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Exploring the 3HDM

with Dark Matter and Machine Learning

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Introduction

- Standard Model
  - Elementary particles
  - Interactions
- Higgs Field
  - Discovered in 2012
  - Explains particle masses
- Multi-Higgs
  - Found one, are there more?

$$SU(3)_c \times SU(2)_L \times U(1)_Y$$

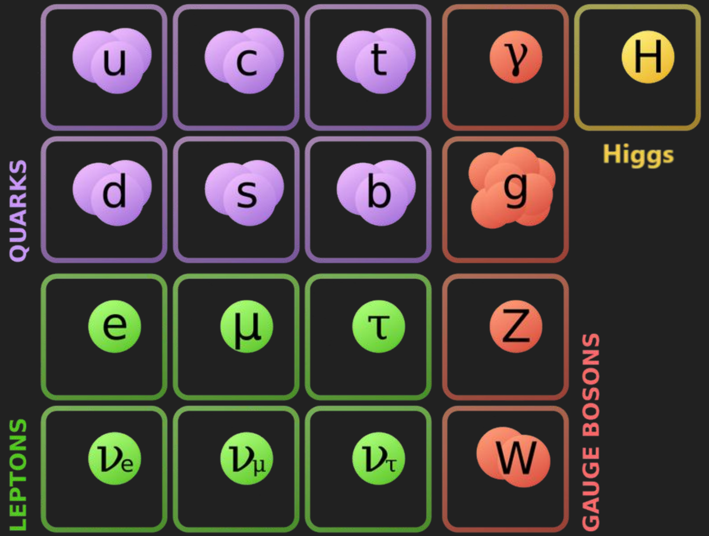


Fig 1: SM Gauge group and particle content.

Introduction

- Dark Matter
  - Galaxy rotation curves
  - Structure formation
  - CMB power spectrum
  - E.g. Bullet Cluster

- Only interacts through gravity?
- What is it made of?

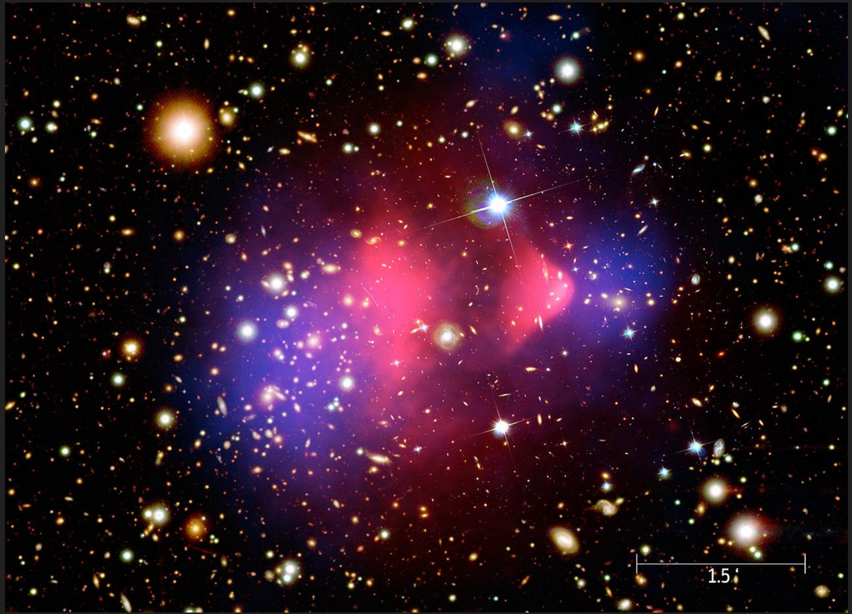


Fig 2: Bullet Cluster. X-Ray, visible and Grav. Lensing.
Chandra X-Ray Observatory: 1E 0657-56

