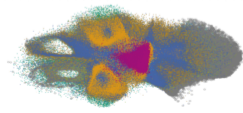
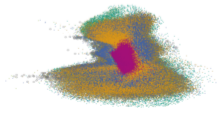
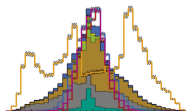
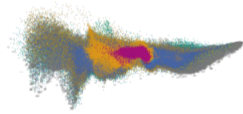
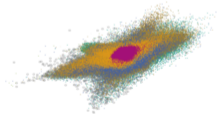
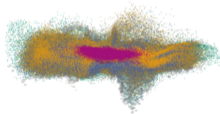
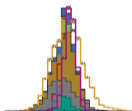


Inelastic Dark Matter with Dark Higgs

Jonas Eppelt | November 14, 2022

ETP



Anomaly Detection in general

- Something that is unlike any other: out-of-distribution
- In HEP typically over-densities

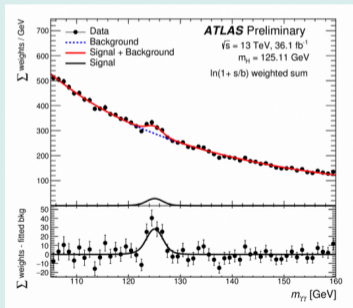


Figure: ATLAS collaboration,
<https://atlas.cern/updates/briefing/new-atlas->

Anomaly Detection in HEP

- physics case: Jet Identification at CMS or ATLAS
- prevalent methods: Classification without labels, Autoencoders

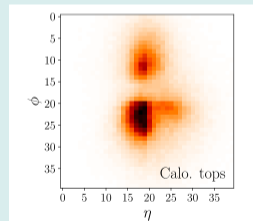
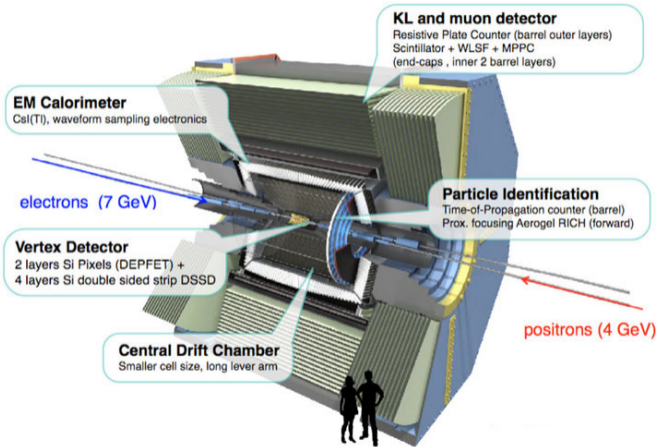
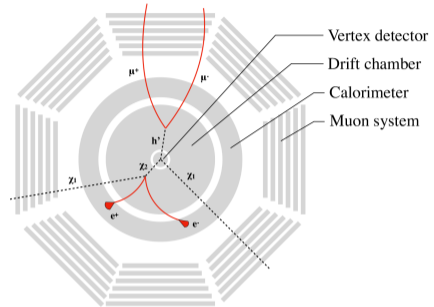
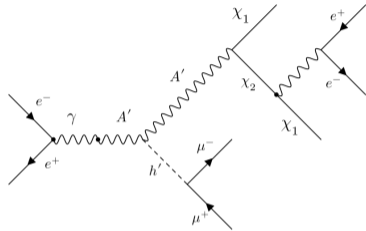


Figure: B. Dillon, T. Plehn, C. Sauer, P. Sorrenson,
"Better Latent Spaces for Better Autoencoders",
SciPost 11 no.3 (Sep, 2021)

Belle II - a e^+e^- collider experiment



Inelastic Dark Matter with Dark Higgs

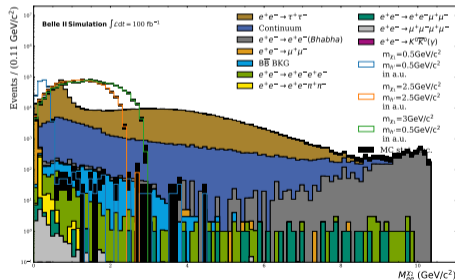
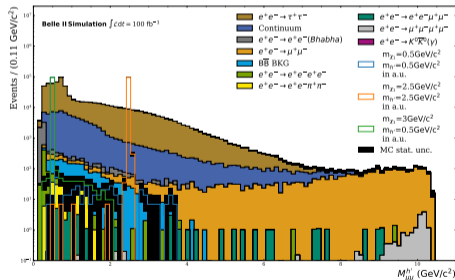


