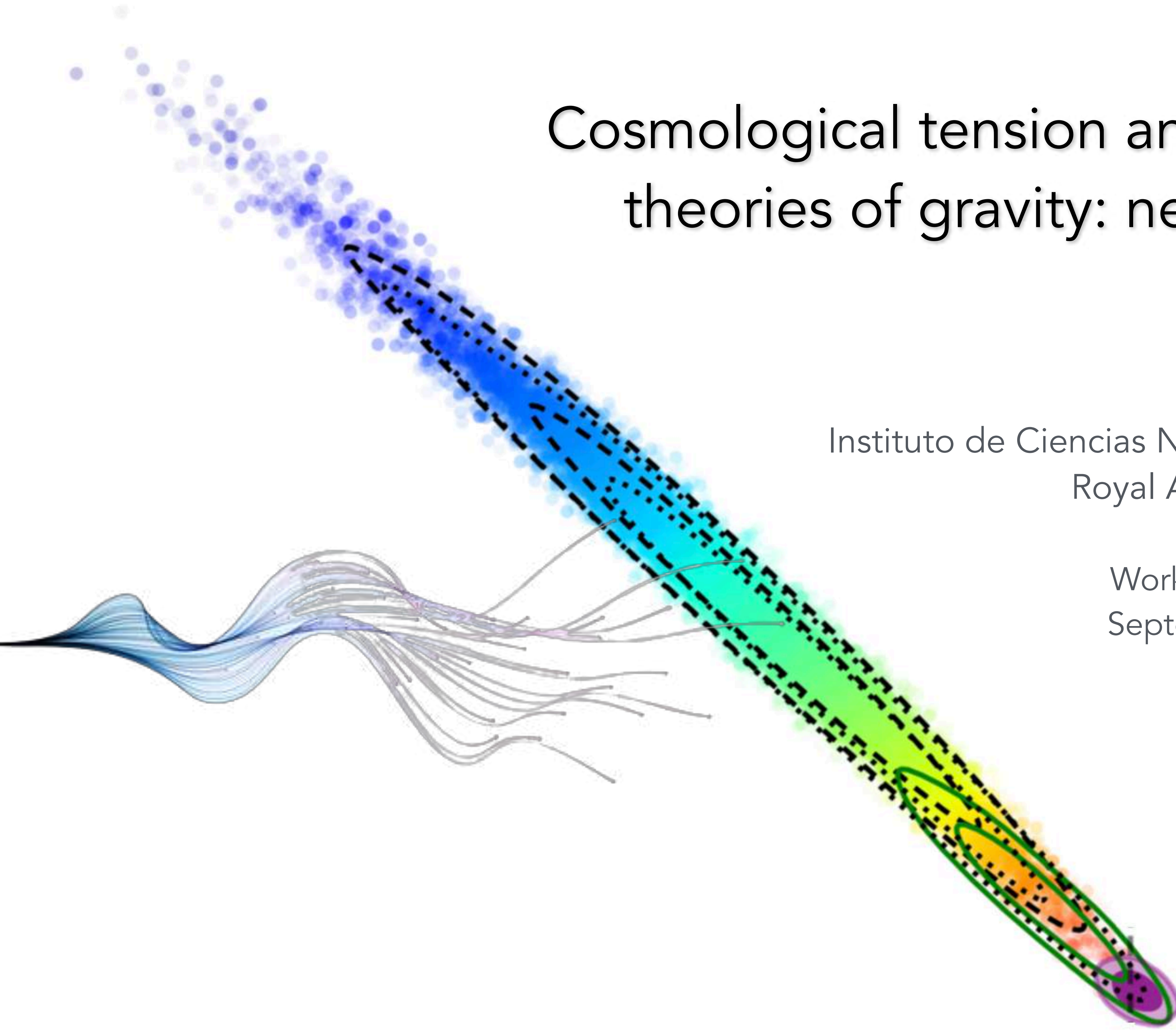
Cosmological tension analyses in extended theories of gravity: neural networks path



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Royal Astronomical Society (RAS, UK)

Workshop on Tensions in Cosmology
September 7-12 2022. Corfu, Greece

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Outline

Setting the scene:

- Neural Networks in Cosmology: an autopsy

Precision problems:

- Analising cosmological datasets: tensions

Neural Networks Applications:

- Beyond standard cosmologies

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Setting the scene:

- **Neural Networks in Cosmology: an autopsy**

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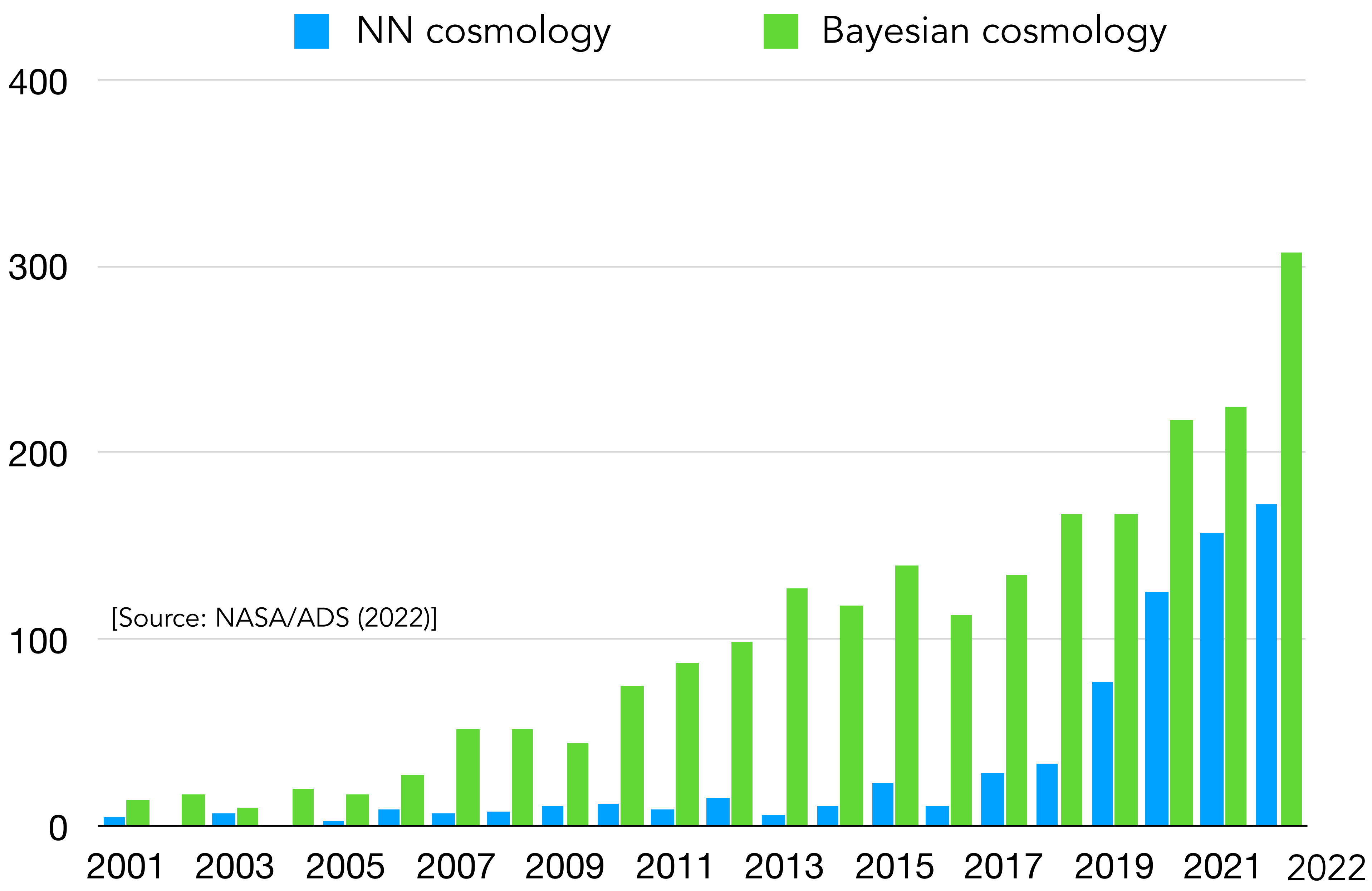
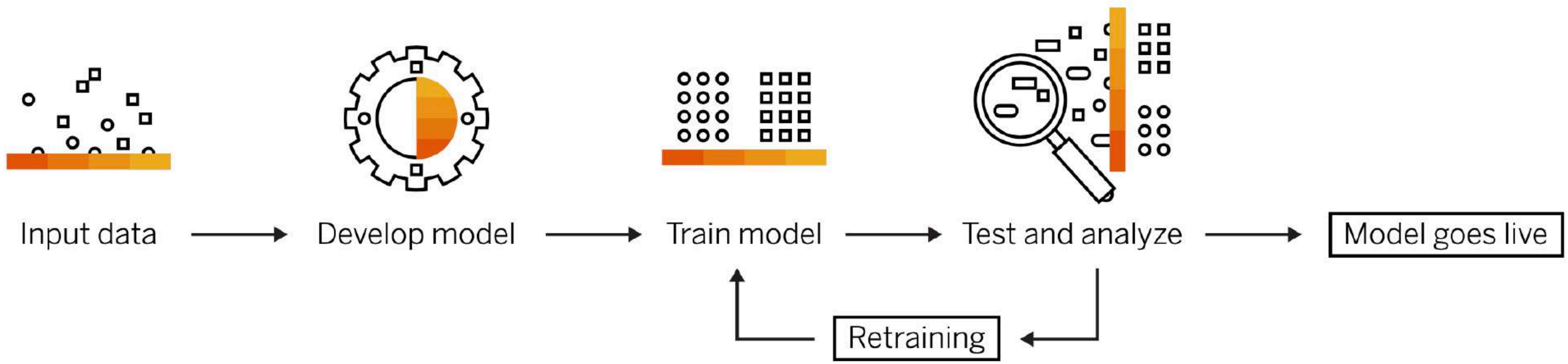
Neural Networks (ANNs) is a tool which learns about a problem through relationship which are intrinsic to the data rather than through a set of predetermined rules.



How NNs (or ANNs) work?

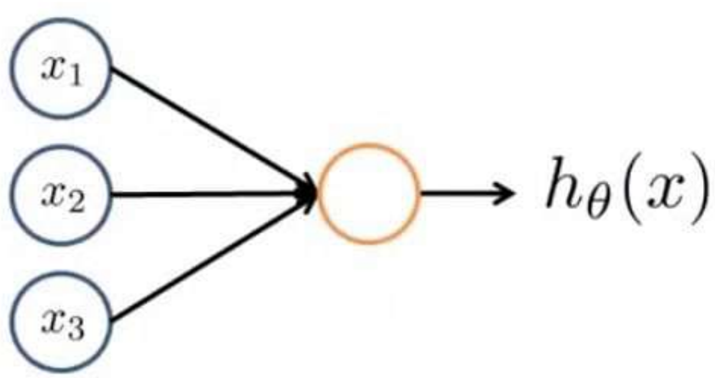
- Neural networks acquire knowledge through a learning process. The NNs learn to perform better in the modelling process.

- The acquired knowledge is stored in the interconnections in the form of weights. These weights keep on changing as the network is trained and thus, the "updated weights" is the "acquired knowledge".

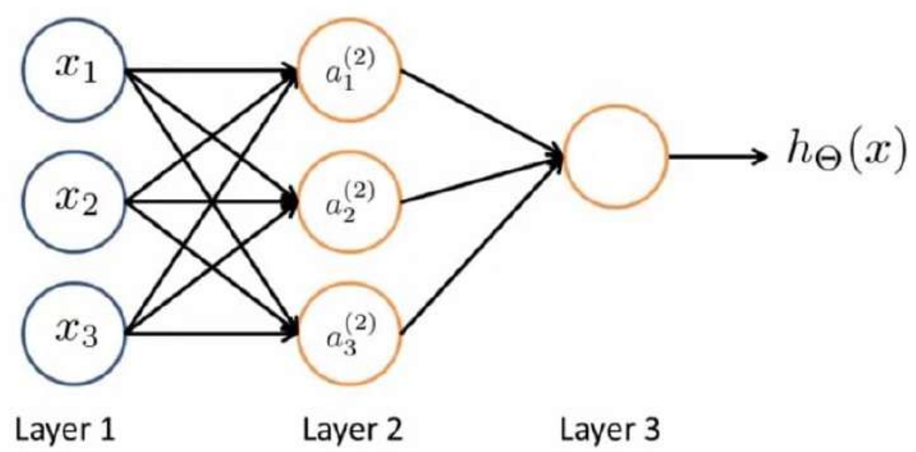


A NN simple architecture

- All neuron layers must be interconnected.
- There must be a process for updating the weights while learning from the model.
- There must be an 'activation function' which essentially determines the output from neuron's weighted inputs.

