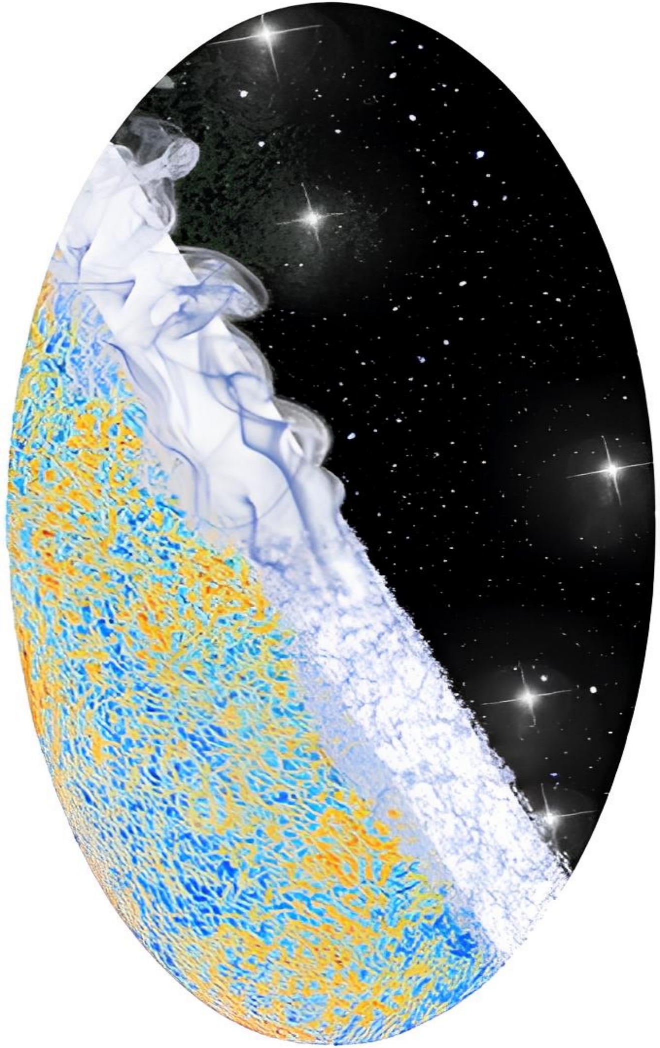

ÉCOLE DE PHYSIQUE DES HOUCHES

Revisiting the Cosmic Distance LADDER with Deep Learning Approaches and Addressing Cosmological Tensions

Learning Algorithm for Deep Distance Estimation and Reconstruction

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The Astrophysical Journal
Supplement Series
273(2), 27 (2024)
[arXiv:2401.17029]

