Application of Machine Learning in HEP-PH

Kun WANG, Jingya ZHU (Wuhan University)

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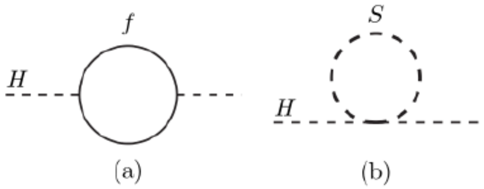
Outline

- Why Supersymmetry ?
- Our new method Heuristically Search and GAN
- Light dark matter and Higgs invisible decay
- Summary

Background: Why Supersymmetry?

- The SM is facing many problems:
  - Fine-turning



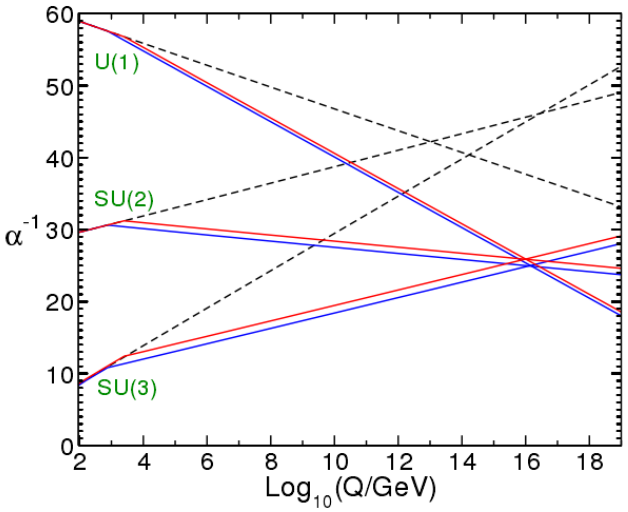
Martin, arXiv:9709356

  - Gauge couplings can't be unified at GUT scale
  - No dark matter candidate

- How SUSY solve these problems:
  - Introduced a new symmetry

$$\Delta m^2_{H(a)} = \boxed{-\frac{|\lambda_f|^2}{8\pi^2}\Lambda^2_{\rm UV}} + \dots$$

$$\Delta m^2_{H(b)} = \boxed{\frac{\lambda_S}{16\pi^2}\left[\Lambda^2_{\rm UV}\right.} - 2m_S^2\ln(\Lambda_{\rm UV}/m_S) + \dots\Big]$$



  - Lightest Supersymmetric Particle (LSP) can be dark matter candidate, because of R-parity.

Model: The semi-constrained NMSSM

- The superpotential of NMSSM:

$$W_{\mathrm{NMSSM}} = y_u \hat{Q} \cdot \hat{H}_u \hat{u}^c + y_d \hat{Q} \cdot \hat{H}_d \hat{d}^c + y_u \hat{L} \cdot \hat{H}_d \hat{e}^c + \lambda \hat{S} \hat{H}_u \cdot \hat{H}_d + \frac{\kappa}{3} \hat{S}^3$$

- The effective μ-term

$$\mu_{\mathrm{eff}} = \lambda v_s$$

- The soft term

$$-\mathcal{L}^{\mathrm{soft}}_{\mathrm{NMSSM}} = -\mathcal{L}^{\mathrm{soft}}_{\mathrm{MSSM}}|_{\mu=0} + m_S^2 |S|^2 + \lambda A_\lambda S H_u \cdot H_d + \frac{1}{3} \kappa A_\kappa S^3 + \mathrm{h.c.}$$

Model: The semi-constrained NMSSM

- The Higgs sector are considered non-universal, the Higgs soft mass and trilinear couplings are allowed to be different at GUT scale.
- Other trilinear couplings, gaugino, and scalar mass are unified at GUT scale

$$M_1 = M_2 = M_3 \equiv M_{1/2},$$
$$M^2_{\tilde{q}_i} = M^2_{\tilde{u}_i} = M^2_{\tilde{d}_i} = M^2_{\tilde{l}_i} = M^2_{\tilde{e}_i} \equiv M^2_0,$$
$$A_t = A_b = A_\tau \equiv A_0.$$

- Hence, in the scNMSSM, the complete parameter sector is

$$\lambda,\ \kappa,\ \tan\beta = \frac{v_u}{v_d},\ \mu,\ A_\lambda,\ A_\kappa,\ A_0,\ M_{1/2},\ M_0$$

Method: Scan the parameter space

From 9 parameters to observables

- Traditional ways:
  - Random
  - MCMC(Markov Chain Monte Carlo)
- New ways:
  - Machine learning (arXiv: 1708.06615, 1905.06047, 1906.03277)

    Classier: discriminate between physical and non-physical regions

    Regressor: fit various physical observables
  - The Heuristically Search and GAN (our new method, arXiv: 2002.05554)

    HS: shift some ‘not so good’ samples to ‘good’ samples

    GAN: generate samples with the similar distribution as the training samples

Method: The Heuristically Search

- Three types of samples

	Type 1	Type 2	Type 3
The basic constraints	$\times$	$\checkmark$	$\checkmark$
The dark matter and muon g$-$2 constraints	—	$\times$	$\checkmark$
	bad samples	marginal samples	perfect samples
Score	None	>0	$=0$

