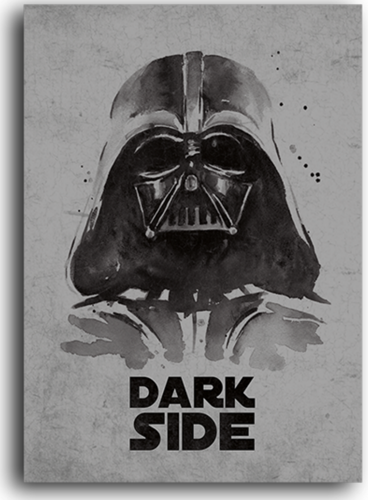
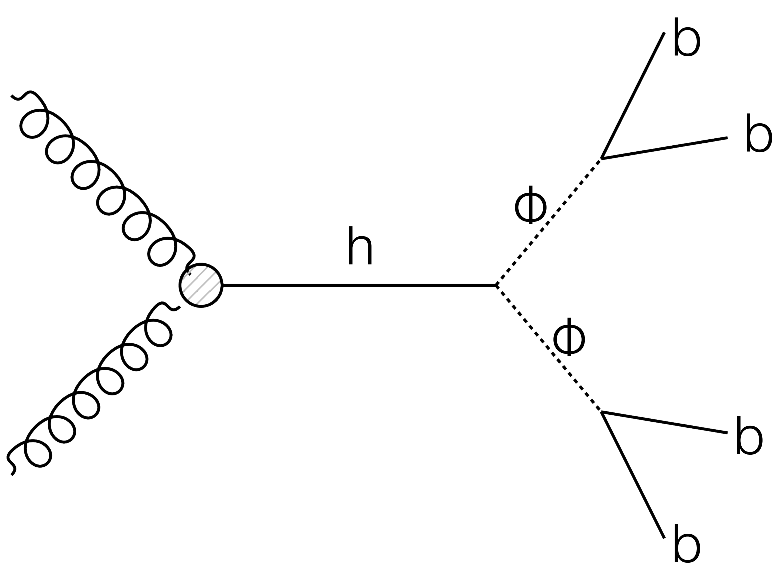
Exploring Higgs Portals to Hidden Sectors with Rep. Learning

Abhijith Gandrakota, Christina Reissel, Phil Harris, Jennifer Ngadiuba, Nhan Tran, Aaron Wang

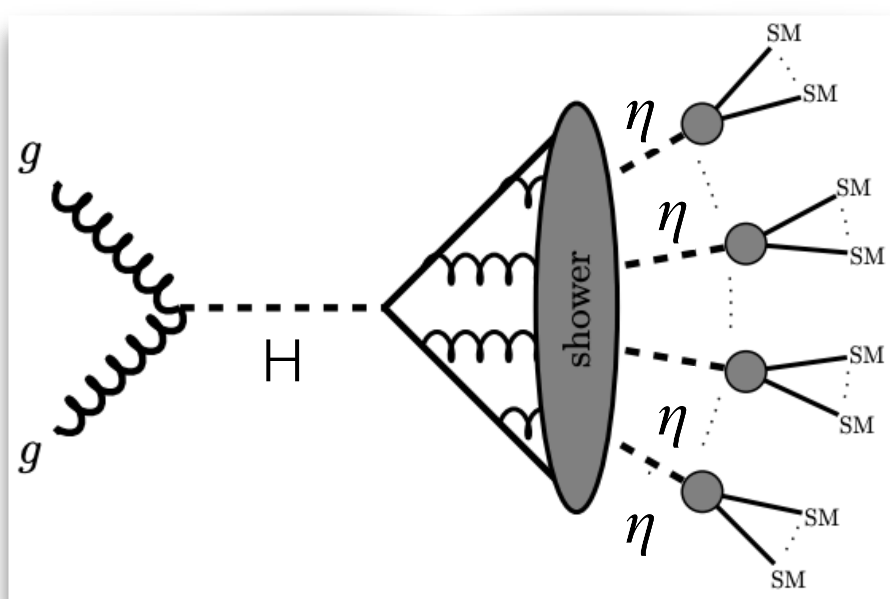


Higgs portal to hidden sectors

- Higgs portal to the hidden sectors is very well motivated
  - Higgs-initiated decays especially well motivated
  - Branching frac. bounded by $Br(h \rightarrow \text{exotic}) < 0.21$
- The nature of a dark shower is determined by the Hooft couplings, $\lambda = g^2 N_c$
  - Huge diversity the nature of Dark Showers (DS)



λ ~ 1



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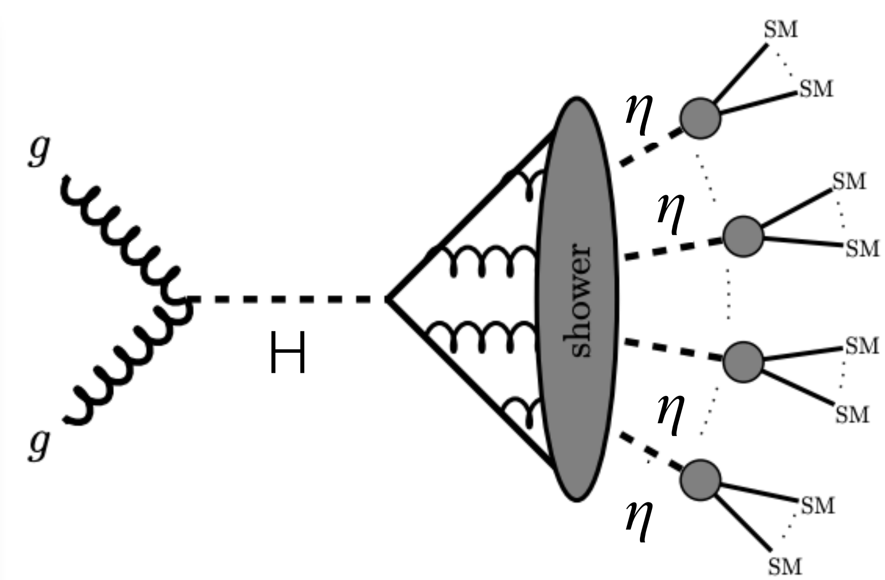

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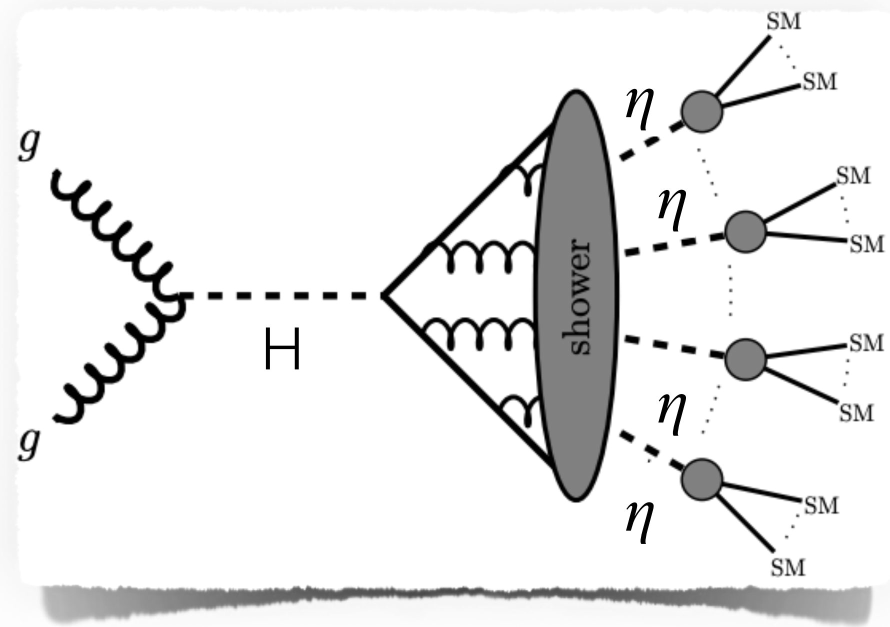
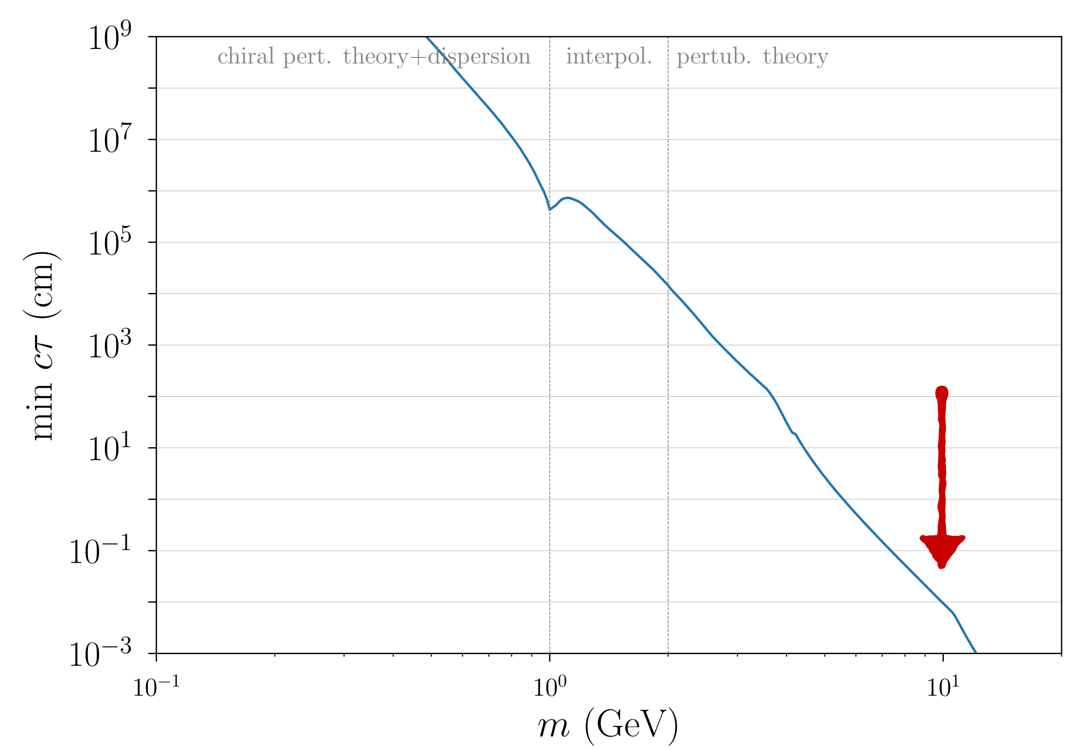