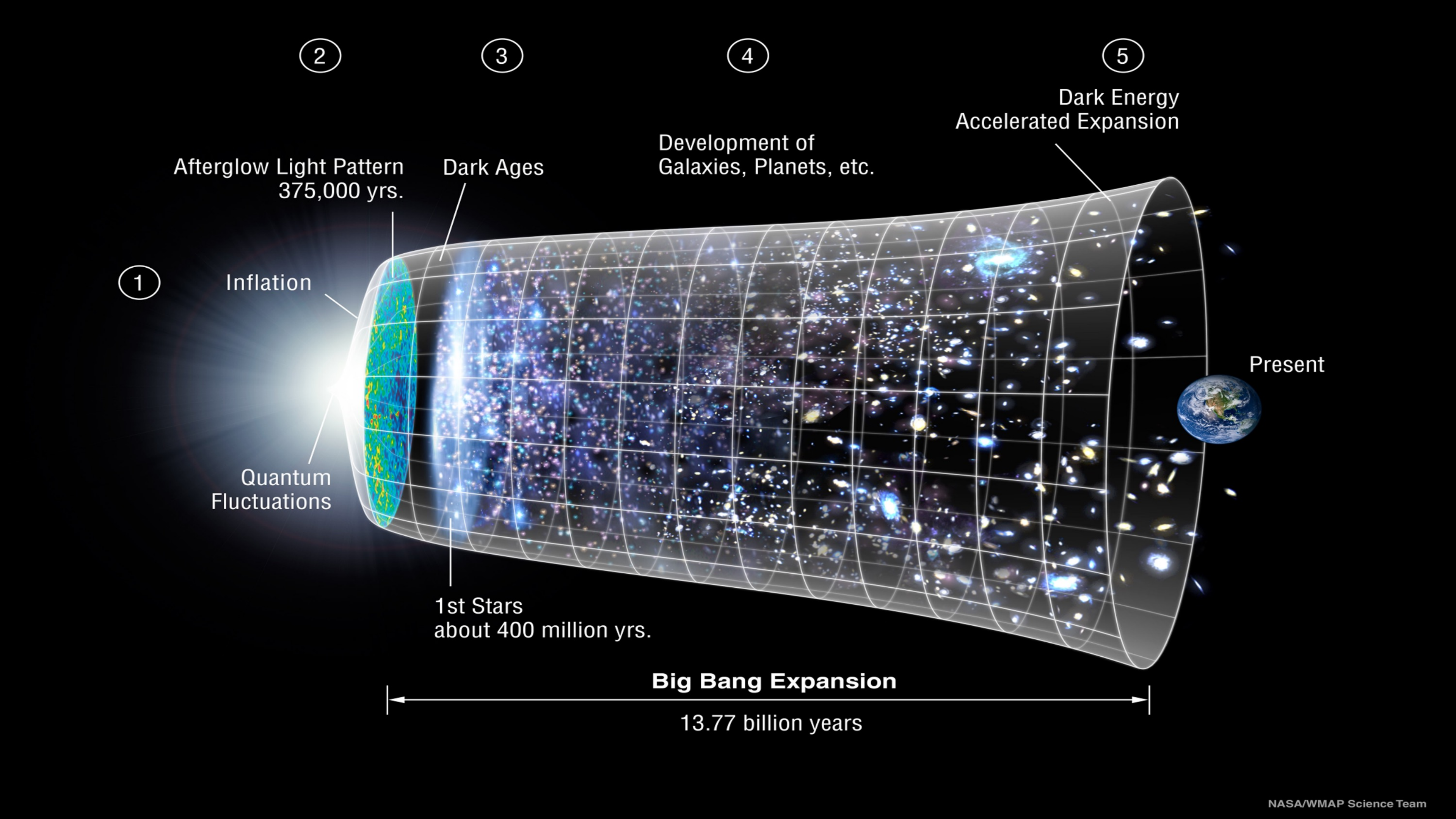
arXiv:2412.14750

Collaborators

Soumadeep Saha, Purba Mukherjee, Utpal Garain, Supratik Pal

“In an investigation, assumptions kill.”

- Jack Reacher



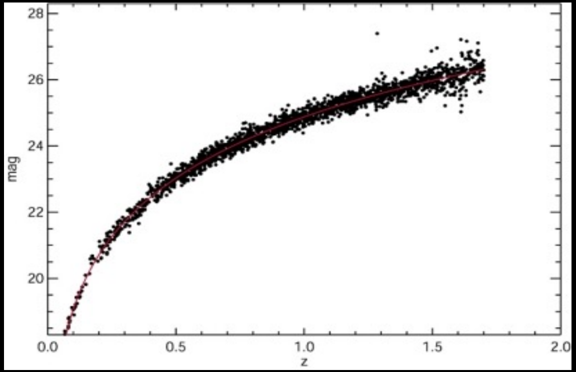
1
2
3
4
5
Dark Energy
Accelerated Expansion
Development of
Galaxies, Planets, etc.
Afterglow Light Pattern
375,000 yrs.
Dark Ages
Inflation
Quantum
Fluctuations
Present
1st Stars
about 400 million yrs.
Big Bang Expansion
13.77 billion years
NASA/WMAP Science Team

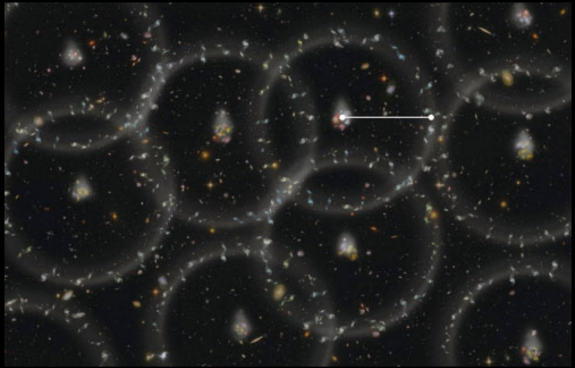
Observing the Cosmological System

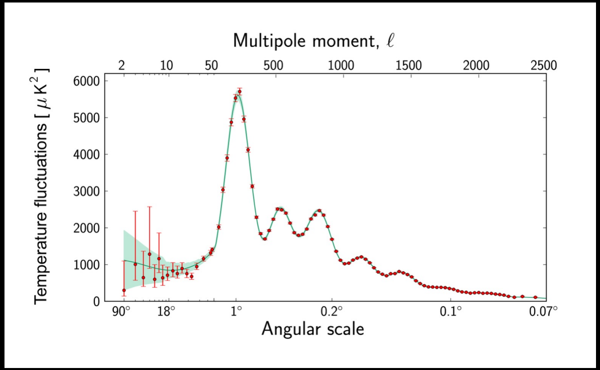
Measure distances to look into the past.

Study patterns in the sky.

