Fingerprint matching of beyond-WIMP dark matter: a neural network approach

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Based on 1906.09141 with

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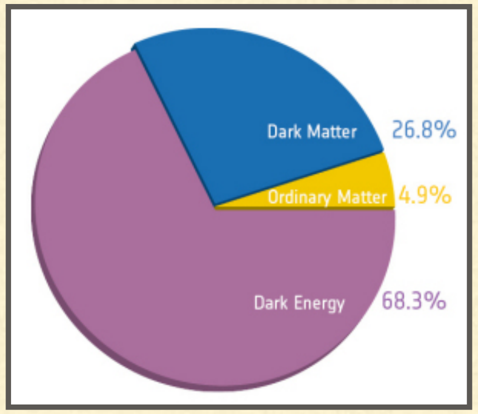
Introduction & summary

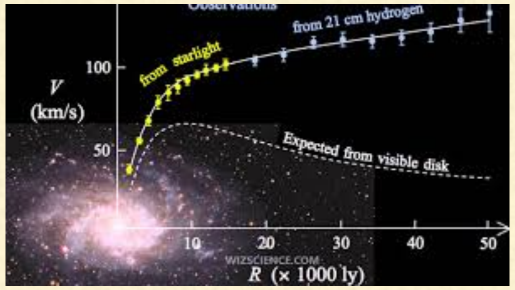
DARK MATTER

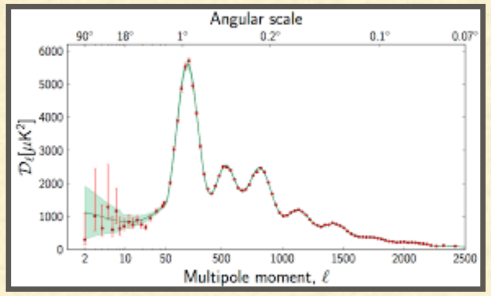


- Properties: 1) Occupies ~30% of the total energy of the Universe

  2) Long-lived (> Gyr) 3) Suppressed interaction with SM ...

- Evidence: Galaxy rotation curves / CMB / Bullet cluster / ...





- Traditional & well motivated candidate: WIMP w/ thermal freeze-out

  - Equilibrium history determines the abundance → Predictive

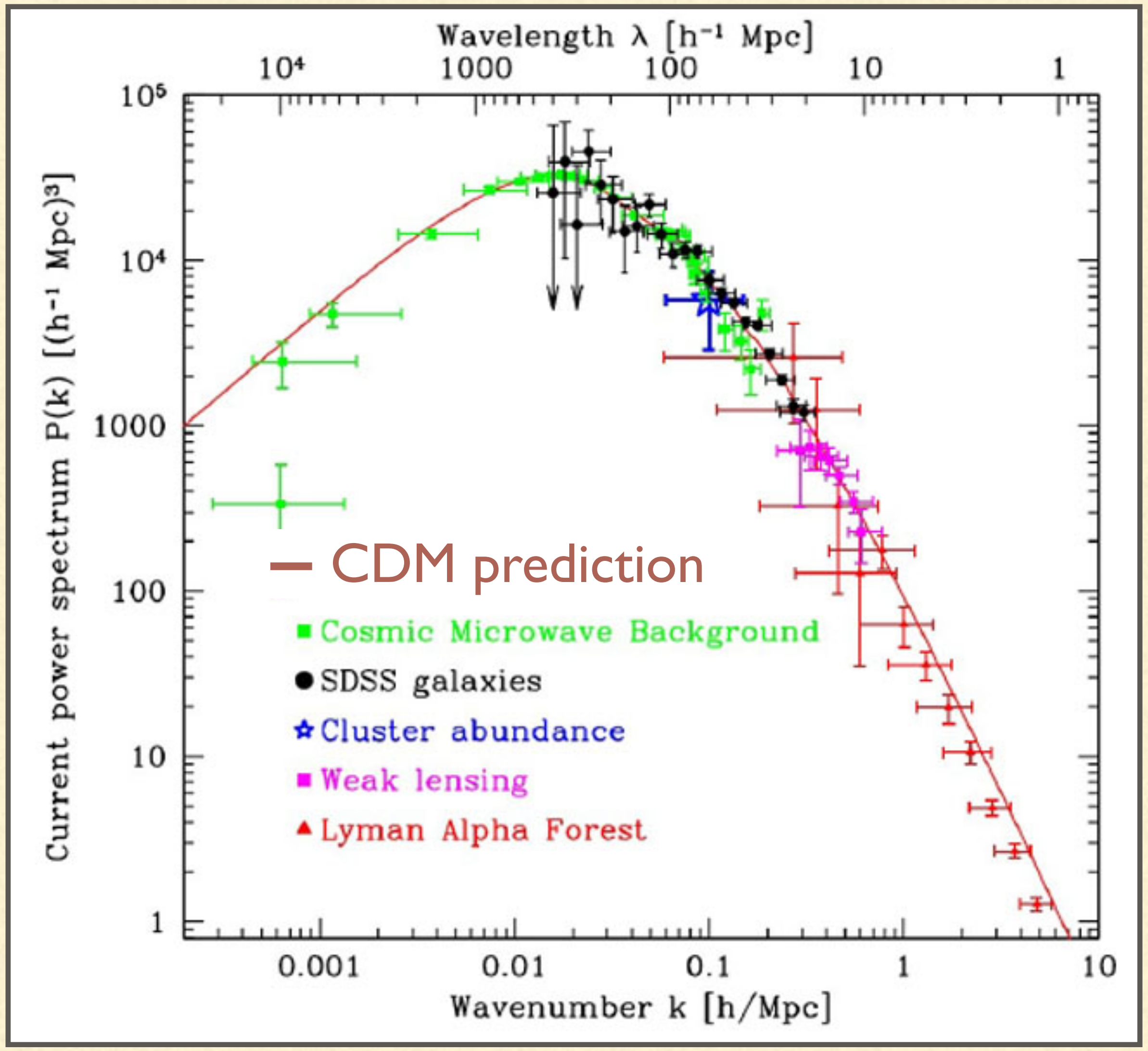
  - Behaves (almost) as cold dark matter (CDM)

  - Problem: null detection in direct/indirect experiments & colliders

- ...thus we are led to think about other candidates

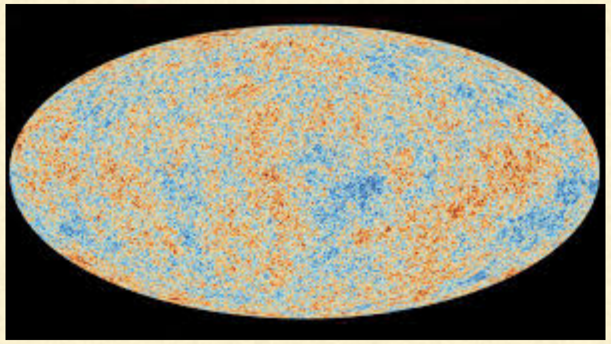
SMALL SCALE ISSUES

Linear matter power spectrum P(k)

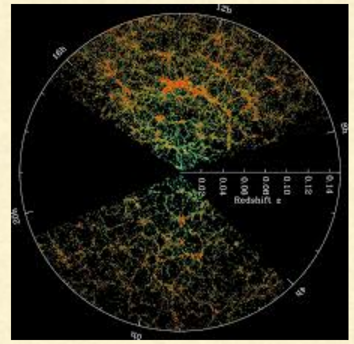


[Tegmark et al. '04]

length scale ← Gpc Mpc

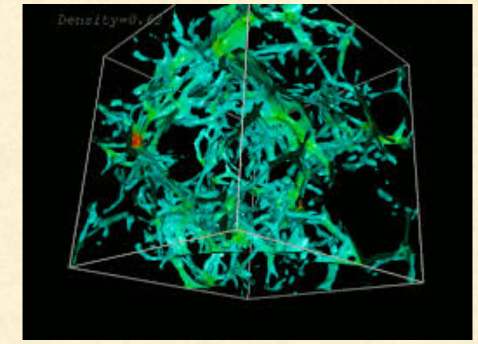


CMB



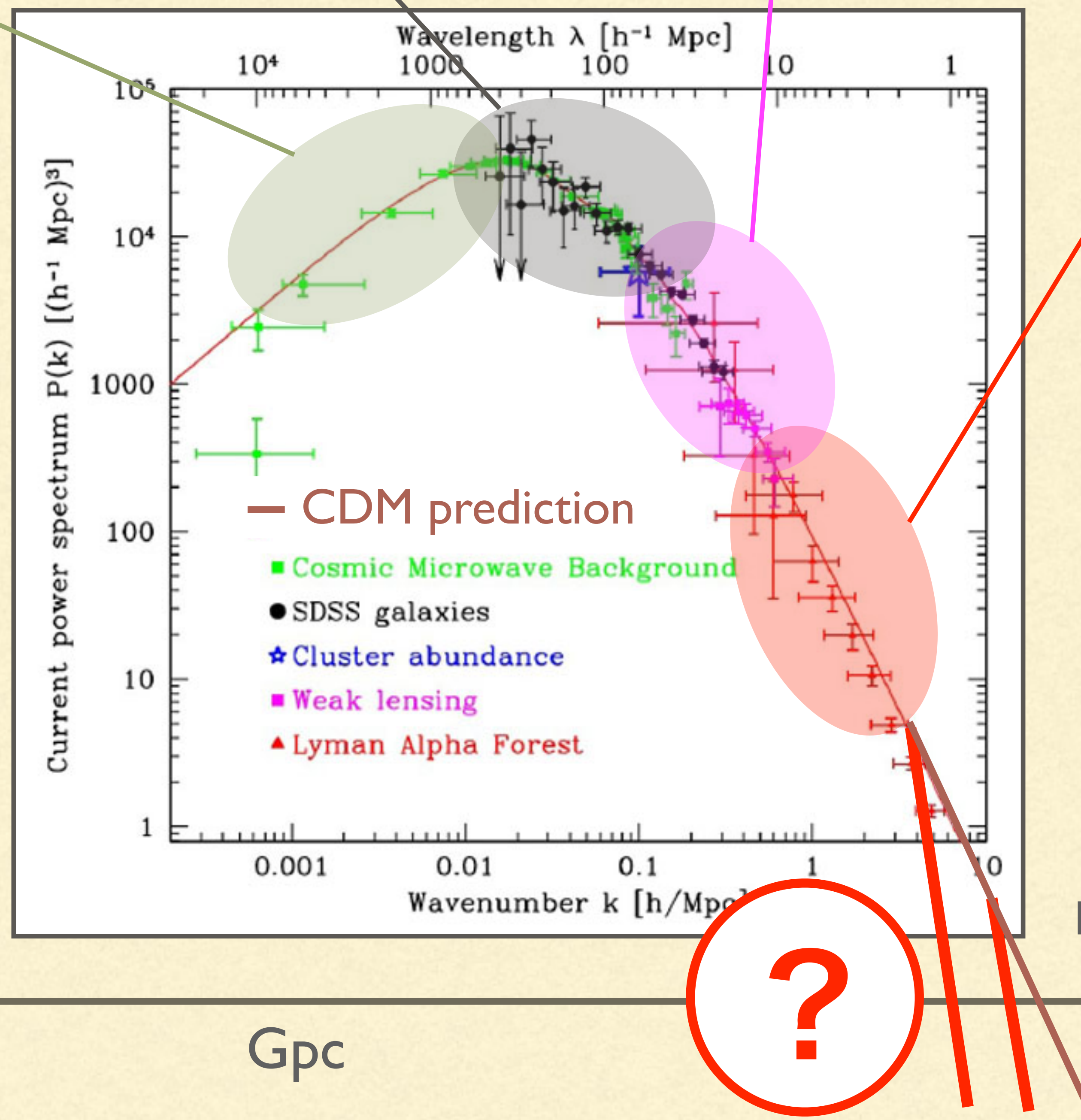
Galaxy survey

weak lensing



Lyman α

Linear matter power spectrum P(k)