- The nature of a dark shower is determined by the Hooft couplings, $\lambda = g^2 N_c$
  - With $m(\eta) \approx 10$ GeV or greater, Dark showers could be nearly prompt



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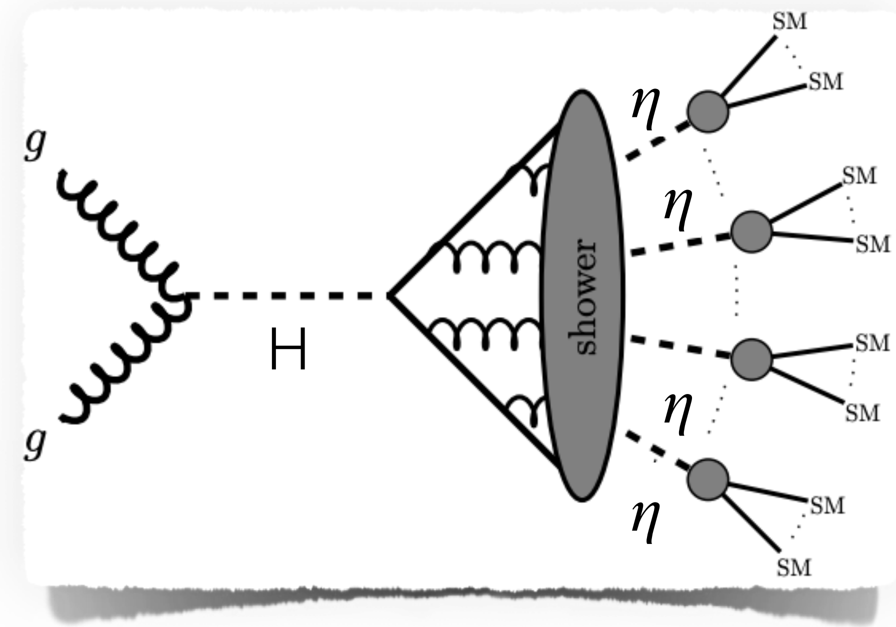

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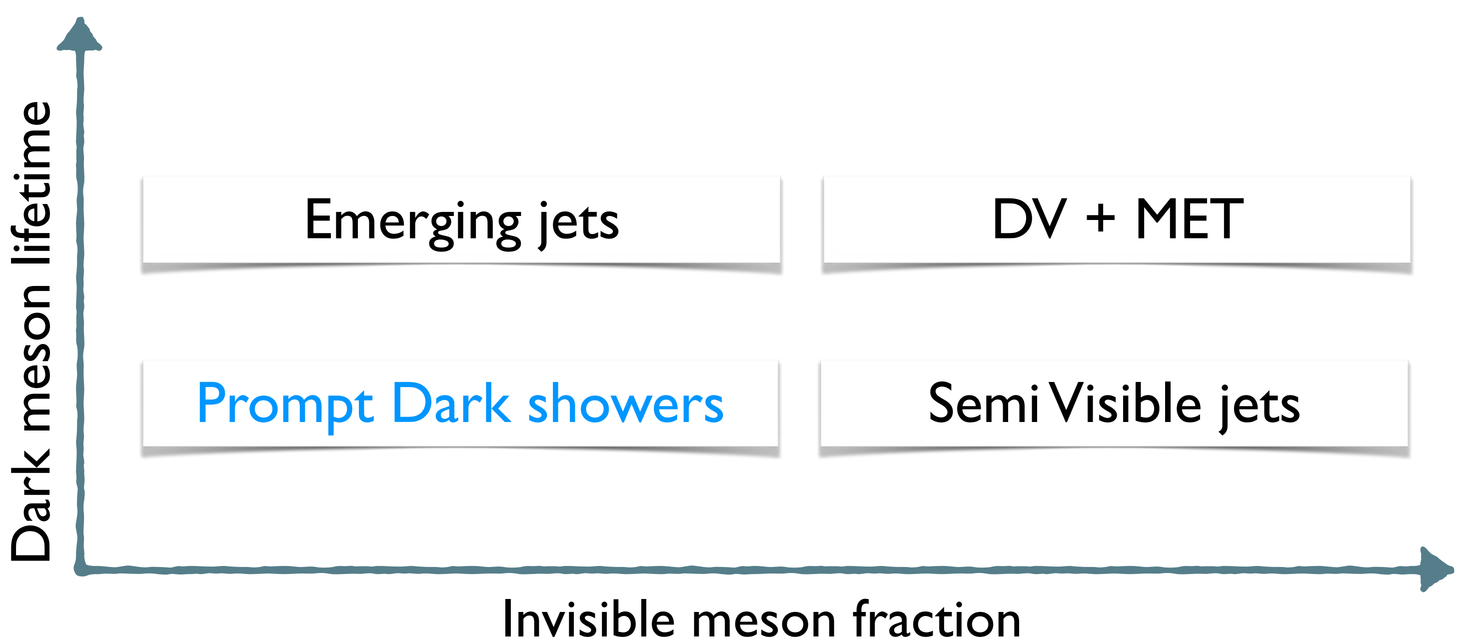