Measuring Distances

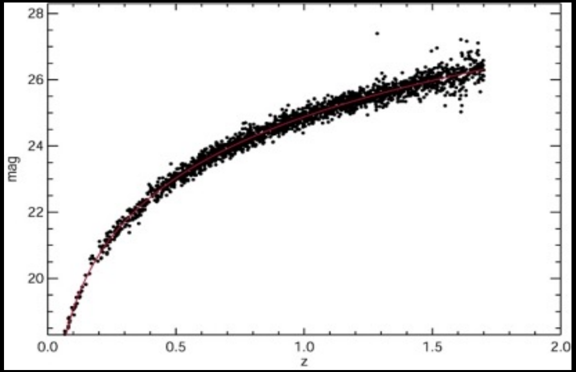


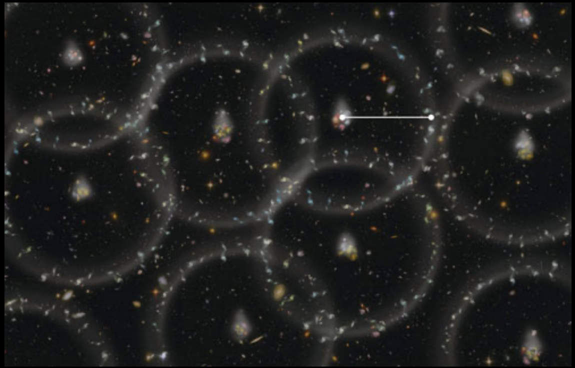


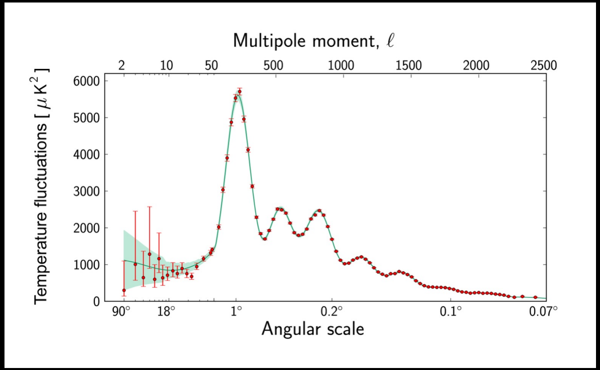


"How far thou art?"

Why Tensions?







Systematics?

Miscalibration?

ΛCDM?

