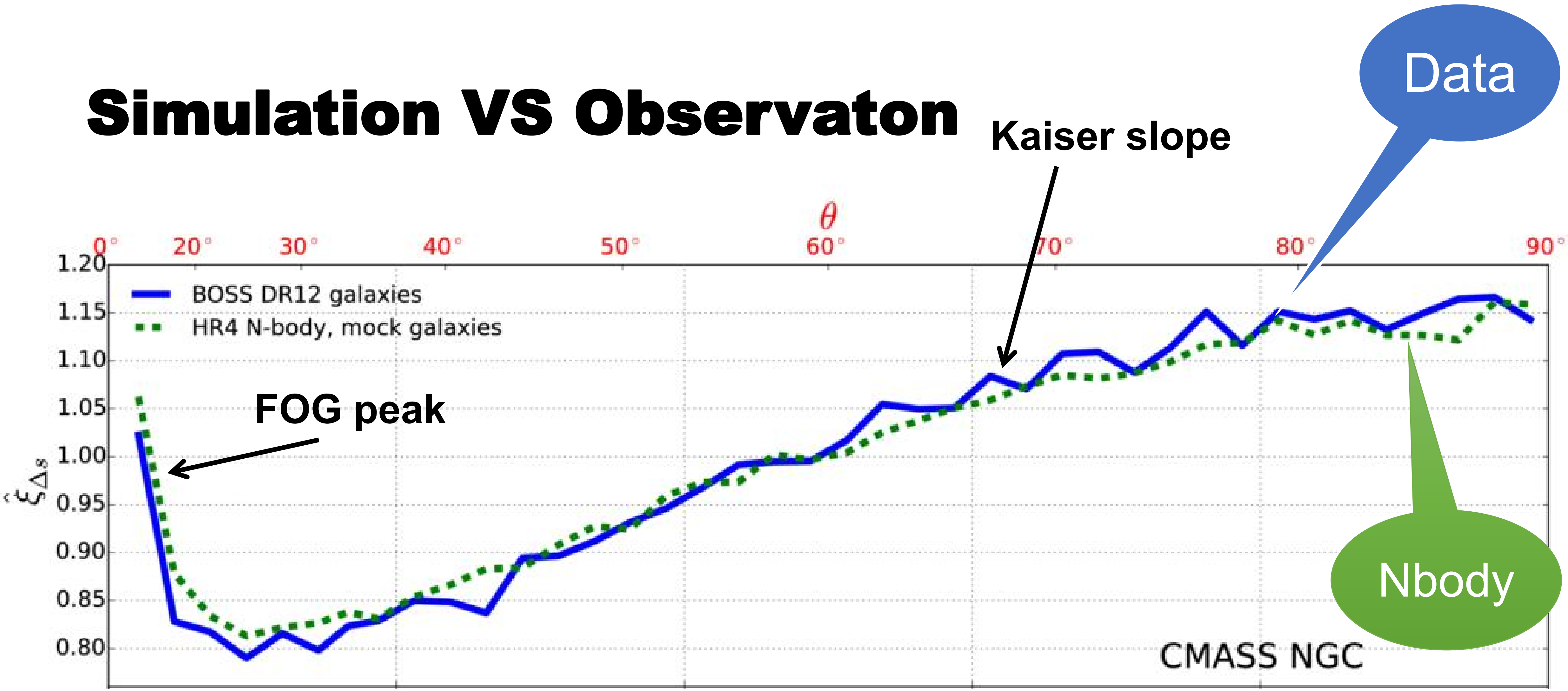
* 108 North / 216 South / 72 North+South mocks made from twenty-seven z<0.7, all-sky lightcones of HR3 PSB halos

- Large number of mocks, suitable for estimating covariance.

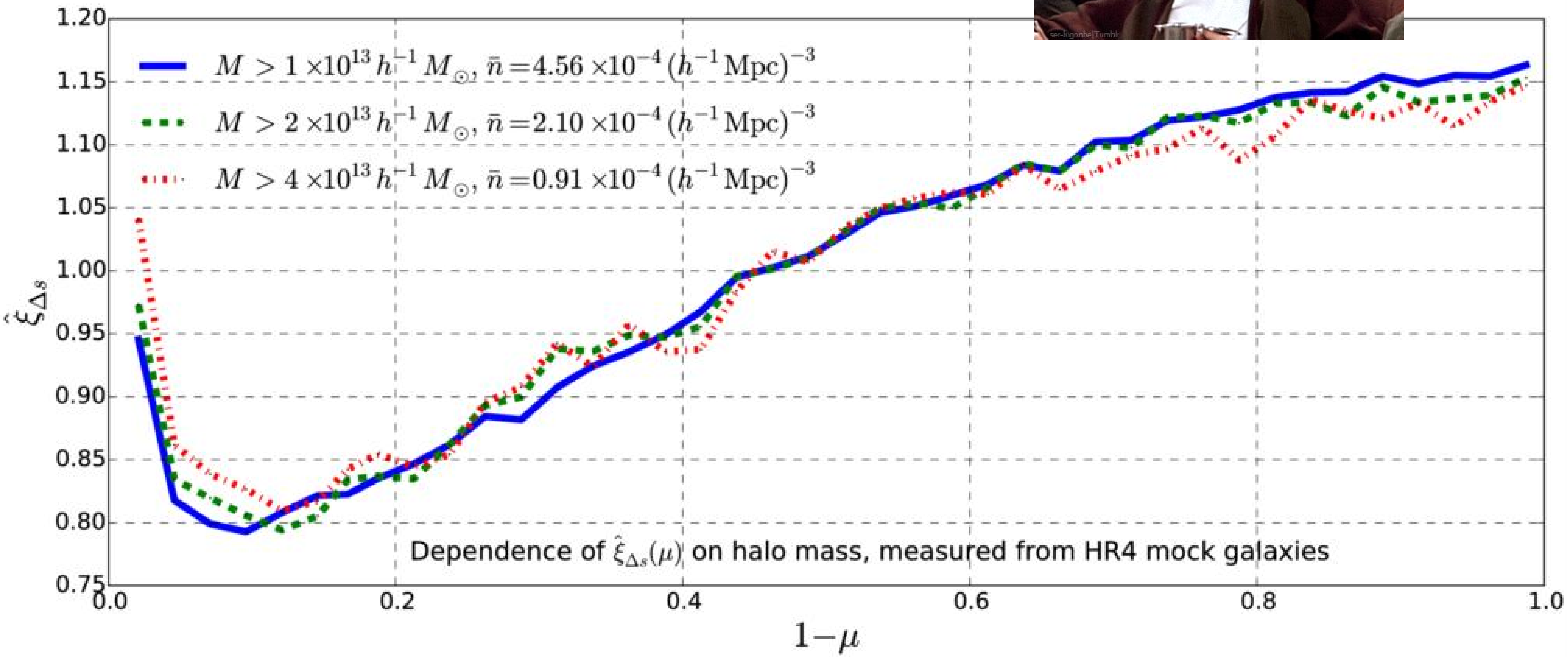
* 4 North / 8 South mocks made from one r<3150 Mpc/h, all-sky lightcone of HR4 mock galaxies

- Faithful to real observational data; suitable for accurate modeling of systematic effects

Simulation VS Observaton

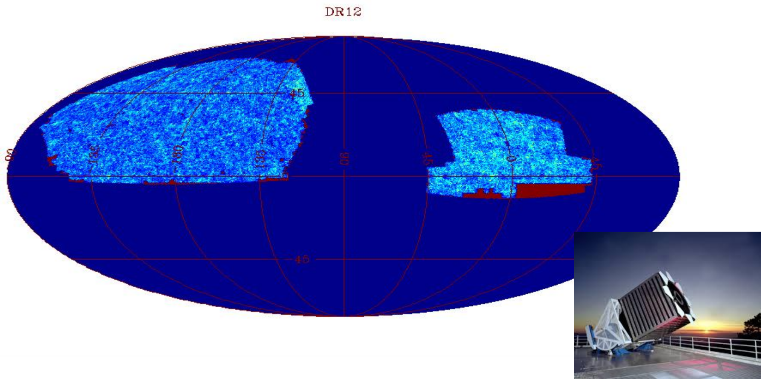


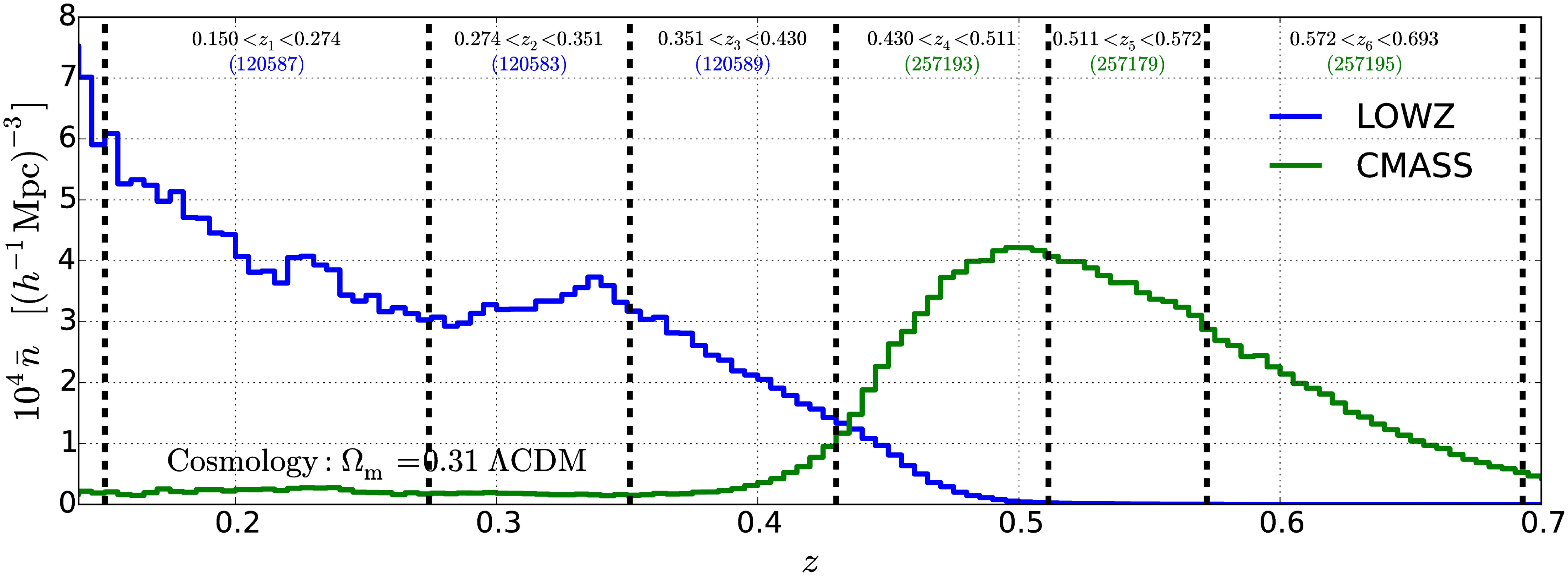
Insensitive to Galaxy Bias



Evolution in 6 bins

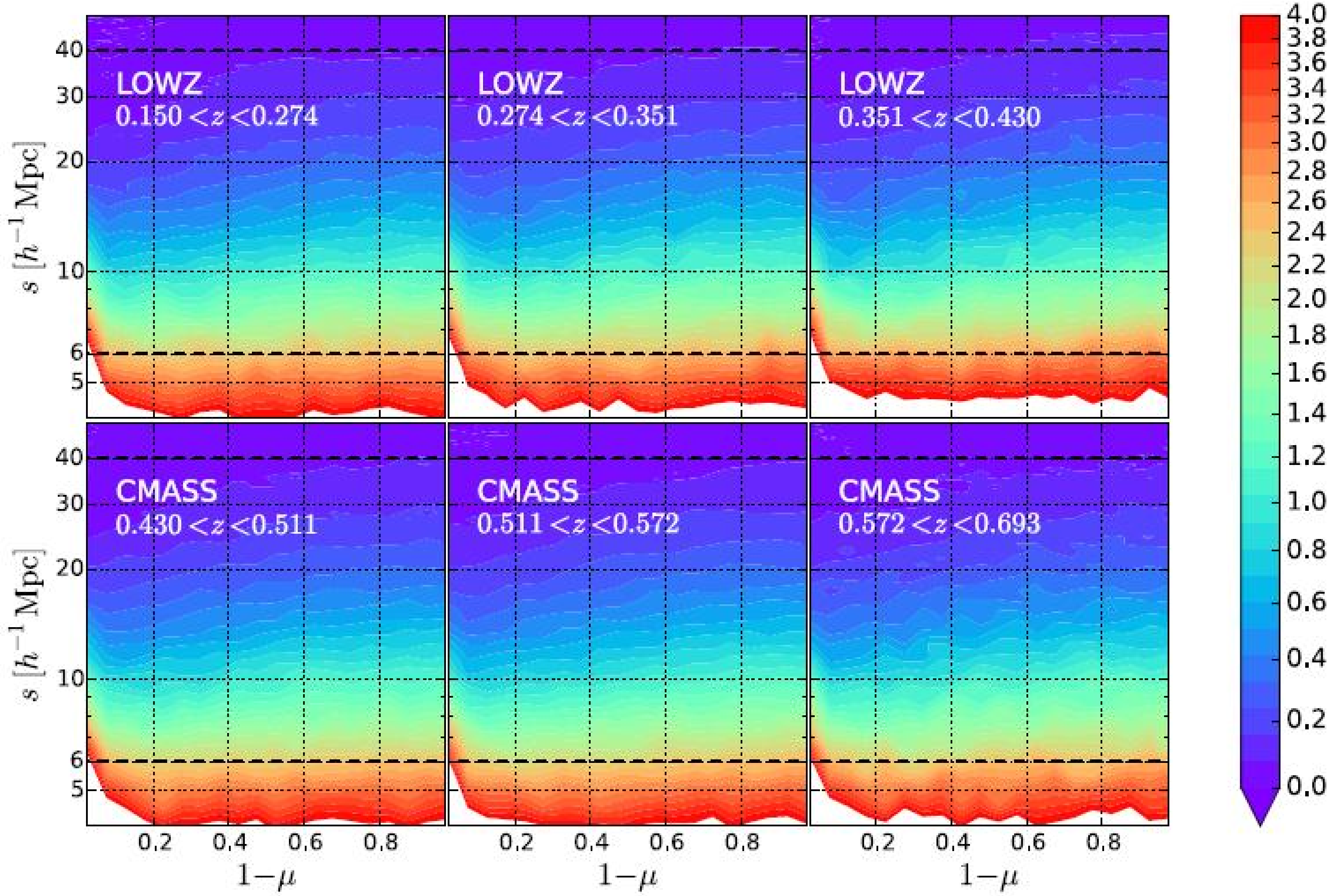
Li, Park, Sabiu, et al. 2016, ApJ

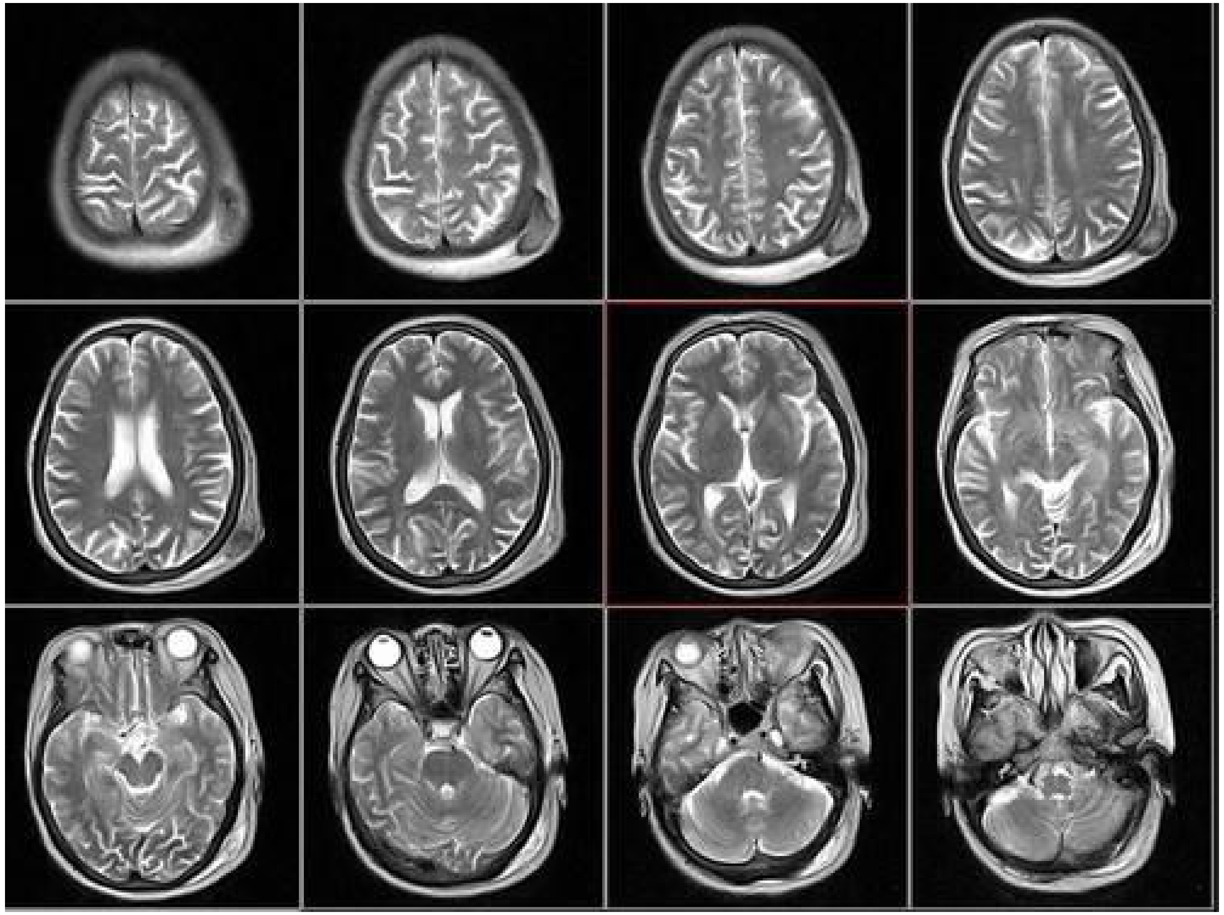




Best-fit = minimal redshift evolution after systematics correction

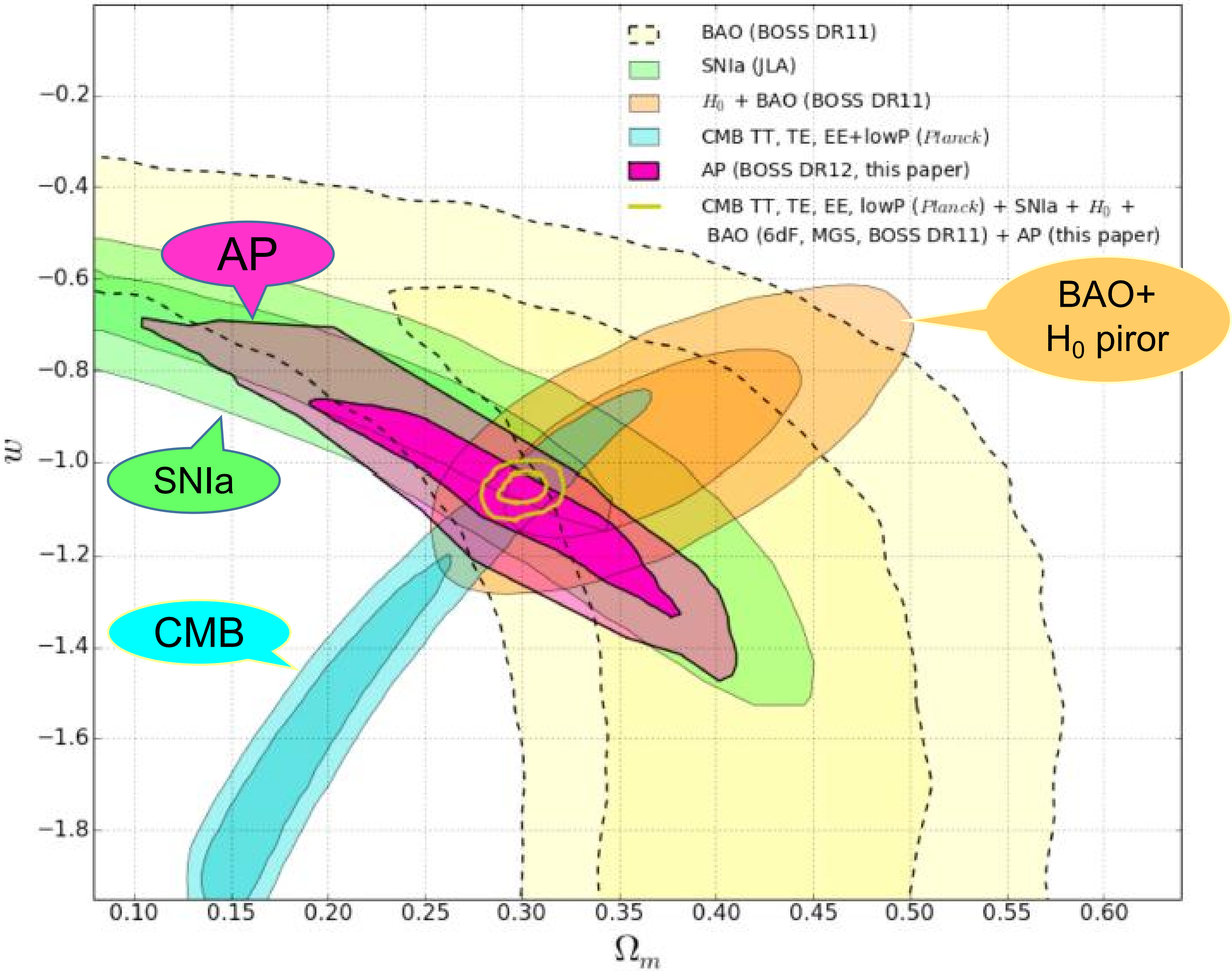
Tomographic Analysis





Tomographic AP applied to SDSS DR

Li, Park, Sabiu, et al. 2016, ApJ



Tighter than SNIa

Consistent with everything.

Combining all:

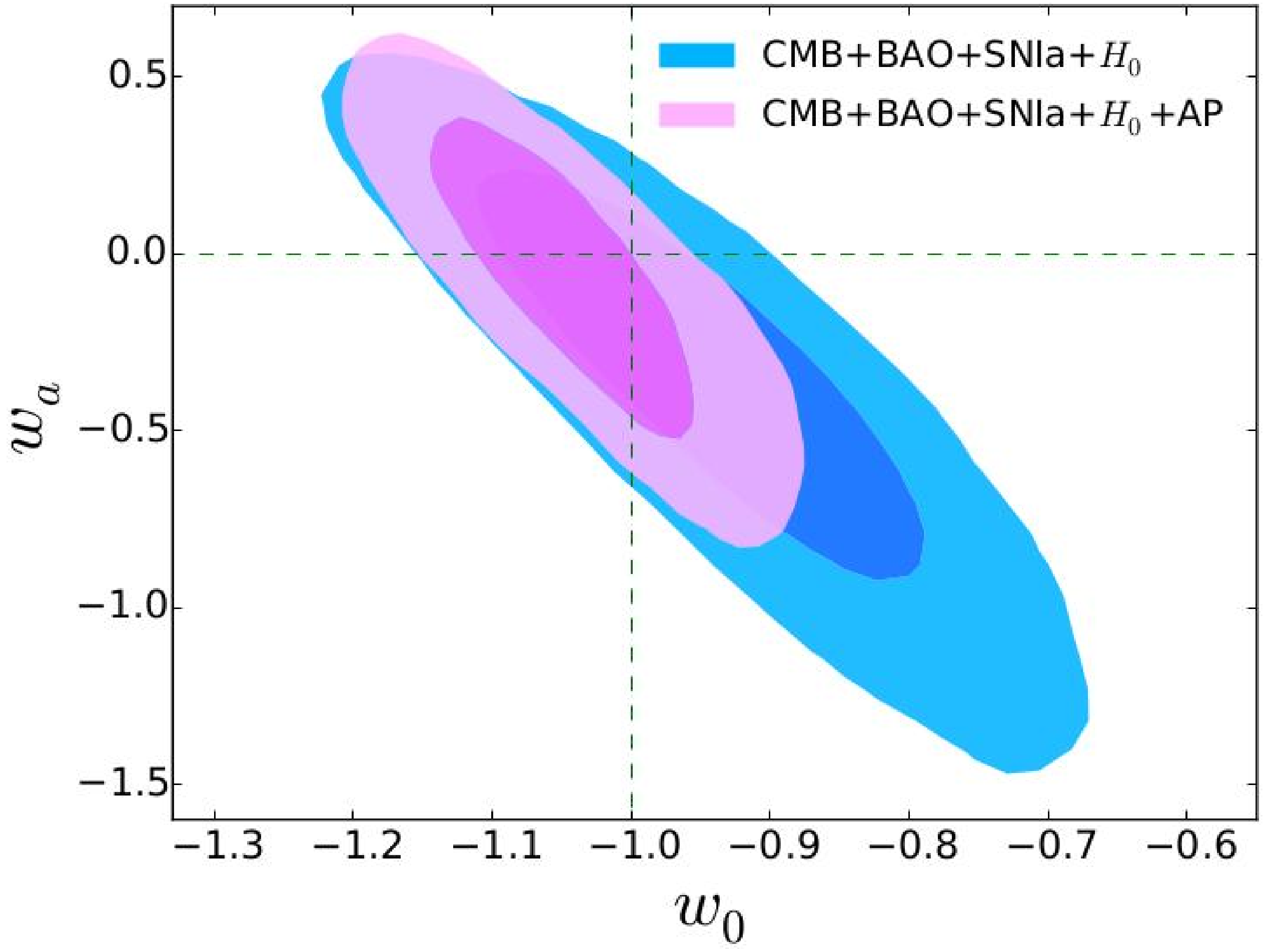
$$\Omega_m = 0.301 \pm 0.006$$

$$w = -1.054 \pm 0.025$$

AP reduces the error of Planck+BAO+SNIa+H0 by 30-40% !

Dynamical dark energy

Li, Sabiu, Park, et al. 2018, ApJ

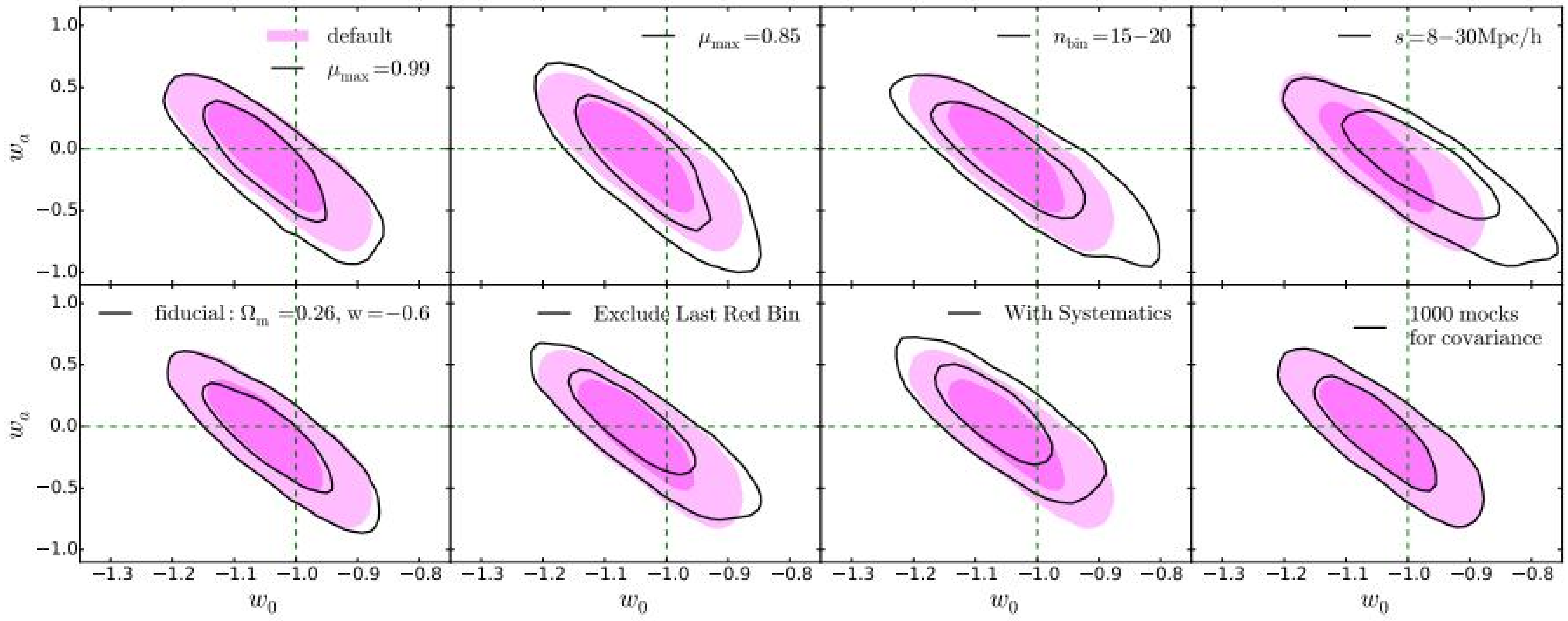


$w = w_0 + w_a\, z / (1+z)$

consistent with cc

AP reduces the contour area by 100%!