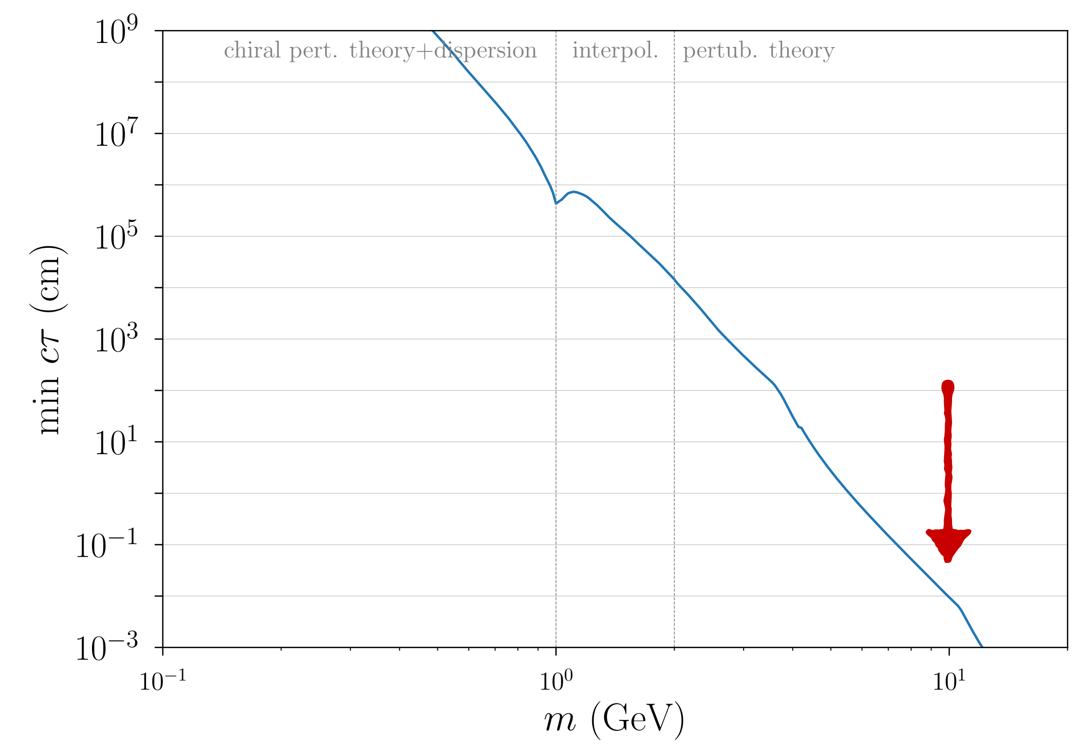

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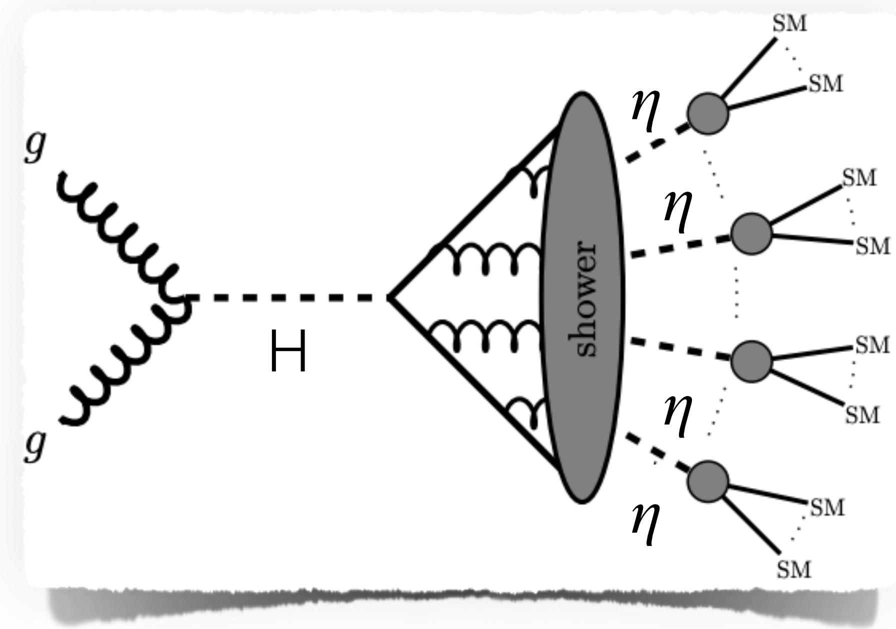
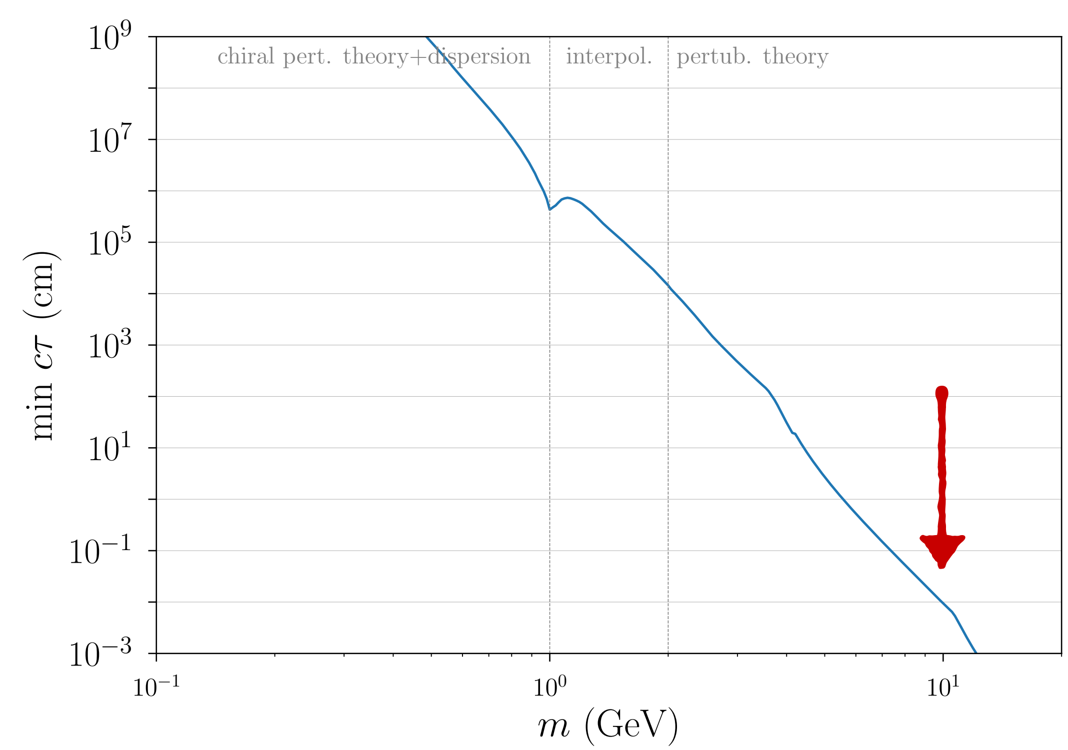


- Studying the Perturbative Benchmark models [1]
  - With $m(\eta) \approx 10$ GeV or greater, Dark showers could be nearly prompt
  - Notoriously challenging signatures to identify
  - Fewer handles to suppress SM background compared to SVJs and Emerging Jets

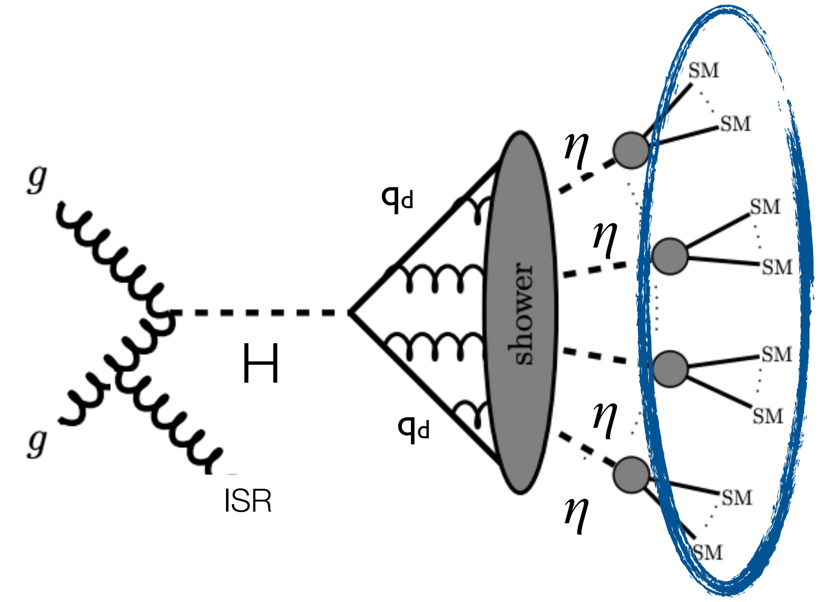


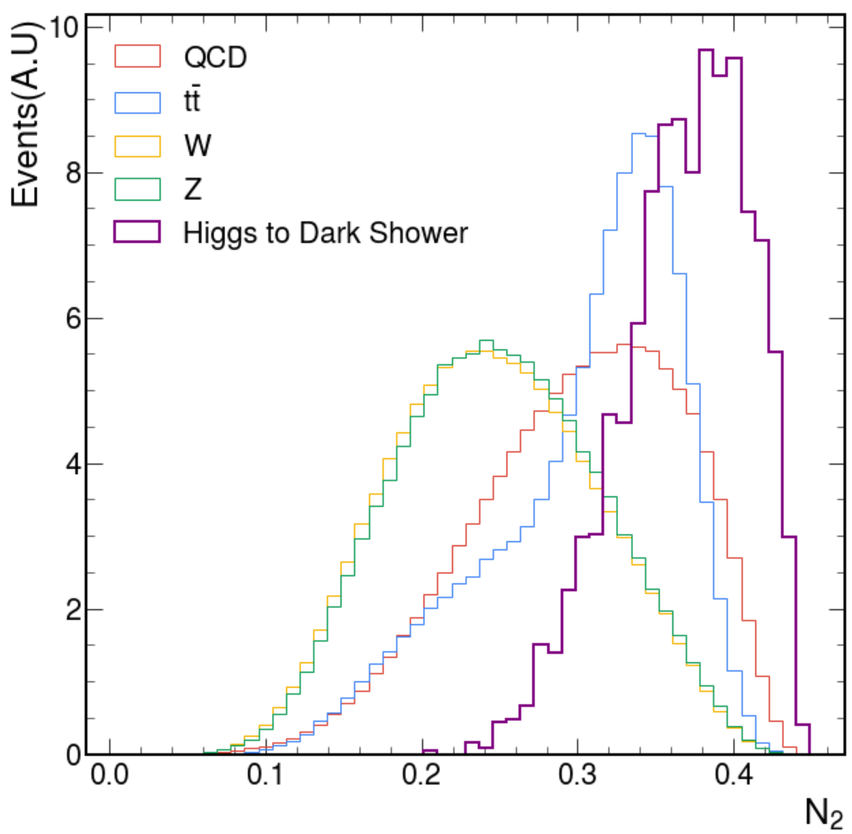
- (On going) Study aims to address this issue and develop techniques identify Higgs to DS

Higgs initiated Dark Showers

- Initially targeting the ggF production of Higgs → DS
  - Leverage the ISR + ggF production of Higgs
  - Capture entire Dark Shower in Large-R jet

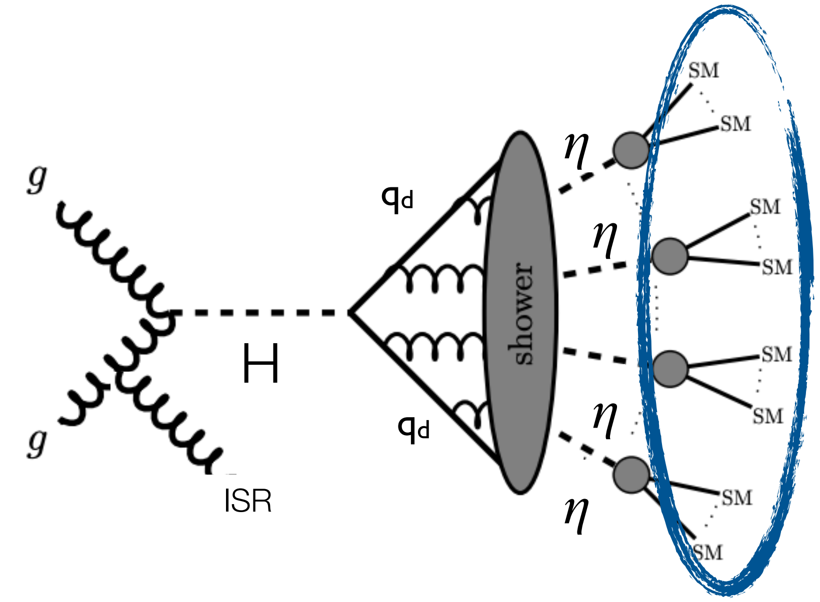
- Final state with huge SM (QCD) background
  - We can't use traditional substructure techniques to identify Darkshowers