Data Driven Approaches

Cosmography

Parametric

Non-Parametric

Data Driven Approaches

Cosmography

Parametric

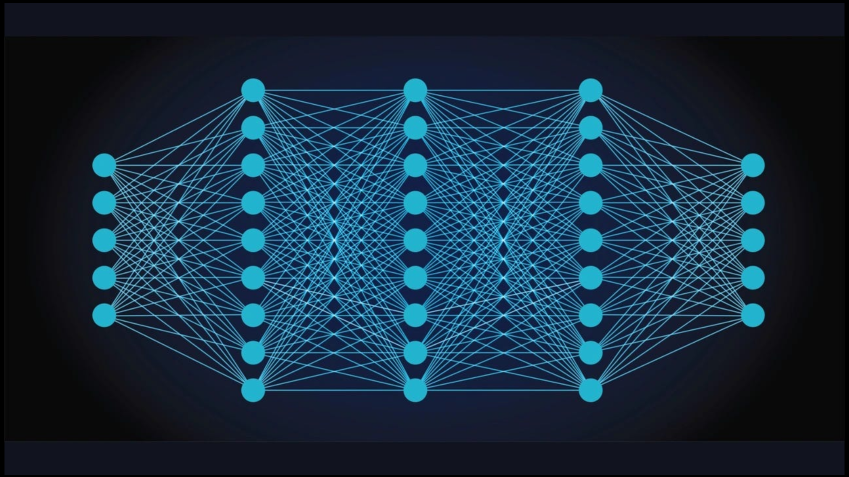
Non-Parametric

Gaussian Processes

Deep Learning

Other Methods

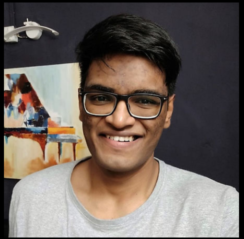
Deep Learning

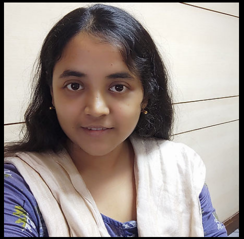


Universal
Function
Approximators

LADDER

Learning Algorithm for Deep Distance Estimation and Reconstruction





Uniqueness of Reconstruction

Overfitting and Underfitting Issues

Accurate Predictions On Precision

Extrapolation Beyond Training Range

https://github.com/rahulshah1397/LADDER *[publicly available]*

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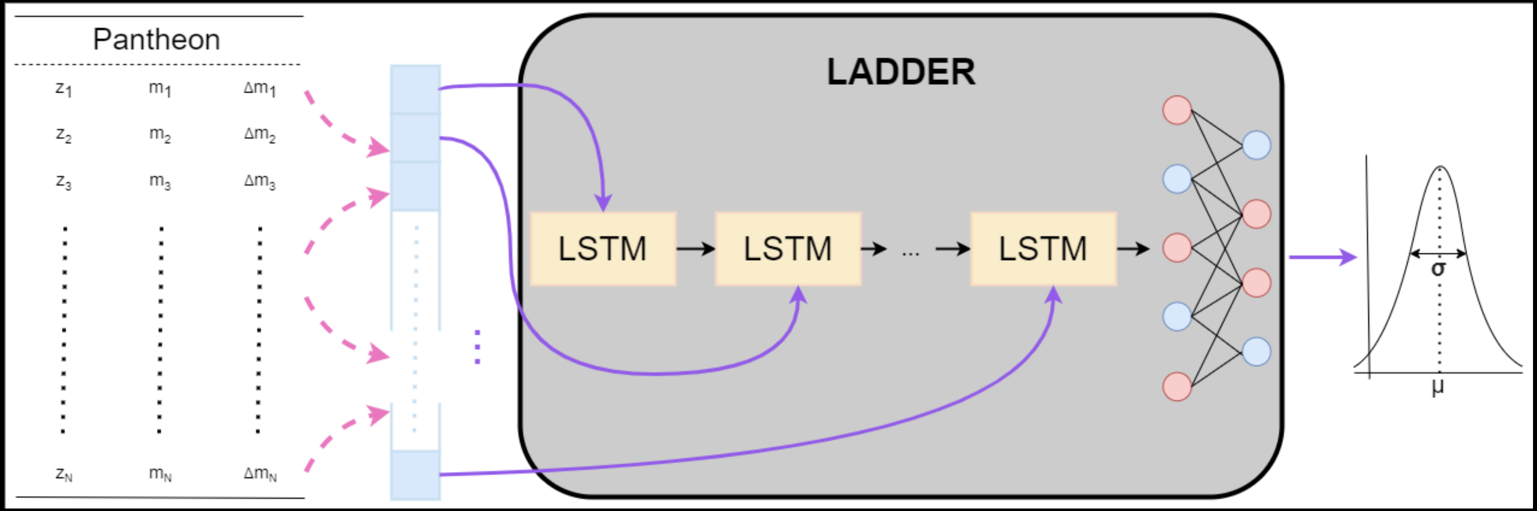
LADDER

Learning Algorithm for Deep Distance Estimation and Reconstruction



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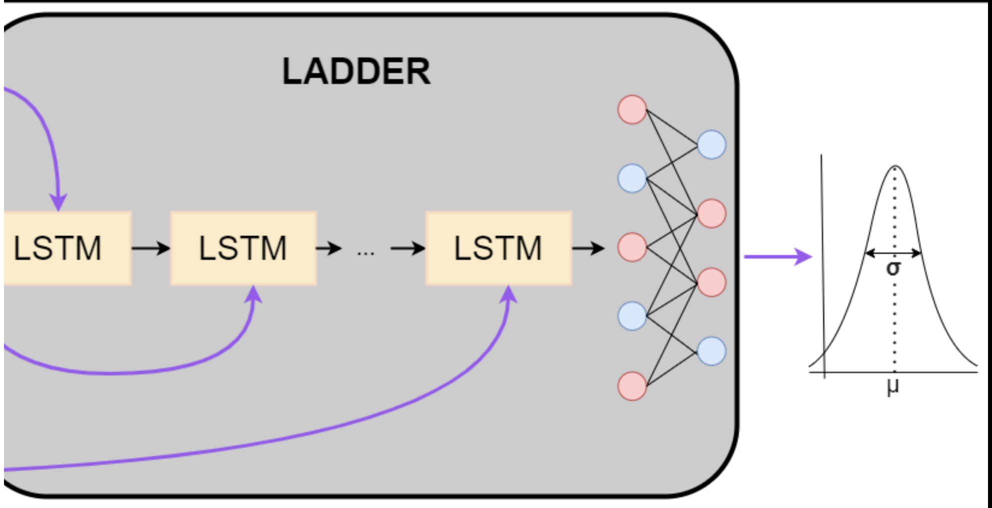
LADDER

Learning Algorithm for Deep Distance Estimation and Reconstruction

---

Given $\mathcal{D}$, $\boldsymbol{C}_{\rm sys}$ and batch size B.
Initialize θ_0.
while not StopCondition **do**
 $l \leftarrow 0$
 for $i = 1, 2, \ldots B$ **do**
 Get K samples from $\mathcal{D}$
  $\{(z_1, m_1, \Delta m_1), \ldots (z_K, m_K, \Delta m_K)\}$
 $Y_i = (m_{j_1}, \Delta m_{j_1})$
 $\hat{m}_{j_2}, \hat{m}_{j_3}, \ldots \hat{m}_{j_K} \sim \mathcal{N}(m_{j_2}, m_{j_3}, \ldots m_{j_K}, \Sigma_m^K)$ ▷ (Equation (9))
 $X_i = (z_{j_1}, z_{j_2}, \hat{m}_{j_2}, \ldots z_{j_K}, \hat{m}_{j_K})$ $z_{j_2} \leqslant z_{j_3} \ldots$
 $\mu, \sigma = f_{\theta_t}(X_i)_1, f_{\theta_t}(X_i)_2$ ▷ Forward pass.
 $l += D_{\rm KL}(\mathcal{N}(m_{j_1}, \Delta m_{j_1}), \mathcal{N}(\mu, \sigma))$
 end for
 Compute $\nabla_{\theta_t} l \quad \forall \theta_t$
 $\theta_{t+1} = \theta_t + \eta \cdot \nabla_{\theta_t}$ ▷ Gradient update (illustrative).
 if … **then** ▷ Check if model converged. StopCondition ← True
 end if
 end while