- Score function: how much they violate the constraints

$$f(\mathbf{X}) = \sum_{i=1}^{N} \max\left[1 - \frac{O^i_{\text{Theor.max}}}{O^i_{\text{Exp.min}}}, 0\right] + \max\left[\frac{O^i_{\text{Theor.min}}}{O^i_{\text{Exp.max}}} - 1, 0\right]$$

Basic constraints:

- Theoretical constraints
- Mass bounds from the LEP , LHC
- B physics
- SM-liked Higgs boson
- Higgs can have invisible decay

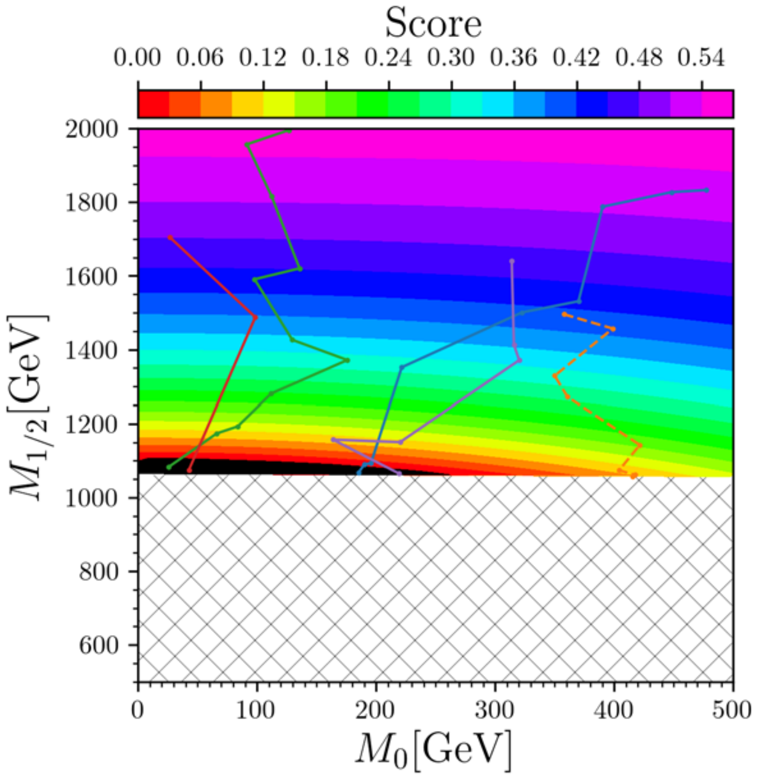
Dark matter and muon g-2 constraints:

- Relic density
- Spin-independent cross section
- Spin-dependent cross section
- Muon g-2

Method: The Heuristically Search

Soiled lines: success
Dashed lines: fail

- With a marginal sample, we search around it and try to find another marginal sample with a smaller score.
- we repeat this process, until we meet a perfect sample whose score is zero, or get failed



$\lambda = 0.278,\ \kappa = -0.0577,\ \tan\beta = 17,$
$\mu = 162\ \mathrm{GeV},\ A_0 = -1924\ \mathrm{GeV},$
$A_\lambda = 2756\ \mathrm{GeV}\ \ A_\kappa = 589\ \mathrm{GeV}$

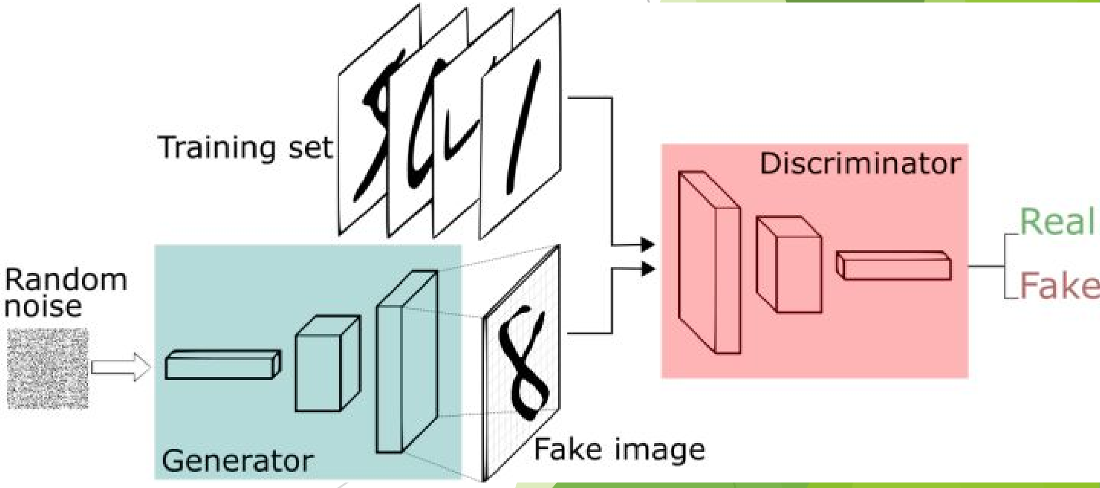
Method: Generative Adversarial Network (GAN)

