Genetic **A**lgorithms with **M**arginalised **E**nsembles
for model-independent reconstruction of cosmological quantities

In collaboration with
Matteo Martinelli, Savvas Nesseris

Matteo Peronaci

Les Rencontres de Noirmoutier, June 5, 2026

We want to test standard cosmology

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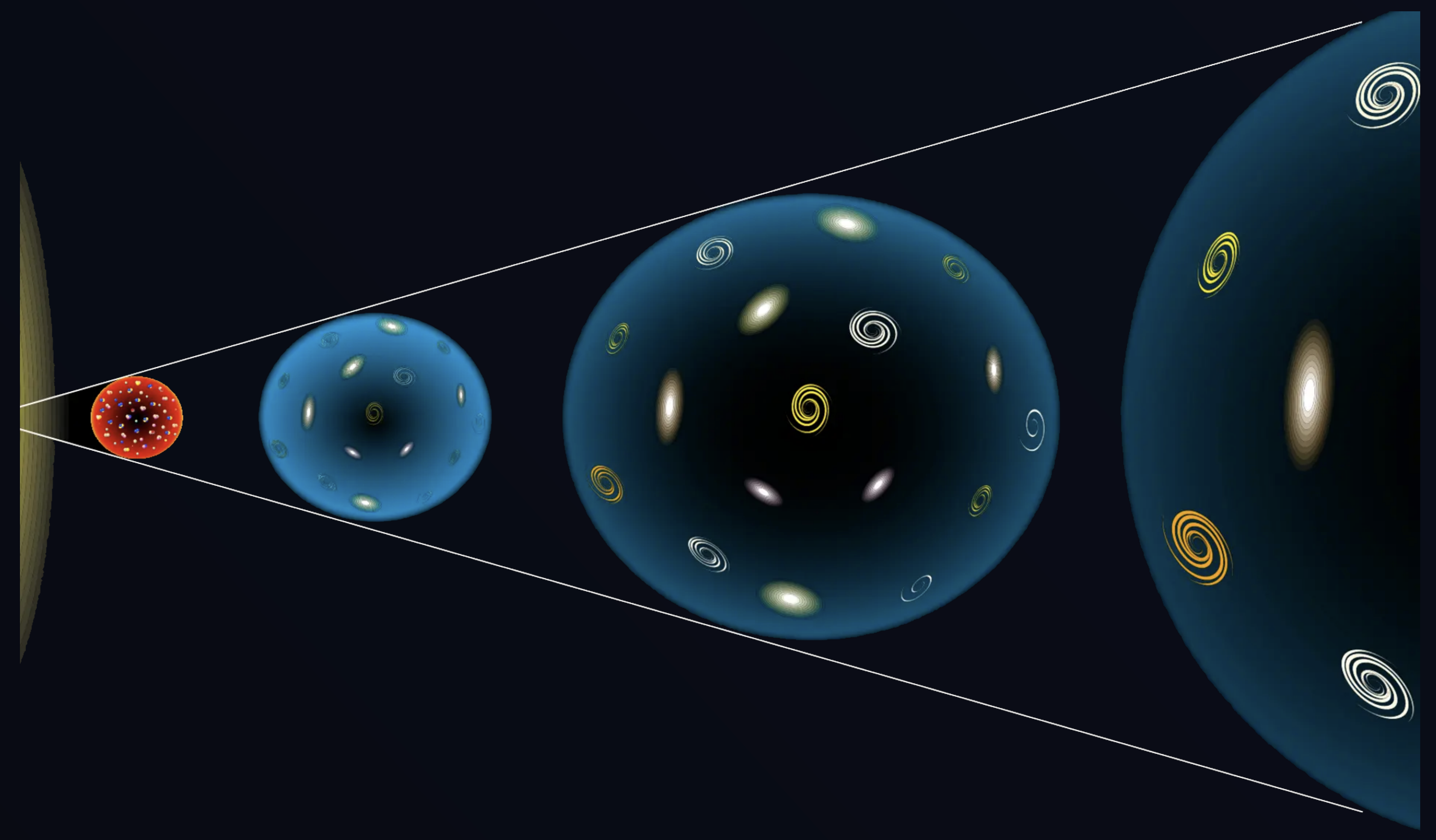
ΛCDM explains a lot of observations



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expanding universe,
CMB, BBN,
perturbations' theory,
galaxy formation…

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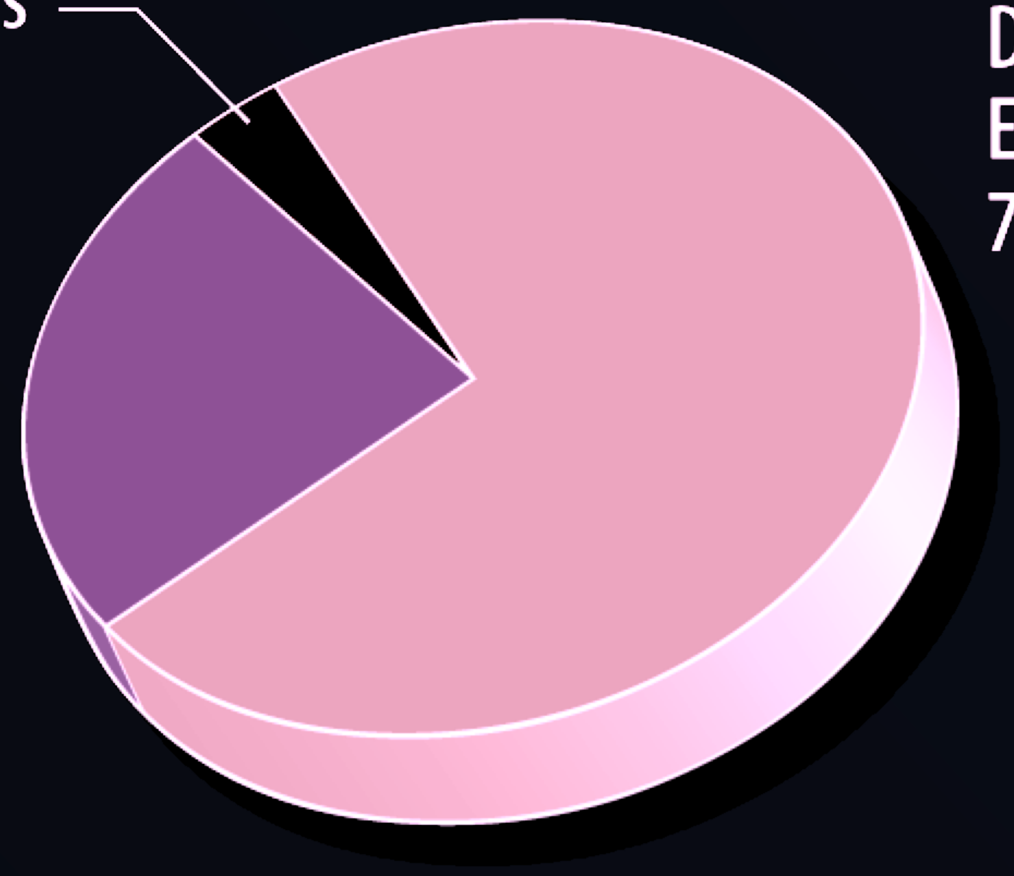

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H_0 tension

S_8 tension

DE interpretation

Dark Energy equation of state as a ΛCDM test

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In ΛCDM, dark energy is a cosmological constant Λ

$$\rho_\Lambda = \frac{\Lambda}{8\pi G} \quad + \quad \rho_{\rm de} = \rho_{\rm de,0}\, a^{-3(1+w_{\rm de})} \quad + \quad P_{\rm de} = w_{\rm de}\,\rho_{\rm de}$$

$$\Longrightarrow \quad w_{\rm de} = w_\Lambda \equiv -1$$

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$$\Longrightarrow \quad w_{\rm de} = w_\Lambda \equiv -1$$

If $w_{\rm de} \neq -1$

$\Longrightarrow$ We have a problem with ΛCDM
We need a new model!

Observables for cosmological evolution

We can express $w_{\rm de}(z)$ as a function of observables quantities

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Luminosity Distances

BAO

$H(z)$

background quantity

Cosmic Chronometers

[...]

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$$\implies \quad w_{\rm bg}(z) = -1 + \frac{1}{3}(1+z)\frac{d}{dz}\ln\left(\frac{H(z)^2}{H_0^2} - \Omega_{\rm m,0}(1+z)^3\right)$$

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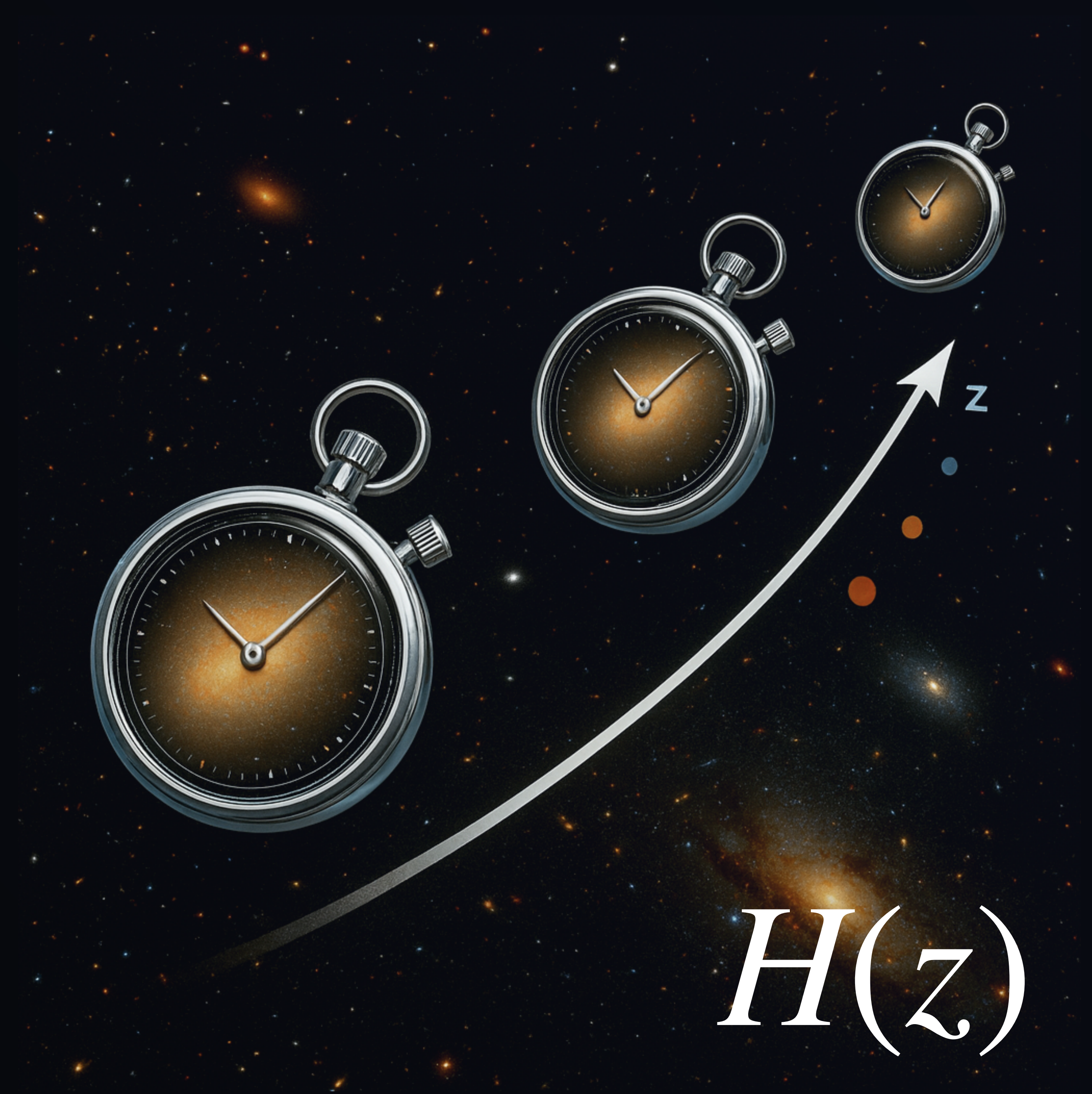
We want to reconstruct $H(z)$ from observational data only!

Model-independent approach

Cosmic Chronometers



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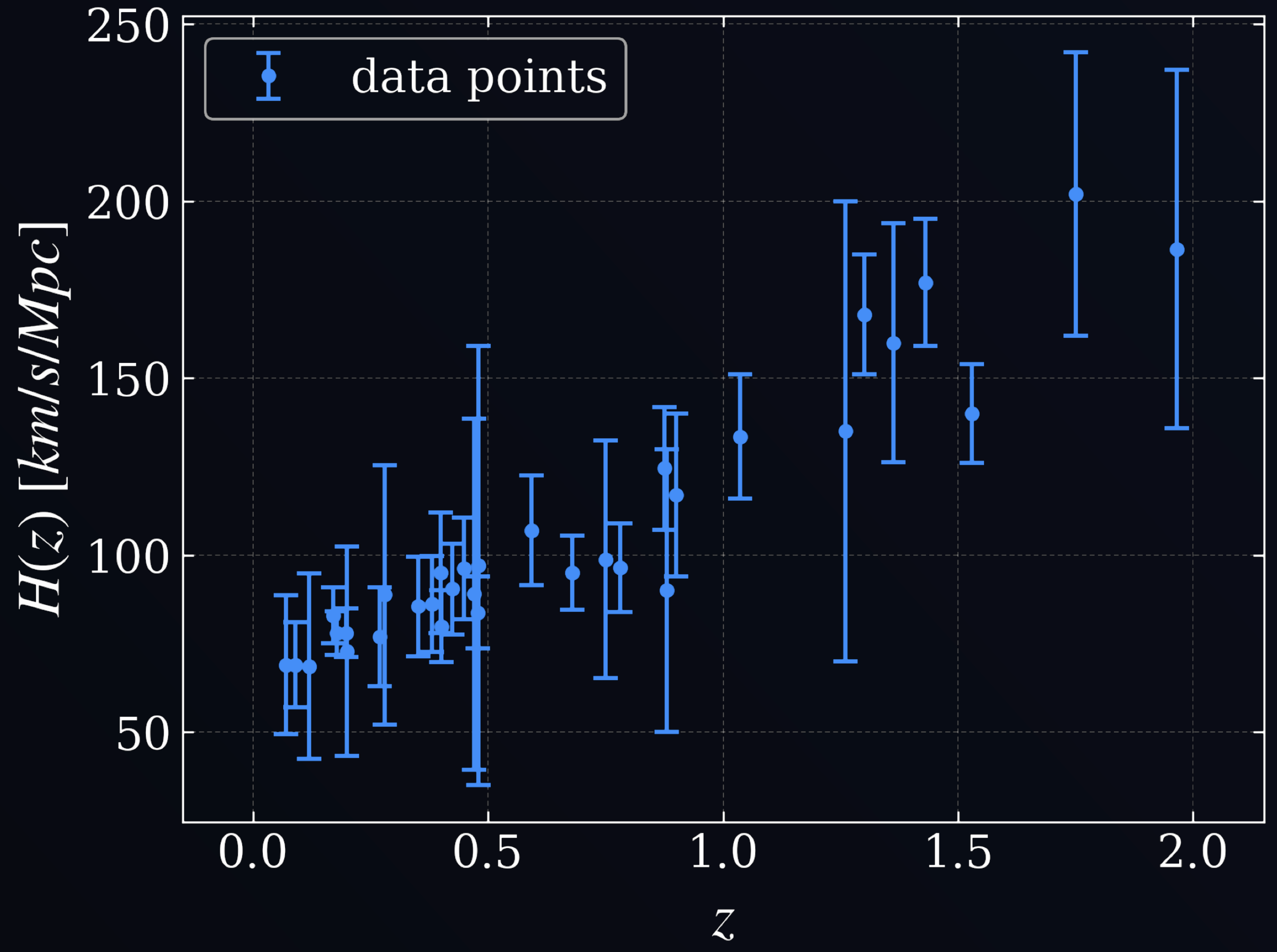

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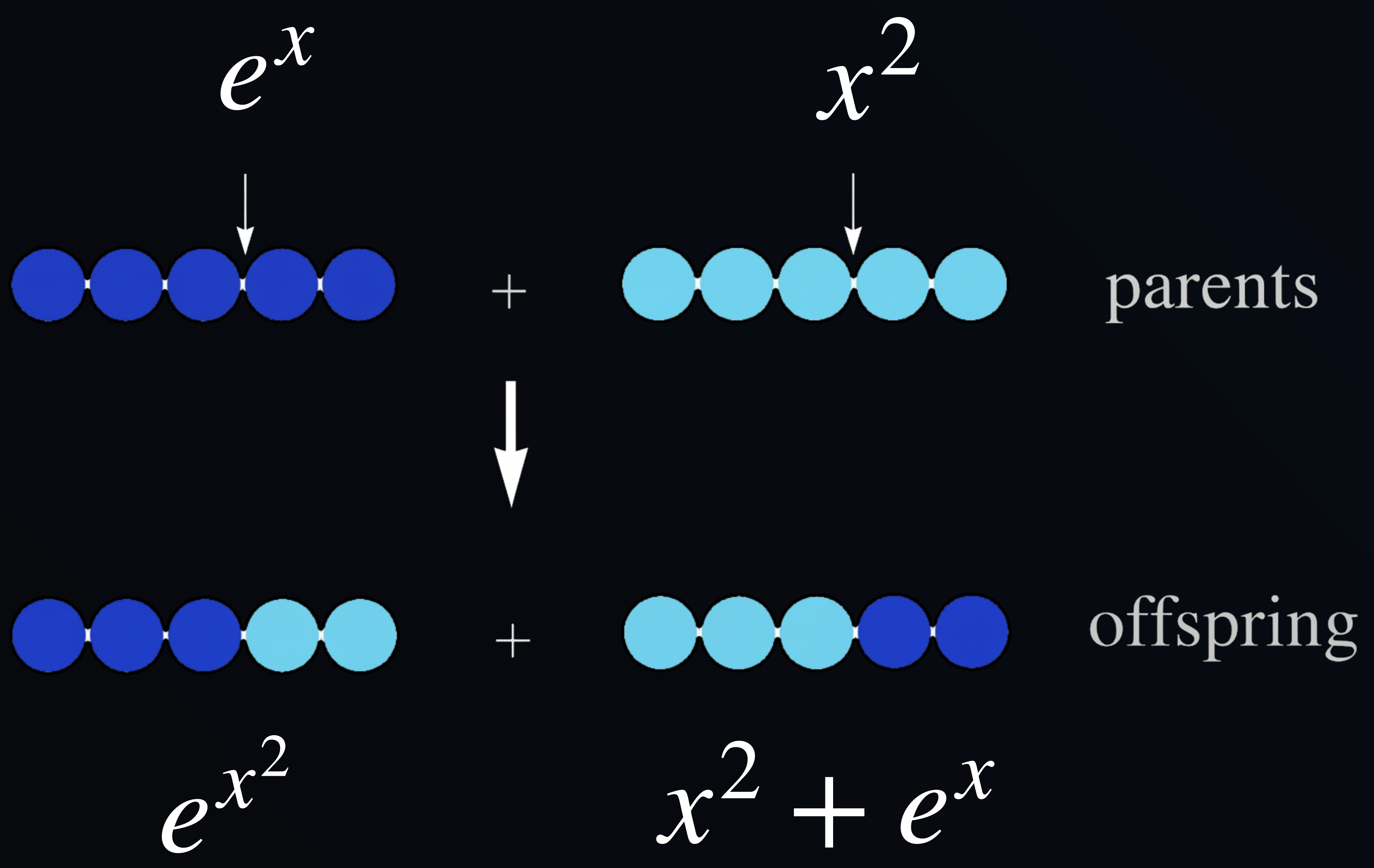
Model-independent approach