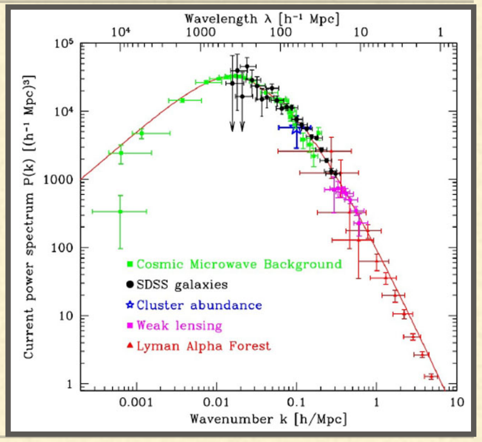


[Tegmark et al. '04]

length scale

Gpc

SMALL SCALE ISSUES



- CDM matches observations on large scales
- In small scales, however, sevaral possible deviations from CDM:

  \- **Missing satellite**: [Klypin, Kravtsov, Valenzuela, Prada '99 / Moore, Ghigna, Governato, Lake, Quinn, Stadel, Tozzi '99]

  Number of observed dwarf galaxies < prediction from N-body simulations

  \- **Too big to fail (to be detected)**: [Boylan-Kolchin, Bullock, Kaplinghat '11]

  Largest subhalos predicted in numerical simulations are too bright to escape detection

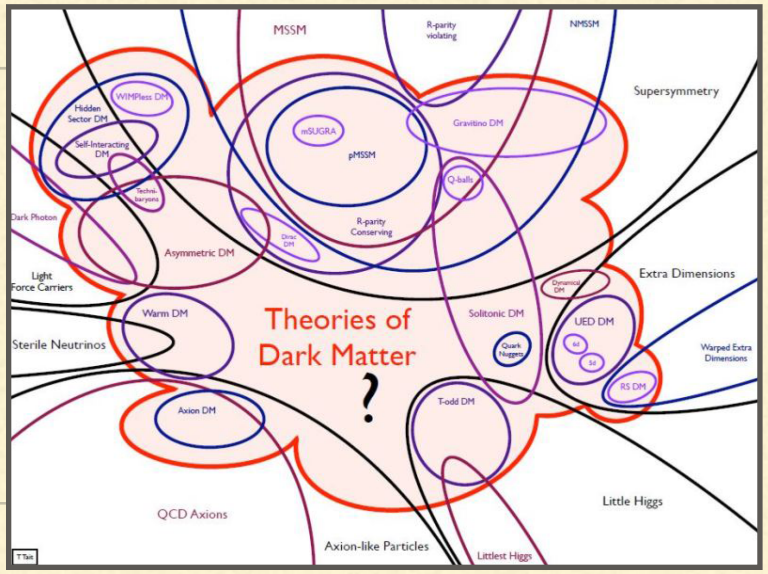
  \- **Core-cusp problem**: [Flores, Primack '94]

  Observations infer cored halo profile, while theory prediction (from NFW) is more cuspy

- So, here we consider <u>modification of dark matter properties from CDM</u>

  (though correct implementation of baryon physics may solve these problems, of course)

BEYOND-WIMP DARK MATTER



[Tim Tait]

- Warm dark matter
  - Free streaming suppress small scale density fluctuations
- Fuzzy dark matter [Hu, Barkana, Gruzinov '00]
  - $m_{\rm DM} \sim 10^{-22}$ eV → Quantum pressure prevents gravitational clustering
- Self-interacting dark matter [Spergel, Steinhardt '00]
- Feebly interacting massive particle (FIMP) [Hall, Jedamzik, March-Russell, West '10]
  - Gradually produced from thermal bath through tiny couplings
  - Never thermalizes with SM thermal bath or within itself

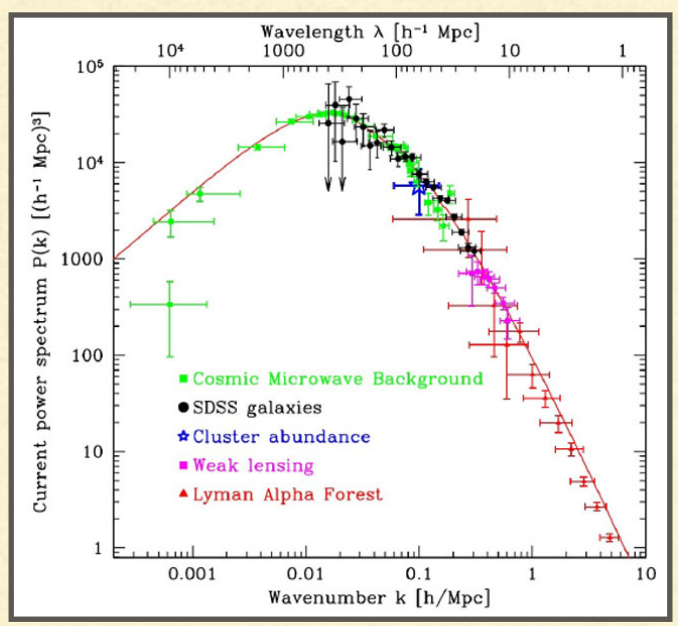
All these have the possibility of reducing matter power spectrum at small scales

ACTUAL PROCESS TO PUT CONSTRAINTS

- Different types of expertise are required:

Dark matter models → Linear matter power spectrum → Observables

$\mathscr{L} = \cdots$



e.g.

Number of Milky-way satellites

Ly-α forest spectrum

(Possibly) particle physics experts

(Possibly) astrophysics experts

S
AINTS

e.g. FIMP case

- Write down Boltzmann eq. $\partial_t f_{\rm DM} + \cdots = \dfrac{C(t,p)}{E_{\rm DM}}$

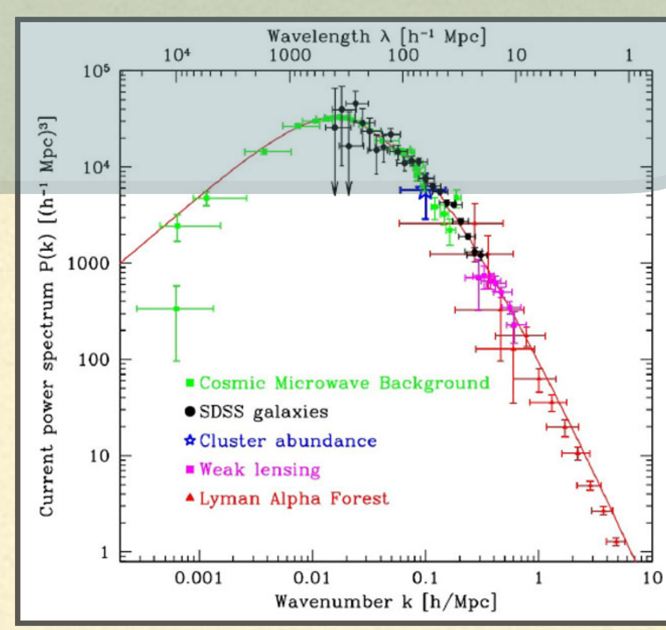
  and integrate to get DM phase space distribution

- Convert to matter power spectrum

ed:

Dark matter models $\rightarrow$ Linear matter power spectrum $\rightarrow$ Observables

$\mathscr{L} = \cdots$



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e.g. FIMP case

- Write down Boltzmann eq. $\partial_t f_{\rm DM} + \cdots = \dfrac{C(t,p)}{E_{\rm DM}}$

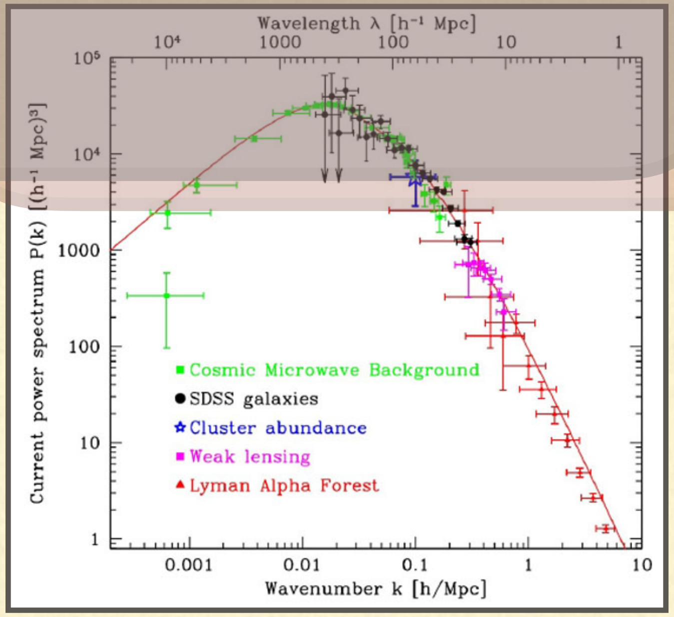
  and integrate to get DM phase space distribution

- Convert to matter power spectrum

- N-body and/or hydrodynamic simulations

Dark matter models → Linear matter power spectrum → Observables

$\mathscr{L} = \cdots$



e.g.

Number of Milky-way satellites

Ly-α forest spectrum

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e.g. FIMP case

- Write down Boltzmann eq. $\partial_t f_{\rm DM} + \cdots = \dfrac{C(t,p)}{E_{\rm DM}}$

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- N-body and/or

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Dark matter models → Linear matter pow... → Observables

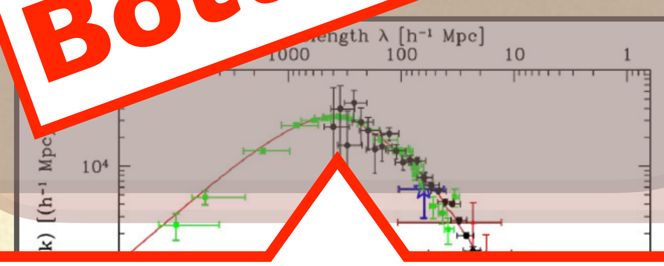
$\mathscr{L} = \cdots$

e.g.

Number of Milky-way satellites

Ly-α forest spectrum

Bottleneck

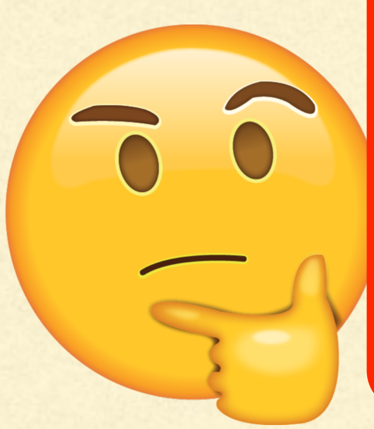


Traditionally...

