Cosmic kite: Auto-encoding the cosmic microwave background

https://arxiv.org/abs/2202.05853

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Outline

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    b. Boltzmann-Einstein Equations
    c. The Cosmic Microwave Background (CMB)
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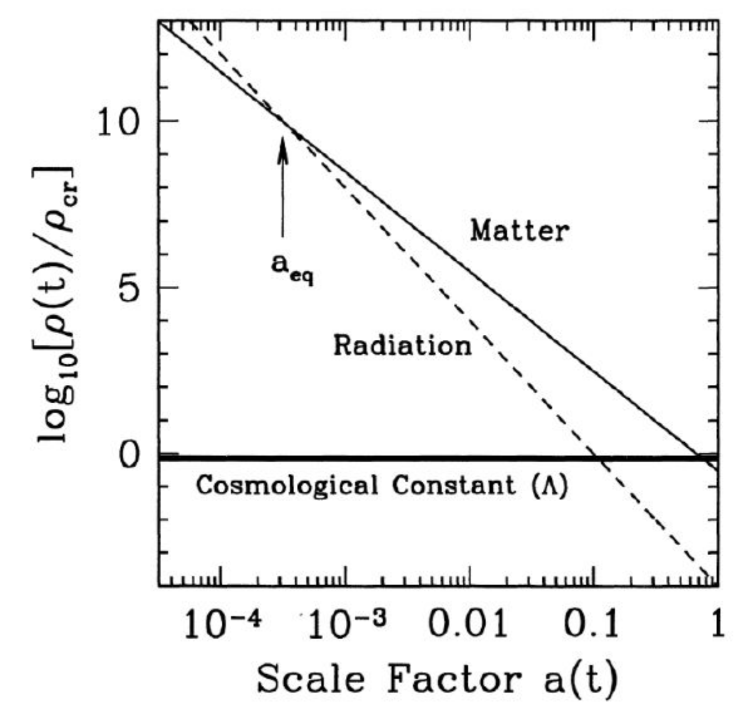
Brief introduction to Cosmology

The Friedman-Lemaître-Robertson-Walker Metric

$$
\begin{aligned}
ds^2 &= -dt^2 + a^2(t)\left[\frac{dr^2}{1-kr^2} + r^2 d\Omega^2\right] \\
\left(\frac{\dot{a}}{a}\right)^2 &= \frac{8\pi G}{3}\rho - \frac{k}{a^2} \\
\frac{\ddot{a}}{a} &= -\frac{4\pi G}{3}(\rho + 3p) \\
\frac{\dot{\rho}}{\rho} &= -3(1+\omega)\frac{\dot{a}}{a} \\
\rho &\propto a^{-3(1+\omega)} \\
T &= \frac{T_0}{a}
\end{aligned}
$$



Modern Cosmology. Dodelson

Brief introduction to Cosmology

The Friedman-Lemaître-Robertson-Walker Metric + Perturbations (Newtonian Gauge)

$$ds^2 = a^2(\tau)[-(1+2\psi)d\tau^2 + (1-2\phi)dx_i dx^i]$$

Brief introduction to Cosmology

The Friedman-Lemaître-Robertson-Walker Metric + Perturbations (Newtonian Gauge)

$$ds^2 = a^2(\tau)[-(1+2\psi)d\tau^2 + (1-2\phi)dx_i dx^i]$$

The Boltzmann Equations

Density distribution function on phase space

$$\frac{df}{dt} = C[f]$$

Collisional term

Brief introduction to Cosmology

The Boltzmann-Einstein Equations

Photons

$$\dot{\Theta} + ik\mu\Theta = -\dot{\phi} - ik\mu\psi - \dot{\tau}\left[\Theta_0 - \Theta + \mu v_b - \frac{1}{2}P_2(\mu)\Pi\right]$$

Baryons

$$\begin{aligned} \dot{\delta}_b + ikv_b &= -3\dot{\phi} \\ \dot{v}_b + \frac{\dot{a}}{a}v_b &= -ik\psi + \frac{\dot{\tau}}{R}[v_b + 3i\Theta_1] \end{aligned}$$

Dark Matter

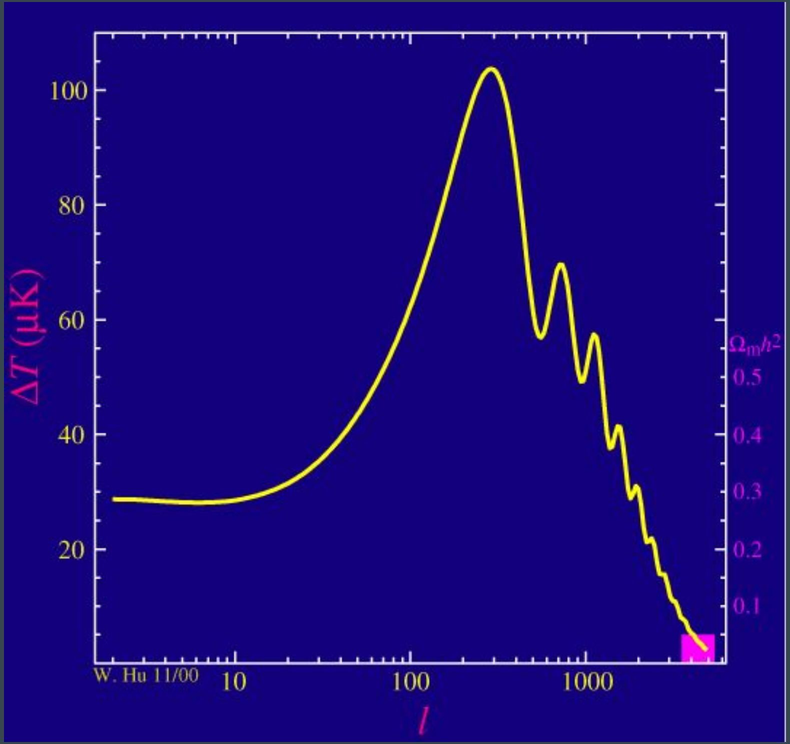
$$\begin{aligned} \dot{\delta} + ikv &= -3\dot{\phi} \\ \dot{v} + \frac{\dot{a}}{a}v &= -ik\psi \end{aligned}$$

Neutrinos

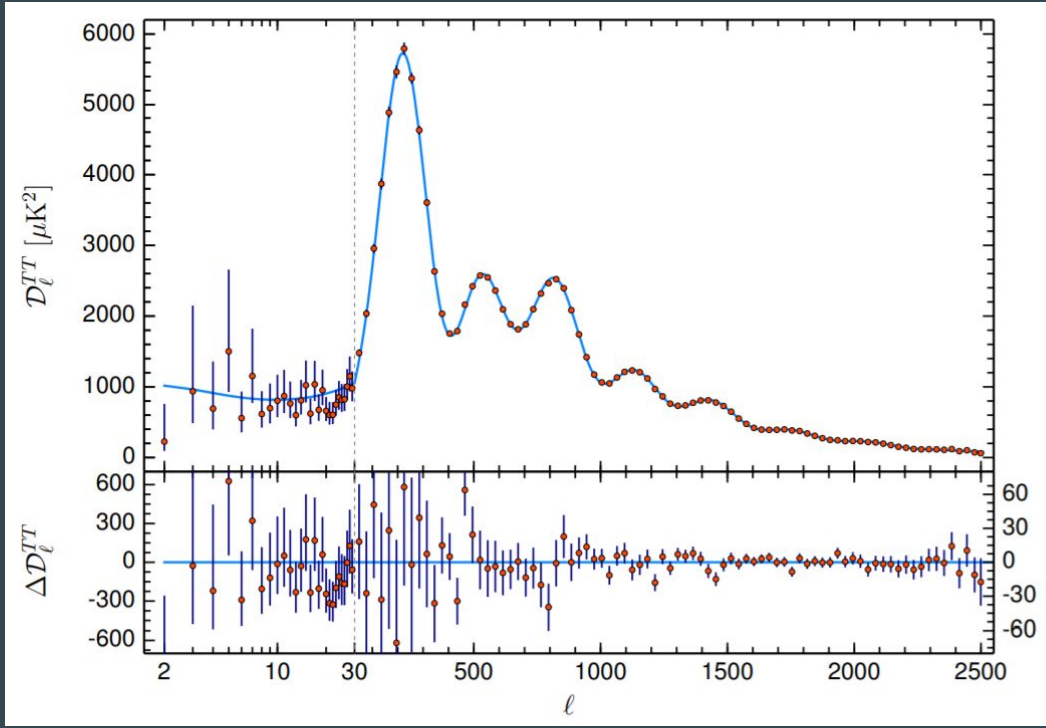
$$\dot{N} + ik\mu N = -\dot{\phi} - ik\mu\psi$$

Brief introduction to Cosmology

The Cosmic Microwave Background (CMB)