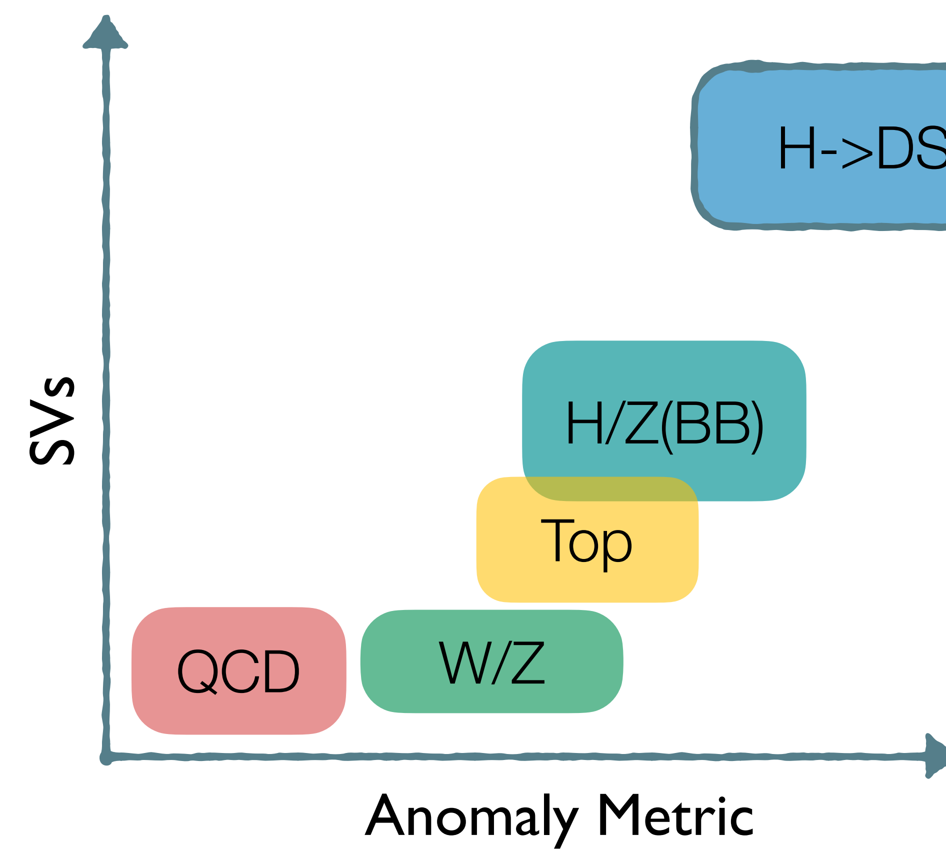




Higgs initiated Dark Showers

- Initially targeting the ggF production of Higgs → DS
  - Leverage the ISR + ggF production of Higgs
  - Capture entire Dark Shower in Large-R jet
- Final state with huge SM (QCD) background
  - Substructure in DS is still different compared to QCD
  - For $m(\eta) > 10$ GeV, tends to dominated by multiple heavy flavor quarks
- Diversity in DS decays, prevents the use of Supervised ML methods
  - We use Representation Learning to identify Higgs → DS signatures





Higgs initiated Dark Showers

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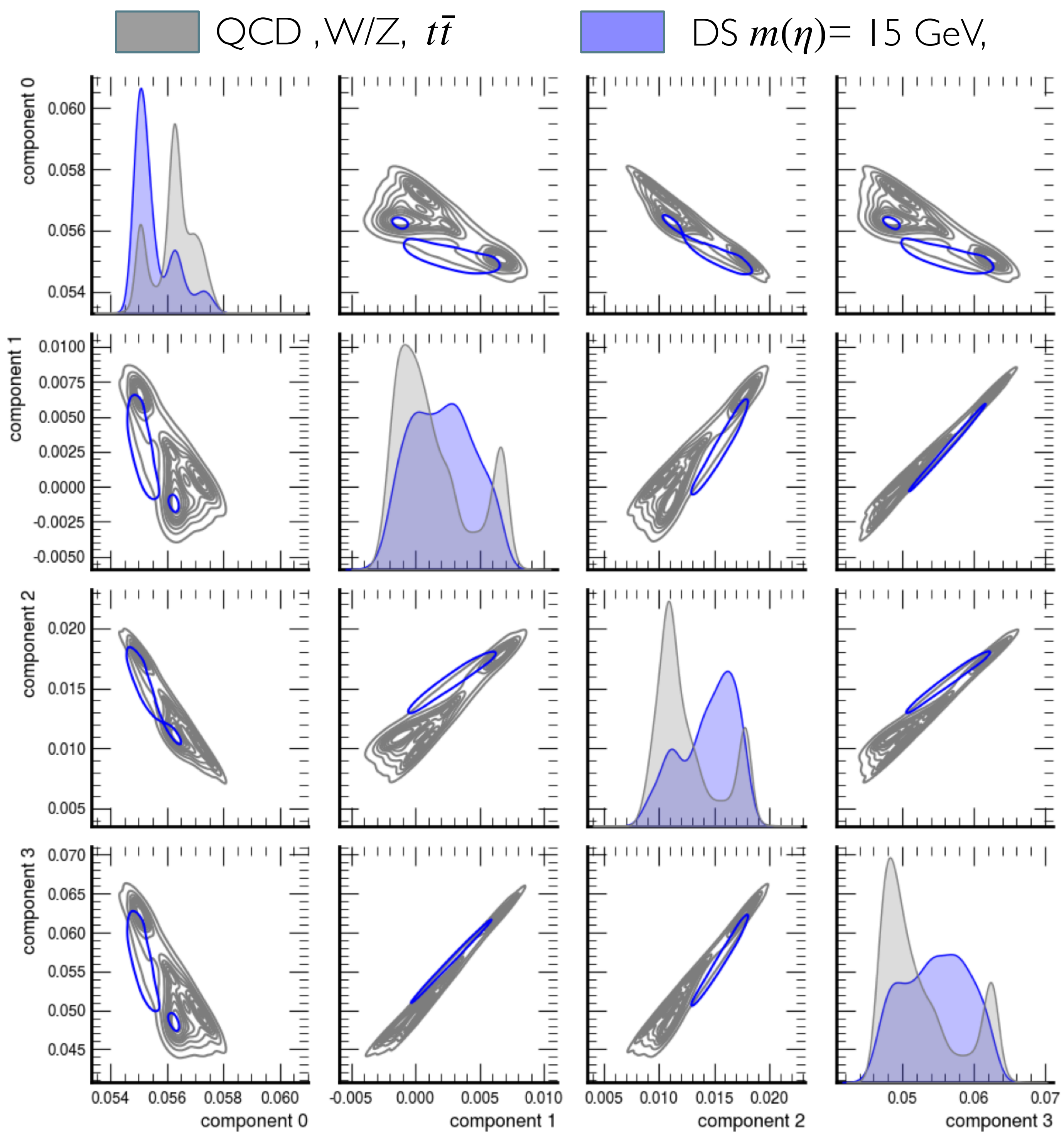
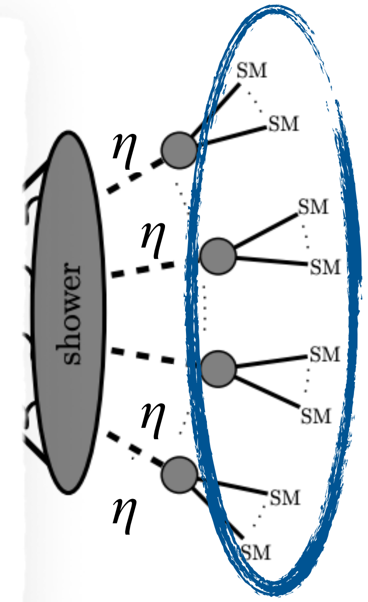
Representation space of Jets



Plot by Christina Reissel

https://arxiv.org/abs/2412.07033



H->DS

BB)