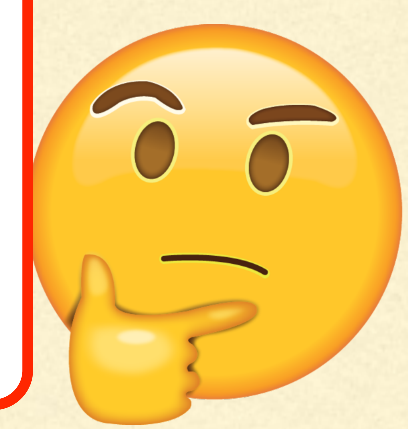
parametrized by **single parameter** ($m_{\rm WDM}$)

However,

this is **not enough** to cover various DM models



(Possibly) particle physics experts

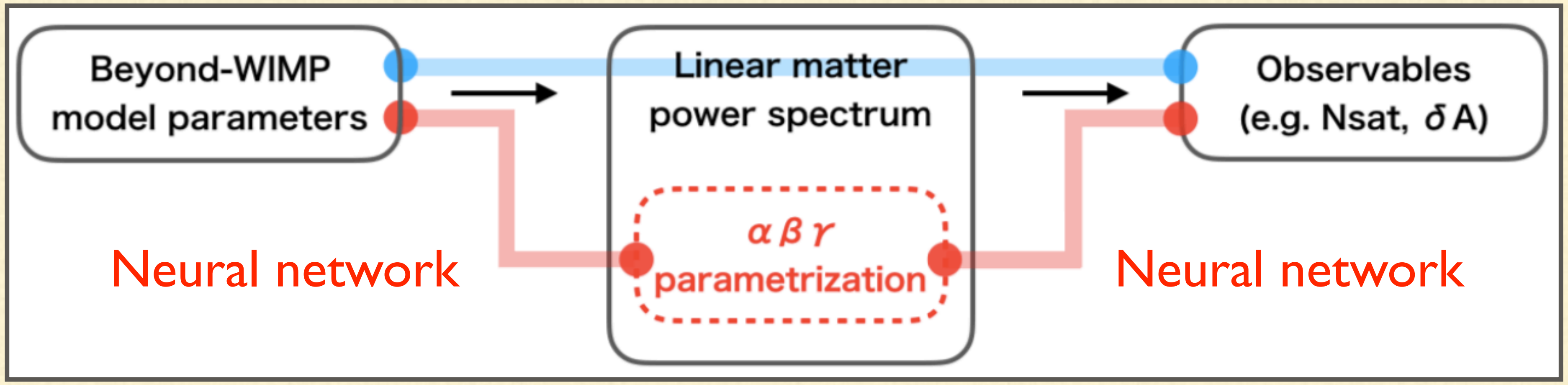


(Possibly) astrophysics experts

SUMMARY

- We propose a simple usage of neural network as a unified format for nonlinear mapping

  to facilitate communication between both sides:



(multiple parameters)

  and show that it indeed works well

- Might be applicable to other situations as well

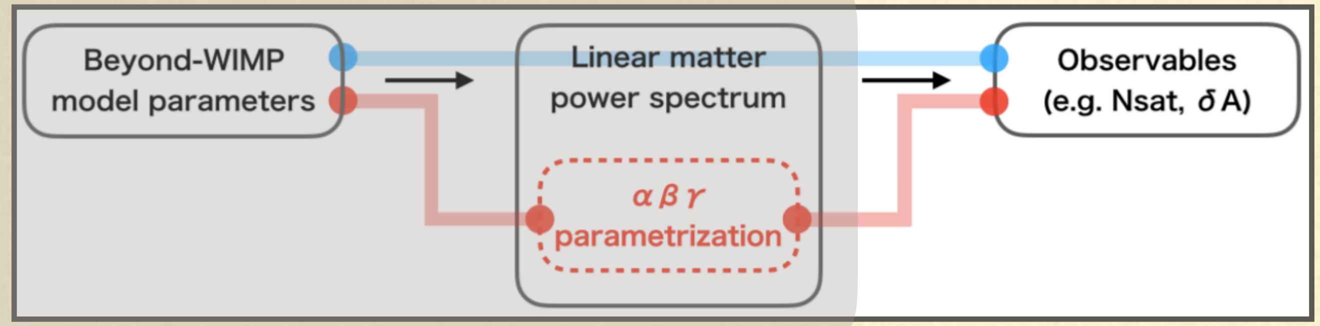
TALK PLAN

0. ~~0~~. Introduction & summary

1. How neural network helps -- FIMP example

2. Summary

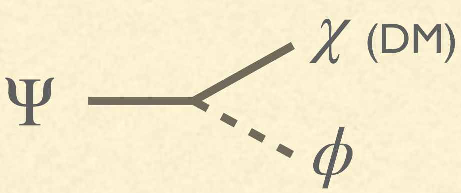
MODEL → SPECTRUM



- We take FIMP example (Both are 3-parameter setups)

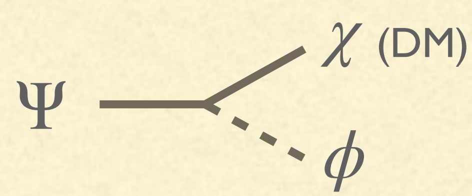
For concrete models, see [Bae, Kamada, Liew, Yanagi '17 & '18]

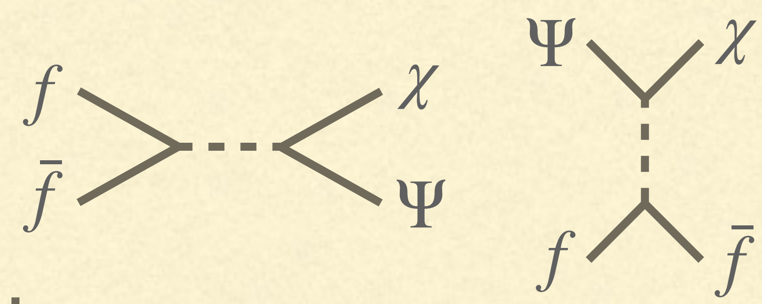
Case A: $\mathscr{L} \supset y_\chi \phi \bar{\Psi} \chi \ (+\,\mathrm{h.c.})$



+ possible late-time entropy injection

Case B: $\mathscr{L} \supset y_\chi \phi \bar{\Psi} \chi + y_f \phi \bar{f} f \ (+\,\mathrm{h.c.})$





Decay

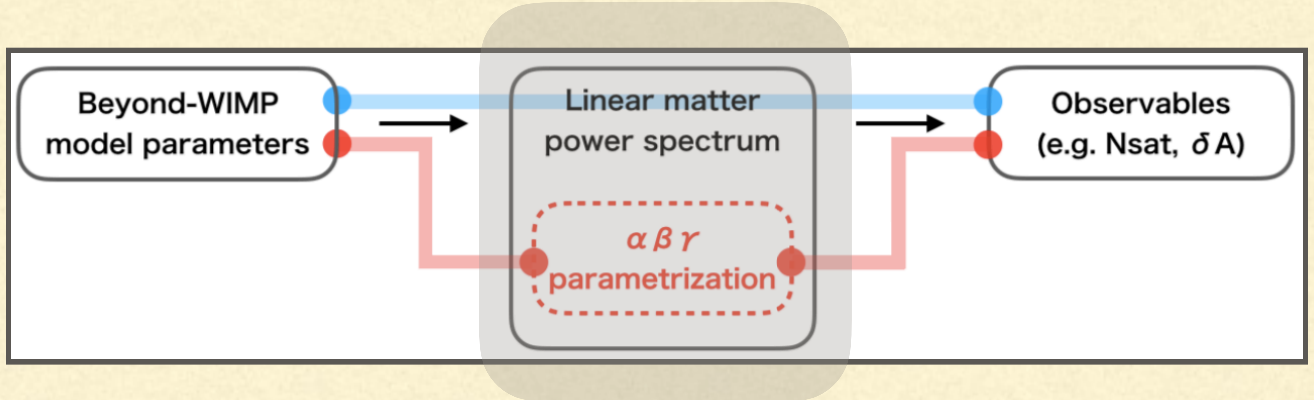
Scattering

- In reality we have one more intermediate step:

Dark matter models $\xrightarrow{\text{Integration of Boltzmann eq.}}$ DM phase space distribution $\xrightarrow{\text{(Public) Boltzmann code}}$ Linear matter power spectrum

We use CLASS [Blas, Lesgourgues, Tram]

SPECTRUM



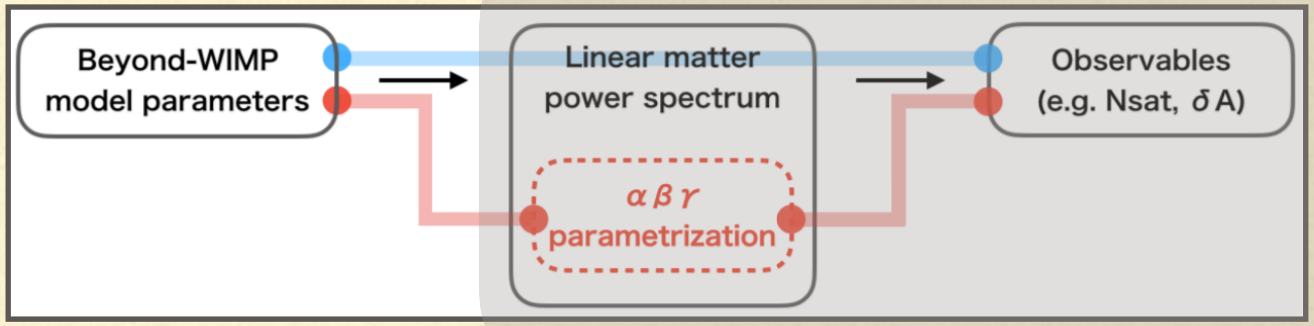
- αβγ parametrization of linear matter power spectrum

$$\frac{P(k)}{P_{\mathrm{CDM}}(k)} = \left[1 + (\alpha k)^{\beta}\right]^{2\gamma}$$

[Murgia, Merle, Viel, Totzauer, Schneider '17]

- This is practically enough to cover the linear matter power spectrum realized in various DM models

SPECTRUM →OBSERVABLE



- Unfortunately we are not experts on N-body or hydrodynamic simulations

- As a simplified procedure (instead of full nonlinear simulation), we try

  1) Extended Press-Schechter approach (for Milky-way satellite counts) : $N_{\rm sat}$

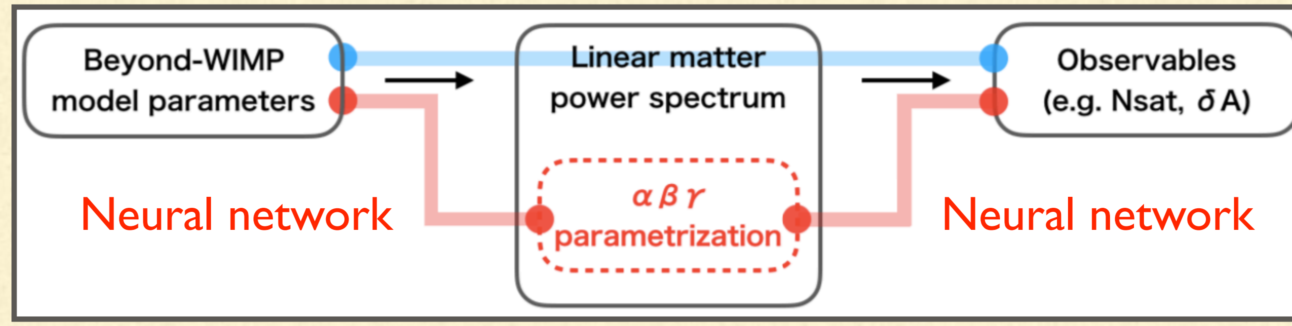
  2) 1D power spectrum ratio (for Lyman-α spectrum) : δA