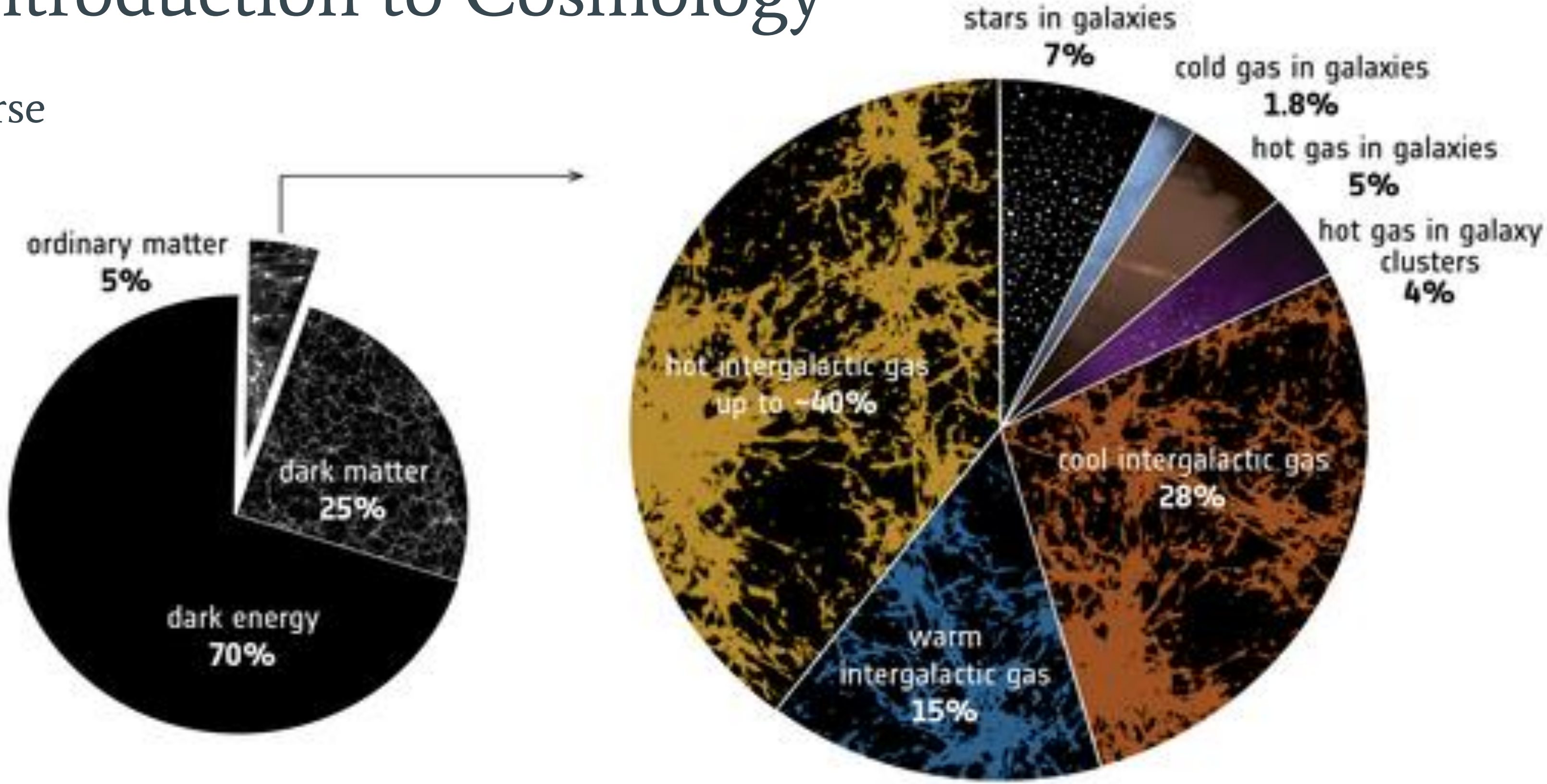
http://background.uchicago.edu/~whu/animbut/anim2.html