Genetic Algorithms

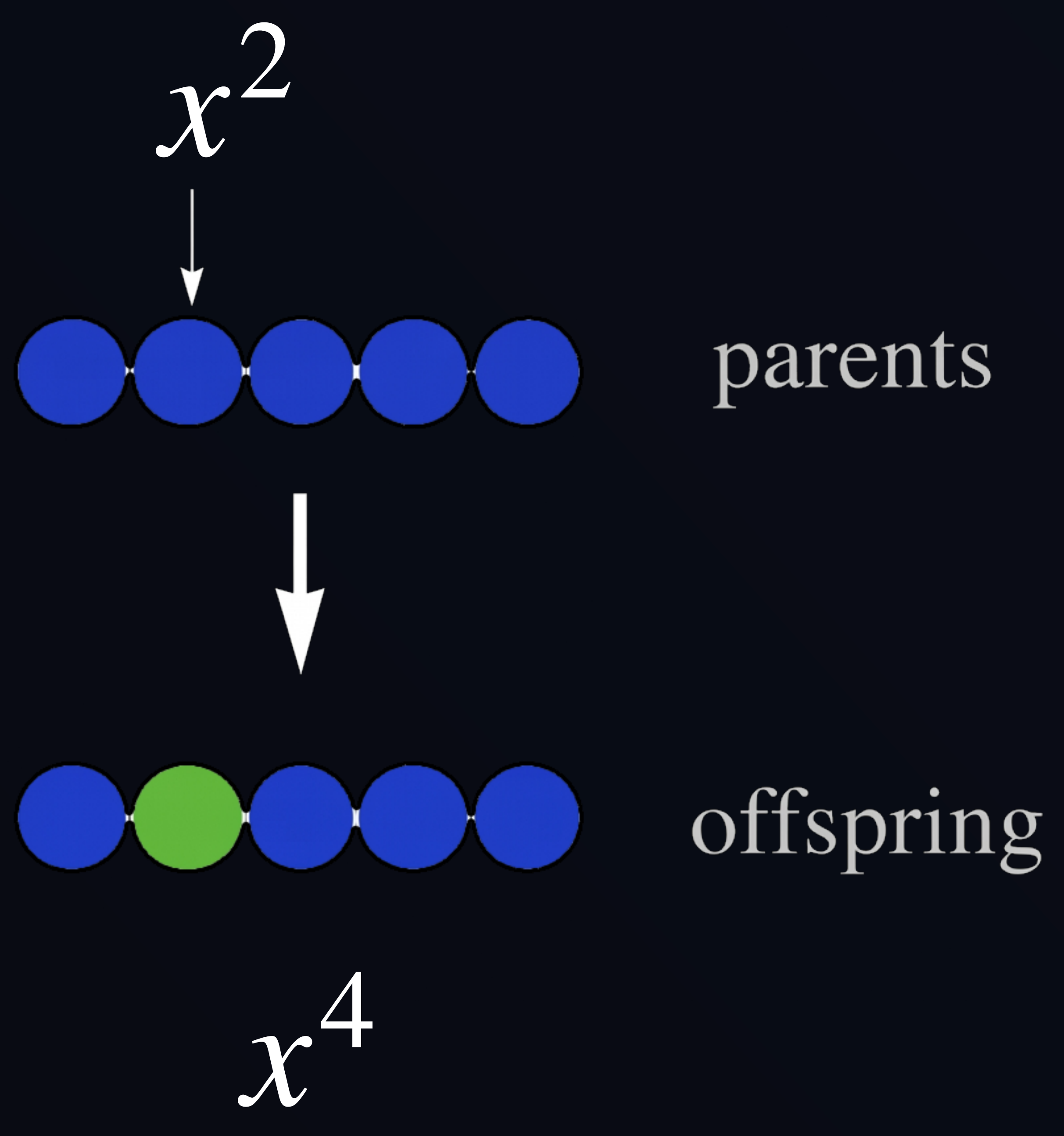
Model-independent approach

Genetic Algorithms

crossover



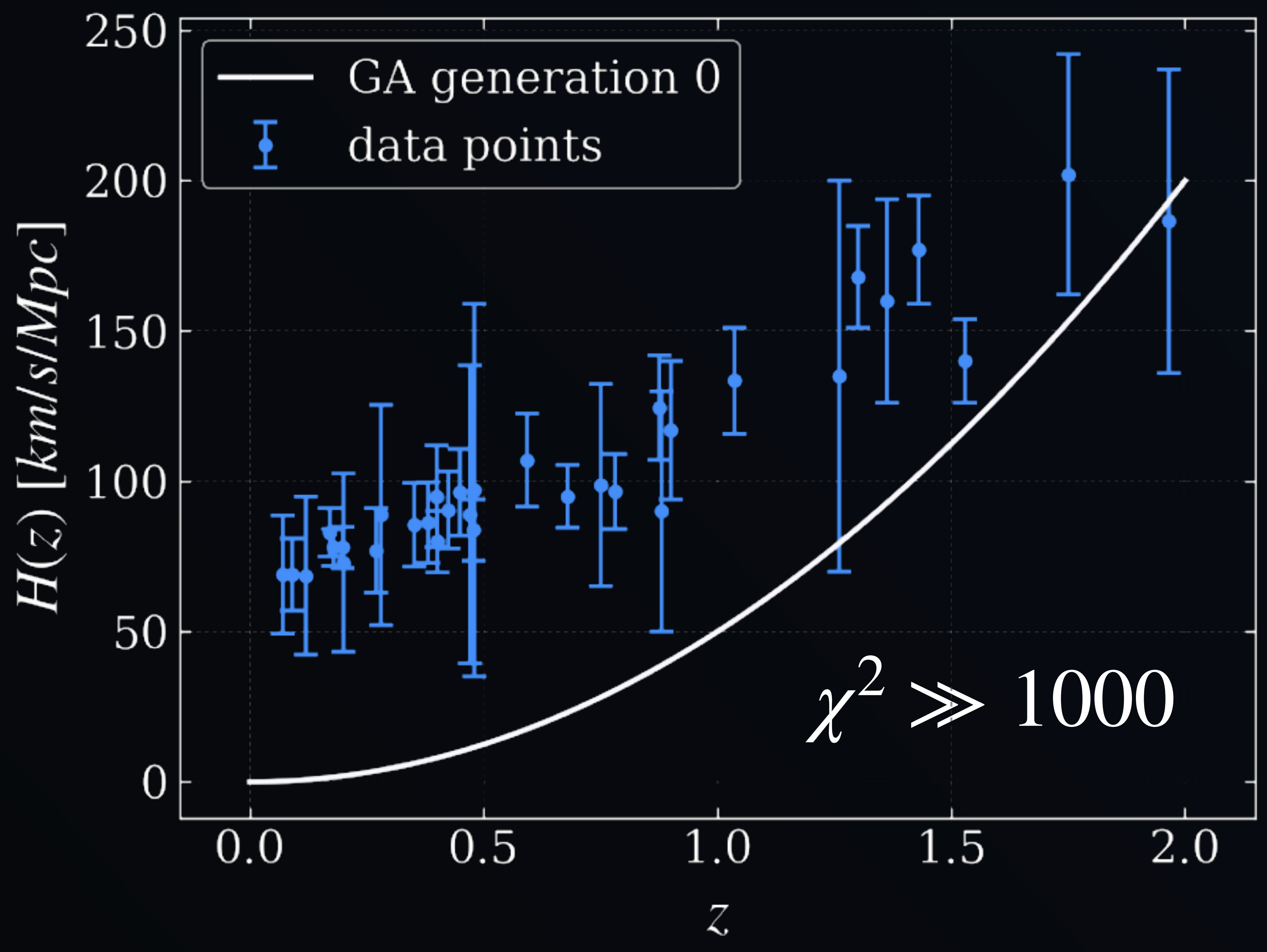
mutation



Genetic Algorithms

random initial function

grammar, random seed, N_{pop}



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random initial function

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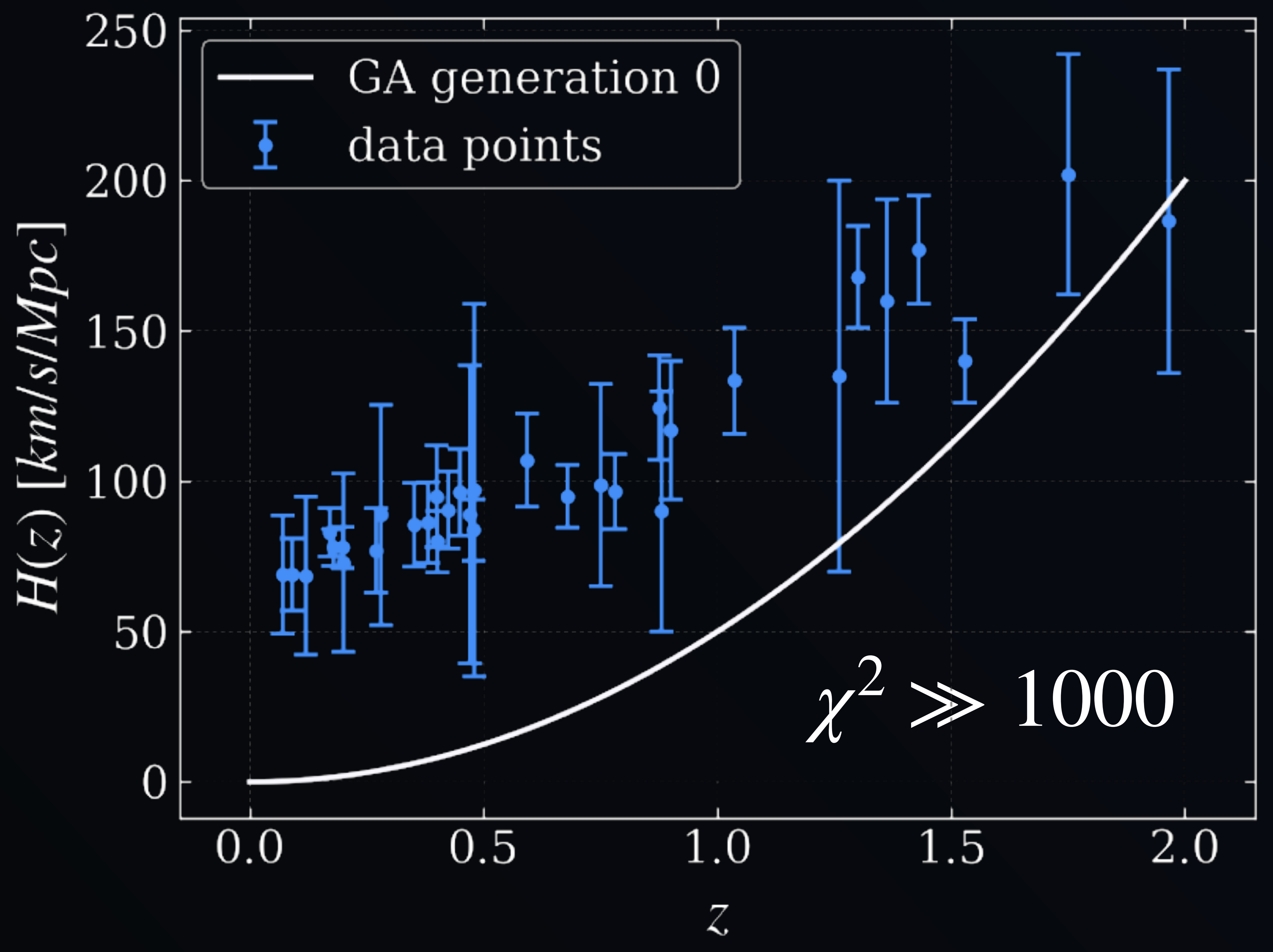
→ improve fitness χ^2 through GA



selection
crossover
mutation

Genetic Algorithms

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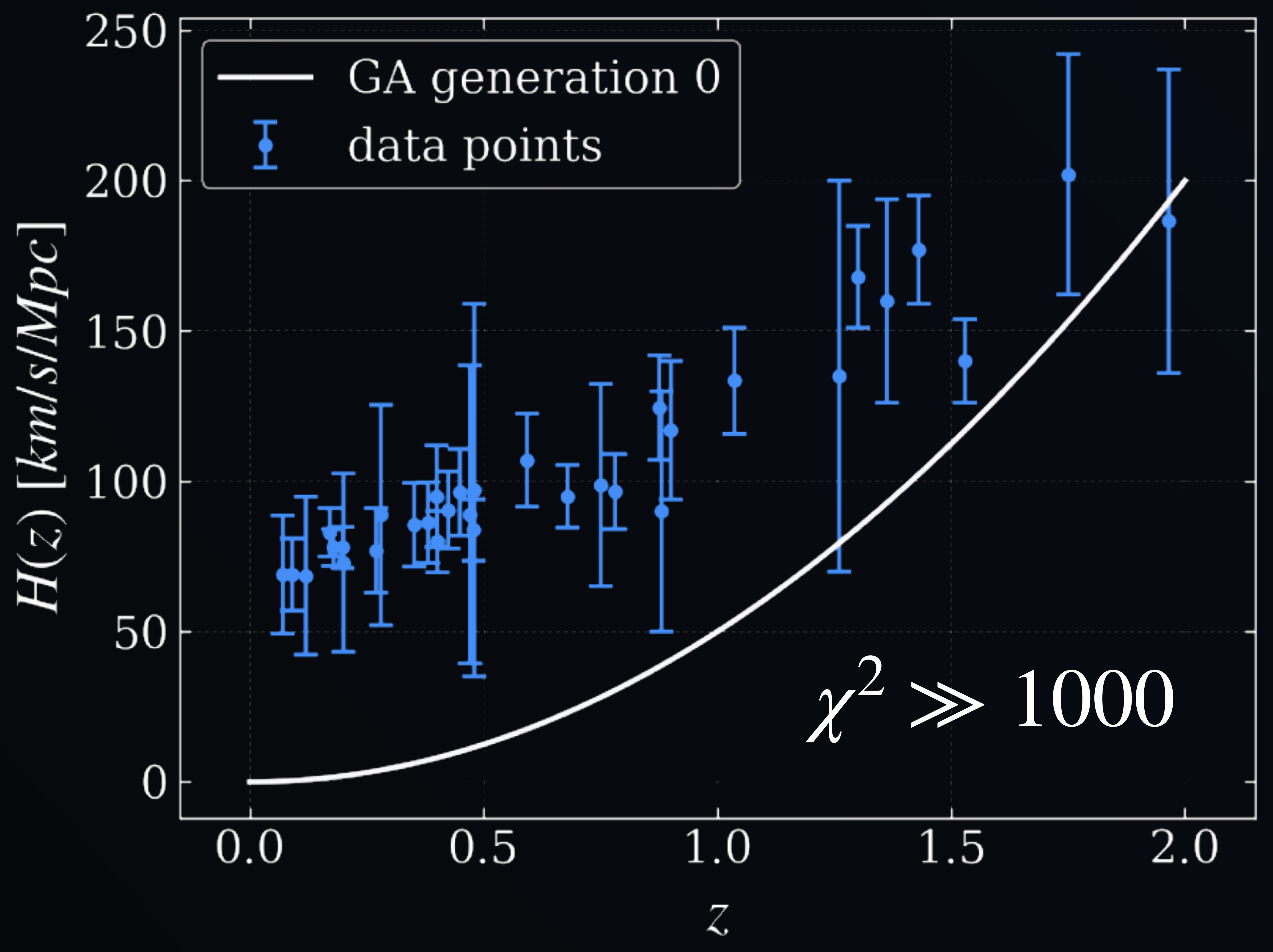
→ improve fitness χ^2 through GA →

final processed function

number of generations



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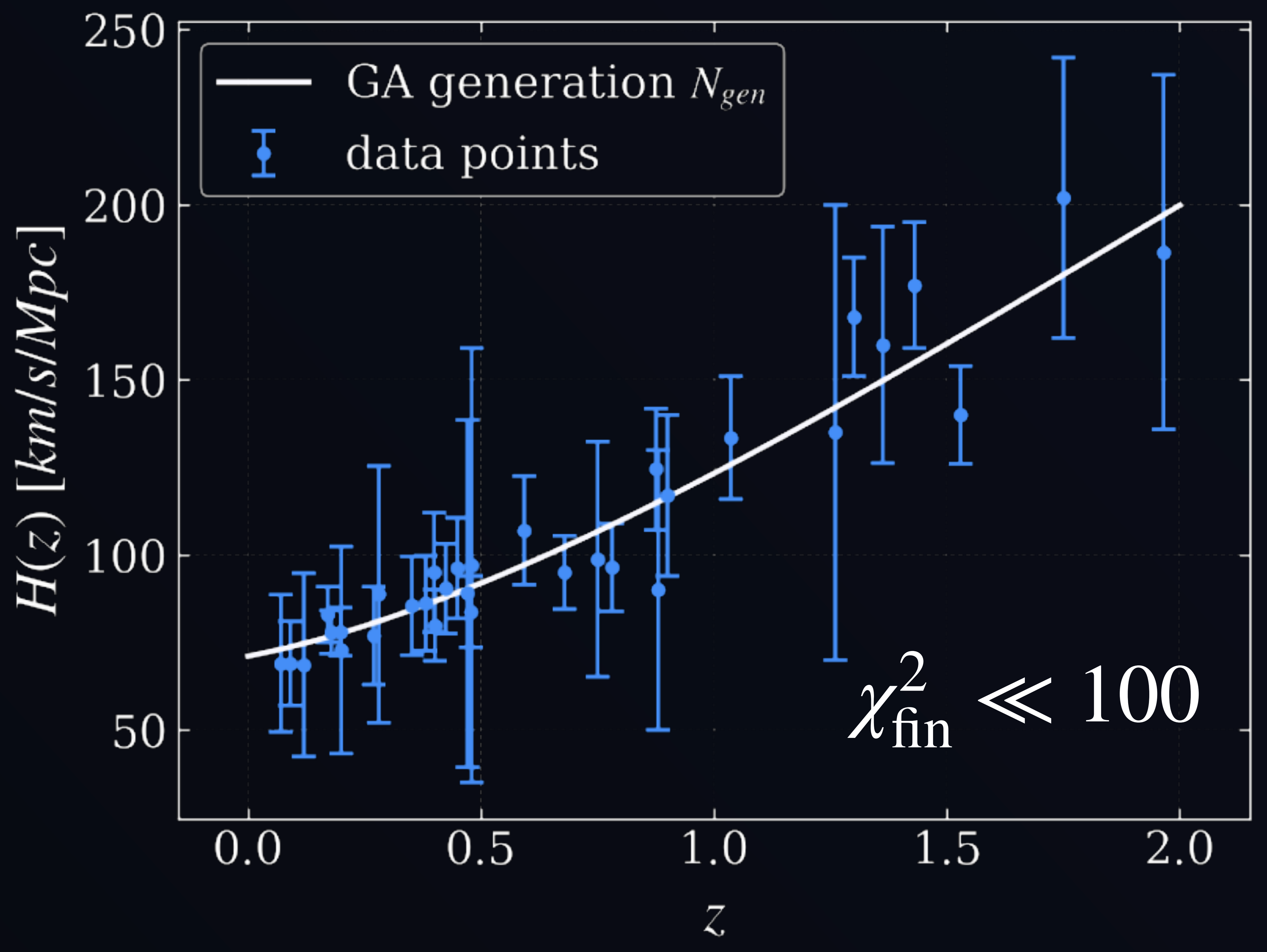

Genetic Algorithms

random initial function → improve fitness χ^2 through GA → final processed function