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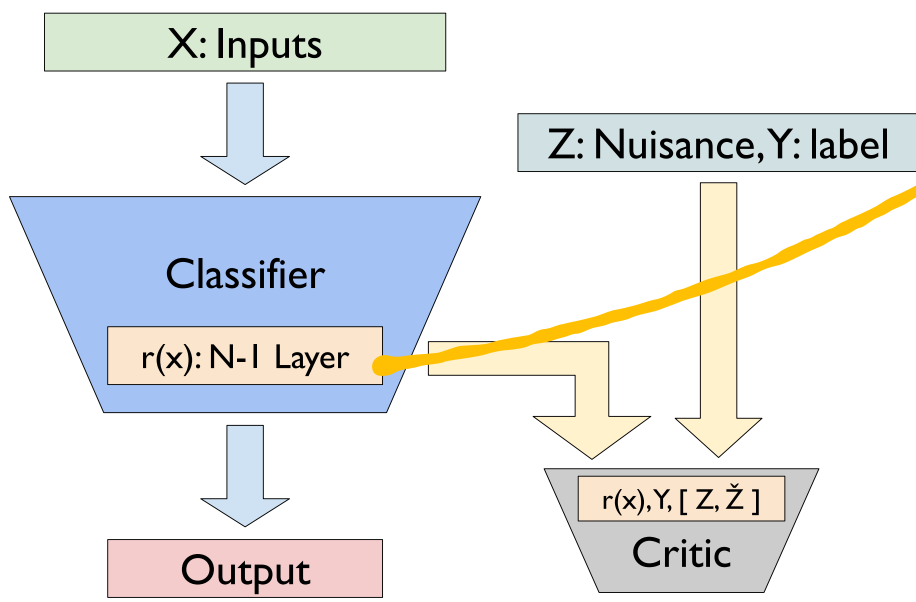
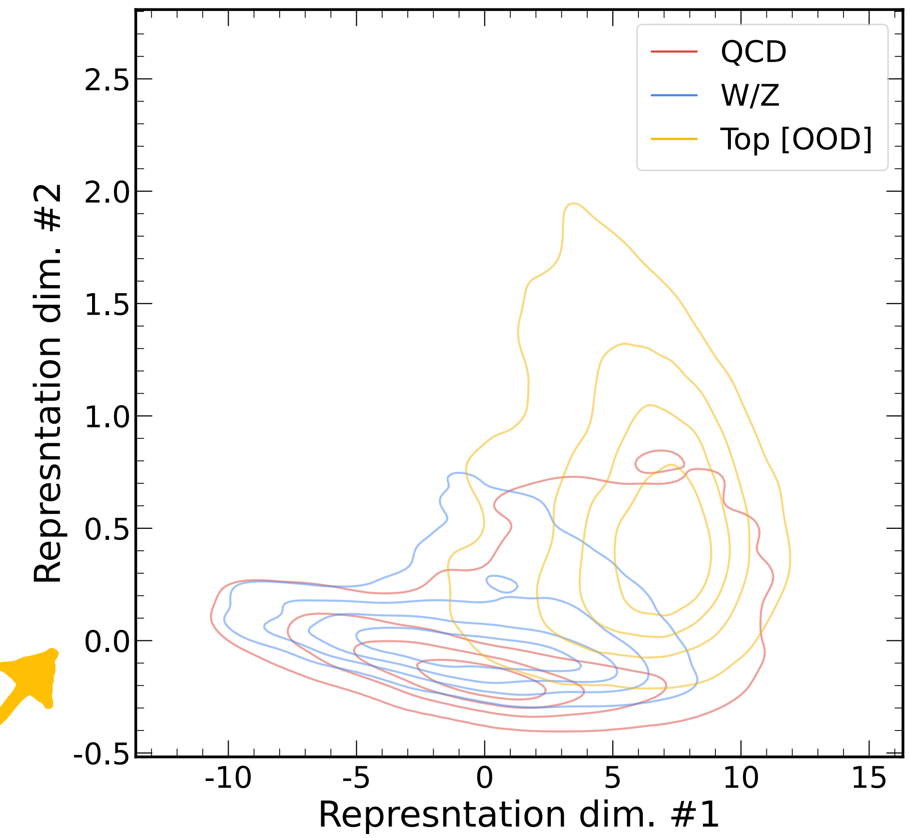
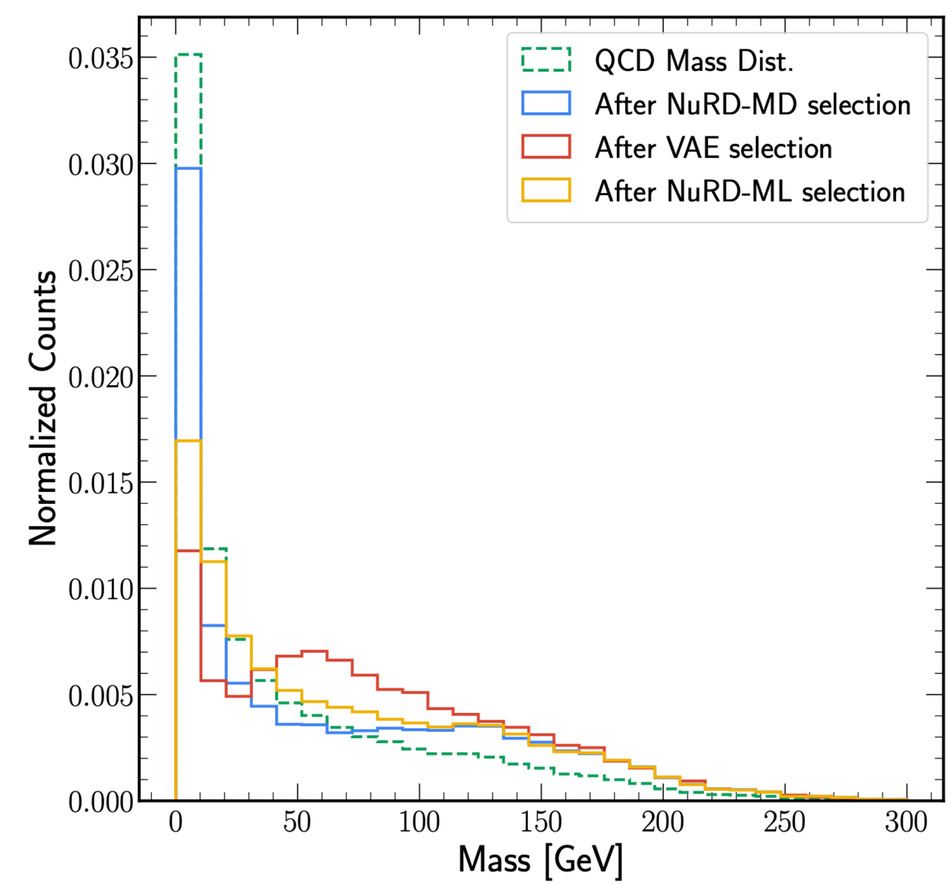
Robust Rep. Learning for AD

- Robust Representation to Characterize the Dark Showers
- Use NuRD to maximize the info in representations
  - Use multiple SM decays, to teach NN physics
  - Build kinematically invariant representations
  - Use these to representations detect anomalies
- Better performance than density estimation



$$\mathscr{L} = w\left(CE(Y_{pred}, Y_{true}) - \lambda \log \frac{p_\phi(r_X, Y, [Z, \check{Z}])}{1 - p_\phi} \right)$$





More info check out : arXiv:2401.08777

[A. G., L. Zhang, A. Puli, K. Cranmer, J. Ngadiuba, R. Ranganath, N. Tran]

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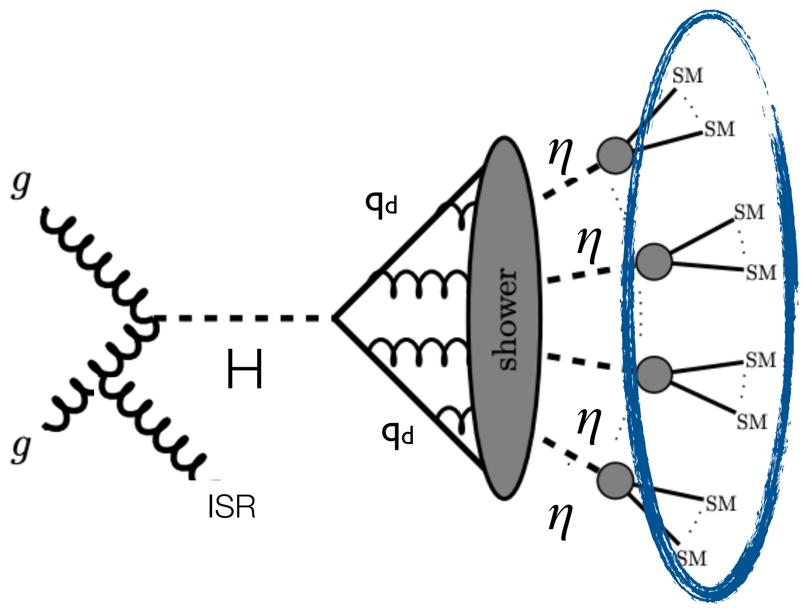
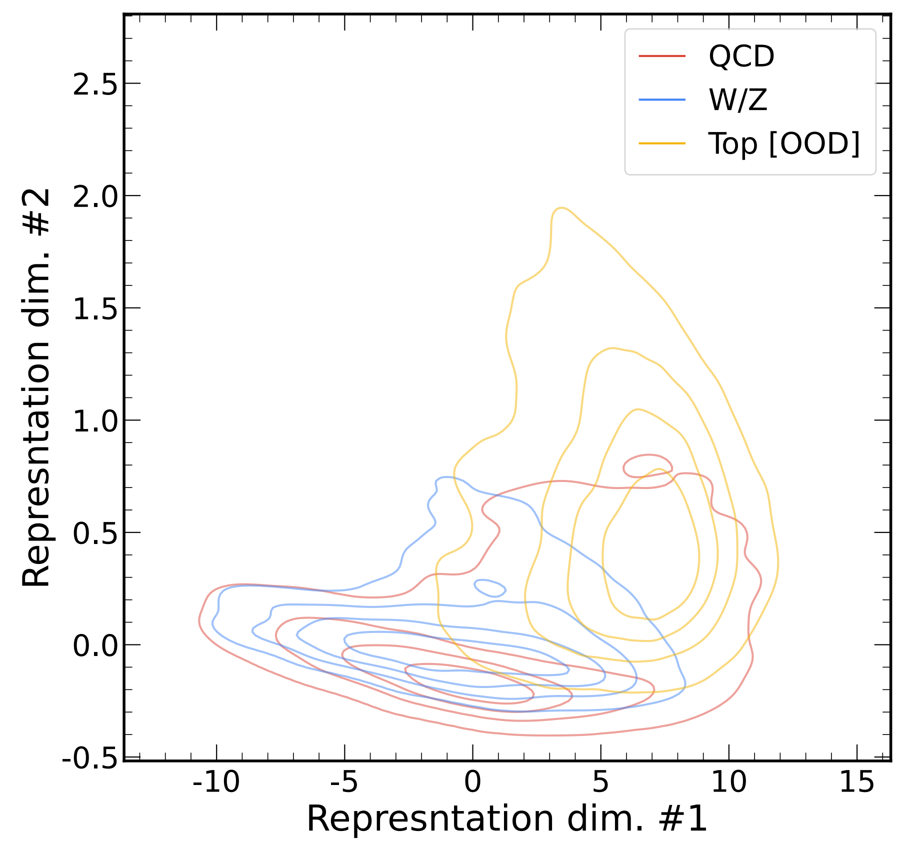
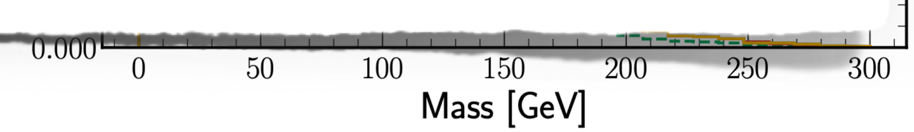


We aim for this

Can we also get this ?