7 free parameters

- Coupling constants for Dark Higgs h' to Dark Matter χ_1/χ_2 and Dark Photon A' to Dark Matter
- Mixing angles for the A' and h'
- Masses for the χ_1 , h' and A'
- described in *Long-lived Dark Higgs and inelastic Dark Matter at Belle II* (DOI:2012.08595)

Searches for Inelastic Dark Matter

- Non prompt decays have low background (→ search by Patrick Ecker)
- Prompt decays hard to identify
- Curse of dimensionality: number of points $\propto n^d$ → Find a model-independent way to select signal



model parameter	values
m_{χ_1}	[0.25, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0]
$m_{h'}$	[0.25, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0]
θ	10^{-2}
ϵ	10^{-2}
$m_{A'}$	$4 \cdot m_{\chi_1}$ 2.746×10^{-1} 1.12

example signals

- light dm: $m_{h'} = 0.5 \text{ G}$, $m_{\chi_1} = 0.5 \text{ G}$
- heavy dm: $m_{h'} = 2.5 \text{ G}$, $m_{\chi_1} = 2.5 \text{ G}$
- high mass splitting: $m_{h'} = 0.5 \text{ G}$, $m_{\chi_1} = 3 \text{ G}$

Goals

- Reduce 'unphysical' background sources (beam background)
- Reduce the amount of events to a 'handleable' level

final state particles

- leptons (e/μ)
 - Trackinghits > 20
 - binaryPID (μ vs e)
 - $e :> 0.1$
 - $\mu :< 0.9$
 - θ in CDCAcceptance
 - nCDCHits > 20
 - $dr < 0.5$ cm
 - $|dz| < 2$ cm

reconstruct particles

$$\mu^+ \mu^- \rightarrow h' / e^+ e^- \rightarrow \chi_2$$

- $dr \leq 0.2$ cm
- $\chi_{\text{Prob}} > 0$ & min one $\chi_{\text{Prob}} \geq 0.01$

Rest of event (ROE)

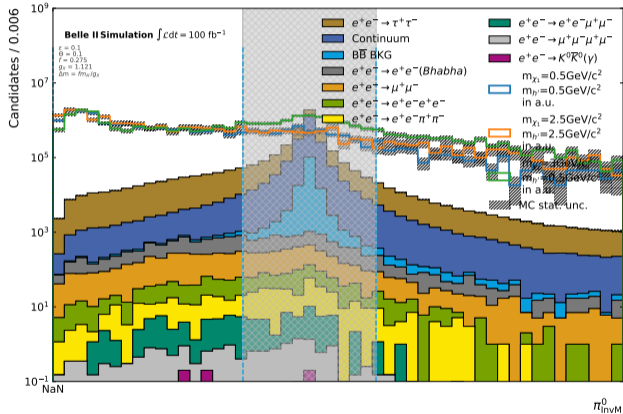
- θ in CDCAcceptance
- nCDCHits > 20
- $dr < 0.5$ cm
- $|dz| < 2$ cm
- $E > 0.05$ GeV

γ :

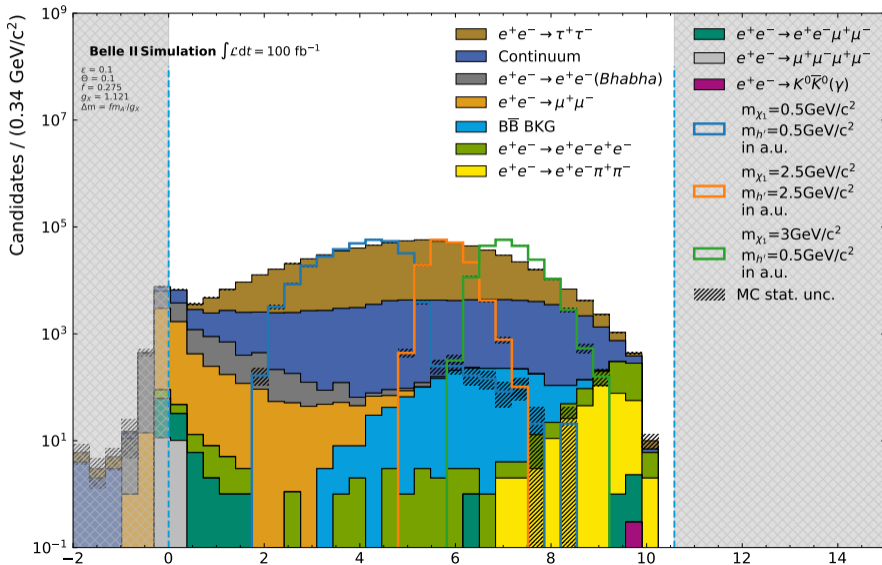
- n cl.Hits > 1.5
- $0.2967 < \theta_{cl} < 2.6180$
- $E < 0.25 \text{ GeV}$, bzw.
 $E > 0.04 \text{ GeV}$
- $|\text{clusterTiming}| < 200$