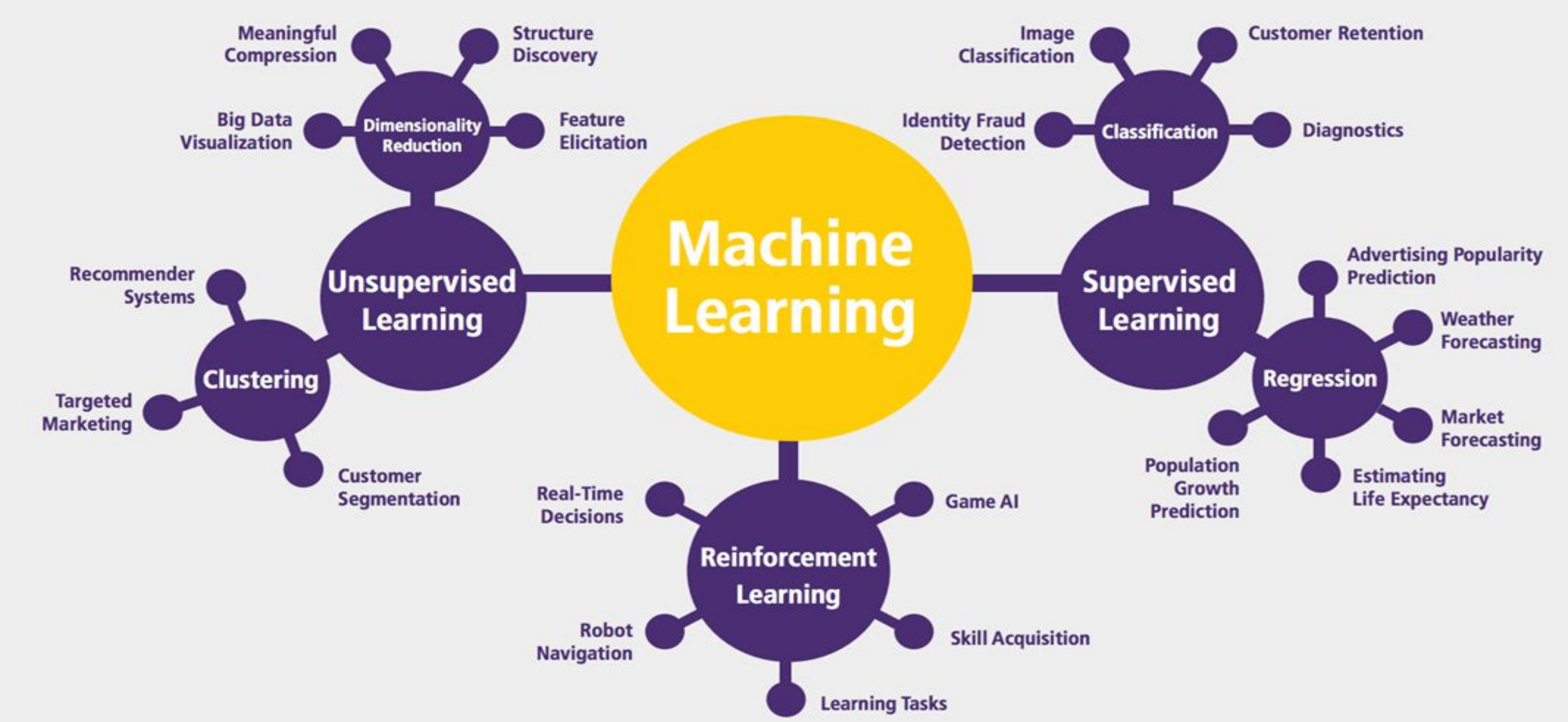
Planck Collaboration 1807.06209

Brief introduction to Cosmology

Our Universe

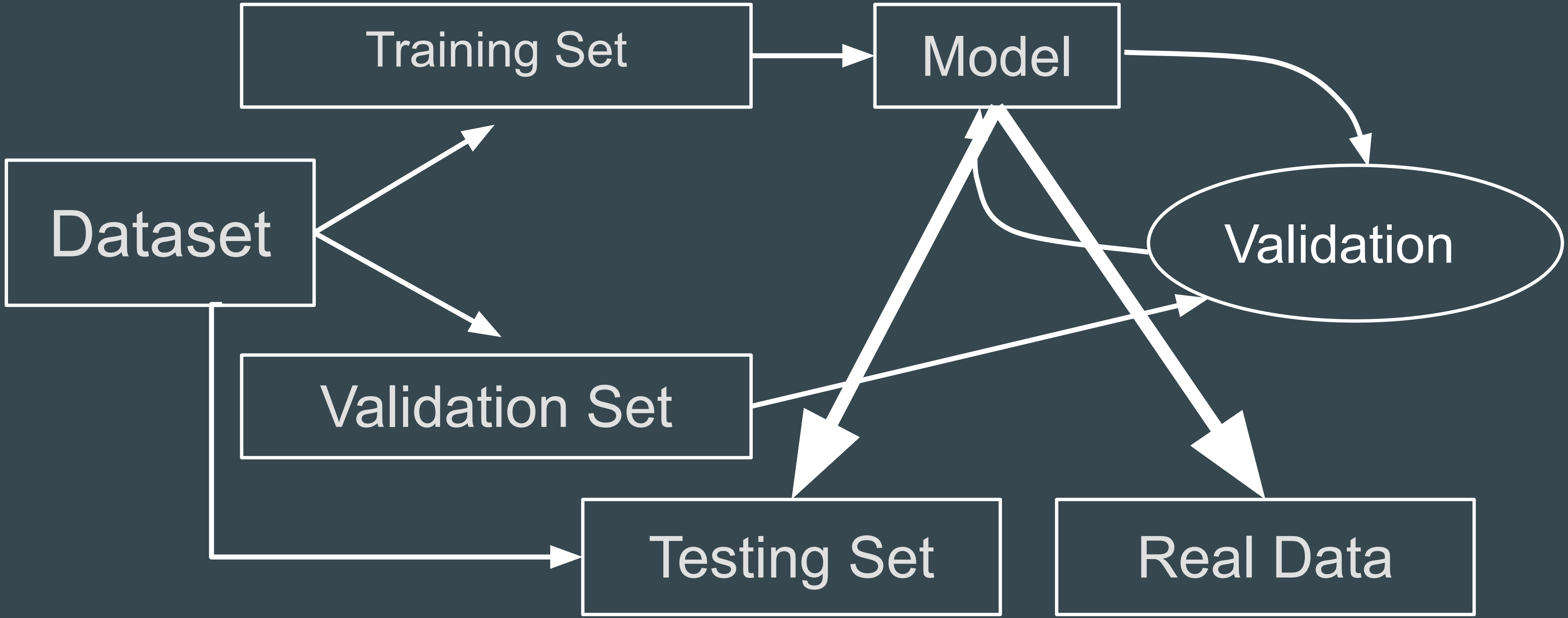


Brief introduction to Machine Learning



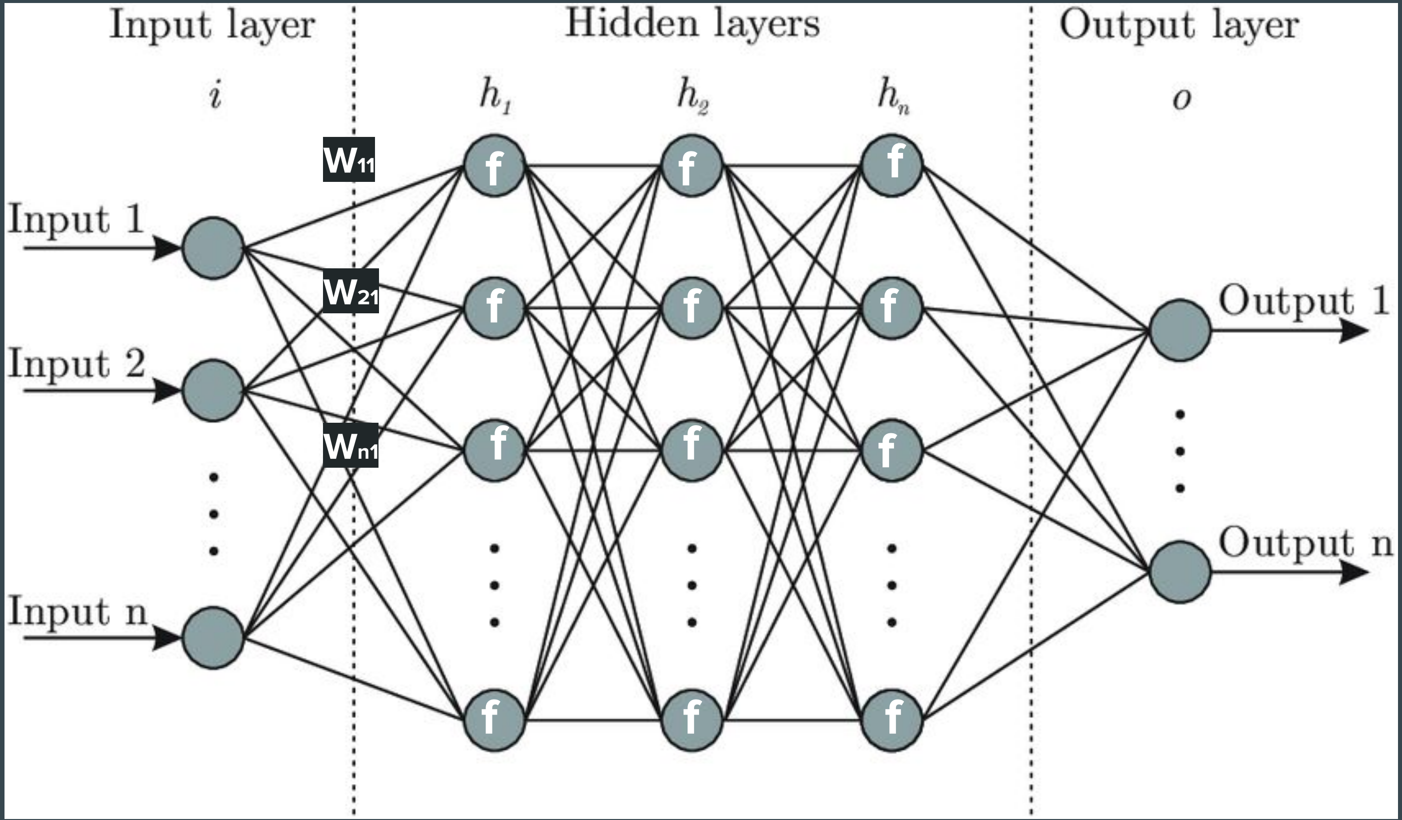