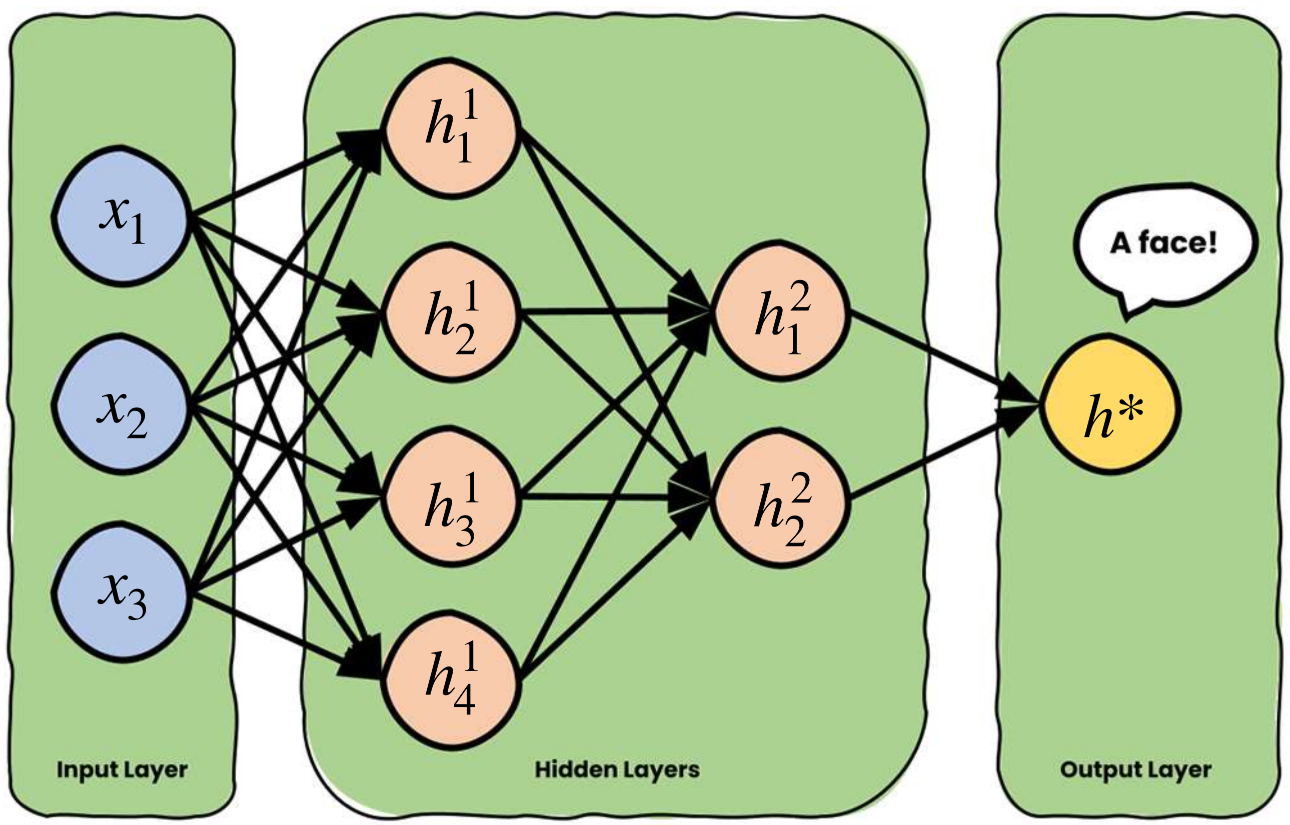


Mapping: $h \approx h^*_\theta(x)$



Feed-forward

A NN complex architecture (non linear activation functions)



[Source: Google: developers.google.com/machine-learning]

$$W^1 = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} \\ w_{21} & w_{22} & w_{23} & w_{24} \\ w_{31} & w_{32} & w_{33} & w_{34} \end{bmatrix} \quad b^1 = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix}$$

$$\tilde{h}^{[1]} = W^{[1]T} \cdot x + b^{[1]}$$

$$h^{[1]} = \sigma(\tilde{h}^{[1]})$$

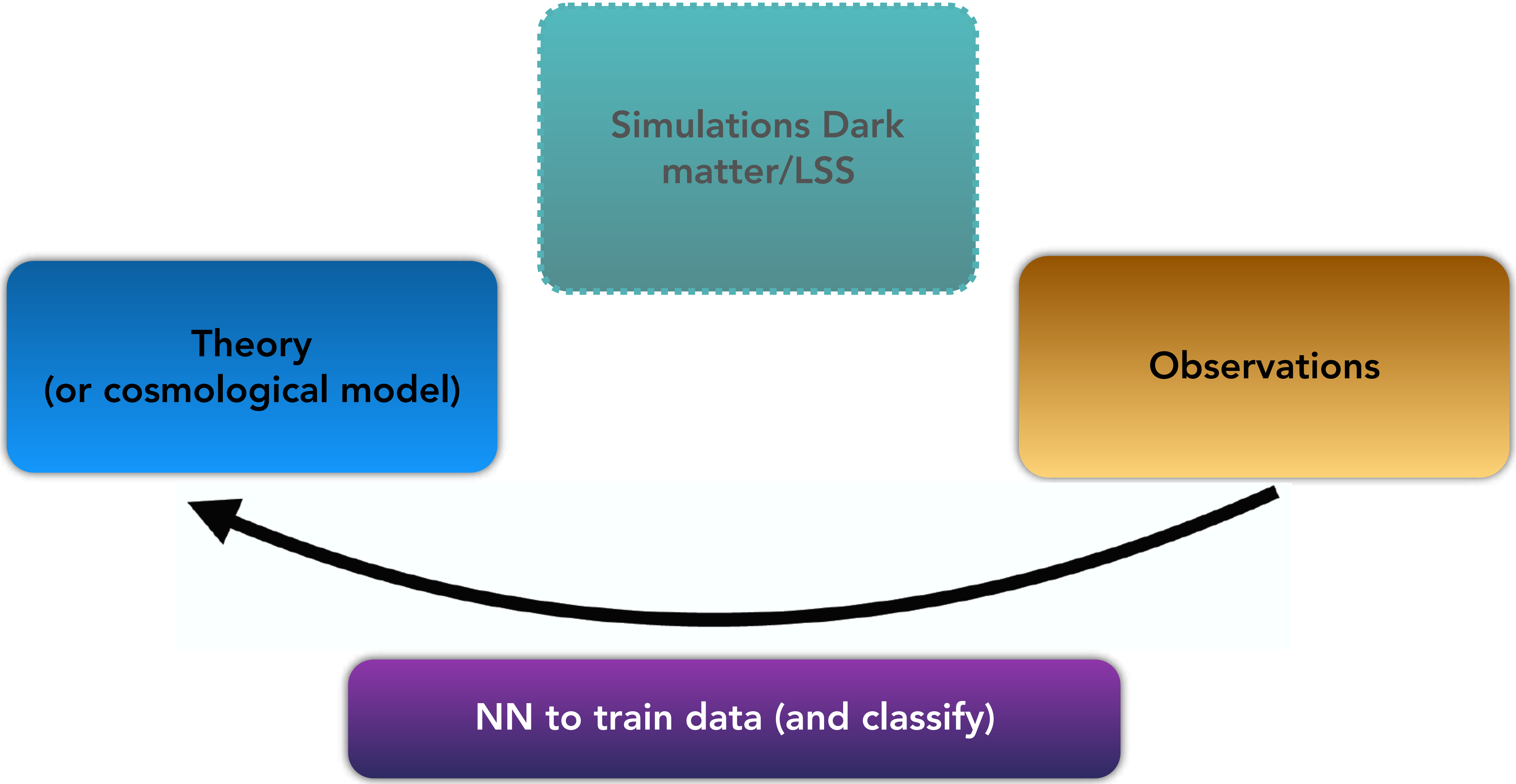
$$\tilde{h}^{[2]} = W^{[2]T} \cdot h^{[1]} + b^{[2]}$$

$$h^{[2]} = \sigma(\tilde{h}^{[2]})$$

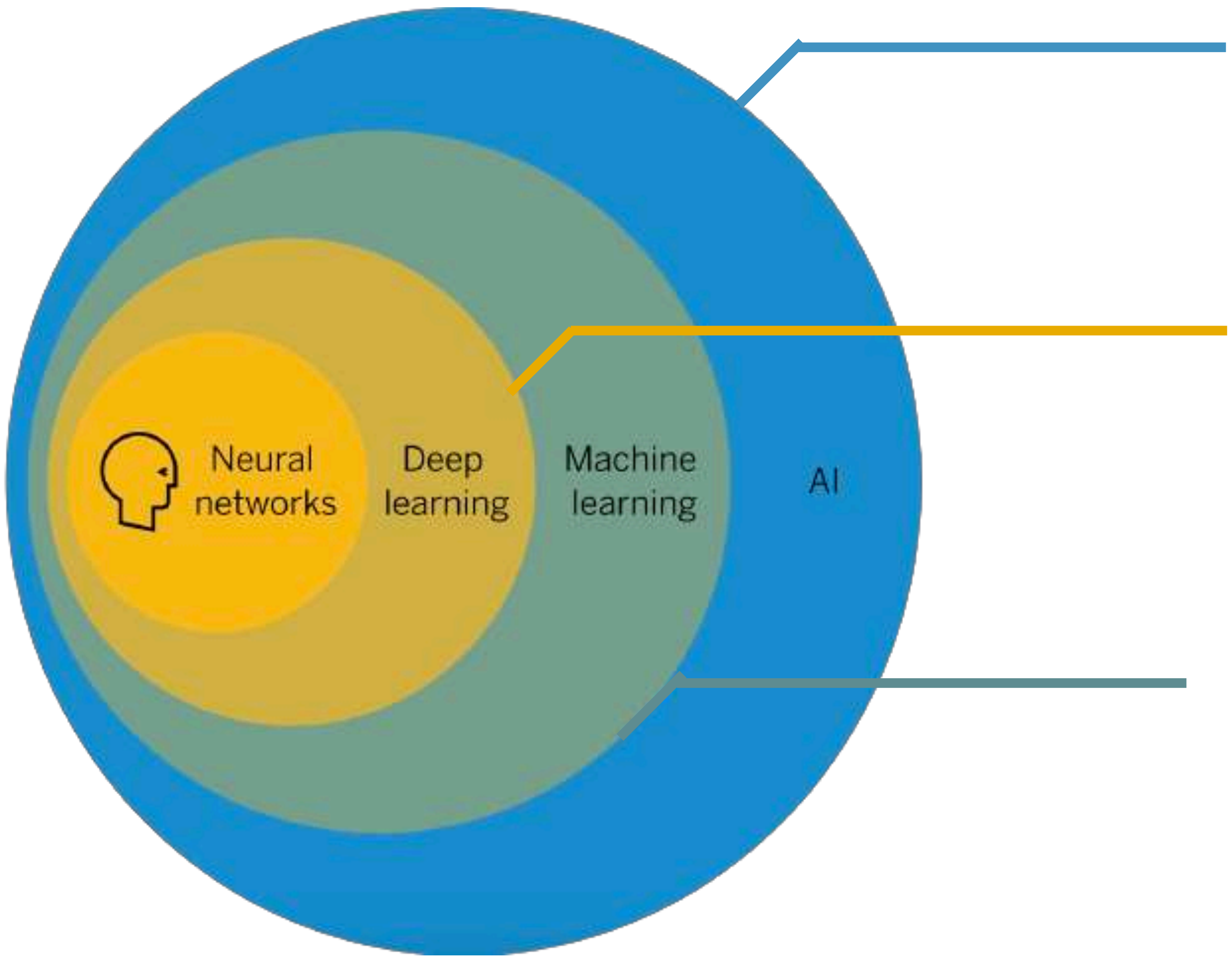
$$\tilde{h}^{[3]} = W^{[3]T} \cdot h^{[2]} + b^{[3]}$$

$$h^{[3]} = \sigma(\tilde{h}^{[3]}) \rightarrow h = \sigma^*(\tilde{h})$$

The mapping


Simulations Dark matter/LSS
Theory
(or cosmological model)
Observations
NN to train data (and classify)

In which stage is "NN" Cosmology?