Introduction

- Boltzmann Equation

$$\Gamma = \sigma v n \lesssim H \ \text{(decoupled)}$$

$$\dot{n}(t) + 3H(t)n(t) = -\langle \sigma v \rangle (n(t)^2 - n_{eq}(t)^2)$$

$$Y \equiv \frac{n}{s} \quad \text{and} \quad x \equiv \frac{m_\chi}{T}$$

$$\frac{dY}{dx} = -Z(x)\left[Y^2(x) - Y_{eq}^2(x)\right]$$

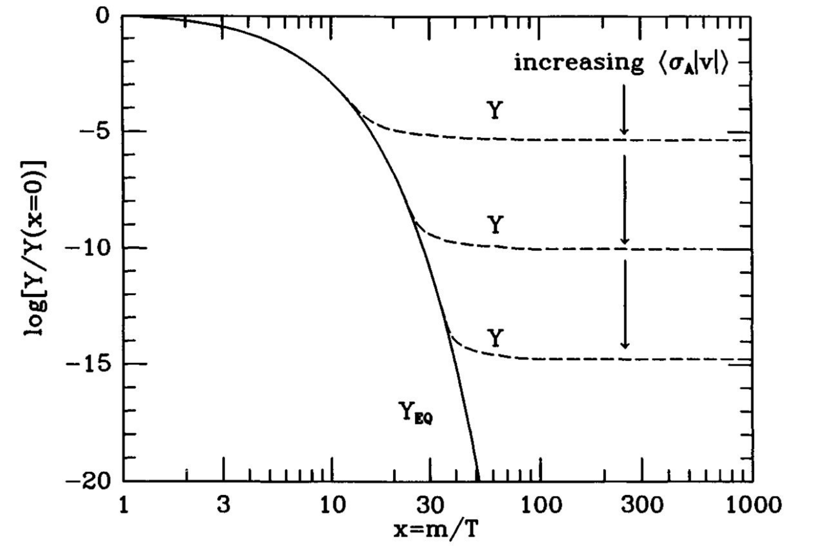


Fig 3: Freeze-out of massive particle.

Inert (2+1) Doublet Model

R. Boto, P. Figueiredo et al,
JHEP 2024, 108 (2024)

$$V = \sum_{i=1}^{3} m_i^2 (\phi_i^\dagger \phi_i) + \sum_{i=1}^{3} \lambda_i (\phi_i^\dagger \phi_i)^2 + \sum_{i<j} \lambda_{ij} (\phi_i^\dagger \phi_i)(\phi_j^\dagger \phi_j)$$
$$+ \sum_{i<j} \lambda'_{ij} (\phi_i^\dagger \phi_j)(\phi_j^\dagger \phi_i) + \sum_{i<j} \left[\lambda''_{ij} (\phi_i^\dagger \phi_j)^2 + \text{h.c.}\right]$$

$$\mathcal{Z}_2 : \quad \phi_1 \to -\phi_1, \quad \phi_2 \to \phi_2, \quad \phi_3 \to \phi_3$$
$$\mathcal{Z}'_2 : \quad \phi_1 \to \phi_1, \quad \phi_2 \to -\phi_2, \quad \phi_3 \to \phi_3$$

$$\phi_j = \begin{pmatrix} H_j^+ \\ \frac{1}{\sqrt{2}}(H_j + iA_j) \end{pmatrix}, \qquad \phi_3 = \begin{pmatrix} G^+ \\ \frac{1}{\sqrt{2}}(v + h + iG^0) \end{pmatrix}$$

Inert (2+1) Doublet Model

- Studied the I(2+1)DM, a DM 3HDM
- Published new results JHEP 2024, 108 (2024)
  - New vacua
  - Complete parameter space analysis
  - Equal contribution of DM candidates

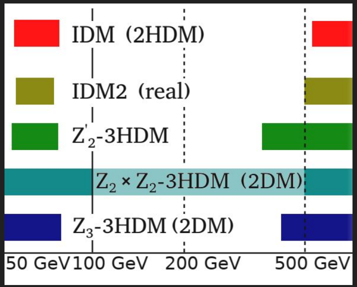


Fig 4: Allowed DM mass range for some MHDM.