Brief introduction to Machine Learning

Supervised Learning



Brief introduction to Machine Learning

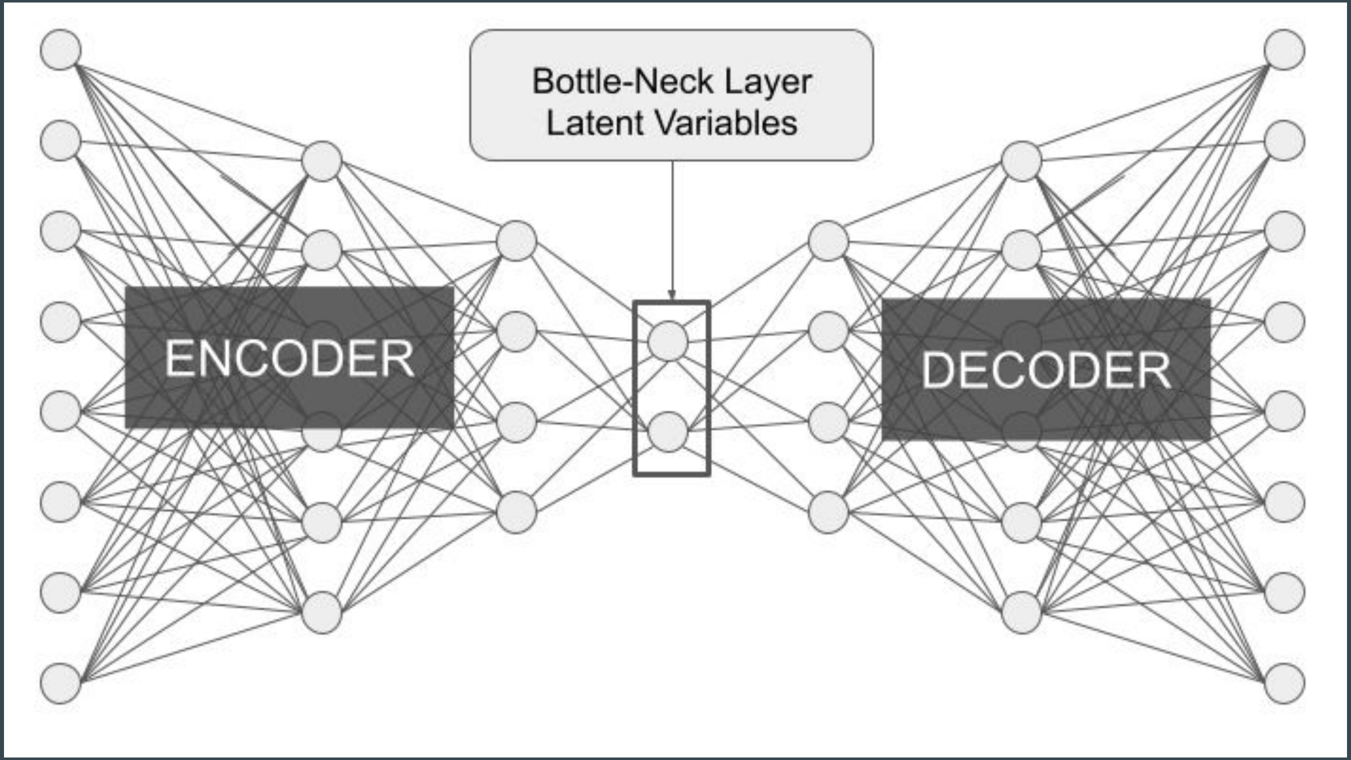
Neural Networks



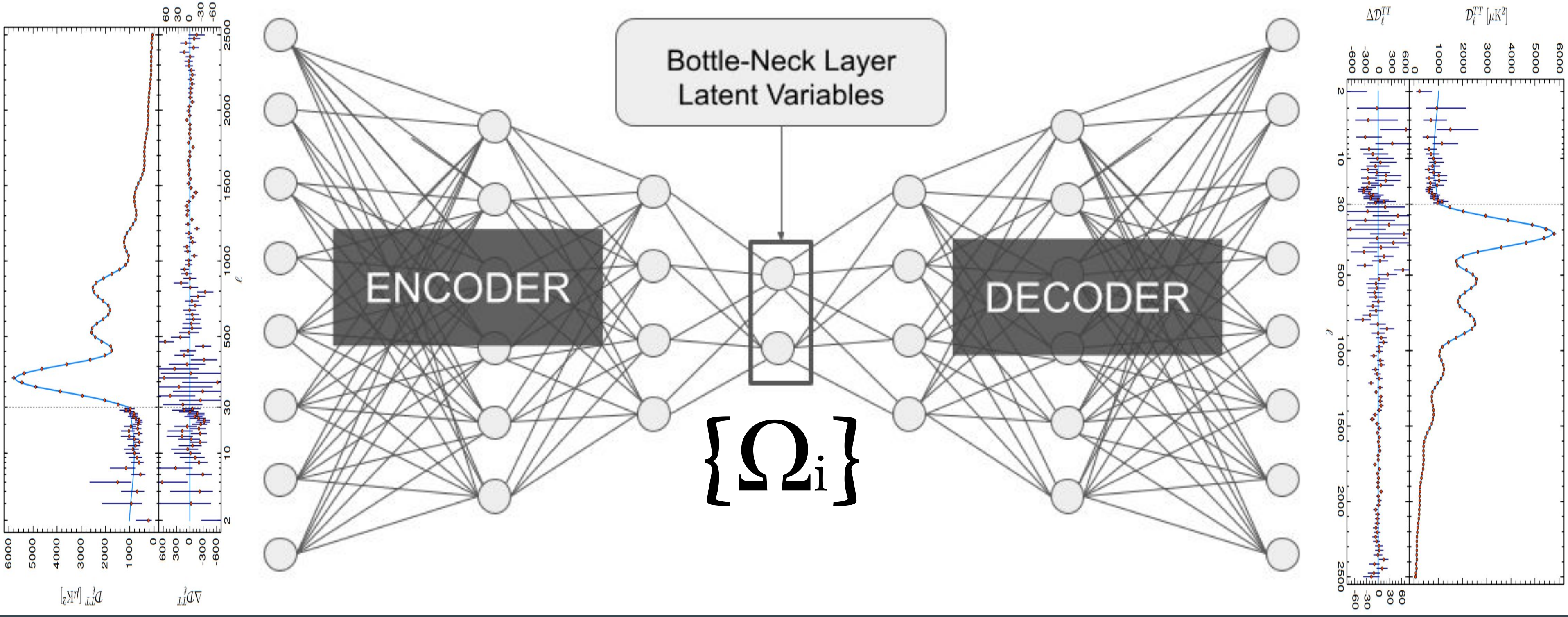
LOSS(Pr, Re)