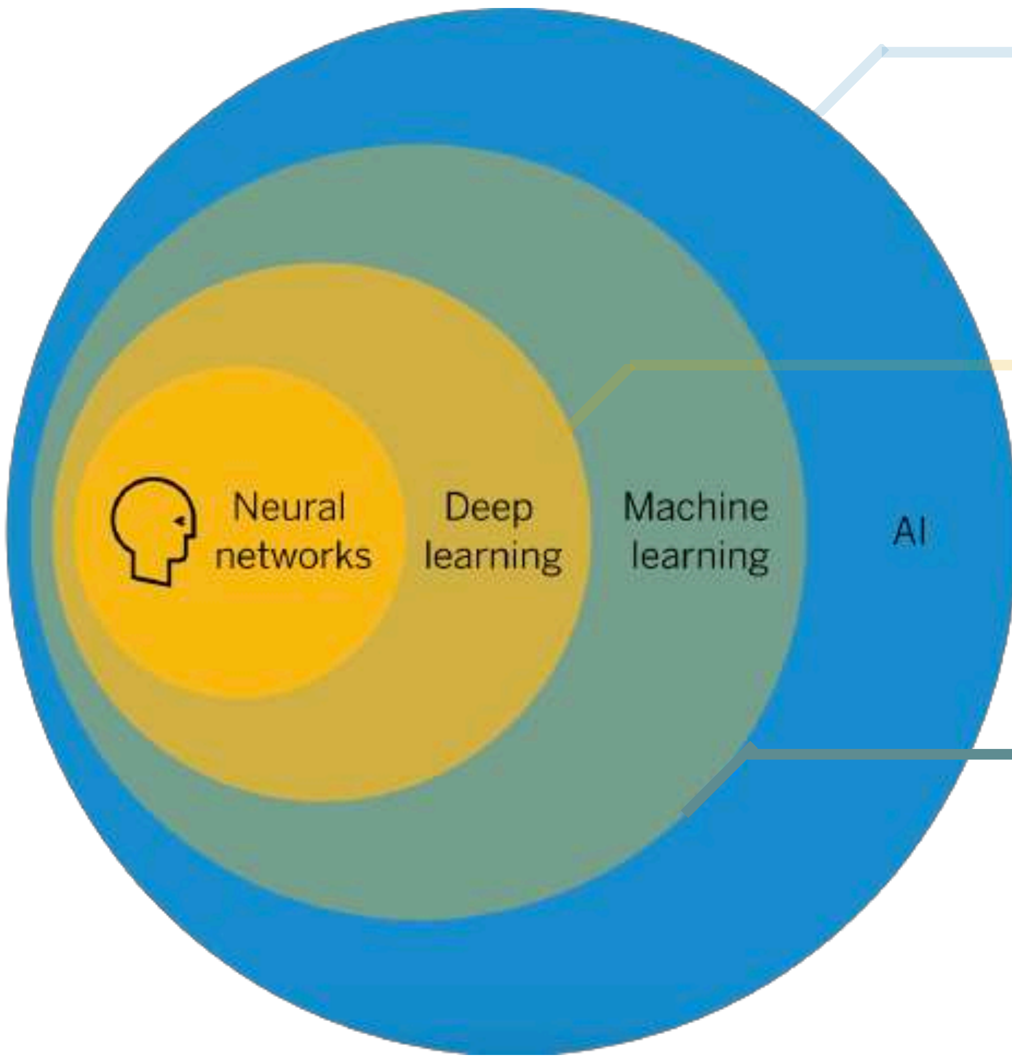


Artificial Intelligence: perceive their environment and define a course of action.

Deep learning: tasks are organised in consecutive layers, builded on the output of previous ones. Mimics the distributed approach to problem-solving.

Machine learning: tasks are complete without being explicitly programmed to do so.

In which stage is "NN" Cosmology?



Artificial Intelligence: perceive their environment and define a course of action.

Deep learning: tasks are organised in consecutive layers, builded on the output

Standard cosmologies

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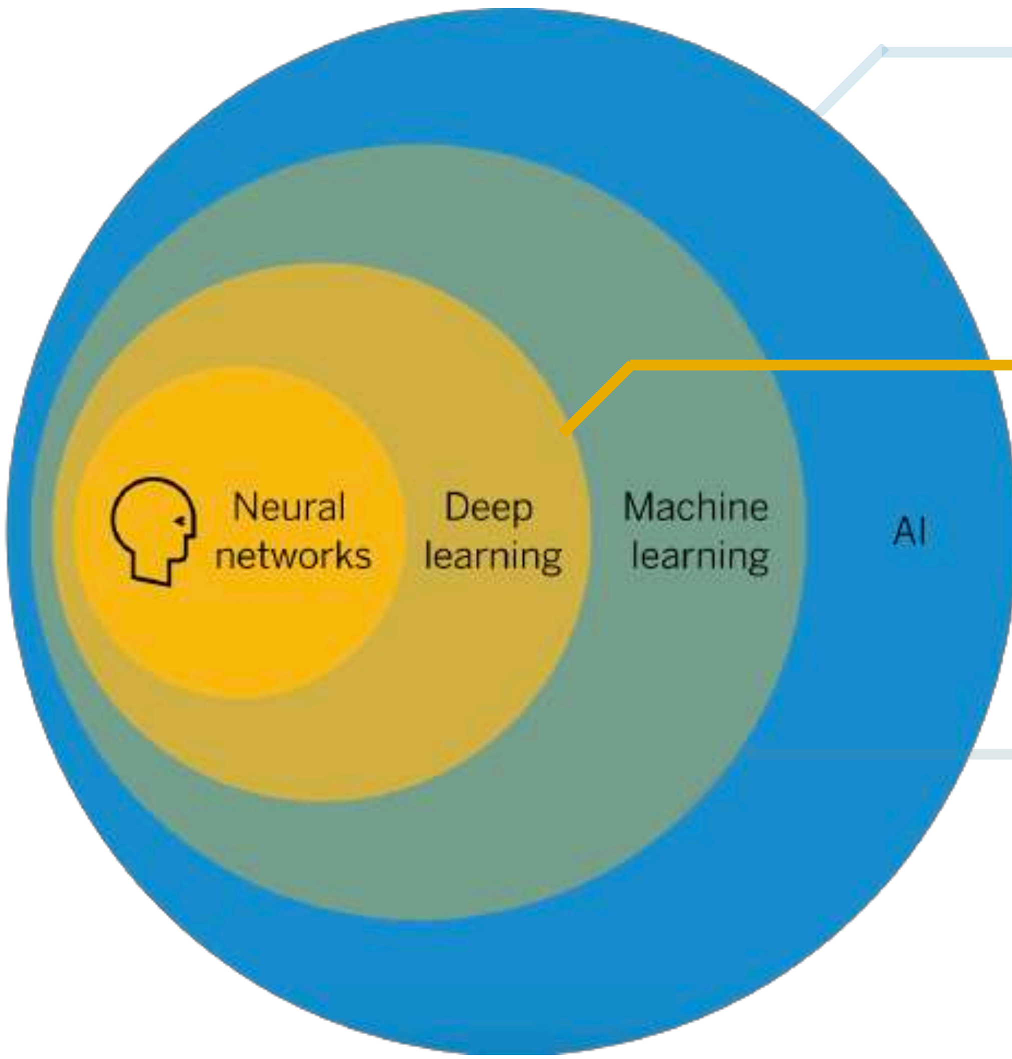

Artificial Intelligence: perceive their

Beyond standard cosmologies

Deep learning: tasks are organised in consecutive layers, builded on the output of previous ones. Mimics the distributed approach to problem-solving.

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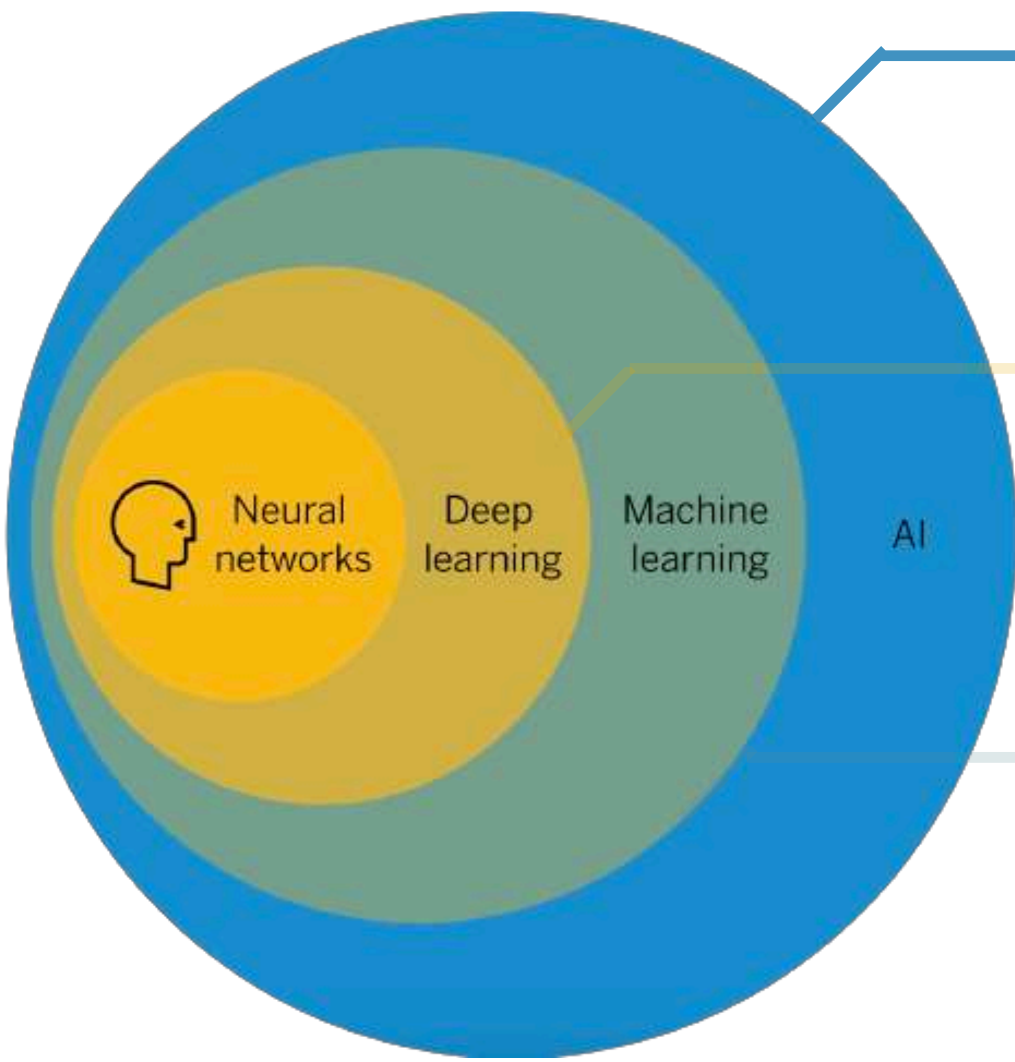
In which stage is "NN" Cosmology?



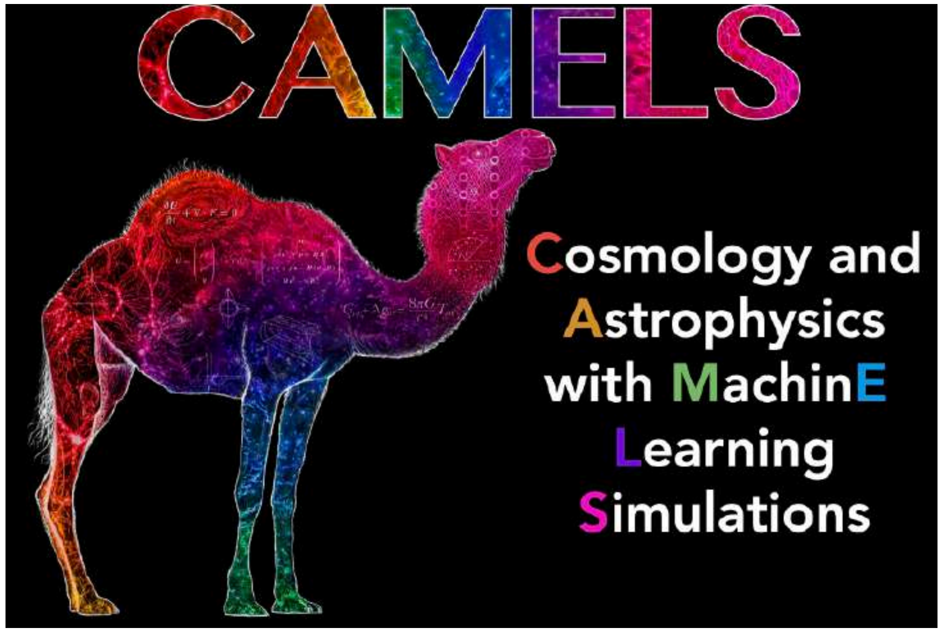
Artificial Intelligence: perceive their environment and define a course of action.

The future…

of previous ones. Mimics the distributed approach to problem-solving.