$\gamma \rightarrow \pi^0$:

- $0 \text{ GeV} < \text{InvM} < 0.3 \text{ GeV}$
- candidate closest to π^0_{InvM}



Missing energy selection

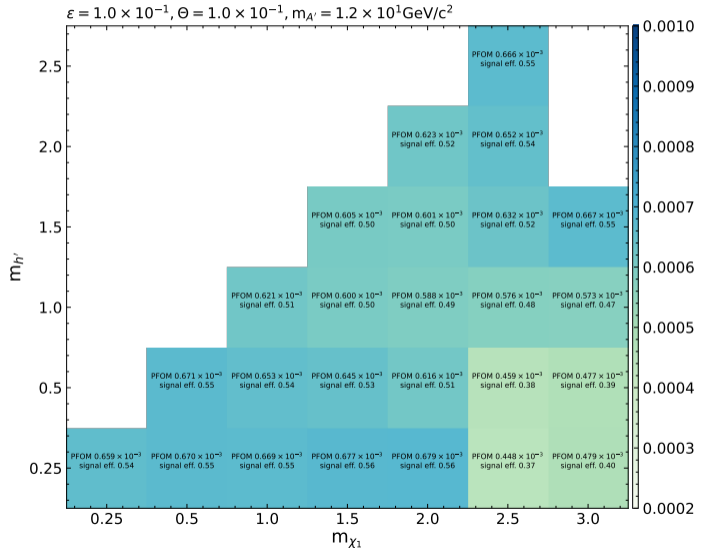


Sensitivities after Reconstruction

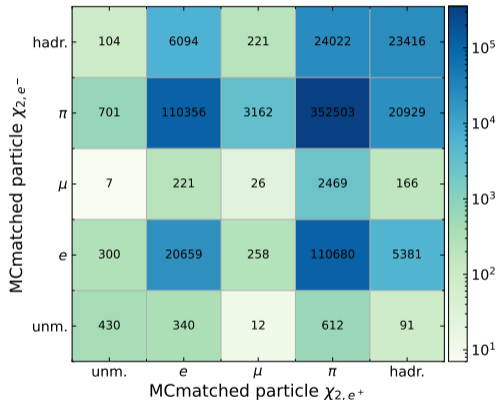
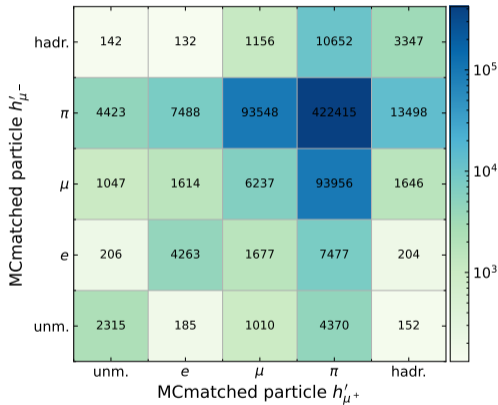
benchmark sensitivity:
 Punzi Figure of Merit
 (PFOM)

$$PFOM = \frac{eff_{signal}}{\frac{1}{2} + \sqrt{N_{background, after}}},$$

eff_{signal} is calculated w.r.t to generated samples (25000).