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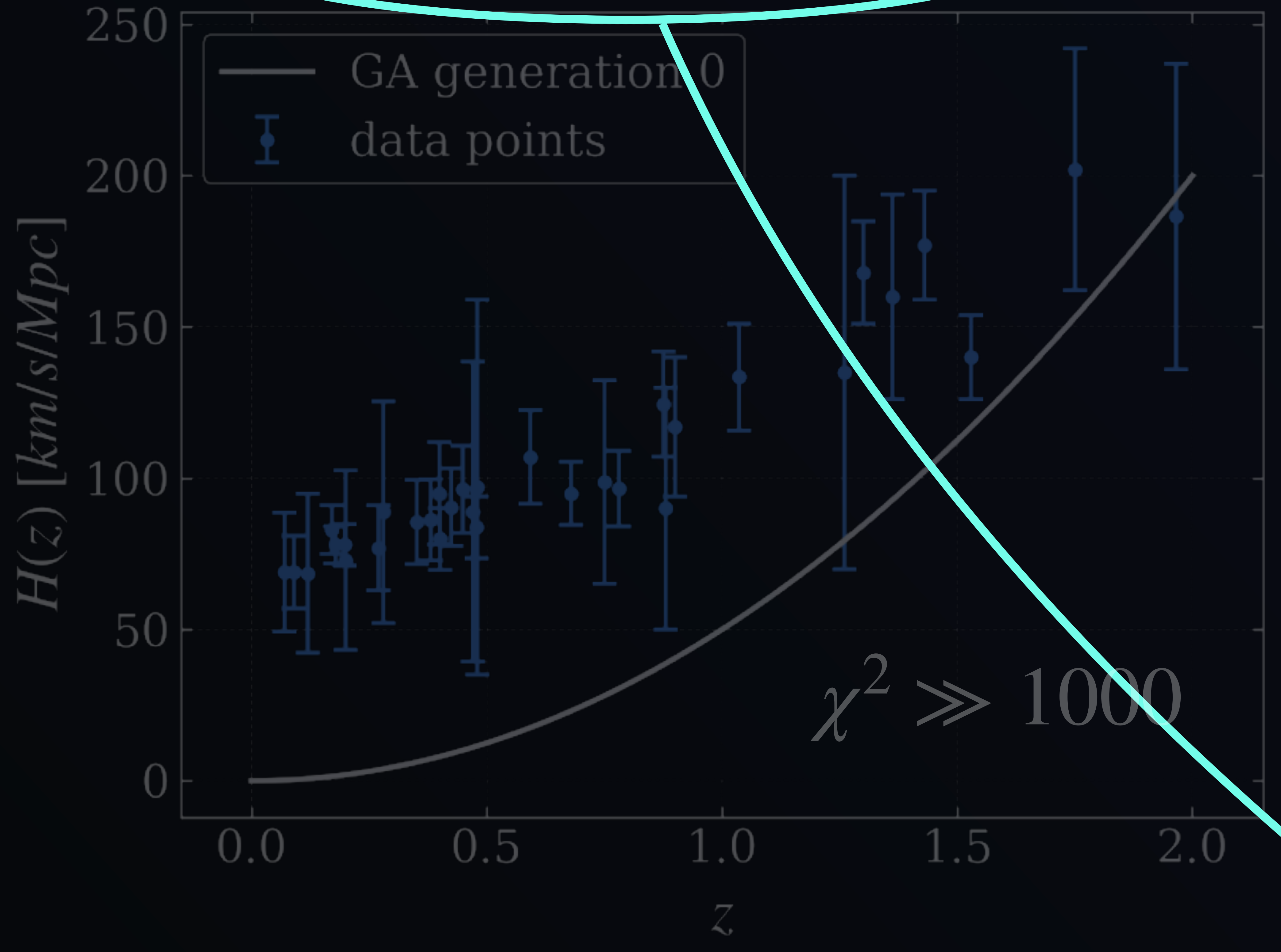

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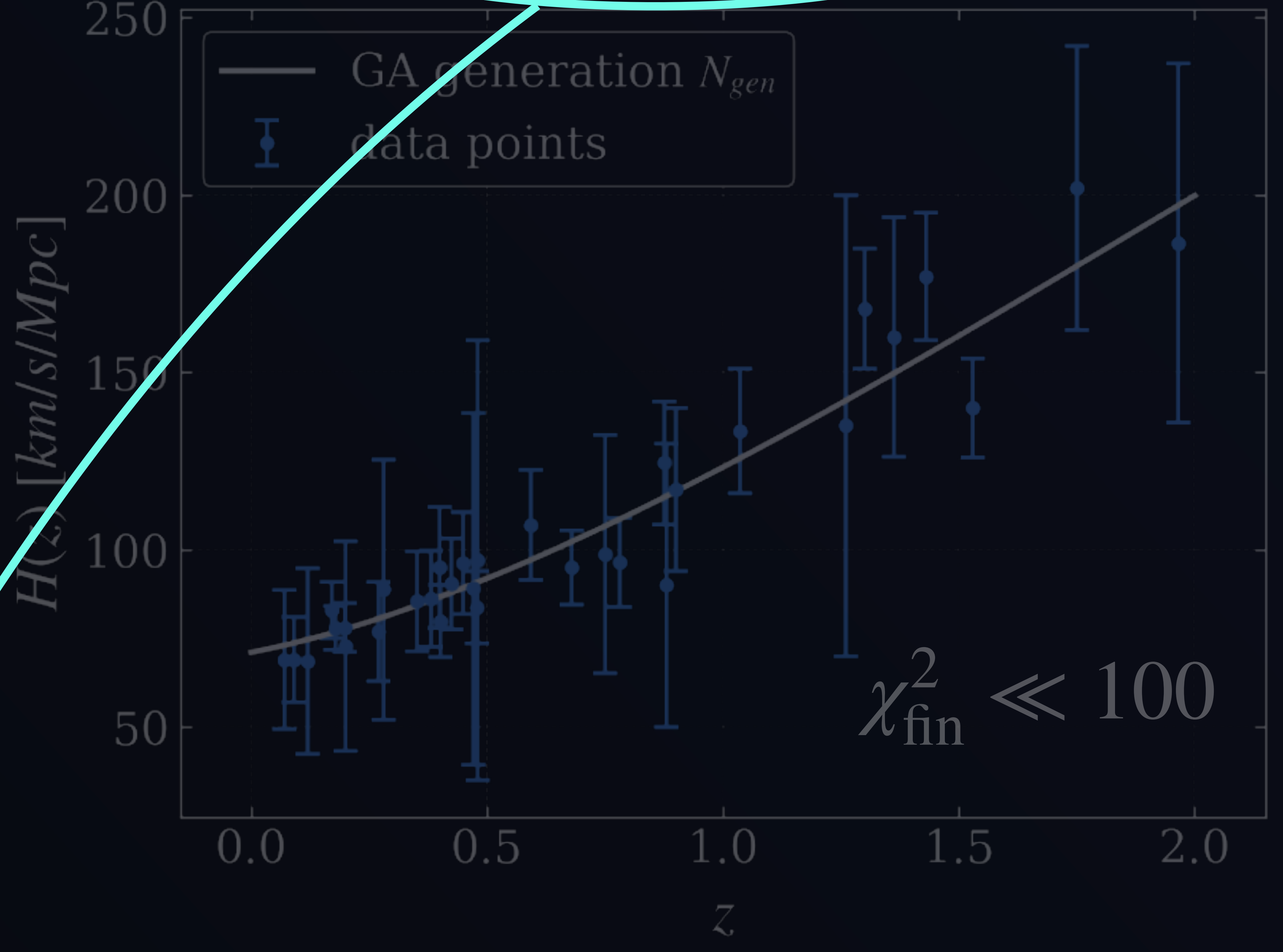
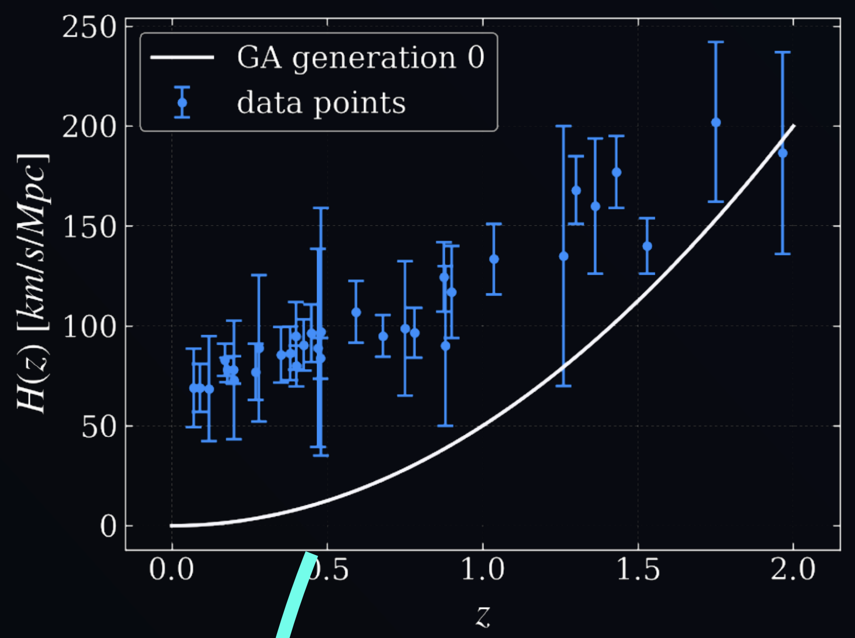


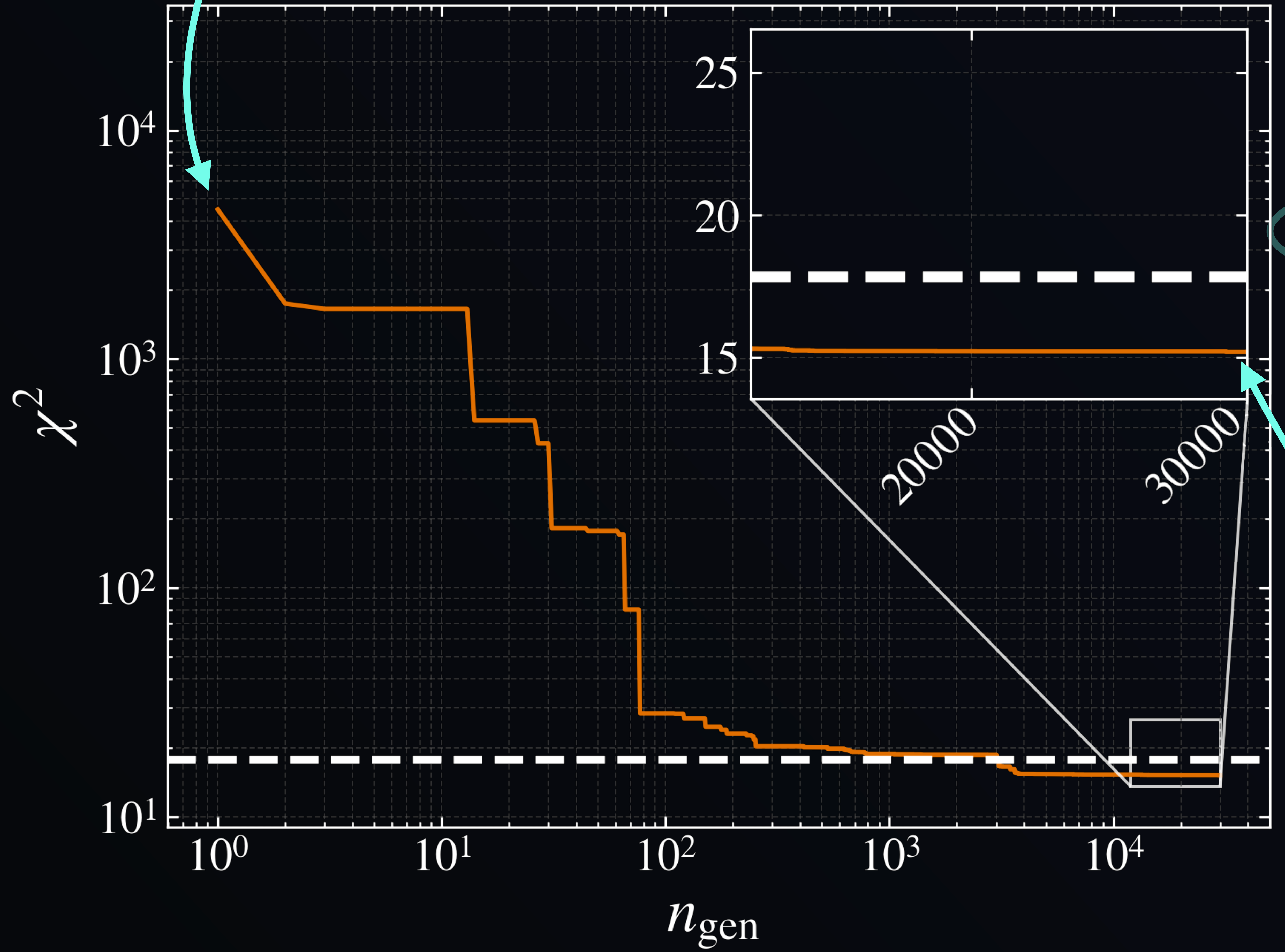
hyperparameters

GA hyperparameters configurations

1 hyperparameters configuration…

GA hyperparameters configurations

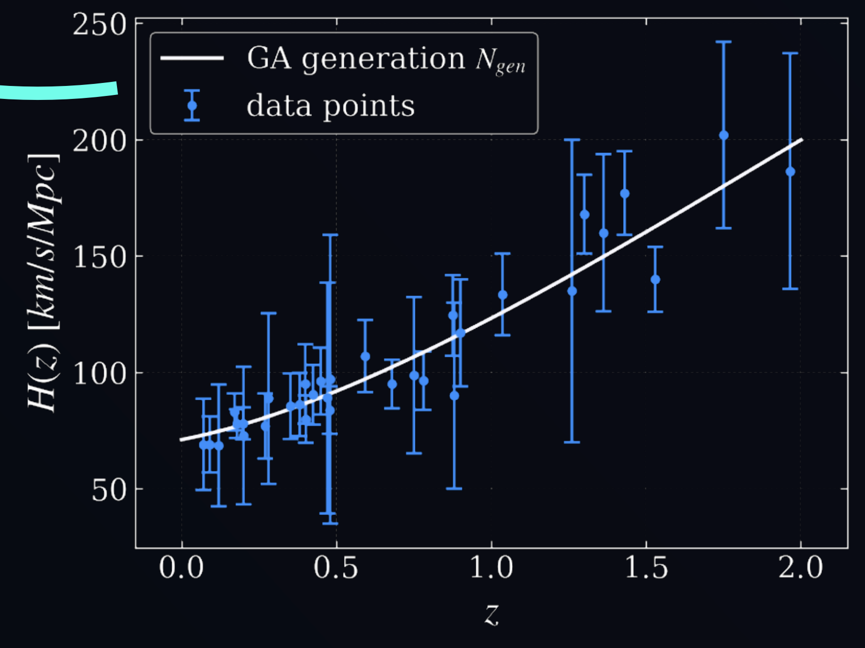




$\chi^2_{thr} = 17.834$

$\chi^2_{min} = 15.192$
seed=76822, cross=0.85, mut=0.85, gramm=['poly', 'exp']

1 hyperparameters configuration...



GA hyperparameters configurations

...many hyperparameters configurations

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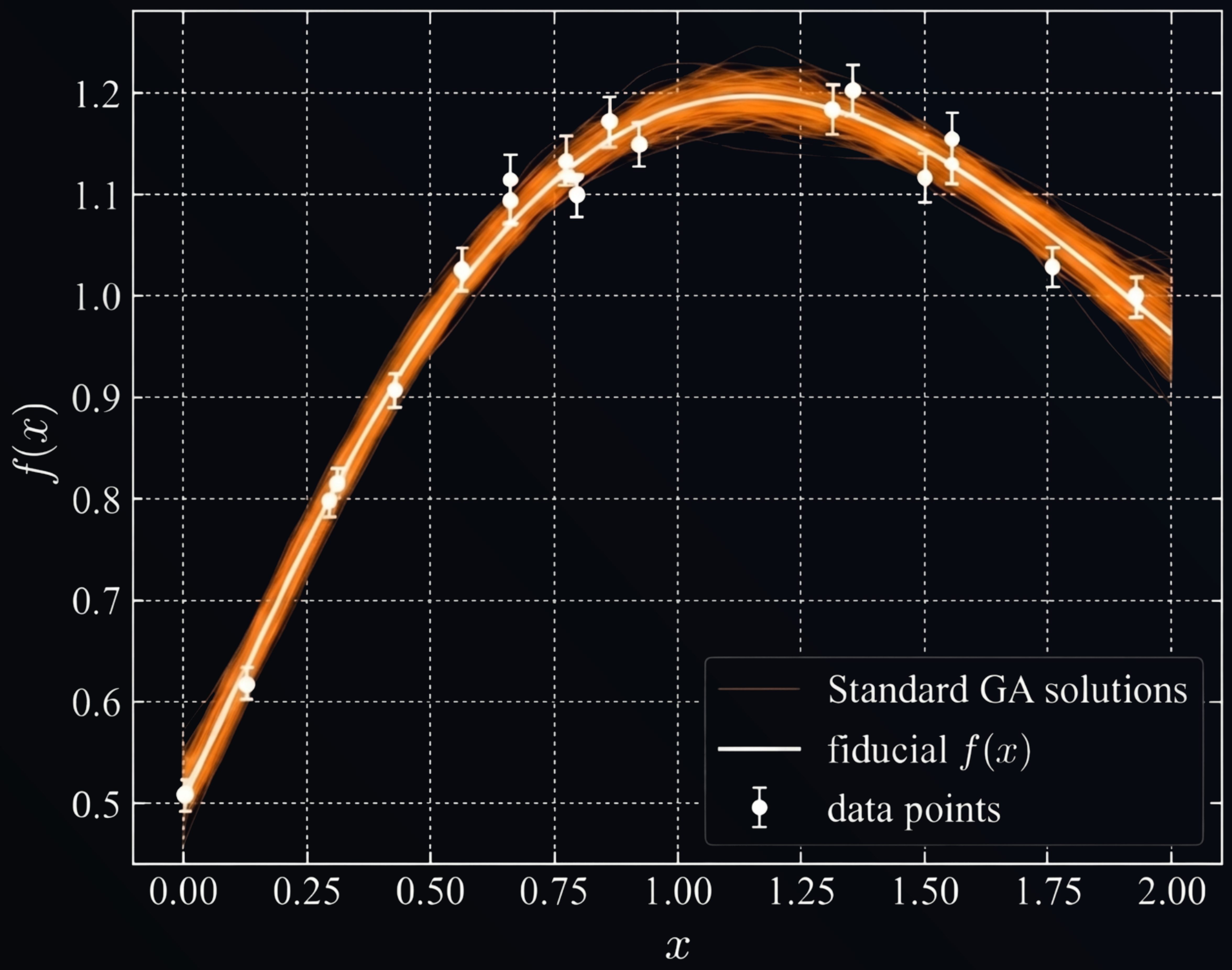
The “Derivative” trap



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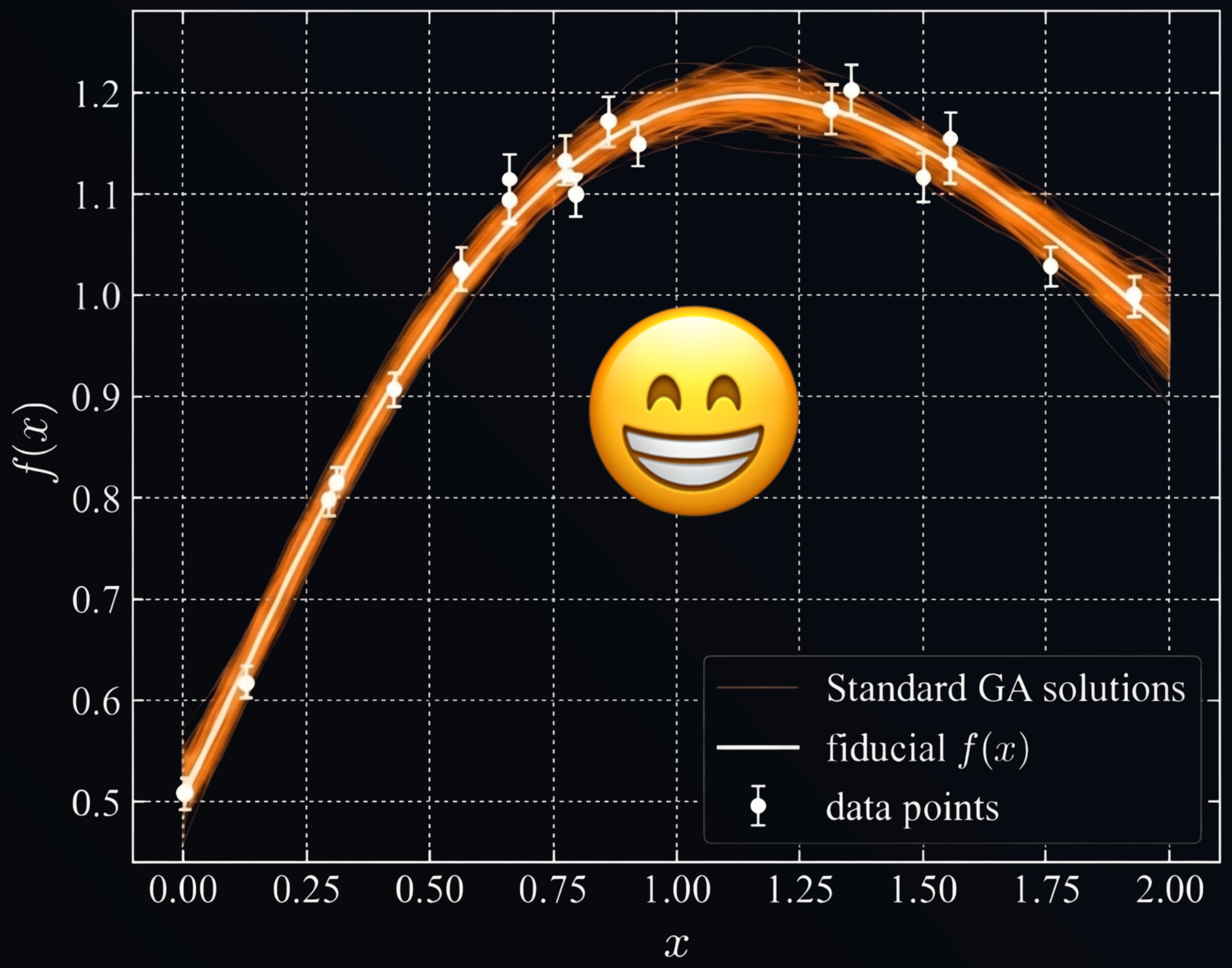