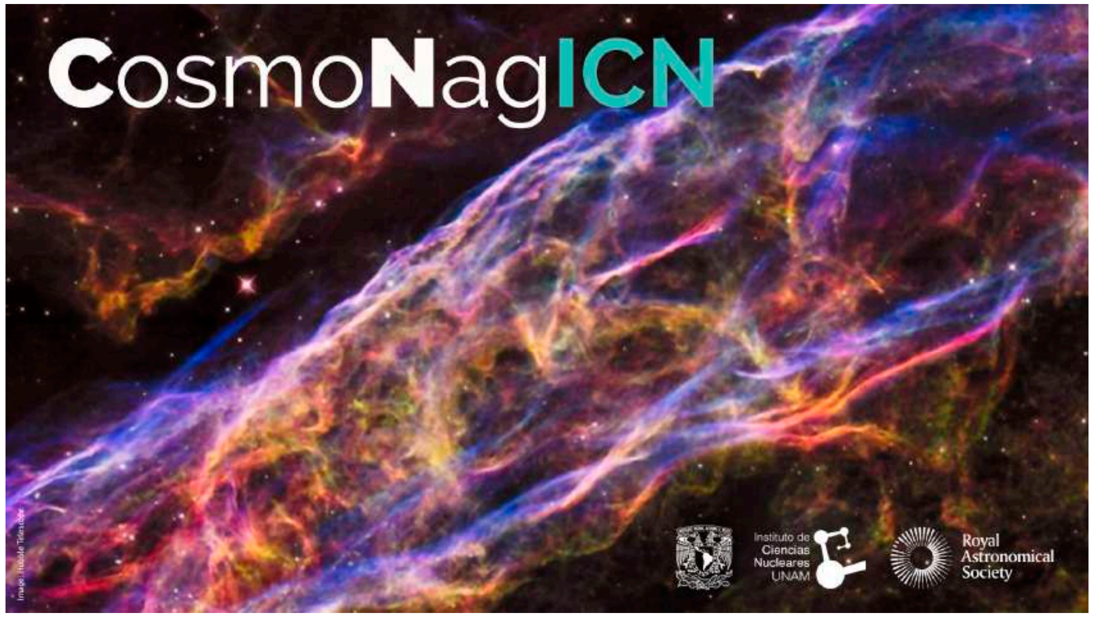
Machine learning: tasks are complete without being explicitly programmed to do so.

- No need to build a likelihood model (likelihood-free inference)
- Need of large number of (realistic) simulations to train the NN



https://www.camel-simulations.org/science

N-body and hydrodynamic simulations



https://www.nucleares.unam.mx/CosmoNag

Modified and extended theories training

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Setting the scene:

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Precision problems:

- **Analising cosmological datasets: tensions**

Neural Networks Applications:

- Beyond standard cosmologies

LCDM cosmological model
(GR+FLRW)

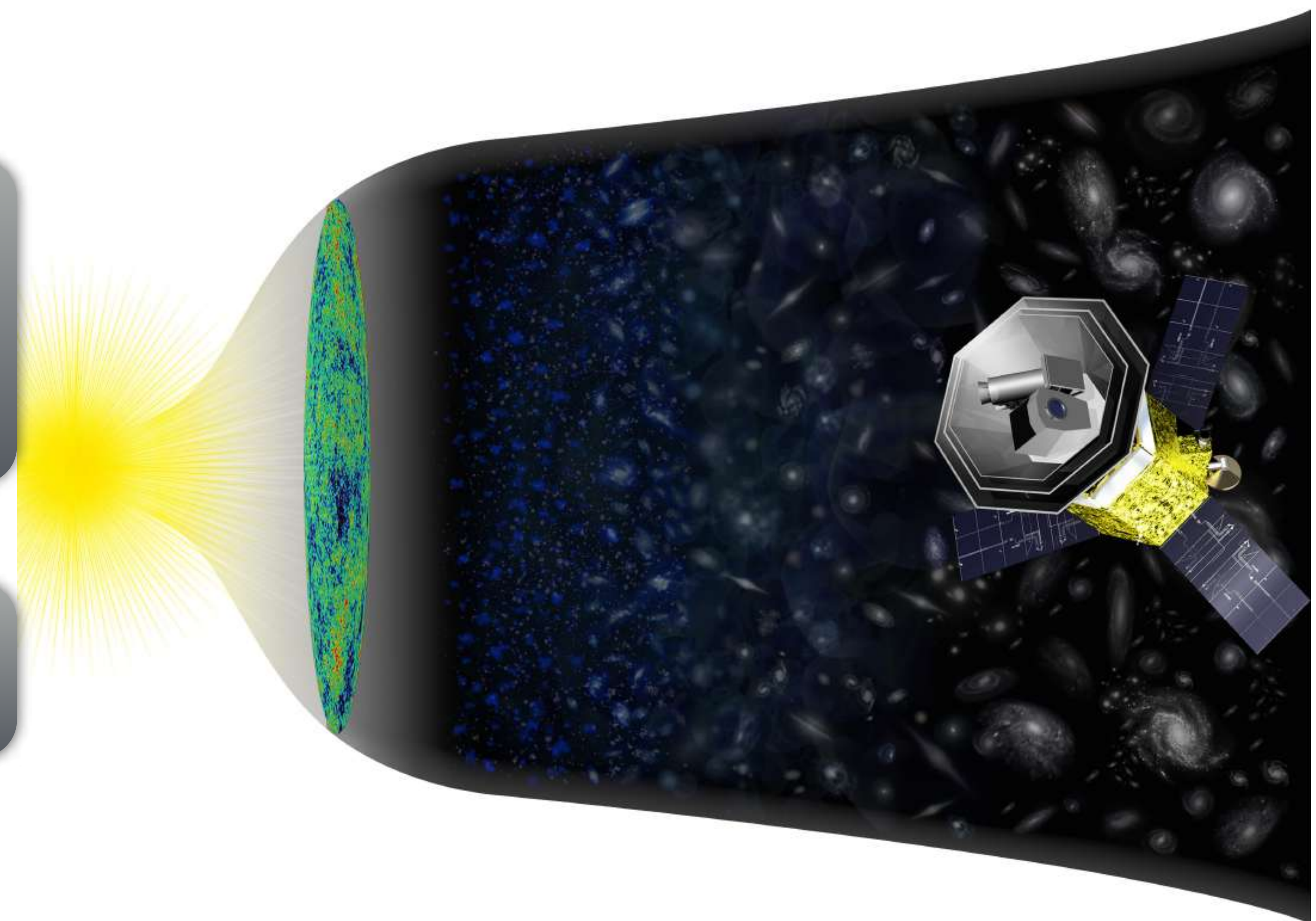
+

CMB: "almost" perfectly Gaussian and highly contaminated

LSS: involve highly non linear physics

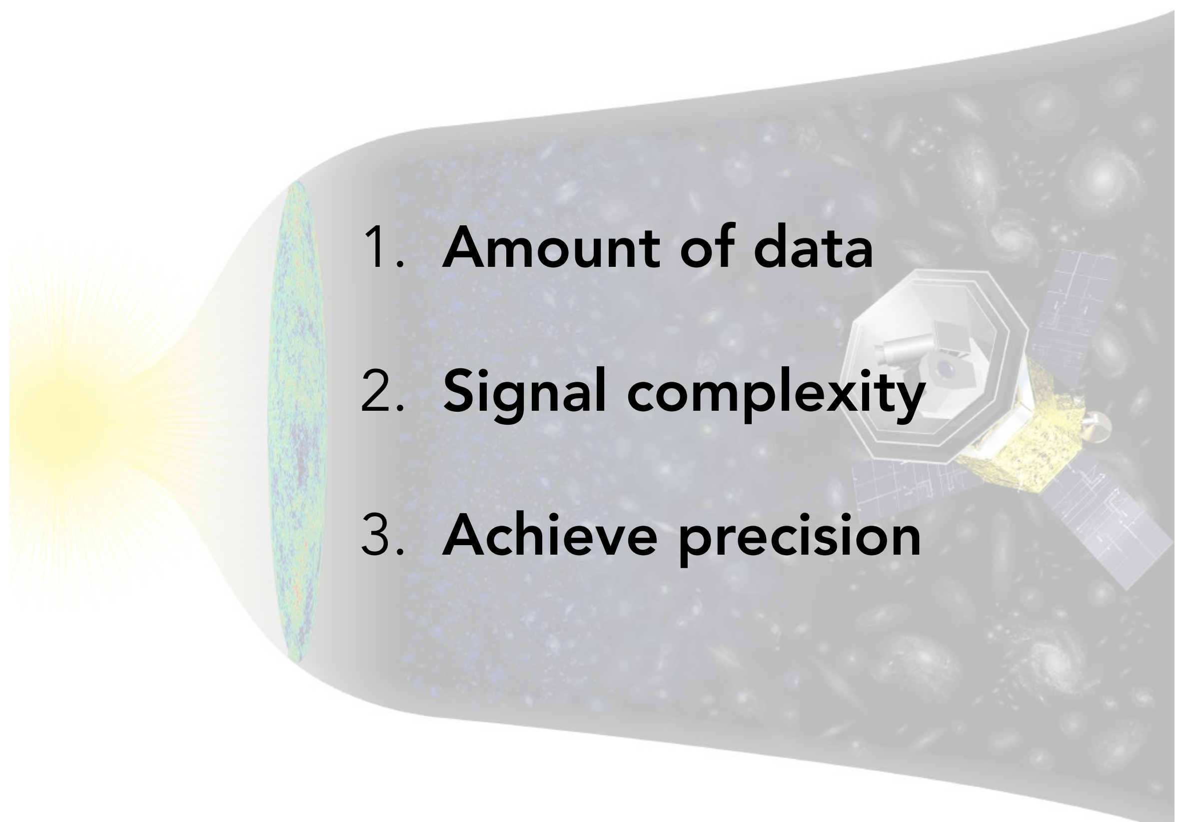
Many open questions: Dark matter? Dark energy? Neutrino masses? Initial conditions?

Issues: Cosmological Tensions



The future is bright… but how we fully exploit the data?