More

[A. G., L. Zhang, A. Puli, K. Cranmer, J. Ngadiuba, R. Ranganath, N. Tran]

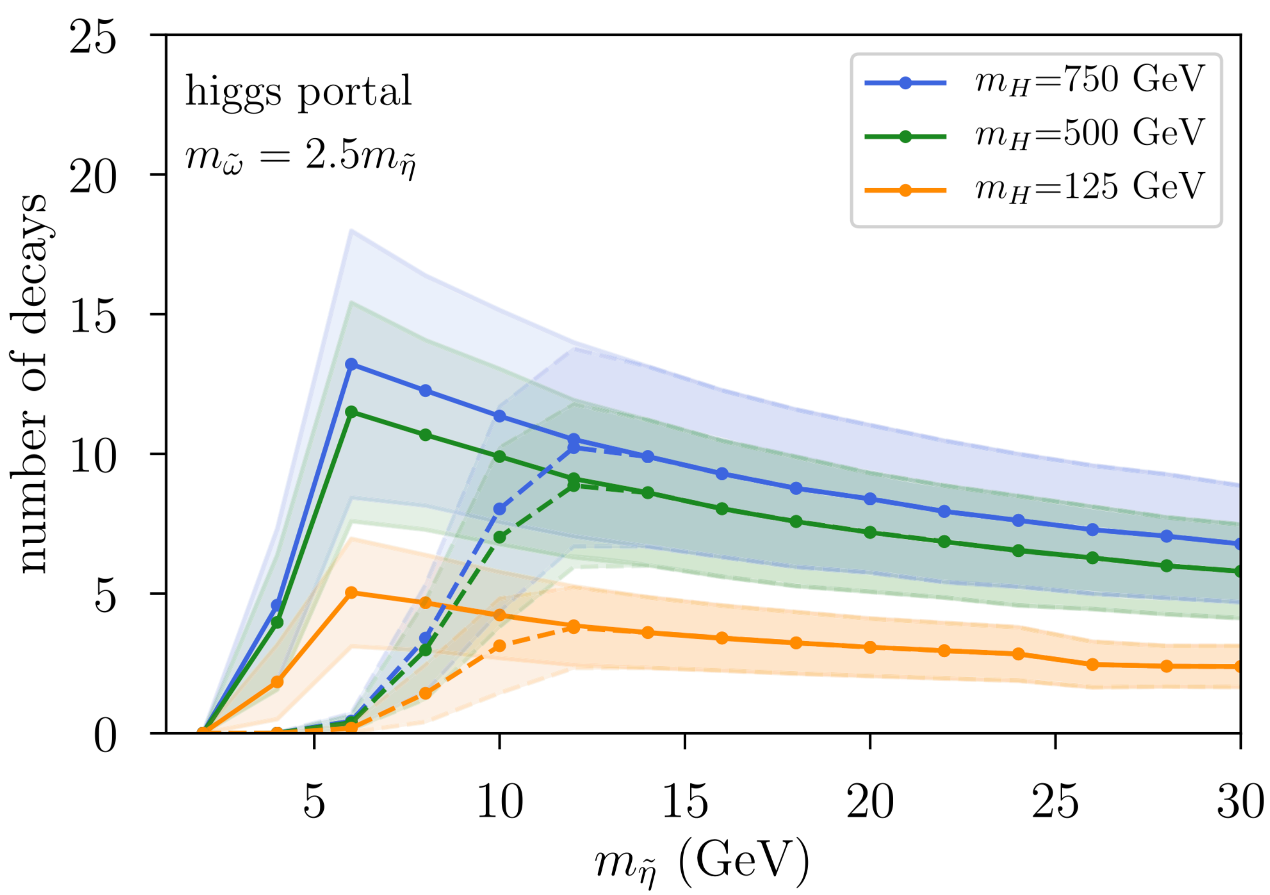
Summary

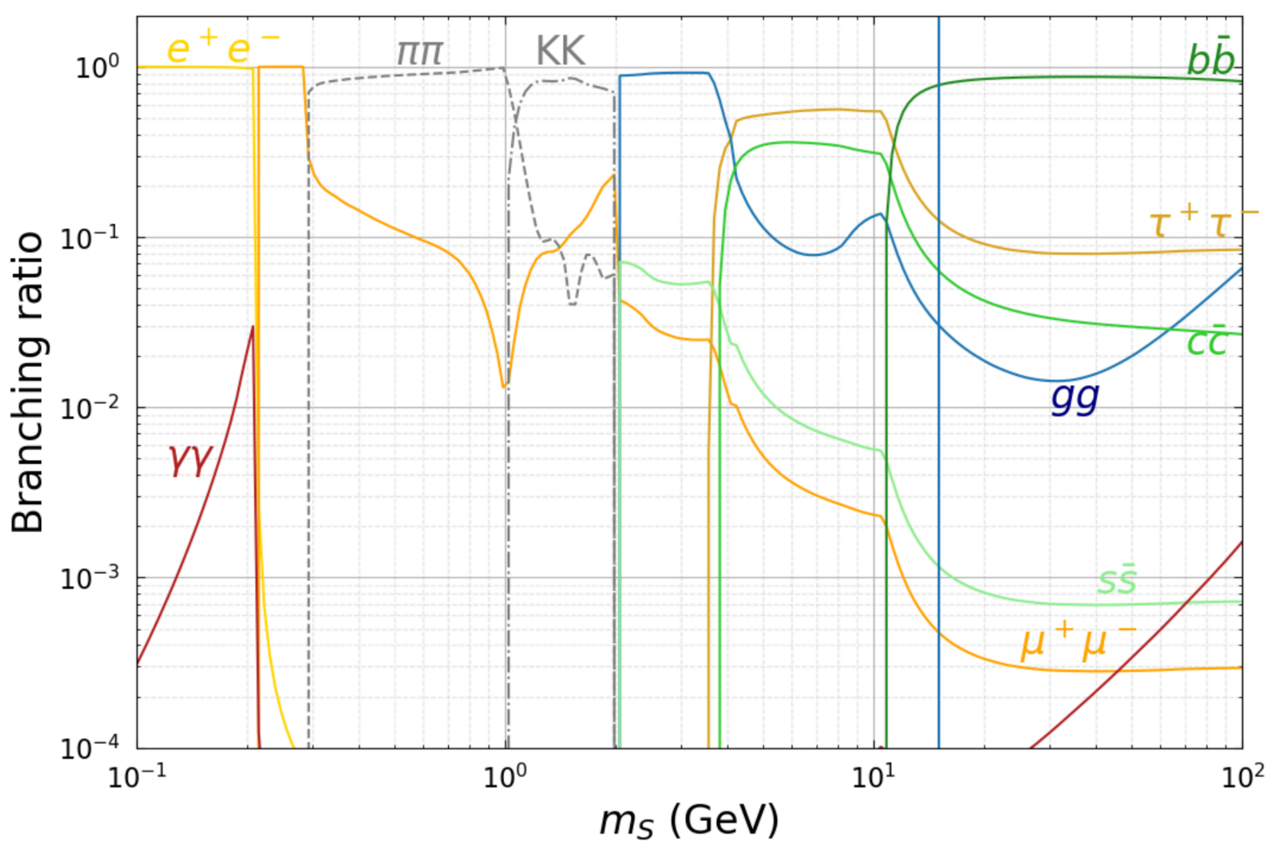
- Higgs mediated dark showers are well motivated, but challenging to detect
  - Prompt Dark Showers arising from this signature are under explored
  - Need deviated techniques to identify these signatures
- Representation Learning: A method to capture diverse DS final states
  - Initial studies show promise to capture DS, with out training on them
  - NuRD ensure the robust and kinematic invariant representations
  - Build a metric space of various DS topologies
- Work underway in developing and publishing these techniques
  - Plan to extend the work to other decay portals
  - Ongoing search in CMS targeting these decay topologies

Thank you !

Higgs initiated Dark Showers

- Expected number of η mesons and their branching fraction
  - Targeting the SM Higgs scenario





Using framework provided in 10.1103/PhysRevD.103.115013

What is it ?

- Lets say we train a algorithm to identify *cows* vs *penguins*
    - We use the photos of *cows* and *penguins* to train the algorithm

Cows typically in grassland backdrop

Penguins typically Photographed in snow

What is it ?

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Robust

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- What about pictures of *cows* on snow ?
  - Does the network get confused due to snow ?

Robust

- Can it predict if this is neither of them ?
  - Will elephant get recognized or mislabeled due to grass ?