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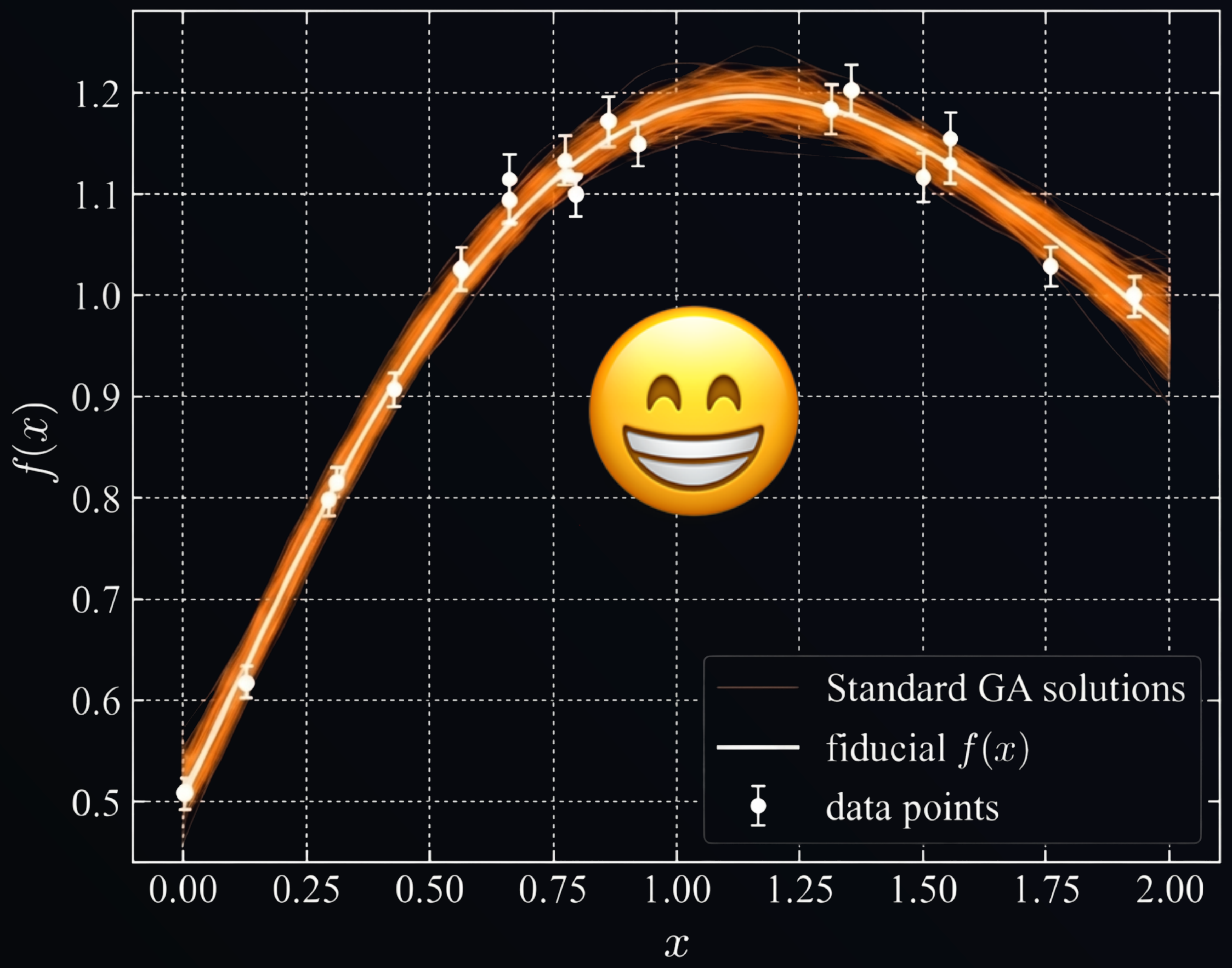

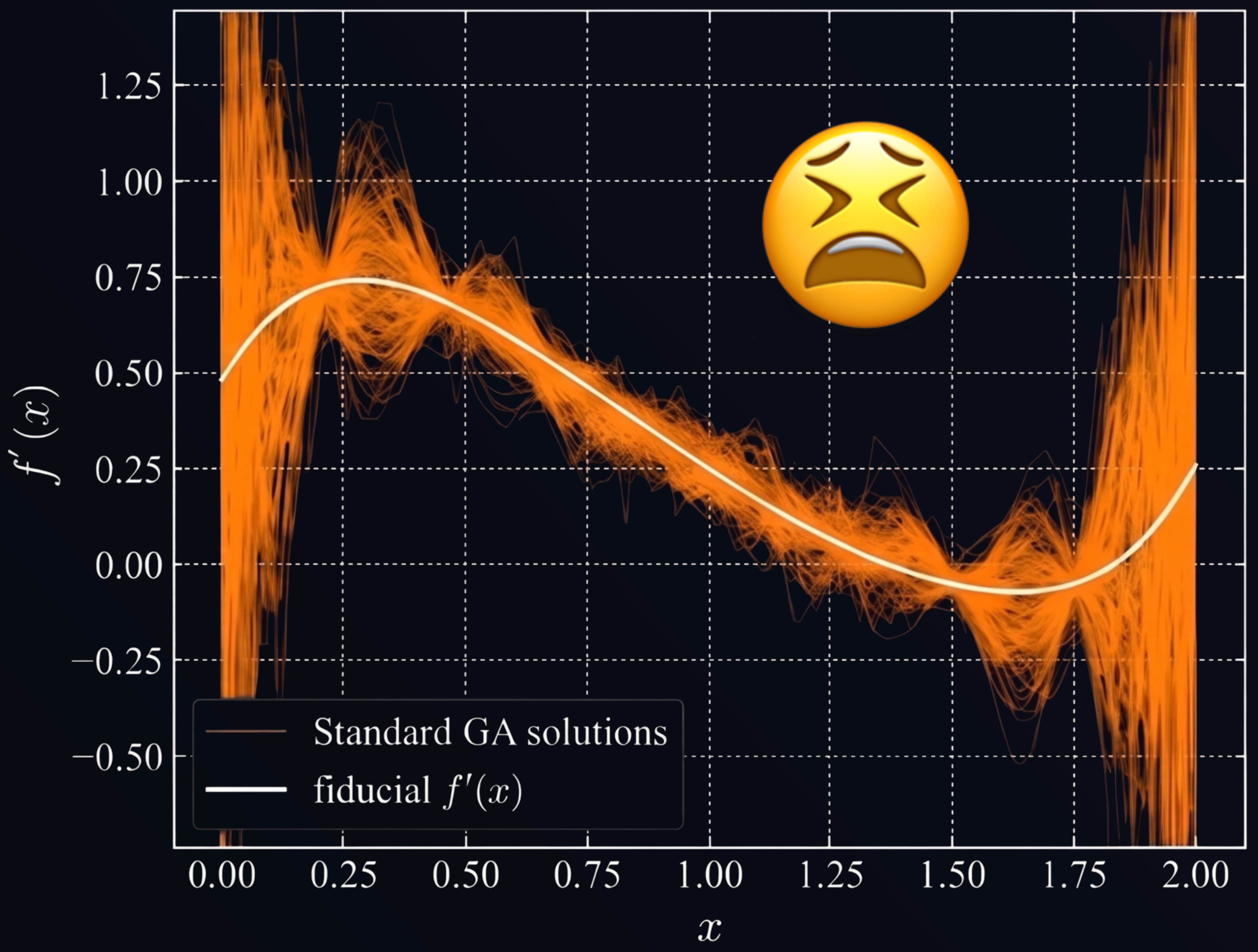

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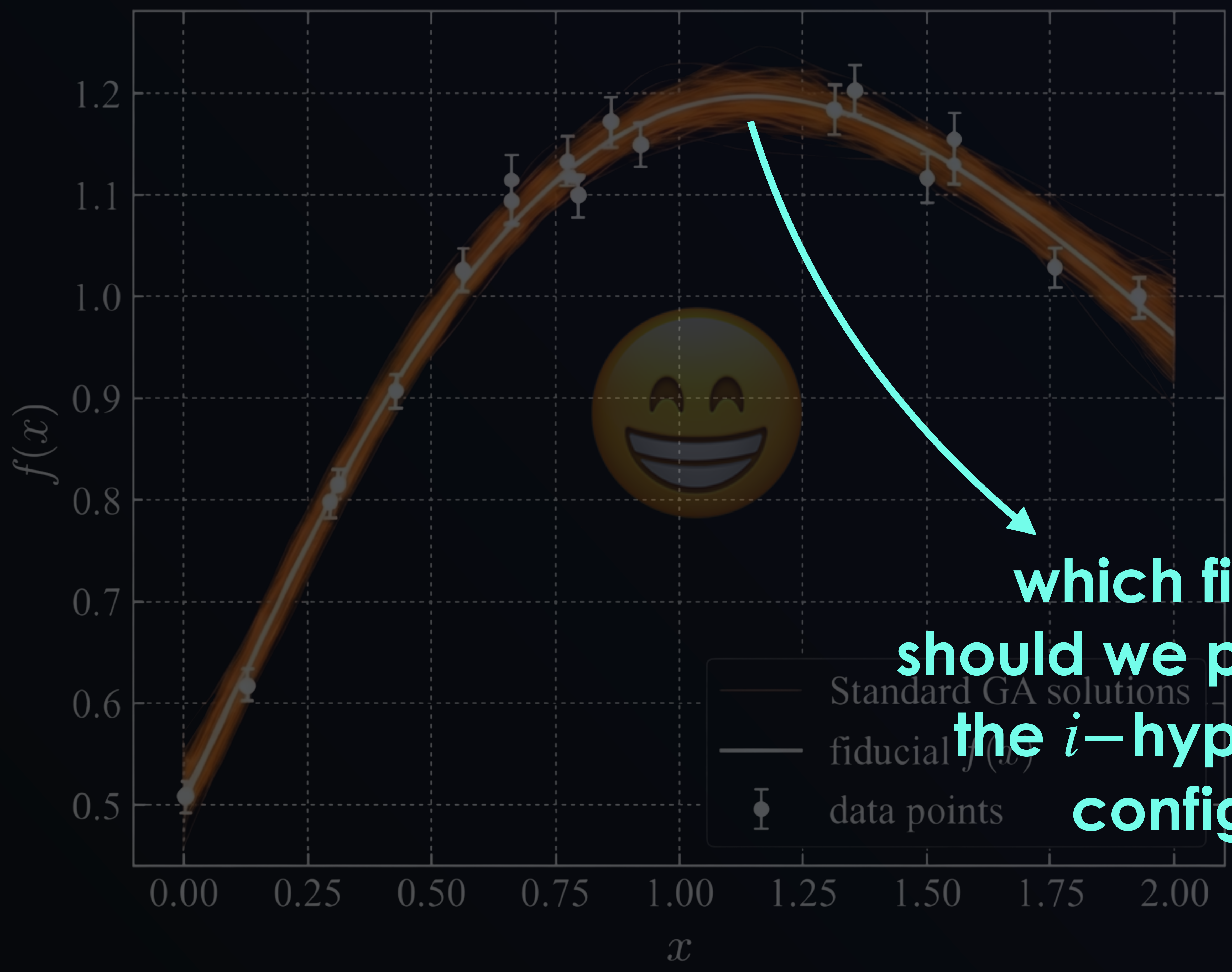
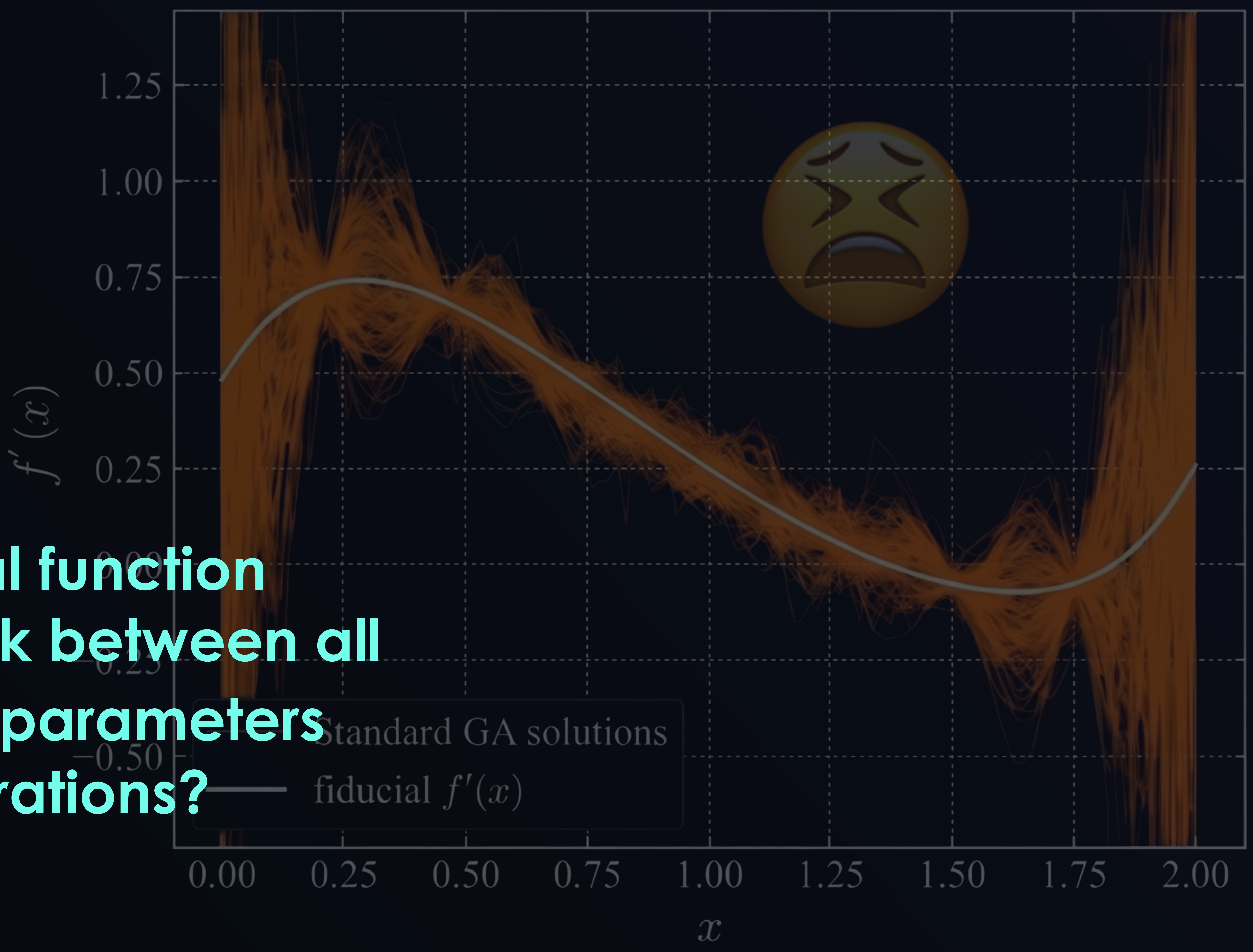
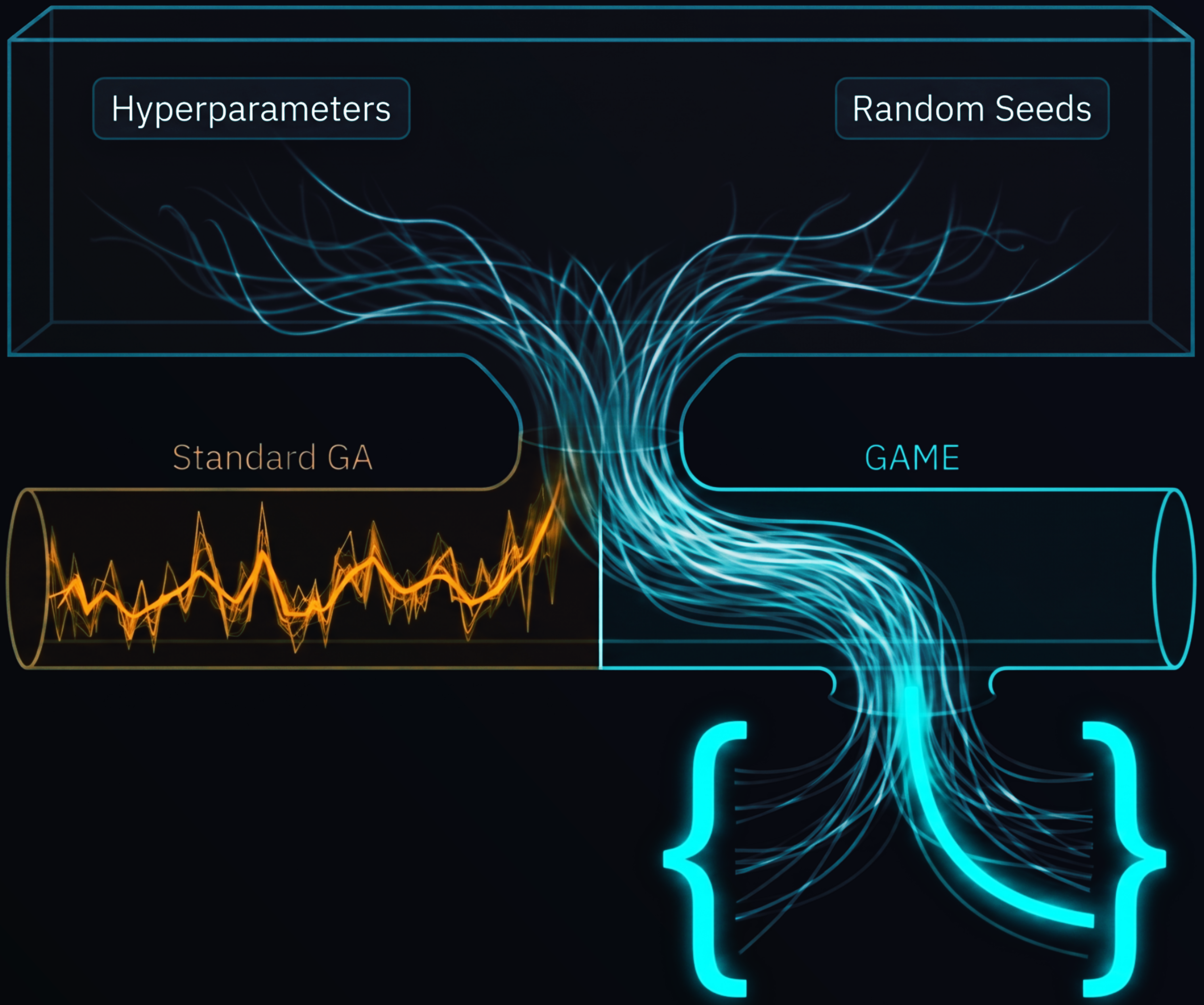




which final function
should we pick between all
the $i-$hyperparameters
configurations?