2029 - 2022

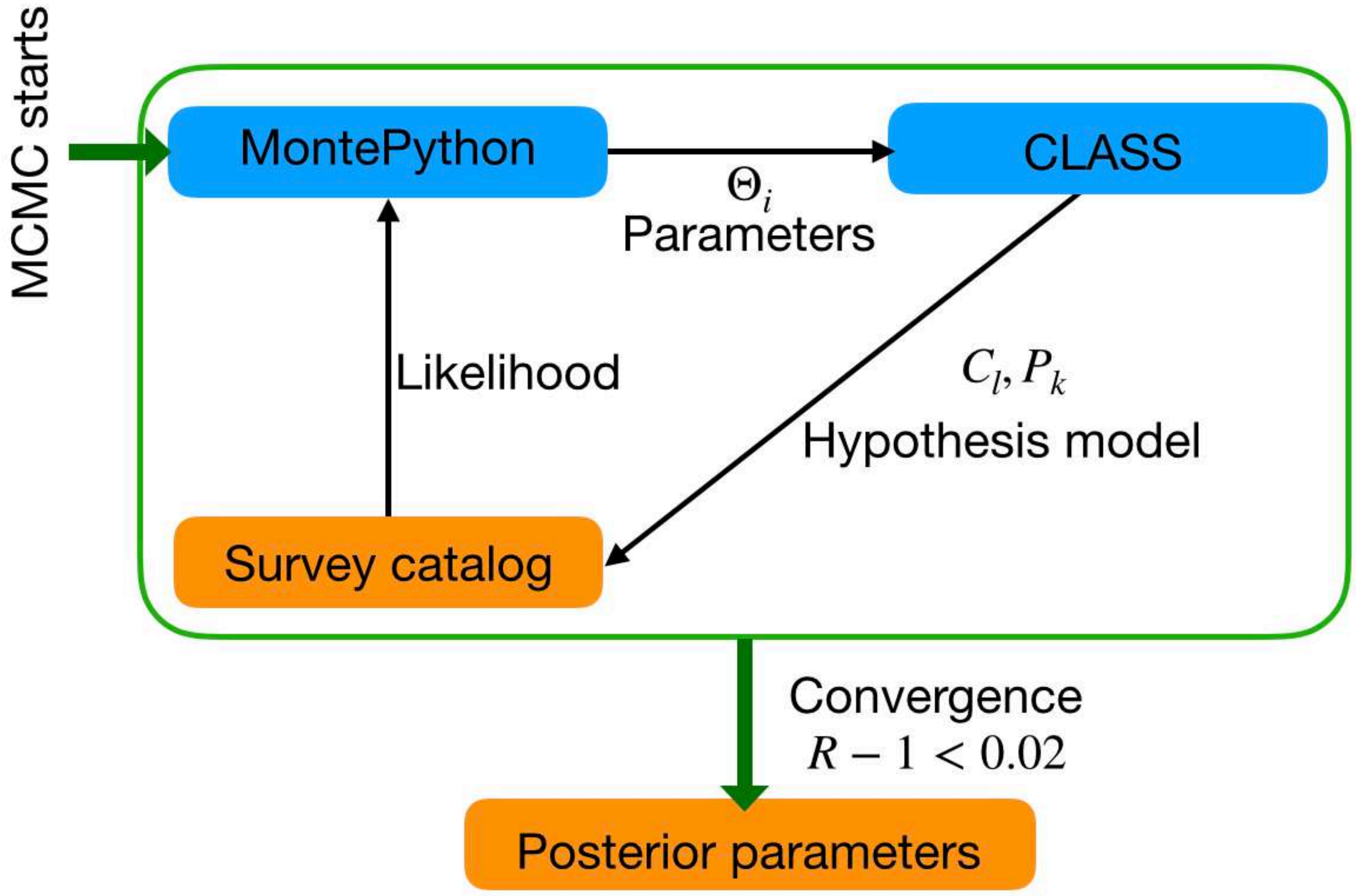


1. **Amount of data**
2. **Signal complexity**
3. **Achieve precision**

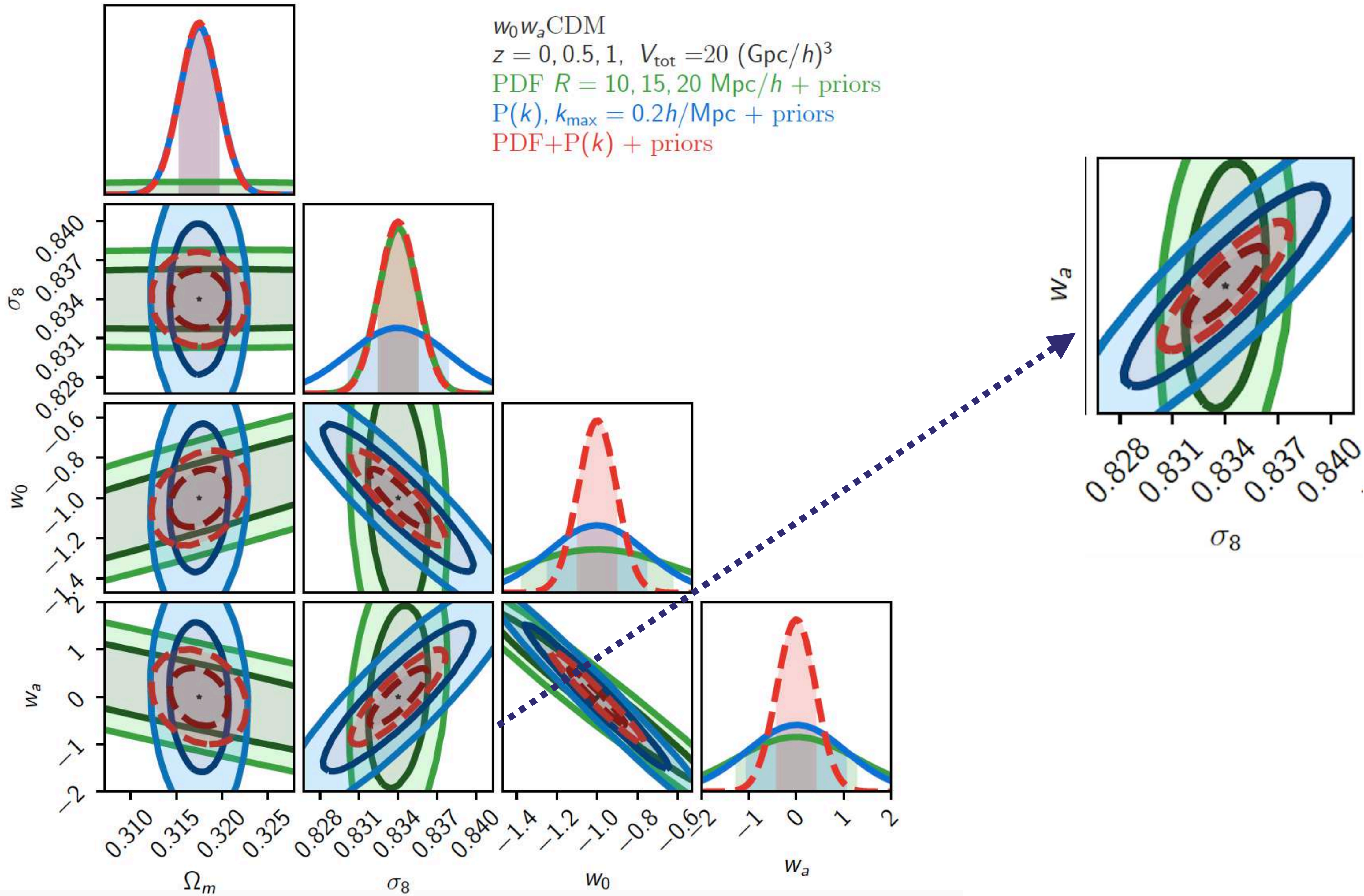
CMB experiments (faint signal)

Galaxy surveys (complex signal)

Parameter estimation and comparison with theoretical expectations



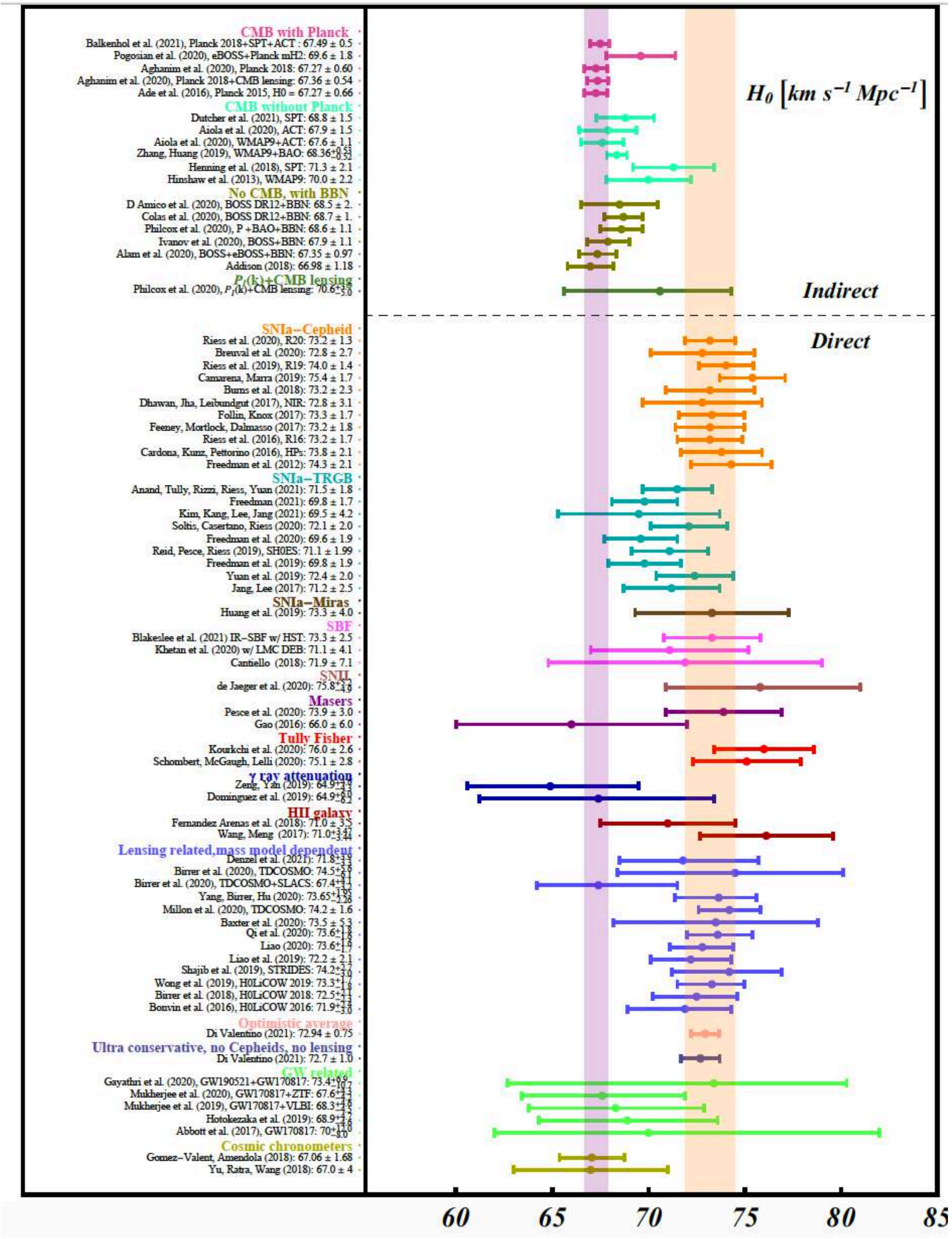
[Source: Teleparallel Gravity: From Theory to Cosmology. S.Bahamonde, K. Dialektopoulos, **C. Escamilla-Rivera**, G. Farrugia, V. Gakis, M. Hendry, M. Hohmann, J. Levi Said, J. Mifsud and E. Di Valentino arXiv:2106.13793(2021)]



[Source: Gough, A et al Universe 2022, 8(1), 55]

H_0 tension analyses

[Cosmology Intertwined: A Review of the Particle Physics, Astrophysics, and Cosmology Associated with the Cosmological Tensions and Anomalies. J. High En. Astrophys. 2204 (2022)]



Hubble tension from the eyeglasses of the Lovelock's theorem break

"The only **second-order**, **local** gravitational field equations **derivable from an action** containing **solely the 4D metric tensor** (plus related tensors) are the Einstein field equations with a cosmological constant"

$$S_{grav} = \frac{M_{\rm Pl}^2}{2}\int\sqrt{-g}\,d^4x\left[\phi R - \frac{\omega(\phi)}{\phi}(\nabla\phi^2) - 2V(\phi)\right]$$

Value: $H_0 = 69.9^{+0.84}_{-0.86}$ km/s/Mpc

[M. Gonzalez et al. JCAP 10 (2021) 028]

$$S_{grav} = \frac{M_{\rm D}^2}{2}\int\sqrt{-\gamma}\,d^Dx[\mathscr{R} + \alpha\mathscr{G}]$$

Value: $H_0 = 68.8 \pm 0.9$ km/s/Mpc

[D. Wang and D. Mota. Phys.Dark Univ. 32 (2021)]

$$S_{grav} = \frac{M_{\rm Pl}^2}{2}\int\sqrt{-g}\,d^4x[R + \beta_1 R\nabla_\mu\nabla^\mu R + \beta_2\nabla_\mu R_{\beta\gamma}\nabla^\mu R^{\beta\gamma}]$$

Value: $H_0 = 69.22^{+0.66}_{-0.73}$ km/s/Mpc

[S. Odintsov et al. Nucl.Phys.B 966 (2021)]

$$S_{grav} = \frac{M_{\rm Pl}^2}{2}\int\sqrt{-g}\,d^4x\left[R + f\left(\frac{1}{\Box}R\right)\right]$$

Value: $H_0 = 68.74^{+0.59}_{-0.51}$ km/s/Mpc

[E. Belgacem et al. JCAP 04 010 (2020)]

$$S_{grav} = ?!$$

Value: $H_0 = ?$

[**C. Escamilla-Rivera**. In Progress]

Hubble tension from the eyeglasses of Modified Teleparallel Gravity

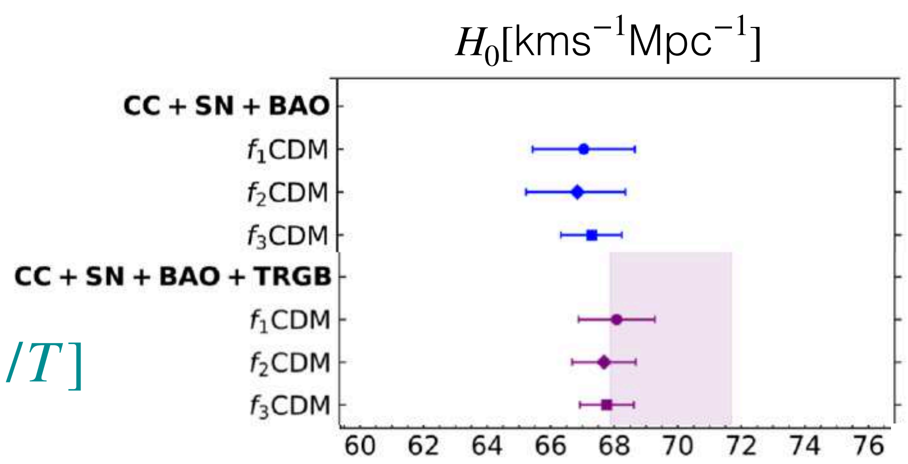
"TG recasts the curvature of GR and its modifications with a torsional geometric framework".