Generalizable

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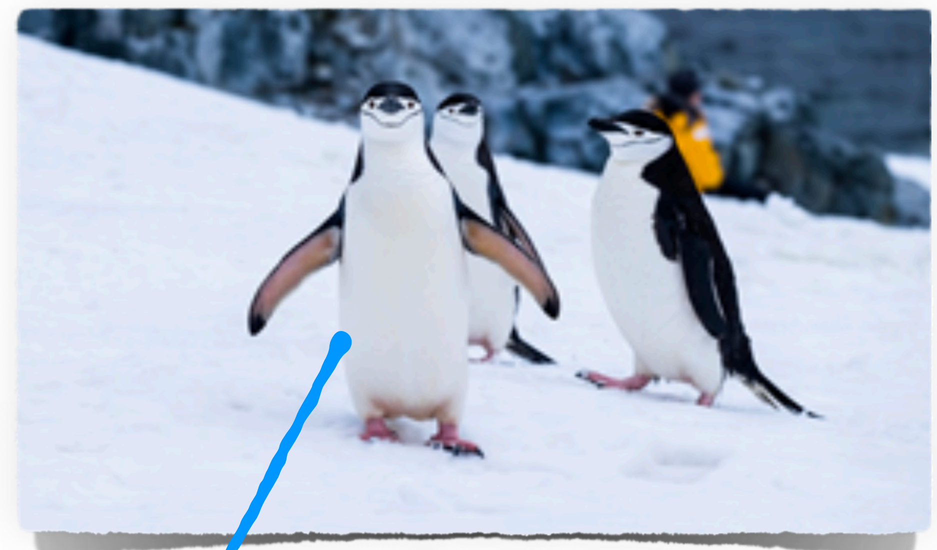

Needs to learn this !

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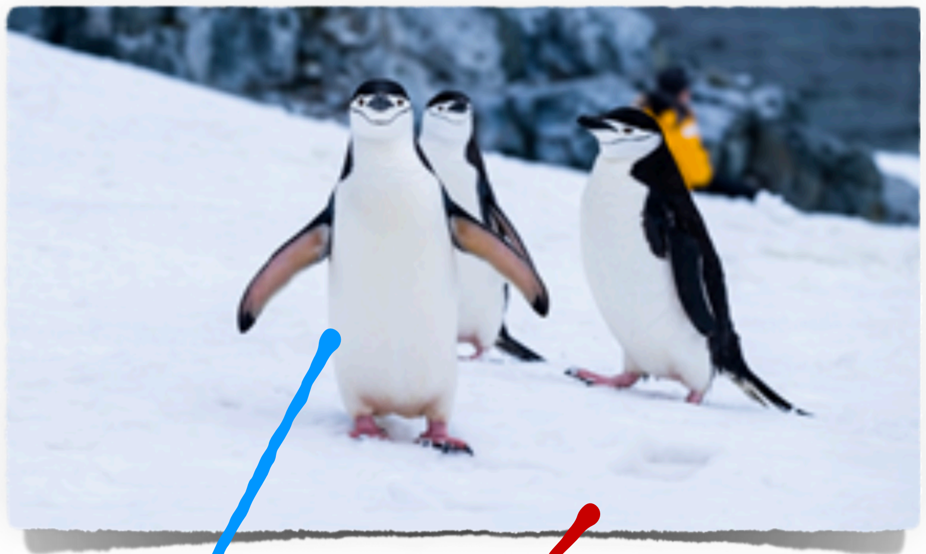
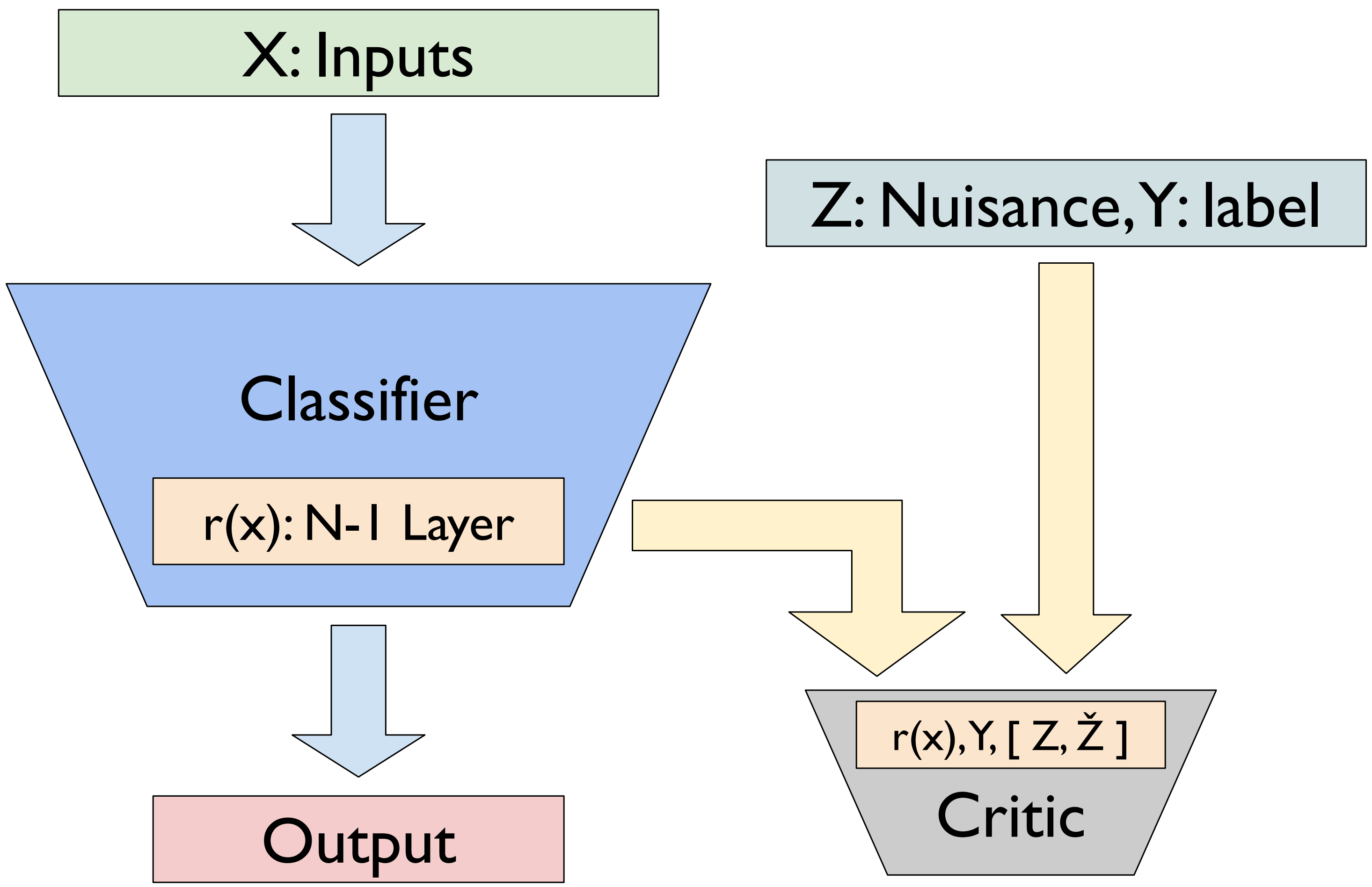


Needs to learn this !

What if it learnt this ?
How do we prevent it ?

Nuisance Randomized Distillation

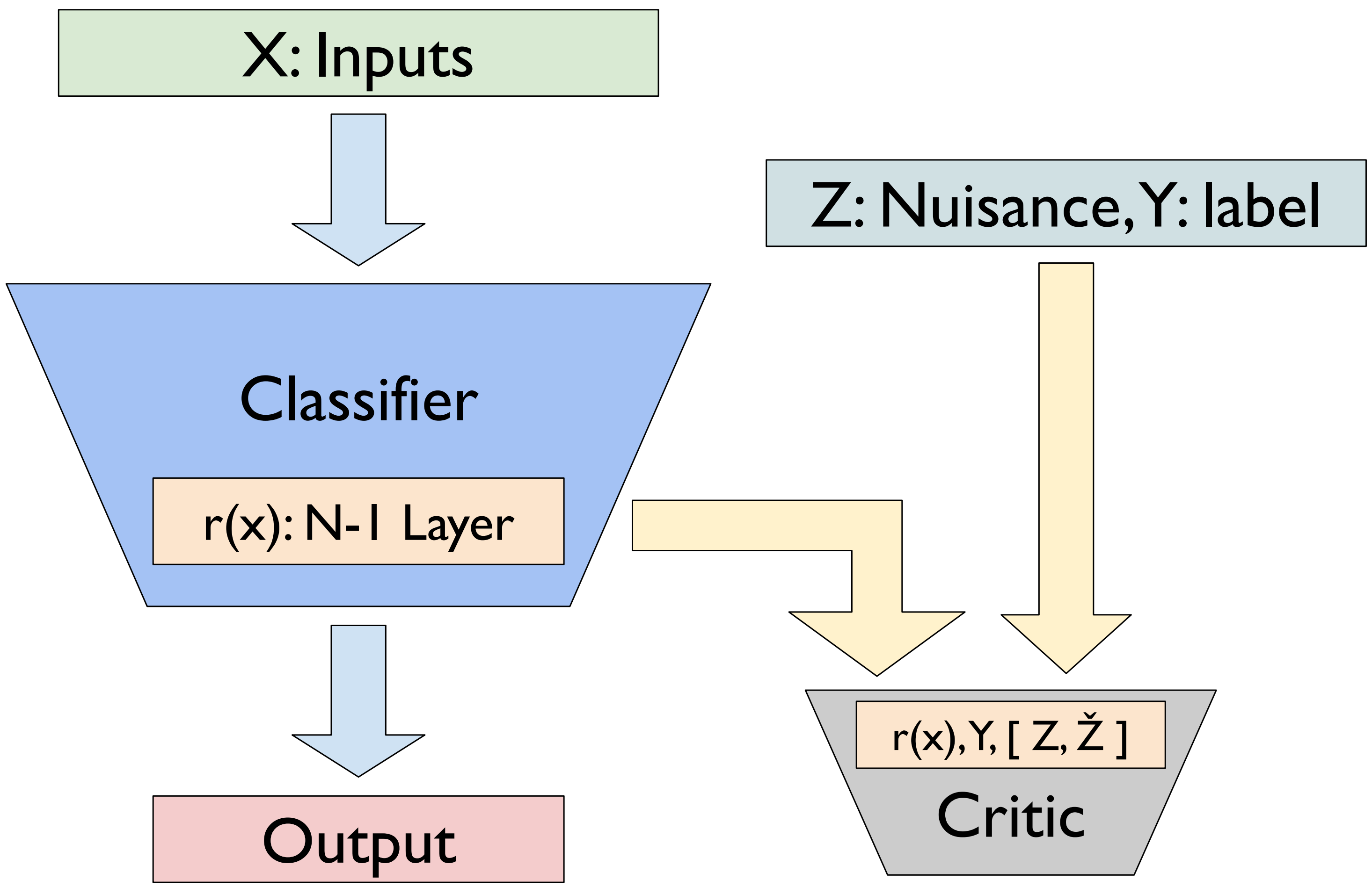
- Penalize mutual information
  - Input $(r_X, Y, [Z, \hat{Z}])$ to critic model (ϕ), a simple MLP
    - Approximates the mutual information, use this to penalize the loss