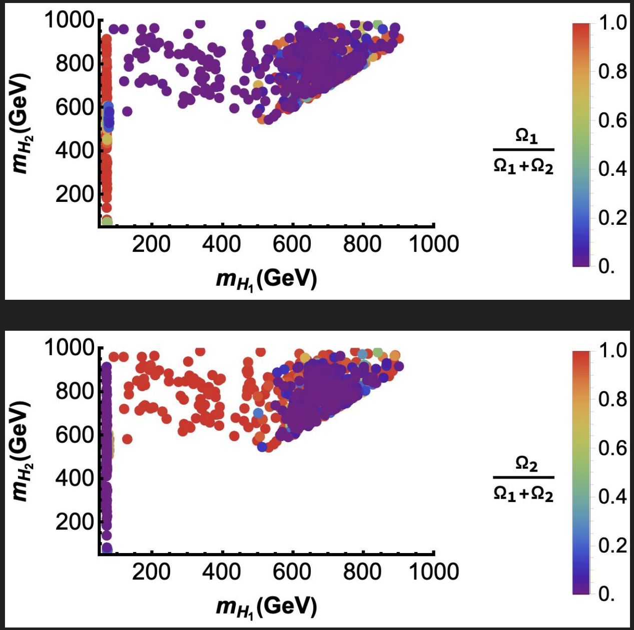


Fig 5: Allowed DM mass range with color code for relic ratio of both components.

Machine Learning

J.C. Romão and M.C. Romão
PRD 109(9):095040, 2024

- Evolutionary Strategy
  - CMAES
  - Localized Multivariate Gaussian
  - Limited exploration!
- Novelty Detection
  - HBOS Density Estimation
  - Add Penalties
  - Incentivises exploration!

$$C(\mathcal{O}) = \max(0, -\mathcal{O} + \mathcal{O}_{LB}, \mathcal{O} - \mathcal{O}_{UB})$$