Robustness check



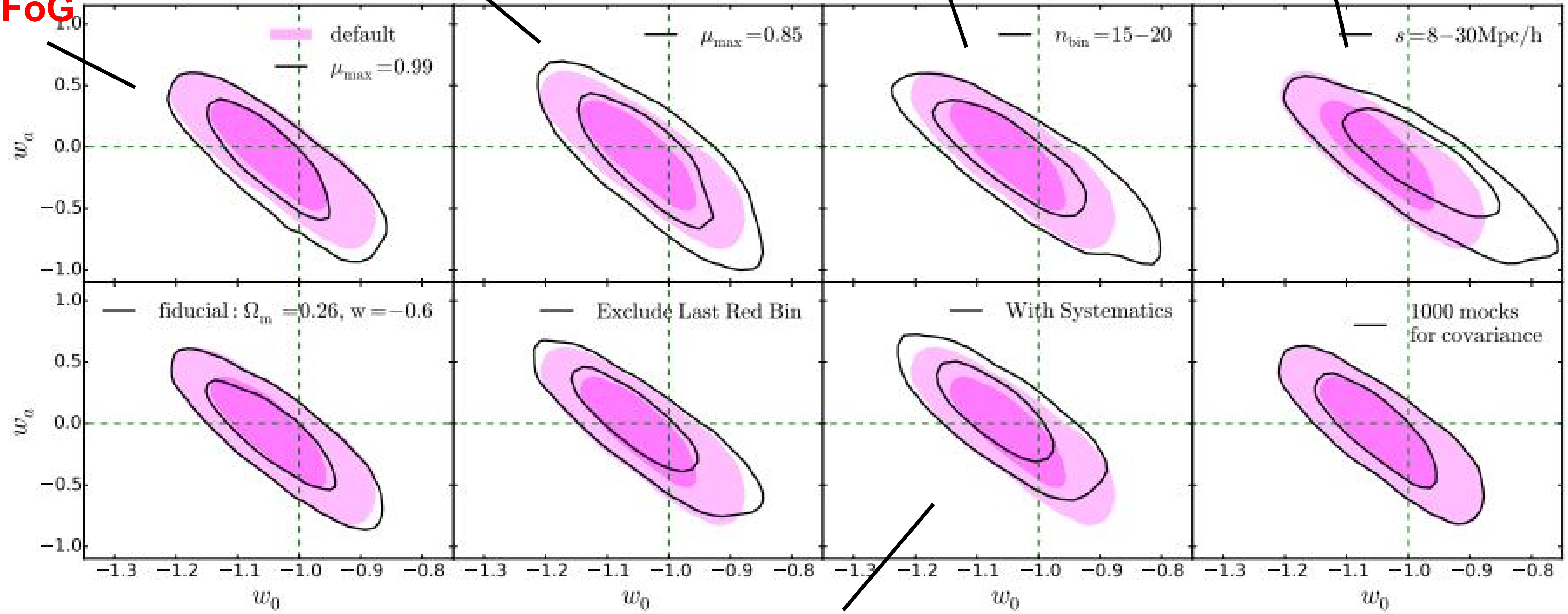
Robustness check

Include
~all FoG

Remove
~all FoG

More conservative
binning

More conservative
clusetering scale



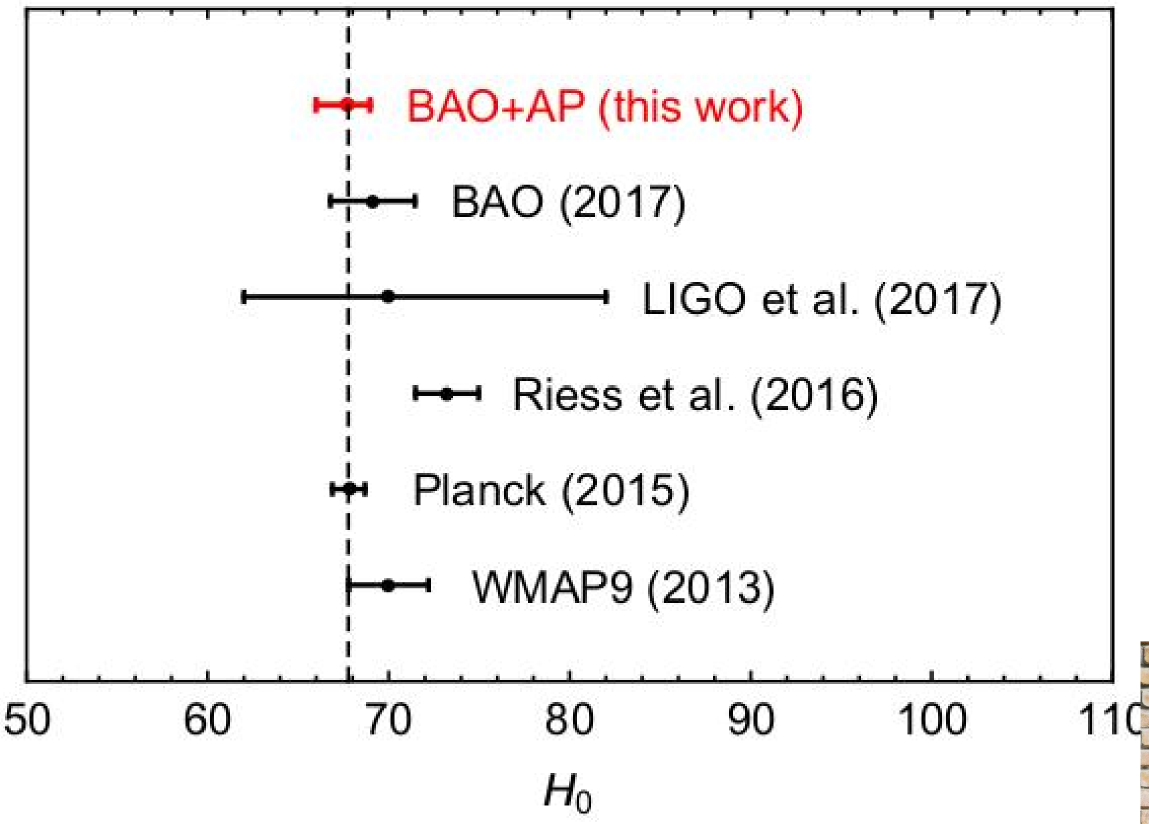
Ignoring all systematics

Cosmological Interpretations

Cosmological Interpretations

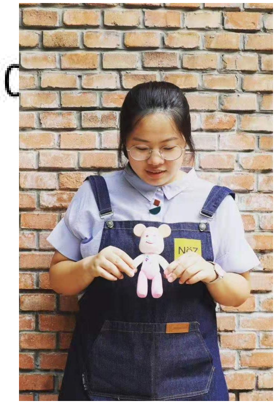
Comological Interpretation

H_0 constraints (1801.07403)



BAO+AP is consistent with CMB

(32% improvement by adding AP)



张雪

理论所博后

Cosmological Interpretations

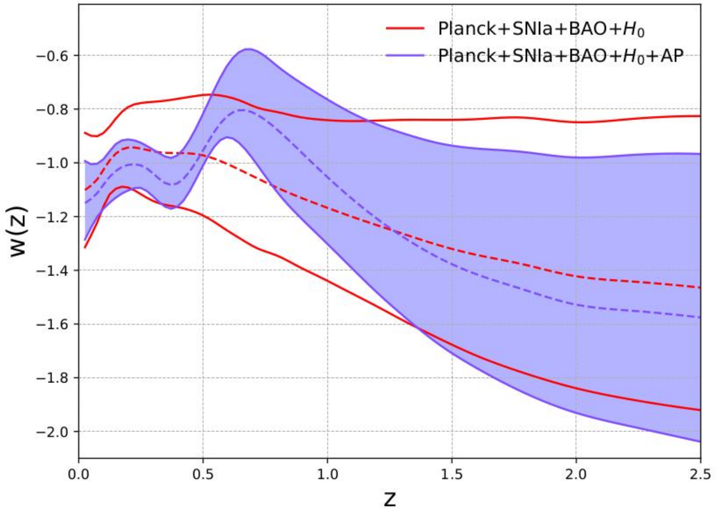
Comological Interpretation

H_0 constraints (1801.07403)

Non-parametric DE constraint (1902.09794)

张震宇
大四

东北大学
李云鹤老师



100% improvement on w(z)

Cosmological Interpretations

张雪
理论所博后

Comological Interpretation

- H_0 constraints (1801.07403)
- Non-parametric DE constraint (1902.09794)
- More parameters (1903.04757)

Parameter	ΛCDM extension		wCDM extension	
	Planck+BAO	+AP	Planck+BAO	+AP
Ω_k	$-0.0002^{+0.0041}_{-0.0040}$	$0.0004^{+0.0042}_{-0.0039}$	$-0.0010^{+0.0066}_{-0.0061}$	$-0.0015^{+0.0042}_{-0.0044}$
$\sum m_\nu$ [eV]	< 0.181	< 0.141	< 0.295	< 0.243
$N_{\rm eff}$	$2.97^{+0.34}_{-0.34}$	$3.07^{+0.33}_{-0.33}$	$2.95^{+0.38}_{-0.37}$	$2.96^{+0.37}_{-0.35}$
$dn_s/d\ln k$	$-0.0023^{+0.0132}_{-0.0138}$	$-0.0025^{+0.0133}_{-0.0136}$	$-0.0024^{+0.0134}_{-0.0136}$	$-0.0025^{+0.0132}_{-0.0139}$
r	< 0.115	< 0.121	< 0.113	< 0.111

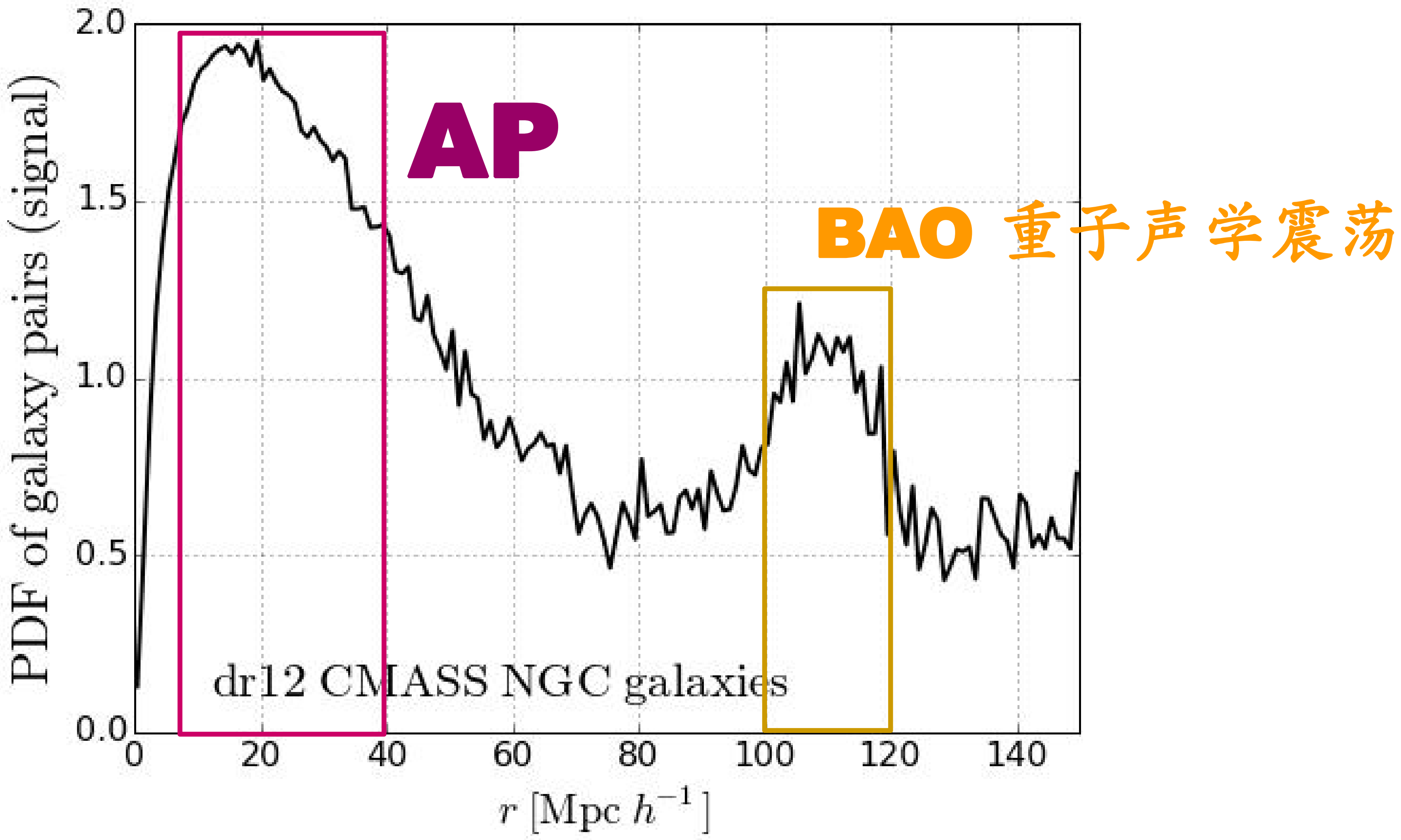
20-30% improvement on Ω_k m_ν $N_{\rm eff}$

I know you have questions.

Let me explain more.

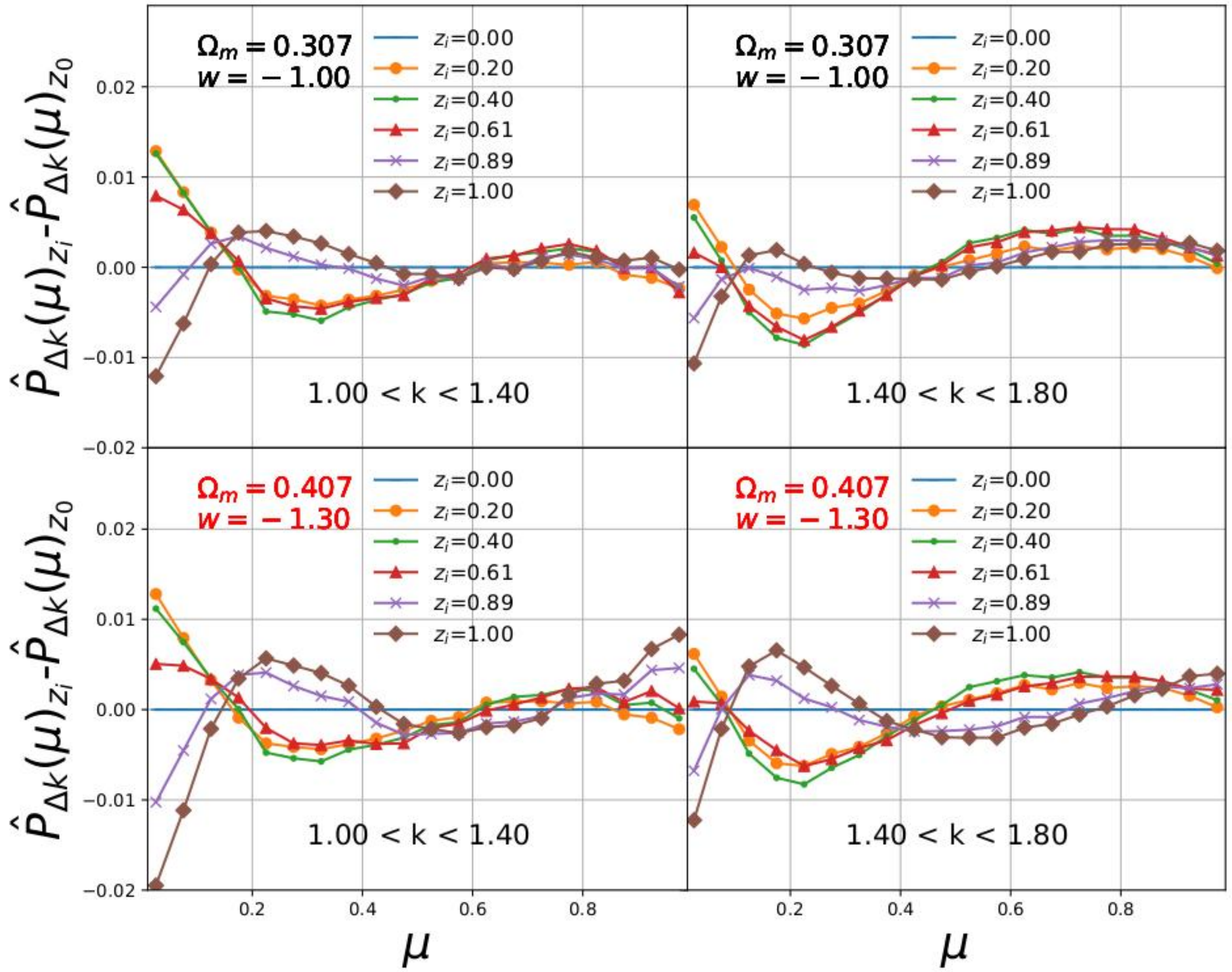
Q: Why results so godd !?

A: By reducing RSD, we can use small-scale clustering.



Actually, method also works for Fourier space

Luo (罗孝麟), Wu, Li, 2019, ApJ



Tomographic AP can work at

k= 1 - 1.8

(test using BigMD Nbody)

Q: But we all know RSD is evolving?!

Q: But we all know RSD is evolving?!

A: We are not saying “RSD is invariant”.

We should say, “in many models AP evolves larger than RSD, these models can be ruled out by our method”.

Also, we do correct RSDs via simulations. We are even planning a model-dependent correction.

Q: “Small evolution of RSD” is just “a phenomenon you find”. You don't have solid proof.

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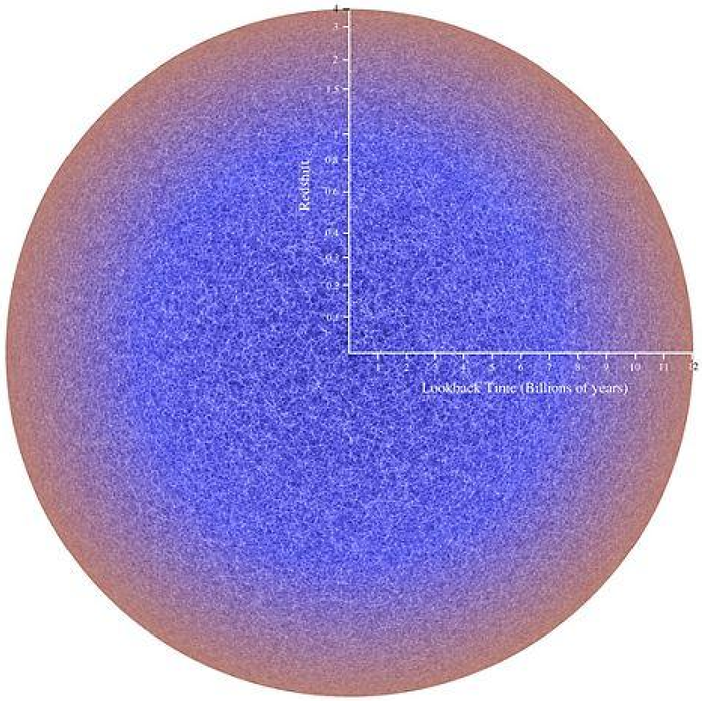
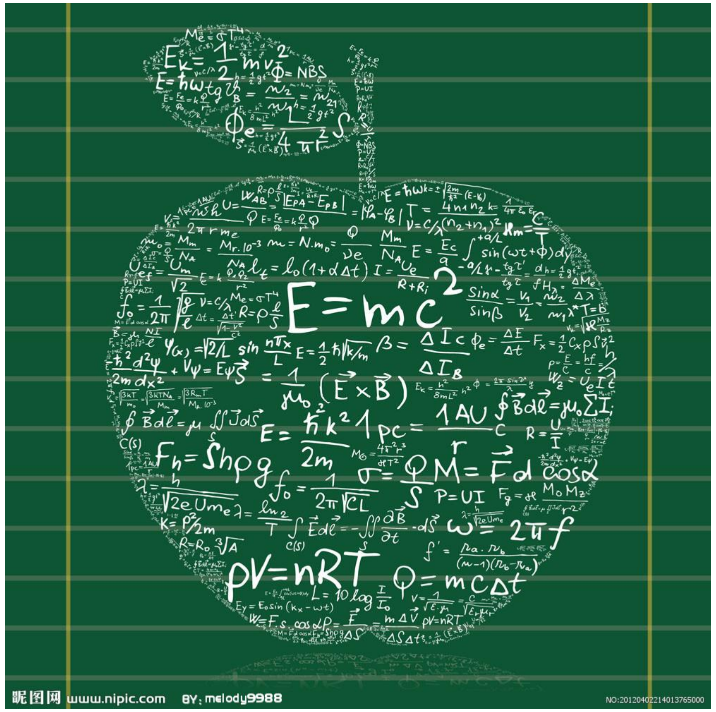
A: 1) On non-linear scales, N-body is a kind of “the best theory”



Q: “Small evolution of RSD” is just “a phenomenon you find”. You don't have solid proof.

A: 1) On non-linear scales, N-body is a kind of “the best theory”

2) If you only rely on analytical approach, you will miss many things



VS

Q: "Small evolution of RSD" is just "a phenomenon you find". You don't have solid proof.

A: 1) On non-linear scales, N-body is a kind of "the best theory"

2) If you only rely on analytical approach, you will miss many things

3) Simulation-based approach is the future trend (emulation, machine learning, ...)

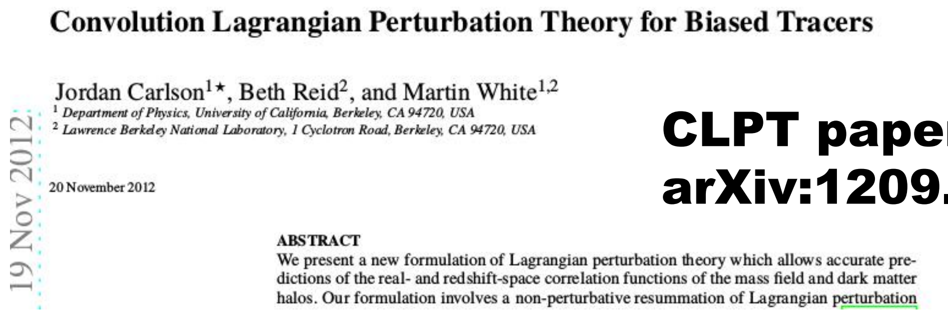
Q: “Small evolution of RSD” is just “a phenomenon you find”. You don't have solid proof.

A: 1) On non-linear scales, N-body is a kind of “the best theory”

2) If you only rely on analytical approach, you will miss many things

3) Simulation-based approach is the future trend (emulation, machine learning, ...)

4) Actually, we are trying to “prove it” using CLPT ...



Convolution Lagrangian Perturbation Theory for Biased Tracers

Jordan Carlson[1★], Beth Reid[2], and Martin White[1,2]
[1] Department of Physics, University of California, Berkeley, CA 94720, USA
[2] Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA

19 Nov 2012

20 November 2012

ABSTRACT
We present a new formulation of Lagrangian perturbation theory which allows accurate predictions of the real- and redshift-space correlation functions of the mass field and dark matter halos. Our formulation involves a non-perturbative resummation of Lagrangian perturbation

CLPT paper
arXiv:1209.0780

王小马
大四

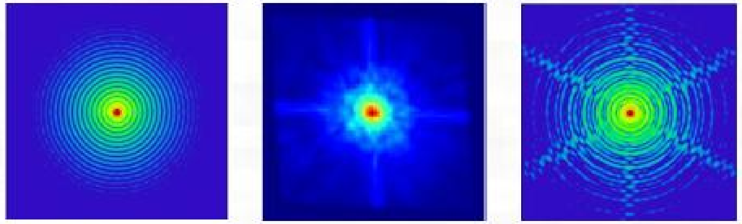
Preparations for future data (preliminary)

Project	Site/ orbit	Launch /op	FoV	R_{EE80}	Num pixels	Area	Wavelength	Num Filters	Spect
			deg^2	"	10^9	deg^2	nm		
CSS-OS	LEO	~2022	1.1	0.15	2.5	17500	255—1000	≥7	yes
Euclid	L2	2020	0.56 0.55	>0.2 pix lmt	0.6 0.07	15000	550—920 1000—2000	1 3	no yes
WFIRST	L2	2025	0.28	>0.2	0.3	~2000	927—2000	4	yes
LSST	Chile	2022	9.6	~0.7	3.2	18000	320—1050	6	no

R_{EE80}: radius encircling 80% energy

	Space Station	HST/ACS WFC	Euclid	WFIRST
R_{EE50}	0.1"	0.06"	0.13"	0.12"
R_{EE80}	0.15"	0.12"	~0.23"	~0.24"

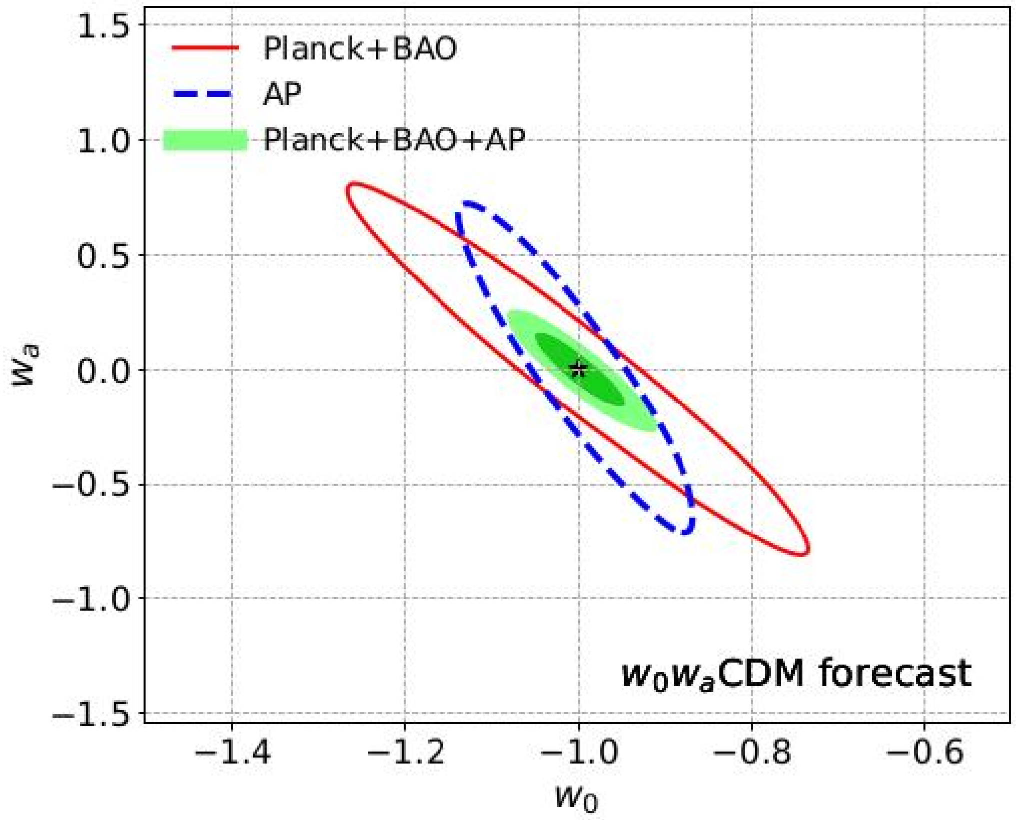
Best image quality among surveys!



CSS-OS HST Euclid

By Zhan Hu

DESI Forecast



张雪
理论所博后

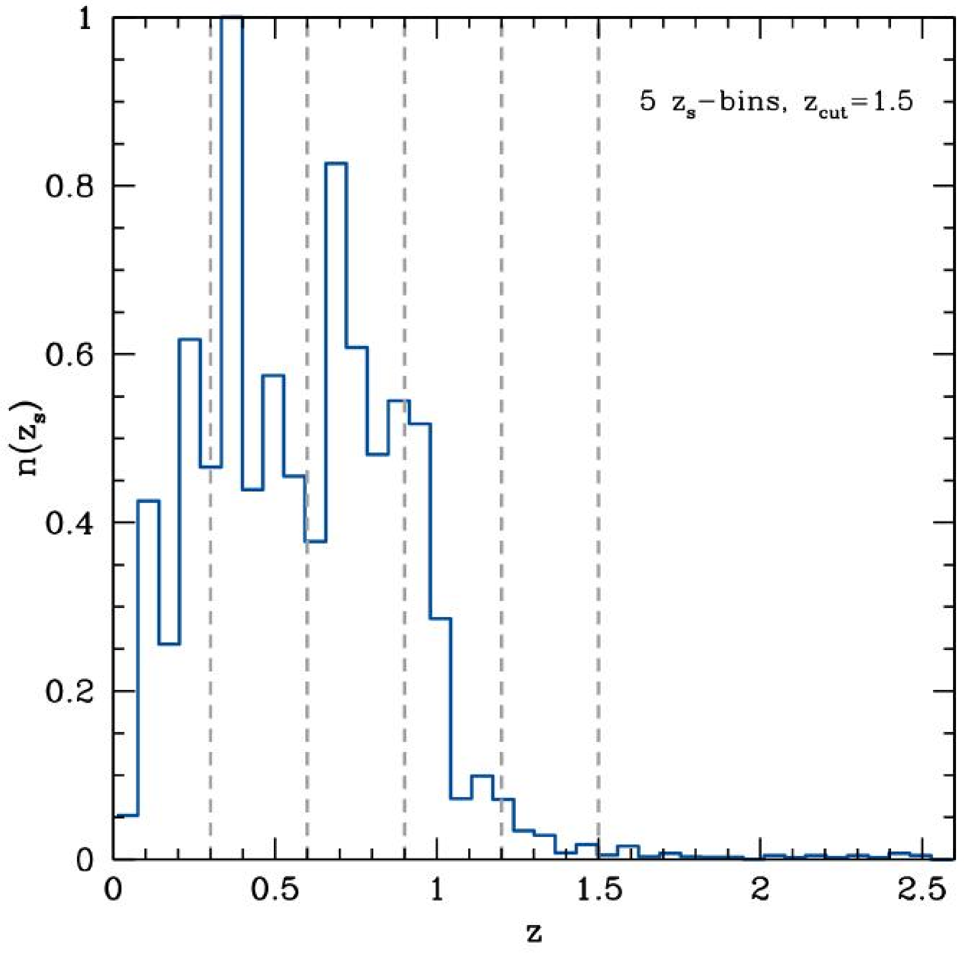
If we can control systematcis, then Planck+DESI BAO/AP is10 times better than Planck+ DESI BAO

Challenges

Big Data (expensive mocks)

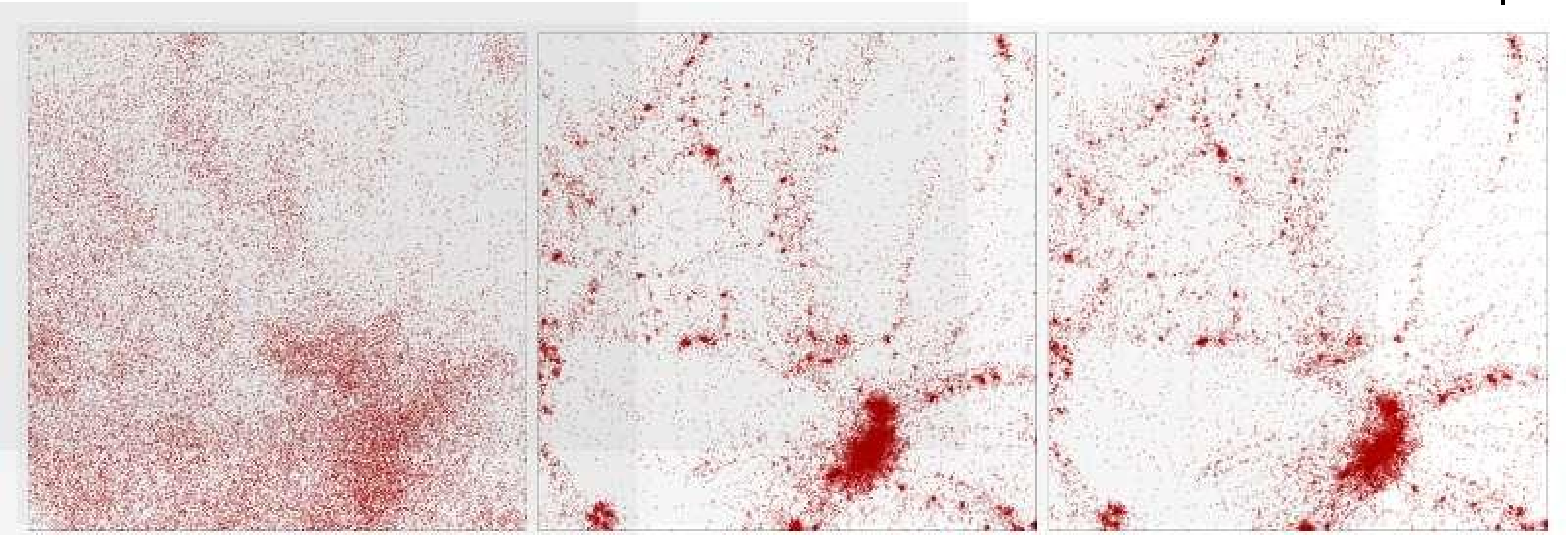
Big Covmat (many, redshfit bins)

Systematic error becomes critical !
(worry about the cosmological dependence of the RSDs)