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LADDER

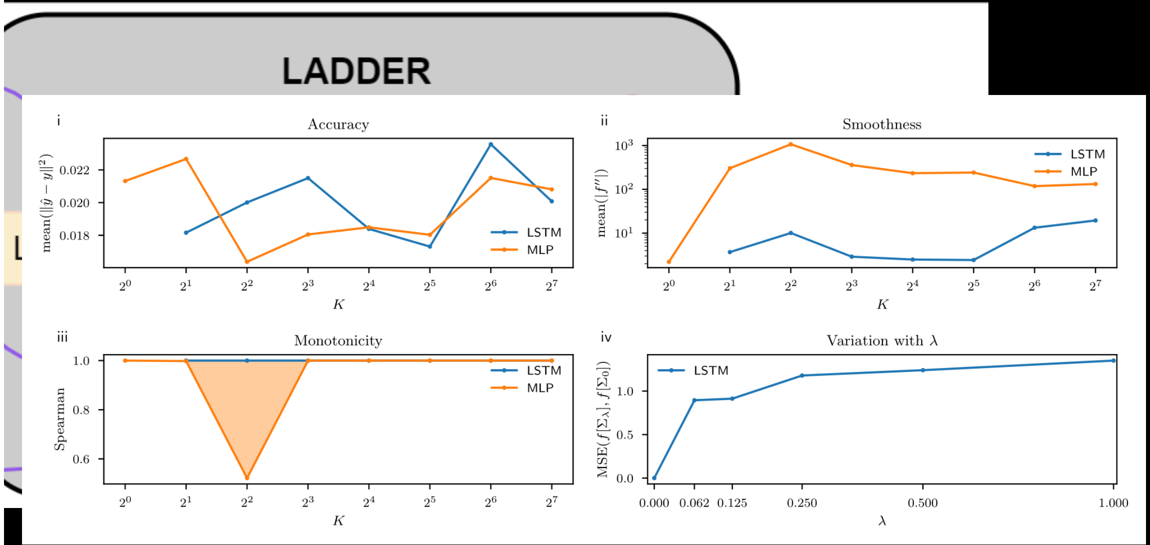
Learning Algorithm for Deep Distance Estimation and Reconstruction

Performance of Various ML Models

Model	MSE (↓)	Monotonicity (↑)	Smoothness (↓)
kNN ($k = 5$)	0.022116	0.99999	90.67500
SVR	0.019358	**1.0**	3.10633
MLP ($K = 1$)	0.022202	**1.0**	**2.21691**
MLP ($K = 32$)	0.020484	0.99997	88.99974
LADDER	**0.018495**	**1.0**	2.30022

Notes. (↓) indicates lower is better; (↑) indicates higher is better. Boldface indicates best performance.

Given $\mathcal{D}$, $\boldsymbol{C}_{\text{sys}}$ and batch size B.
Initialize θ_0.
while not StopCondition **do**
$l \leftarrow 0$
for $i = 1, 2, \ldots B$ **do**
Get K samples from $\mathcal{D}$
$\{(z_1, m_1, \Delta m_1), \ldots (z_K, m_K, \Delta m_K)\}$
$Y_i = (m_{j_1}, \Delta m_{j_1})$
$\hat{m}_{j_2}, \hat{m}_{j_3}, \ldots \hat{m}_{j_K} \sim \mathcal{N}(m_{j_2}, m_{j_3}, \ldots m_{j_K}, \Sigma_m^K)$ ▷ (Equation (9))
$X_i = (z_{j_1}, z_{j_2}, \hat{m}_{j_2}, \ldots z_{j_K}, \hat{m}_{j_K}) \quad z_{j_2} \leqslant z_{j_3} \ldots$
$\mu, \sigma = f_{\theta_t}(X_i)_1, f_{\theta_t}(X_i)_2$ ▷ Forward pass.
$l \mathrel{+}= D_{\text{KL}}(\mathcal{N}(m_{j_1}, \Delta m_{j_1}), \mathcal{N}(\mu, \sigma))$
end for
Compute $\nabla_{\theta_t} l \quad \forall \theta_t$
$\theta_{t+1} = \theta_t + \eta \cdot \nabla_{\theta_t}$ ▷ Gradient update (illustrative).
if … **then** ▷ Check if model converged. StopCondition ← True
end if
end while



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Credit: xkcd comics

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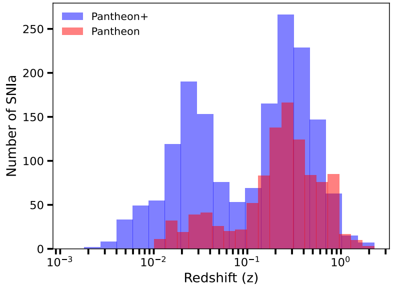
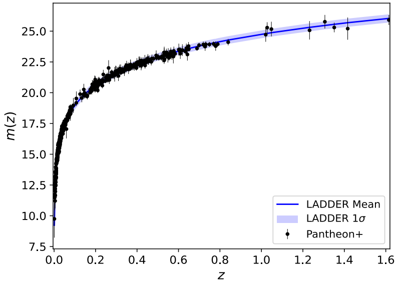
Pantheon, LADDER vs Pantheon+

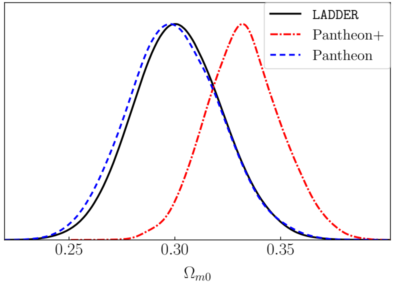
- Why Pantheon+? Range overlaps with Pantheon, high data density at lower z, more precise.
- Concerns regarding the Pantheon+: overestimation of errors, uncorrected systematics[1].