GAME – Genetic Algorithms with Marginalised Ensembles



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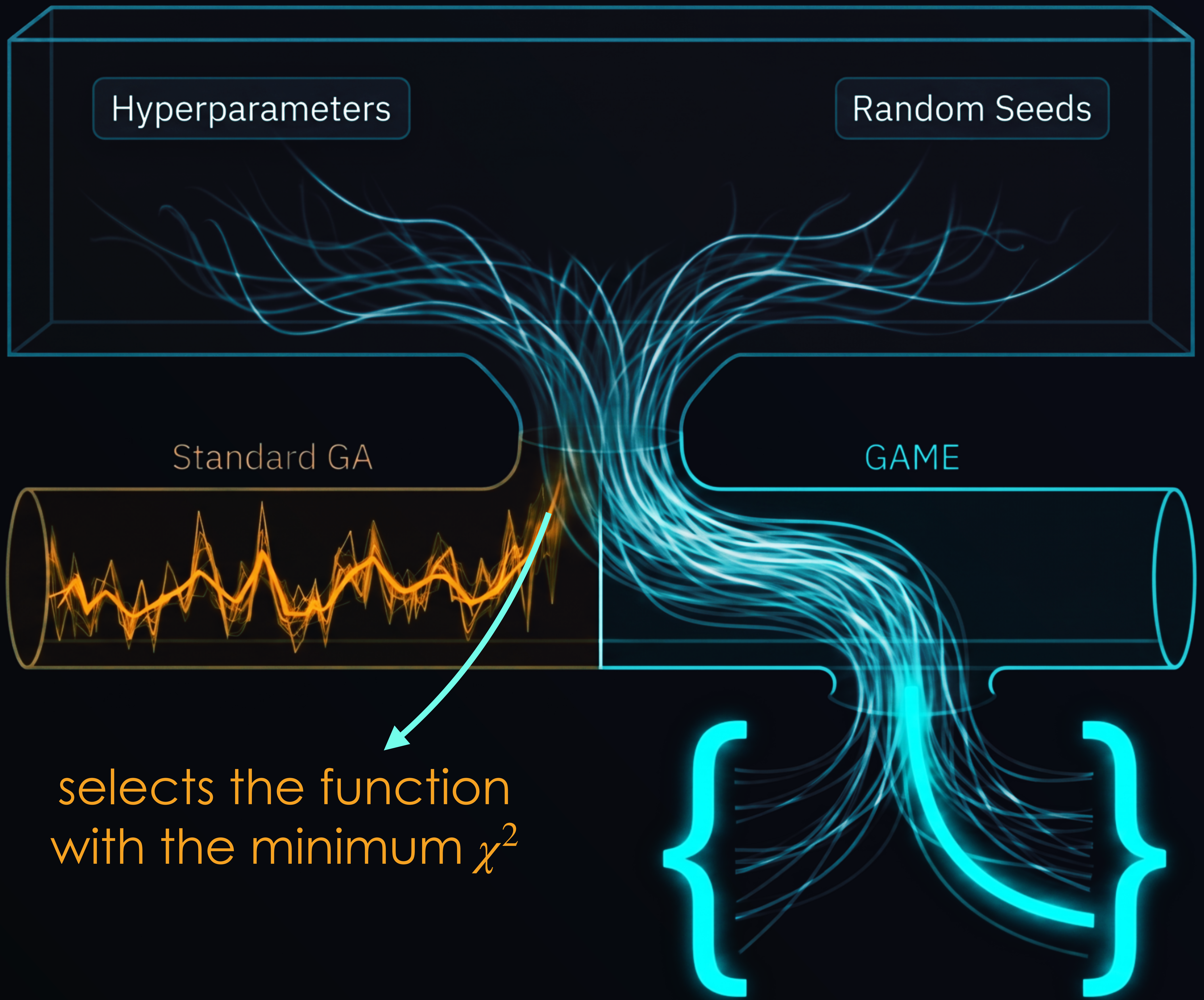

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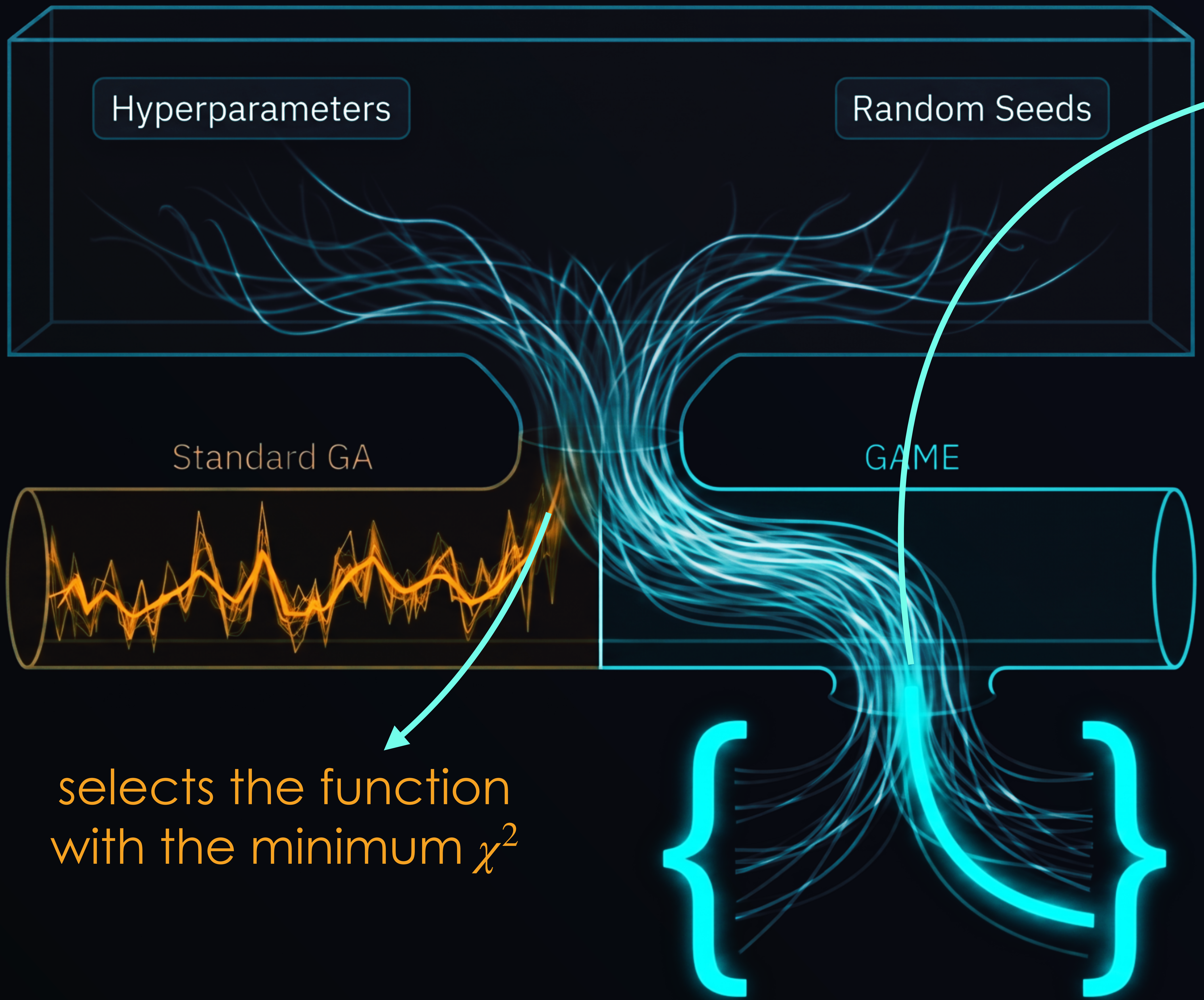

computes a weighted average of all the i – configurations functions

$$f_{\mathrm{GAME}}(x) = \sum_{j}^{N_{\mathrm{conf}}} w_j \cdot f_{j,\mathrm{GA}}(x)$$

selects the function with the minimum χ^2

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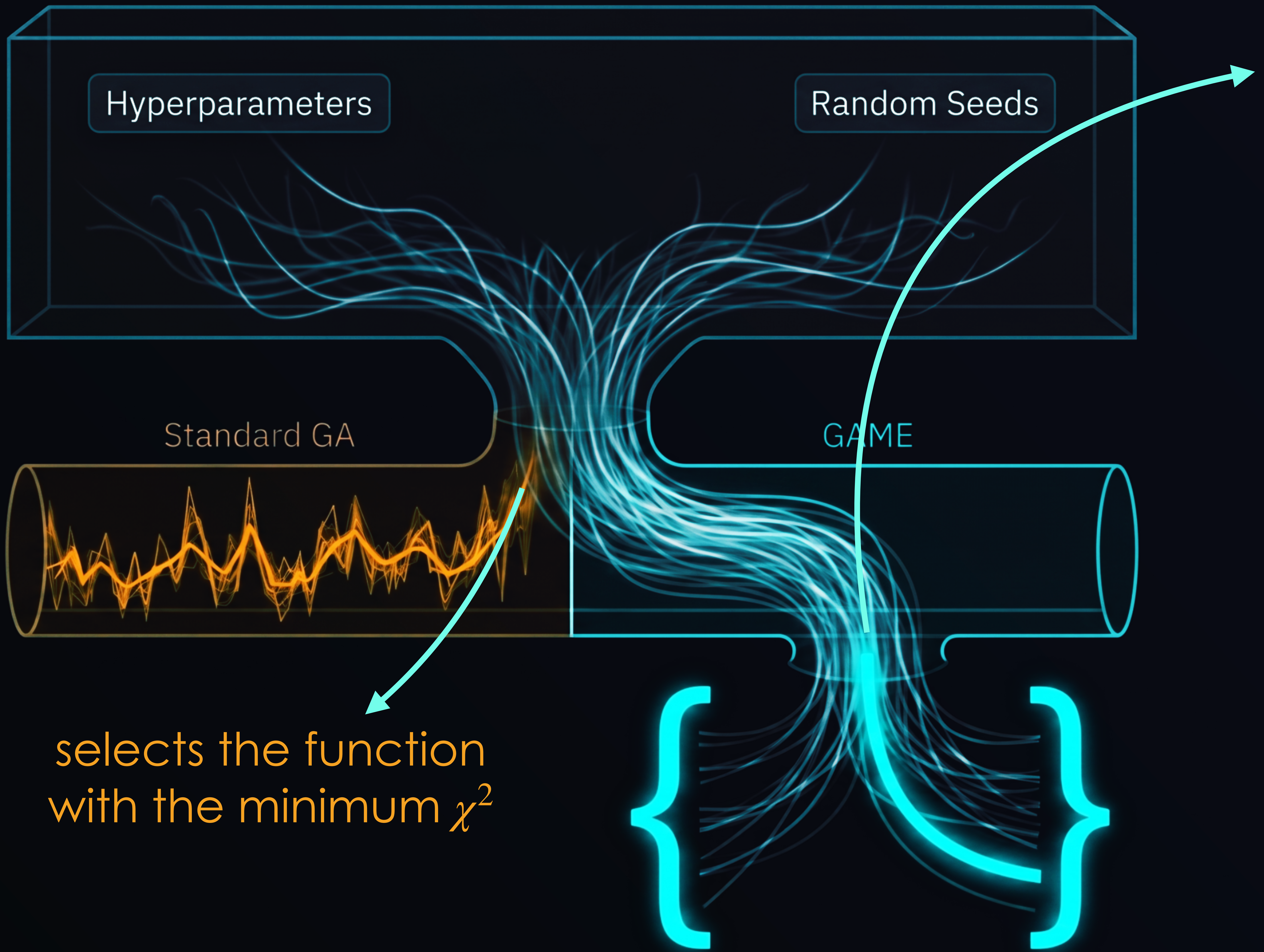

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$$w_j \propto S_j = \chi_j^2 + \lambda R_j$$

and

$$R_j = \int \left| f_j''(x) \right|^2 dx$$

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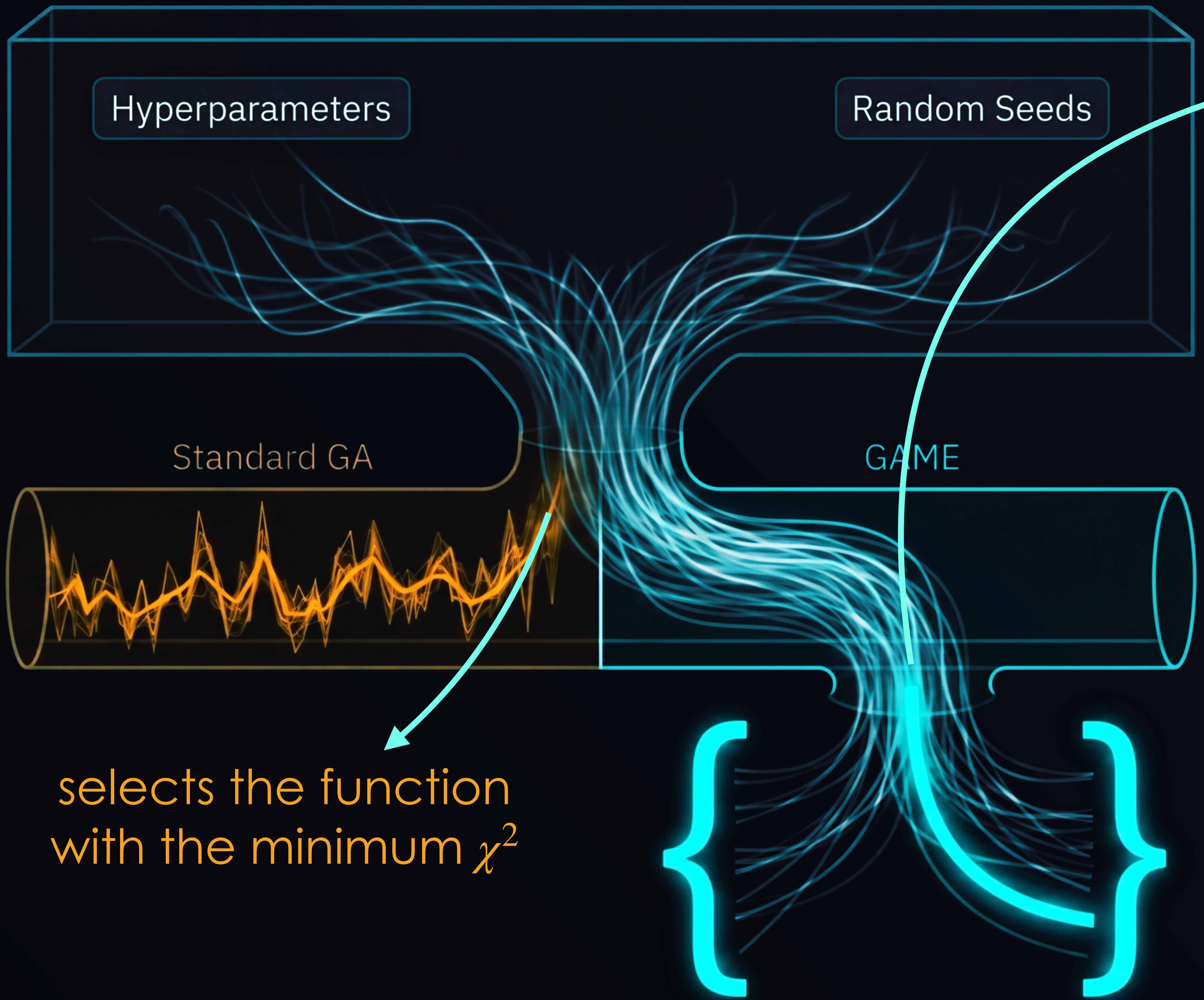

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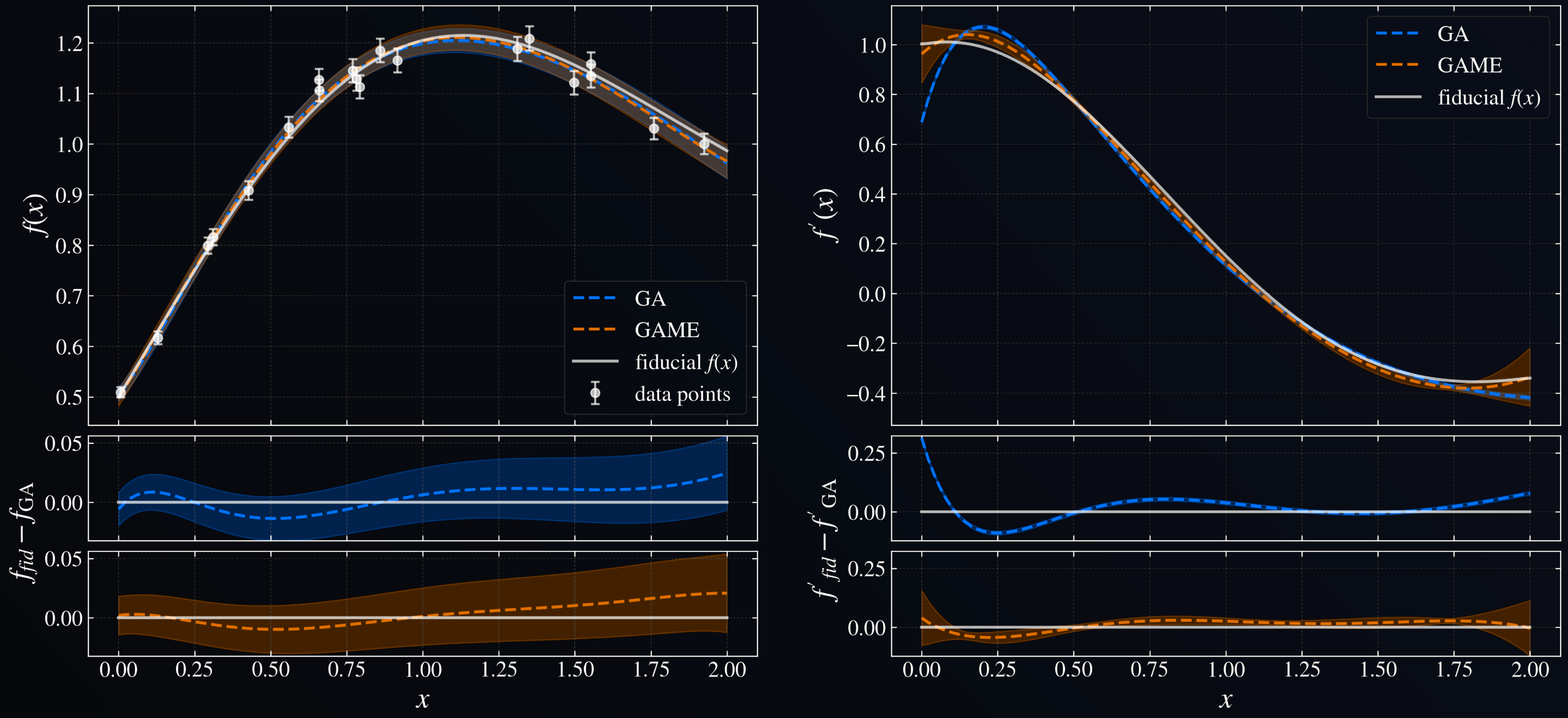
GAME – generic test function