Fast mocks using COLA algorithm
(COLA paper: arXiv:1301.0322)

boxsize = 100 Mpc/h



2LPT

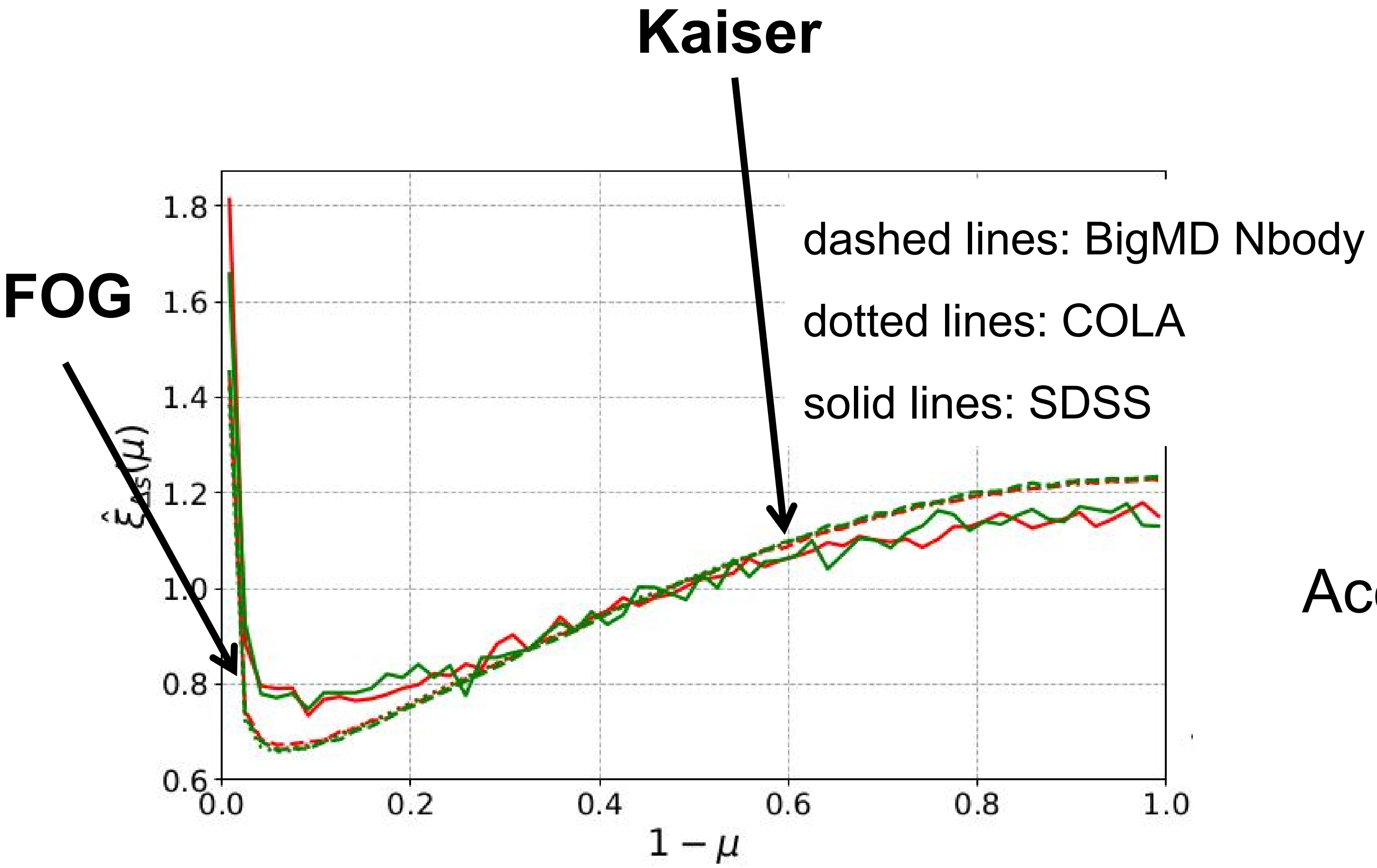
COLA, 10 timesteps

N-body, 2000 timesteps

CLOA strategy = Lage-scale 2LPT + small-scale Nbody

RSD estimation using COLA

Ma, Guo, Li, et al., 2020, ApJ



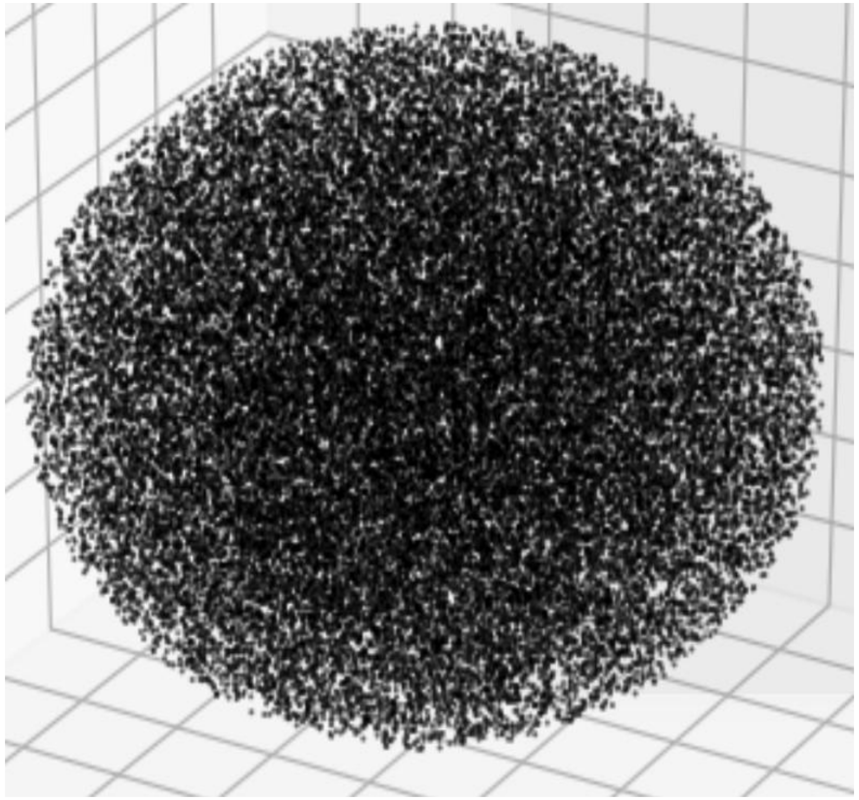
马庆麟

大三

Accuracy of **COLA** seems to be good

COLA in lightcone

(Using L-PICOLA code: arXiv:1506.03737)



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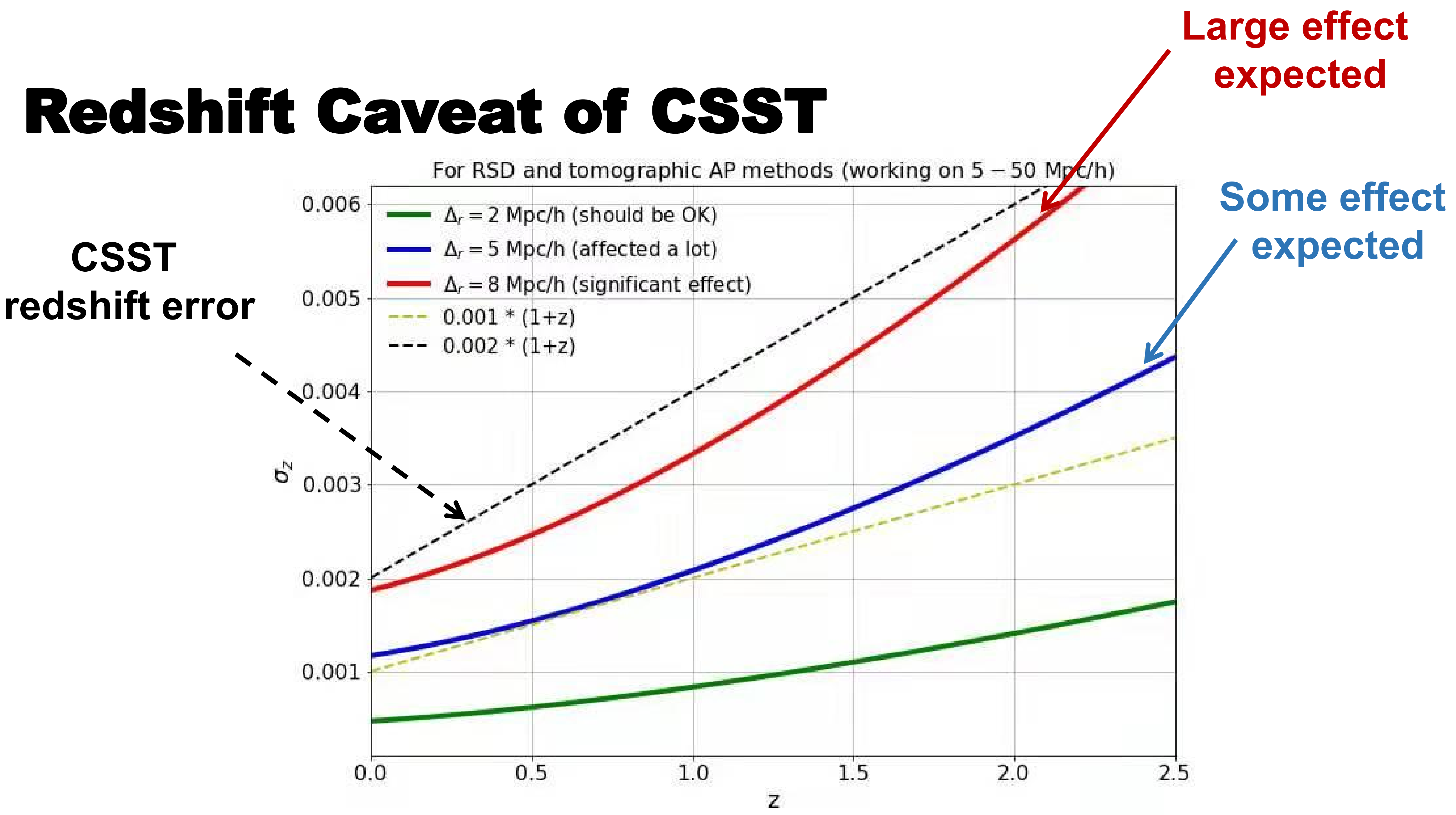
3000^3 particles, ~100 cores,

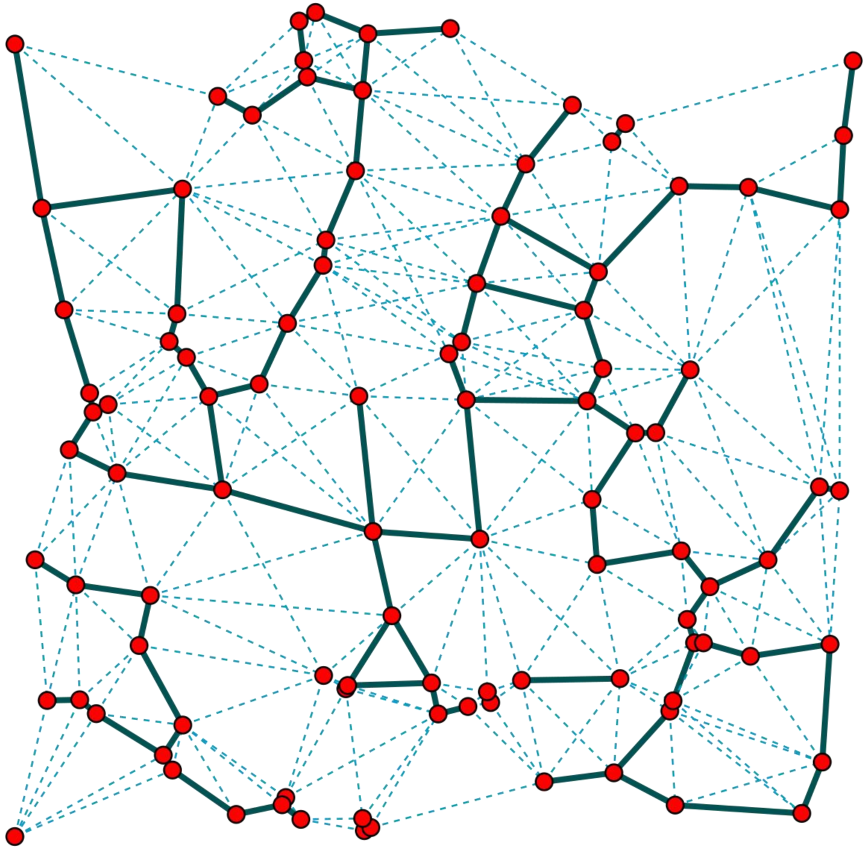
finished in ~ weeks

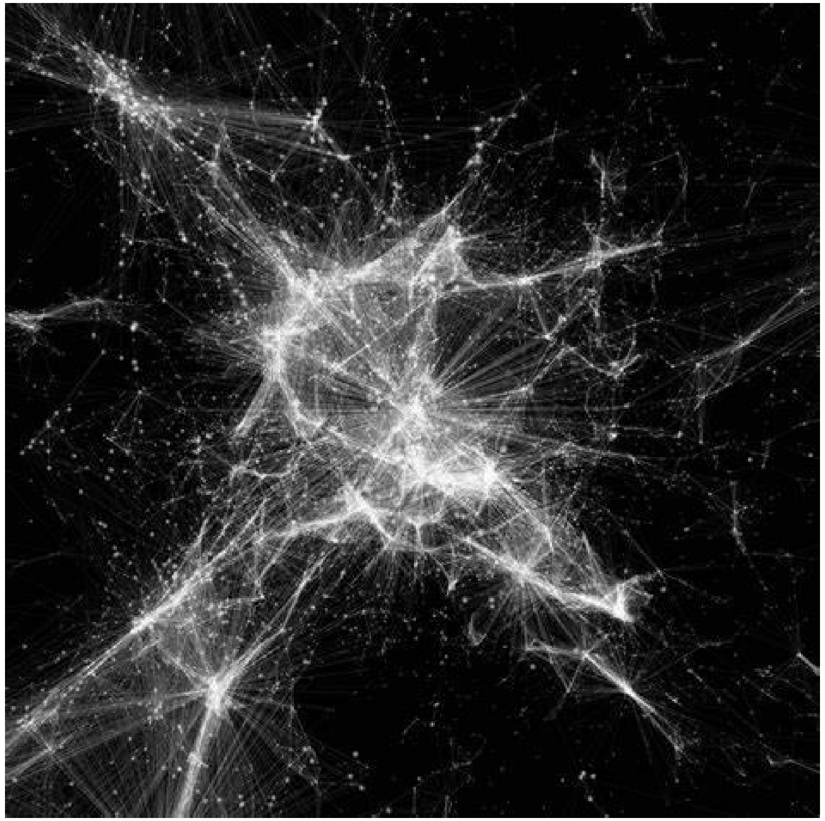
we will need 10^3 runs in single/multi - cosmologies for covmat/systematics

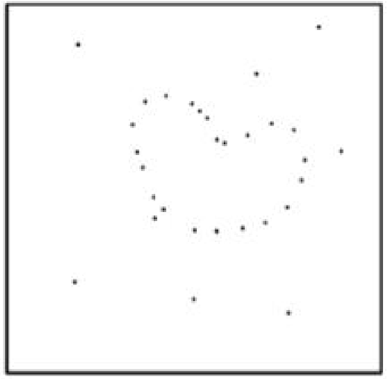
Redshift Caveat of CSST



II. Topology

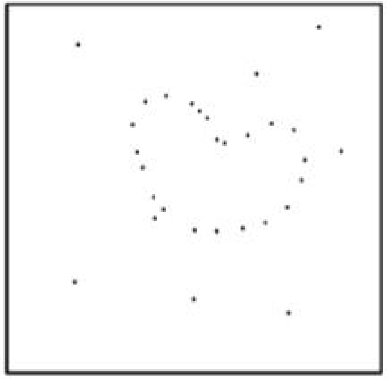






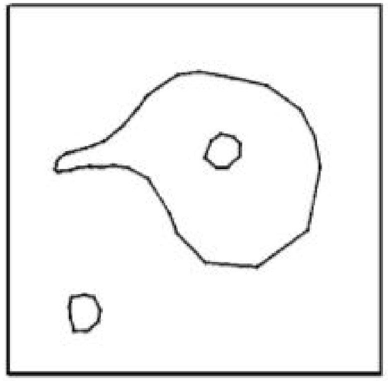
β-SKELETON

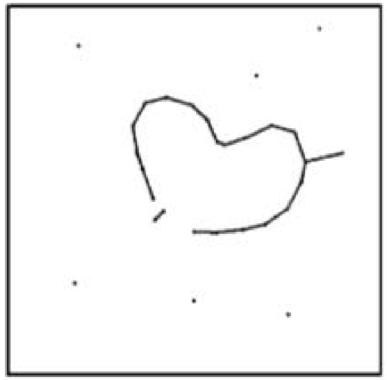
Nina Amenta et. 1998



Jaime Forero Romero

β-SKELETON

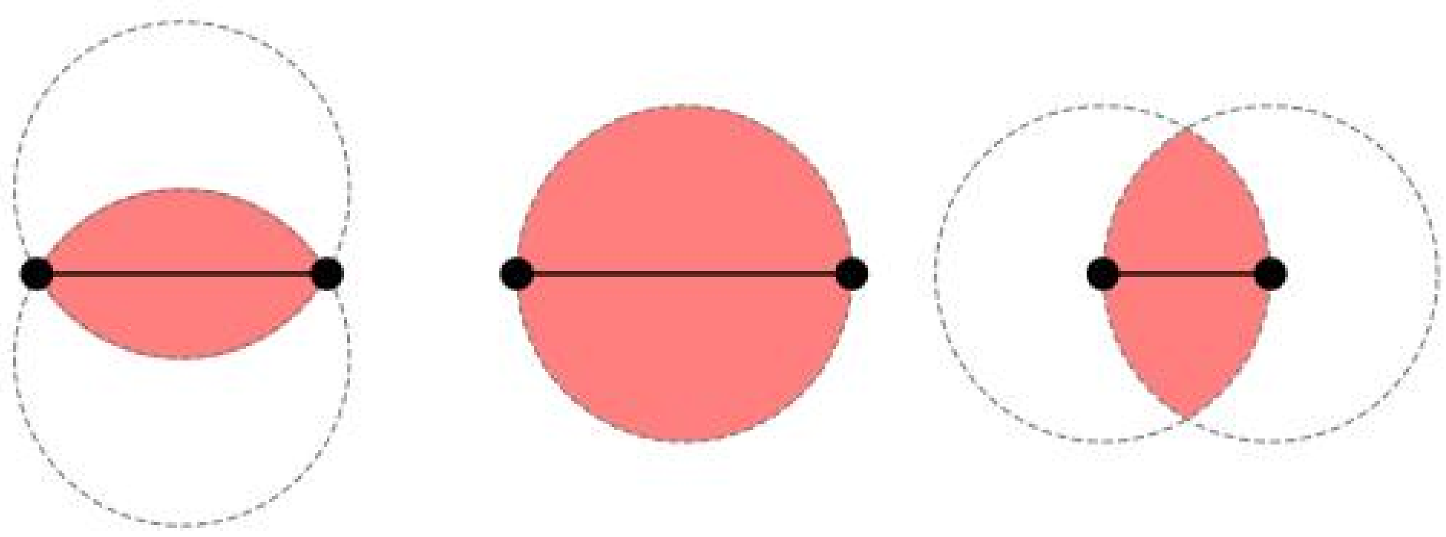




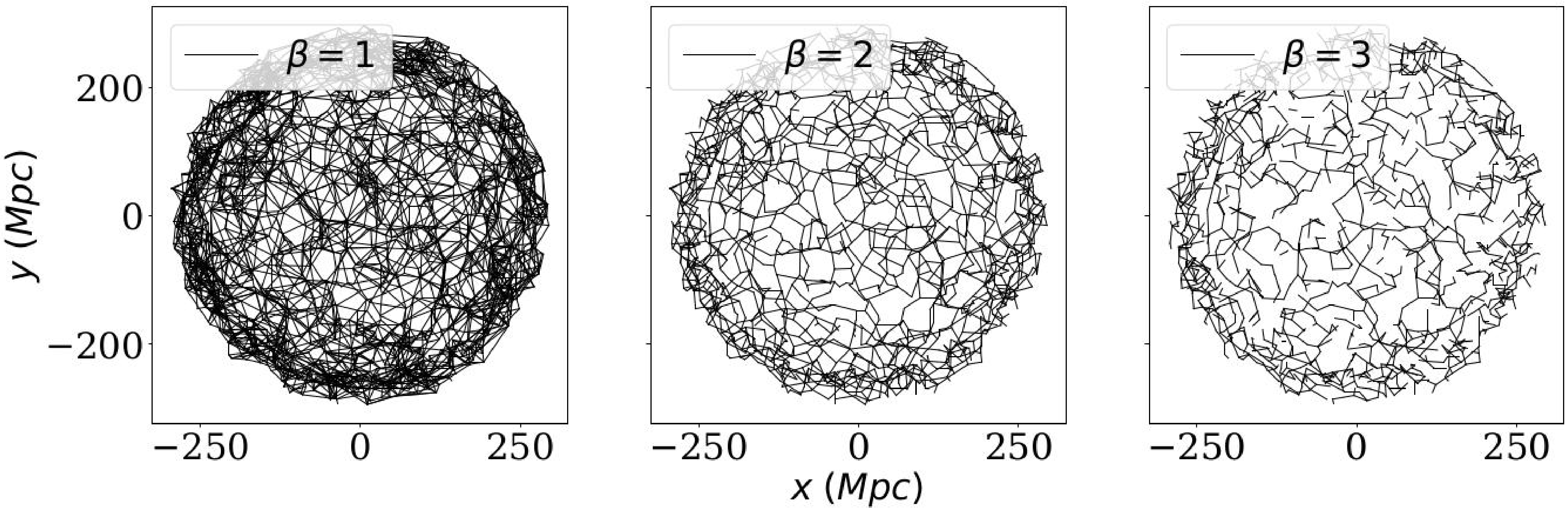
Nina Amenta et. 1998

β-SKELETON: Connection based on empty space

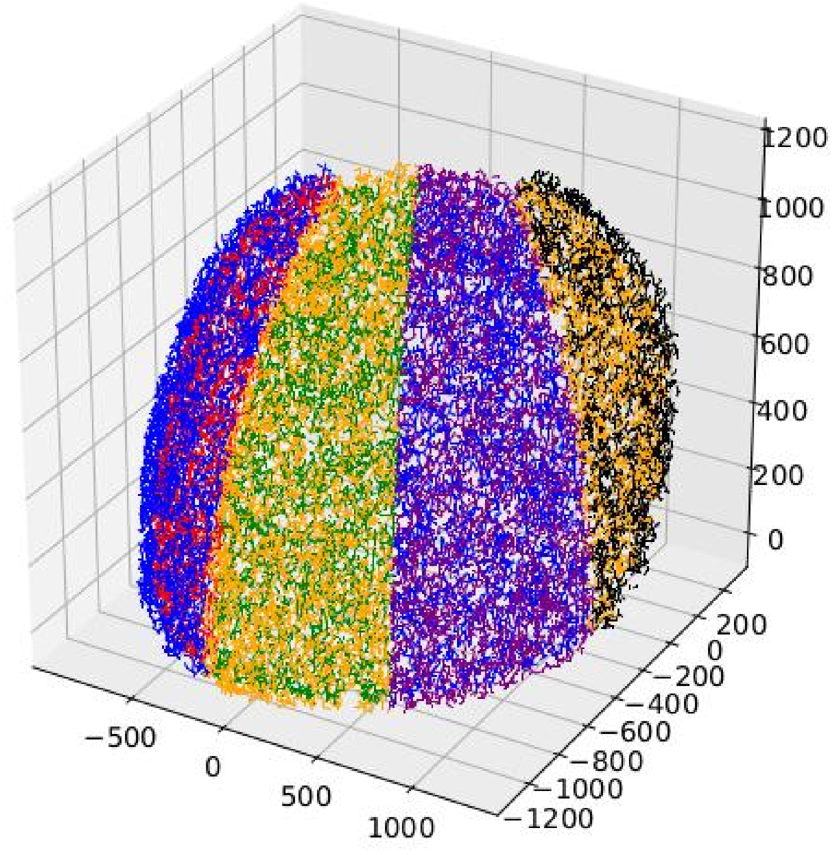
Feng et al., MNRAS, 2018

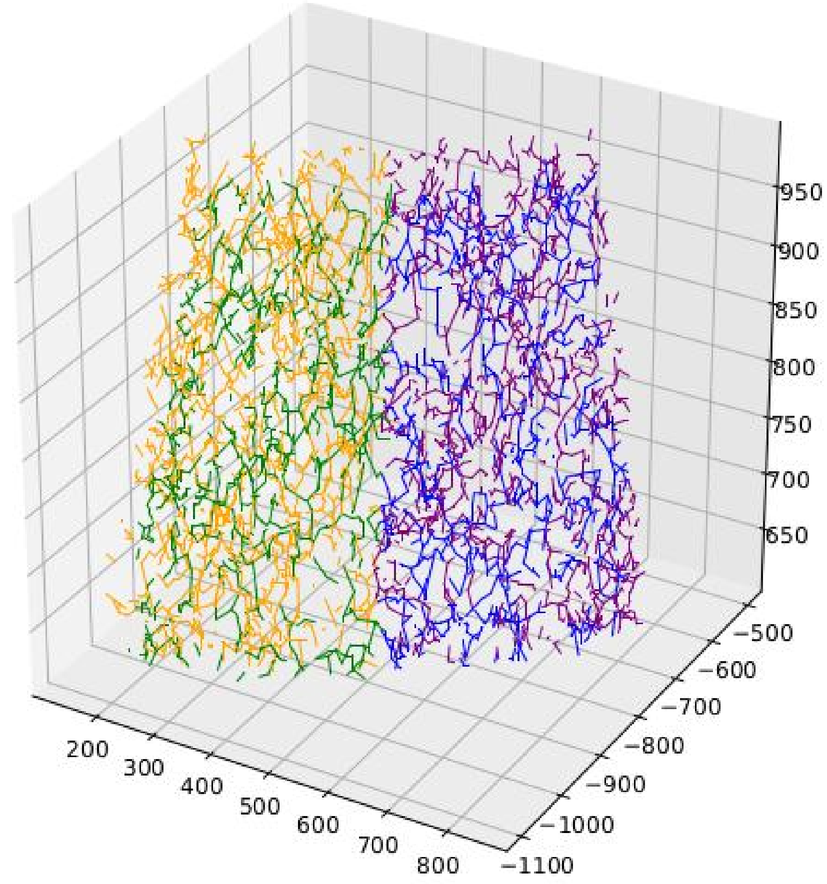


β<1 β=1 β>1



📖 β controls the intensity



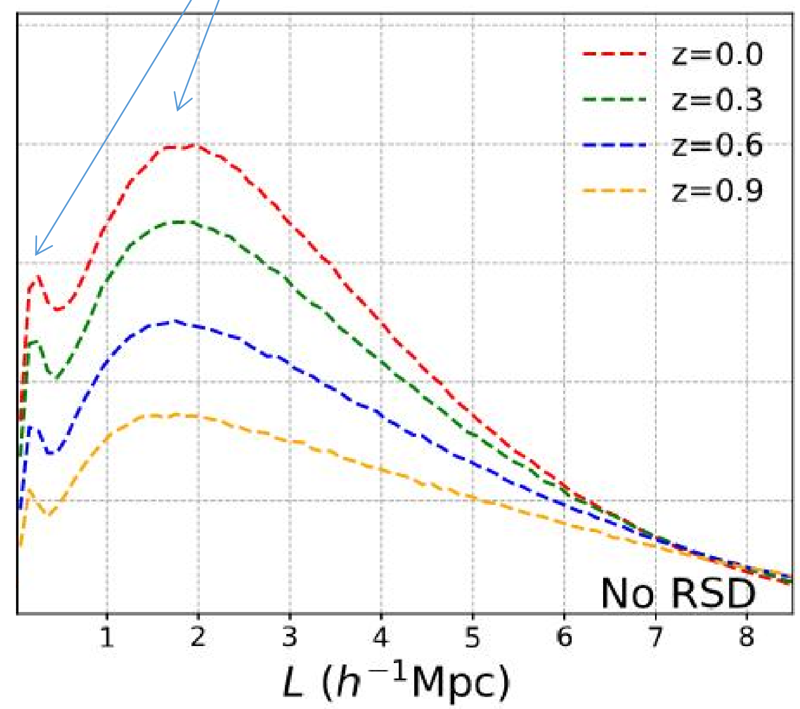


📖 β web of SDSS galaxies

Length of connections

Feng et al., MNRAS, 2018

Two peaks

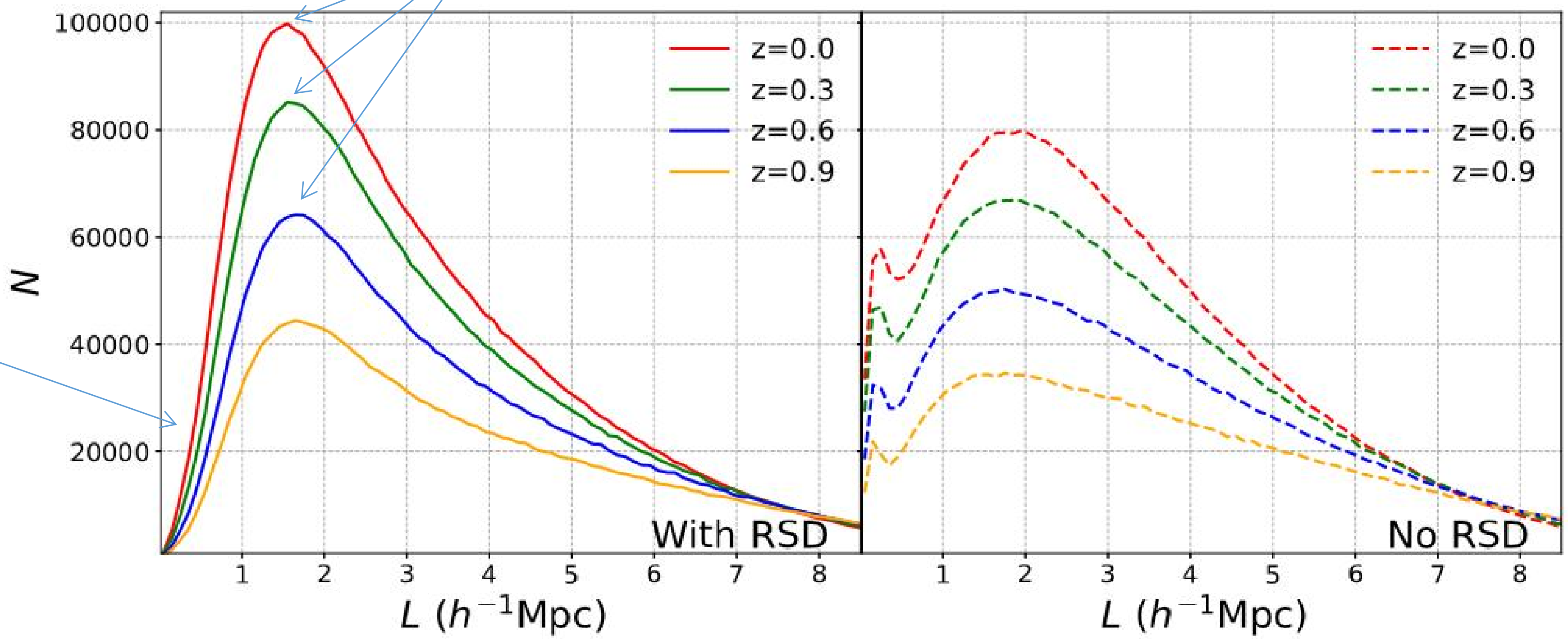


Length of connections

Feng et al., MNRAS, 2018

Robust major peak

Minor peak disappears!



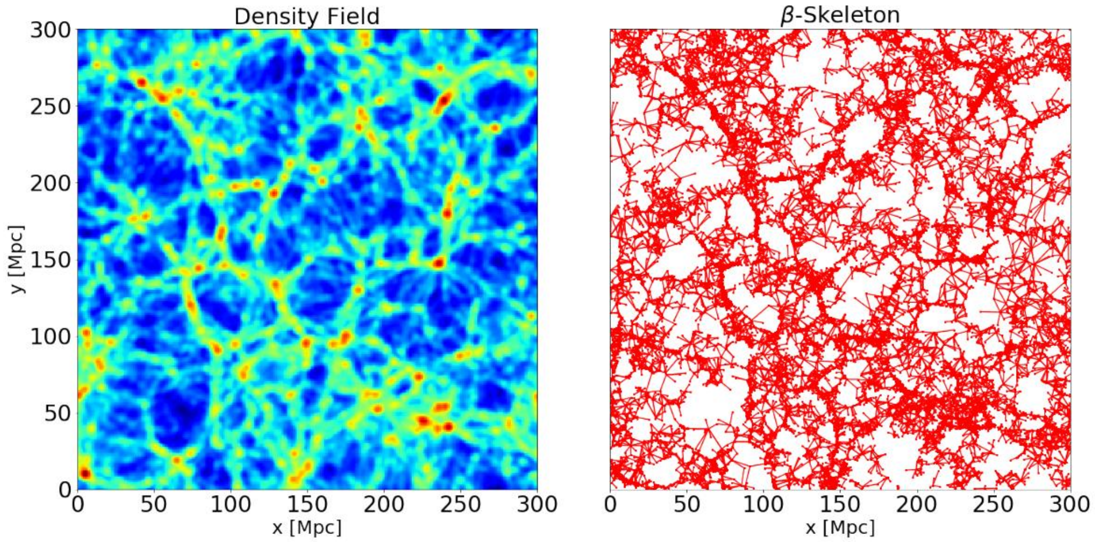
Adding RSDs

In-progress works

Topology

Entropy of cosmic web (Garcia-Alvarado et al., MNRAS submitted)

Relationship with other methods using Machine Learning (Suarez-Perez et al., in progress)



In-progress works

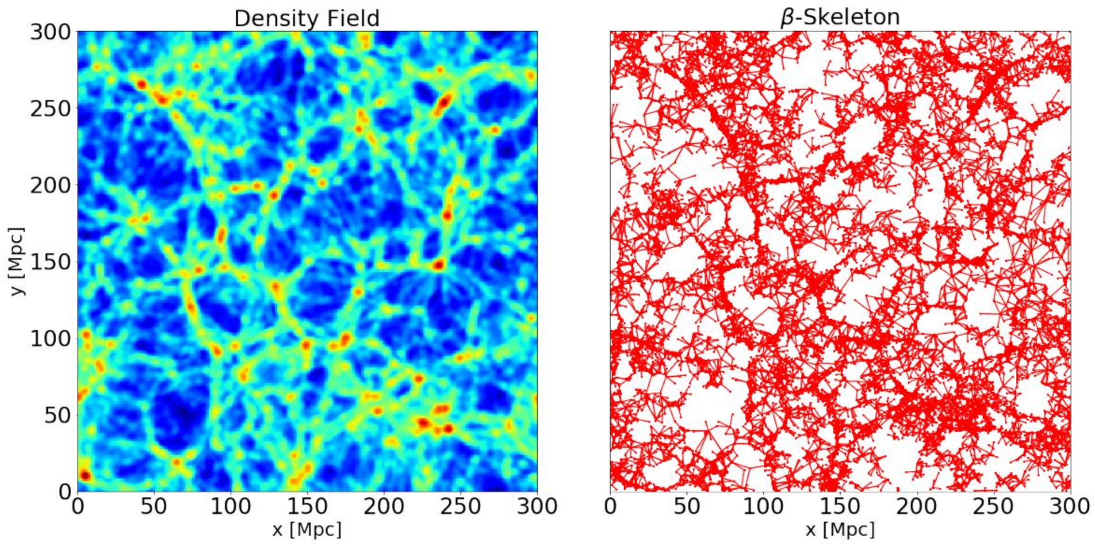
Topology

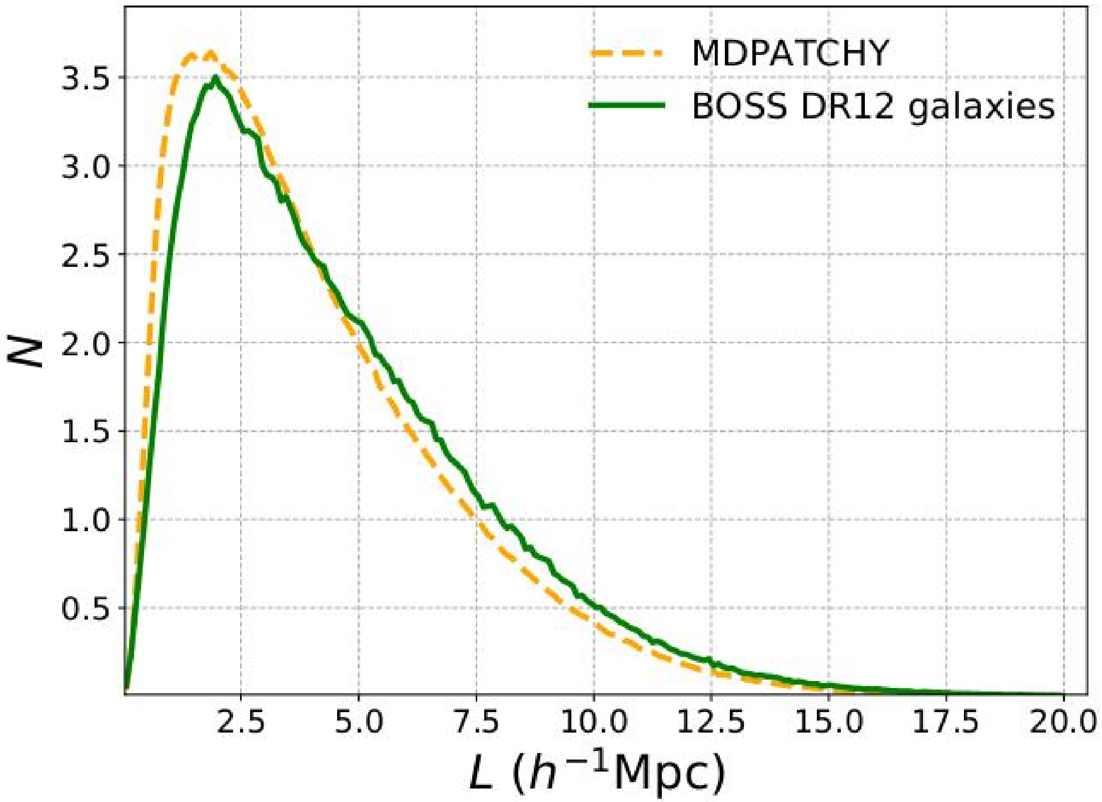
Entropy of cosmic web (Garcia-Alvarado et al., MNRAS submitted)

Relationship with other methods using Machine Learning (Suarez-Perez et al., in progress)

Cosmology (more difficult)

Under investigation...