arXiv:1406.2661

Proposed in 2014 by Ian Goodfellow

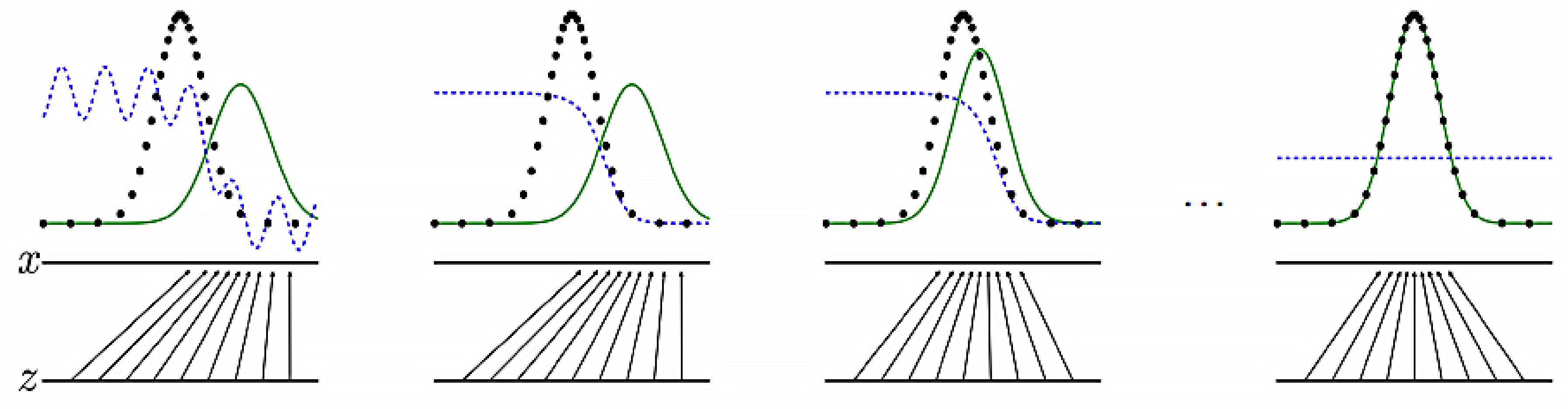
- Two neural networks in GAN:
  - Generator: generate fake samples
  - Discriminator: classify samples into real and fake

- The basic ideas is:
  - G: try to generate almost 'real' samples, fool the D
  - D: try to find out fake samples which are generated by G