Brief introduction to Machine Learning

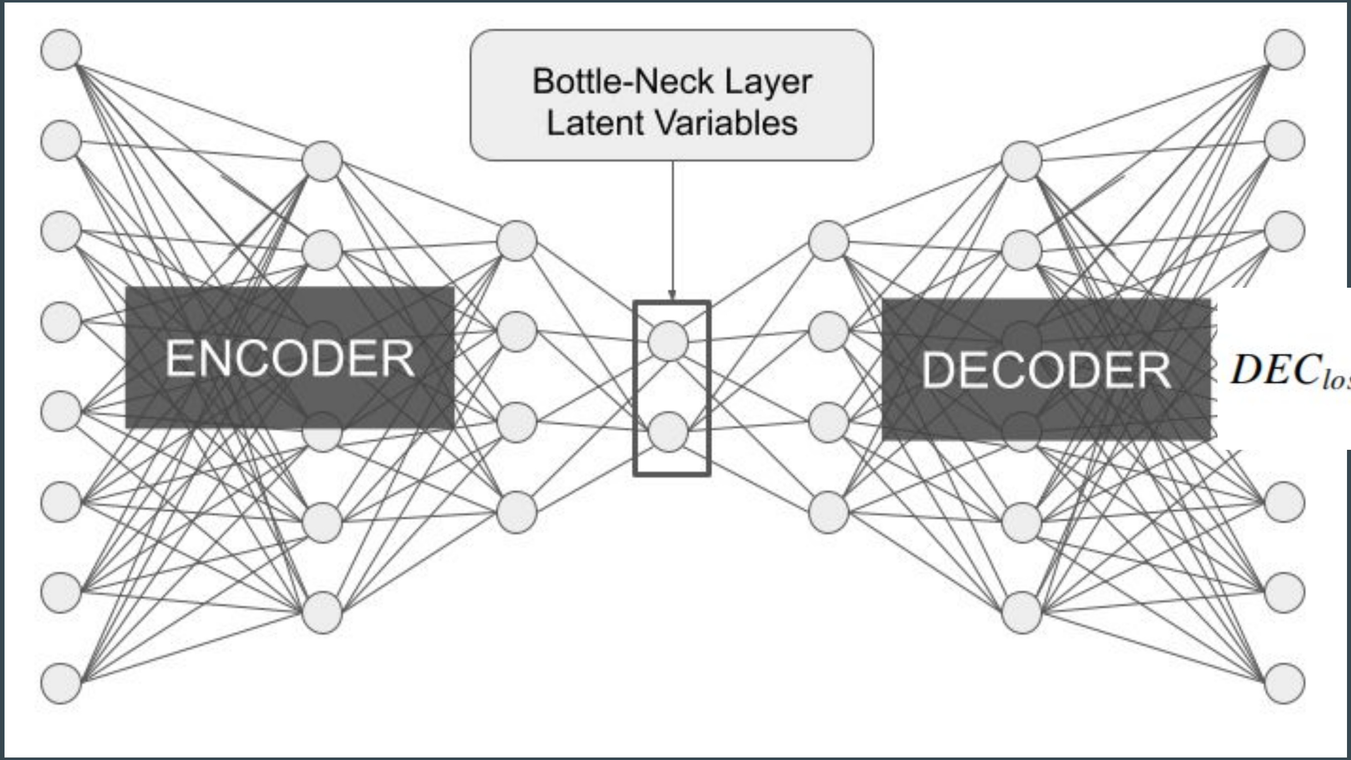
Auto-Encoders



Cosmic-Kite

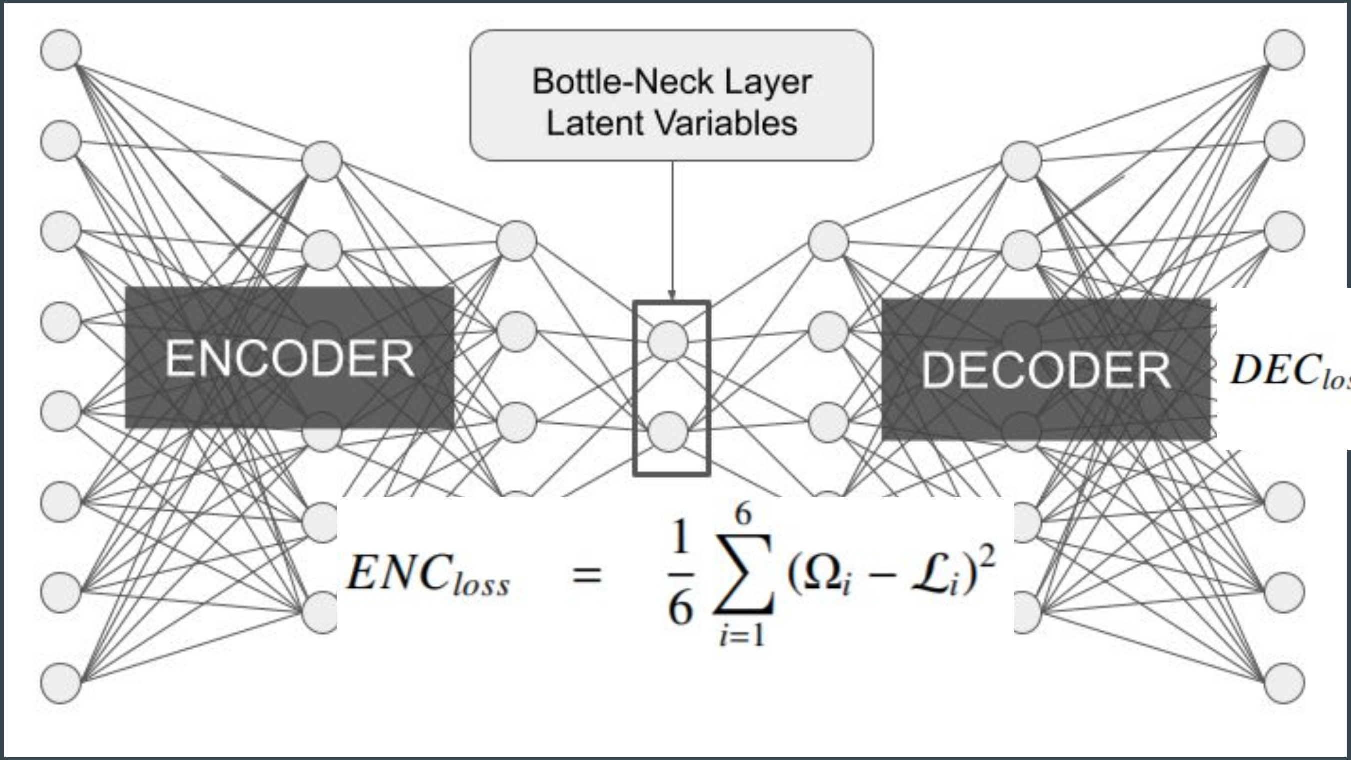

Bottle-Neck Layer
Latent Variables
ENCODER
DECODER
$\{\Omega_i\}$

Cosmic-Kite



$$DEC_{loss} = \frac{1}{2648}\sum_{i=2}^{2650}\left(C_l^R - C_l^P\right)^2$$

Cosmic-Kite



$$DEC_{loss} = \frac{1}{2648}\sum_{i=2}^{2650}\left(C_l^R - C_l^P\right)^2$$

$$ENC_{loss} = \frac{1}{6}\sum_{i=1}^{6}(\Omega_i - \mathcal{L}_i)^2$$

Cosmic-Kite

$$LOSS = \frac{1}{N}\sum_{j=1}^{N}\left[\omega_{enc}ENC_{loss,j} + \omega_{dec}DEC_{loss,j}\right]$$

Cosmic-Kite

Building of the dataset

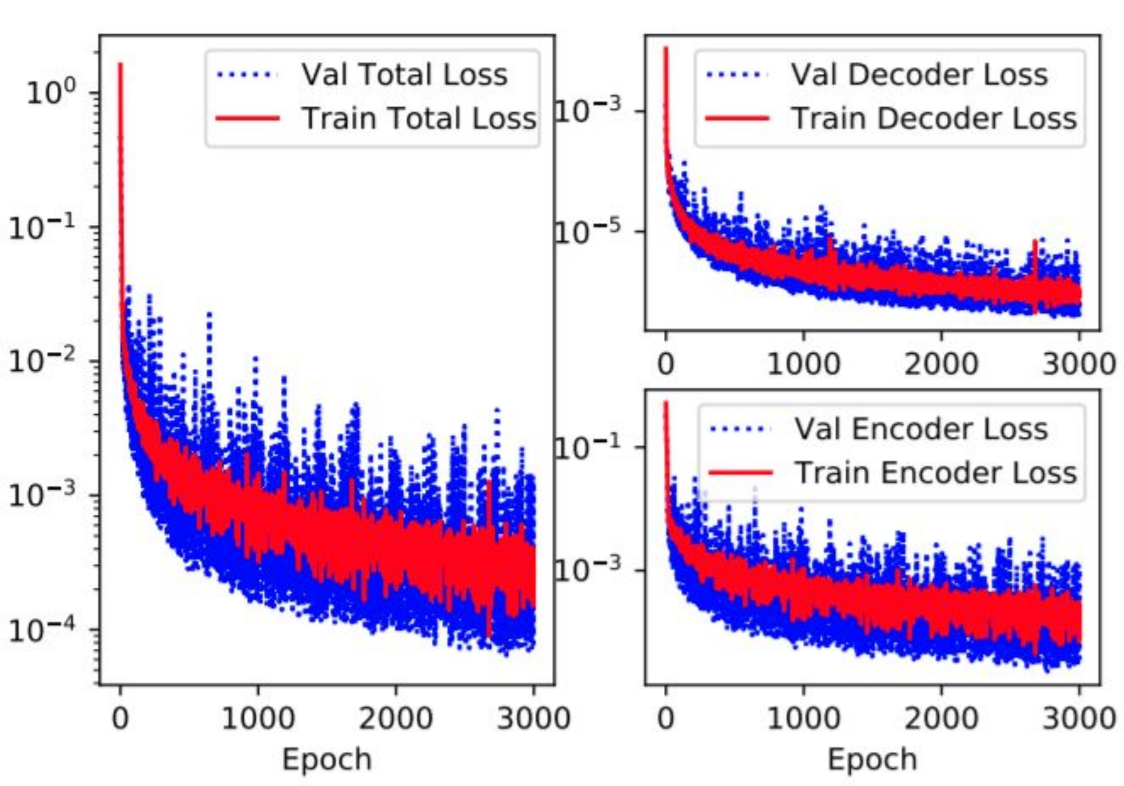
- CAMB[1] (Lewis et al.)
- 6 Cosmological Parameters
- 80.000 random cosmologies

Parameter	Minimum	Maximum	Planck
$\Omega_c h^2$	0.1096	0.130	0.120
$\Omega_b h^2$	0.02128	0.02348	0.02237
H_0	58.12	76.52	67.36
n	0.9375	0.9945	0.9649
A_s	$1.930 * 10^{-9}$	$2.270 * 10^{-9}$	$2.098 * 10^{-9}$
τ	0.014	0.094	0.0544