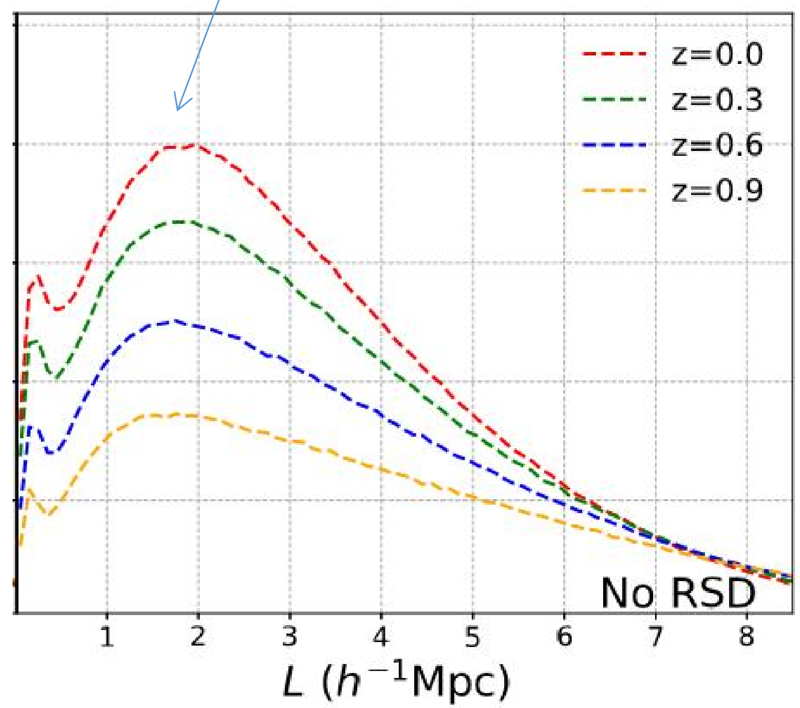


🕮 β web of SDSS galaxies

β-skeleton

Feng et al., MNRAS, 2018

Clustering

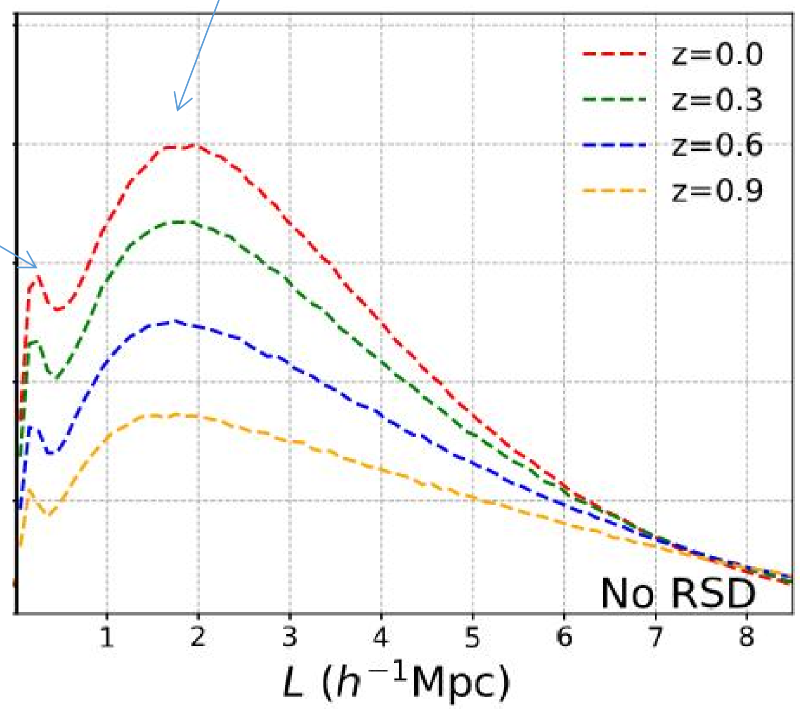


β-skeleton

Feng et al., MNRAS, 2018

Clustering

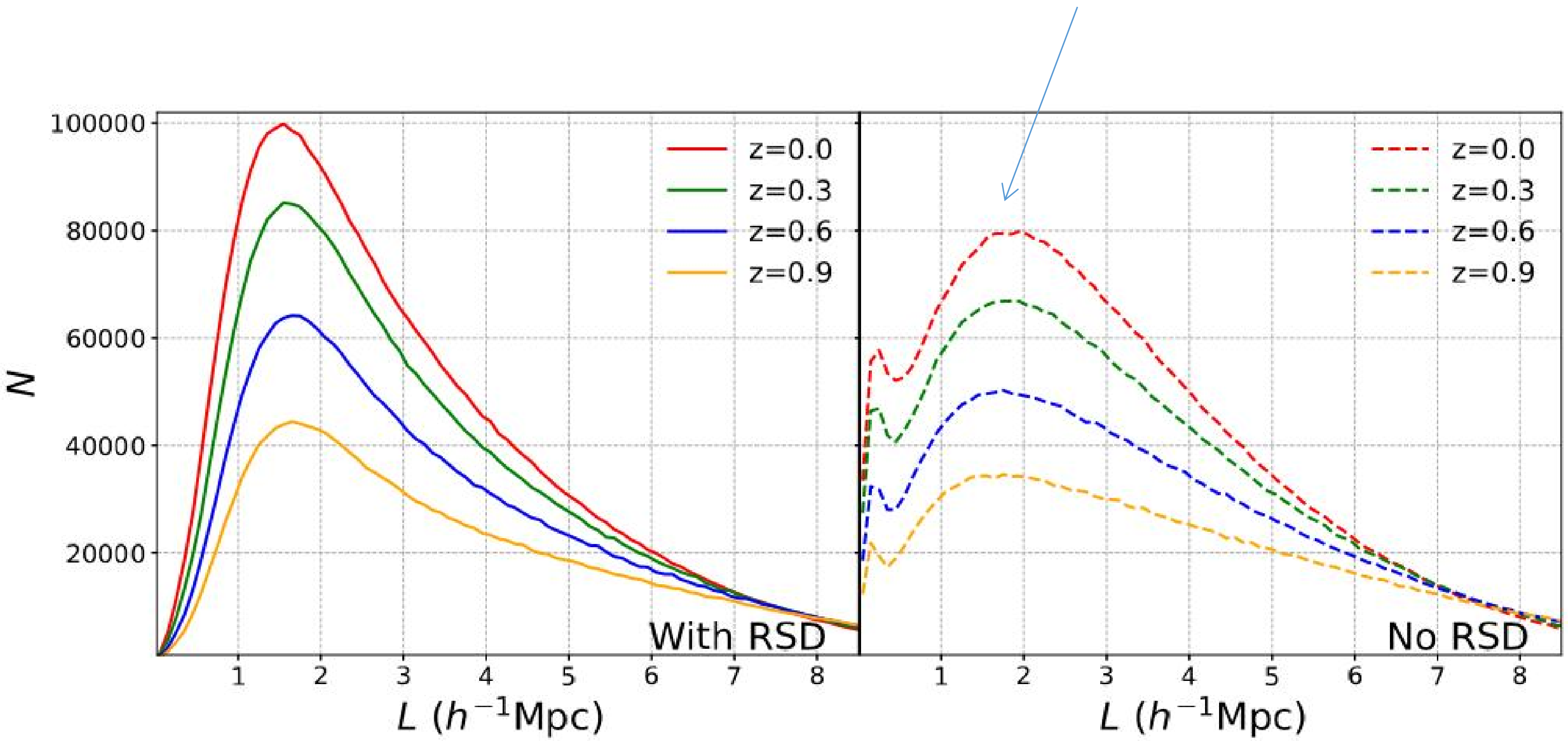
small scale
compact structures



β-skeleton

Feng et al., MNRAS, 2018

Clustering



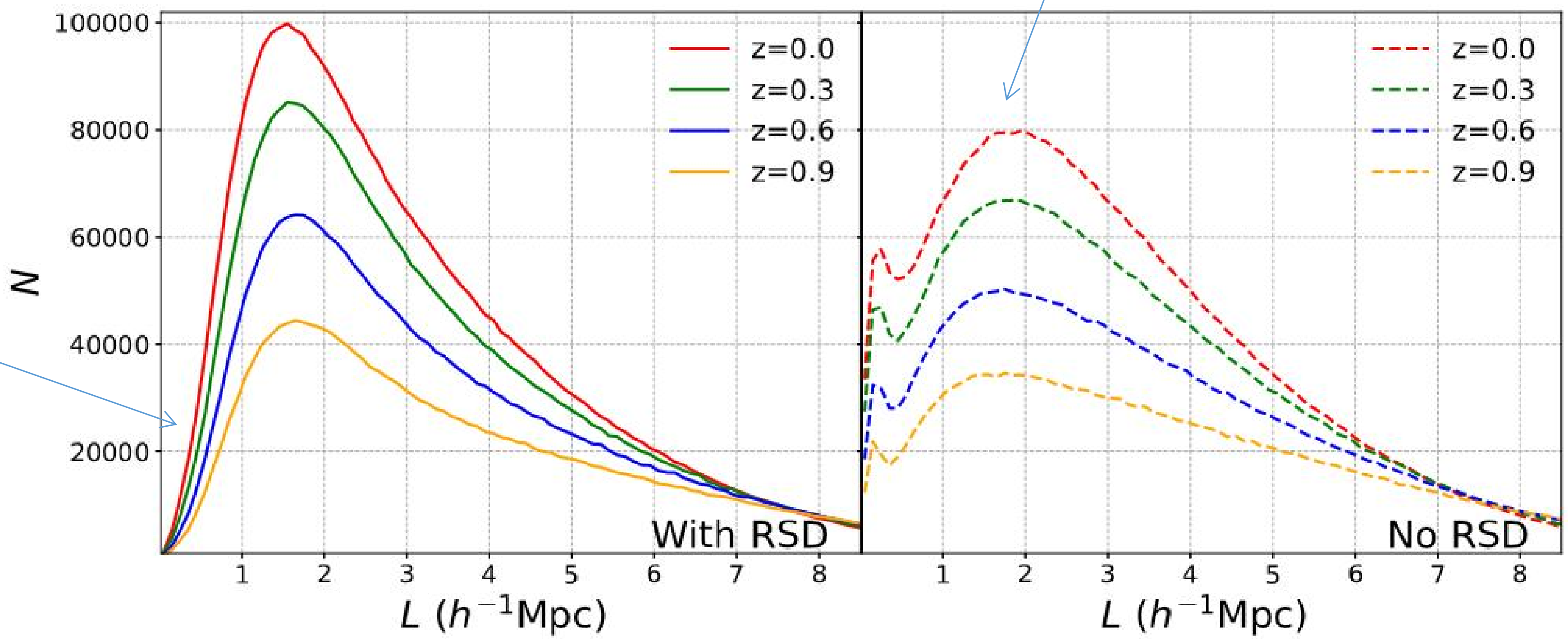
Adding RSDs

β-skeleton

Feng et al., MNRAS, 2018

Clustering

Minor peak disappears! (FoG)



Adding RSDs

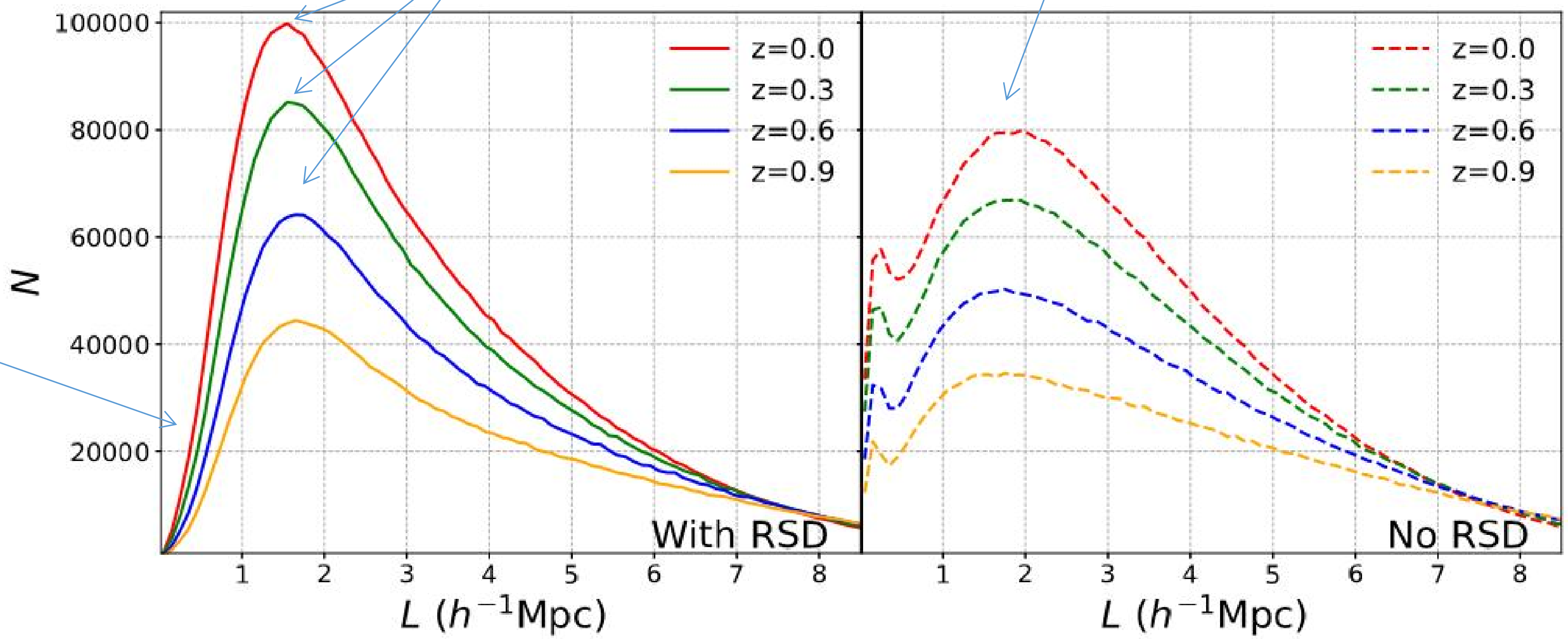
β-skeleton

Feng et al., MNRAS, 2018

Major peak becomes stable and redshift-invariant

Clustering

Minor peak disappears! (FoG)



Adding RSDs

β-skeleton

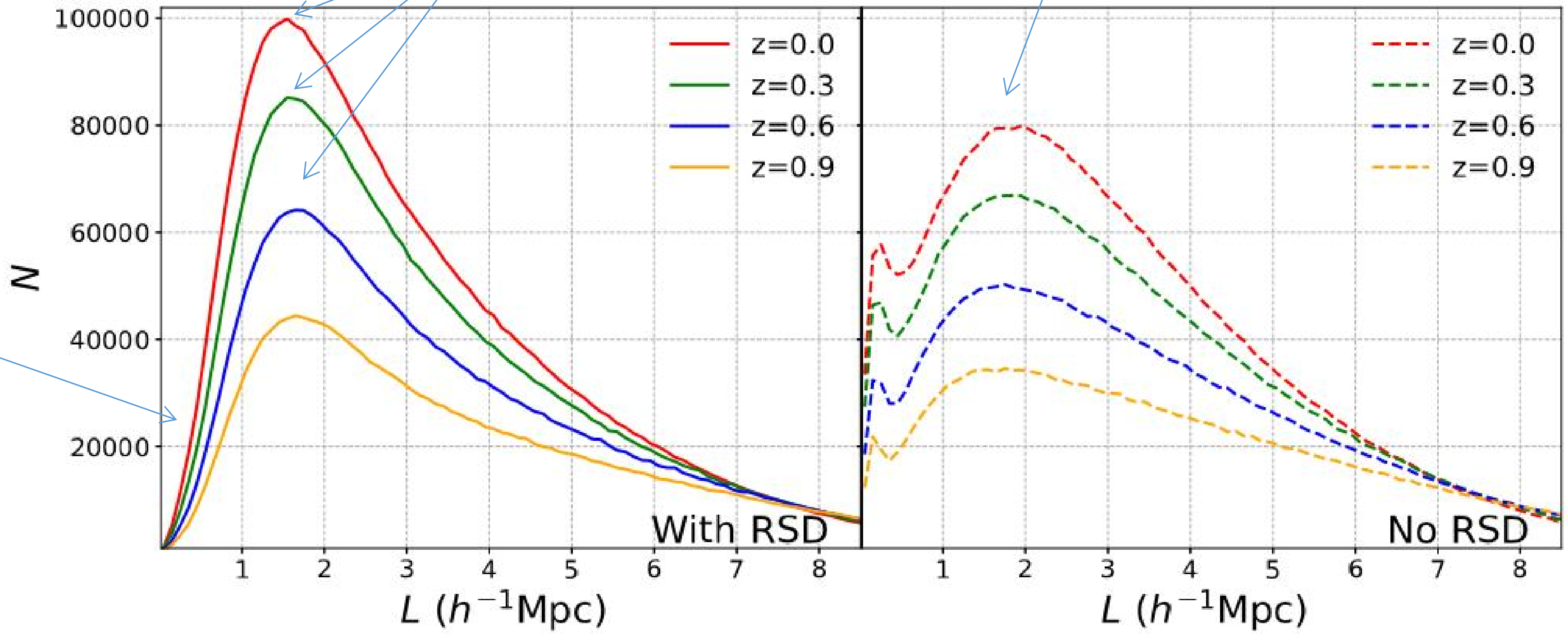
Feng et al., MNRAS, 2018

Major peak becomes **stable and redshift-invariant**

Clustering

Looks like another standard ruler!

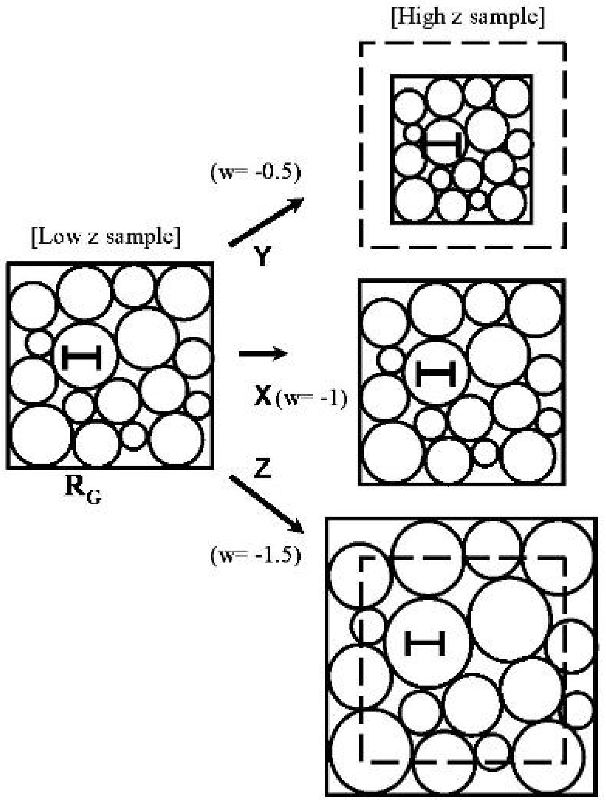
Minor peak disappears! (FoG)

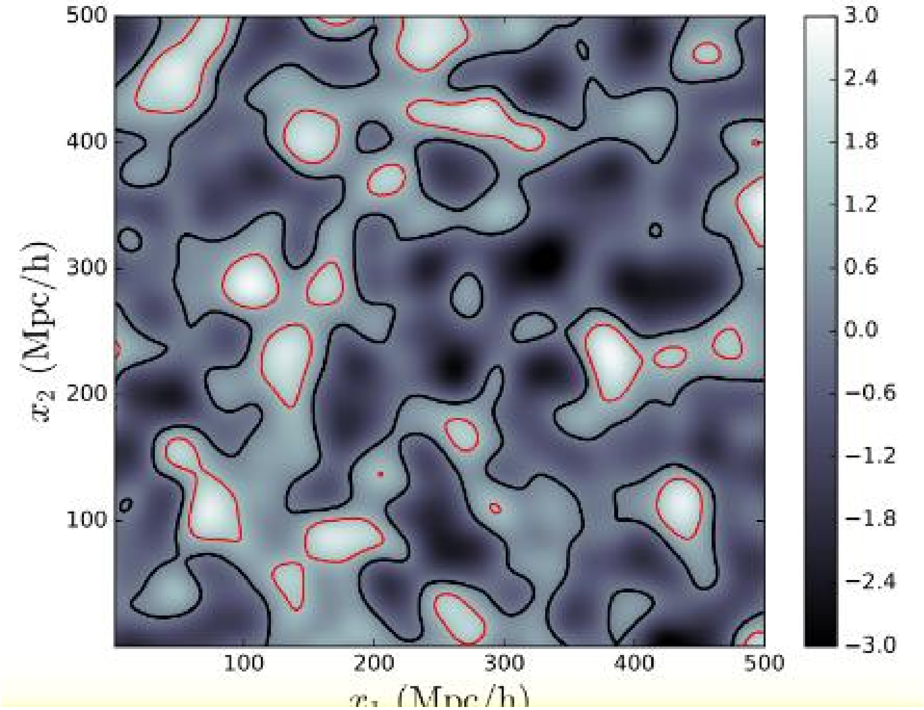


Adding RSDs

Just mention two more methods ...

Topology as standard ruler





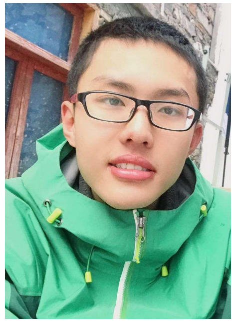
Changbom & Young-Rae, 0905.2268

Stephen & Changbom, to appear

Mark weighted Correlation Function

Yang et al., appear soon

weighting all objects by ρ^{α}

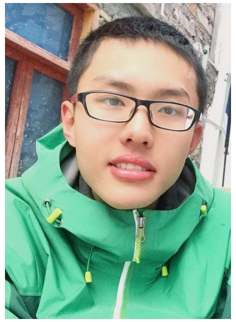


杨以钊 大三

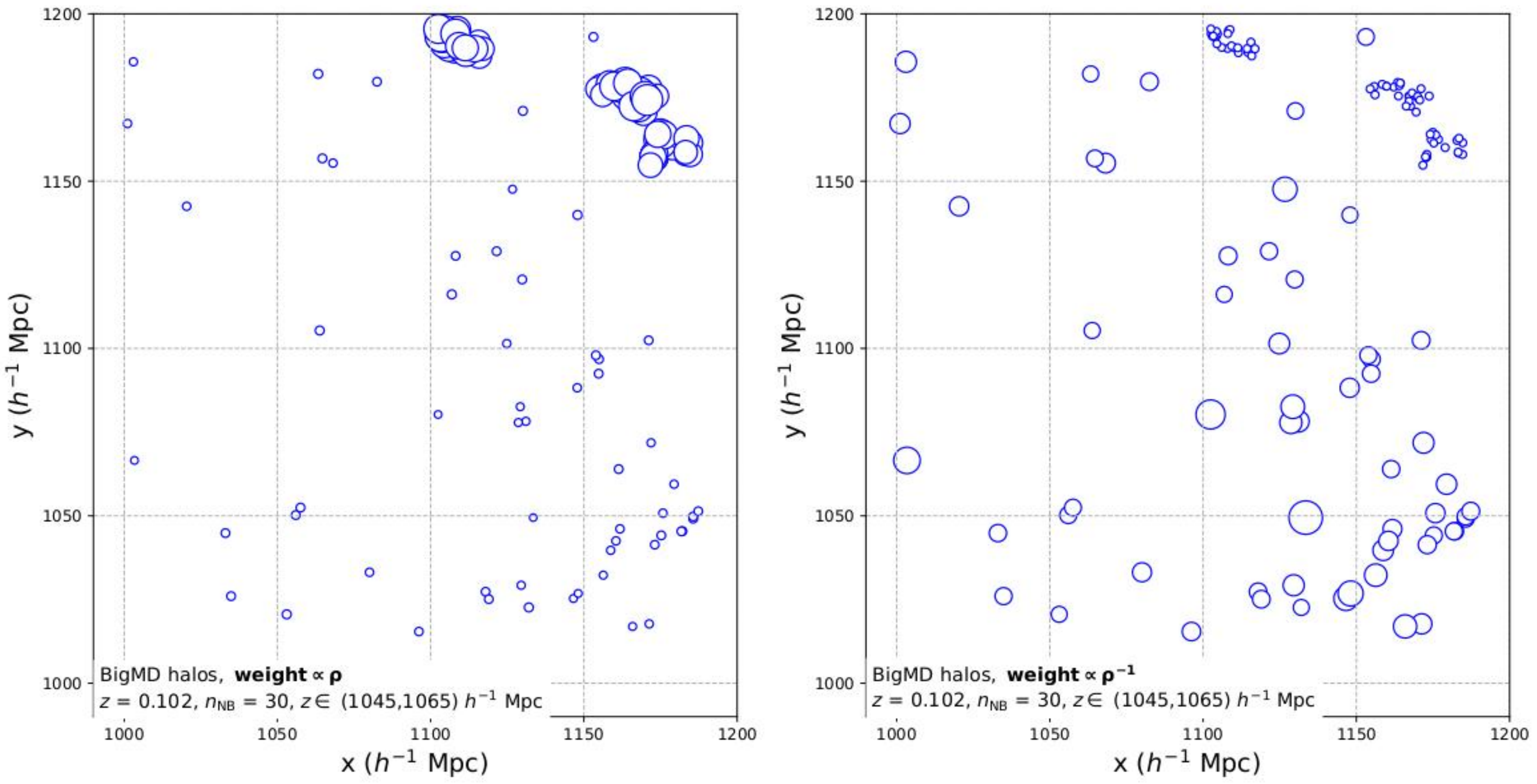
Mark weighted Correlation Function

Yang et al., appear soon

weighting all objects by ρ^α



杨以钊 大三

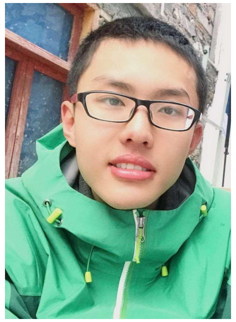


α=1: focus on clusters/filaments **α= -1**: voids

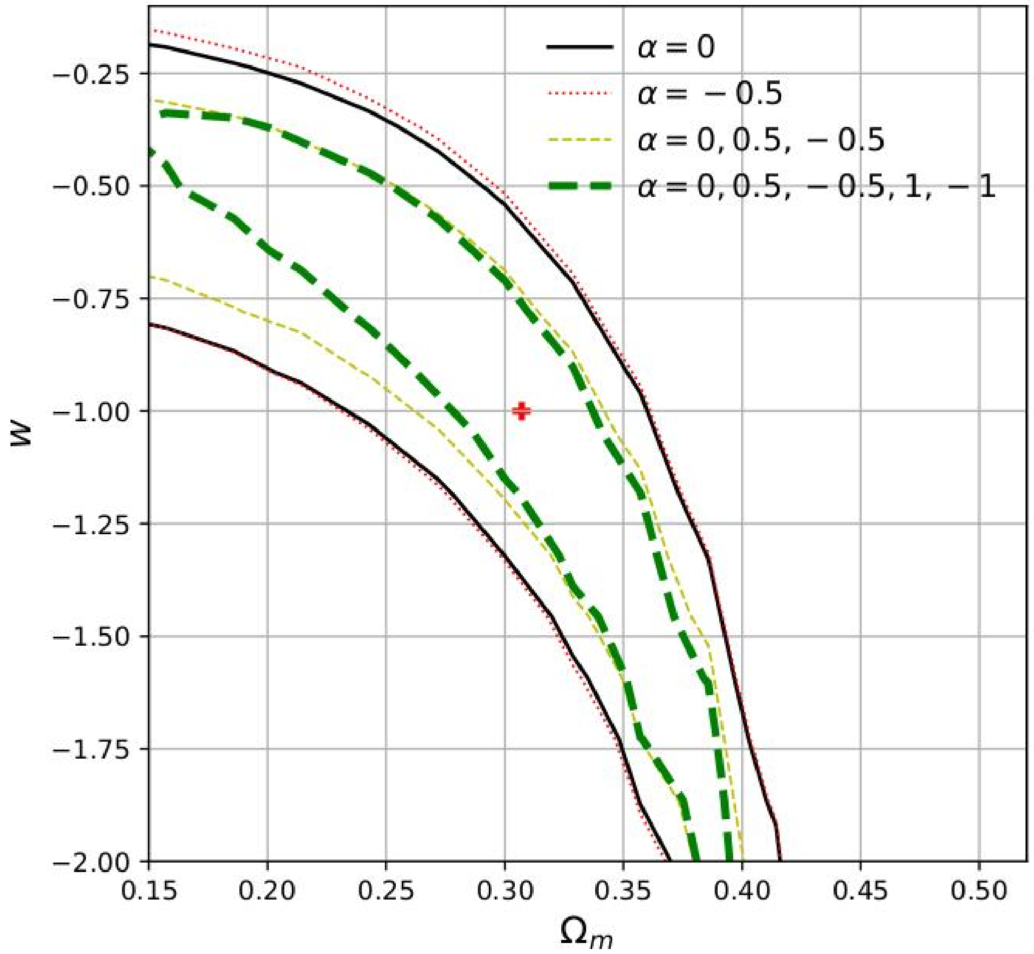
Mark weighted Correlation Function

Yang et al., appear soon

weighting all objects by ρ^{α}



杨以钊 大三



Combining information from different weights

β-skeleton

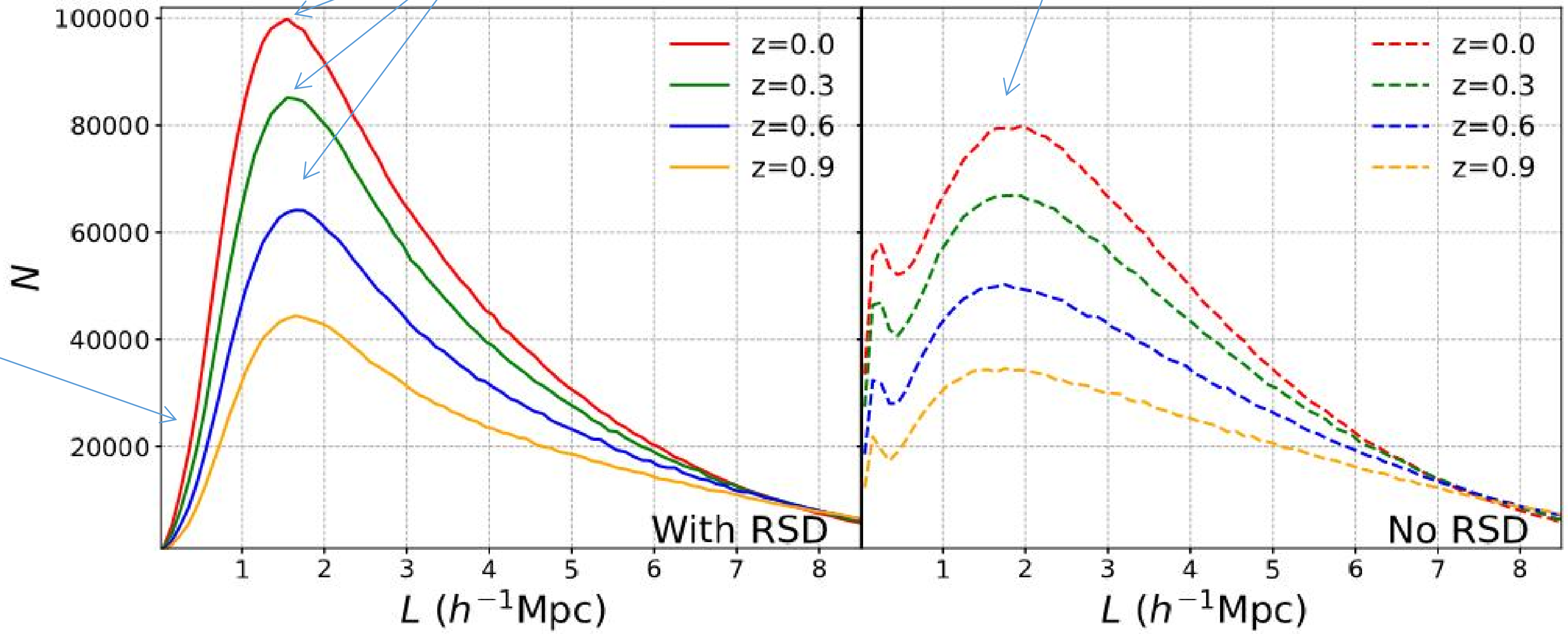
Feng et al., MNRAS, 2018

Major peak becomes **stable and redshift-invariant**

Clustering

Looks like another standard ruler!