Method: Training GAN

Black dotted: real data
Blue line: D
Green line: G



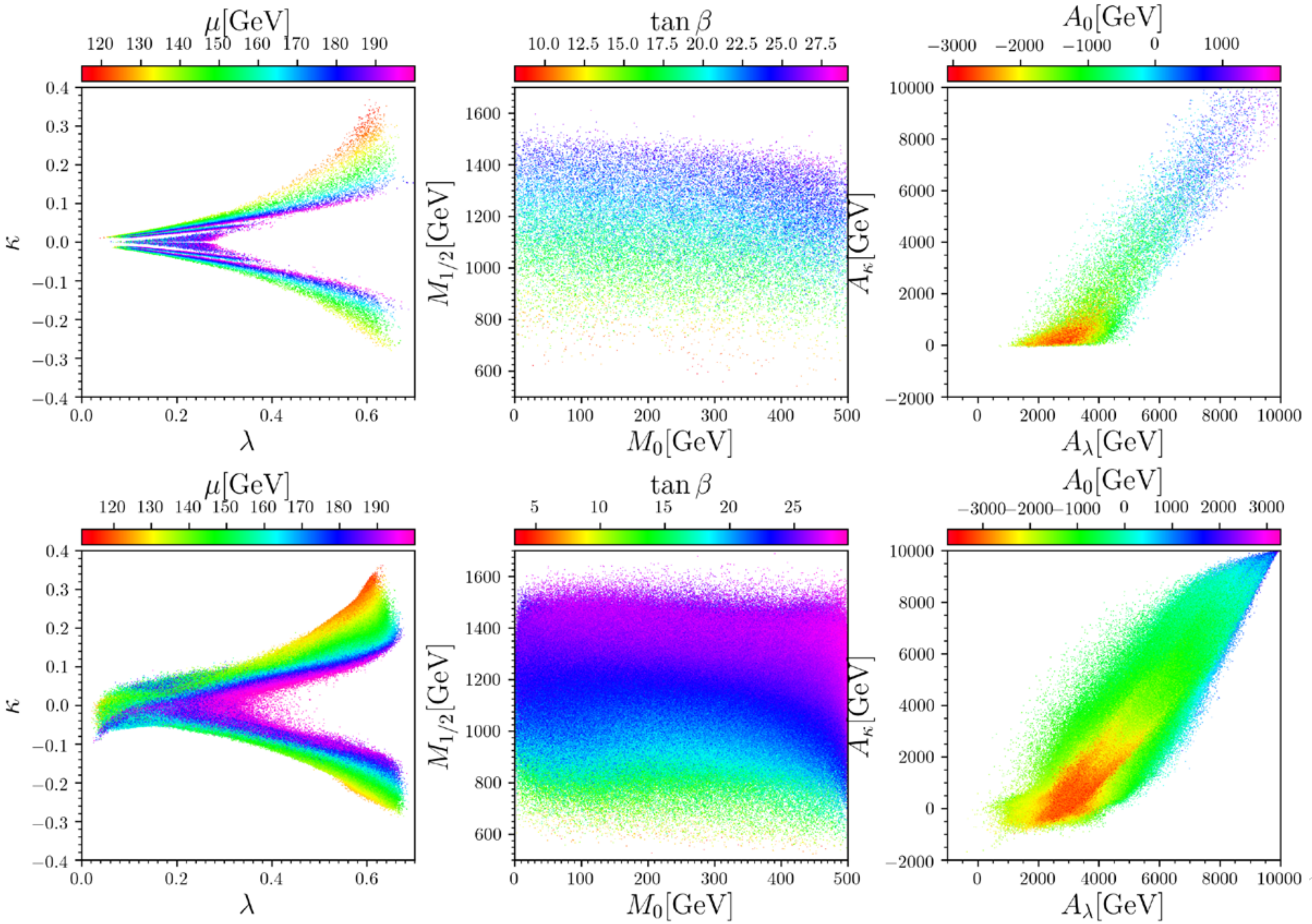
Initial state

- keep G
- optimized D
- until D is well trained

- keep D
- optimized G
- until D cannot distinguish fake and real

Nash equilibrium

Use GAN to recommend samples

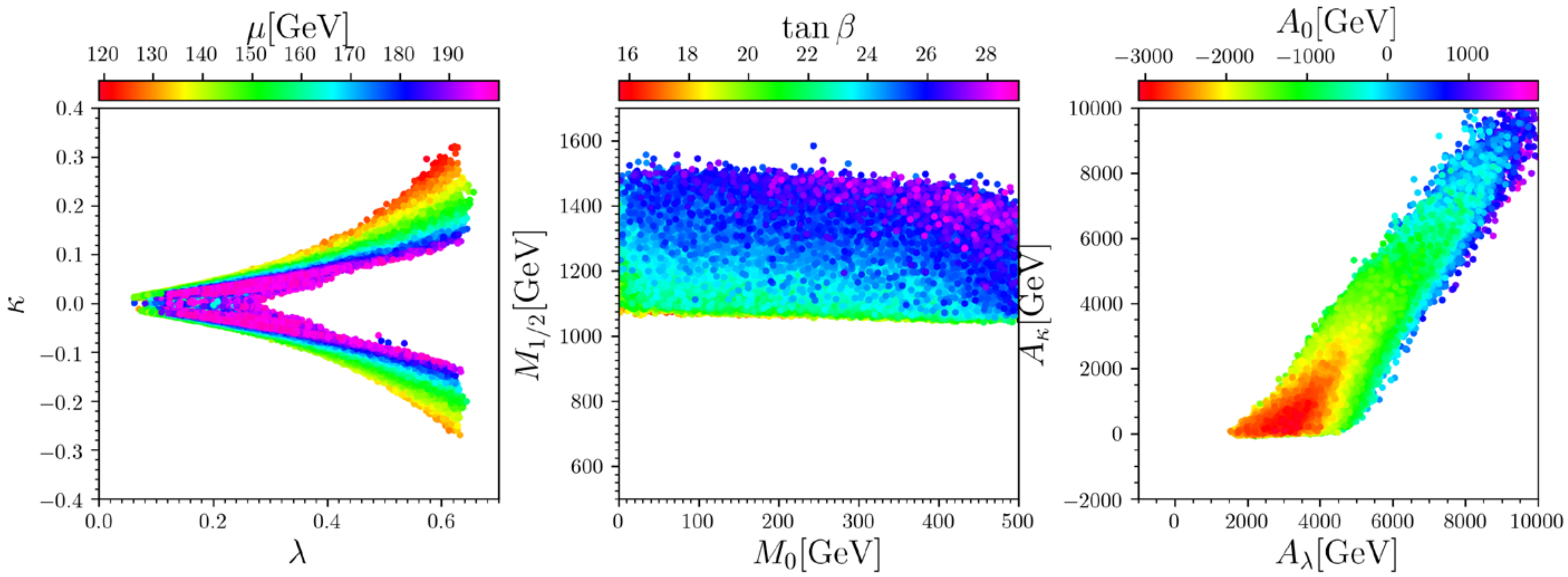


Training data

Generated data from G

millions samples generated in a few seconds