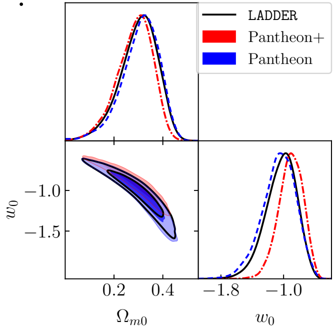
Pantheon vs Pantheon+



LADDER vs Pantheon+



ΛCDM constaints



wCDM constraints

Datasets	ΛCDM	wCDM	
	Ω_{m0}	Ω_{m0}	w_0
Pantheon	$0.299^{+0.023}_{-0.022}$	$0.316^{+0.067}_{-0.083}$	$-1.049^{+0.199}_{-0.228}$
Pantheon+	$0.332^{+0.018}_{-0.017}$	$0.292^{+0.065}_{-0.081}$	$-0.902^{+0.150}_{-0.162}$
LADDER	$0.301^{+0.021}_{-0.021}$	$0.308^{+0.069}_{-0.083}$	$-1.015^{+0.179}_{-0.216}$

- ❐ LADDER traces Pantheon results: good reconstruction.
- ❐ Pantheon, LADDER and Pantheon+ consistent within 1σ.

[1] Keeley et al. (2022); Perivolaropoulos & Skara (2023)

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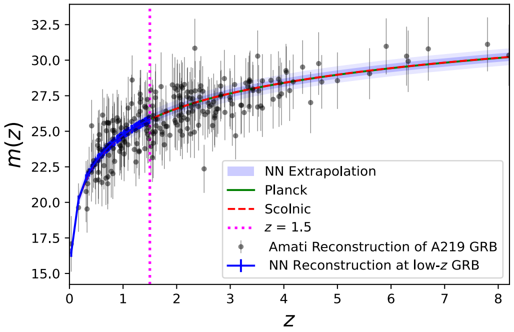
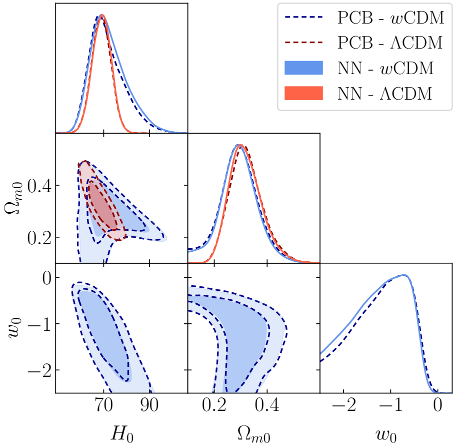
Calibration of high-z GRBs

- GRB A219 sample [Liang *et al.* (2022)] - redshift range $0.03 < z < 8.2$ - use Amati relation [Amati *et al.* (2002)].
- Split this GRB data into low-$z < 1.5$ and high-$z > 1.5$ samples, consisting of 89 and 130 points respectively.



`LADDER` calibrated GRB dataset



Constraints from CC Hubble + high-z GRBs

- Calibration via LADDER: provide a unique high-z GRB dataset in a model-independent setting.
- Constraints obtained are consistent, irrespective of the calibration method.
- Marginal widening of errors for the model-independent LADDER calibration.

Model	ΛCDM		wCDM	
Calibrator	`LADDER`	PCB	`LADDER`	PCB
H_0	$69.203^{+4.050}_{-4.150}$	$68.996^{+4.187}_{-4.095}$	$71.224^{+9.058}_{-6.365}$	$70.265^{+8.989}_{-5.915}$
Ω_{m0}	$0.313^{+0.066}_{-0.055}$	$0.317^{+0.067}_{-0.057}$	$0.289^{+0.068}_{-0.074}$	$0.287^{+0.072}_{-0.085}$
w_0	...	...	$-1.257^{+0.627}_{-0.867}$	$-1.172^{+0.599}_{-0.866}$

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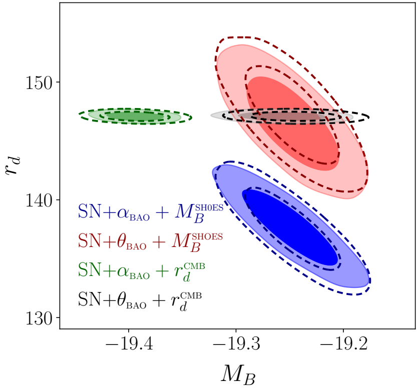
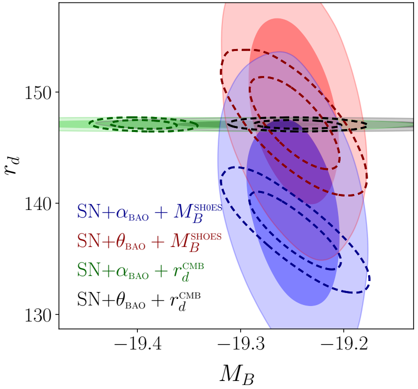
Angular vs Anisotropic BAOs

- Transverse Angular BAO ($\theta_{\rm BAO}$): 15 model-independent data in the range $0.11 < z < 2.22$.
- Anisotropic BAO ($\alpha_{\rm BAO}$): 8 data points in the range $0.38 < z < 2.35$.