  These are known to give reasonable constraints, <u>though calculated from linear power</u>

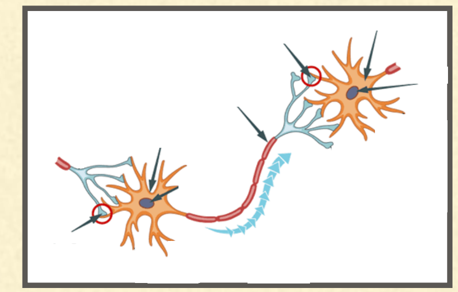
  [Schneider, MNRAS 451('14)] [Schneider, JCAP 1604('16)]

- Details → Backup slides

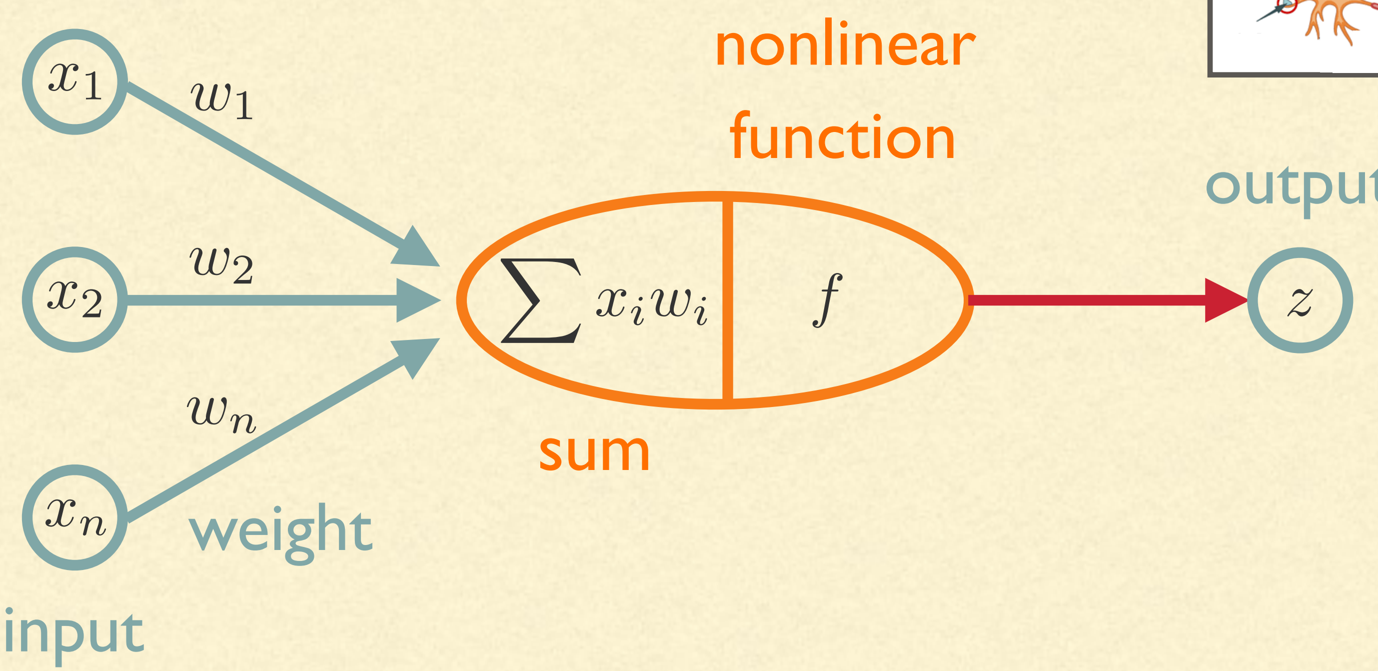
NEURAL NETWORK



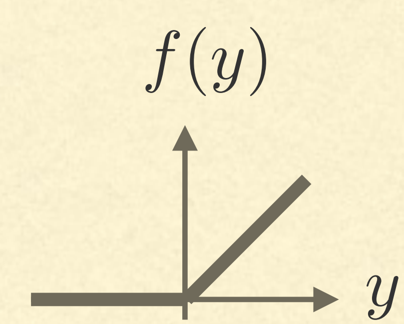
- Artificial neuron mimics biological neuron



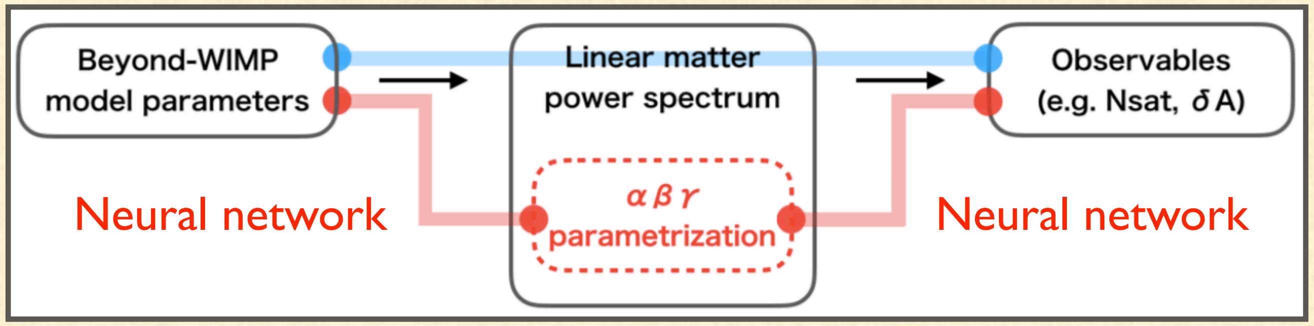
Diagramatic notation



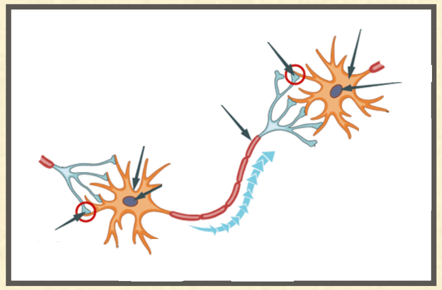
Equation $z = f\left(\sum x_i w_i + b\right)$
w_i : weight
b : bias
f : ReLU (rectified linear unit)

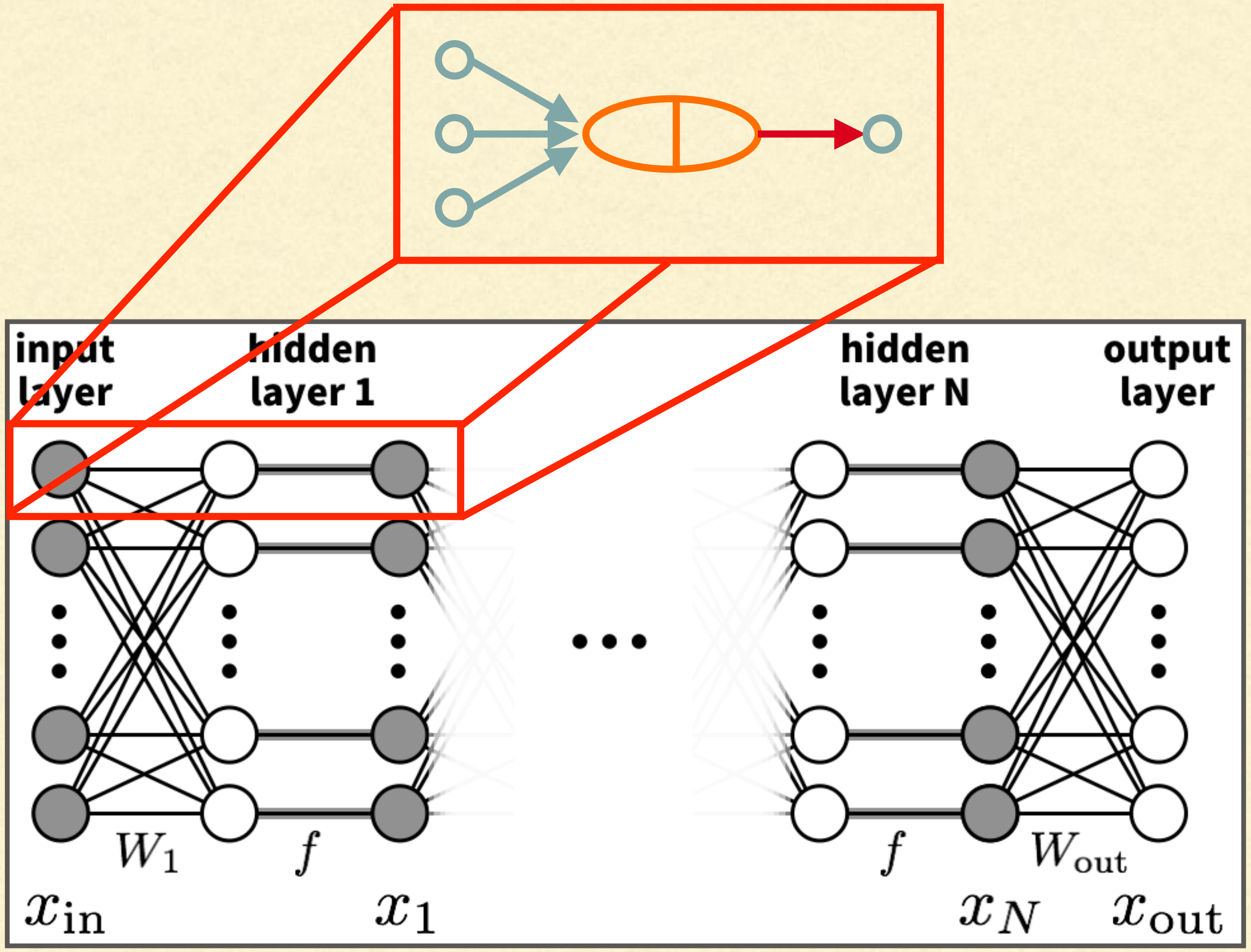


NEURAL NETWORK



- Neural network = network of artificial neurons





$$\begin{cases} x_1 = f\left(W_1 x_{\rm in} + b_1\right) \\ x_n = f\left(W_n x_{n-1} + b_n\right) \\ \qquad (2 \leq n \leq N) \\ x_{\rm out} = W_{\rm out} x_N + b_{\rm out} \end{cases}$$

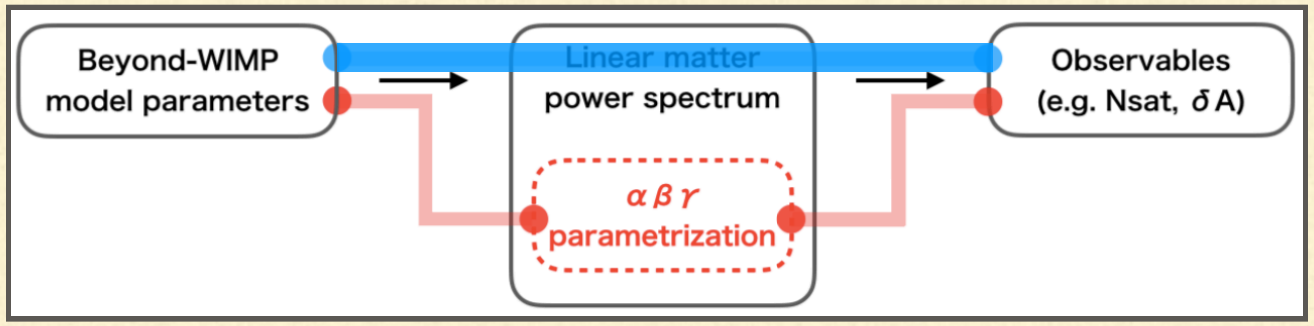
WHY NEURAL NETWORK?