HS after the GAN recommend



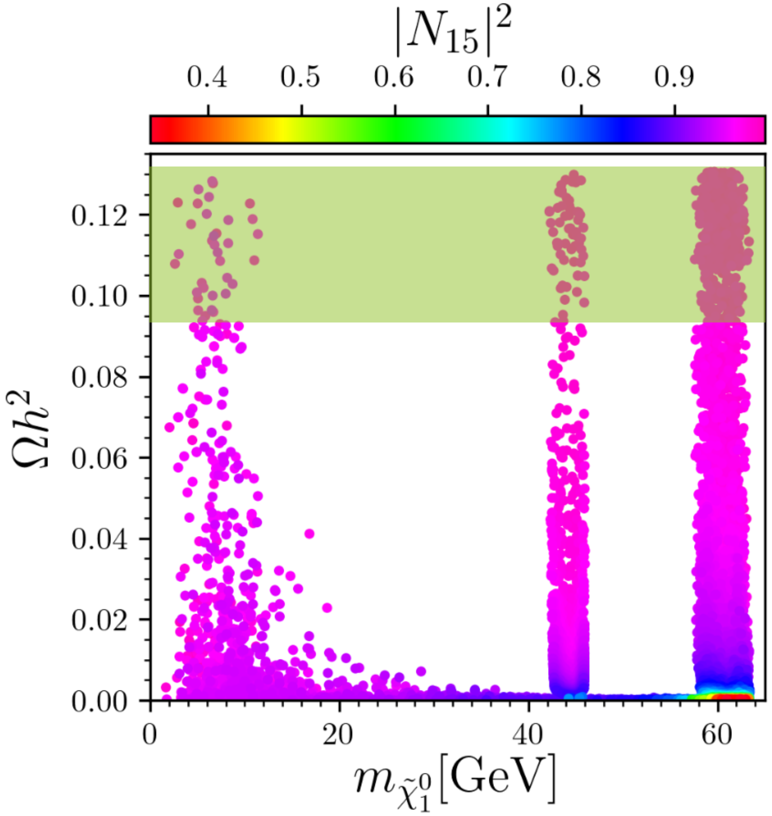
- HS+GAN: 280k samples in 30 hours, much faster than previous
- Previous: 10k samples in 24 hours

Light dark matter

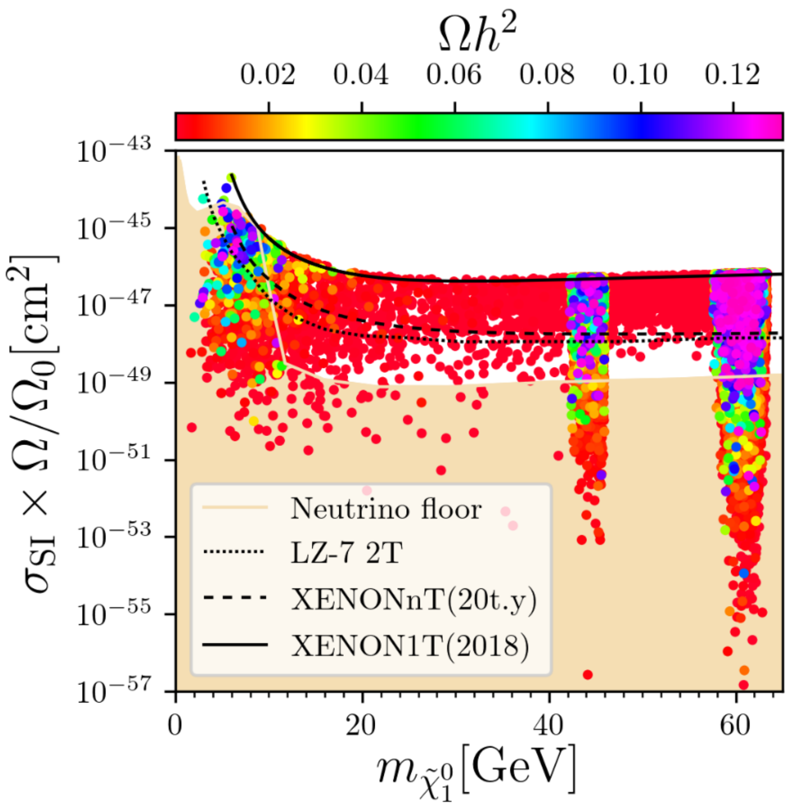
Case I: $m_{\tilde{\chi}_1^0} \simeq m_{h_2}/2$

Case II: $m_{\tilde{\chi}_1^0} \simeq m_Z/2$

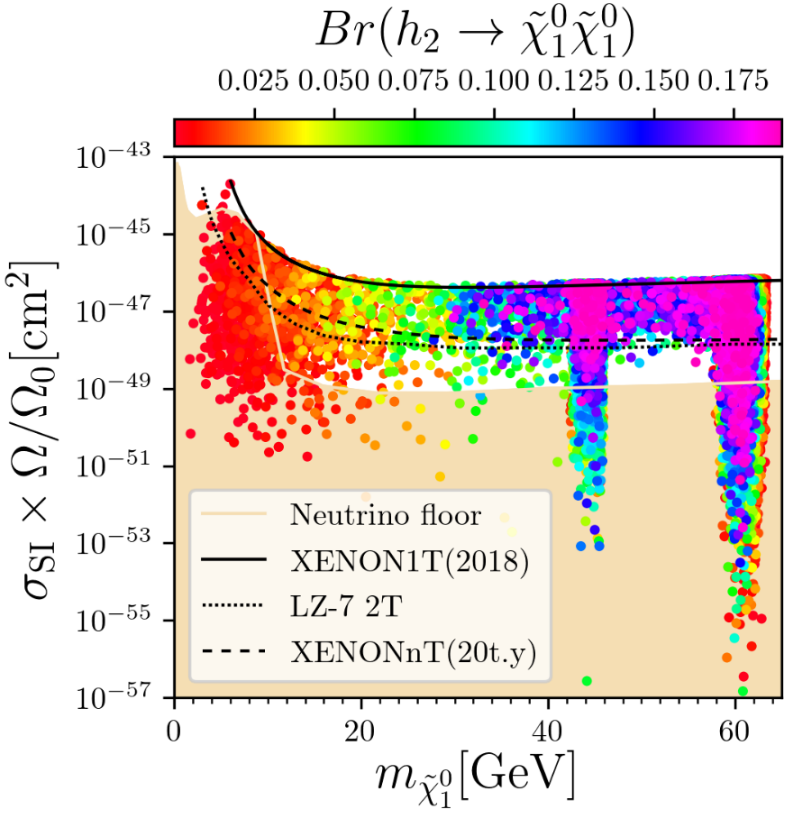
Case III: $m_{\tilde{\chi}_1^0} \lesssim 12$ GeV