`LADDER` mean vs ΛCDM



`LADDER` mean + 1σ vs ΛCDM

- ❐ Underlying cosmology close to ΛCDM.
- ❐ Existence of internal inconsistency between angular vs anisotropic BAOs [Carter et al. 2020].
- ❐ No apparent tension between Pantheon and $\theta_{\rm BAO}$, unlike $\alpha_{\rm BAO}$.
- ❐ Data-driven selection of $M_B - r_d$ parameter space.

Datasets	`LADDER`		ΛCDM			
	M_B	r_d	H_0	Ω_{m0}	M_B	r_d
SN+$\alpha_{\rm BAO}$+$M_B^{\rm SH0ES}$	$-19.249^{+0.029}_{-0.029}$	$137.651^{+2.157}_{-2.153}$	$73.195^{+1.054}_{-1.032}$	$0.315^{+0.019}_{-0.019}$	$-19.248^{+0.030}_{-0.029}$	$137.484^{+2.312}_{-2.228}$
SN+$\theta_{\rm BAO}$+$M_B^{\rm SH0ES}$	$-19.248^{+0.028}_{-0.029}$	$146.423^{+2.697}_{-2.569}$	$73.372^{+1.023}_{-1.010}$	$0.302^{+0.022}_{-0.021}$	$-19.248^{+0.028}_{-0.029}$	$147.246^{+2.795}_{-2.712}$
SN+$\alpha_{\rm BAO}$+$r_d^{\rm CMB}$	$-19.394^{+0.018}_{-0.017}$	$147.090^{+0.250}_{-0.267}$	$68.437^{+0.820}_{-0.826}$	$0.314^{+0.020}_{-0.019}$	$-19.394^{+0.021}_{-0.022}$	$147.087^{+0.258}_{-0.256}$
SN+$\theta_{\rm BAO}$+$r_d^{\rm CMB}$	$-19.257^{+0.028}_{-0.027}$	$147.085^{+0.261}_{-0.253}$	$73.448^{+1.042}_{-1.025}$	$0.304^{+0.022}_{-0.021}$	$-19.245^{+0.028}_{-0.027}$	$147.088^{+0.259}_{-0.256}$

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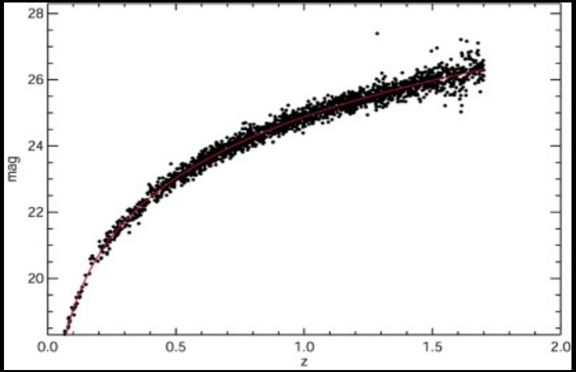
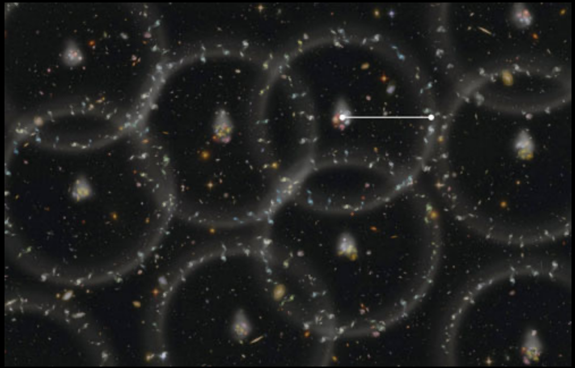
Cosmological Parameter Estimation

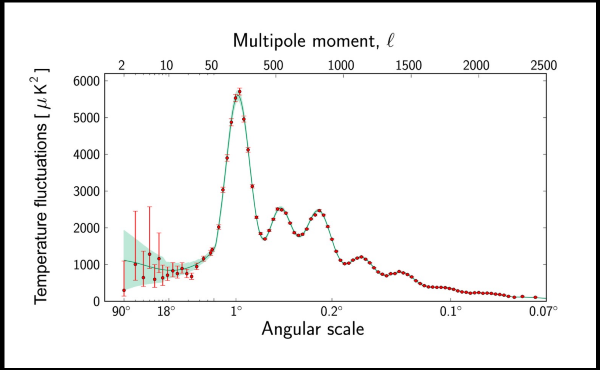
Supernovae



Baryon Acoustic Oscillations



Cosmic Microwave Background



Recalibrate BAO with LADDER?