- Efficiently learns nonlinear relations between multiple parameters
- Learns without being explicitly taught
- Useful public libraries are available e.g. TensorFlow
- Provides a unified format with a few matricies and vectors

$$\begin{cases} x_1 = f\left(W_1 x_{\text{in}} + b_1\right) \\ x_n = f\left(W_n x_{n-1} + b_n\right) \qquad (2 \leq n \leq N) \\ x_{\text{out}} = W_{\text{out}} x_N + b_{\text{out}} \end{cases}$$

RESULTS

This

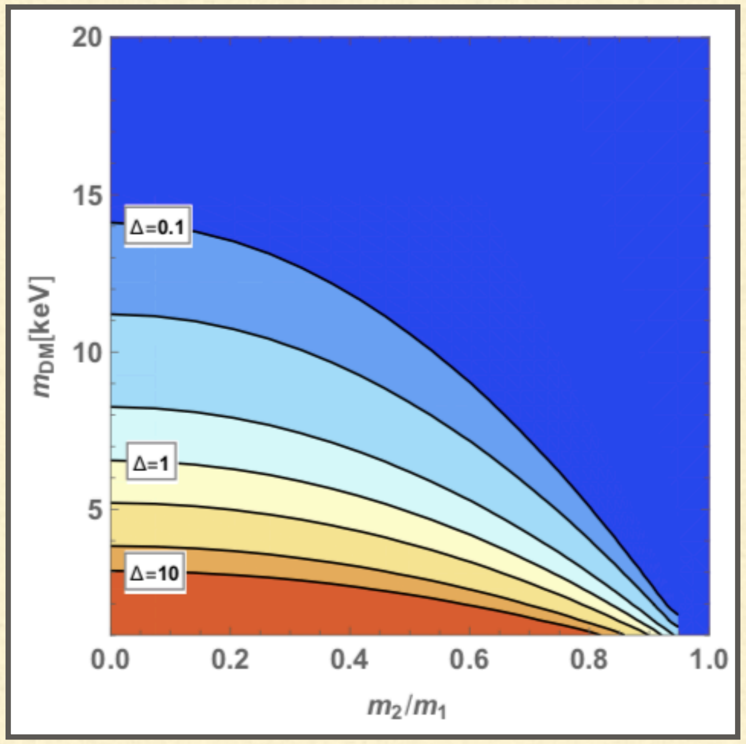


- Constraints directly estimated without neural network:

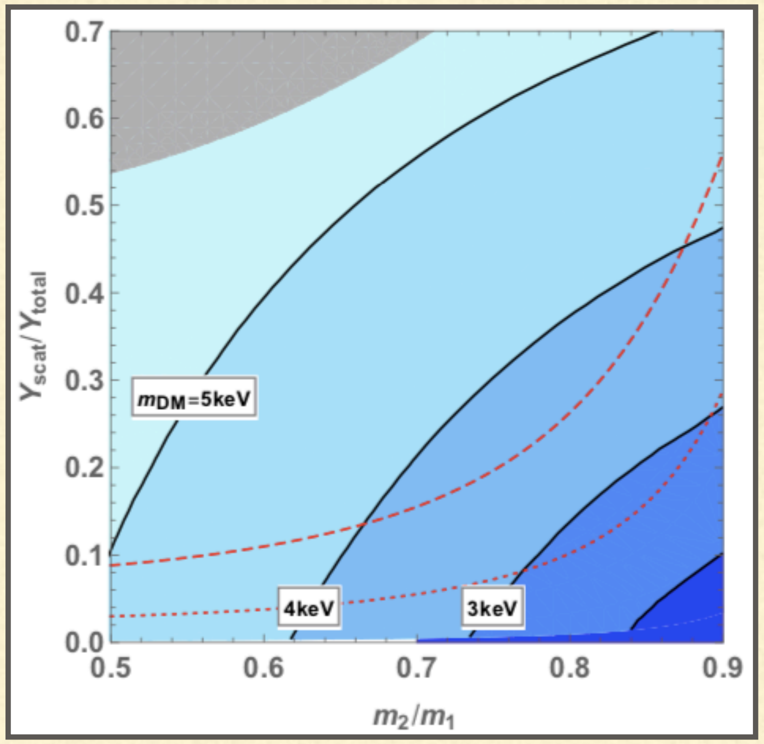
  Collaboration btwn. particle physics & astrophysics experts would be able to do this

1) From N_{sat}

Case A

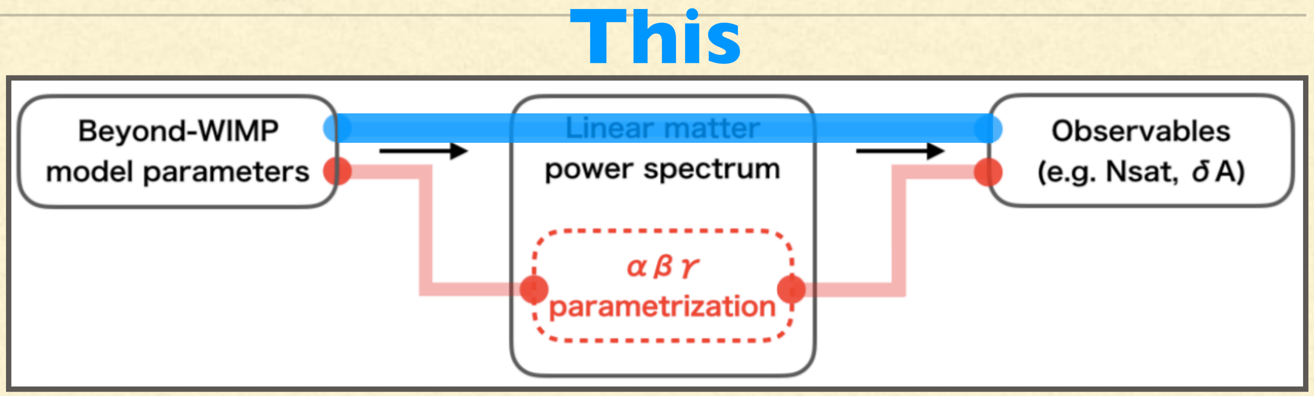


Case B



Note : we derived these constraints for the first time

RESULTS



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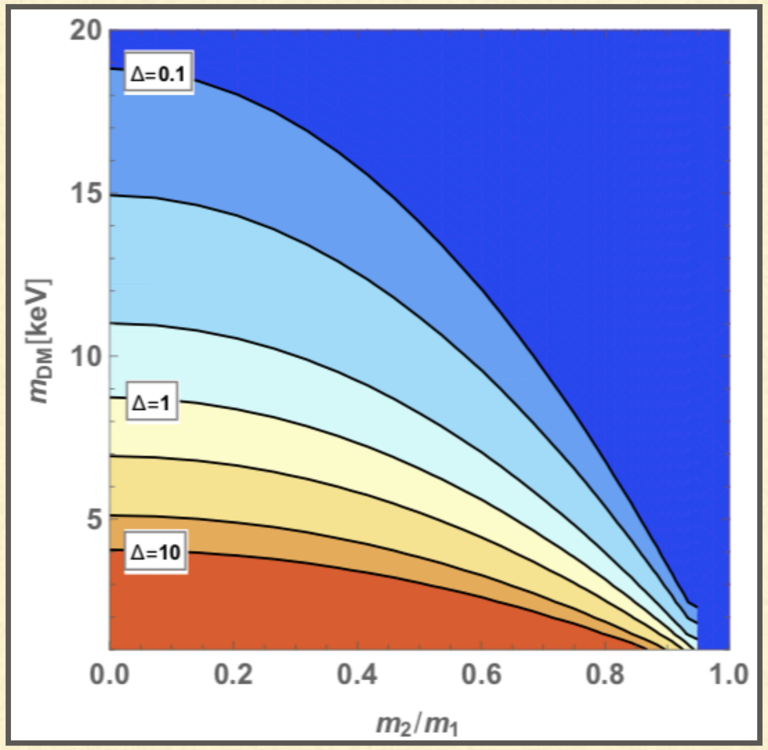
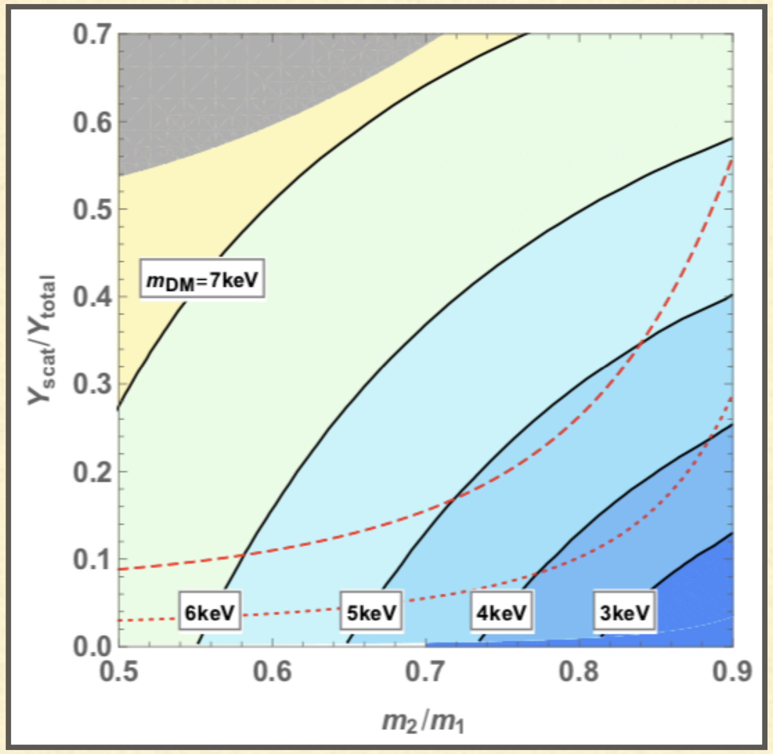
2) From δA

Case A



Case B



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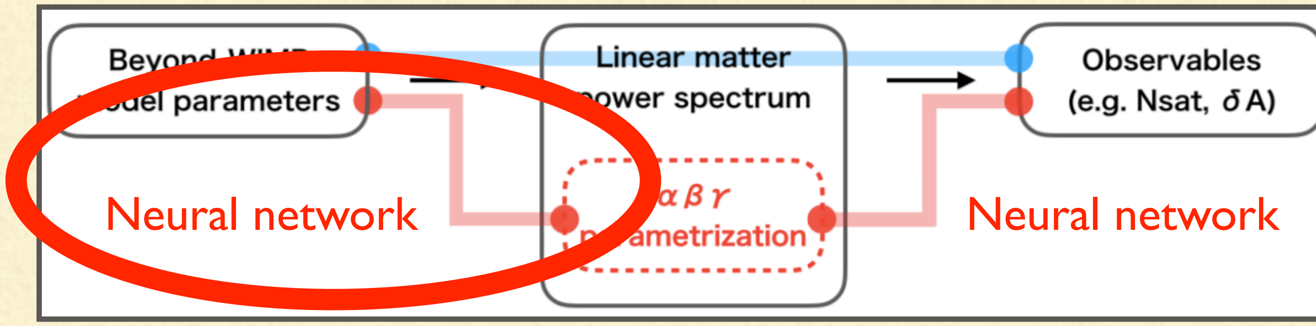
RESULTS