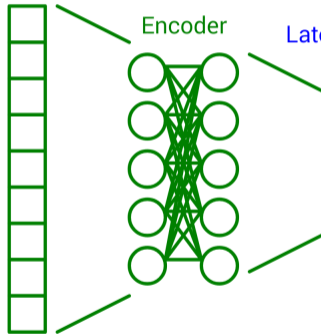


Truthmatching



Autoencoder

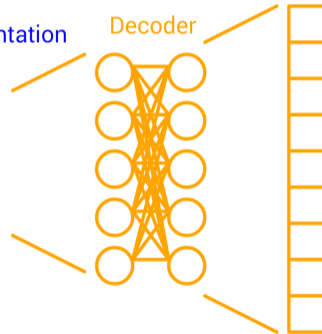
Event features



Latent representation



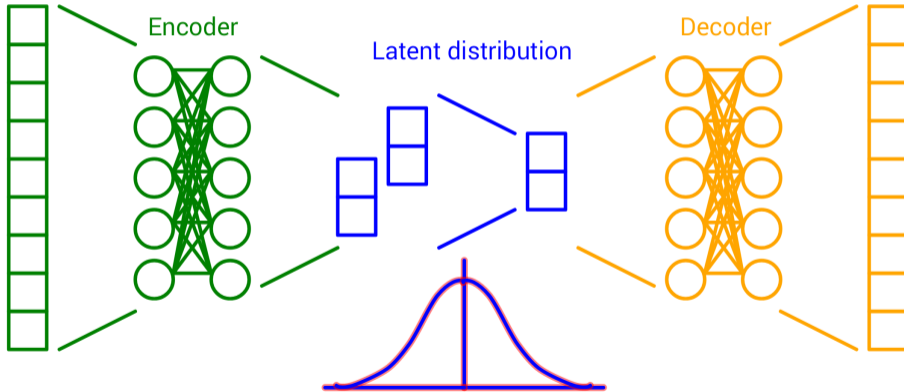
Reconstructed event



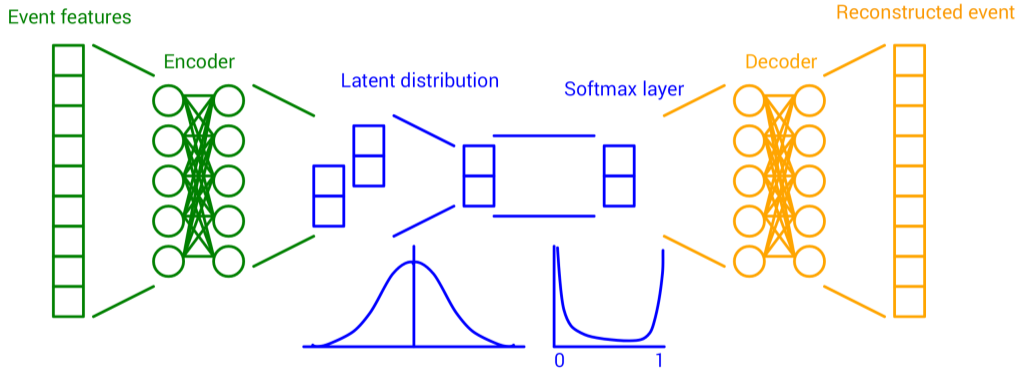
Variational Autoencoder

Event features

Reconstructed event



Dirichlet Variational Autoencoder

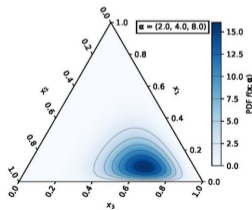
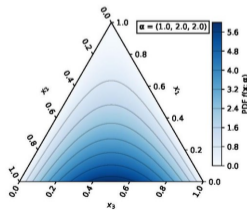
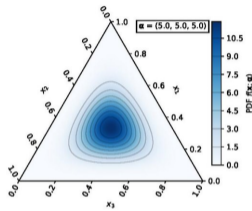
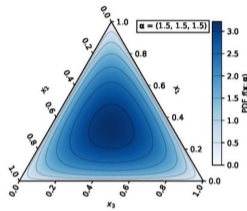


basics

- probability for categorical distributions, e.g.:
 - 30% 'anomalous' → 70% 'normal'
 - 10% 'Bhabha', 80% ' $\tau\tau$ ', 10% 'anomalous'
- with k categories k parameters α_k

approximation

- $D_\alpha(r) \approx \text{softmax}[N(z, \mu, \sigma)]$ with
 - $\mu_i = \log \alpha_i - \frac{1}{R} \sum_i^d \log \alpha_i$
 - $\sigma_i = \frac{1}{\alpha_i} (1 - \frac{2}{R}) + \frac{1}{R^2} \sum_i^d \frac{1}{\alpha_i}$
- add a softmax layer after resampling
- distribution characterized by d parameter α_j



Input features

- final state leptons 4-vectors (E, p_x , p_y , p_z)
- order of (e^- , e^+ , μ^- , μ^+)
- missing Energy as 4-vector
- prescale by standardize:

$$x' = \frac{x - \hat{x}}{\sigma(x)} \quad (1)$$

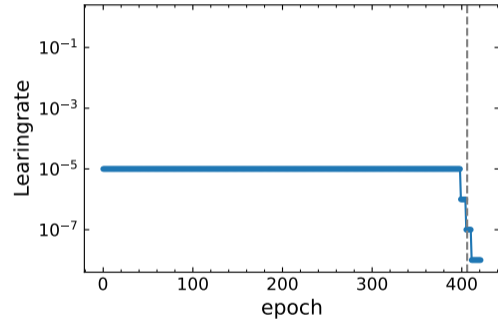
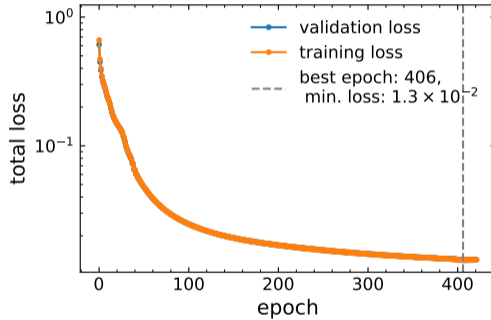
Architecture