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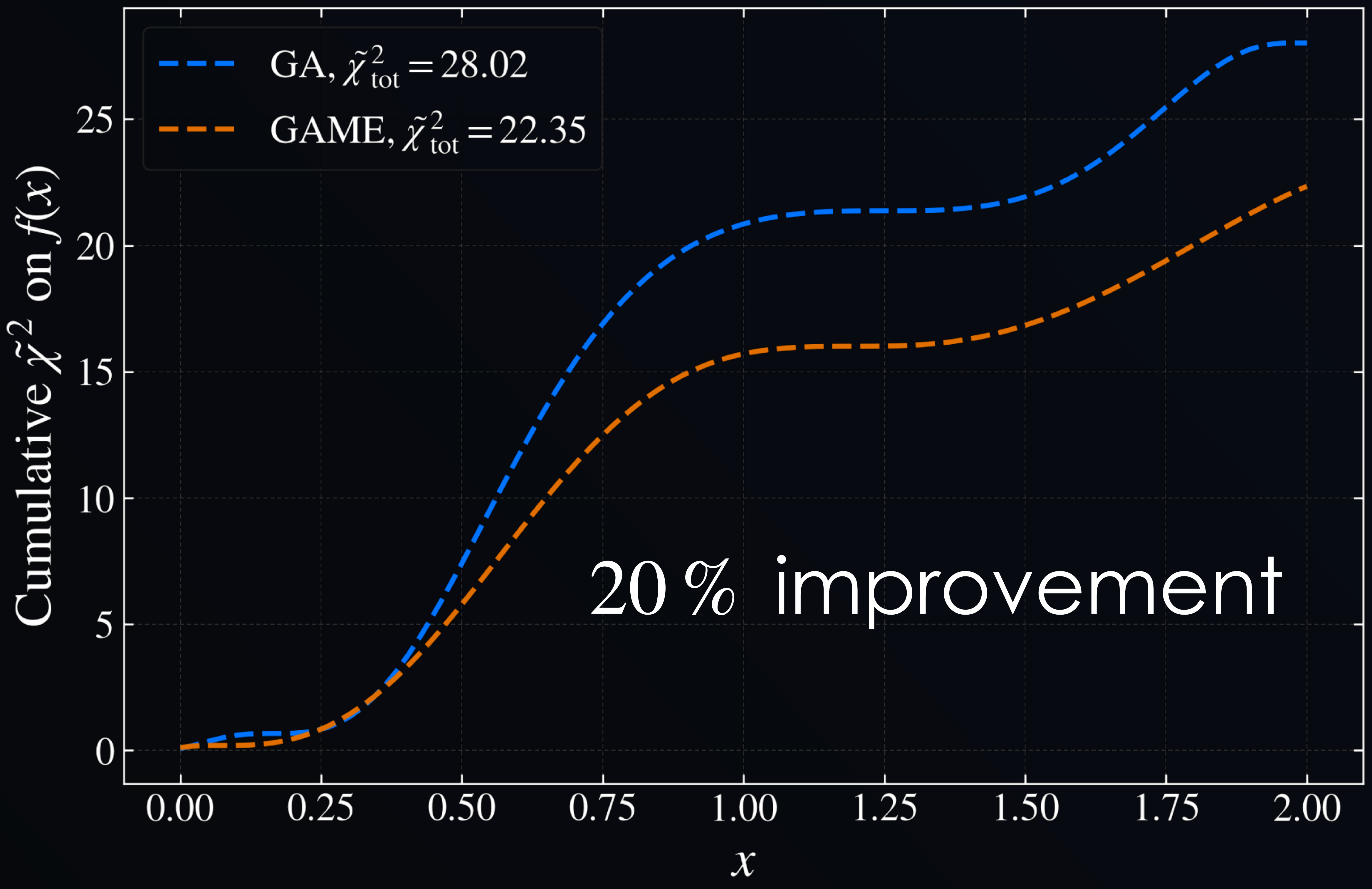
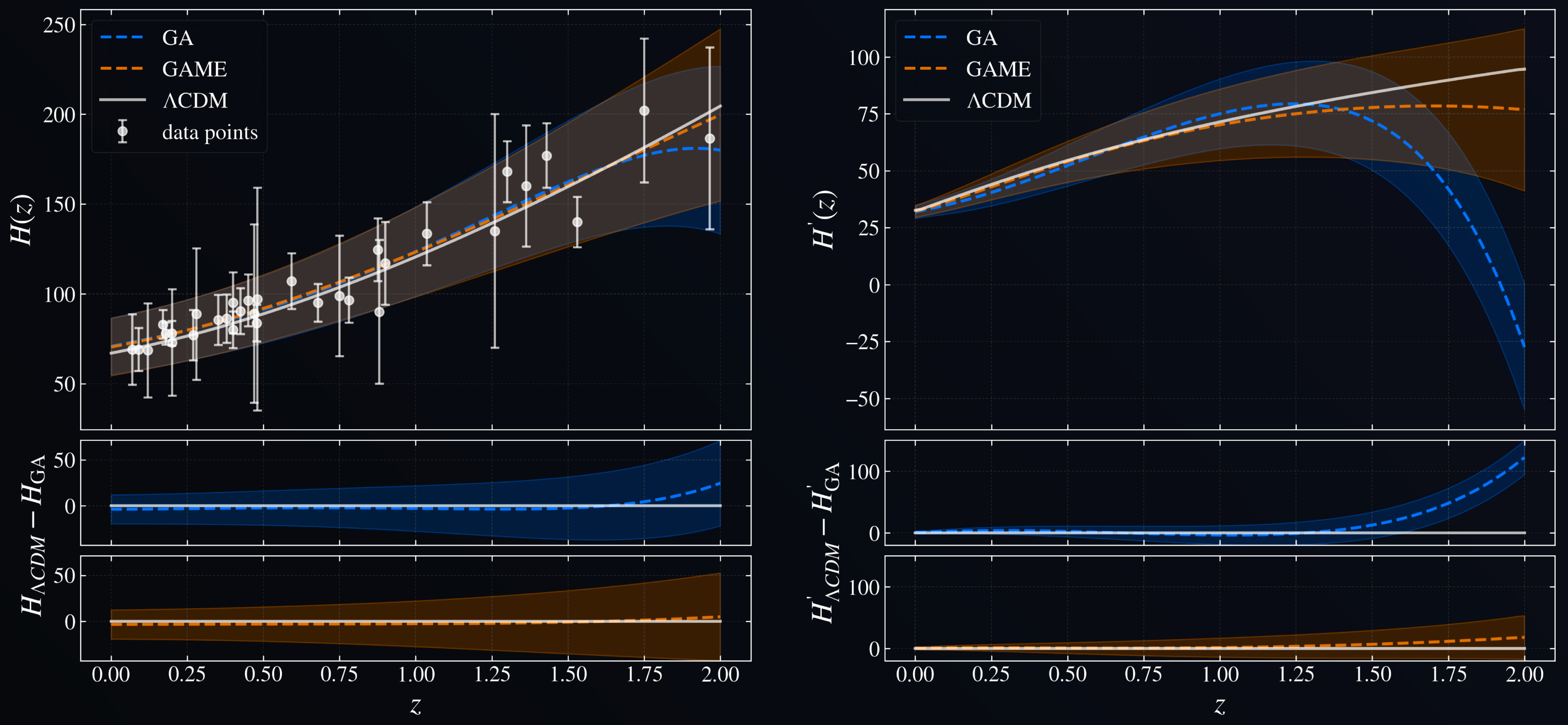
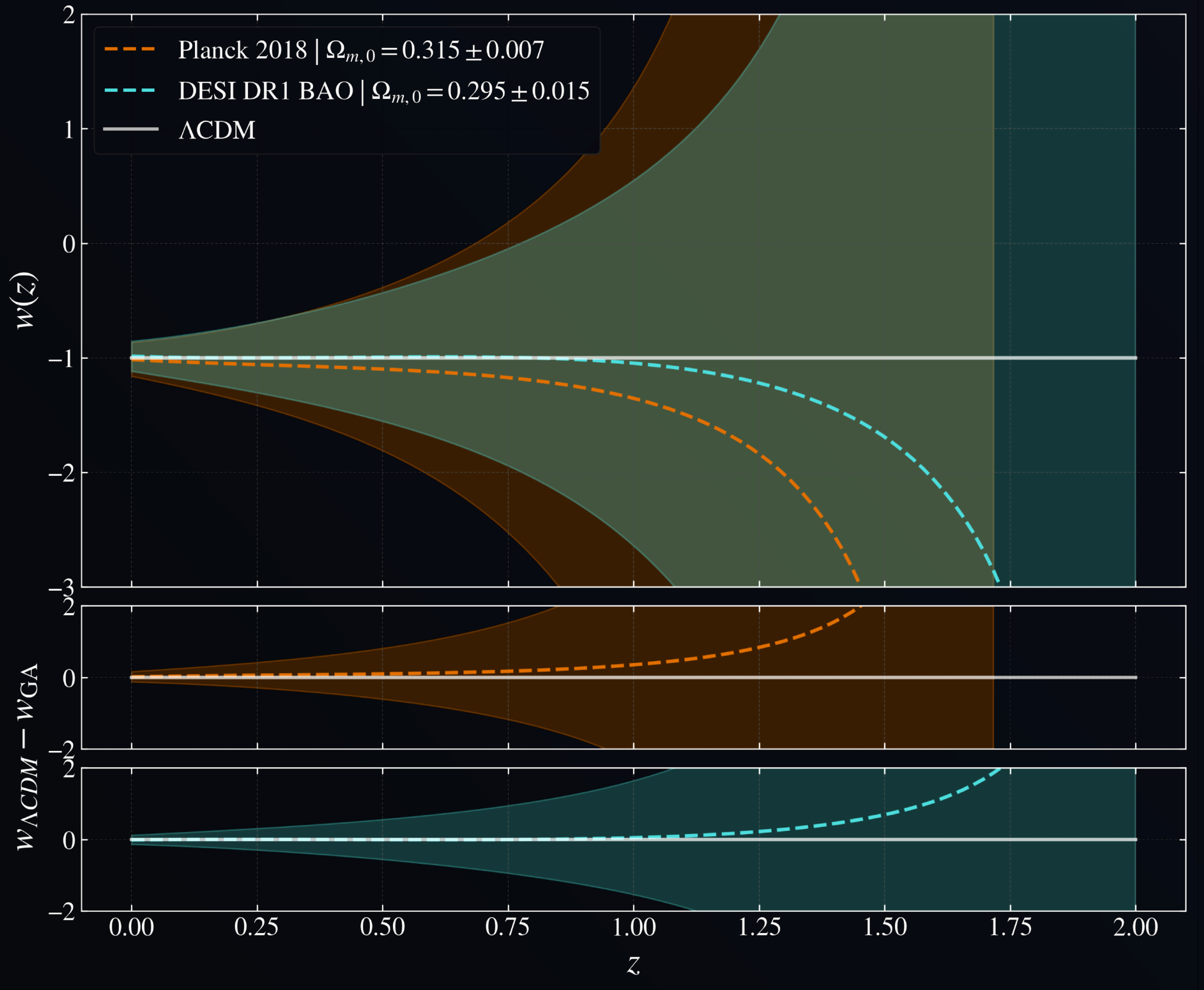


Reconstruction of $H(z)$ from CC



Reconstruction of $w_{\rm bg}(z)$ from CC



$$w(0) = -0.986 \pm 0.132$$

Perfectly compatible with ΛCDM but large uncertainties bands using current CC data

Conclusions and next steps

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- GAME is a powerful tool that can reconstruct smooth analytical functions with a particular sensitivity to derivatives, only from data.

- By applying GAME to current CC data, we get an expression for $w_{\rm bg}(z)$ that is perfectly compatible with ΛCDM, but with large uncertainties bands due to data quality.

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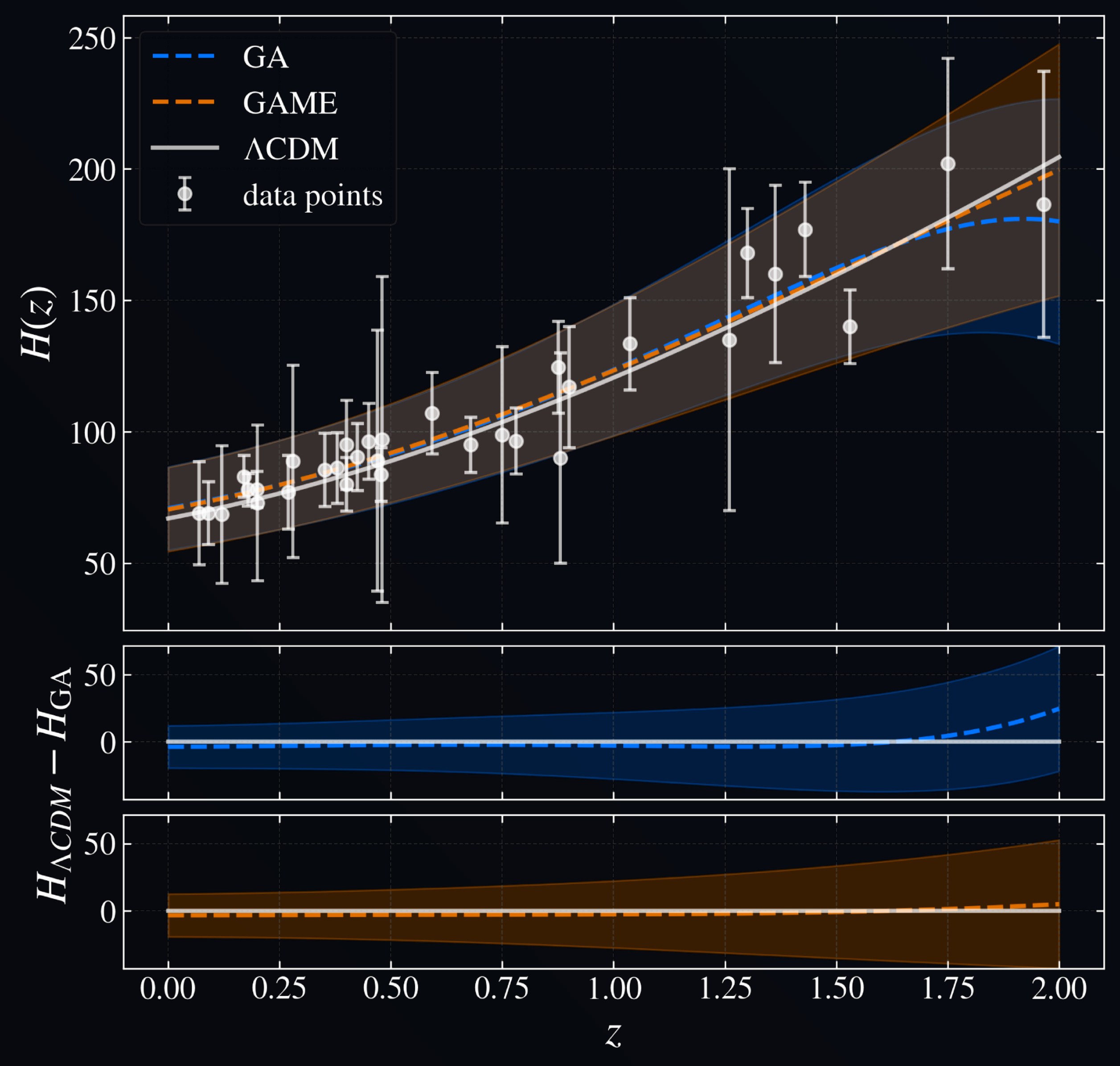
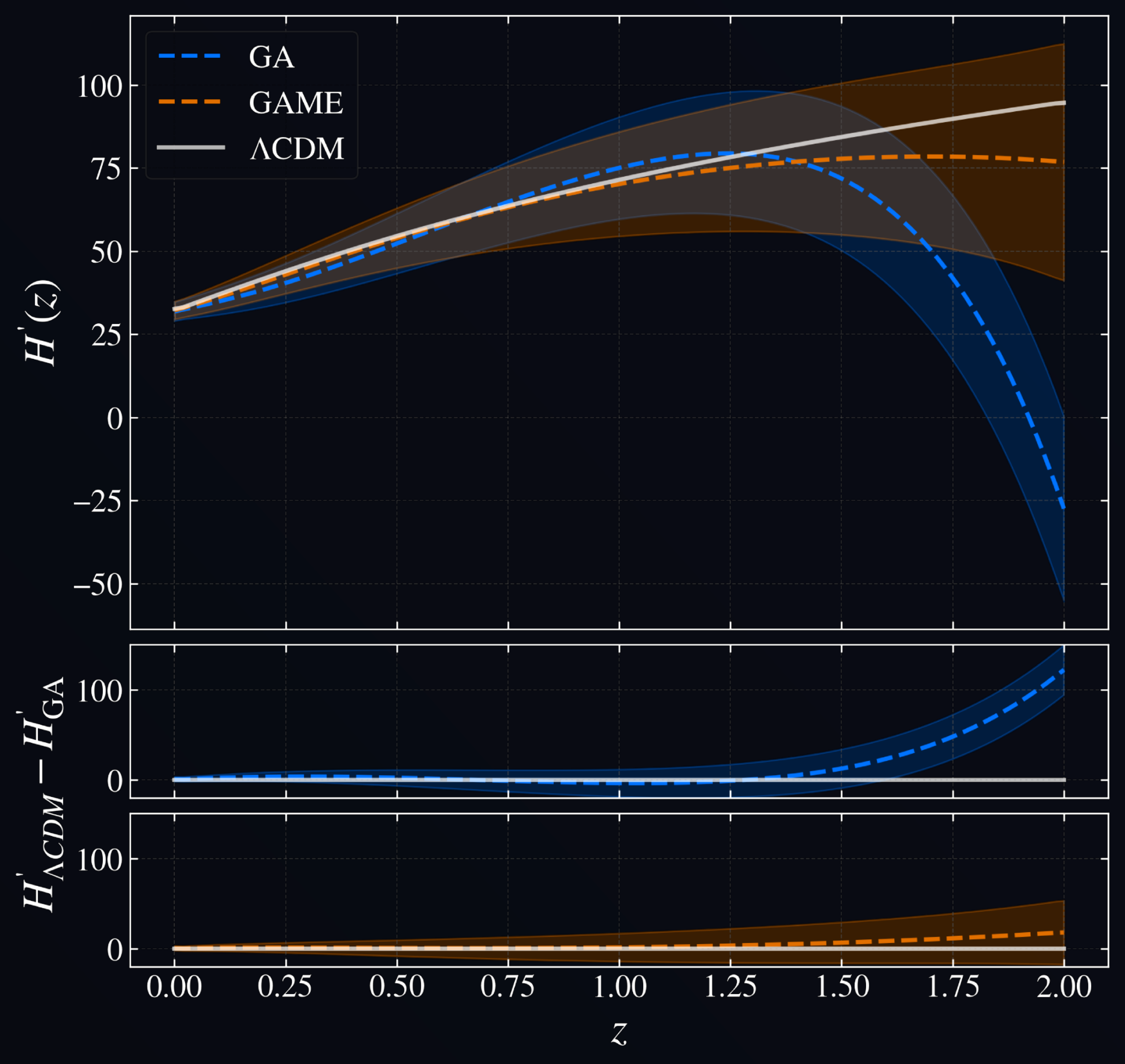
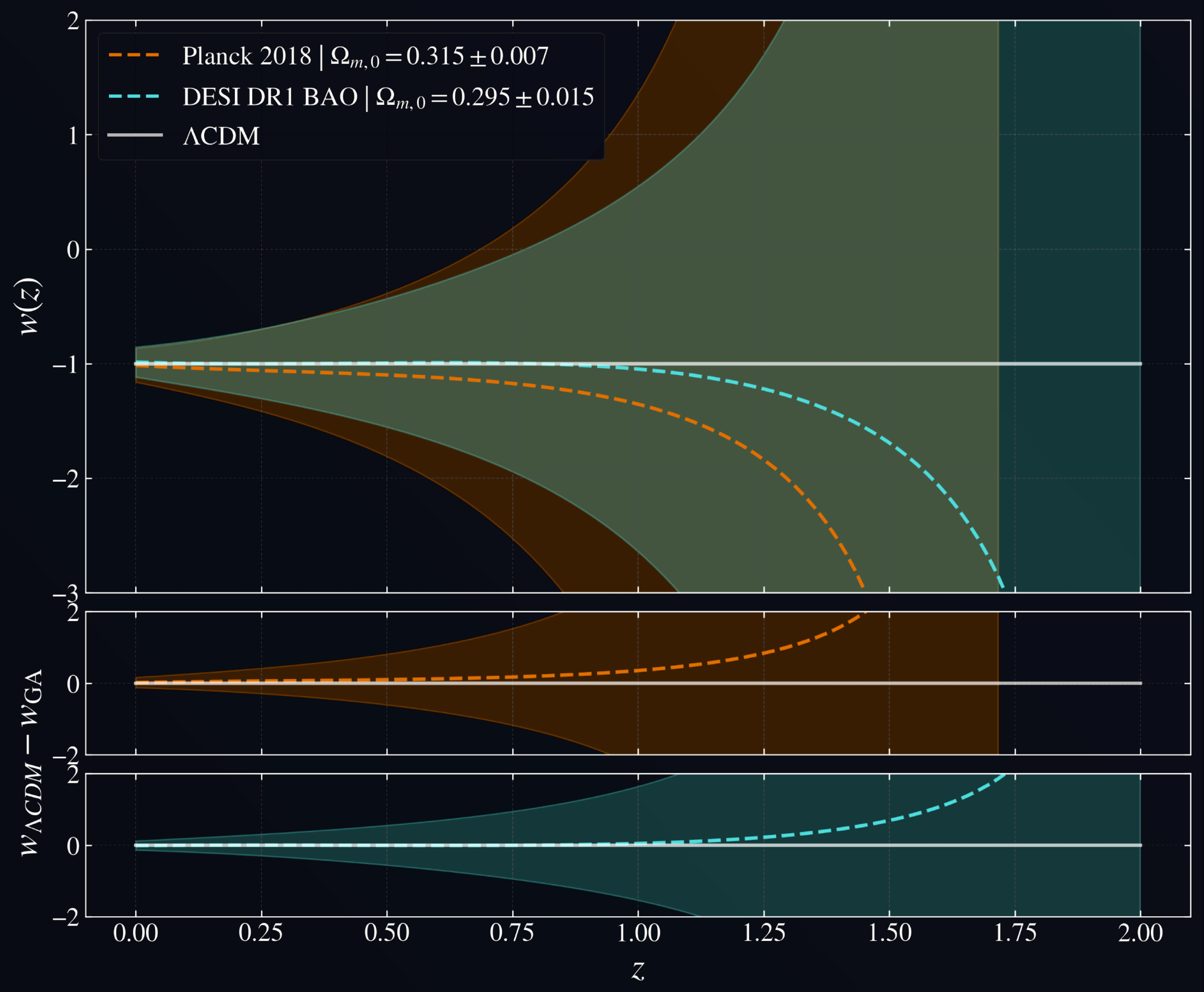
- GAME is a powerful tool that can reconstruct smooth analytical functions with a particular sensitivity to derivatives, only from data.
- By applying GAME to current CC data, we get an expression for $w_{bg}(z)$ that is perfectly compatible with ΛCDM, but with large uncertainties bands due to data quality.