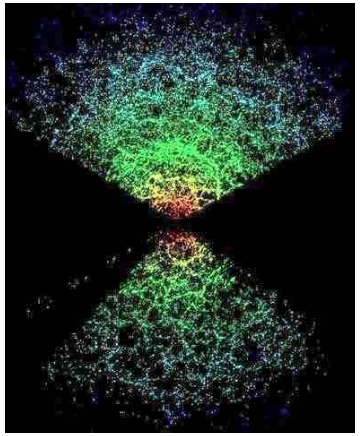
Minor peak disappears! (FoG)

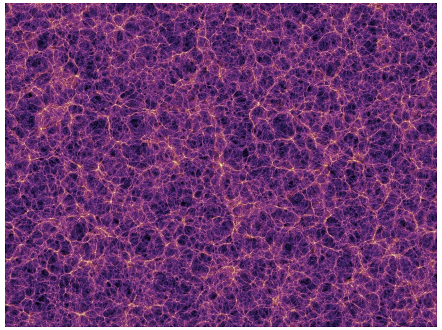


Adding RSDs

This peak is insensitive to everything.
Cannot be used to do cosmology.

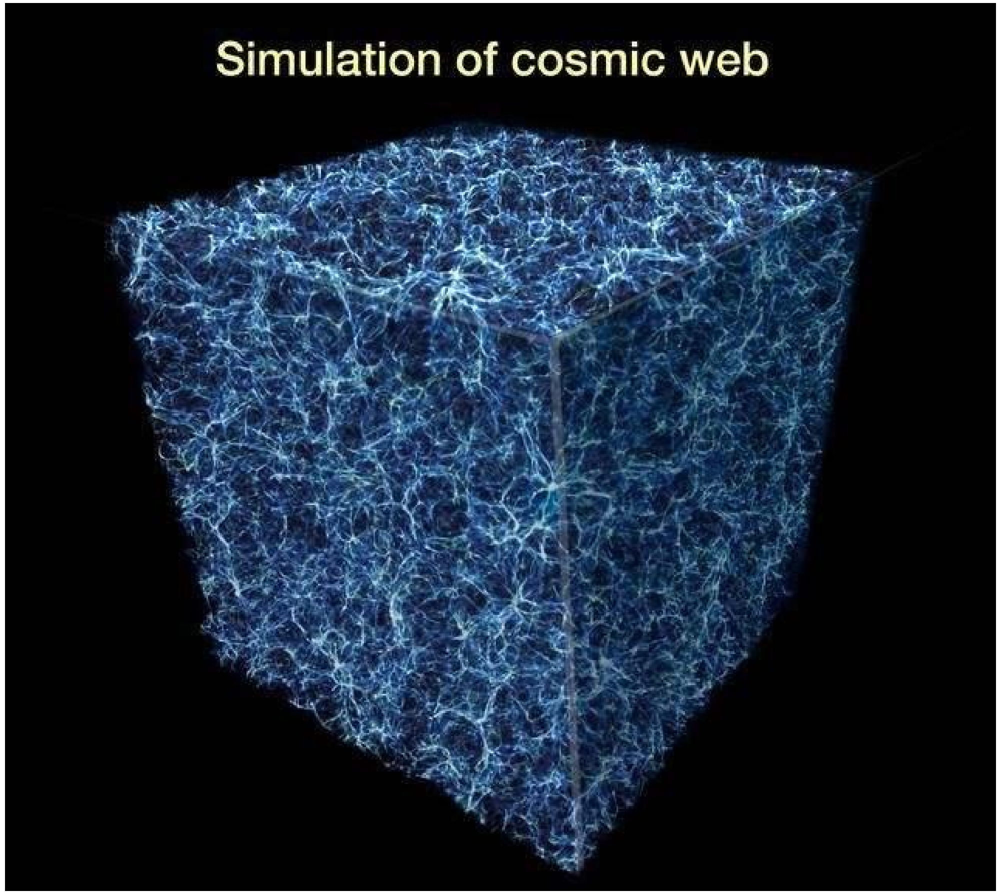
III. Machine Learning Cosmology





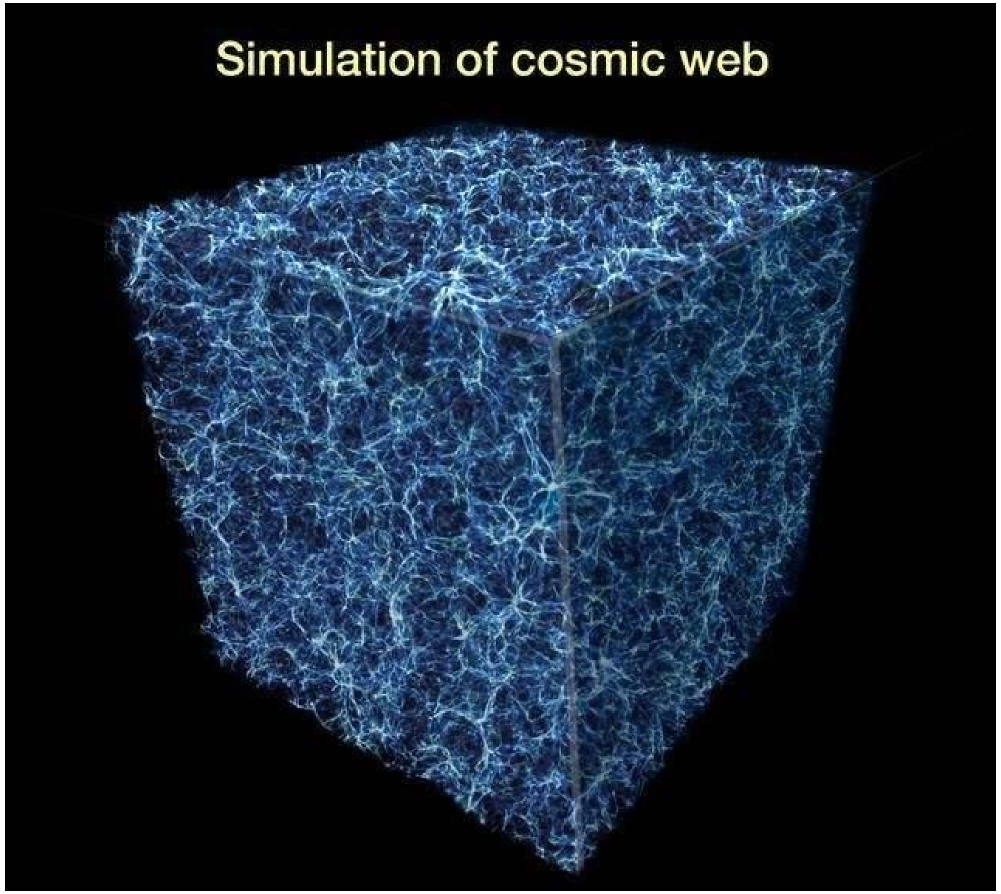
For me so easy

Motivation

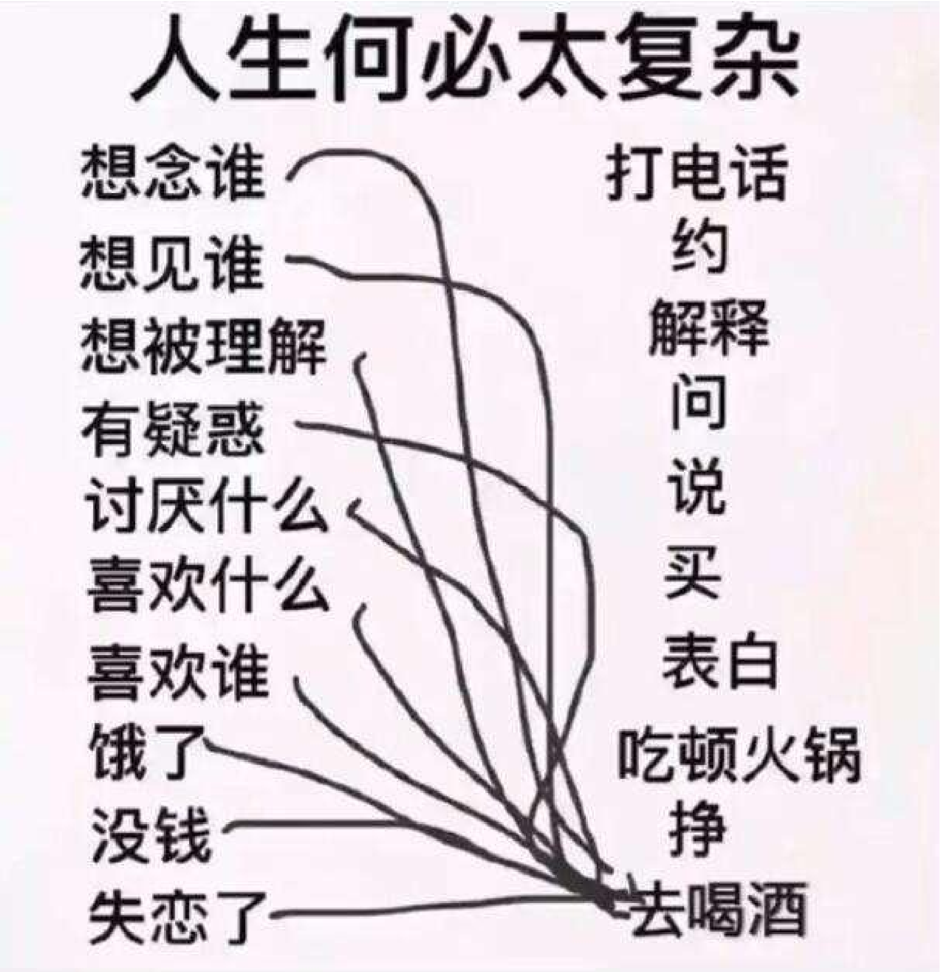


The Extremely Complicated LSS

Motivation



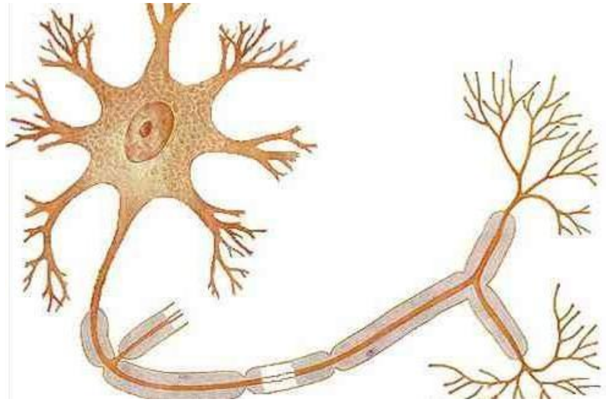
The Extremely Complicated LSS



Connectionism (联结主义)

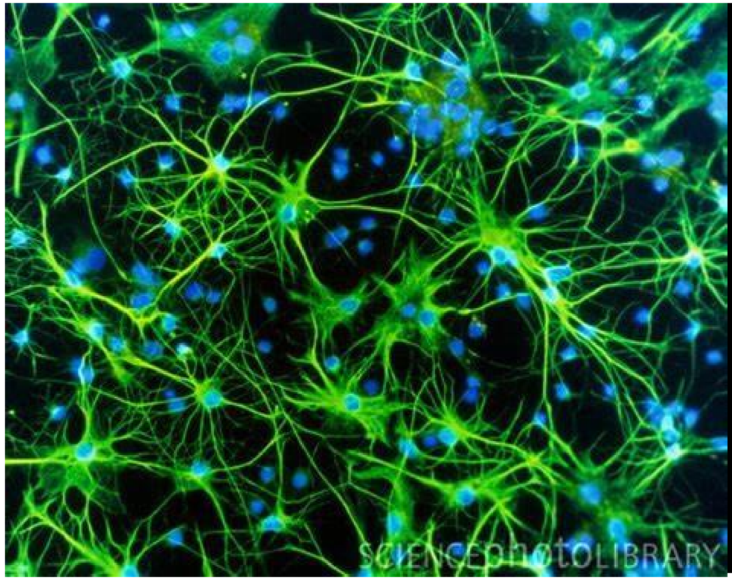
- “When connecting together **a large number of simple units**, the system becomes **intellegent**.”

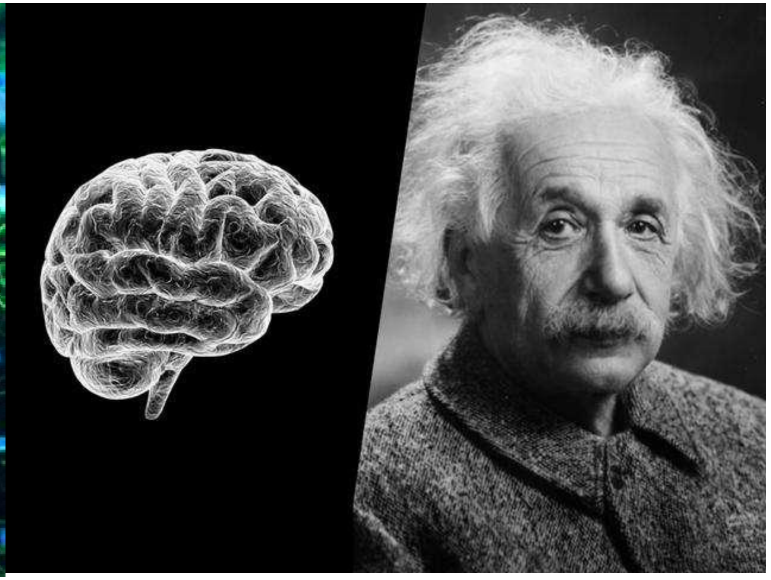
Connectionism (联结主义)



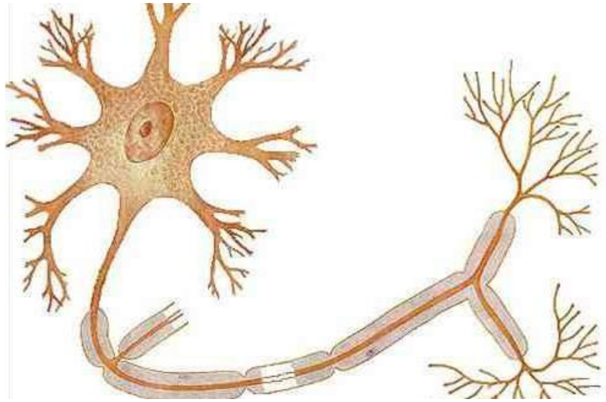
- “When connecting together **a large number of simple units**, the system becomes **intellegent**.”

- Example: Our Brain

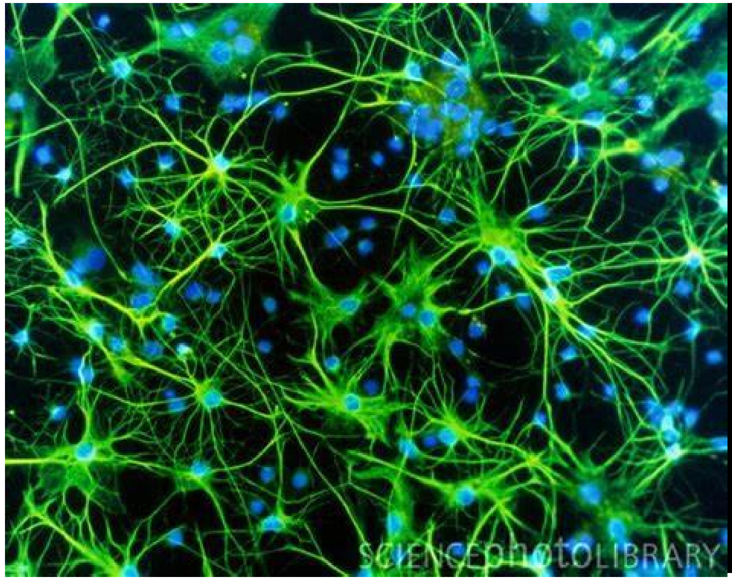


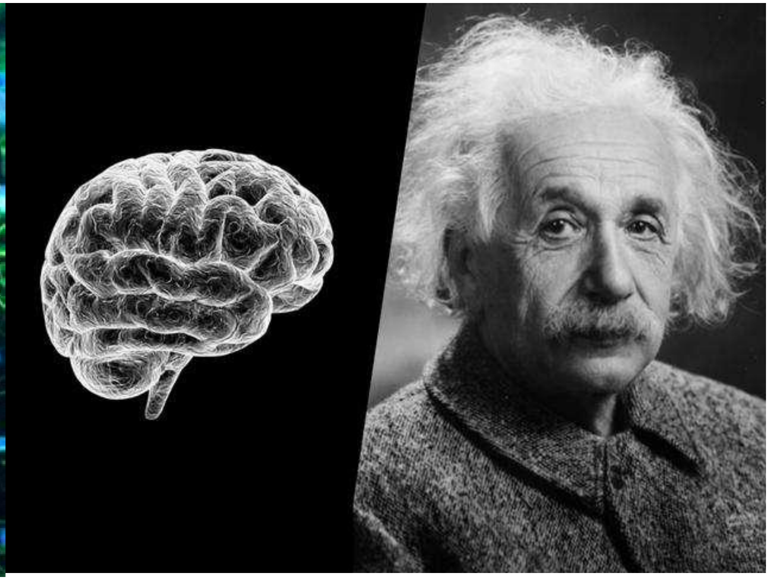


Connectionism (联结主义)

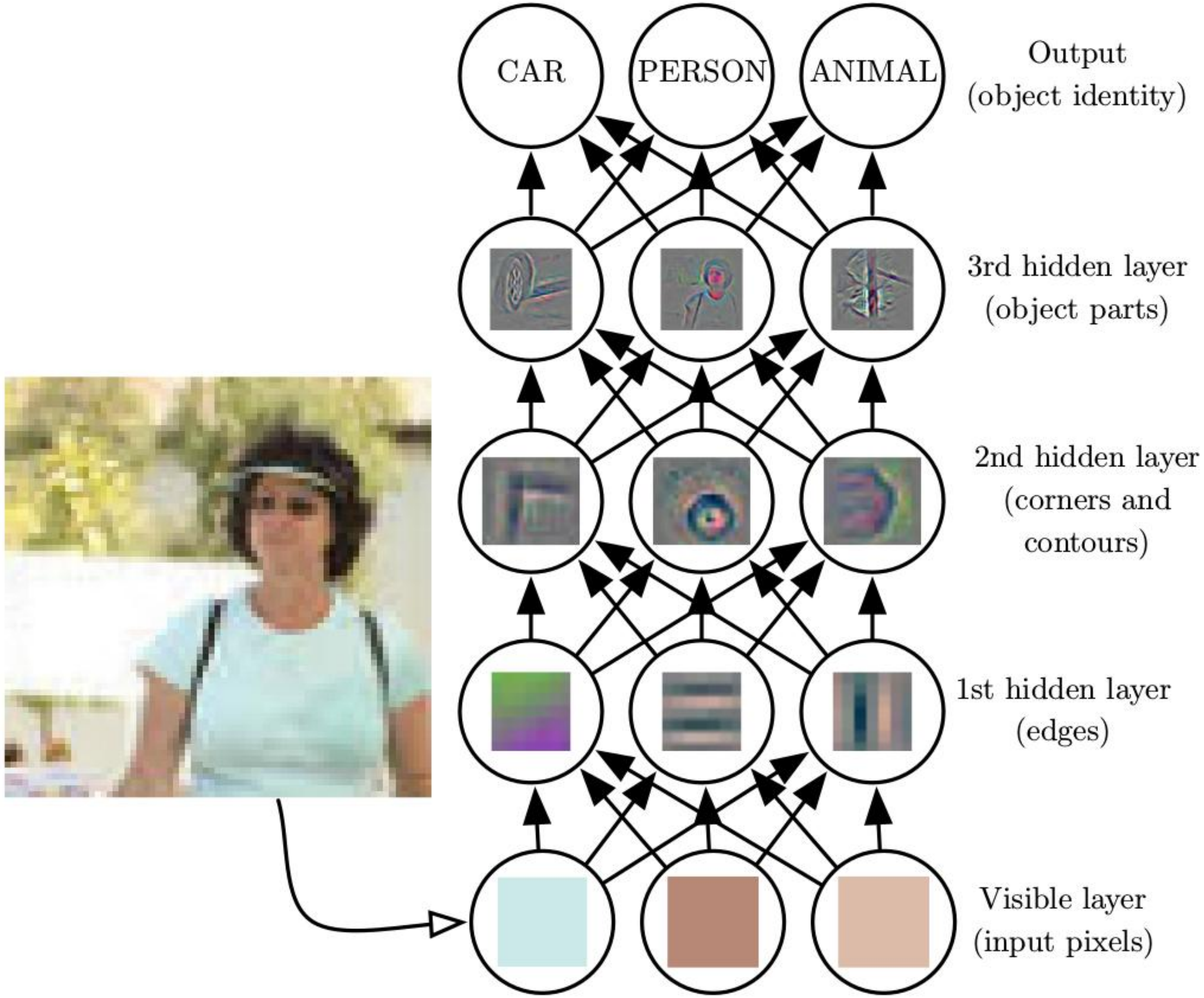


Our brain is just a
collection of naieve things



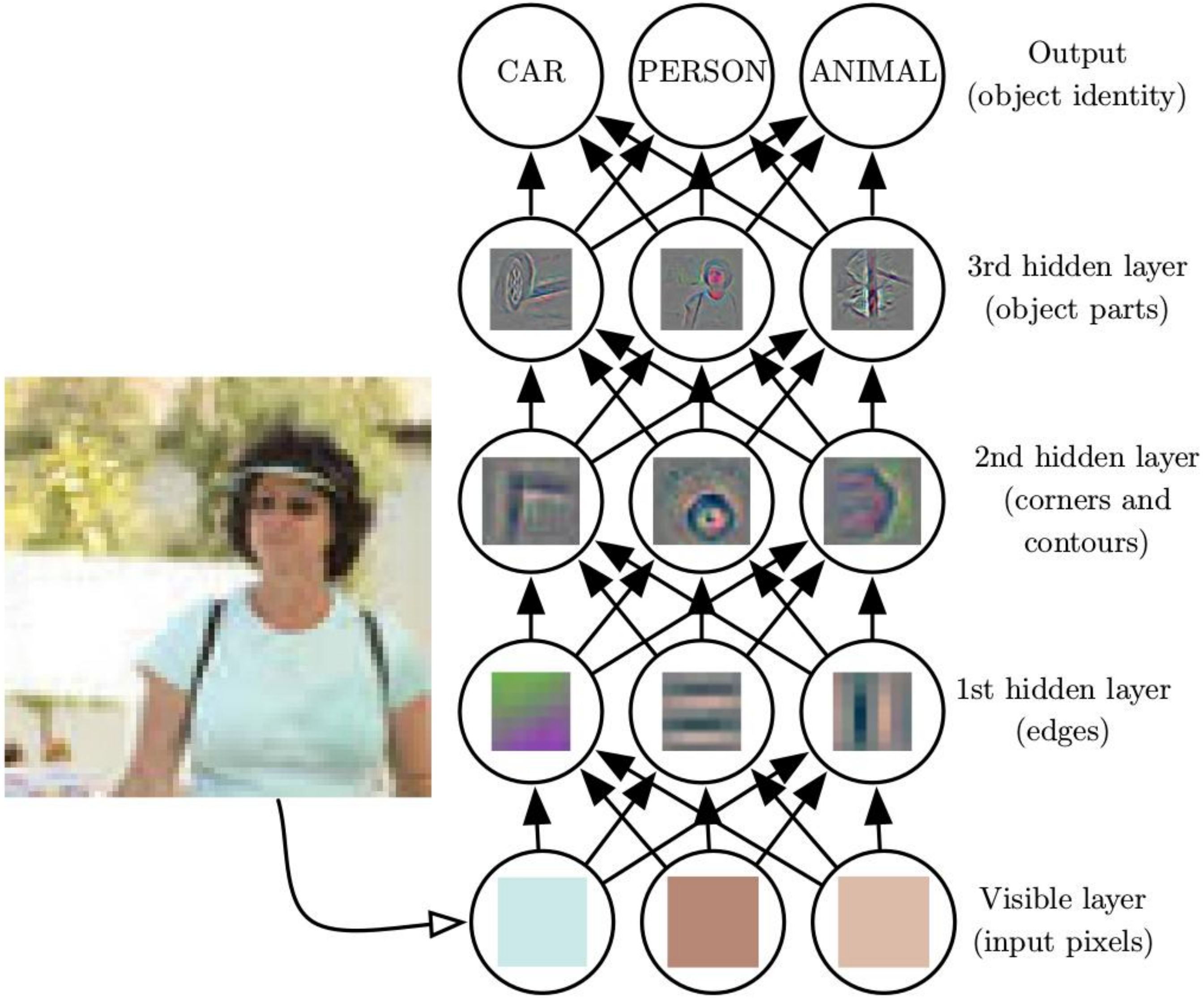


Deep Learning in one slide



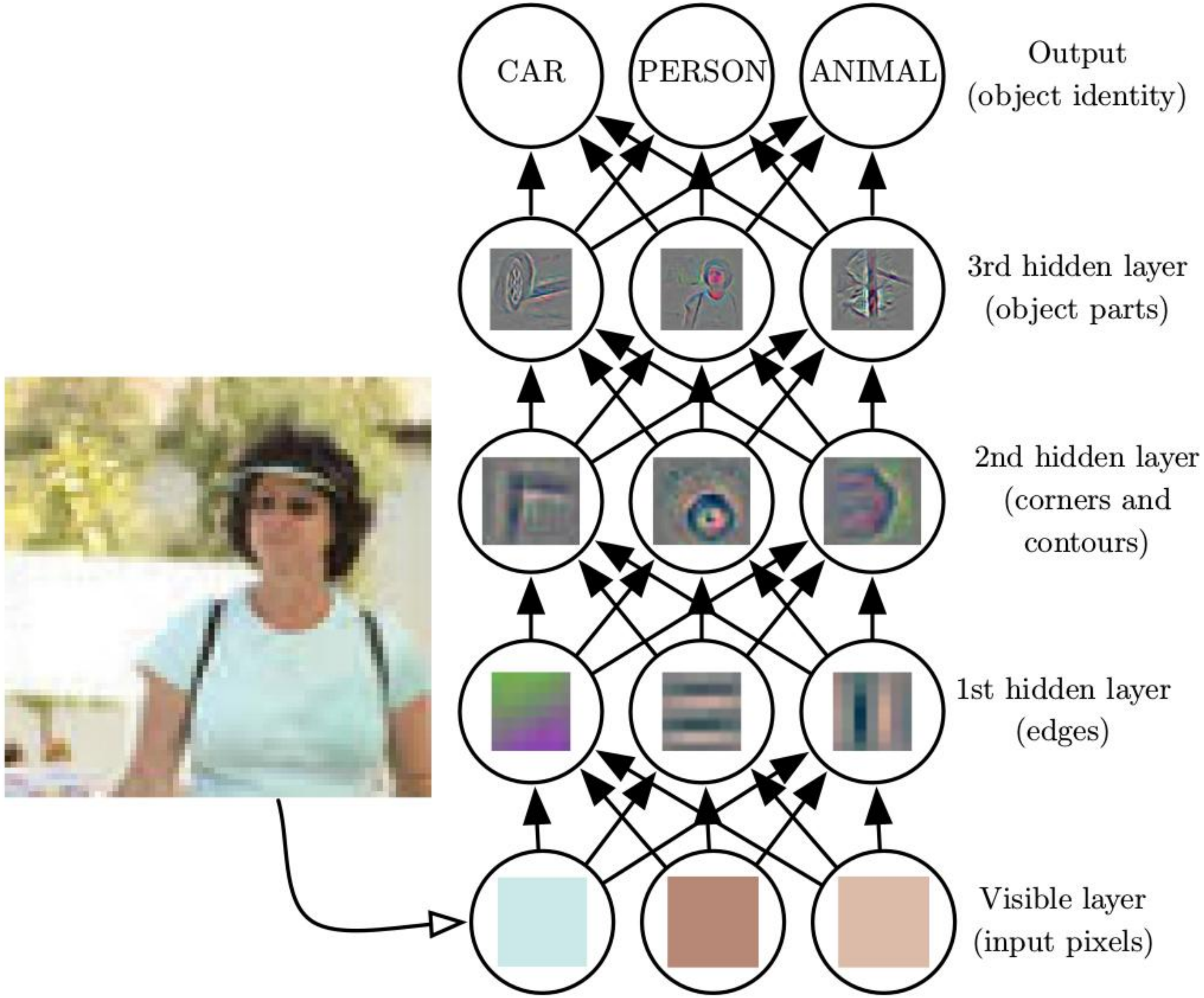
- Inputs are just pixels

Deep Learning in one slide



- Inputs are just pixels
- Based on that, more sophisticated features constructed. See hidden layers.

Deep Learning in one slide

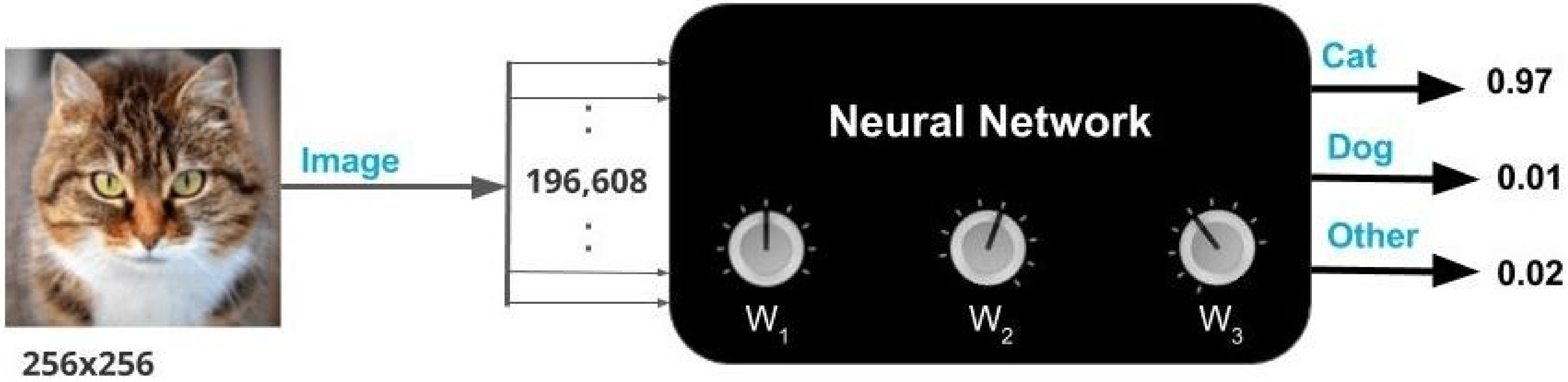


- Inputs are just pixels

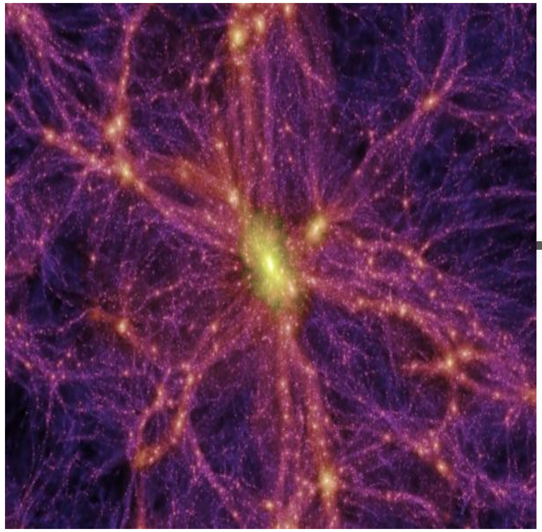
- Based on that, more sophisticated features constructed. See hidden layers.