- both parts 3 hidden layers @ 100 neurons
- 1 to 10 latent dimensions
- ReLU activation

Training

- Adam with learning rate 10^{-5}
- early stopping after 15 epochs without new best epoch (max 500)
- Cross-validation with 20 % split
- Stochastic Weighted Average
- Batch size 128
- LR scheduling on plateau (factor 0.1 10 epochs, relative change of 10^{-4})

Training AE(l=10)



Trainings results

AE

lat. dim	h	mse
1	1.6	0.7
2	17	0.3
3	22	0.22
4	26	0.14
5	23	0.1
6	27	0.08
7	28	0.06
8	25	0.04
9	21	0.028
10	27	0.013

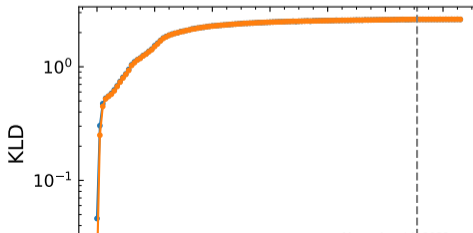
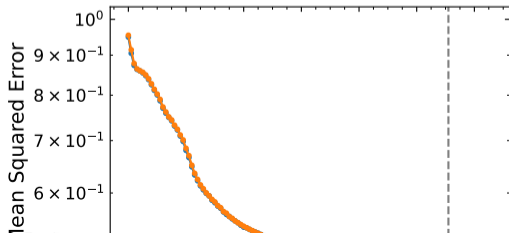
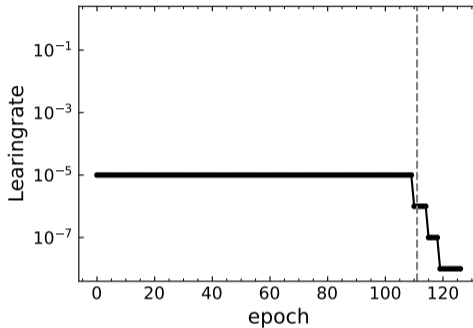
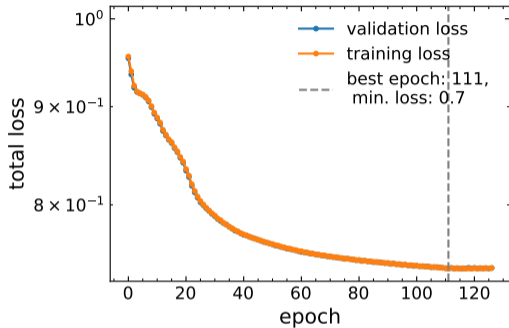
VAE

lat. dim	h	mse
1	2.1	0.9
2	8	0.8
3	9	0.7
4	7	0.7
5	9	0.7
6	7	0.7
7	9	0.7
8	8	0.7
9	8	0.8
10	8	0.7

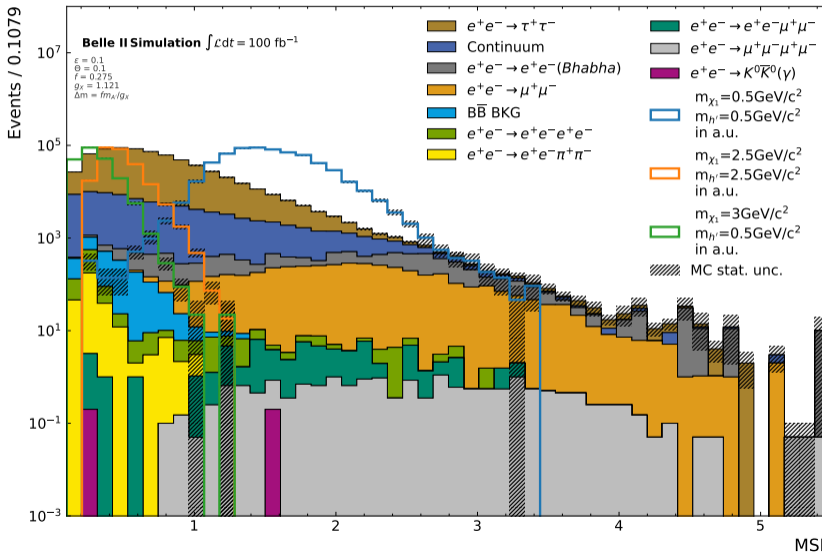
DVAE

lat. dim	h	mse
2	8	0.7
3	18	0.4
4	21	0.29
5	20	0.28
6	30	0.2
7	30	0.15
8	30	0.12
9	28	0.09
10	40	0.08