1. Apply GAME to BAO and Supernovae (to obtain $H(z) \rightarrow w(z)$).
2. Derive $w(z)$ from reconstructions of perturbations quantities (i.e $\sigma_8(z)$).
3. Compare GAME with other ML regression algorithms (i.e Gaussian Processes).
4. Wait for new CC points to reveal potential departures from ΛCDM.

GAME for the riconstruction of cosmological quantities







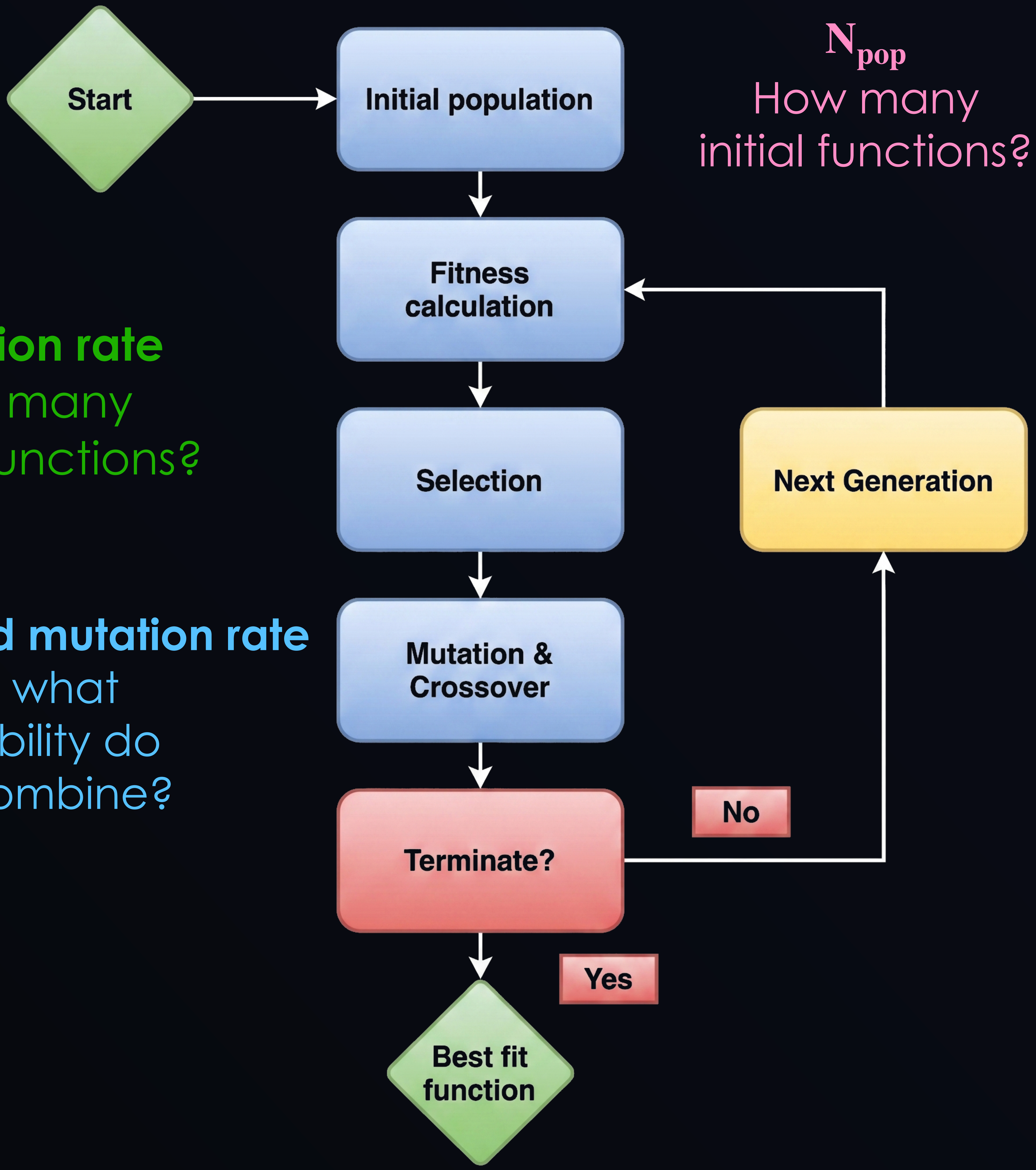
contact

matteo.peronaci@uniroma1.it

Backup slides

Genetic Algorithms hyperparameters

random seed



N_{pop}
How many initial functions?

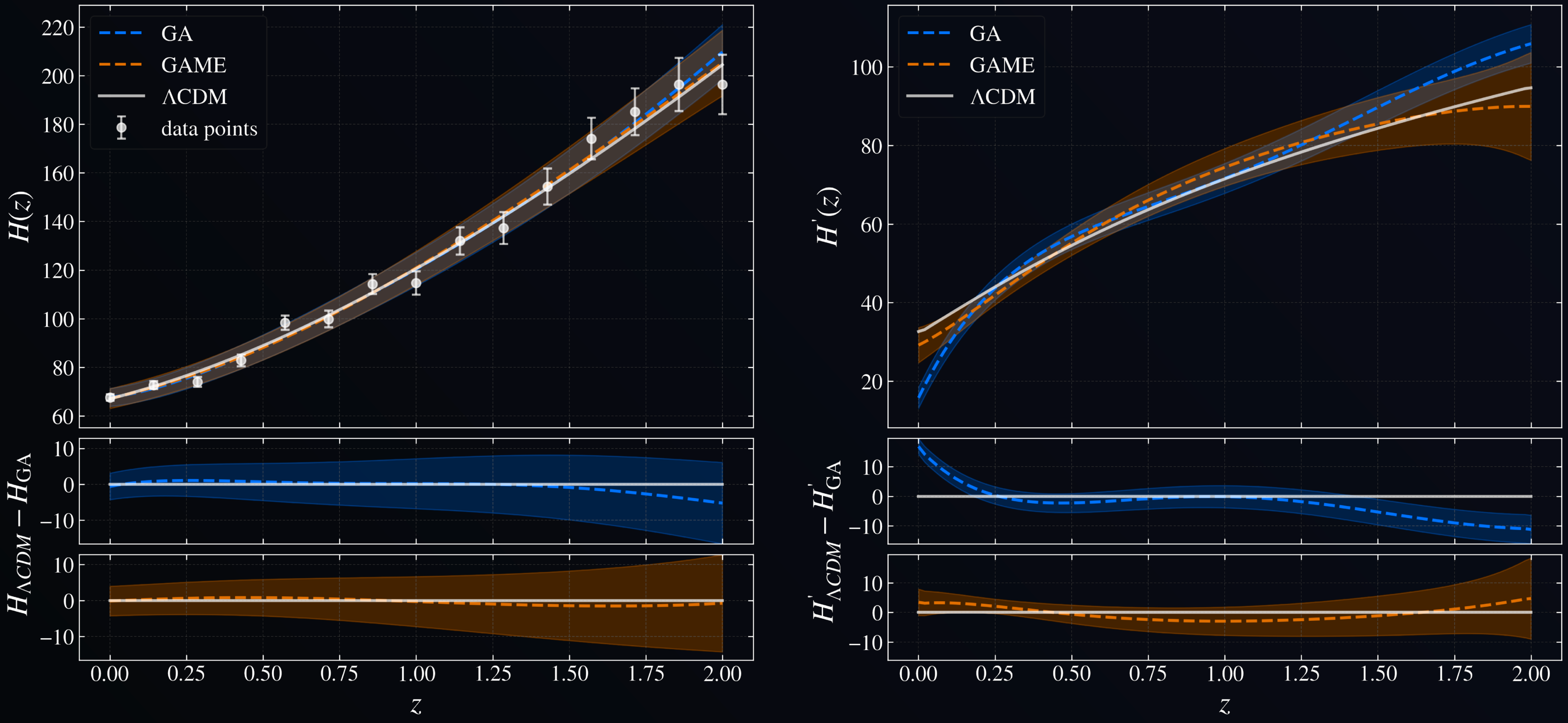
selection rate
How many "best" functions?

crossover and mutation rate
With what probability do they combine?

N_{gen}
How many generations?

GAME consistency test with mock data

Reconstruction of $H(z)$ from mock data



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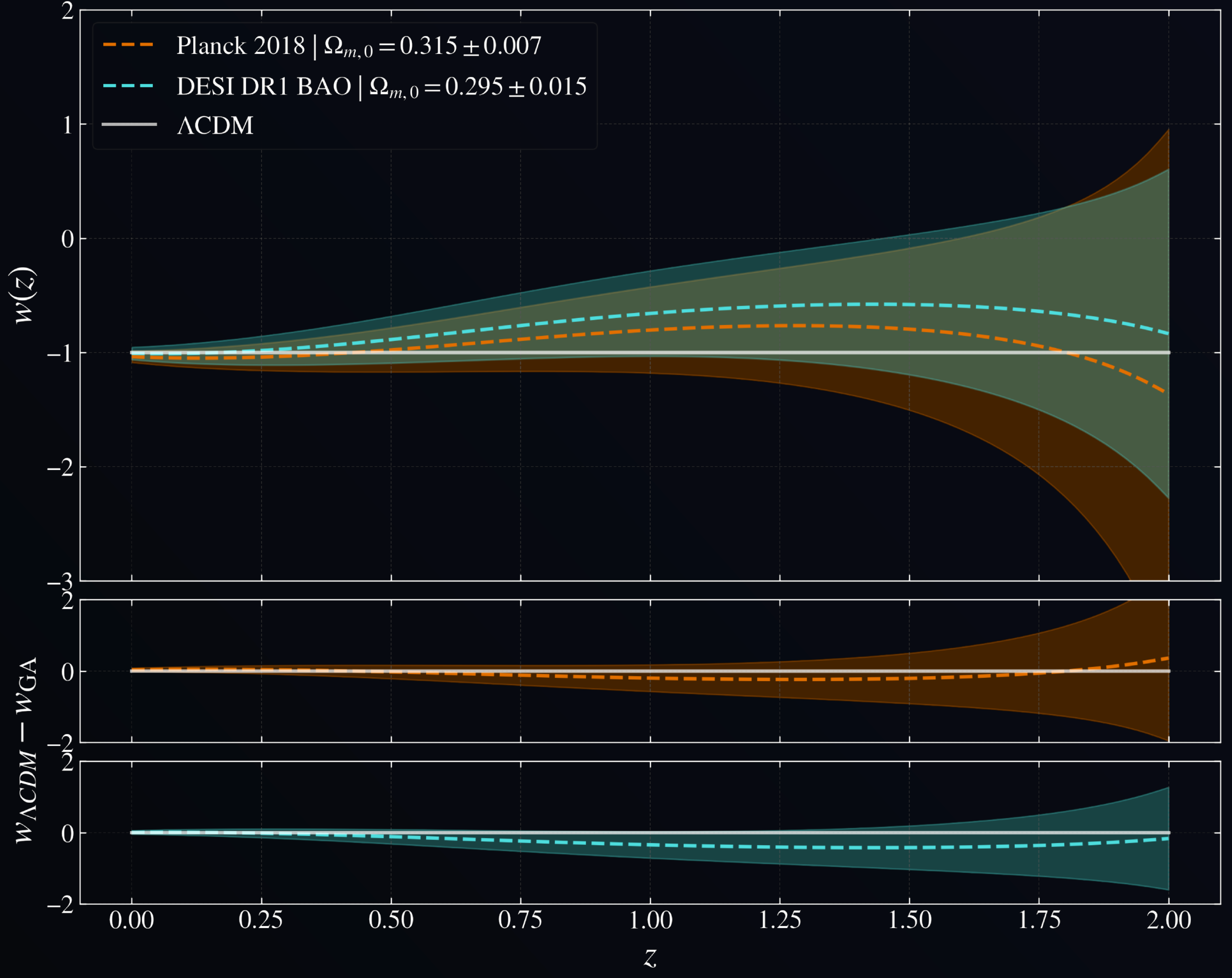
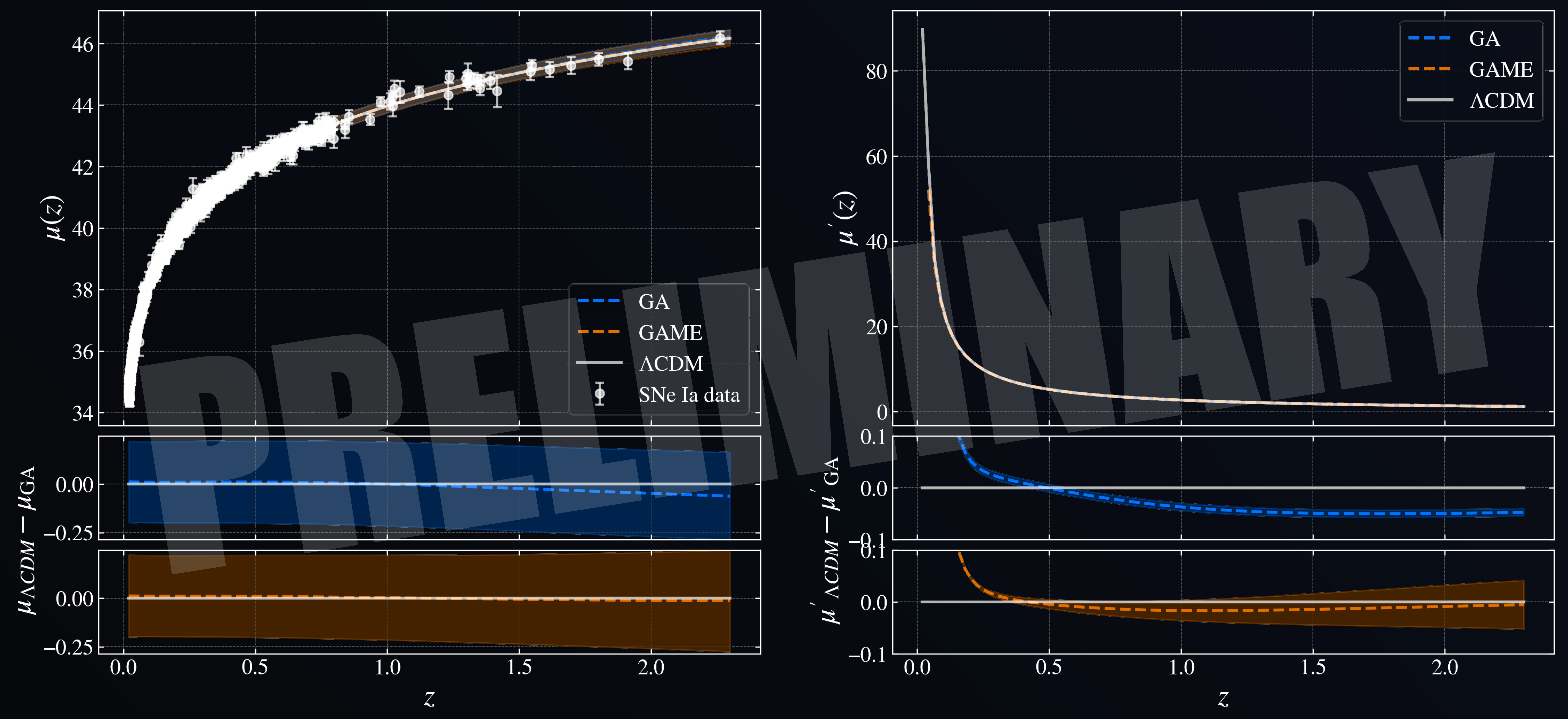