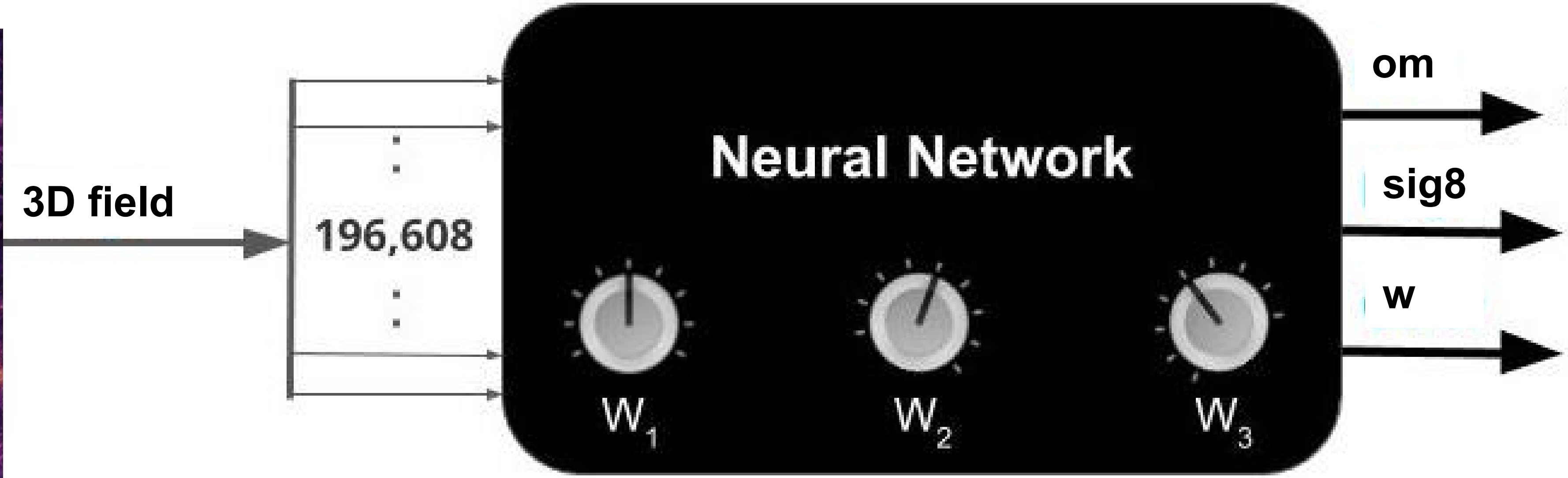
  - First layer identifies **edges** based on brightness contrast;
  - Second layer identifies **angles and boundaries** based on edges;
  - Third layer groups together angles and boundaries and can identify some **objects**

Deep Learning in one slide



Deep Learning in one slide

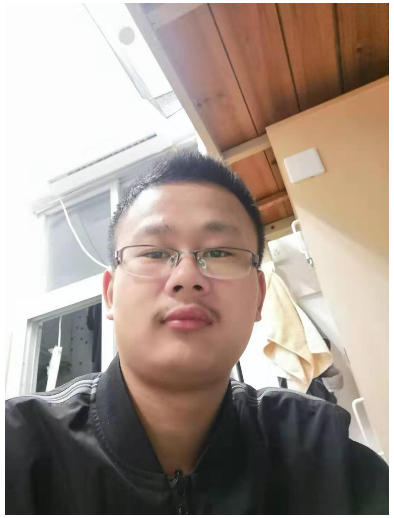




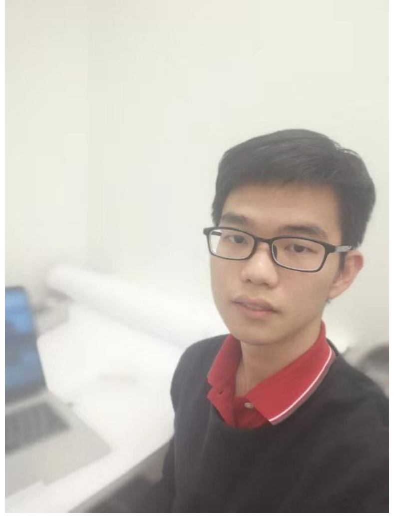
Pan et al., arXiv:1908.10590

COSMOLOGICAL PARAMETER ESTIMATION FROM LARGE-SCALE STRUCTURE DEEP LEARNING

Shuyang Pan, Miaoxin Liu,[1] Jaime Forero-Romero,[2] Cristiano G. Sabiu,[3] Zhigang Li,[4] Haitao Miao,[1] and Xiao-Dong Li *[1]



We propose a light-weight deep convolutional neural network to estimate the cosmological parameters from simulated 3-dimensional dark matter distributions with high accuracy. The training set is based on 465 realizations of a cubic box size of 256 h^{-1} Mpc on a side, sampled with 128^3 particles interpolated over a cubic grid of 128^3 voxels. These volumes have cosmological parameters varying within the flat ΛCDM parameter space of $0.16 \leq \Omega_m \leq 0.46$ and $2.0 \leq 10^9 A_s \leq 2.3$. The neural network takes as an input cubes with 32^3 voxels and has three convolution layers, three dense layers, together with some batch normalization and pooling layers. We test the error-tolerance abilities of the neural network, including the robustness against smoothing, masking, random noise, global variation, rotation, reflection and simulation resolution. In the final predictions from the network we find a 2.5% bias on the primordial amplitude σ_8 that can not easily be resolved by continued training. We correct this bias to obtain unprecedented accuracy in the cosmological parameter estimation with statistical uncertainties of $\delta\Omega_m$=0.0015 and $\delta\sigma_8$=0.0029. The uncertainty on Ω_m is 6 (and 4) times smaller than the Planck (and Planck+external) constraints presented in Ade et al. (2016).



潘书洋 大二
计算机太牛了

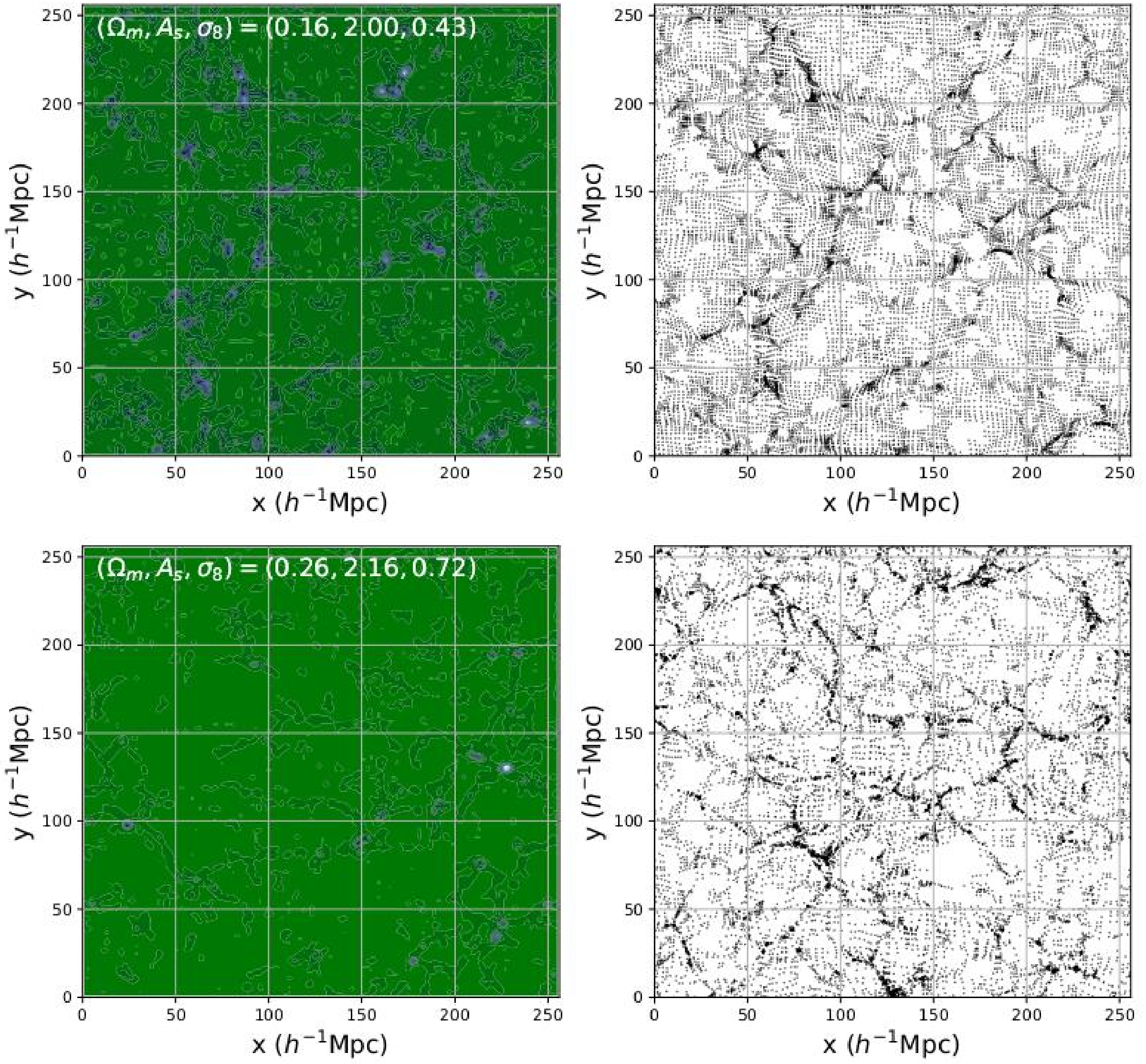
刘淼昕 大二

Fore more reference: ***Ravanbakhsh et al. 2017, Mathuriya et al. 2018***

Training Set

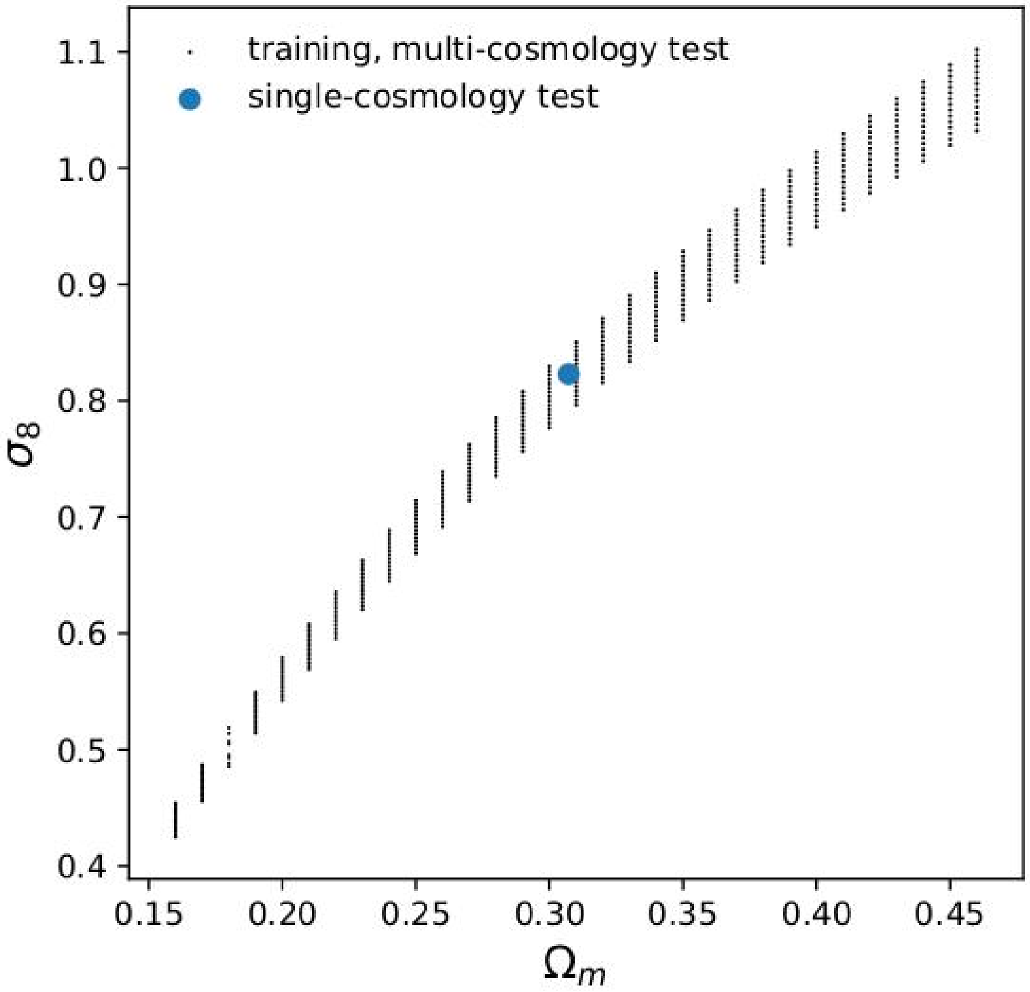
500 cosmologies

- 128^3 particles, $(256\ h^{-1}\ \mathrm{Mpc})^3$ box,
  - $0.16 \le \Omega_m \le 0.46$
  - $2.0 \le 10^9 A_s \le 2.3$

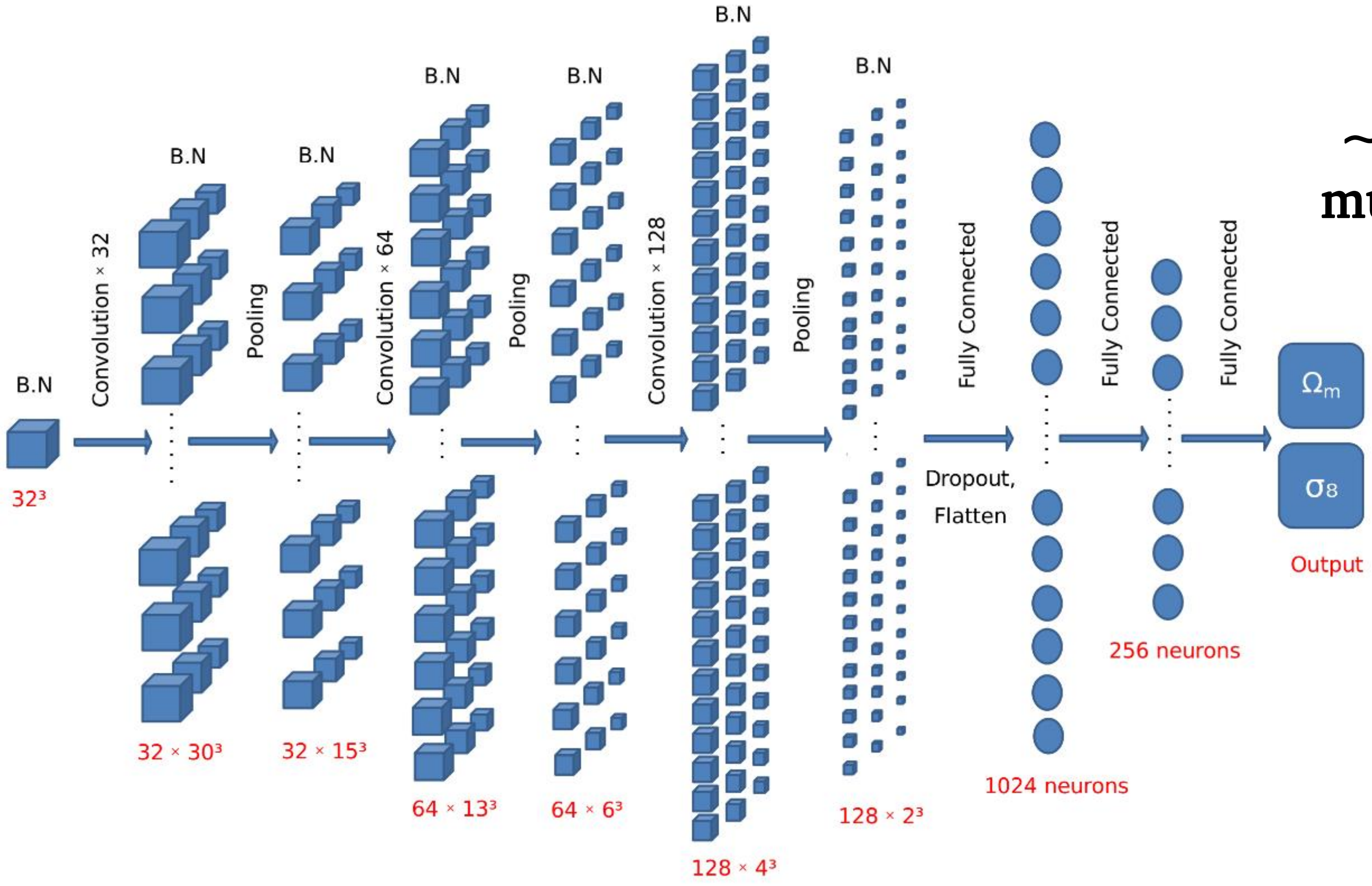


Distribution in Ω_m-σ_8 space

From Ω_m-A_s to Ω_m-σ_8
a degeneracy happens

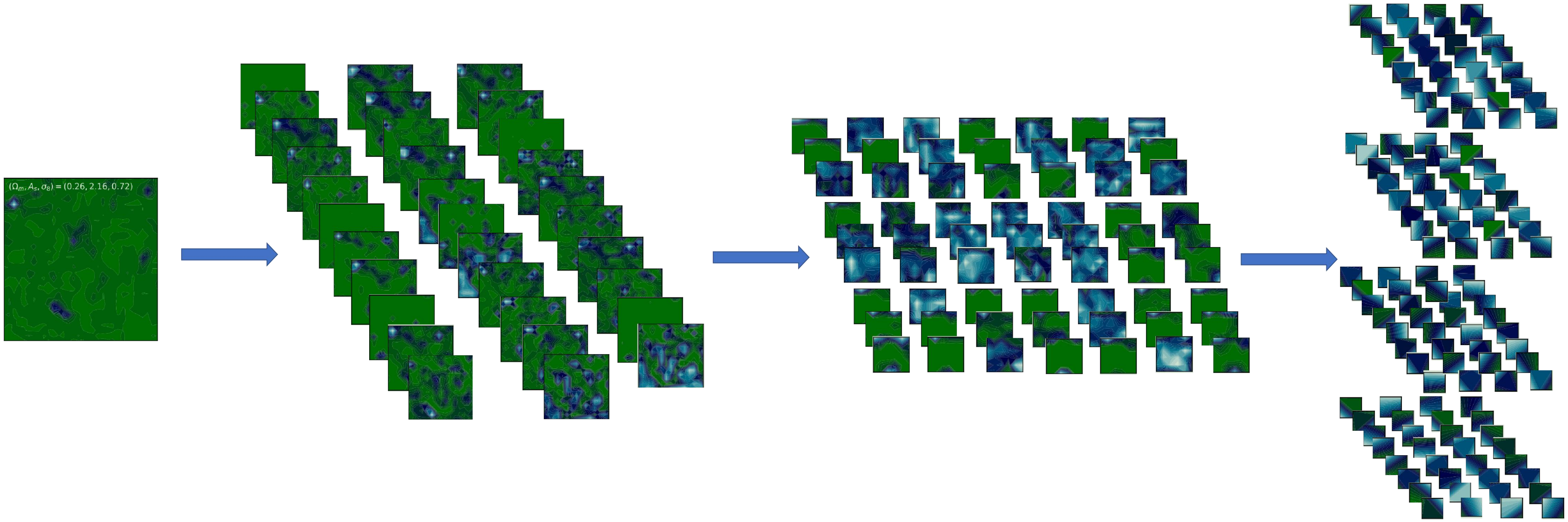


Our Architecture



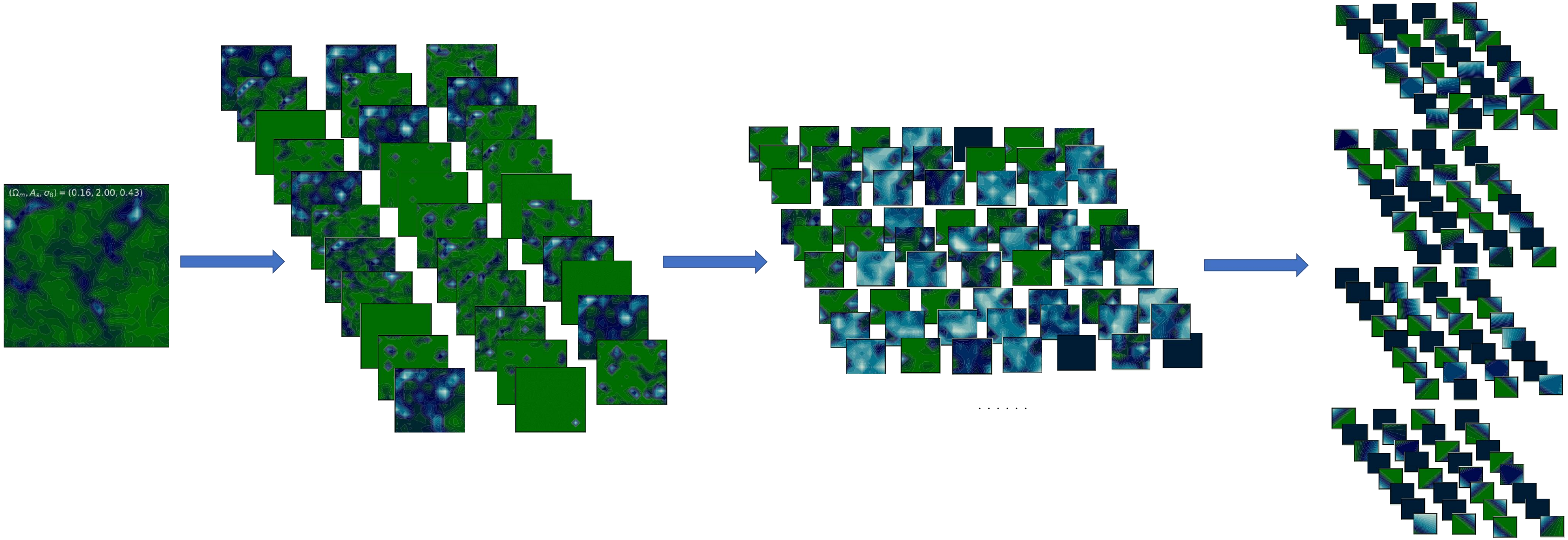
~10^3 of neurons, much simpler than our head

Features



$(\Omega_m - \sigma_8)$ = 0.26, 0.72

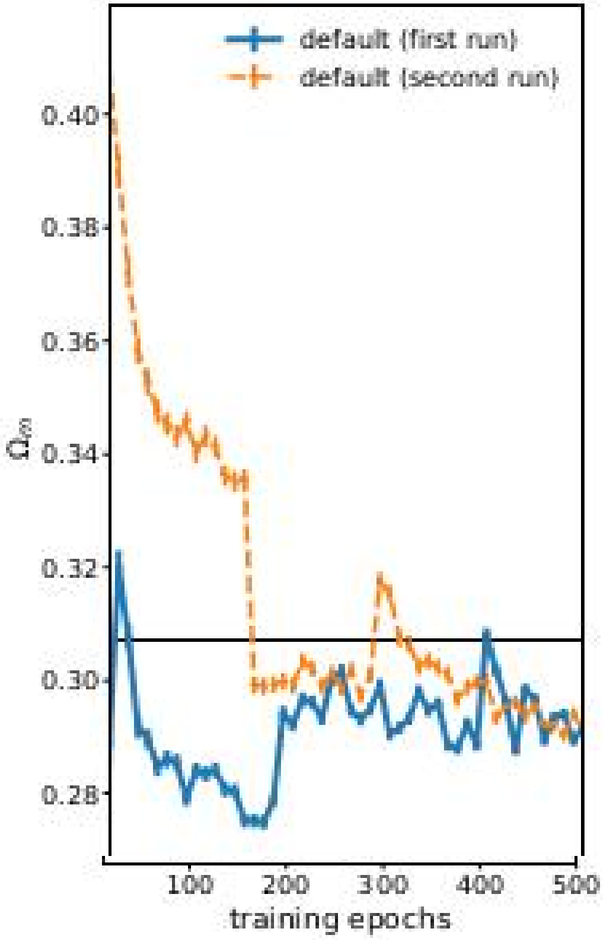
Features

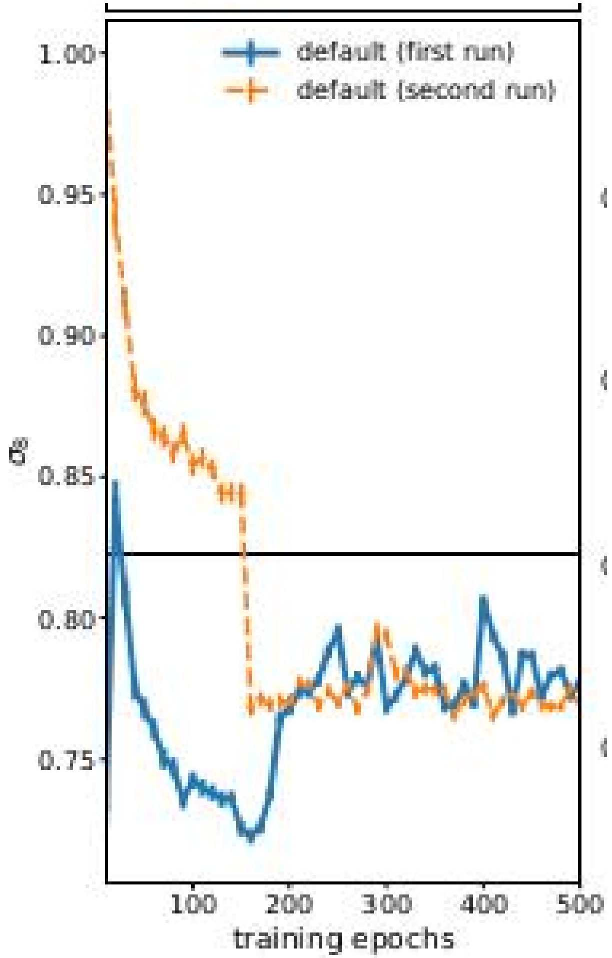


$(\Omega_m - \sigma_8)$ = 0.16, 0.43

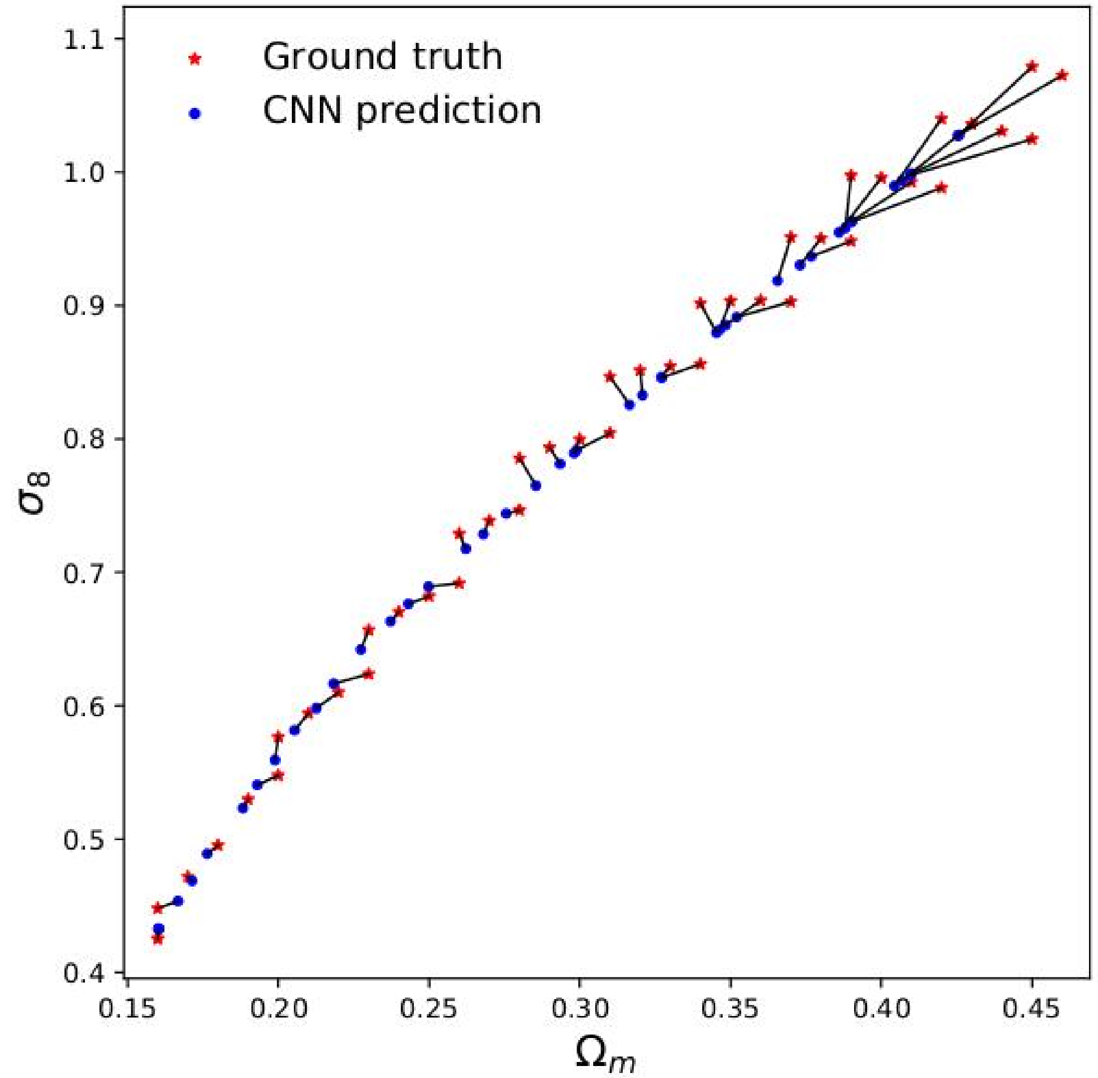
Training (converge after 200 epochs)