Training VAE($l=5$)



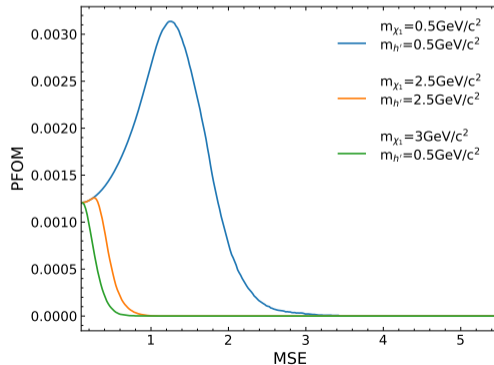
MSE of AE(l=1)



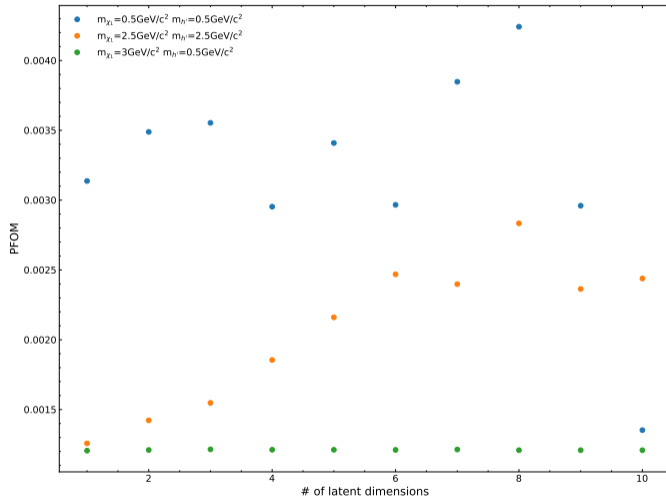
benchmark sensitivity: Punzi Figure of Merit (PFOM)

$$\text{PFOM} = \frac{\text{eff}_{\text{signal}}}{\frac{1}{2} + \sqrt{N_{\text{background, after}}}},$$

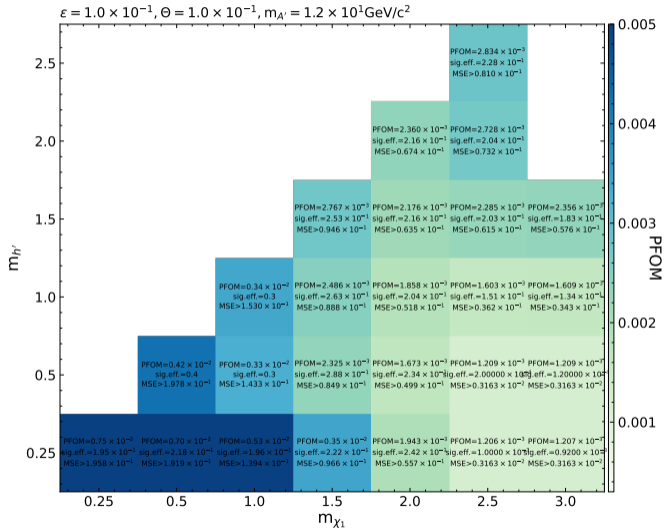
$\text{eff}_{\text{signal}}$ relative to selected samples