$$S = \frac{1}{16\pi G}\int d^4xe[-T + f(T,B)] + S_{\text{matter}}$$

$$f_1(T) = \alpha_1(-T)^{b_1}$$

$$f_2(T) = \alpha_3 T_0[1 - e^{(-b_3 T/T_0)}]$$

$$f_3(T) = \alpha_4 T_0\sqrt{T/(b_4T_0)}\ \log[b_4T_0/T]$$

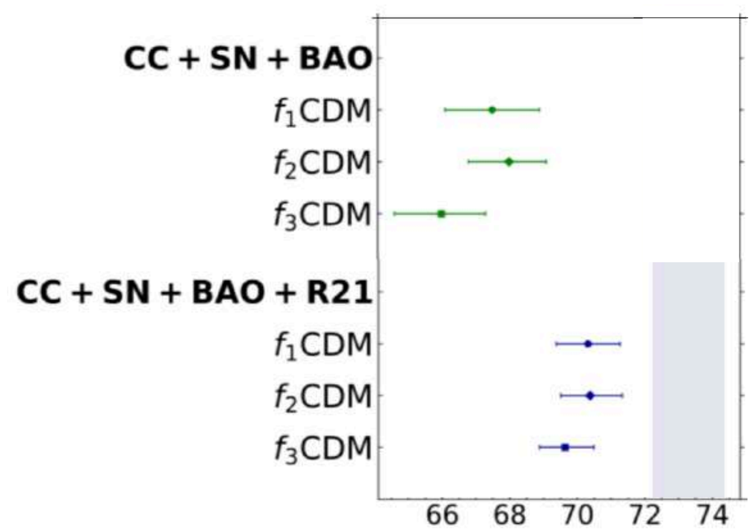


[Briffa, R et at. Eur.Phys.J.Plus 137 (2022)]

$$f_1(T,B) = \alpha B^n + \beta T^m$$

$$f_2(T,B) = \alpha B^n T^m$$

$$f_3(T,B) = \alpha \log B + \beta T$$



[Briffa, R et at. 2205.13560 (2022)]

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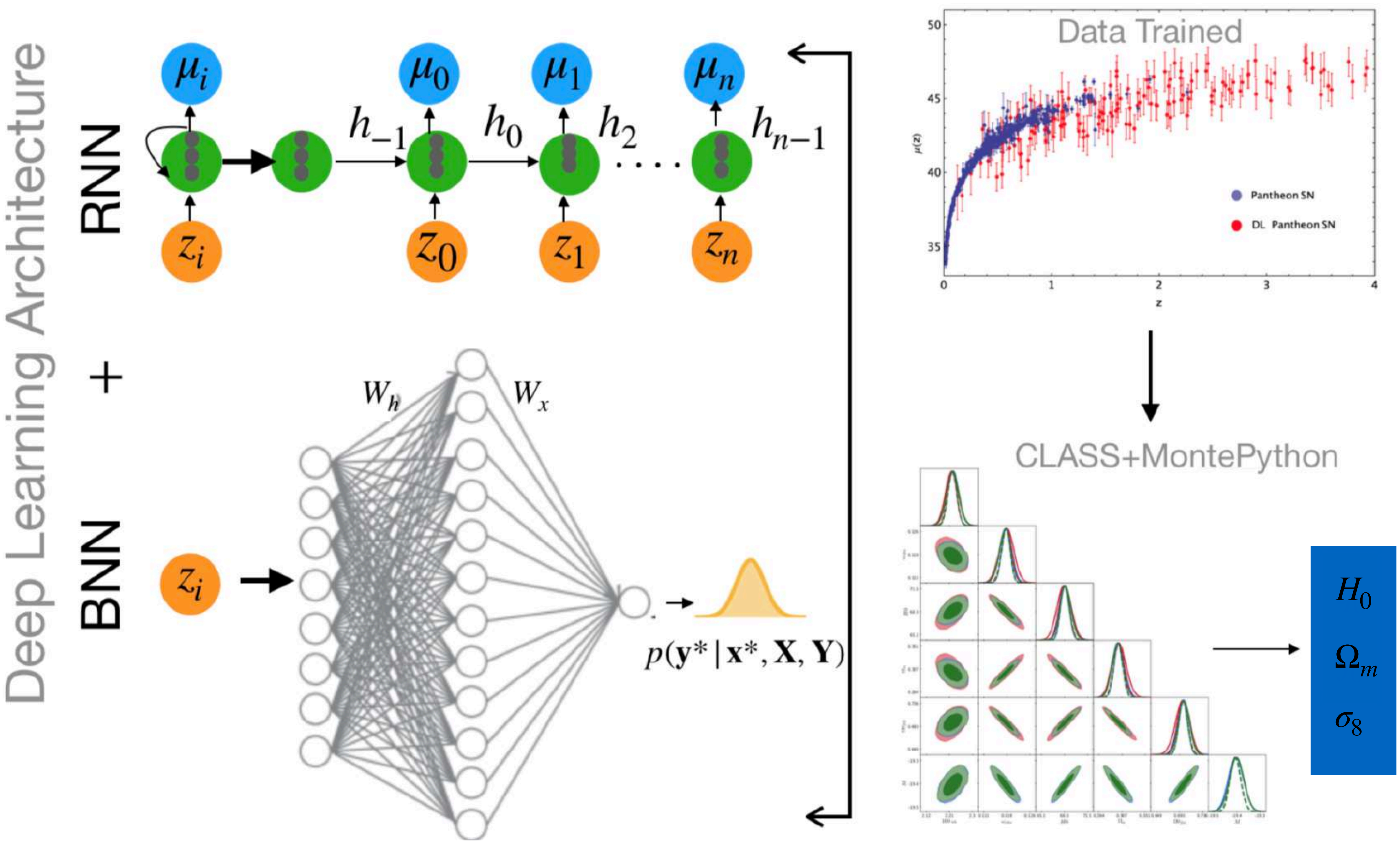
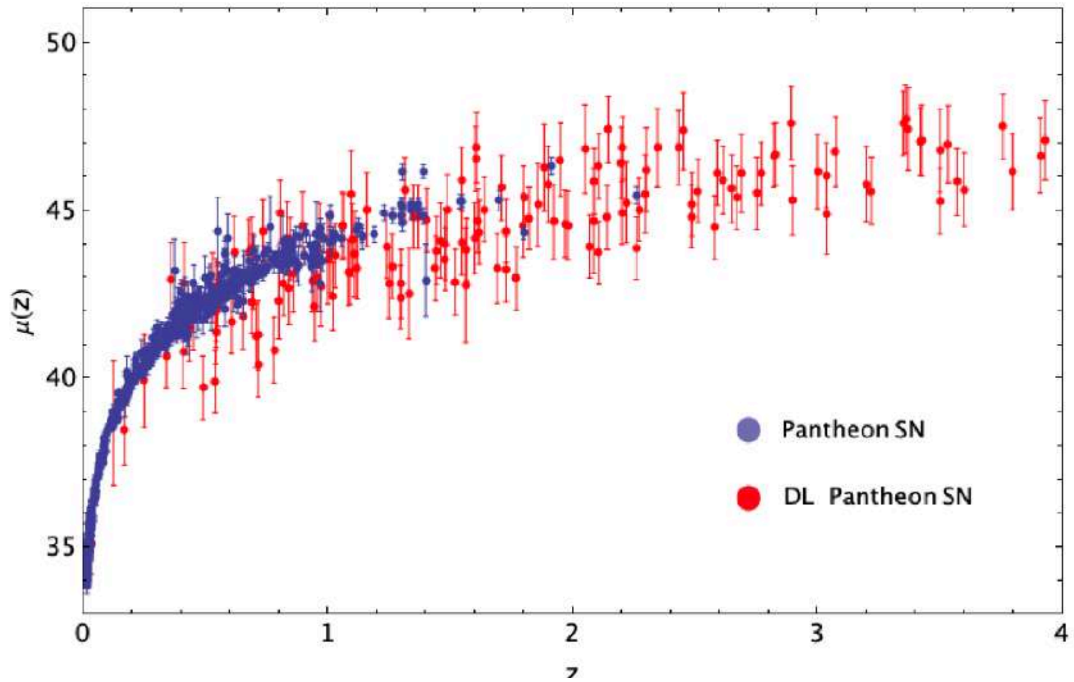
Maping from observations to theory



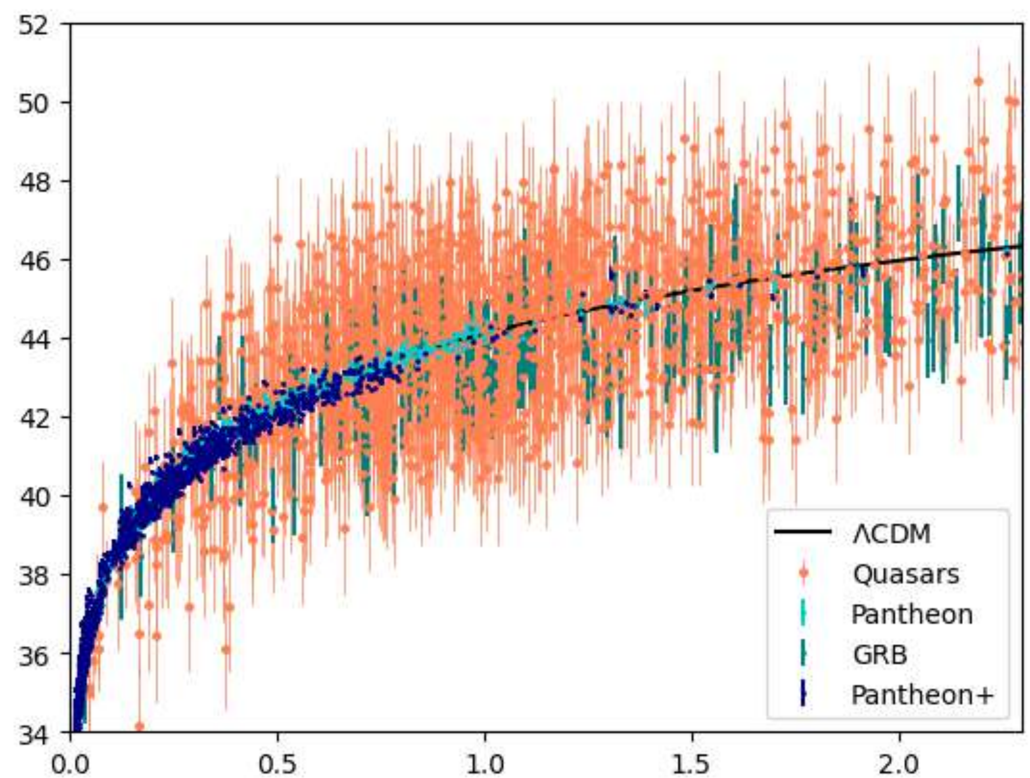
[Source: **C. Escamilla-Rivera,** *PoS* AISIS2019 (2020)]

Observations data mining results



Pantheon SN: $0.01 < z < 2.3$
DL Pantheon SN: $0.01 < z < 4$

[**C. Escamilla-Rivera,** M.Carvajal and S. Capozziello. JCAP 03 (2020) 008]



Pantheon SN: 1048
DL Pantheon SN: 2100

Pantheon+ SN: 1550
DL Pantheon+ SN: 1900

Quasars: 130
DL Quasars: 1081

GRB: 57
DL GRB: 110

[**C. Escamilla-Rivera** et al**,** in preparation (2022)]