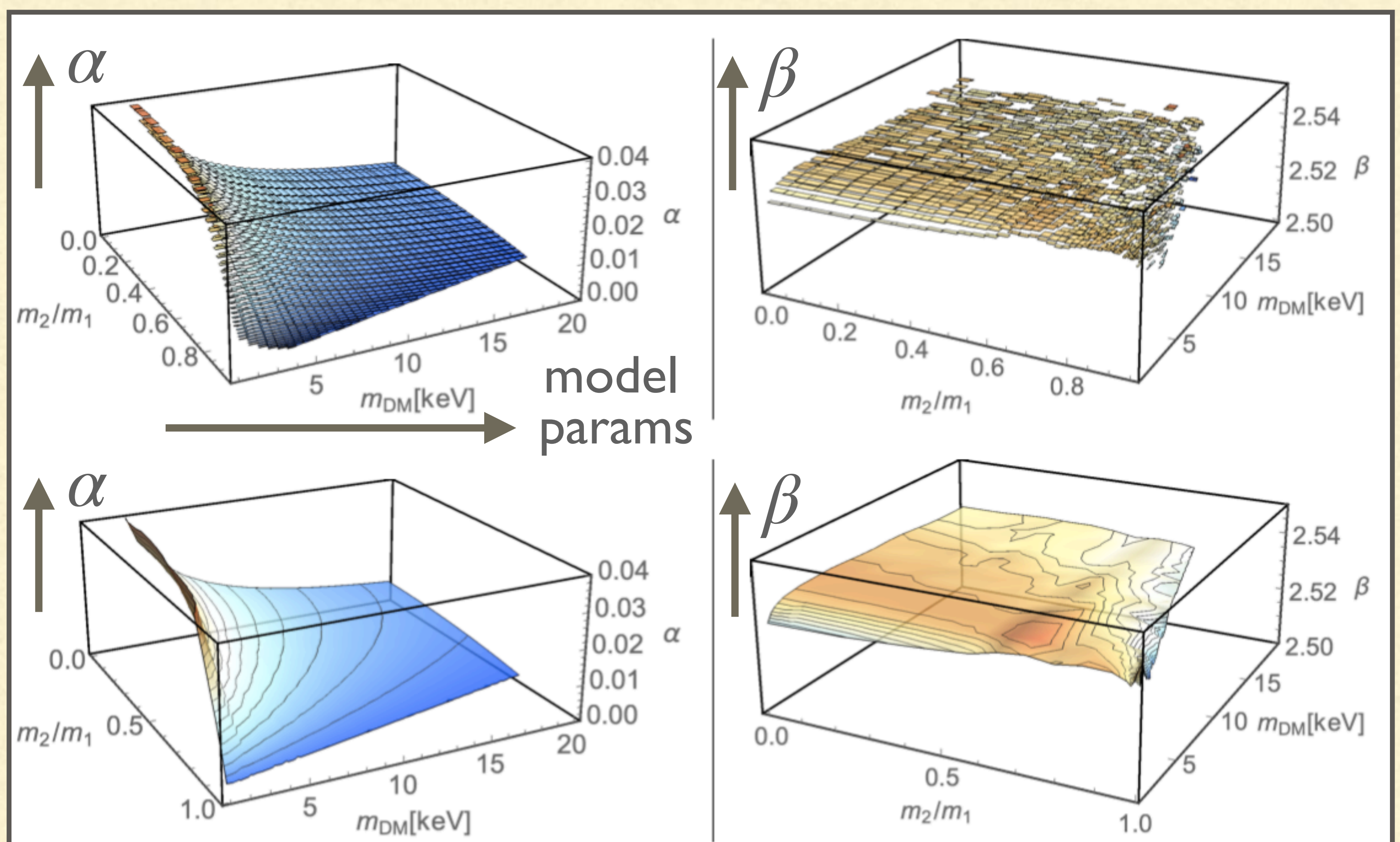
This side

- Neural network (Case A):

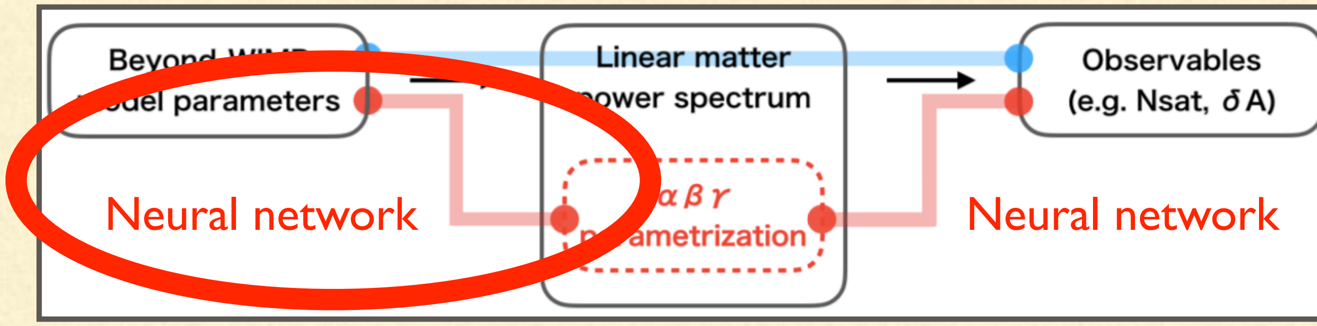
Particle physics & astrophysics experts will be able to report separately

Original data

Neural network fit



RESULTS



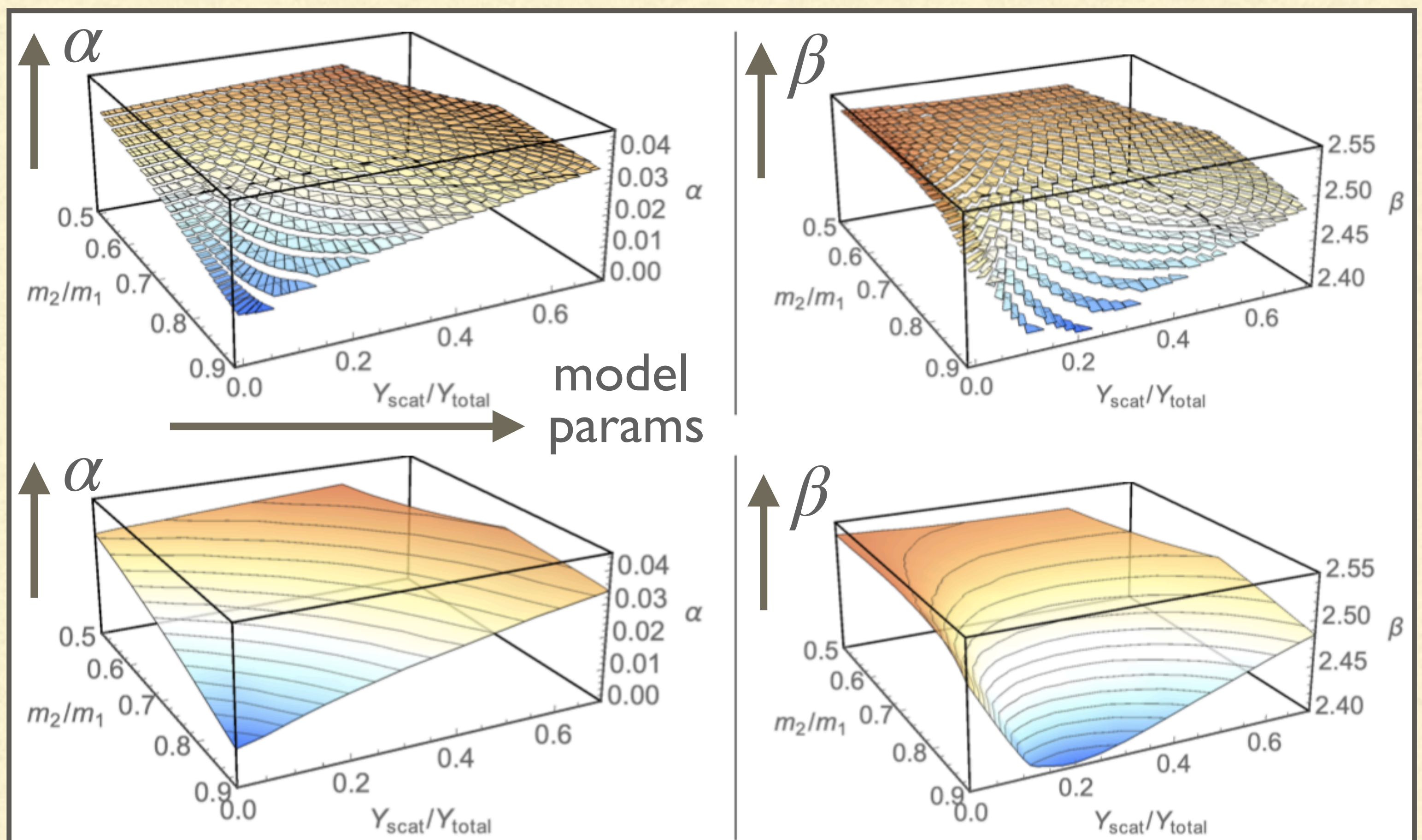
This side

- Neural network (Case B):

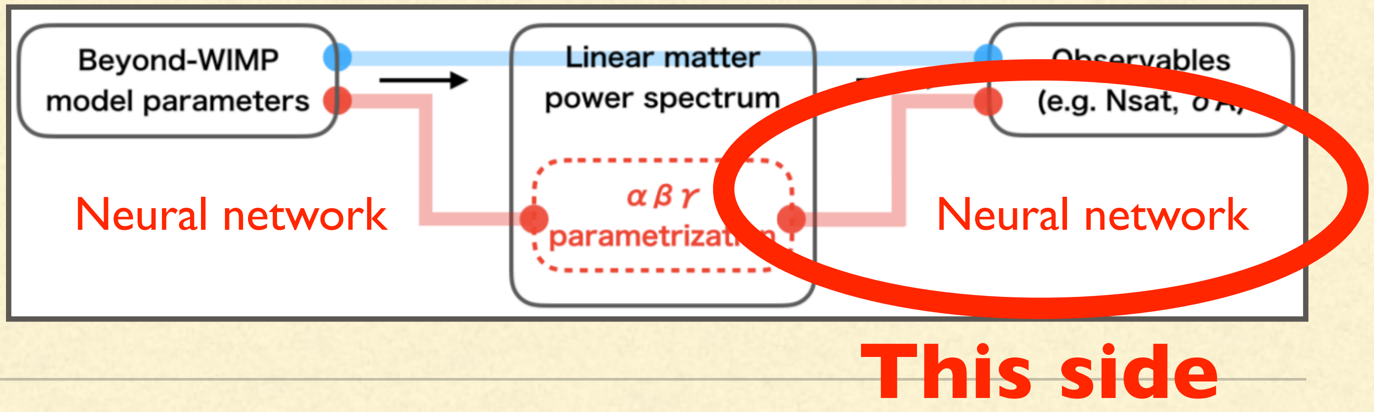
Particle physics & astrophysics experts will be able to report separately

Original data

Neural network fit



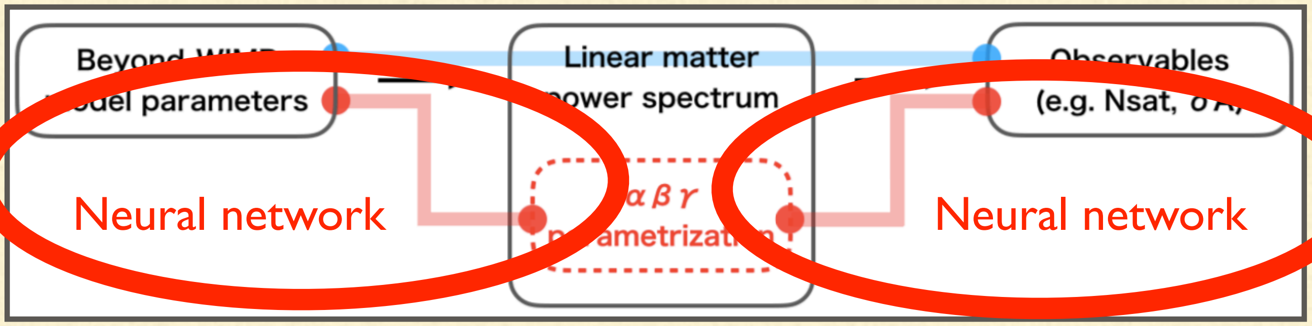
RESULTS



Skipped!!