1 https://camb.info/

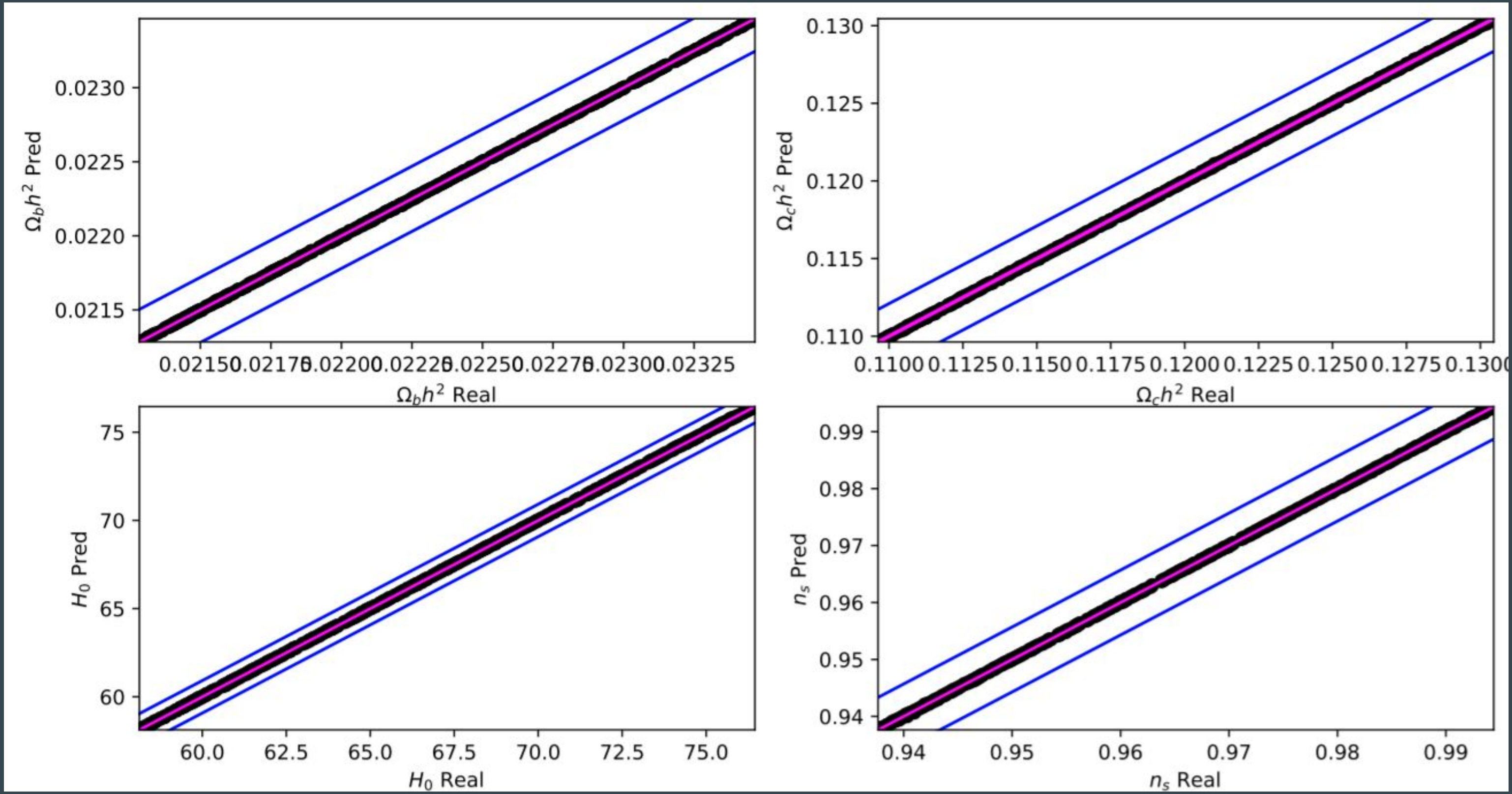
Cosmic-Kite

Training



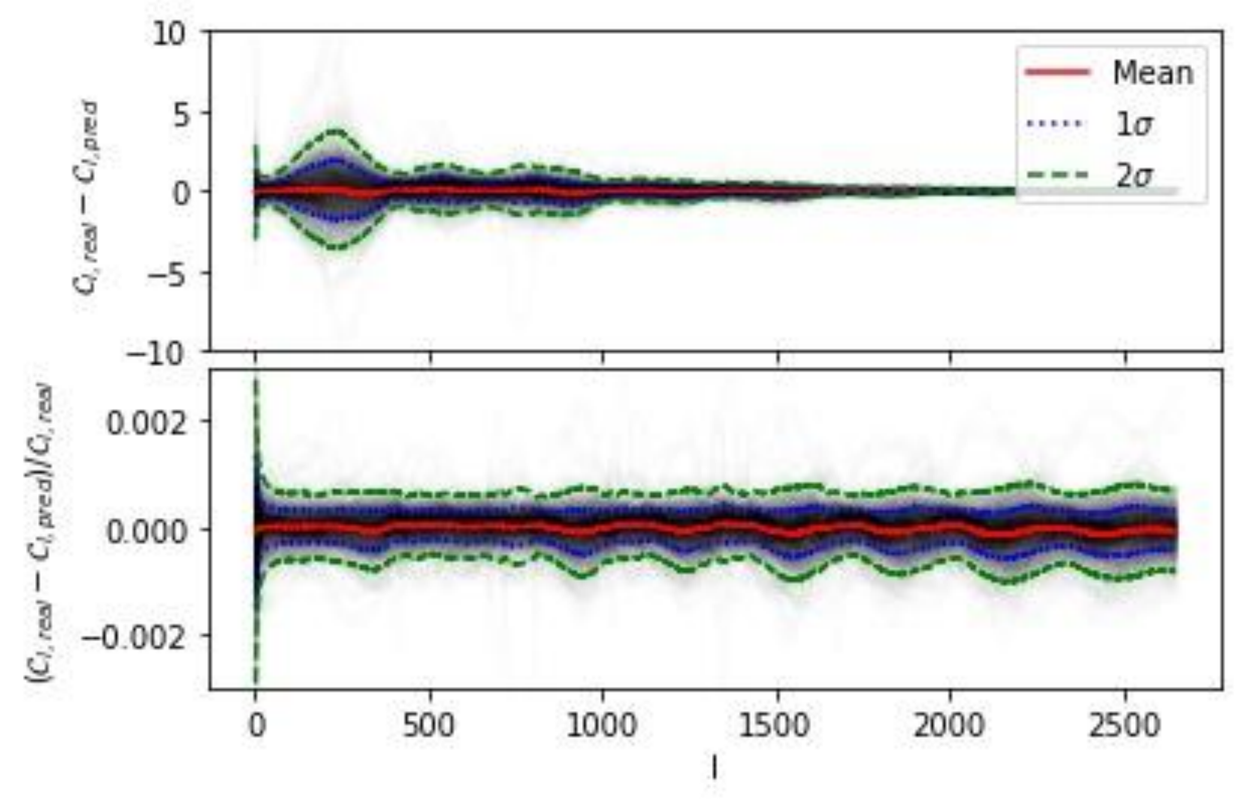
Cosmic-Kite

Encoding the CMB

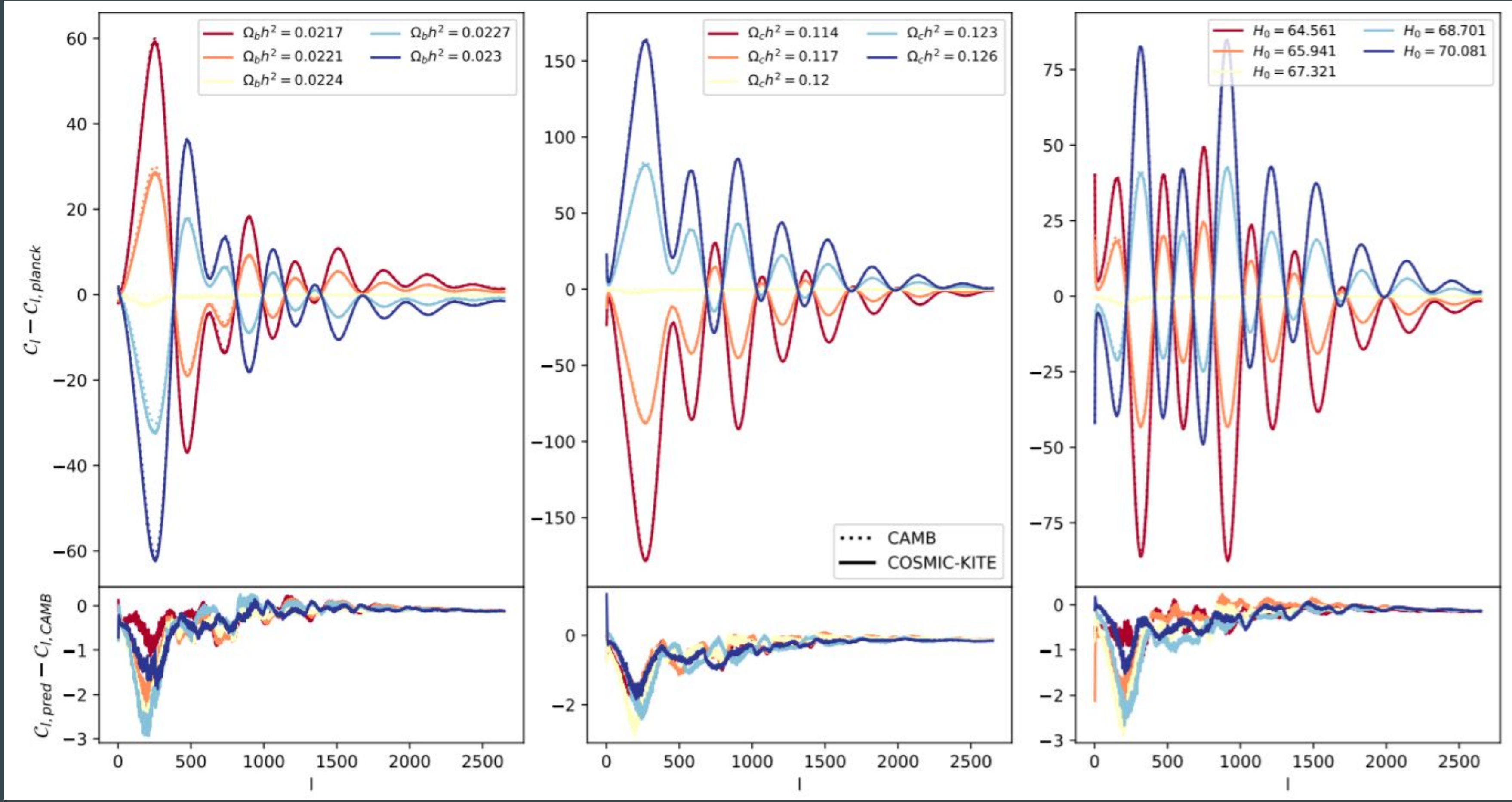


Cosmic-Kite

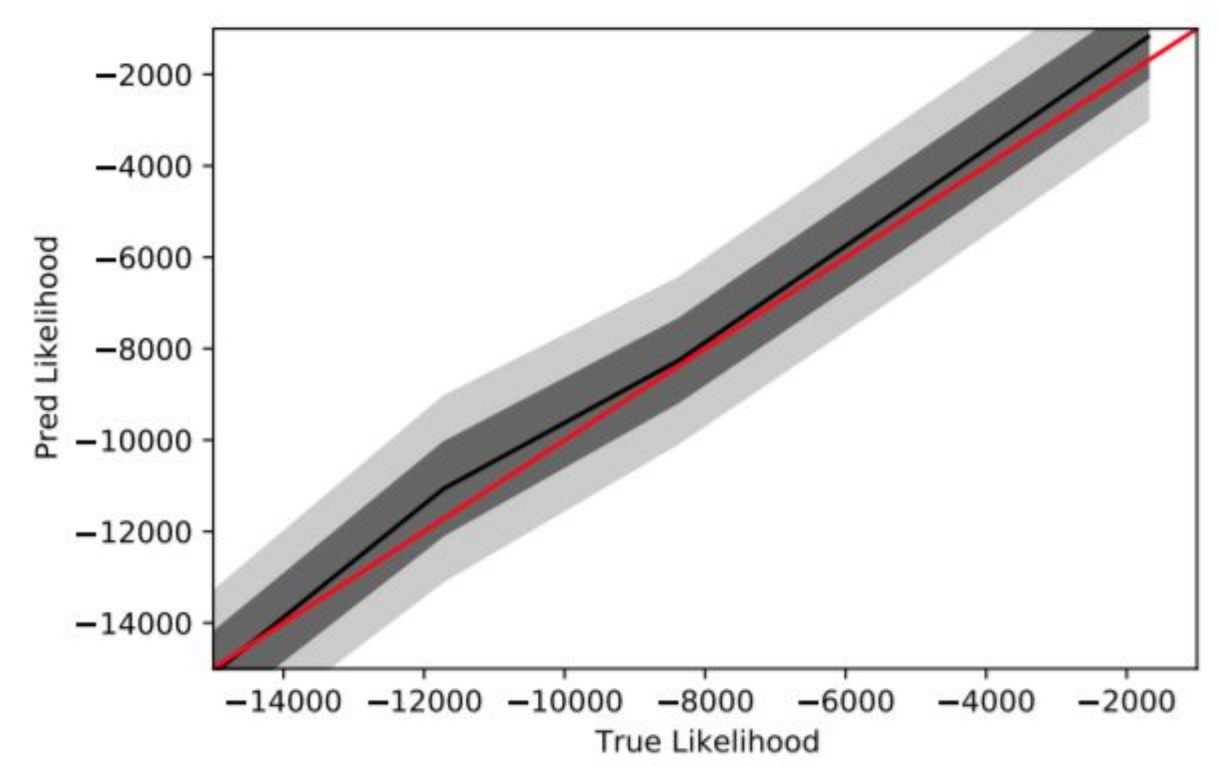
Decoding the CMB



Cosmic-Kite


$\Omega_b h^2 = 0.0217$
$\Omega_b h^2 = 0.0221$
$\Omega_b h^2 = 0.0224$
$\Omega_b h^2 = 0.0227$
$\Omega_b h^2 = 0.023$
$\Omega_c h^2 = 0.114$
$\Omega_c h^2 = 0.117$
$\Omega_c h^2 = 0.12$
$\Omega_c h^2 = 0.123$
$\Omega_c h^2 = 0.126$
$H_0 = 64.561$
$H_0 = 65.941$
$H_0 = 67.321$
$H_0 = 68.701$
$H_0 = 70.081$
CAMB
COSMIC-KITE
$C_l - C_{l,planck}$
$C_{l,pred} - C_{l,CAMB}$
l

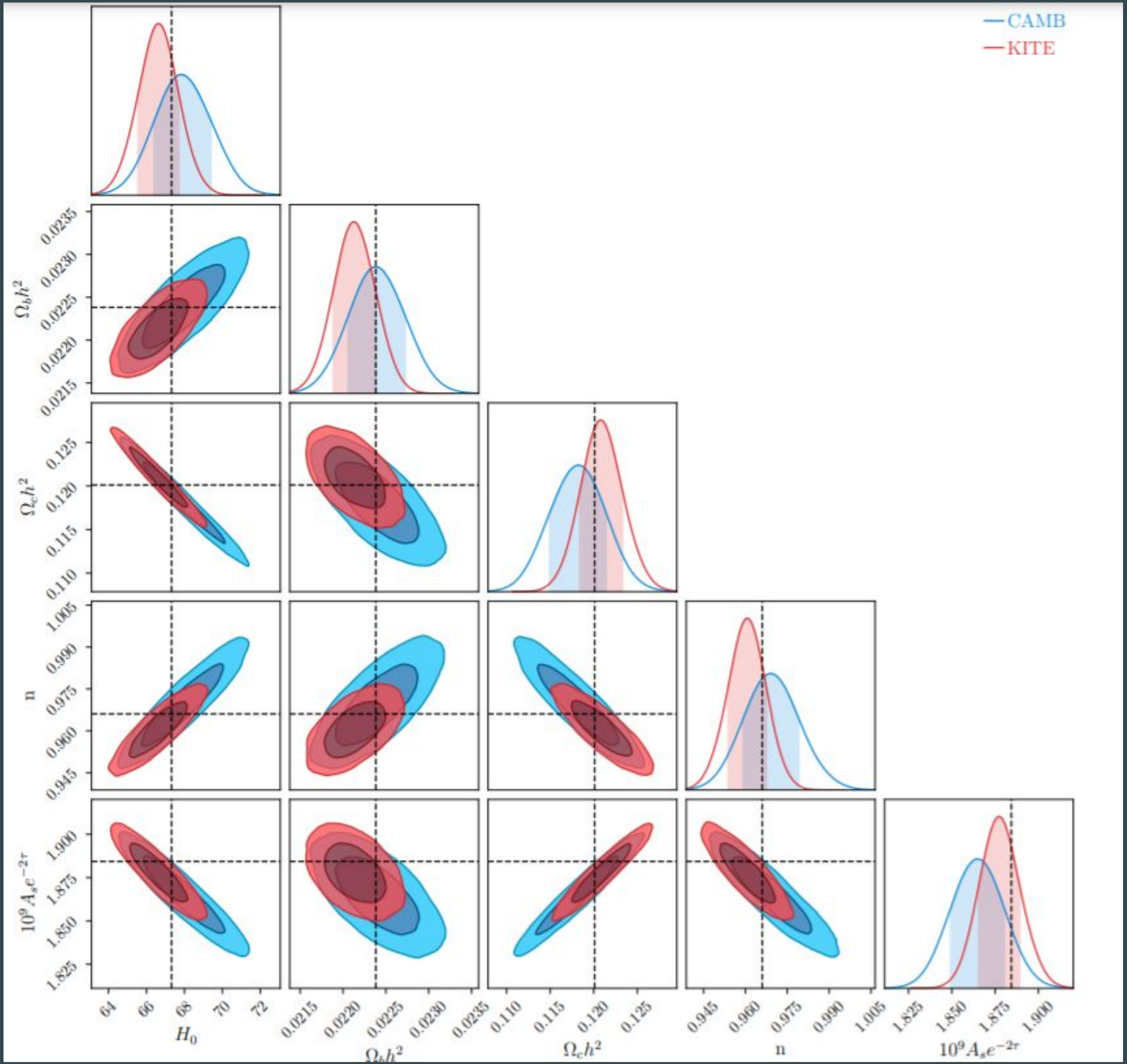
Cosmic-Kite



−2000
−4000
−6000
−8000
−10000
−12000
−14000
Pred Likelihood
−14000
−12000
−10000
−8000
−6000
−4000
−2000
True Likelihood

Cosmic-Kite

Bayesian Inference



Cosmic-Kite

https://github.com/Martindelosrios/cosmic-kite/

Python Library

```
from cosmic_kite import cosmic_kite

H0_true  = 67.32117
omb_true = 0.0223828
omc_true = 0.1201075
n_true   = 0.9660499
tau_true = 0.05430842
As_true  = 2.100549e-9

true_pars = np.array([omb_true, omc_true, H0_true, n_true, tau_true, As_true]).reshape(1,-1)

# The input of the pars2ps function must be an array of shape (n, 6)
#  where n is the number of cosmological models to be computed

ps = cosmic_kite.pars2ps(true_pars)[0]
# The input of the ps2pars function must be an array of shape (n, 2450)
#  where n is the number of cosmological models to be computed
pred_pars = cosmic_kite.ps2pars(ps.reshape(1,-1))[0]
```

Conclutions

- We performed an auto-encoding analysis of the CMB power spectra.
- Using the encoder, we are able to predict the cosmological parameters from the power spectra with an error ~0.2%.
- Using the decoder we are able to predict the power spectra from the cosmological parameters with a mean error ~ 0.0018%.
- Although this algorithm does not improve the precision of the measurements compared with the traditional methods, it reduces significantly the computation time.
- Represents the first attempt (to my knowledge) towards forcing the latent variables to have a physical interpretation.
- It can be extended to other signals.