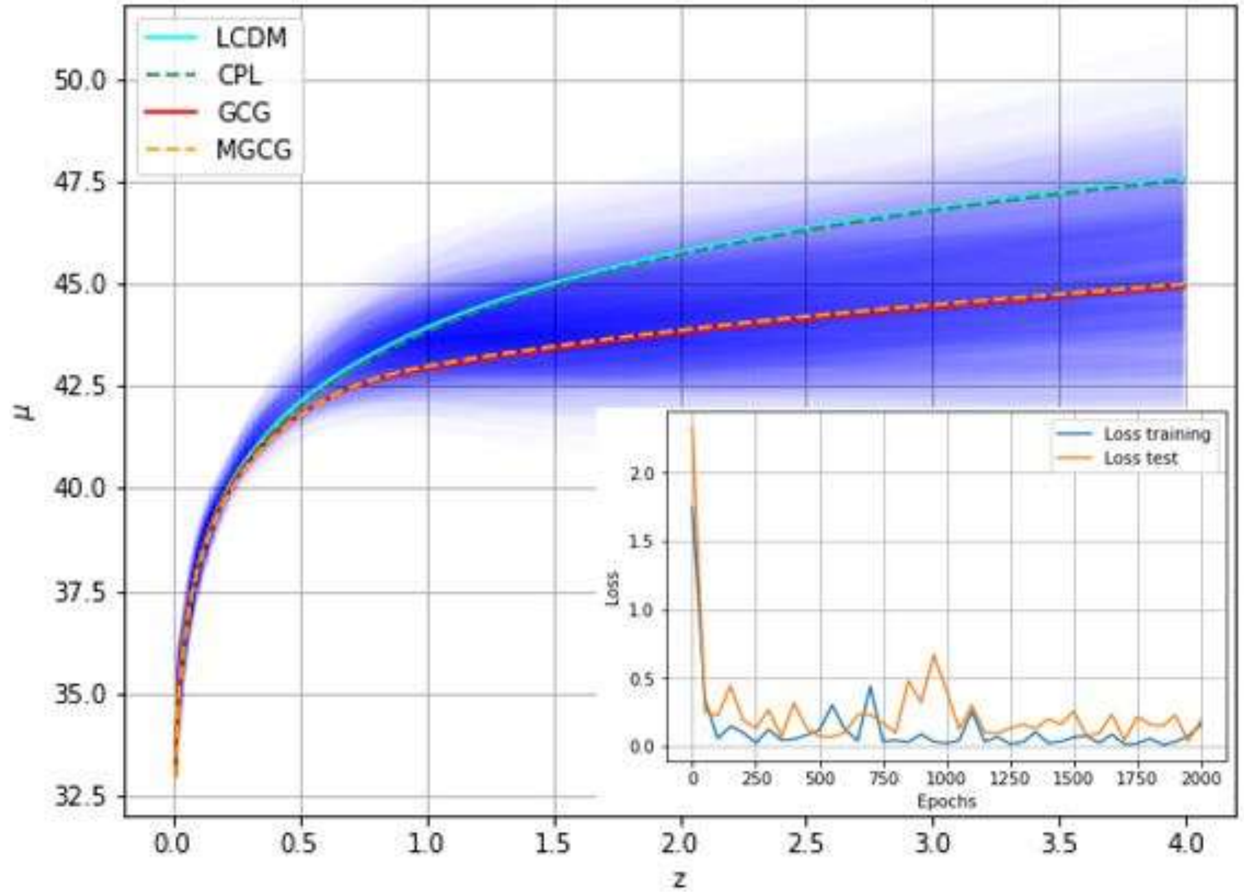
DLCosmo for dynamical dark energy: Code for Bayesian Neural Networks Analysis of gravity models

[**C. Escamilla-Rivera,** M.Carvajal and S. Capozziello. JCAP 03 (2020) 008]

- ✅ SNeIa (Pantheon)

$$w_{\rm gcg}(z) = -\frac{b_s}{b_s + (1-b_s)\left(\frac{1}{1+z}\right)^{-3(1+\alpha)}}\,.$$

$$w_{\rm mcg}(z) = B - \frac{B_s(1+B)}{B_s + (1-B_s)\left(\frac{1}{1+z}\right)^{-3(1+B)(1+\alpha)}}\,.$$

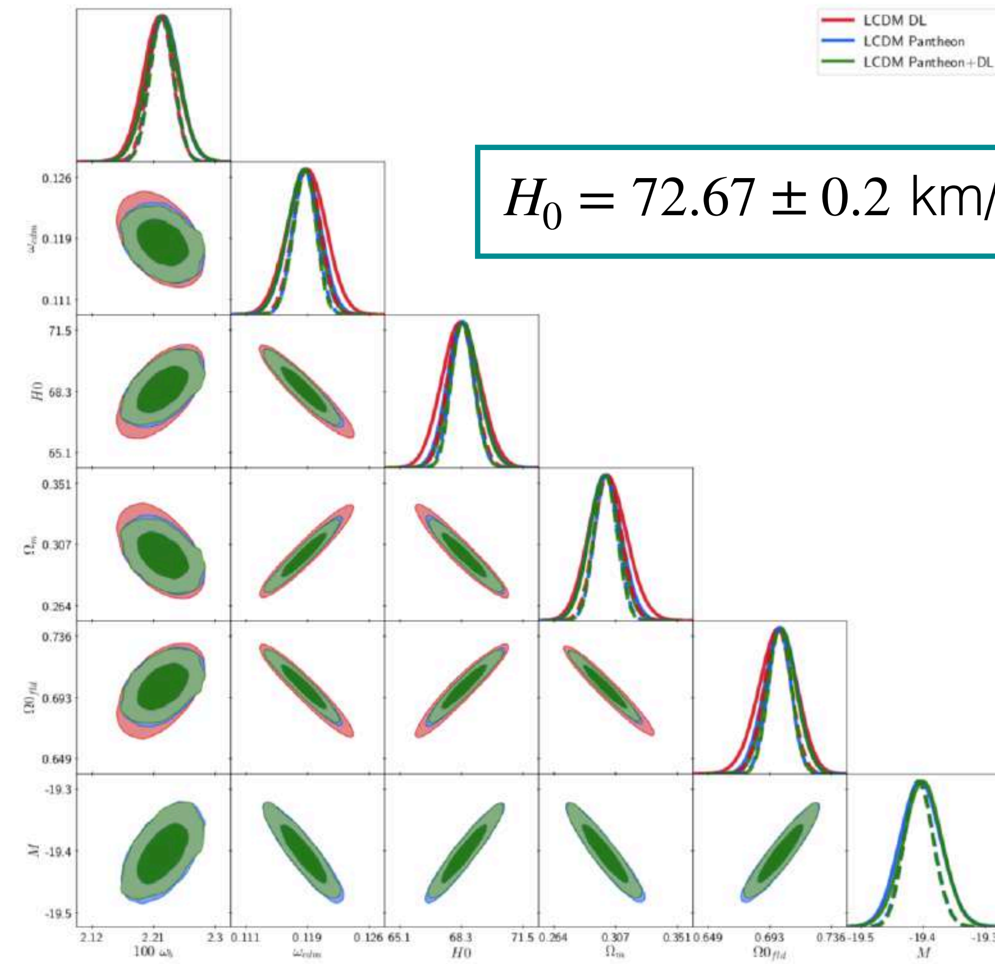


$H_0 = 72.47^{+0.5}_{-0.2}$ km/s/Mpc

DLCosmo for <u>standard cosmography</u>

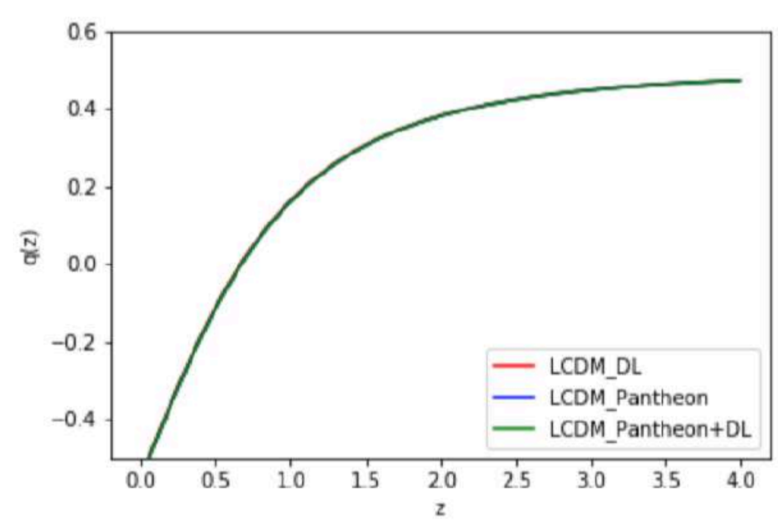
[C. Zamora and **C. Escamilla-Rivera.** JCAP 12 (2020) 007]

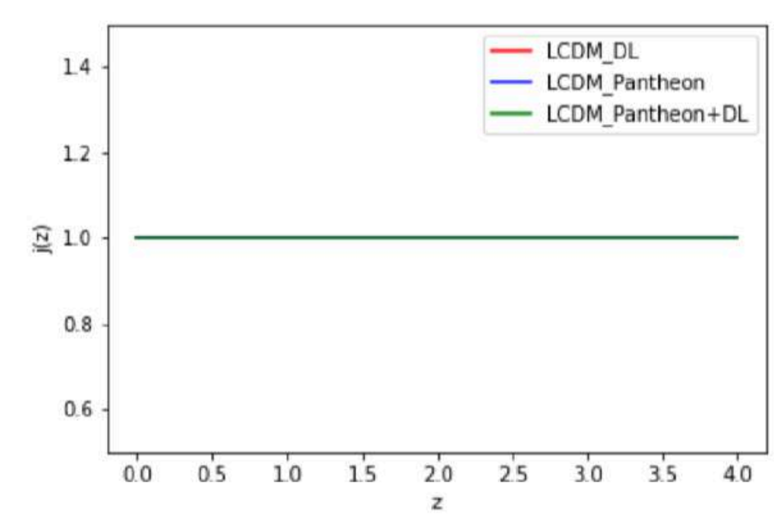
- SNeIa (Pantheon)
- H(z) (passive old galaxies)
- BAO (SDSS-DR7, DR10, DR11)



$H_0 = 72.67 \pm 0.2$ km/s/Mpc

$$w(z) = -1 + \frac{1}{3}(1+z)\frac{f_i(z)'}{f_i(z)} .$$

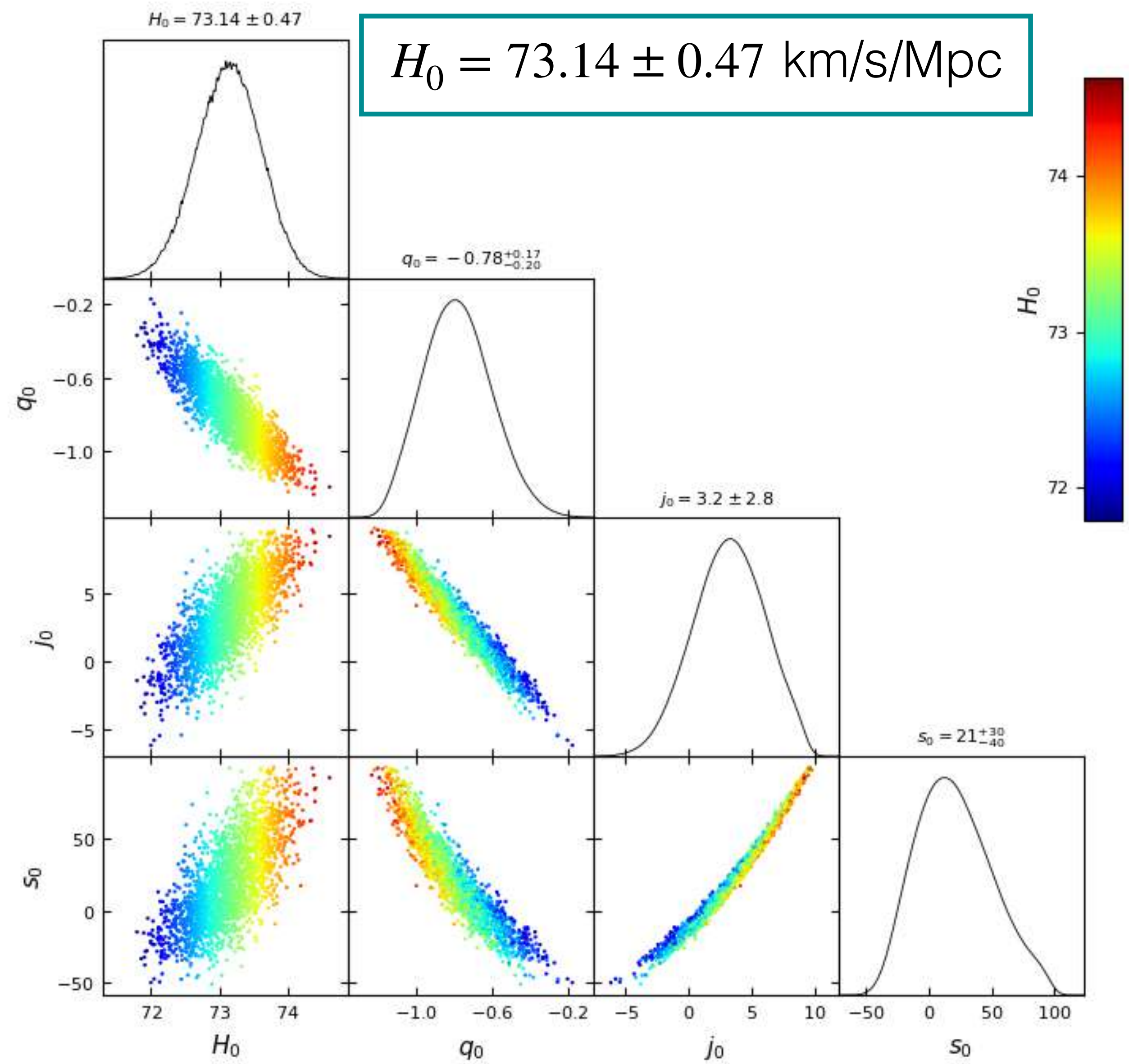




DLCosmo for extended cosmography

[**C. Escamilla-Rivera,** M. Carvajal, C. Zamora and M. Hendry JCAP 2109.00636 (2022)]