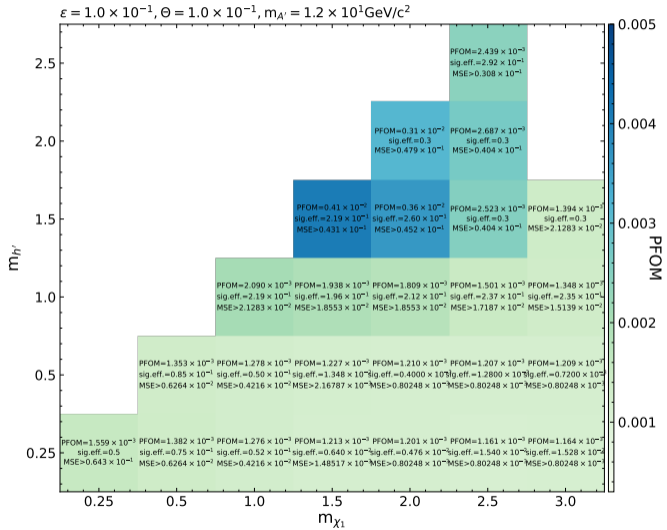
Punzi comparison AE



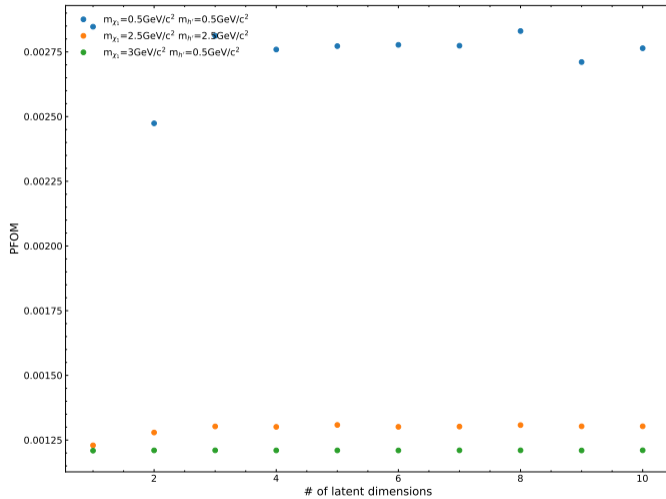
AE(l=8)



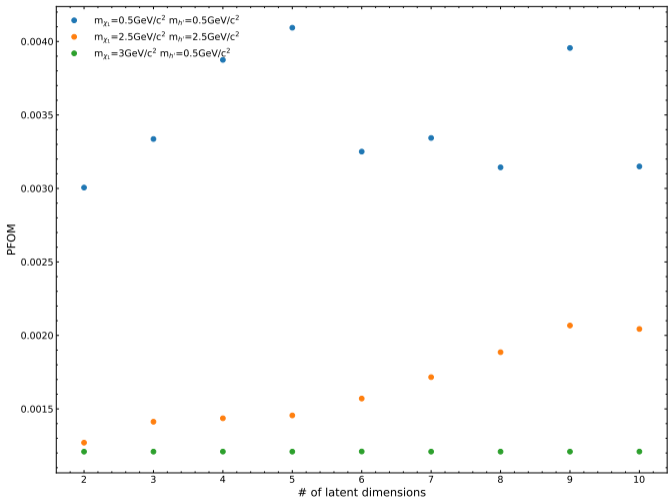
AE(l=10)



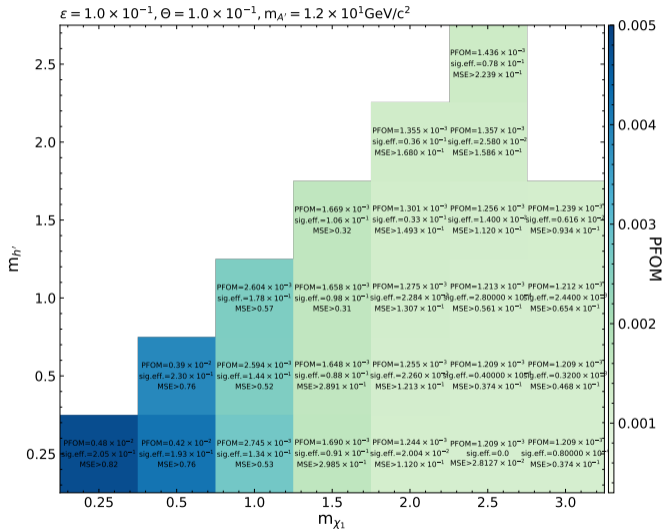
Punzi comparison VAE



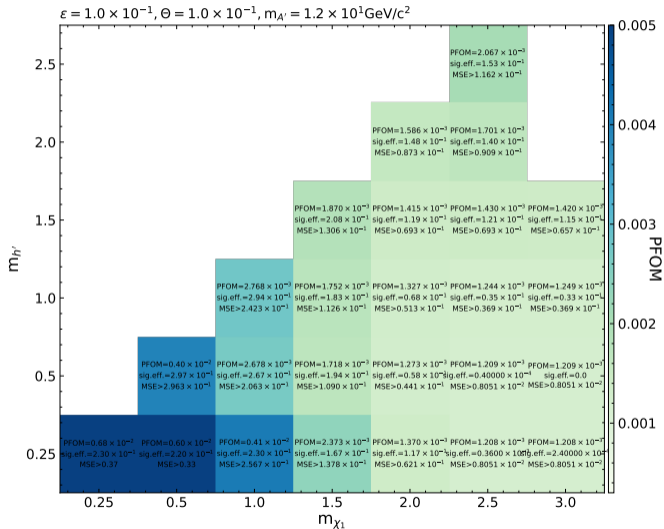
Punzi comparison DVAE



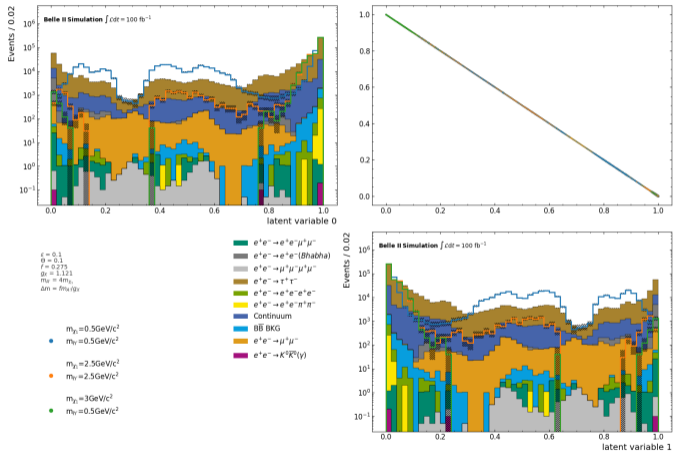
DVAE(I=4)