$$L(\theta) = \sum_{i=1}^{N_c} C(\mathcal{O}_i(\theta))$$

$$L_T(\theta) = \tilde{L}(\theta) + \frac{1}{N_p}\sum_{i=1}^{N_p} p_i$$

$$\sum_i C(\mathcal{O}_i) = 0 \Rightarrow L_T \in [0, 1]$$

Machine Learning

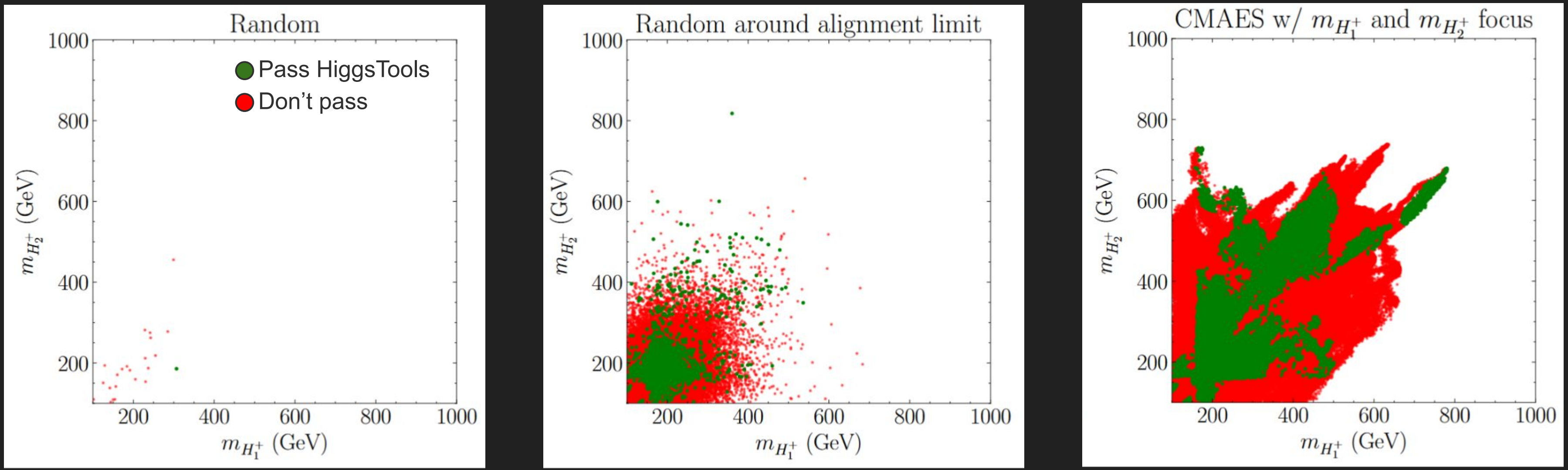
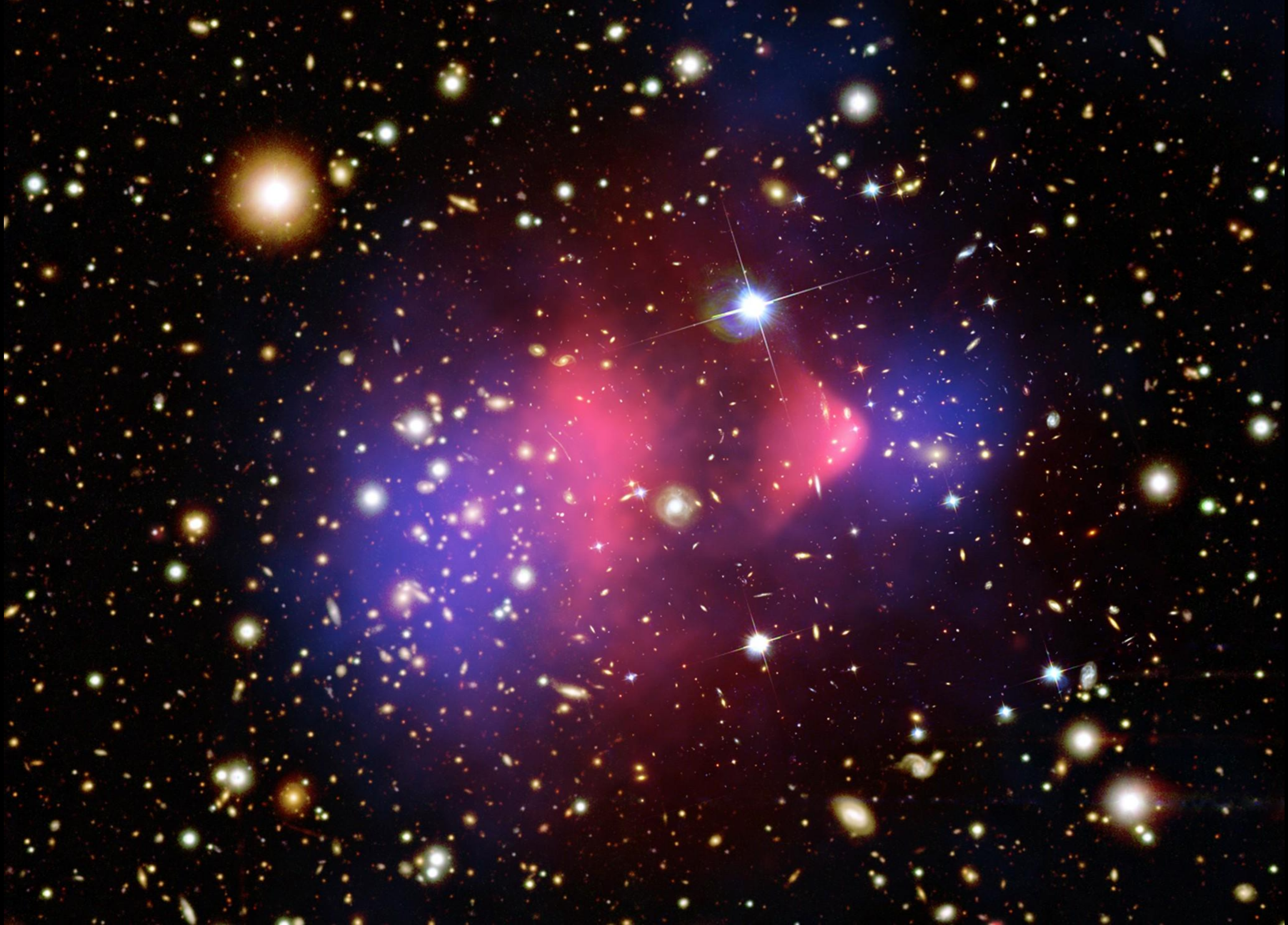


Fig 6: From left to right: runs on the charged scalar mass plane for a random scan with and without imposing alignment, and a CMAES with novelty reward scan.