- SNeIa (Pantheon)
- H(z) (passive old galaxies)
- BAO (SDSS-DR7, DR10, DR11)
- GRB



$$d_L(z) = \frac{c}{H_0}\{z + \frac{1}{2}(1-q_0)z^2 - \frac{1}{6}(1 - q_0 - 3q_0^2 + j_0 + \frac{kc^2}{H_0^2 a^2(t_0)})z^3 + +\frac{1}{24}[2 - 2q_0 - 15q_0^2 - 15q_0^3 + 5j_0 + 10q_0 j_0 + s_0 + \frac{2kc^2(1+3q_0)}{H_0^2 a^2(t_0)}]z^4 + \dots$$

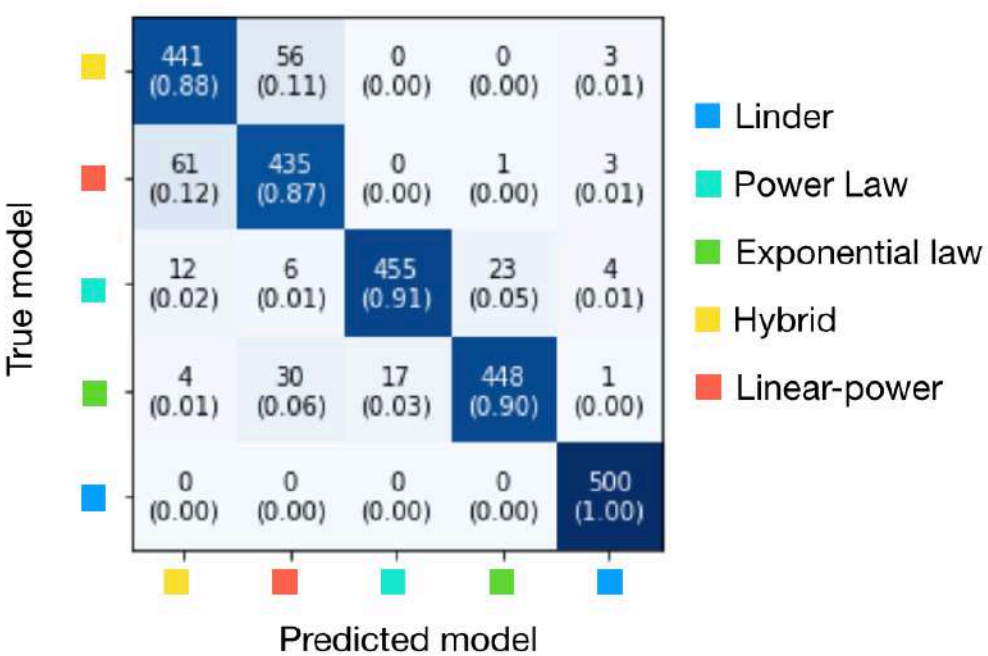
DLCosmo for teleparallel cosmologies

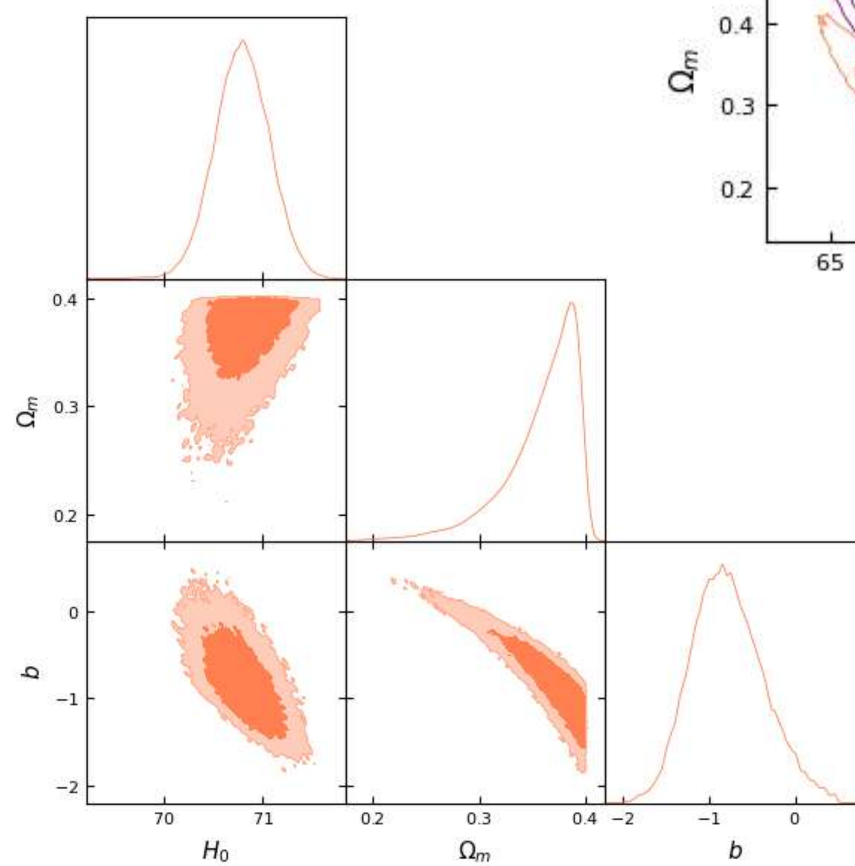
[**C. Escamilla-Rivera** et al**,** in preparation (2022)]

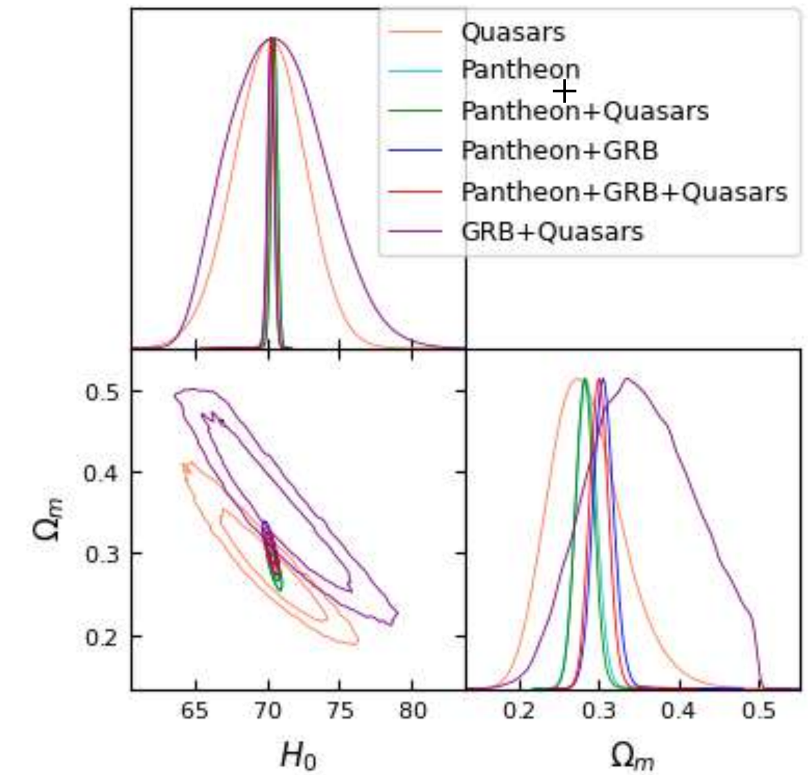
$$H_0 = 71.22 \pm 0.2 \text{ km/s/Mpc}$$

- SNeIa (Pantheon, Pantheon+)
- Quasars
- GRB

$$f_2(T) = \alpha_3 T_0[1 - e^{(-b_3 T/T_0)}]$$







DL dynamical dark energy

[**C. Escamilla-Rivera,** M.Carvajal and S. Capozziello. JCAP 03 (2020) 008]

DL standard cosmography

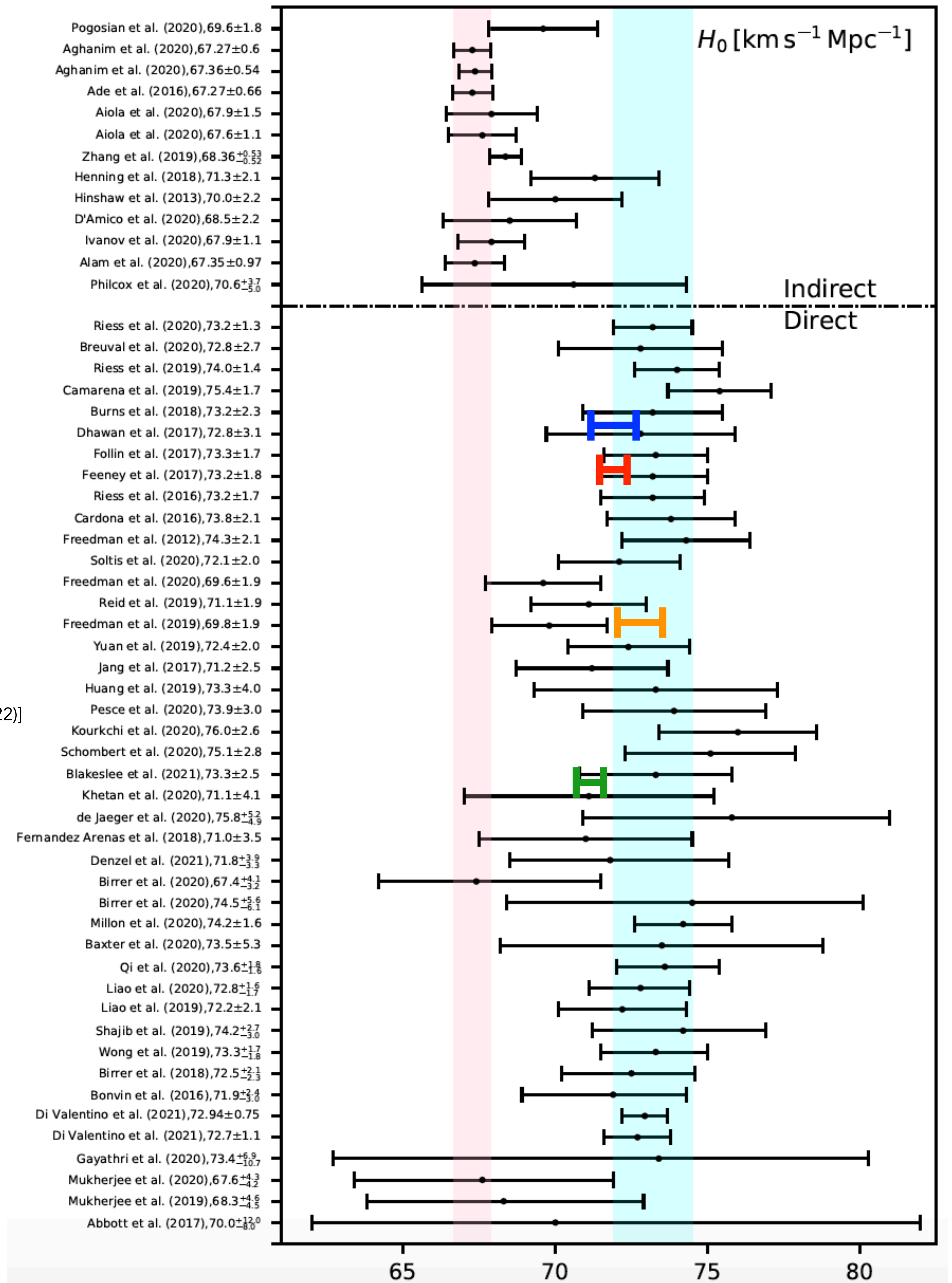
[C. Zamora and **C. Escamilla-Rivera.** JCAP 12 (2020) 007]

DL extended cosmography

[**C. Escamilla-Rivera,** M. Carvajal, C. Zamora and M. Hendry JCAP 2109.00636 (2022)]

DL for teleparallel cosmologies

[**C. Escamilla-Rivera,** et al in preparation (2022)]



Conclusions

- Neural Networks (NN) in Cosmology is growing fast and so the amount of cosmological data
- NN complement and support standard data analysis tools, e.g parameter estimation
- Data + NN can improve constraints on cosmological parameters, e.g H_0
- We can now classify models (likelihood free inference) using training data
- Important to understand the NN role in the future of Cosmology

Thank you

CosmoVerse 2022