Understanding the Universe in ~1 week



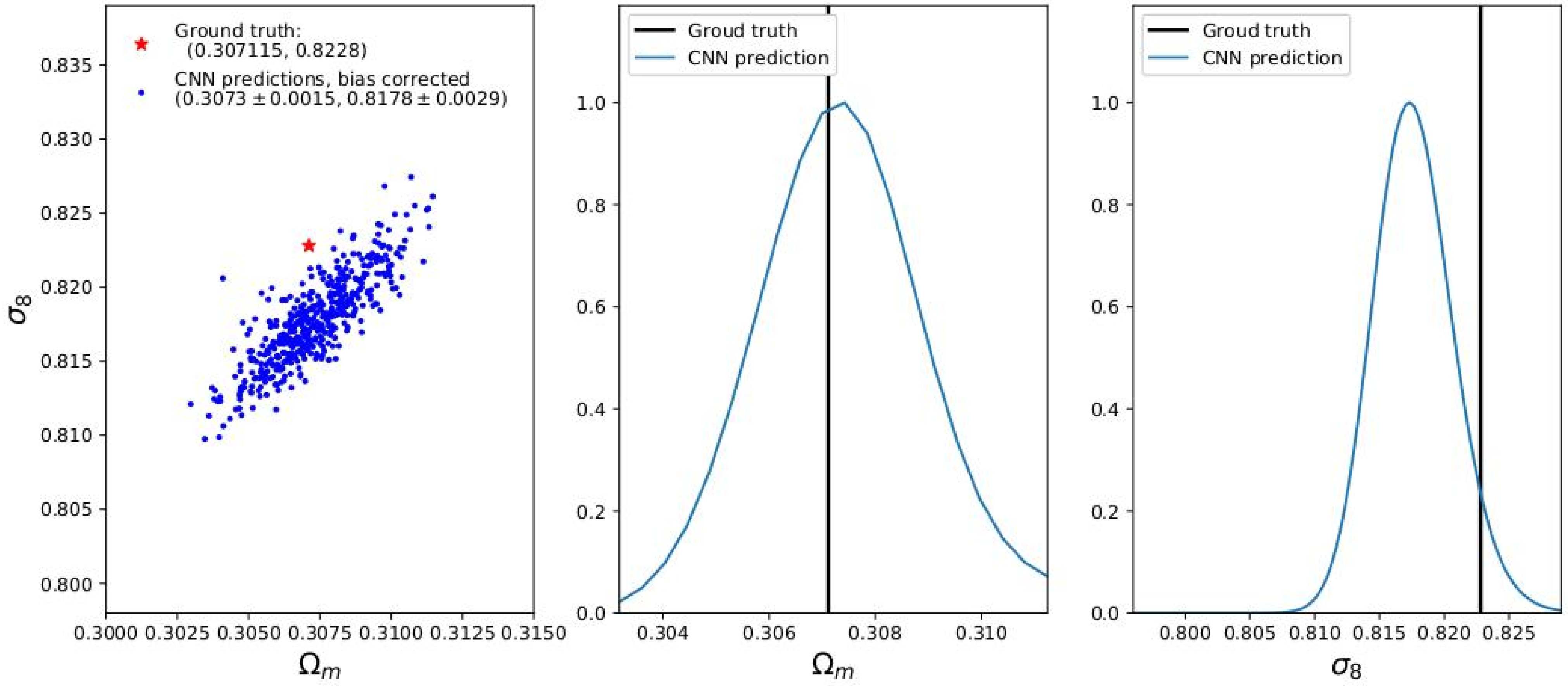


Controlling Bais



We add a regression to fit the bias and correct it

Cosmological Constraint



Precision

$(256\ \mathrm{Mpc}/h)^3$ + CNN yields to

$\delta\Omega_m$ =0.0015, $\delta\sigma_8$ =0.0029

Accuracy of Ω_m **6 times better** than Planck

Precision

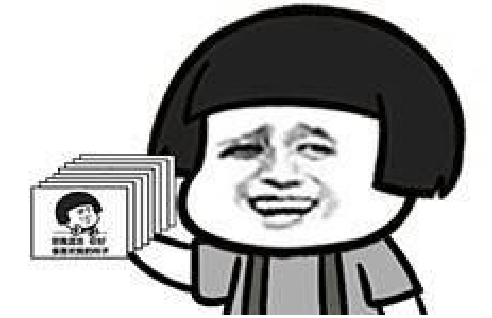
	Relative error of (Ω_m, σ_8)[a]
CNN	(0.0048, 0.0053)
2pcf, $s \in (0, 130)h^{-1}$Mpc	(0.017, 0.012)
2pcf, $s \in (10, 130)h^{-1}$Mpc	(0.1, 0.06)

smallest

3 times larger

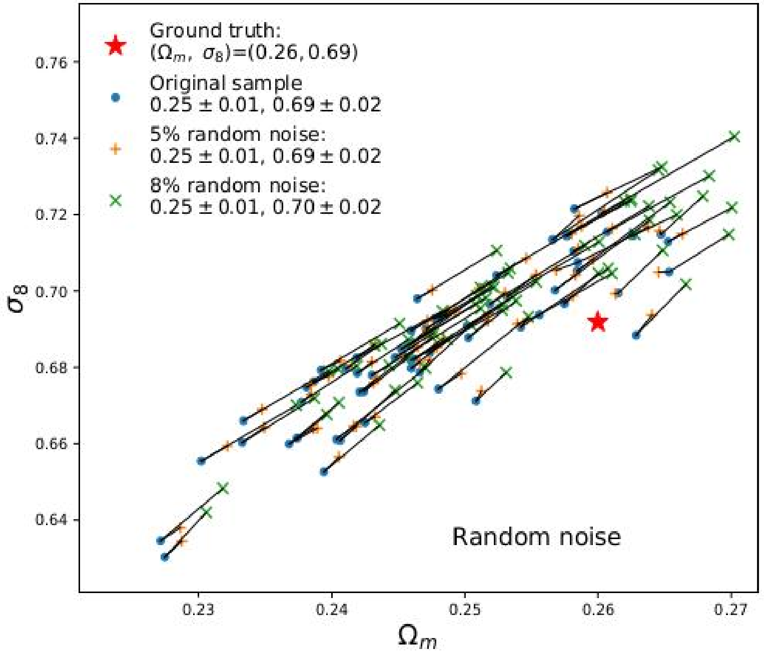
10-20 times larger

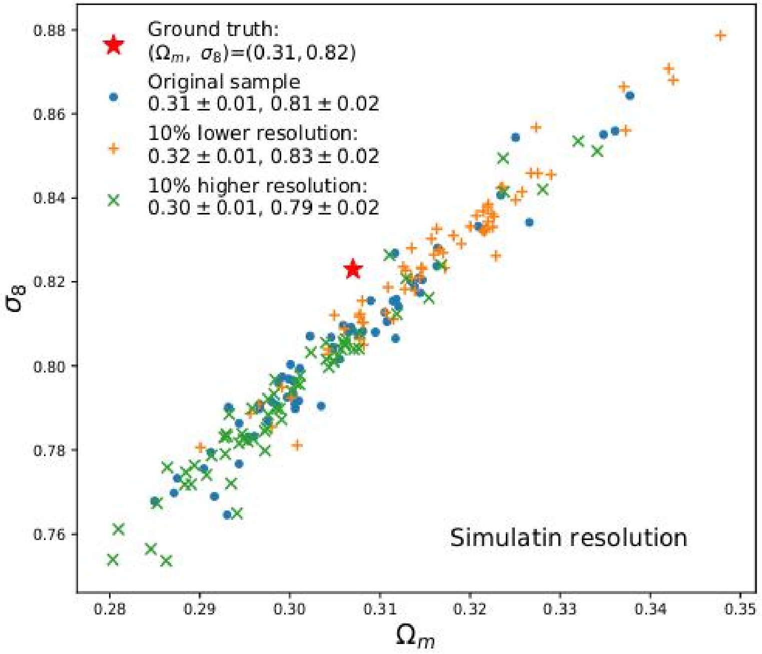
[a] Defined as $\Delta y/y$ (y stands for Ω_m, σ_8)



Machine outperforms 2pCF

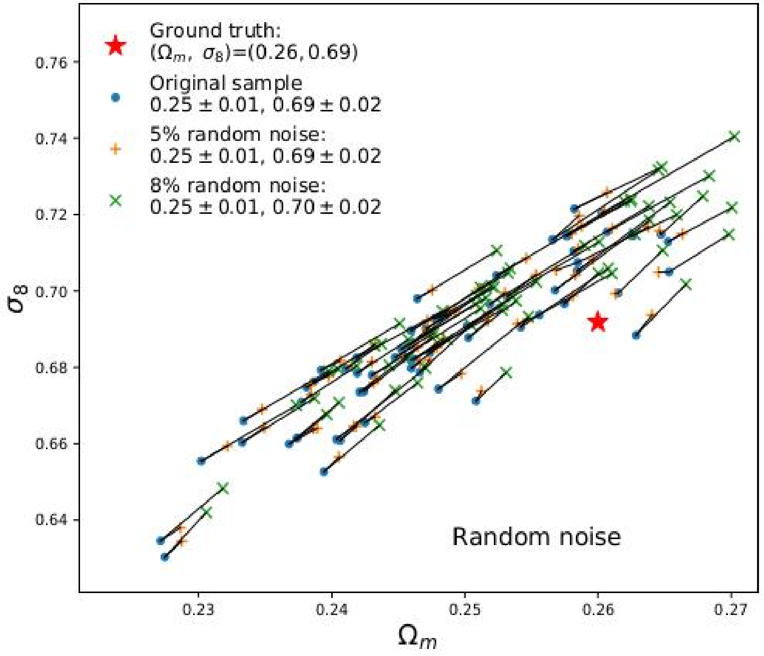
Robustness Tests

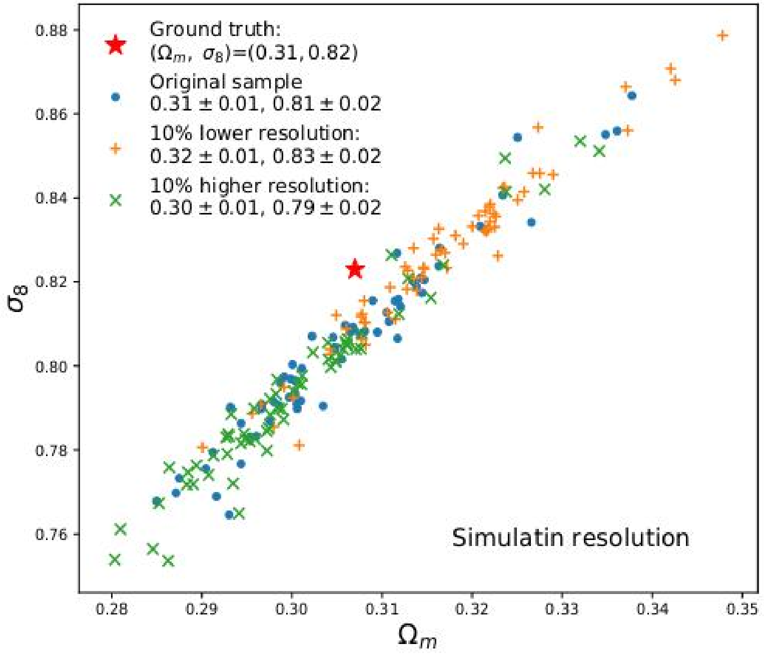




Robustness tests on samples having 32^3 voxels.

Robustness Tests

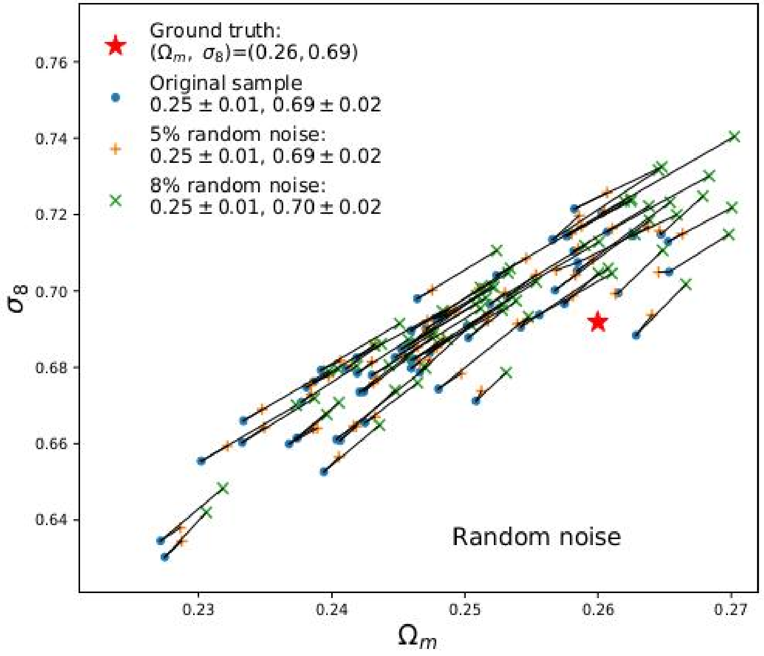


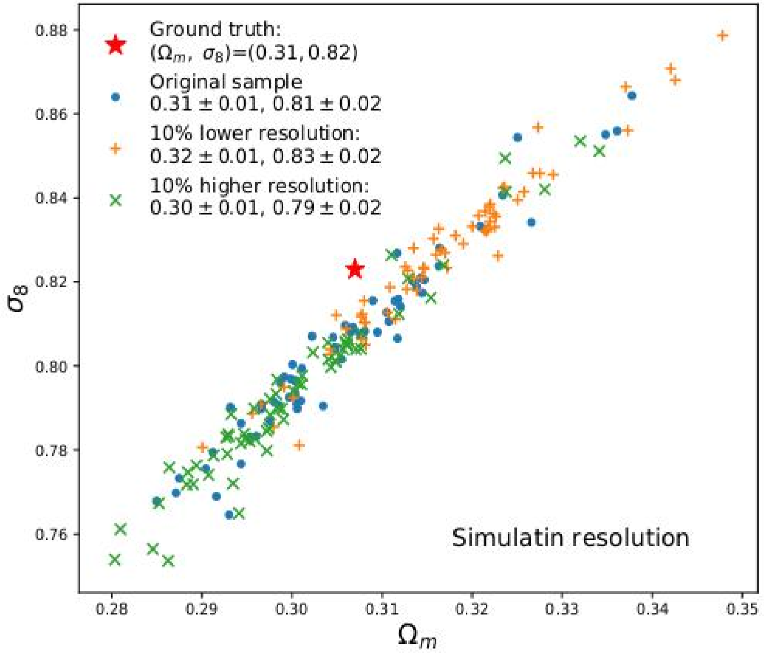


Robustness tests on samples having 32^3 voxels.

3% smoothing or 10% global variation :$\sim$ 2σ shift in central values, $\sim$ 100% enlarged errors

Robustness Tests



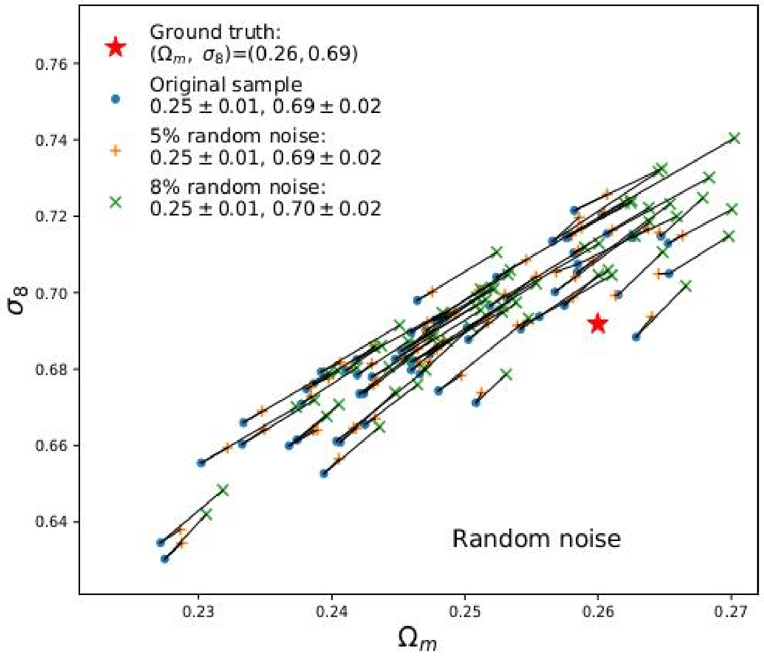


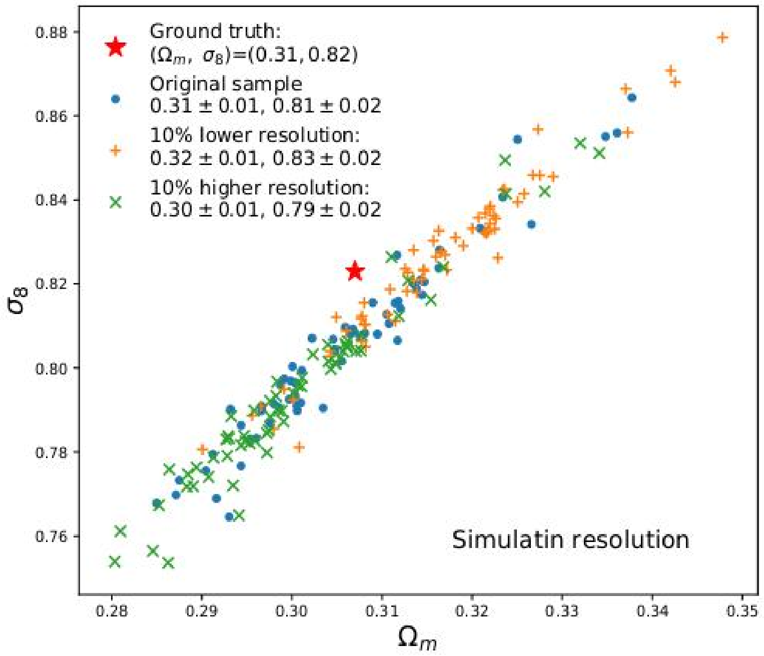
Robustness tests on samples having 32^3 voxels.

3% smoothing or 10% global variation :～ 2σ shift in central values, ～ 100% enlarged errors

1% smoothing, 5% global variation,10% change in the simulation's resolution: 1σ shift in central values,

Robustness Tests





Robustness tests on samples having 32^3 voxels.

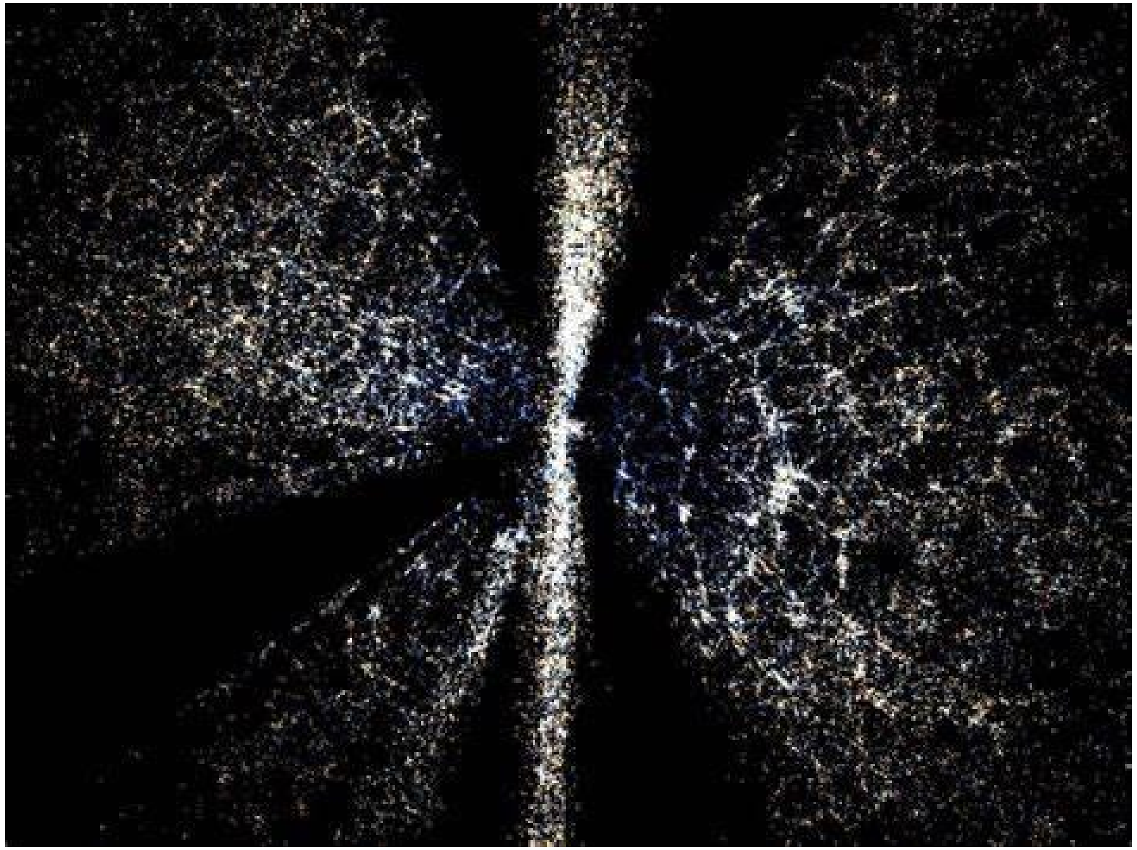
3% smoothing or 10% global variation :$\sim$ 2σ shift in central values, $\sim$ 100% enlarged errors

1% smoothing, 5% global variation,10% change in the simulation’s resolution: 1σ shift in central values,

1 or 4 3 voxels removal, 5% or 8% random noise, rotation & relfection: no change

Next Step

ML on realistic SDSS mock surveys



再罗嗦两句

(a few more words)

LSS Reconstruction using Machine Learning

潘书洋 大二

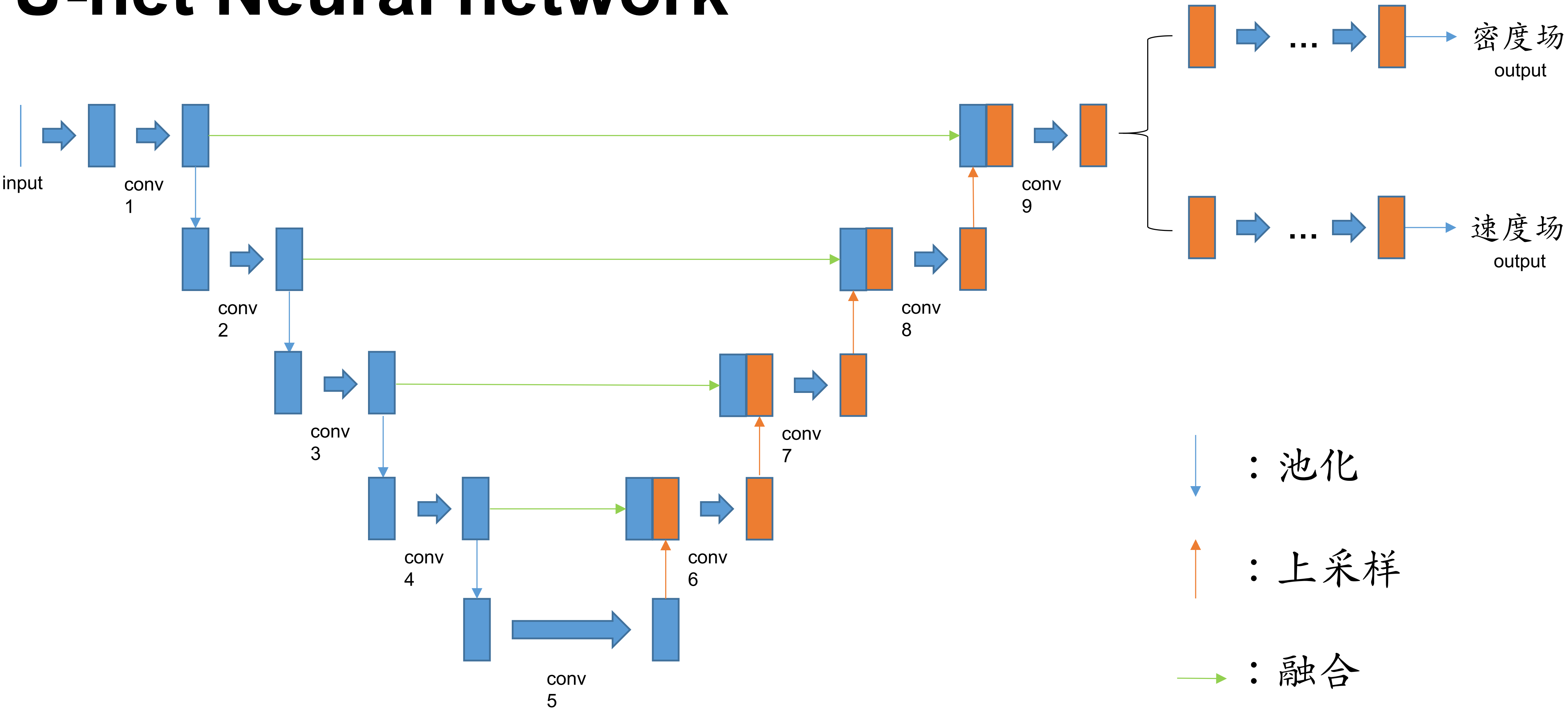
张震宇 大四

吴子泳 大三

LSS Reconstruction using Machine Learning

Just like image transforming...

U-net Neural network



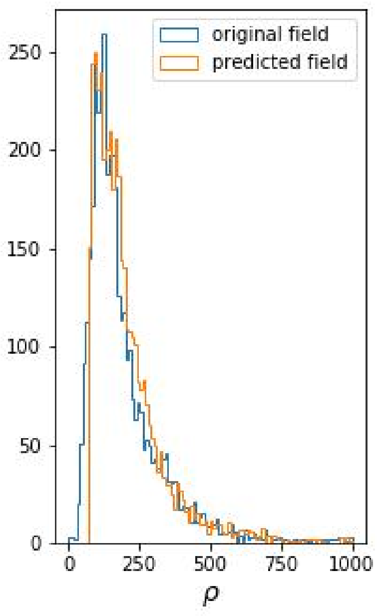
Non-trival mapping between fields

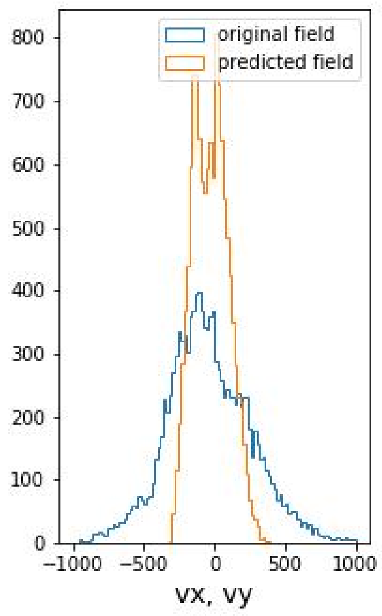
IC & Velocity Reconstruction

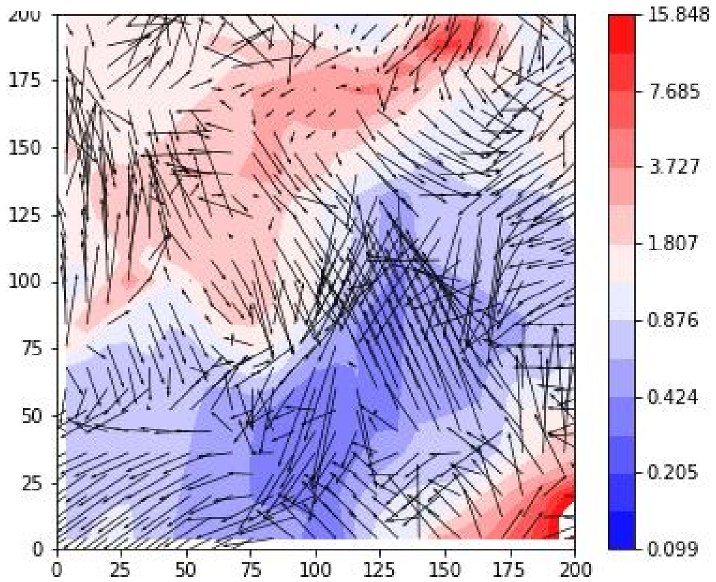
Very preliminary trials

Based on z=0 density field...