Reconstruction of $\mu(z)$ from SNe Ia



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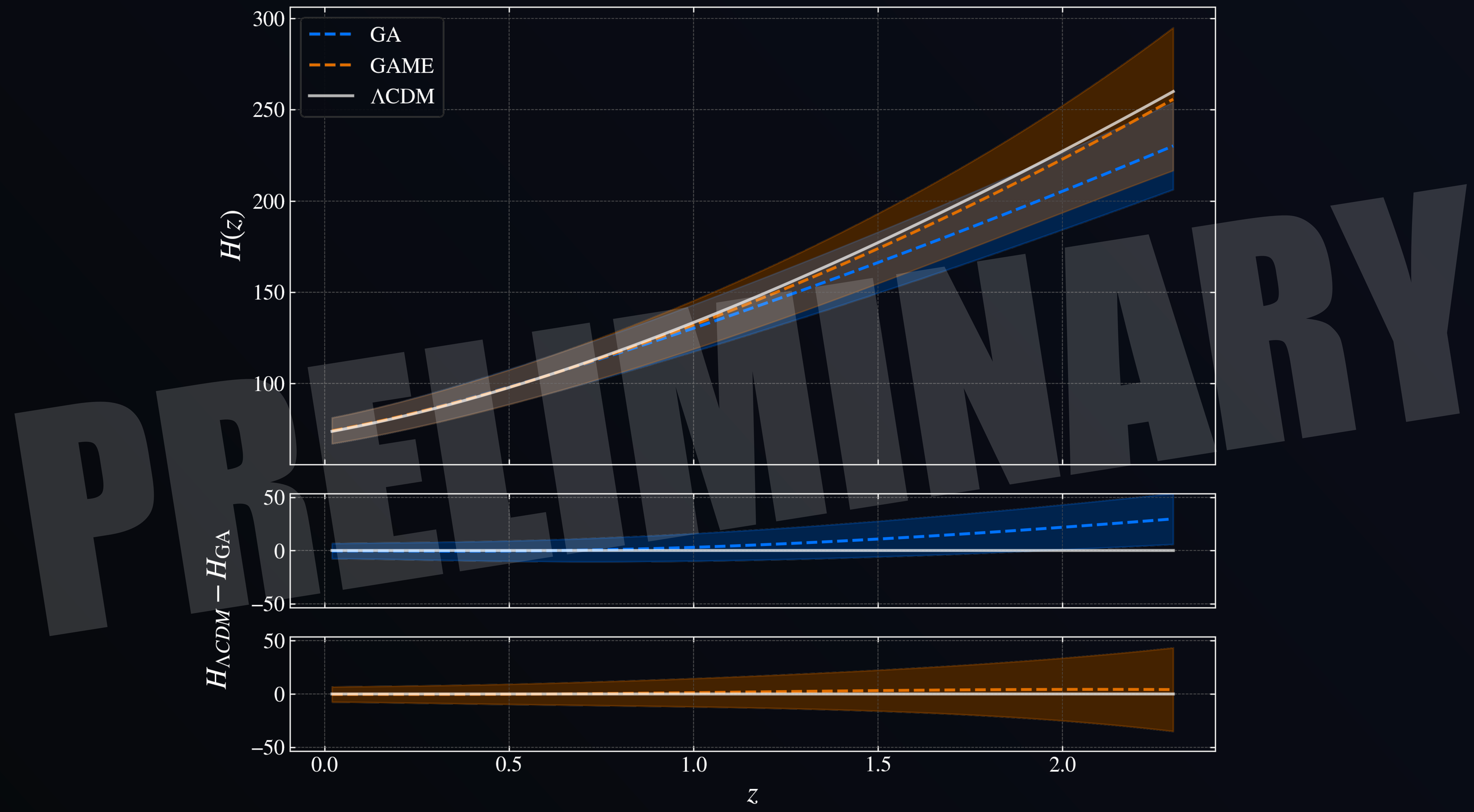
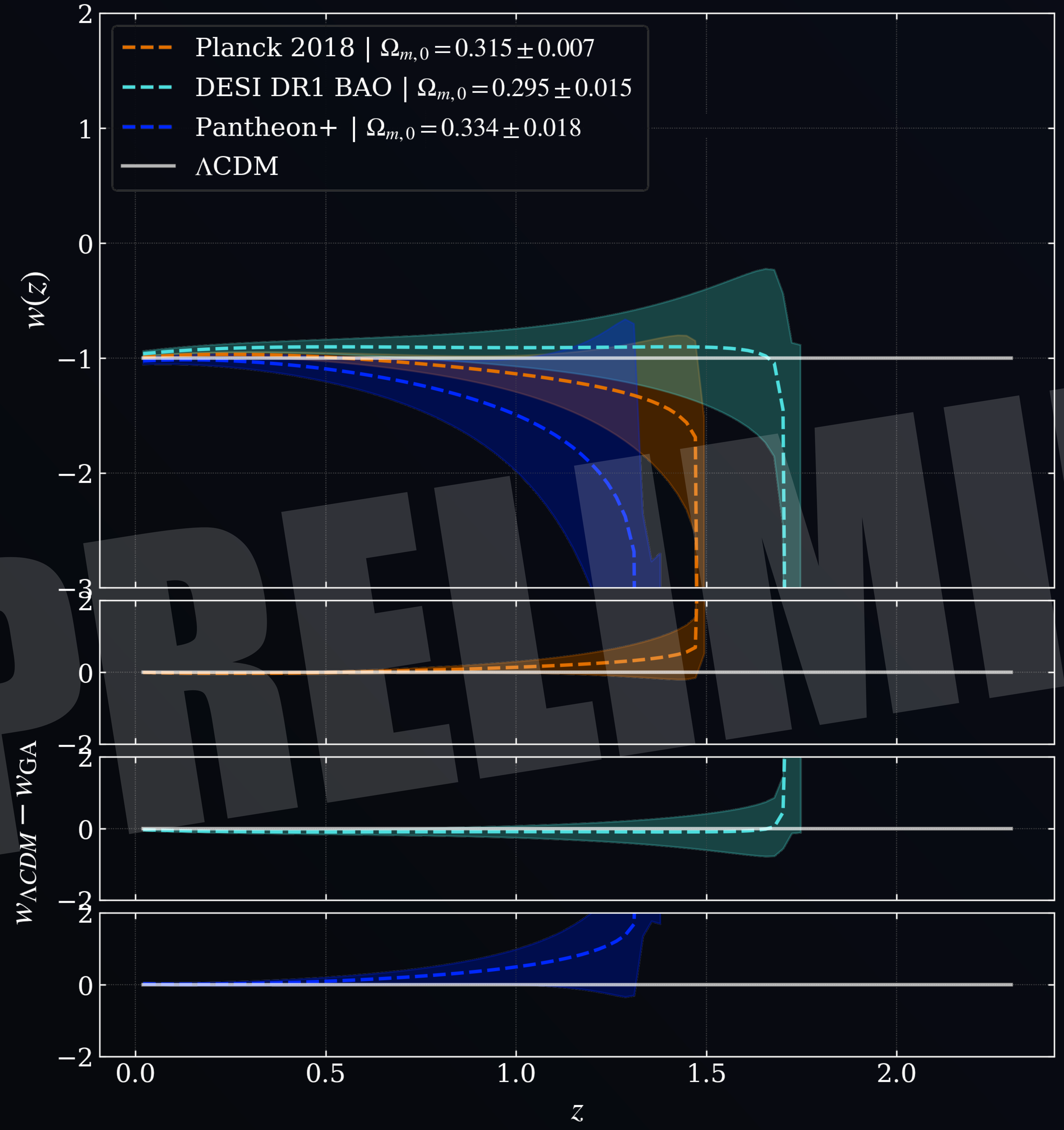


Reconstruction of $w_{\mathrm{bg}}(z)$ from SNe Ia

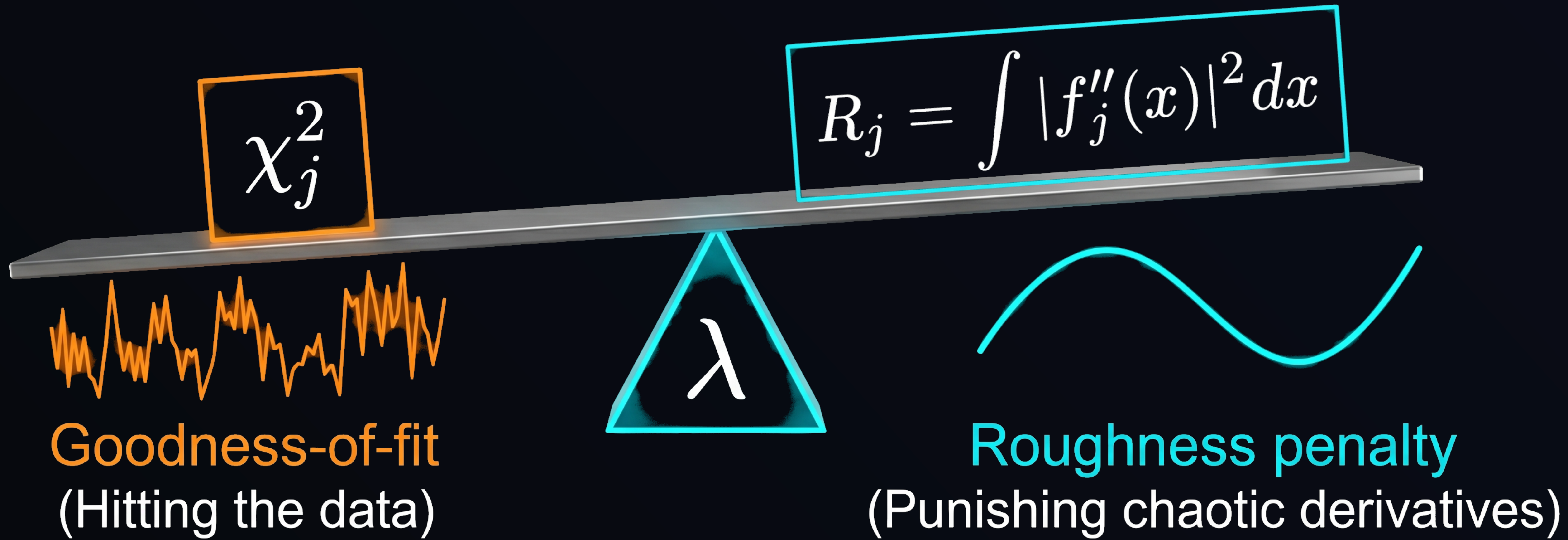


$$w(0.02) = -0.995 \pm 0.024$$

Perfectly compatible with ΛCDM using current SNe Ia data

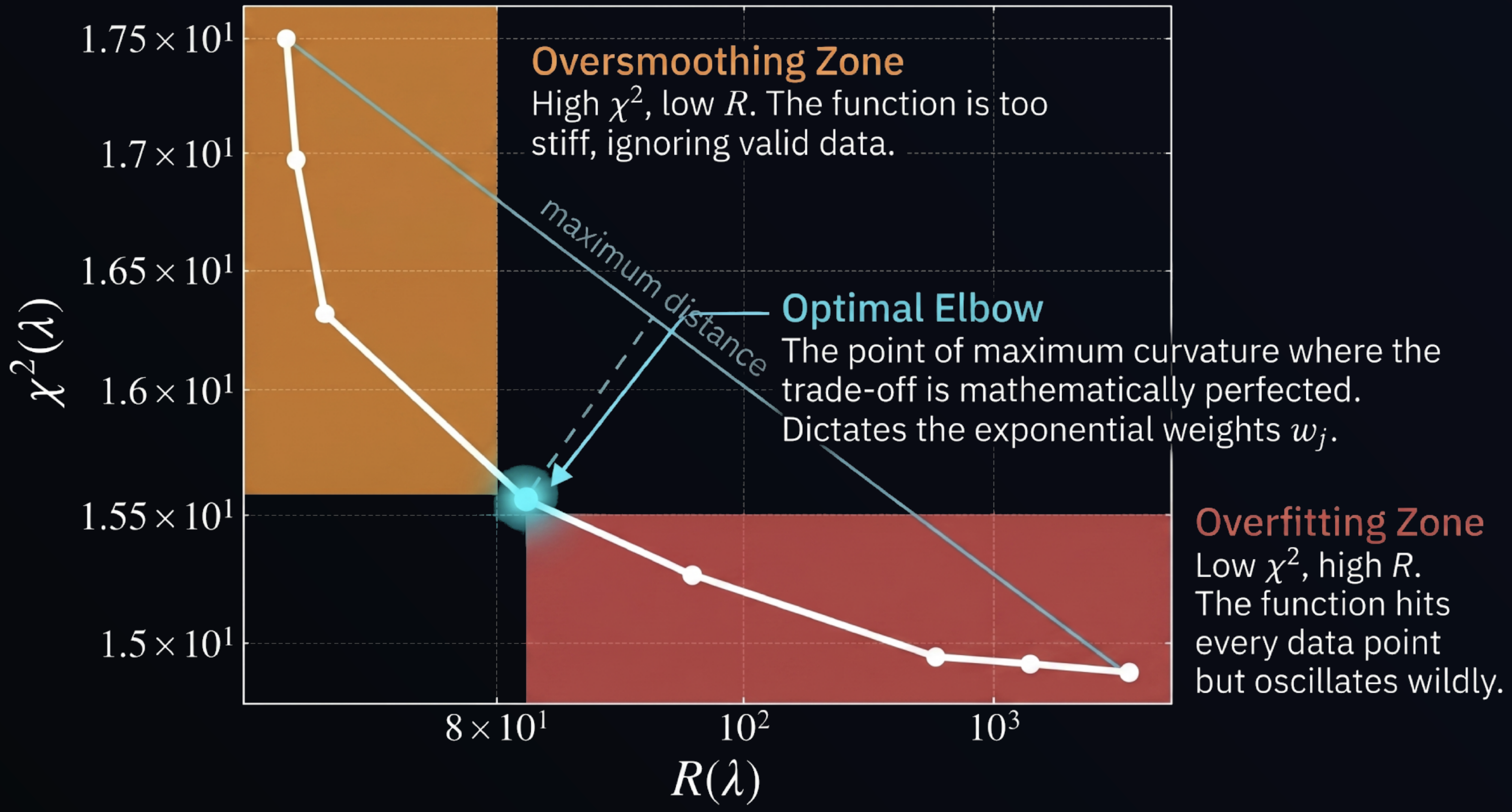
Elbow point estimation for λ

$$S_j = \chi_j^2 + \lambda R_j$$

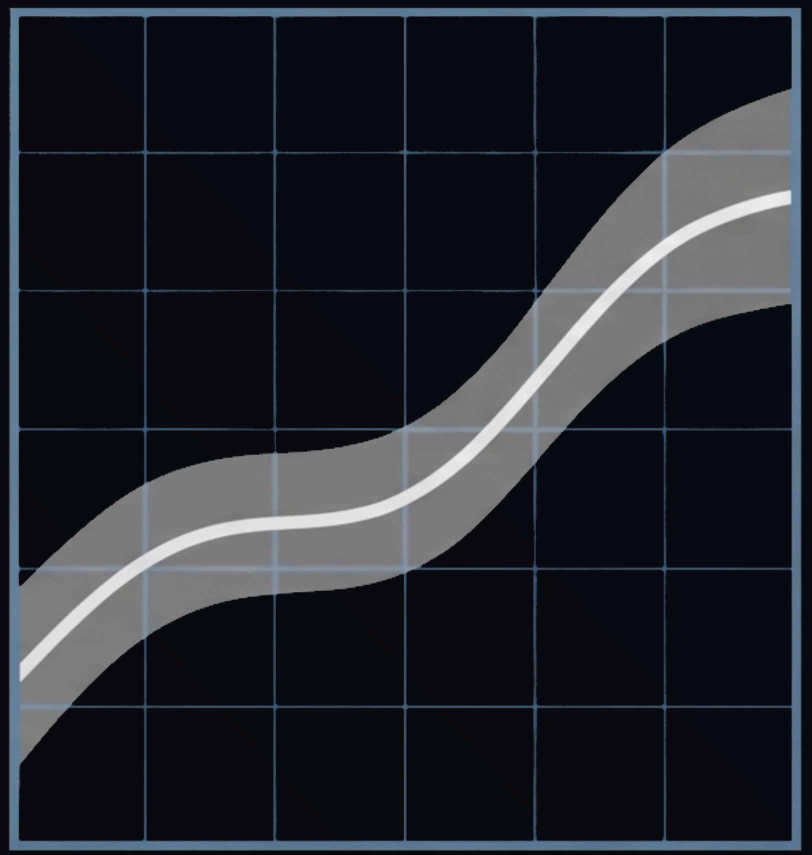


By replacing pure χ^2 with S_j, the algorithm stops chasing random noise and starts hunting for the true, smooth underlying physical model.

Elbow point estimation for λ



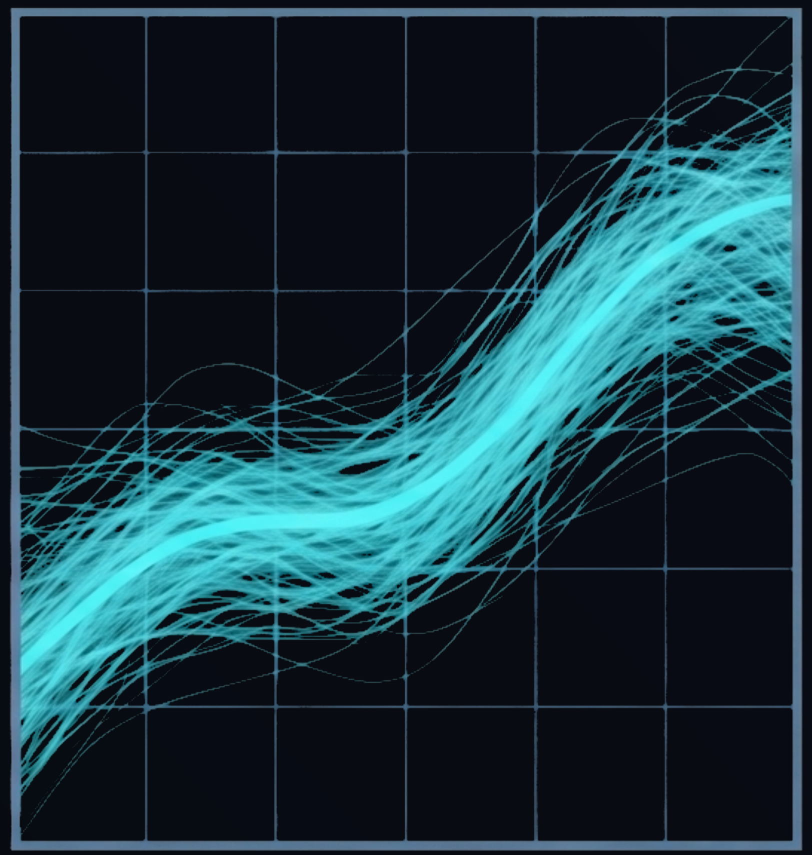
Uncertainties estimation



δf_{PI}

Statistical Uncertainty. Computed via Path-Integral, representing standard measurement noise.

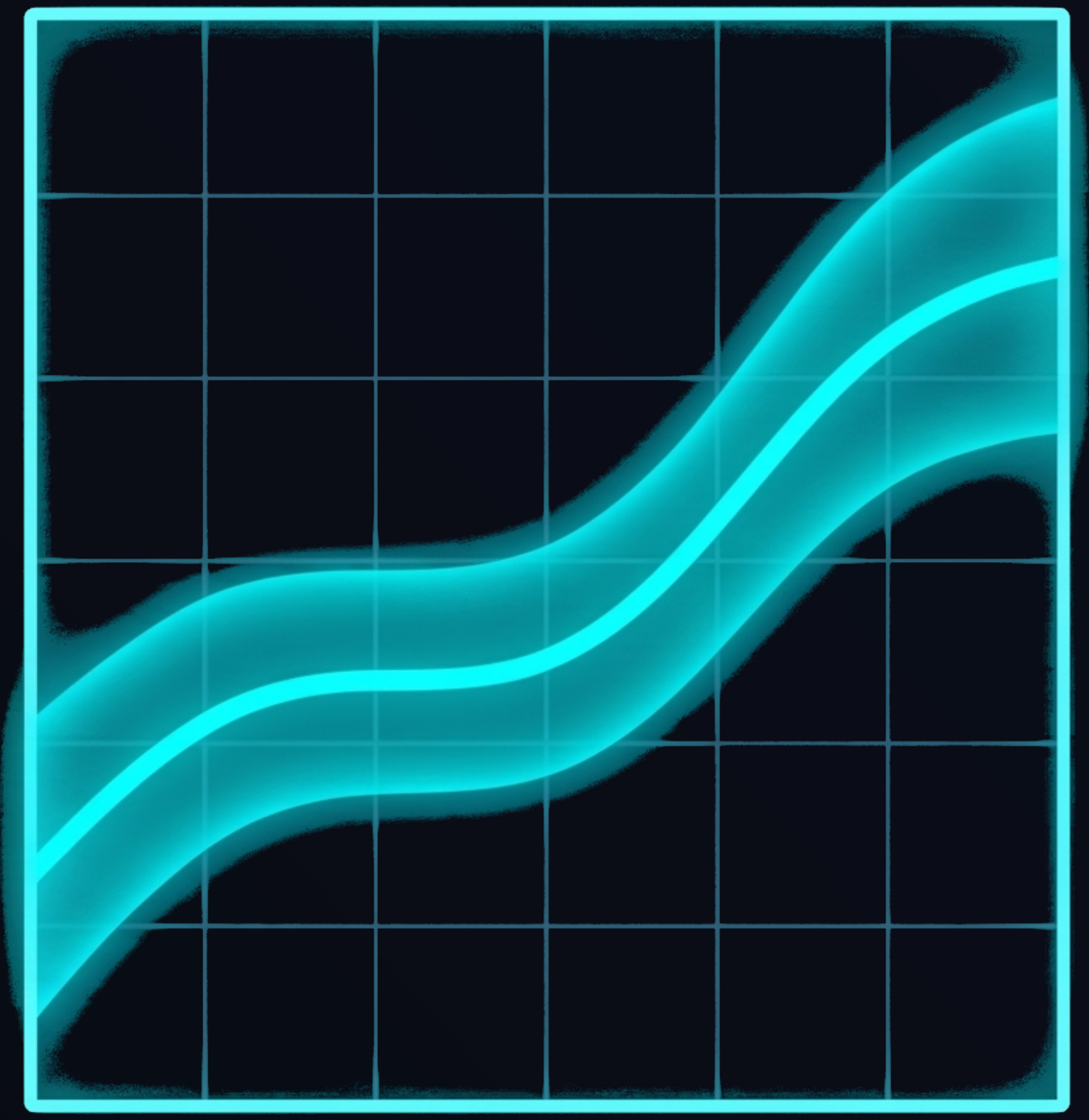
$\oplus$



σ_{ens}

Configuration Uncertainty. The weighted variance across the algorithmic ensemble.

$=$



σ_{tot}

Total GAME Confidence.

$$\sigma_{tot}^2 = \delta f_{PI}^2 + \sigma_{ens}^2$$