(essentially the same as the left side)

RESULTS



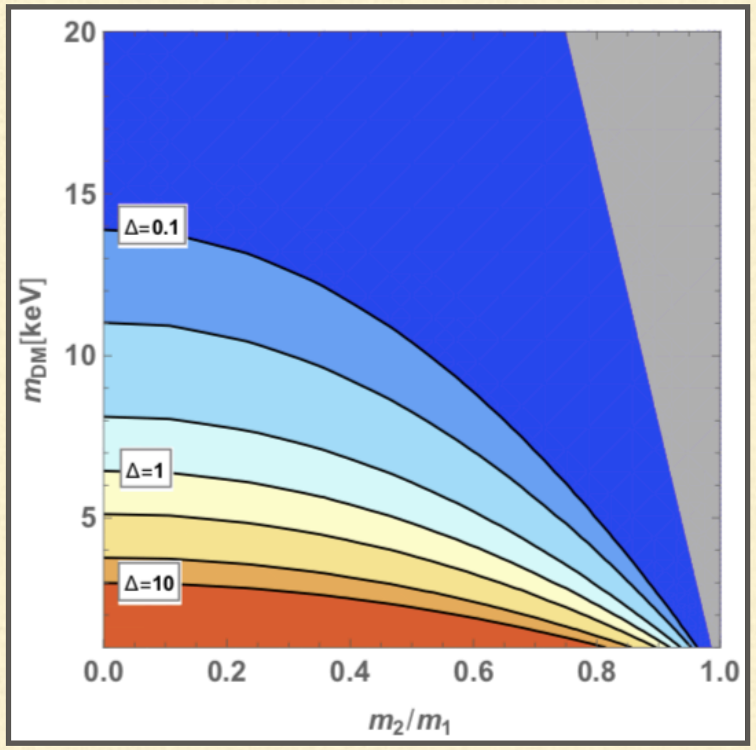
Combined

- Neural network (Combined):

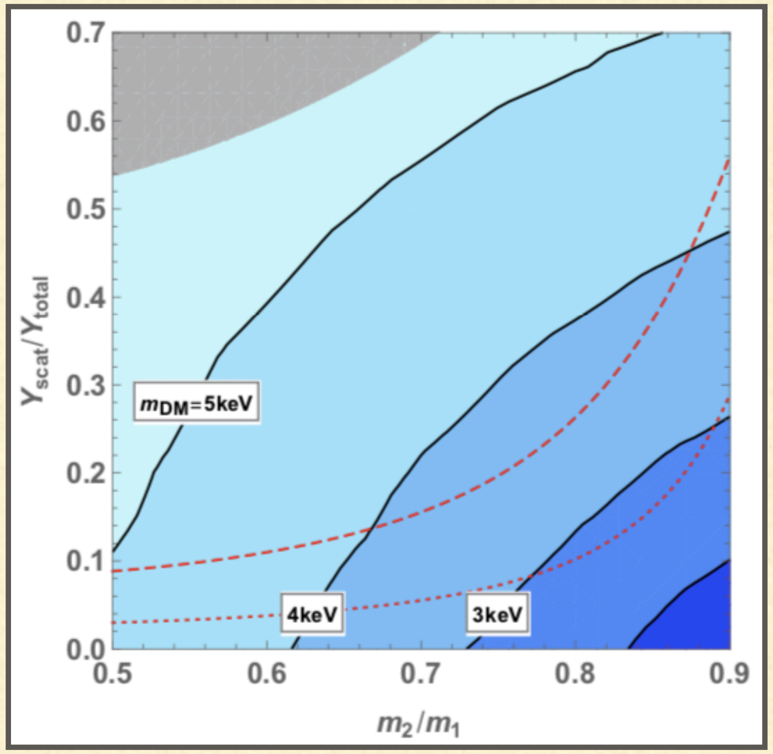
Particle physics & astrophysics experts will be able to report separately

1) From $N_{\rm sat}$

Case A

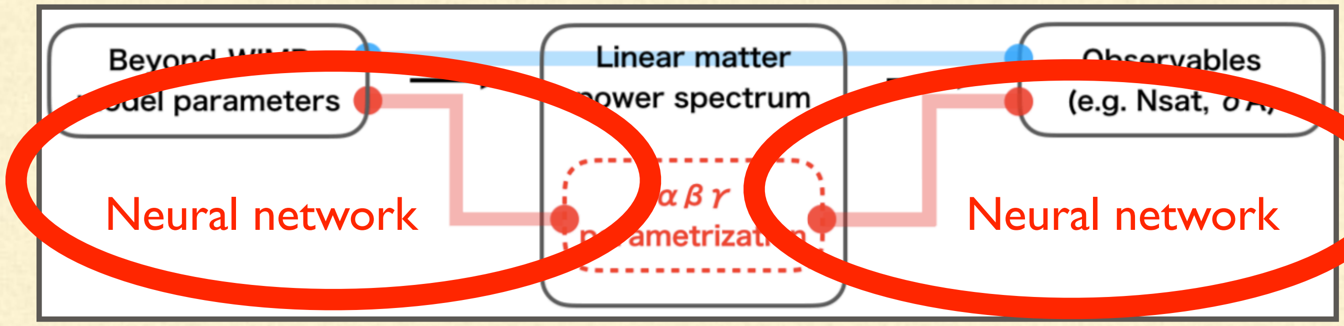


Case B



Nicely reproduces the direct constraints

RESULTS



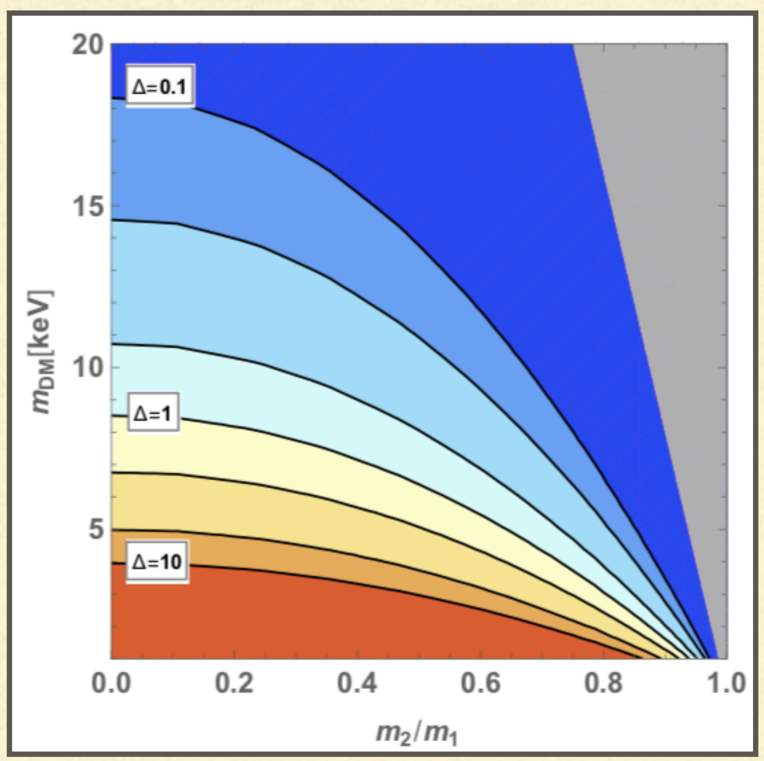
Combined

- Neural network (Combined):

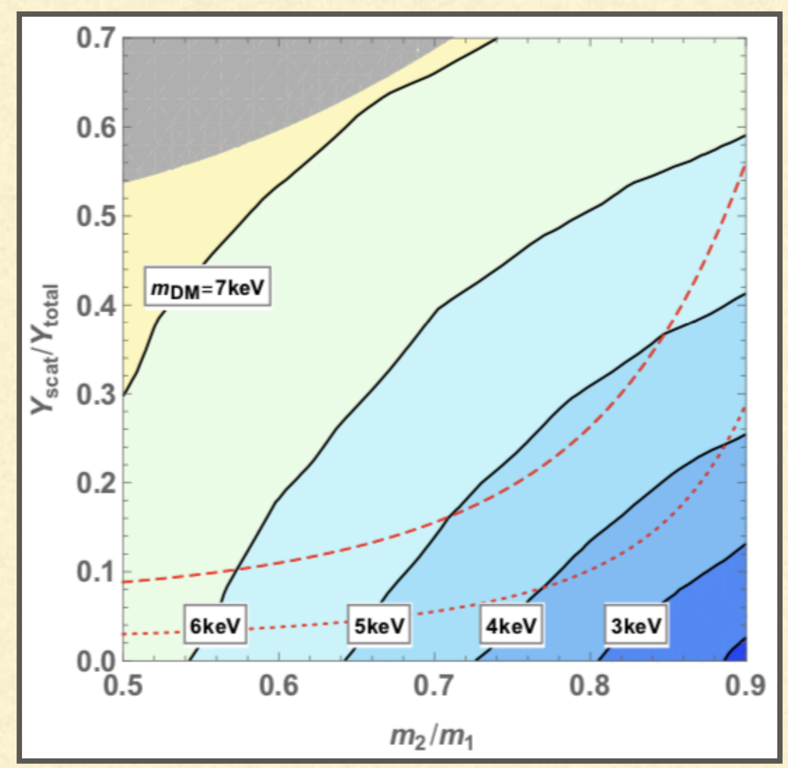
Particle physics & astrophysics experts will be able to report separately