Highly singlino dominated

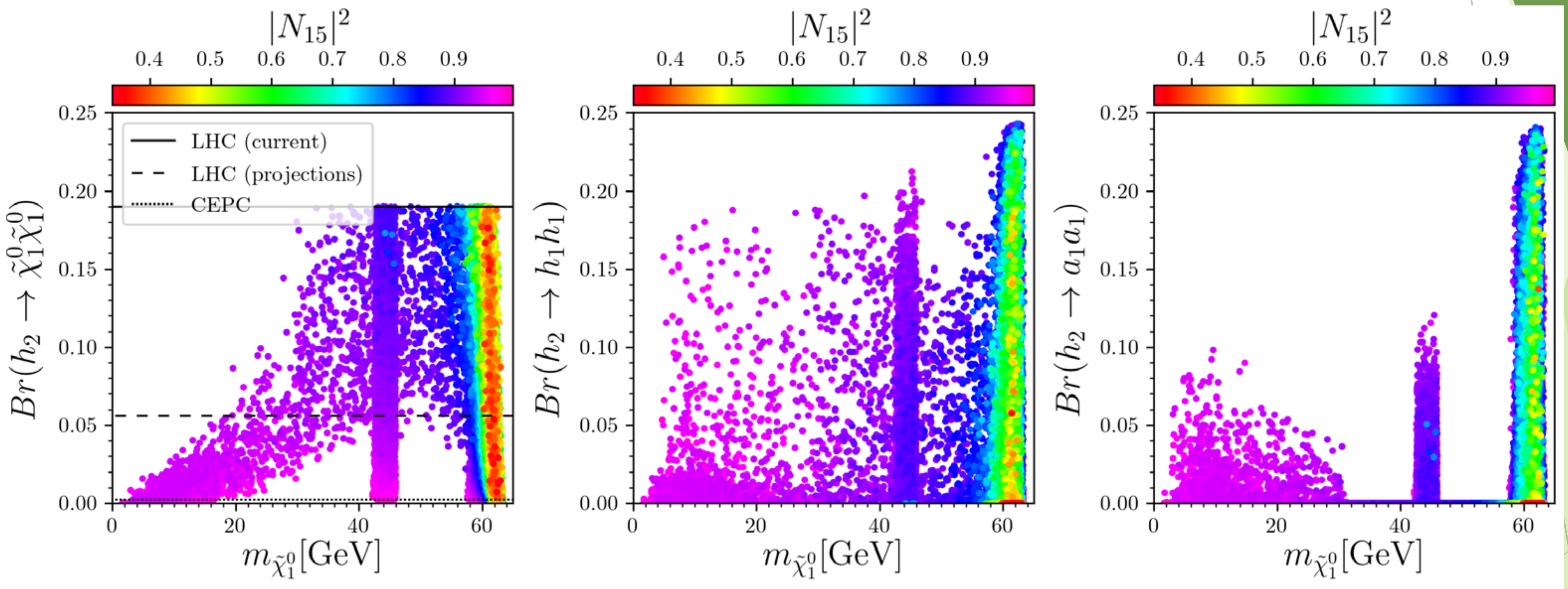


These two future direct detections are crucial to check this model



Higgs can decay to h_1 and a_1, then Higgs invisible decay BR become small

Higgs invisible decay



- Higgs invisible decay at the future HL-LHC may cover half of the samples, and that of the CEPC may cover most

Summary

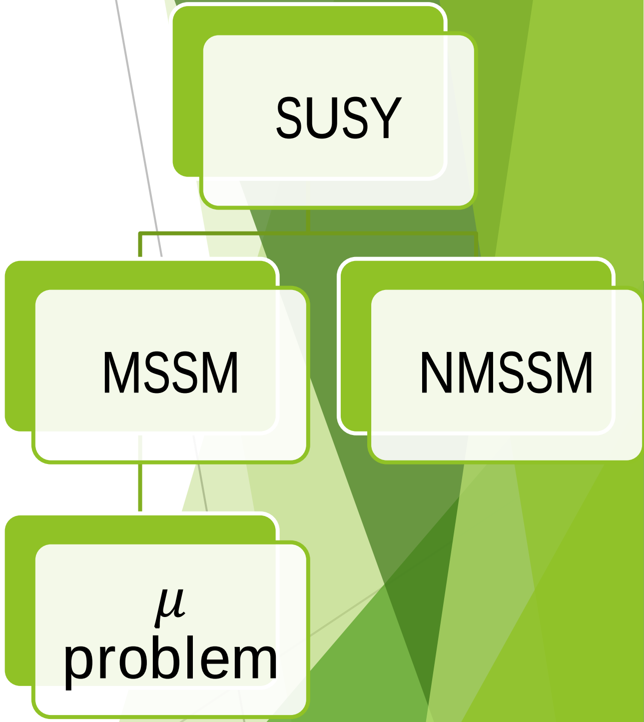
- Our new method HS and GAN can real speed up the scan process.
- In this model, both muon g-2 and right DM relic density can be satisfied, along with the high mass bound of gluino, etc.
- The future direct detections XENONnT and LUX-ZEPLIN (LZ-7 2T) can give strong constraints to this scenario.
- Higgs invisible decay at the future HL-LHC may cover half of the samples, and that of the CEPC may cover most.