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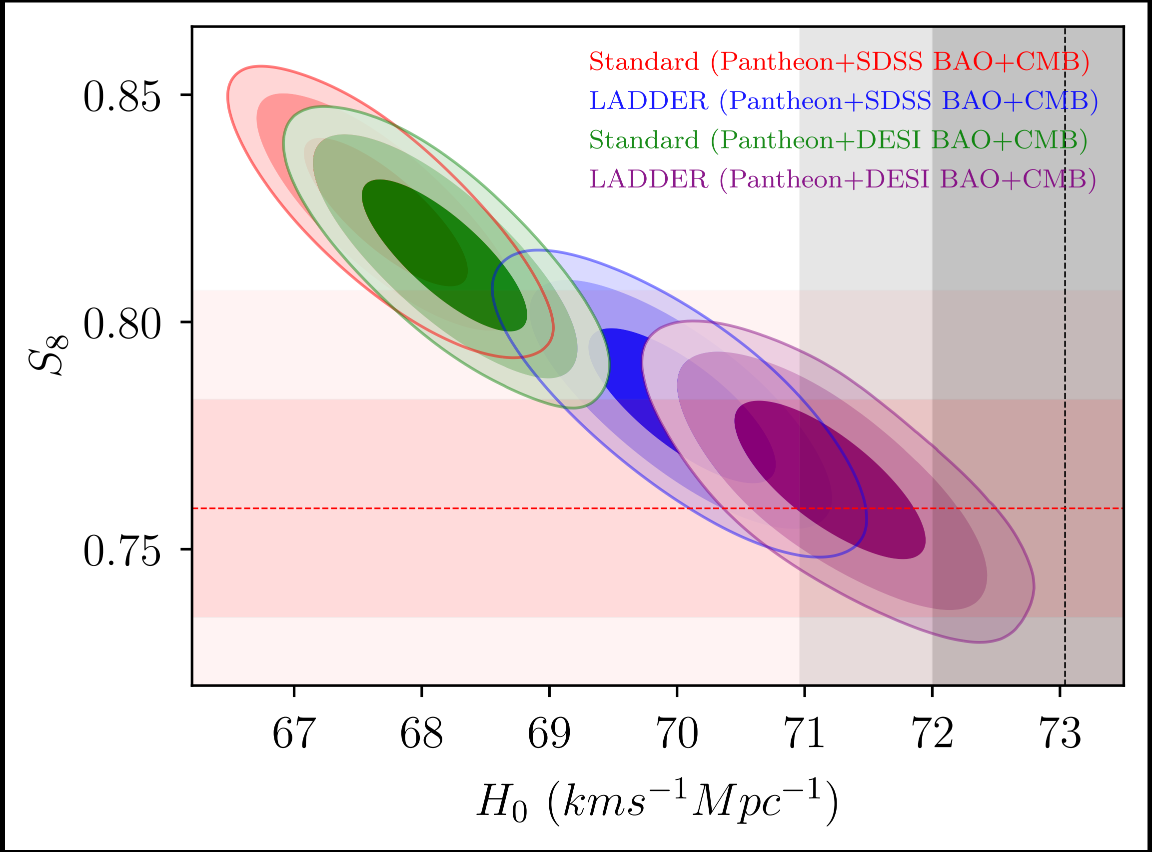
arXiv:2412.14750



In-plane shift in the H_0 – S_8 plane

Alleviates both tensions simultaneously (?!)

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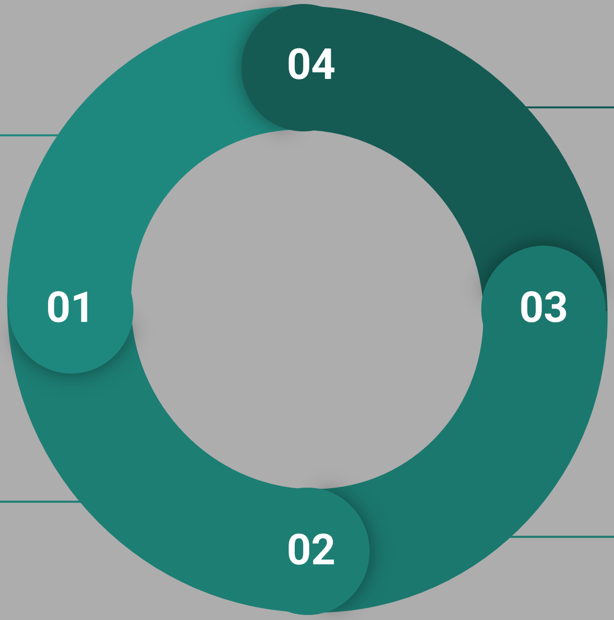
arXiv:2412.14750

LADDER

Learning Algorithm for Deep Distance Estimation and Reconstruction

https://github.com/rahulshah1397/LADDER

Summary



ML Caveats

Overfitting/underfitting issues in deep learning can lead to both inaccurate and imprecise predictions.

Covariance Learning

LADDER thus proposed, learns sequential data, utilizing the full covariance information.

ML in Cosmology

LADDER's potential could usher in new avenues for future exploration.

Extrapolation

LADDER exhibits stability, even in data-sparse regions, gives reliable error + mean predictions beyond the training data range.

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