Future Work

$$P(\Omega|X) = P(X|\Omega)\ P(\Omega)/P(X)$$

Future Work

$$P(\Omega|X) = P(X|\Omega)\, P(\Omega)/P(X)$$

Posterior

Future Work

$$P(\Omega|X) = P(X|\Omega)\, P(\Omega)/P(X)$$

Posterior

Likelihood

Future Work

Prior

$$P(\Omega|X) = P(X|\Omega)\, P(\Omega)/P(X)$$

Posterior

Likelihood

Future Work

$$\underbrace{P(\Omega|X)}_{\text{Posterior}} = \underbrace{P(X|\Omega)}_{\text{Likelihood}}\ \overbrace{P(\Omega)}^{\text{Prior}}/\underbrace{P(X)}_{\text{Evidence}}$$

Future Work

Prior

$$P(\Omega|X) = P(X|\Omega)\ P(\Omega)/P(X)$$

Posterior

Likelihood

Evidence

Future Work

$$P(X|FM(\Omega)) \rightarrow P(X|ML(\Omega))$$

$$P(X|\Omega)$$

Future Work

$$
\begin{tikzcd}
 & P(X|FM(\Omega)) \arrow[r] & P(X|ML(\Omega)) \\
P(X|\Omega) \arrow[ur] \arrow[r] & G(X|\Omega) \arrow[r] & ML(X|\Omega)
\end{tikzcd}
$$

Future Work

$$\begin{tikzcd} & P(X|FM(\Omega)) \arrow[r] & P(X|ML(\Omega)) \\ P(X|\Omega) \arrow[ur] \arrow[r] \arrow[dr] & G(X|\Omega) \arrow[r] & ML(X|\Omega) \\ & P(S(X)|\Omega) \arrow[r] & P(ML(X)|\Omega) \end{tikzcd}$$

Future Work

$$
\begin{tikzcd}
& P(X|FM(\Omega)) \arrow[r] & P(X|ML(\Omega)) \\
P(X|\Omega) \arrow[ur] \arrow[r] \arrow[dr] \arrow[ddr] & G(X|\Omega) \arrow[r] & ML(X|\Omega) \\
& P(S(X)|\Omega) \arrow[r] & P(ML(X)|\Omega) \\
& P(C(X)|\Omega) \arrow[r] & P(ML(X)|\Omega)
\end{tikzcd}
$$

Future Work

$$\underbrace{P(\Omega|X)}_{\text{Posterior}} = \underbrace{P(X|\Omega)}_{\text{Likelihood}} \overbrace{P(\Omega)}^{\text{Prior}} / \underbrace{P(X)}_{\text{Evidence}}$$

Future Work

$$P(\Omega|X) \longrightarrow ML(X|\Omega)$$

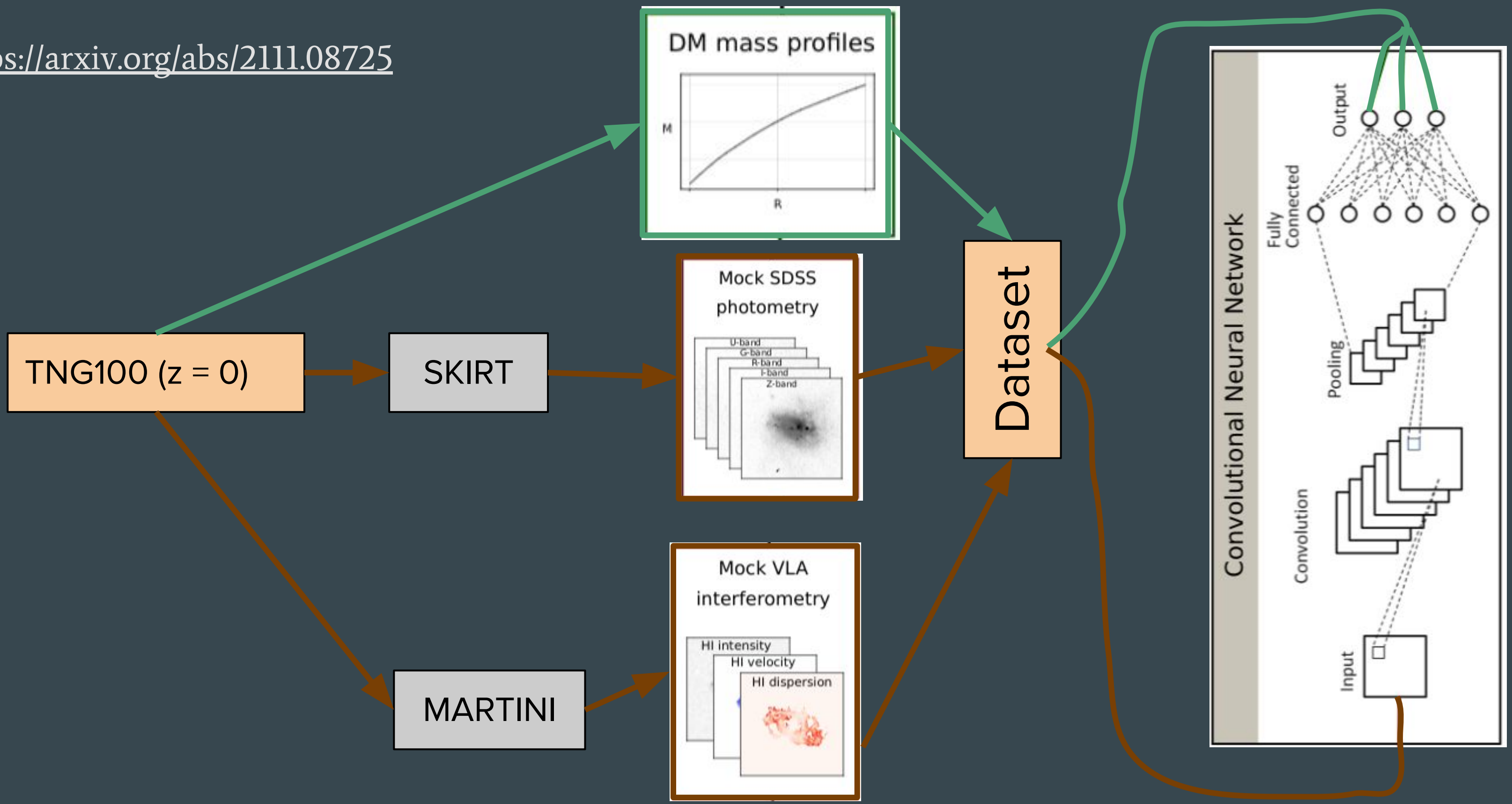

THANK YOU

Back-up Slides

Determining the Dark Matter distribution in galaxies with Deep Learning

Martín de los Rios, Mihael Petac, Bryan Zaldivar, Nina Bonaventura, Francesca Calore, Fabio Iocco

https://arxiv.org/abs/2111.08725

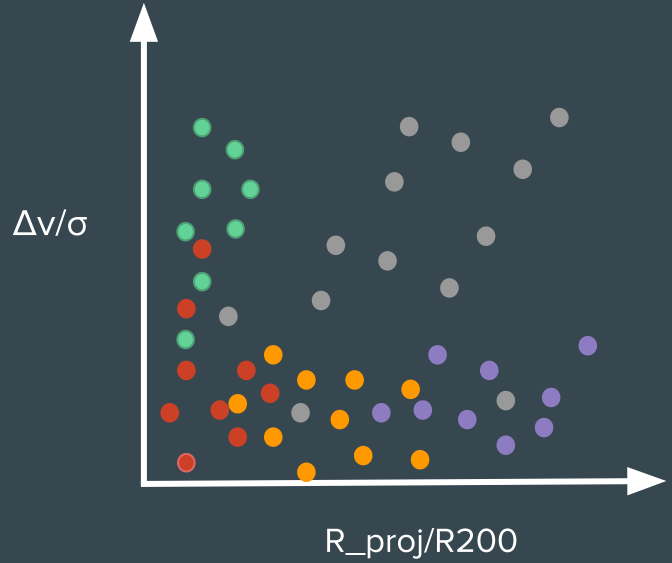


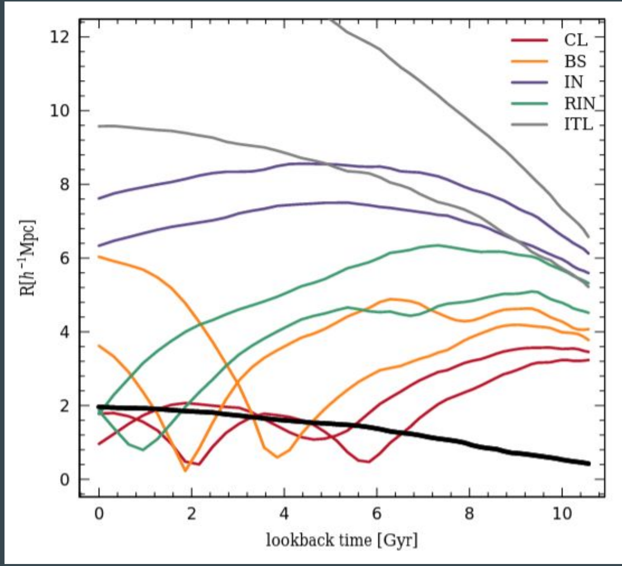
ROGER: Reconstructing Orbits of Galaxies in Extreme Regions using machine learning techniques

Martín de los Rios, Héctor J. Martínez, Valeria Coenda, Hernán Muriel, Andrés N. Ruiz, Cristian A. Vega-Martínez, Sofía A. Cora

https://arxiv.org/abs/2010.11959
https://arxiv.org/abs/2112.01552

Observational Information → **ROGER** → 3D Information





The MeSsI (Merging Systems Identification) Algorithm

Martín de los Rios, Mariano J. Domínguez R., Dante Paz, Manuel Merchán

https://arxiv.org/abs/1509.02524

https://arxiv.org/abs/1801.01498

https://arxiv.org/abs/1905.10303