Will be used for future analysis!



CMAES

- Covariant Matrix Adaptation Evolutionary Strategy

- Generates gaussian point distribution
- Keeps best points that minimize the Loss function
- Calculates new Mean and Covariance Matrix without derivatives

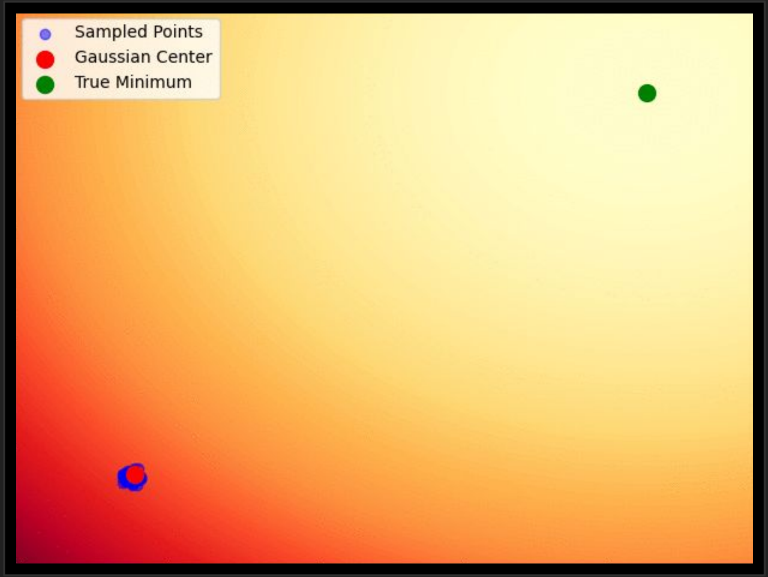


Fig E: CMAES converging to function minimum.

HBOS

- Histogram Based Outlier Score

- Fits Histogram with N bins for each dimension (parameter)
- Sums height of bins
- Penalties are normalized
  - New point score ➡ ~ 0
  - Similar point ➡ ~ 1

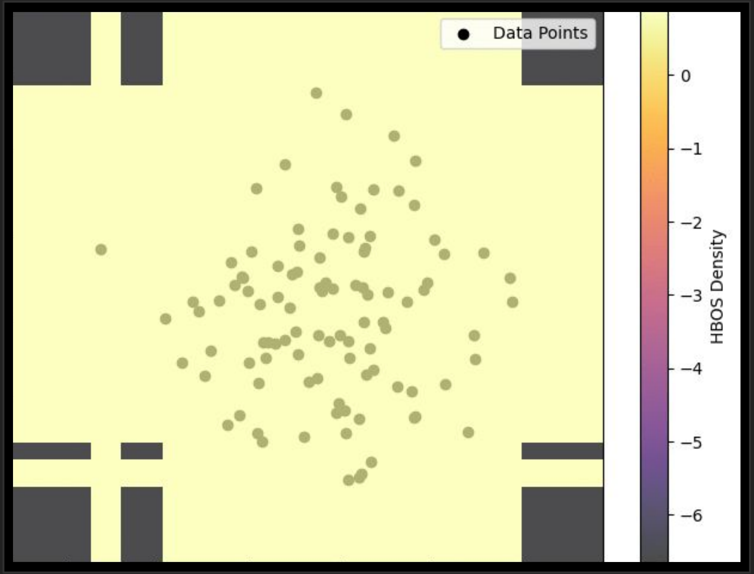


Fig F: Density estimation by HBOS.