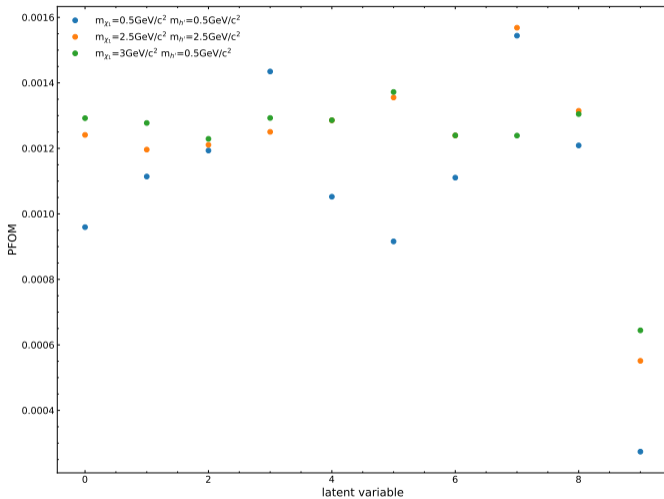
DVAE(l=9)



Latent space DVAE(l=2)

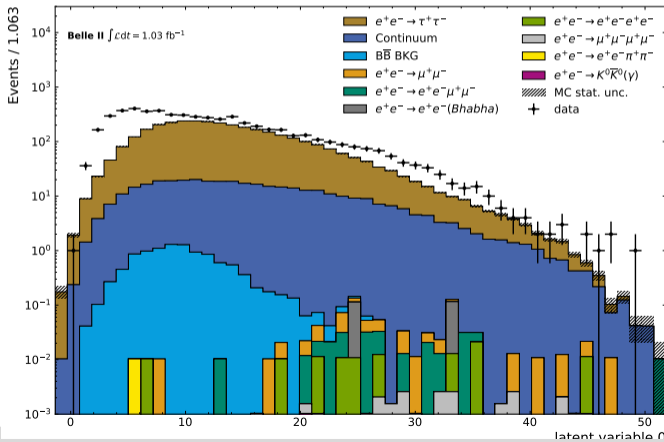


Punzi comparison DVAE($l=10$) latent space



Look in data

- Idea: validate that latent-dimension looks similar for data
- Selecting three track Trigger and HLT



Selecting Anomalies using $AE(l=8)$, $MSE > 0.1978$

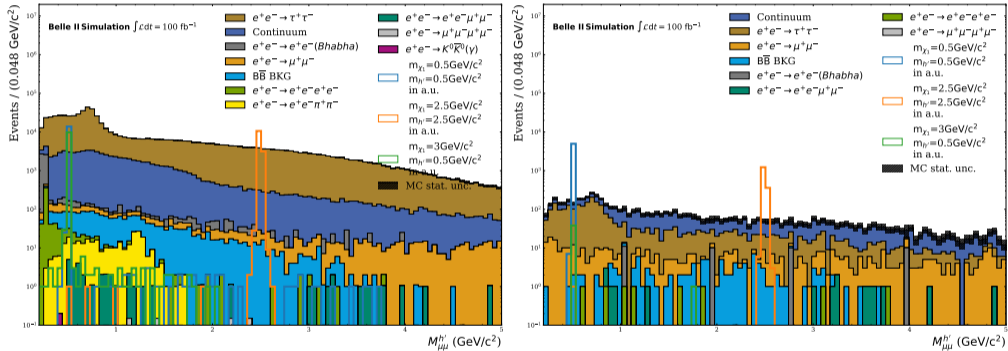




Figure: courtesy of L. Reuter

Anomaly Detection for Inelastic Dark Matter

- Differently sized latent spaces are sensitive to different model parameter configurations
- Trade-off between model independence and sensitivities
- only little use of PID information was made

Use and Future of Autoencoders

- AEs outperform VAEs & DVAEs
- Further tuning of Hyperparameters possible
- DVAEs priors for the latent space require more investigation
- architectures could be further improved (Normalized Autoencoder, Graph Neural Networks)