2) From δA

Case A



Case B

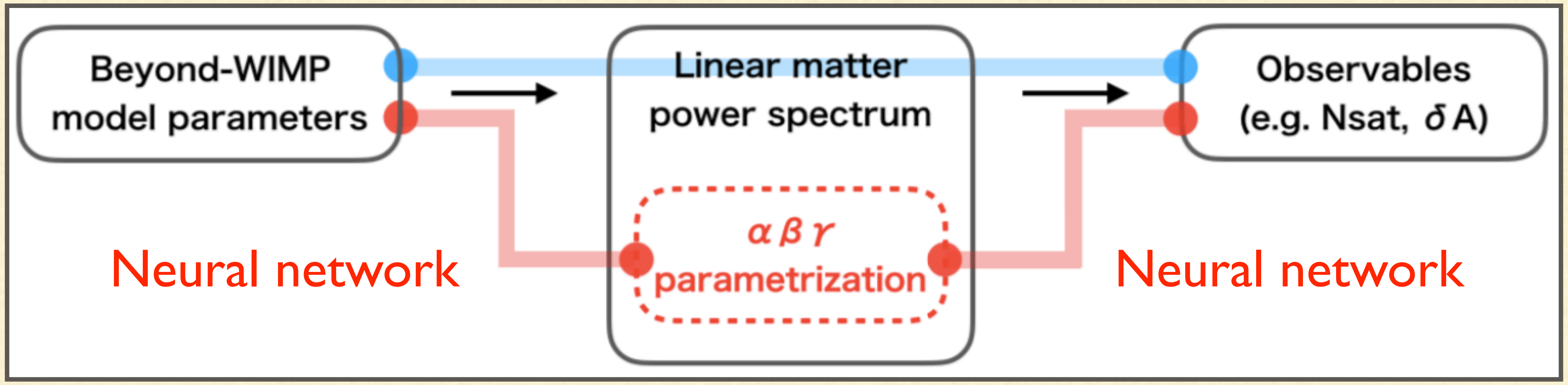


Nicely reproduces the direct constraints

SUMMARY

- We propose a simple usage of neural network as a unified format for nonlinear mapping

  to facilitate communication between people with different expertises

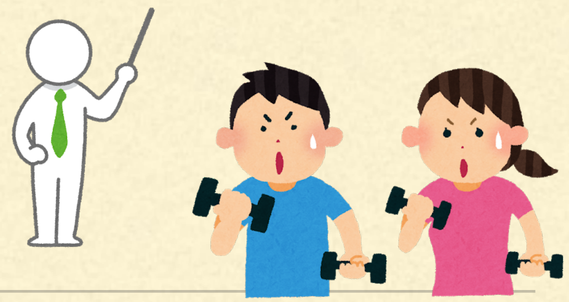


  and show that it indeed works well for FIMP case

- Might be applicable to other situations as well

BACK UP

NEURAL NETWORK: SUPERVISED LEARNING



- How to train the neural network with supervised learning

  - Suppose we have many data of $(x_{\rm in}, x_{\rm out}^{\rm (true)})$

  - Then we can define how poorly the machine predicts:

    Error function $E \overset{\text{e.g.}}{=} \sum_{\rm data} \sum_{i:\rm component} \left| (x_{\rm out})_i - (x_{\rm out}^{\rm (true)})_i \right|$

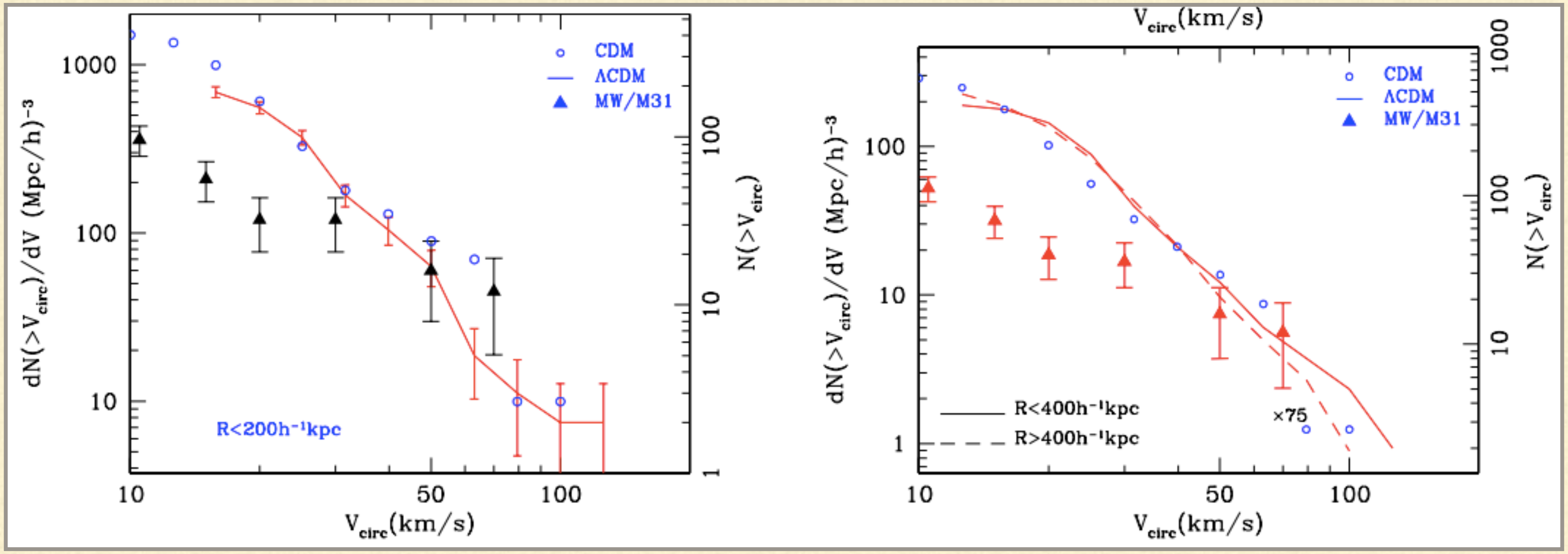
  - Training of neural network = update of weights W and biases b using E

$$\boxed{W \to W - \alpha \frac{\partial E}{\partial W} \qquad b \to b - \alpha \frac{\partial E}{\partial b}}$$

α : constant

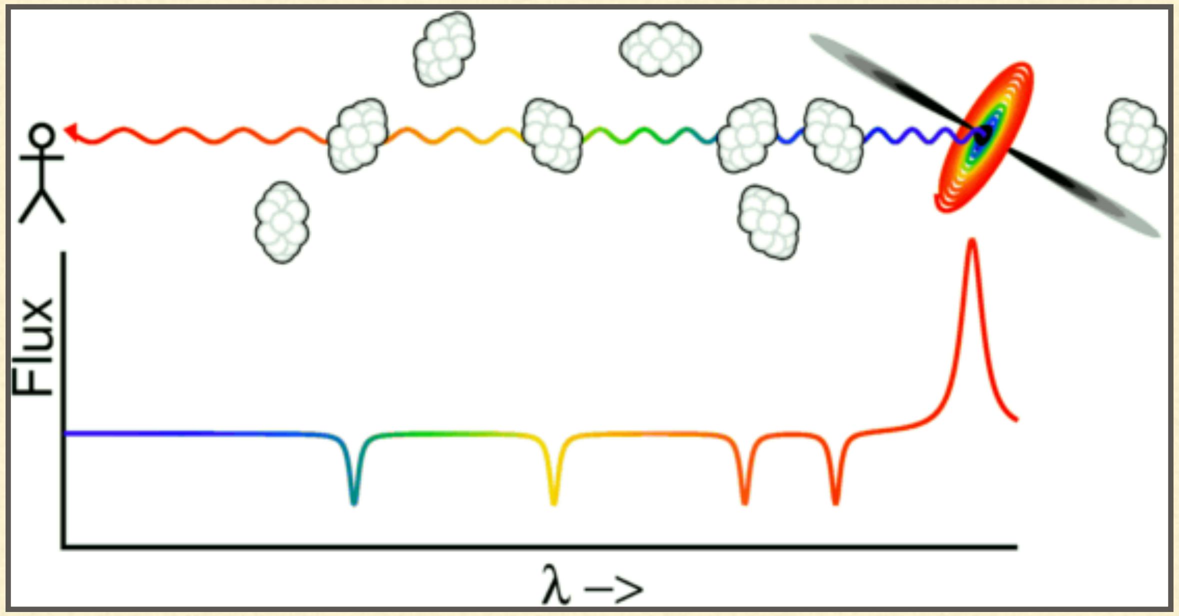
Note : there are more sophisticated algorithms, e.g. AdaGrad, Adam, ...

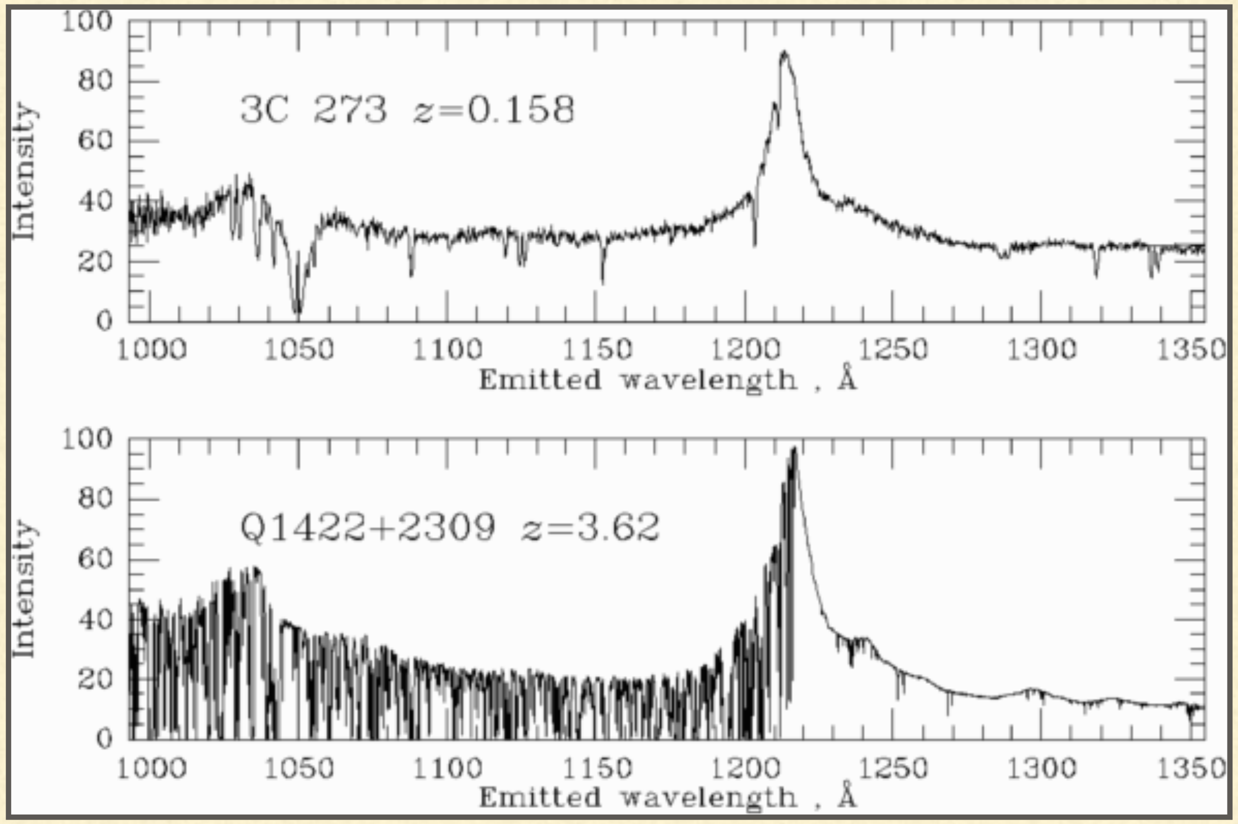
MISSING SATELLITE PROBLEM



[Klypin, Kravtsov, Valenzuela, Prada '99]

LYMAN-ALPHA FOREST





http://www.astro.ucla.edu/~wright/Lyman-alpha-forest.html