Thank you !

BACK UP

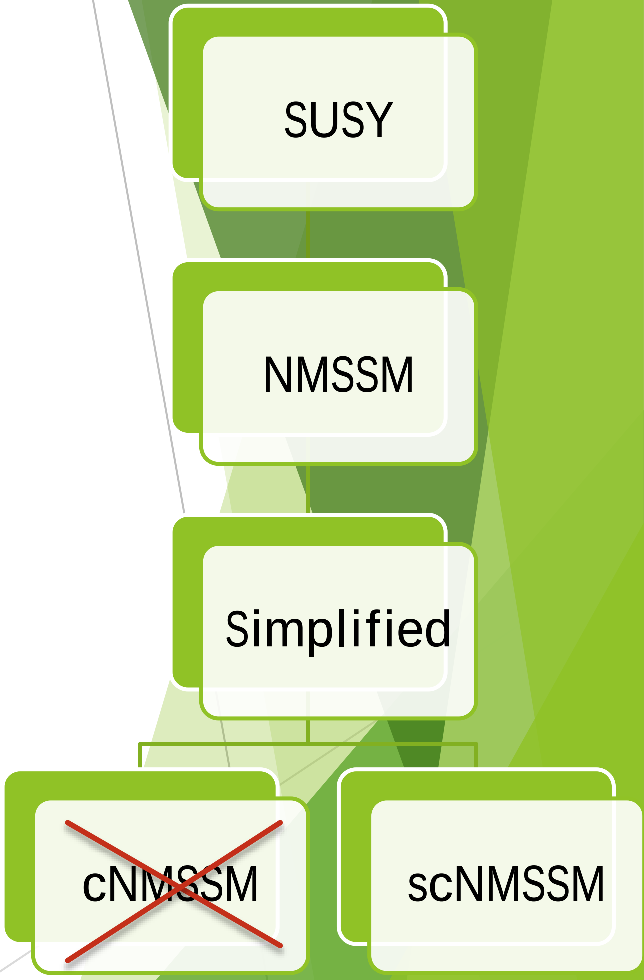
Background: The Next-to Minimal Supersymmetric Standard Model (NMSSM)

- The simplest SUSY Models is Minimal Supersymmetric Standard Model (MSSM)
- There is a so-called μ-problem in MSSM, the μ parameter has mass dimension, can be chosen artificially
- The NMSSM solves it by introducing a complex singlet superfield, dynamically generates an effective μ -term



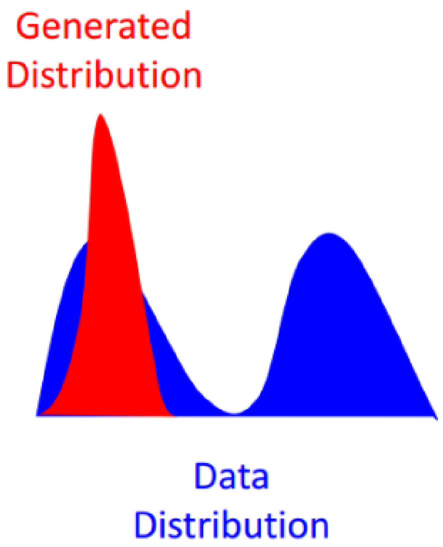
Background: Why the semi-constrained NMSSM

- Too many free parameters in NMSSM
- Fully-constrained NMSSM (cNMSSM): trilinear couplings, gaugino, and scalar mass parameters unify at GUT scale
- But in tension with current experimental constraints including 125 GeV Higgs mass, high mass bound of gluino, muon g-2, and dark matter
- So we consider the scNMSSM that relaxes the unification of scalar masses, NMSSM with non-universal Higgs mass