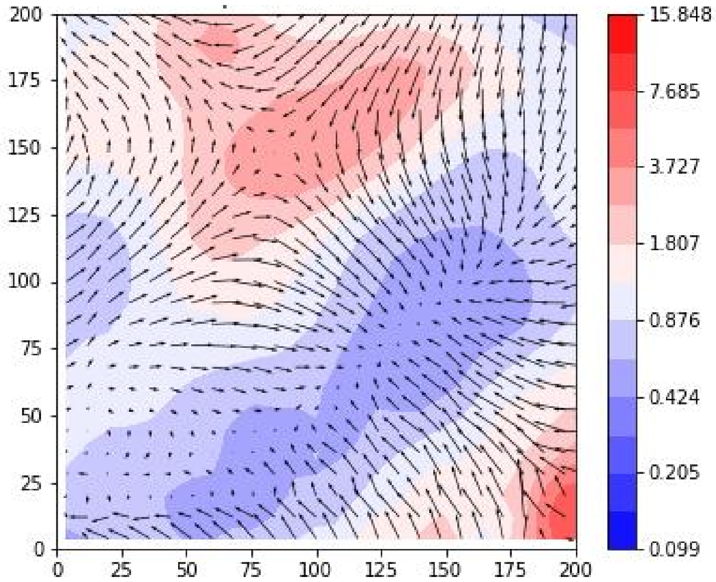
$$\Omega_m = 0.205$$







z=1 density & velocity, ground truth

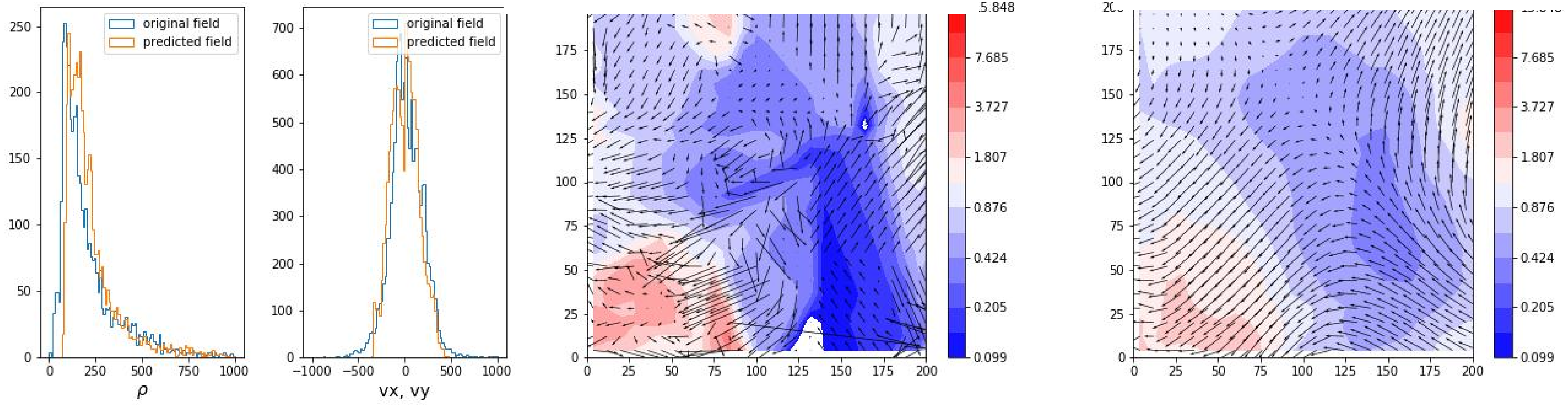


z=1 density & velocity, AI results

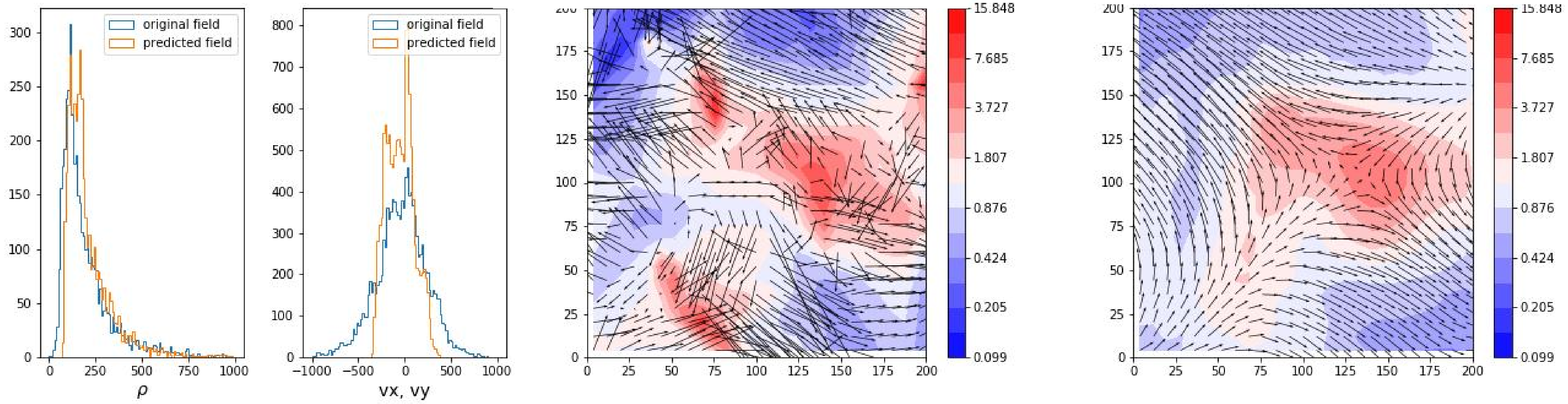
Very preliminary trials

$\Omega_m = 0.290$

Grouth truth **AI**



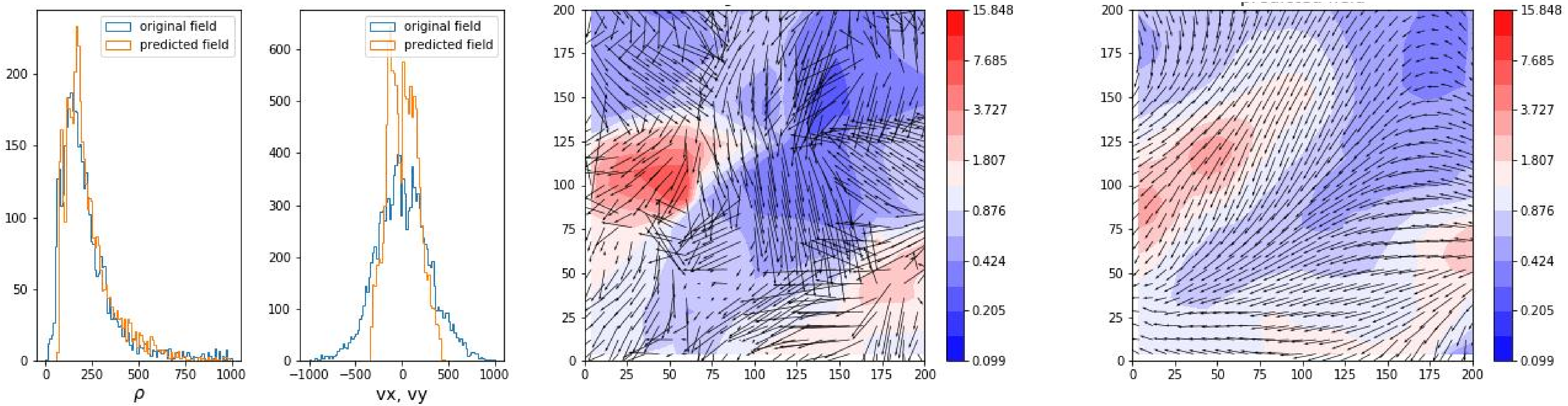
$\Omega_m = 0.315$



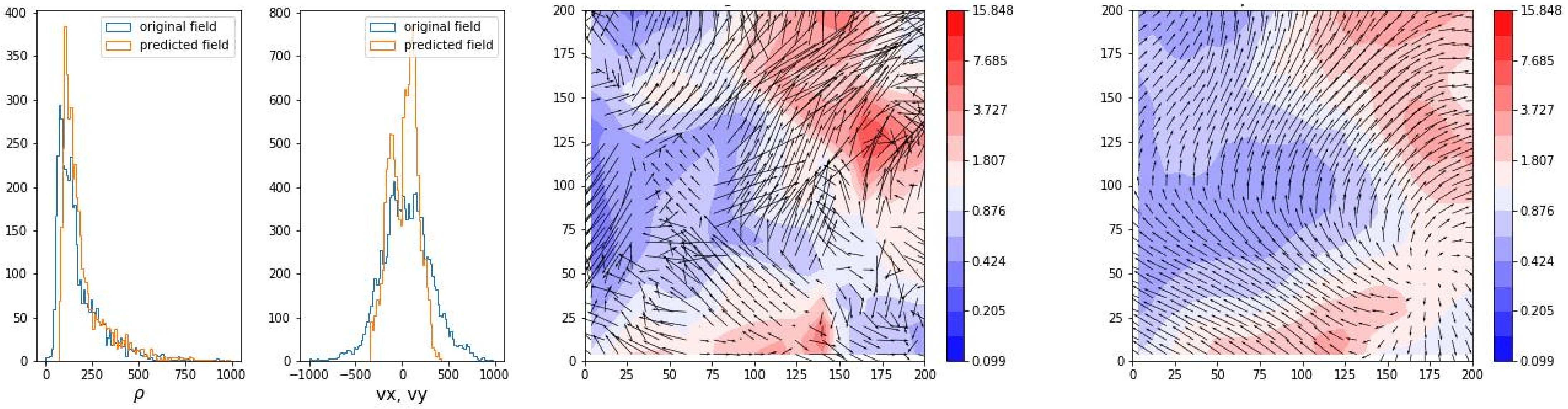
Very preliminary trials

$\Omega_m = 0.320$

Groud truth **AI**



$\Omega_m = 0.445$



Conclusion & Future

Theory

Observation

Traditional methods

Traditional methods

Theory

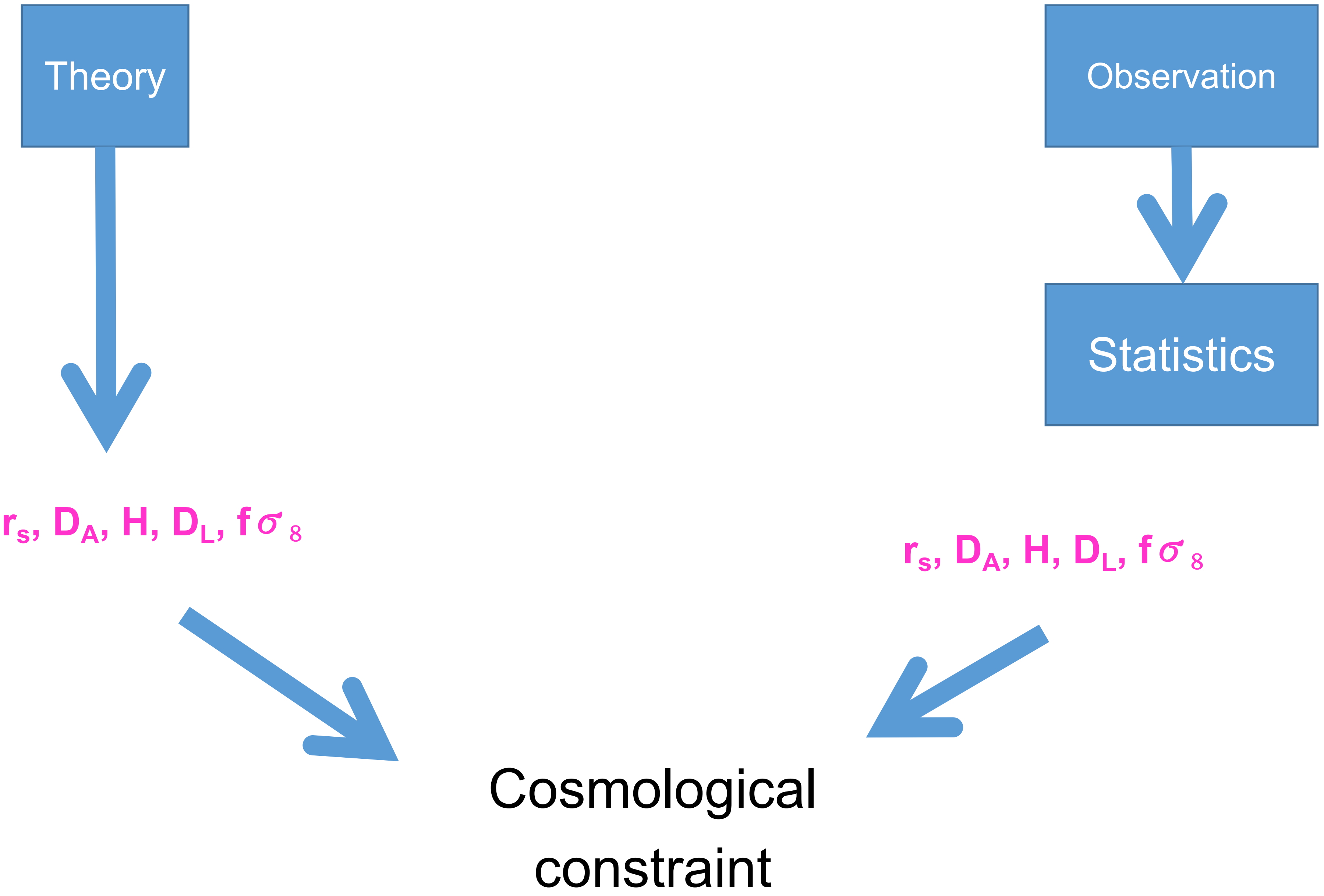
r_s, D_A, H, D_L, $f\sigma_8$

Observation

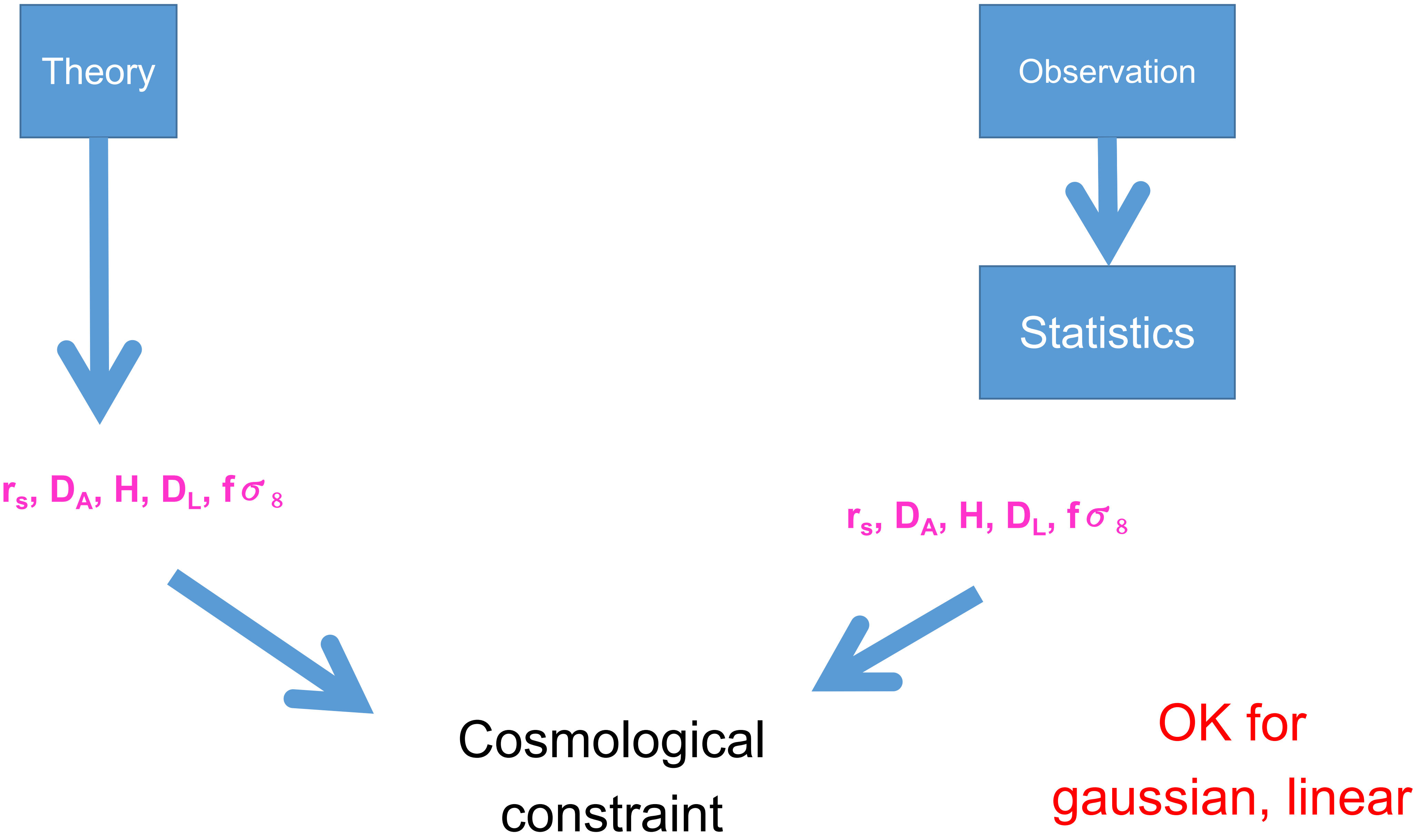
Statistics

r_s, D_A, H, D_L, $f\sigma_8$

Traditional methods



Traditional methods



Novel Method

Novel Method

Theory

Observation

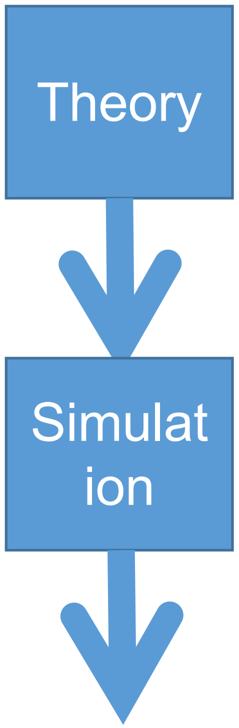
Simulat
ion

Some features

e.g. z-evolv

of AP, RSD

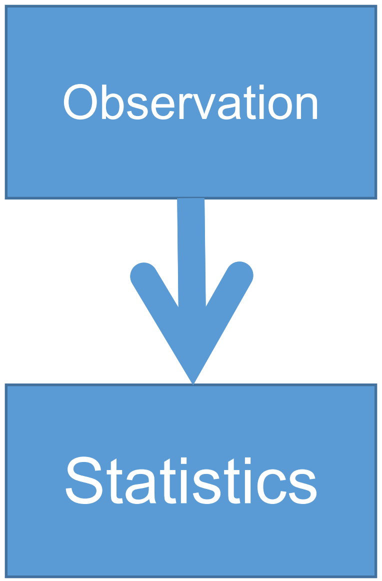
Novel Method



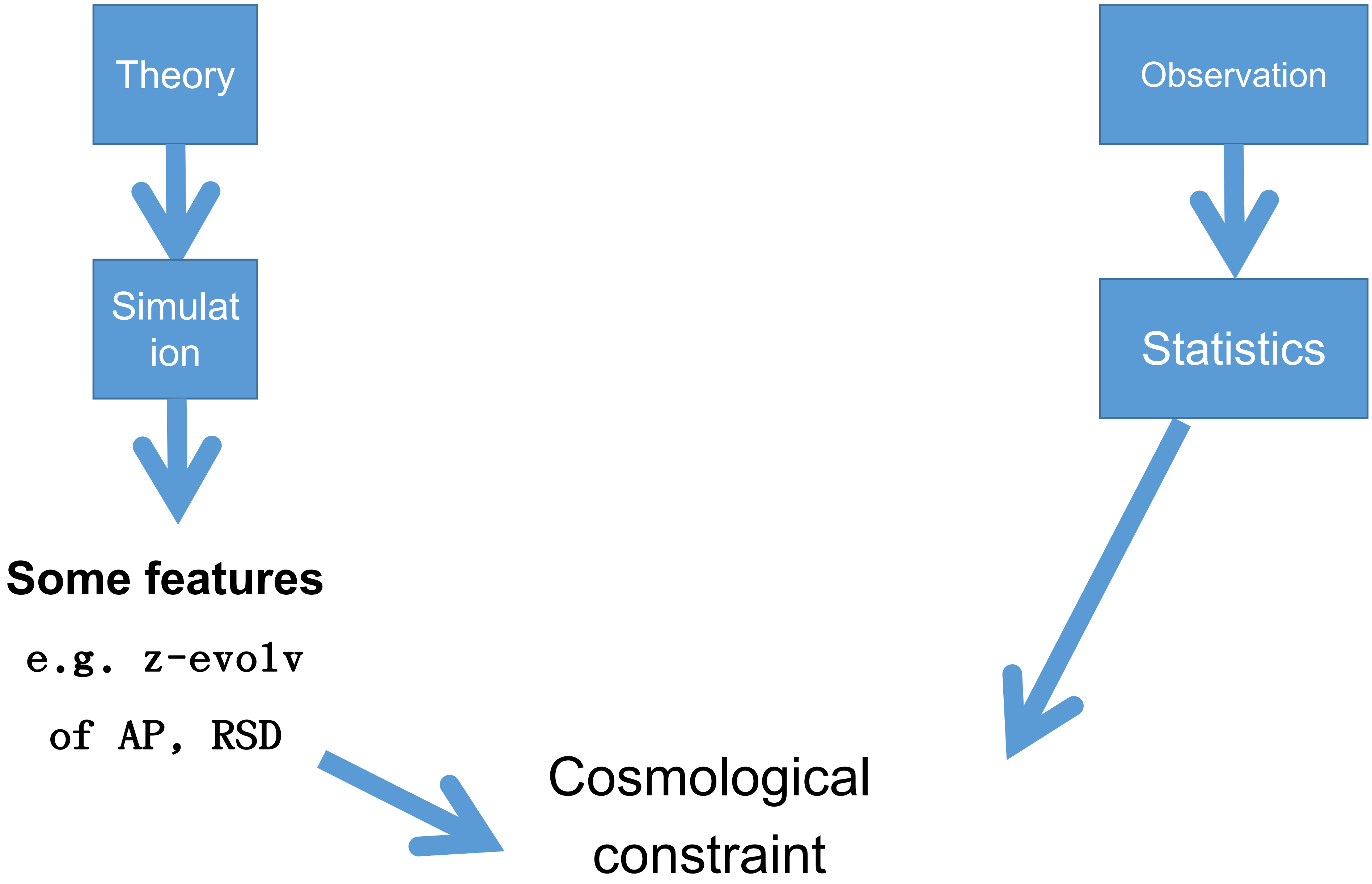
Some features

e.g. z-evolv

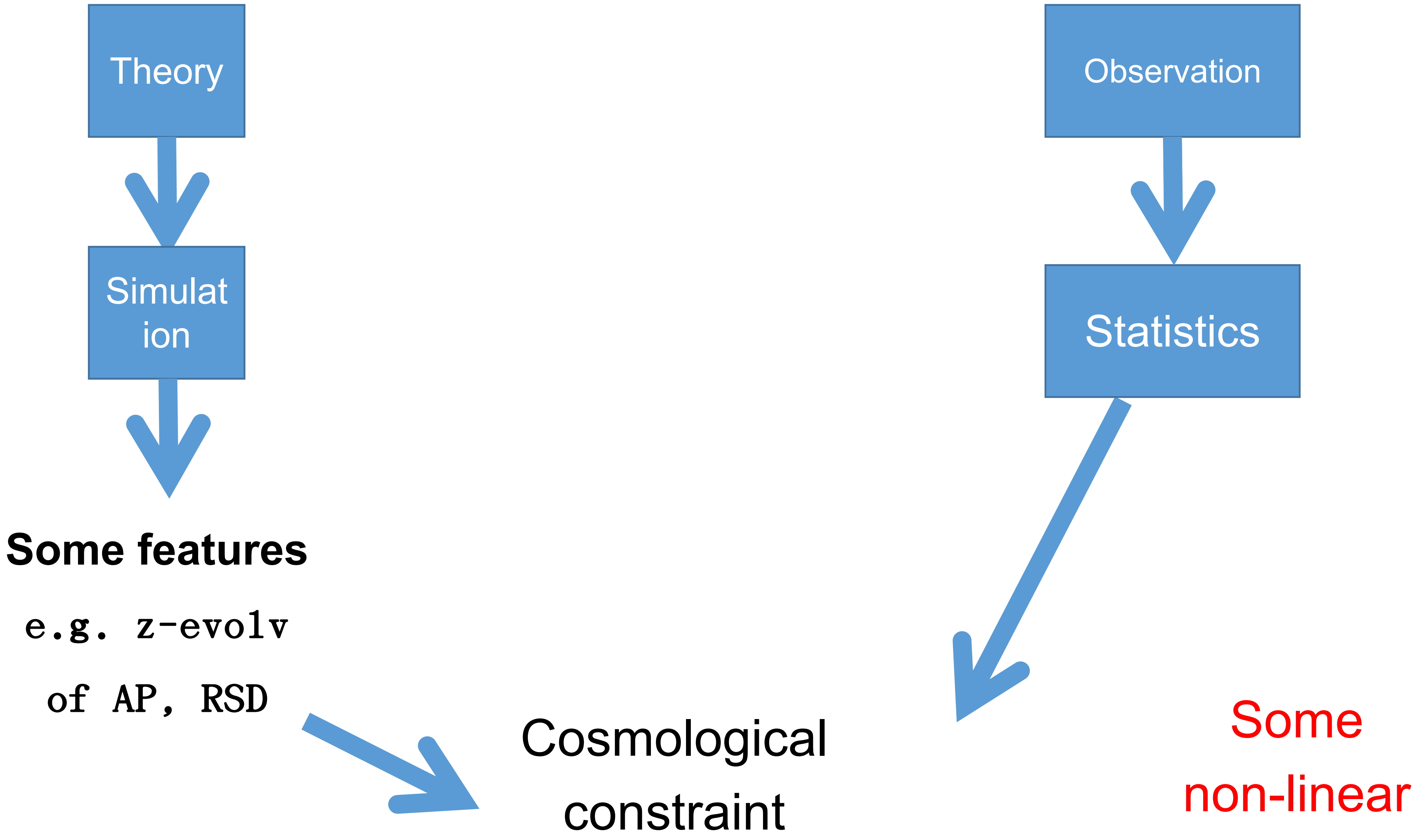
of AP, RSD



Novel Method

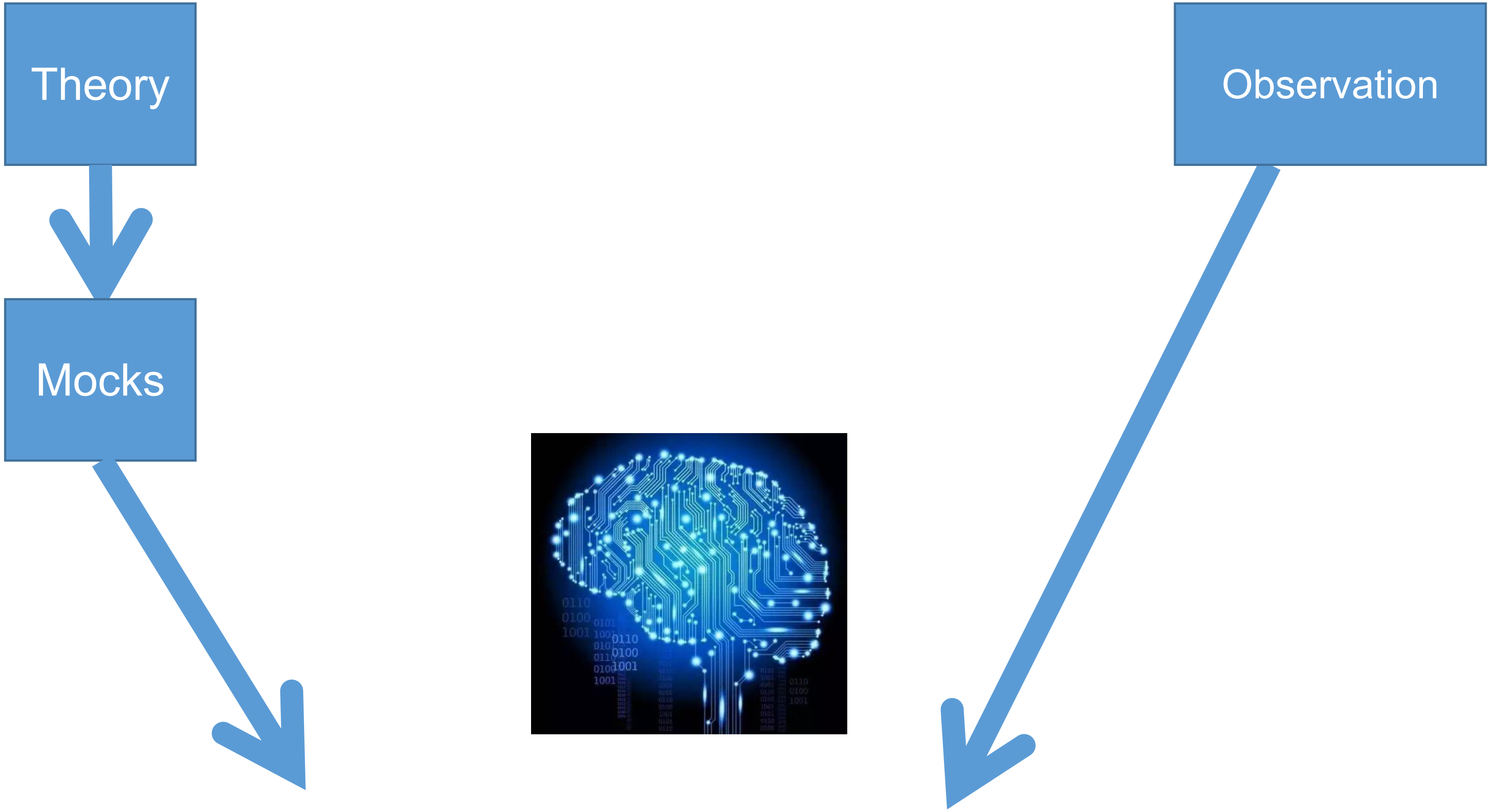


Novel Method

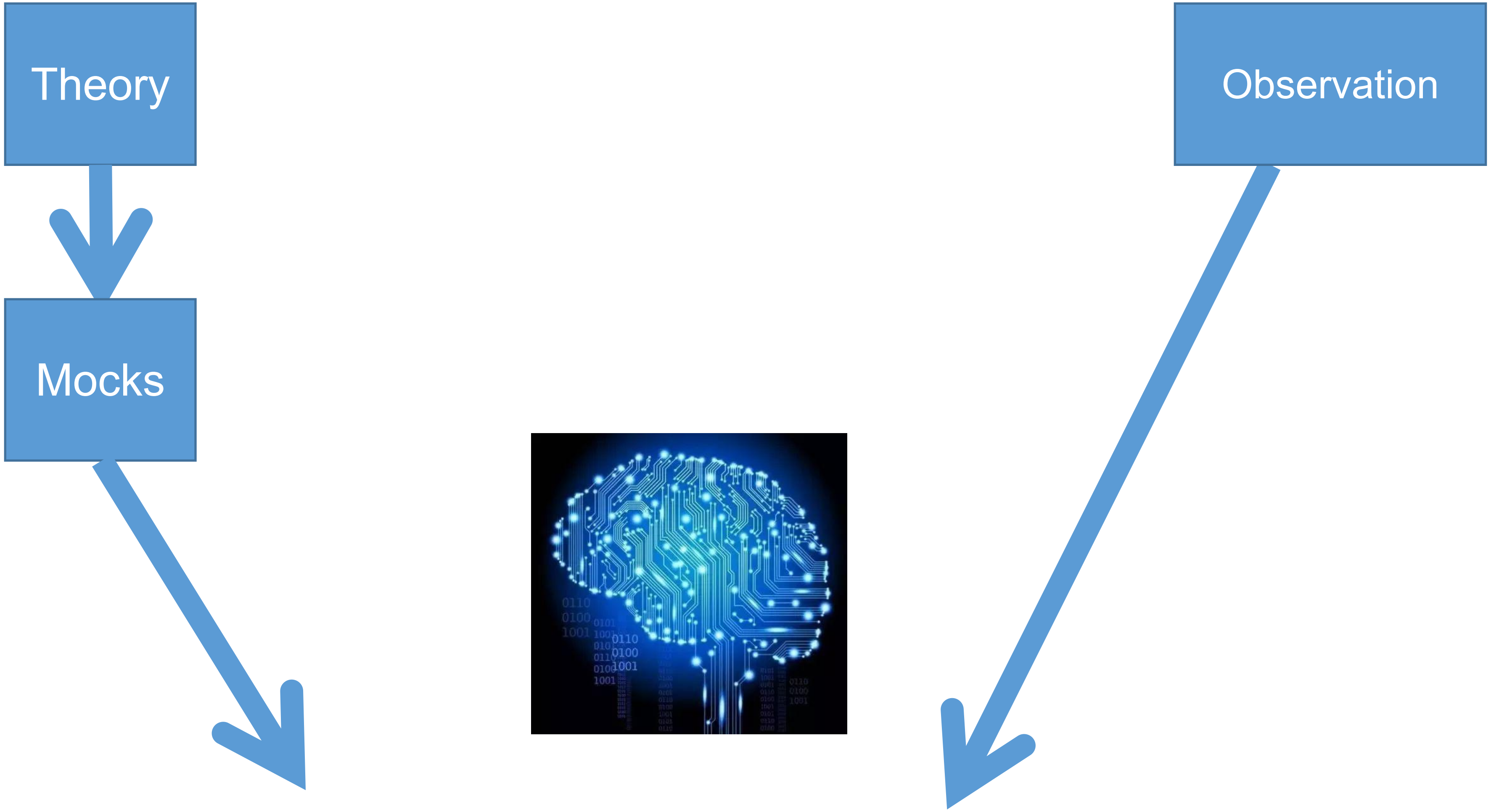


Machine Learning

Machine Learning



Machine Learning

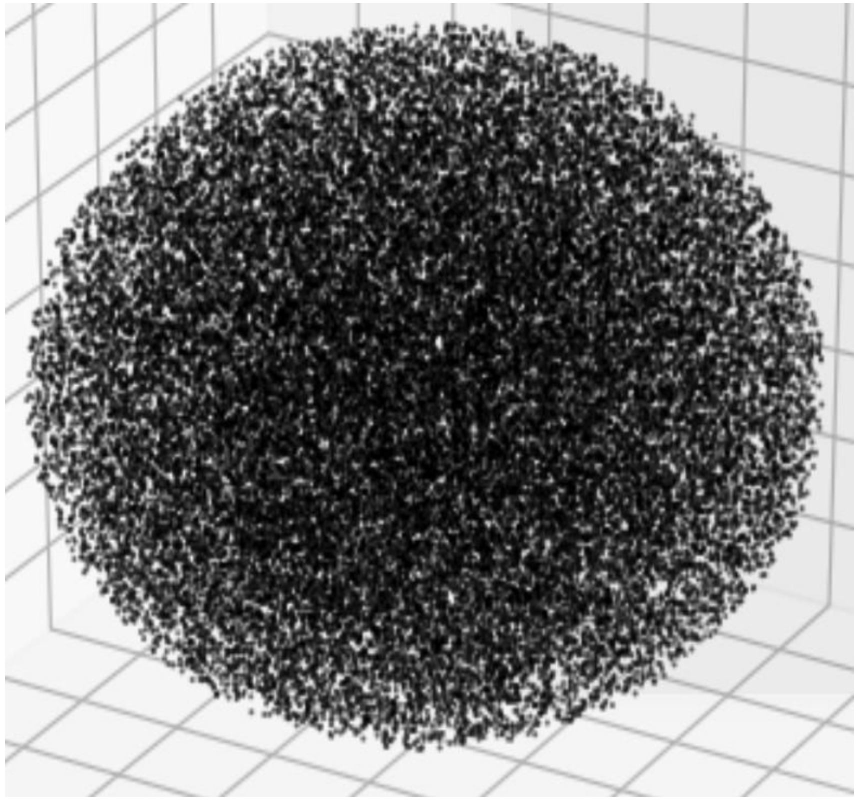


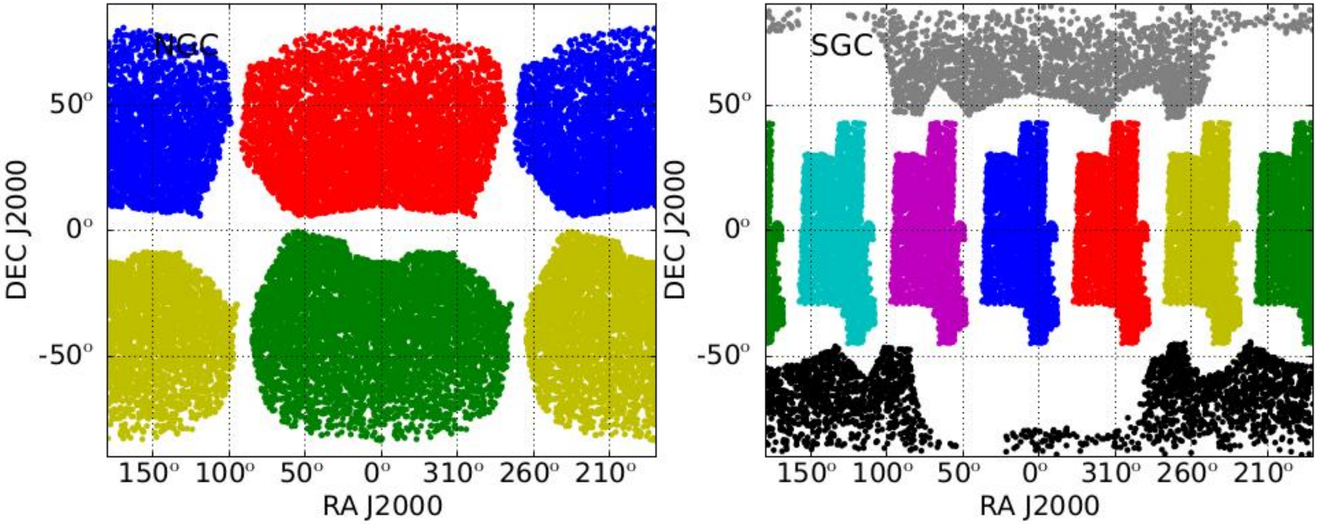
Cosmological constraint

(Hopefully) non-linear

Application to future surveys

all methods need a lot of mocks!





1. systematics correction
   (~10^3 runs, multi-cosmologies)
2. covariance matrix
   (~10^3 runs, single cosmology)
3. machine learning training/test samples
   (~10^3-10^4 runs, multi-cosmologies)

Sun Yat-Sen University
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- Positions
  - Professor/Associate Professor
  - Researcher
  - Postdoc

- Research Fields
  - TianQin (GW)
  - **Astronomy (Cosmology and galaxies, Milky way, stellars, planets, high-energy physics, observational astronomy,...)**
  - Theortical physics
  - Quantum physics

天文系目前有

教授、副教授22人，

专职研究员、博士后19人

错过别后悔哦

谢谢观看