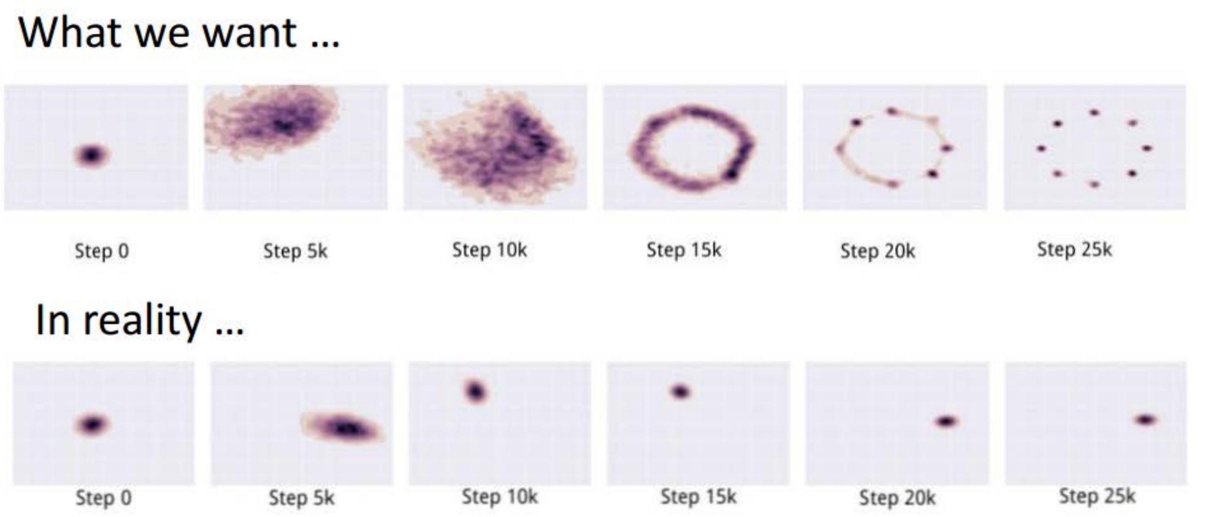


Method: Problems of GAN and Solution

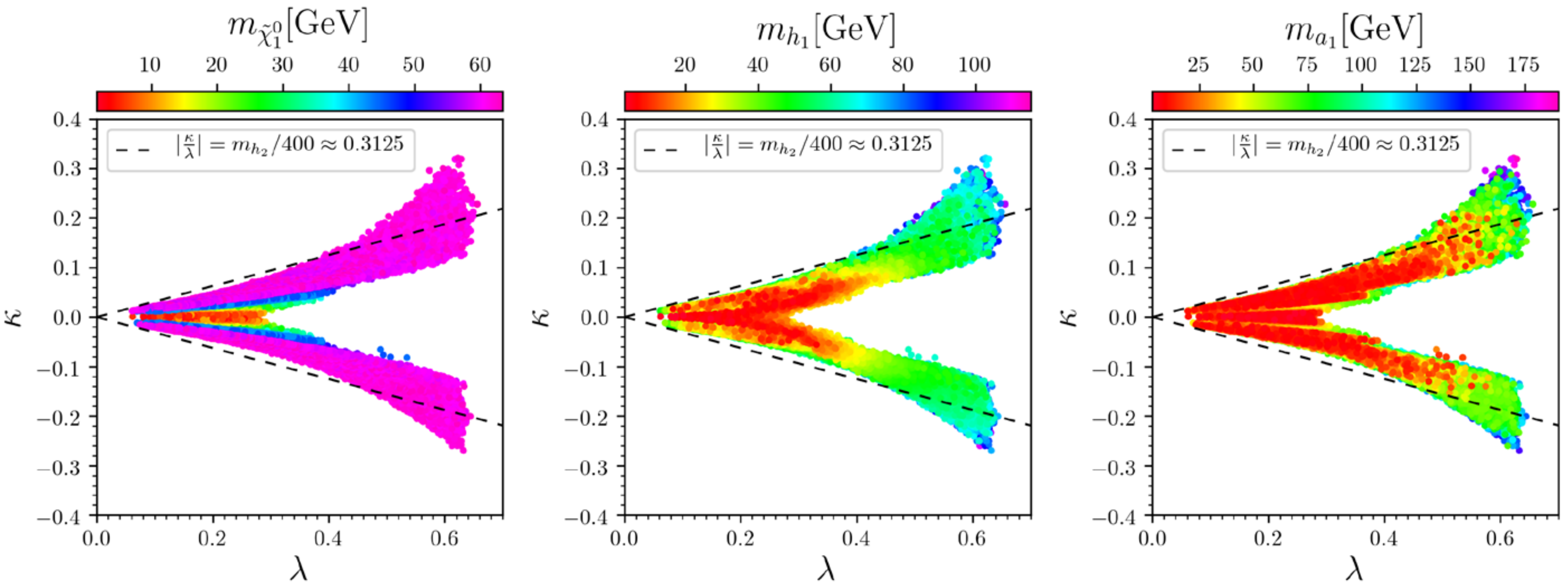
- Difficult to training GAN: not stable
- Mode Collapse: lack of diversity



- Wasserstein GAN (WGAN)
  - Training stable
  - Solved mode collapse



Light dark matter



$$m_{\tilde{\chi}_1^0} = 2\kappa v_s = 2\frac{\kappa}{\lambda}\mu \leq m_{h_2}/2\,.$$

$$\left[\frac{\kappa}{\lambda}\right]_{\max} \leq \left[\frac{m_{h_2}}{4\mu}\right]_{\min} = \frac{m_{h_2}}{4\times 100} \approx 0.3125\,.$$

- Singlino-dominated for samples between the two dash line
- h_1 and a_1 possibly lighter than half of the SM-like Higgs