- Critic is trained to differentiate $(r_X, \text{Y}, \text{Z})$ vs $(r_X, \text{Y}, \hat{Z})$
  - Critic model is updated for every batch of the classifier training
  - It is proxy as the likelihood approximator

Nuisance Randomized Distillation

- Training
  - Train and update critic model for every batch of classifier training



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$$\mathscr{L} = w\left(CE(Y_{pred}, Y_{true}) - \lambda \log \frac{p_\phi(r_X, Y, [Z, \hat{Z}])}{1 - p_\phi}\right)$$

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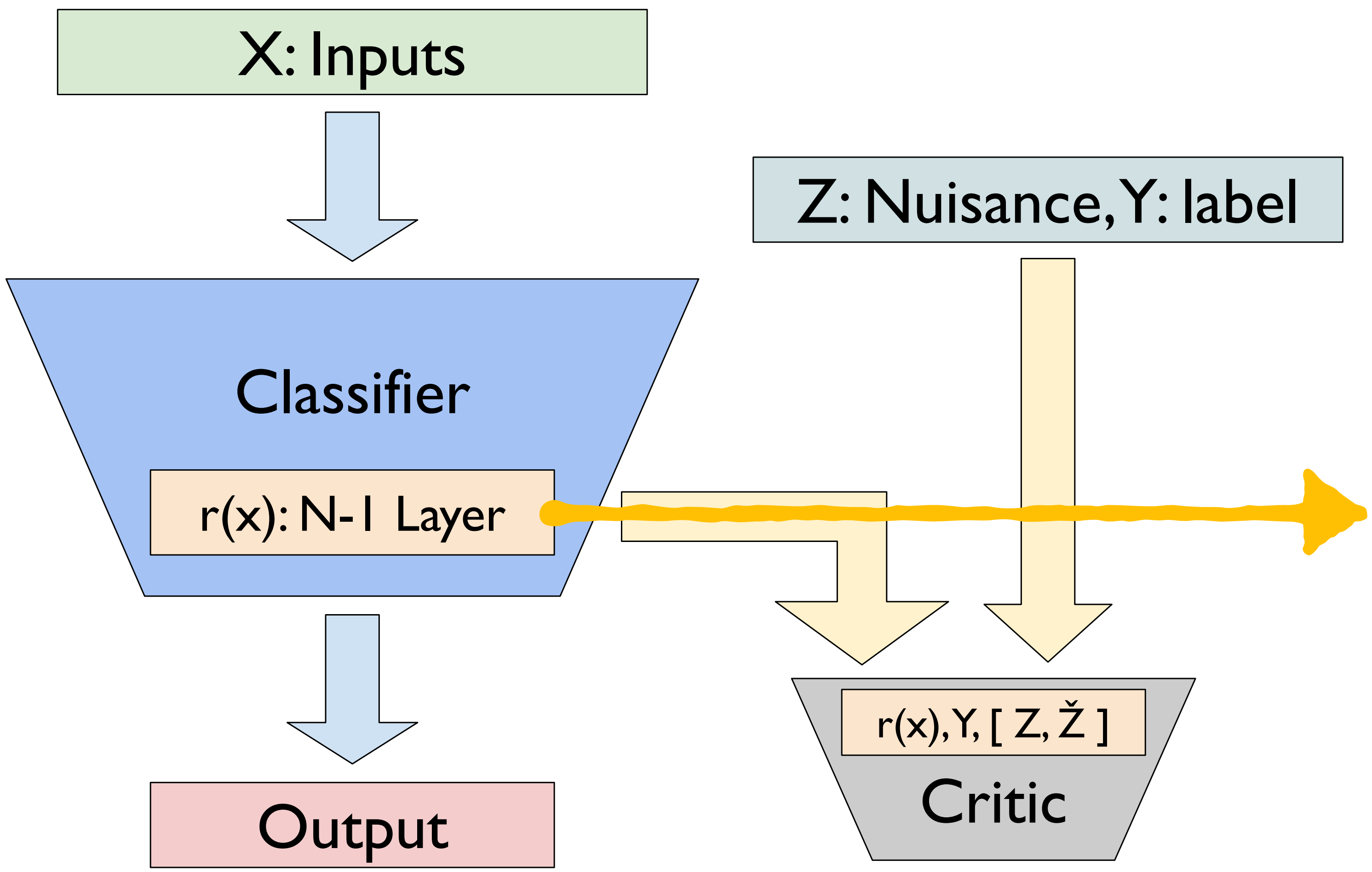

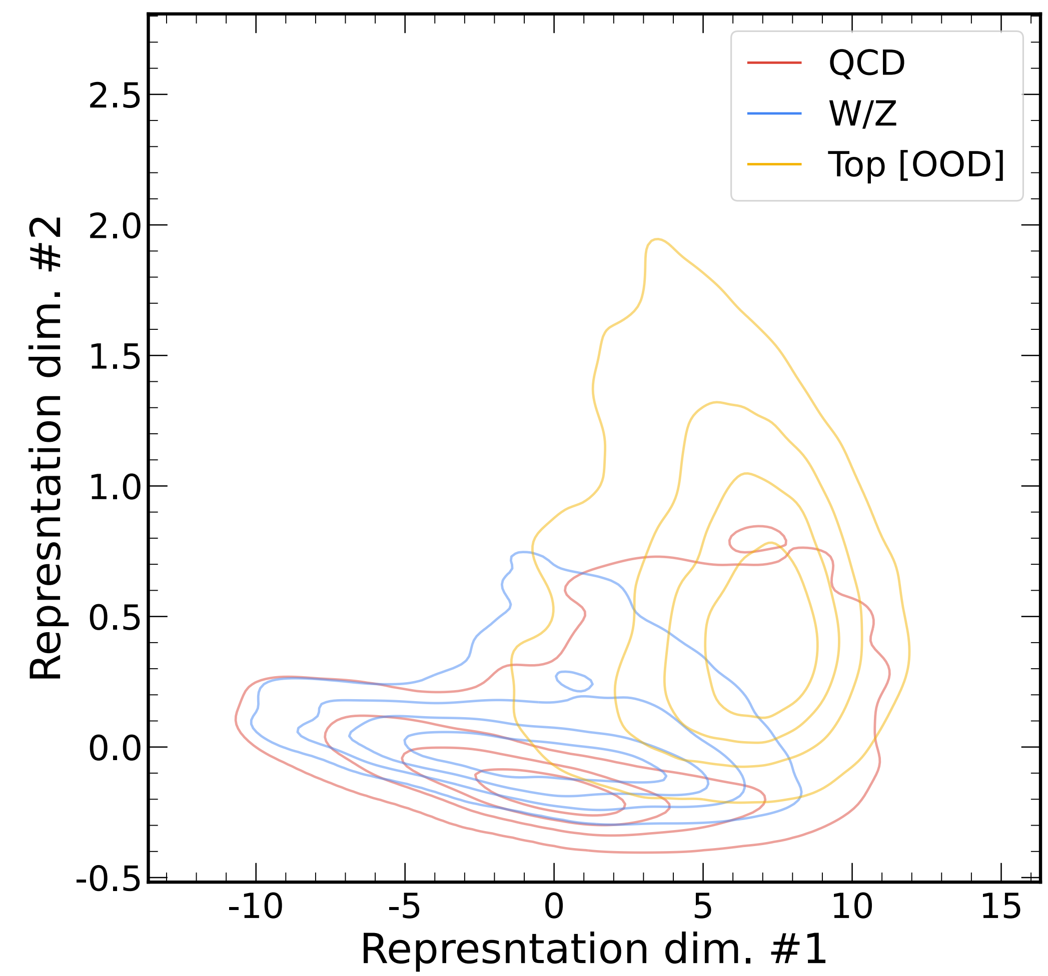

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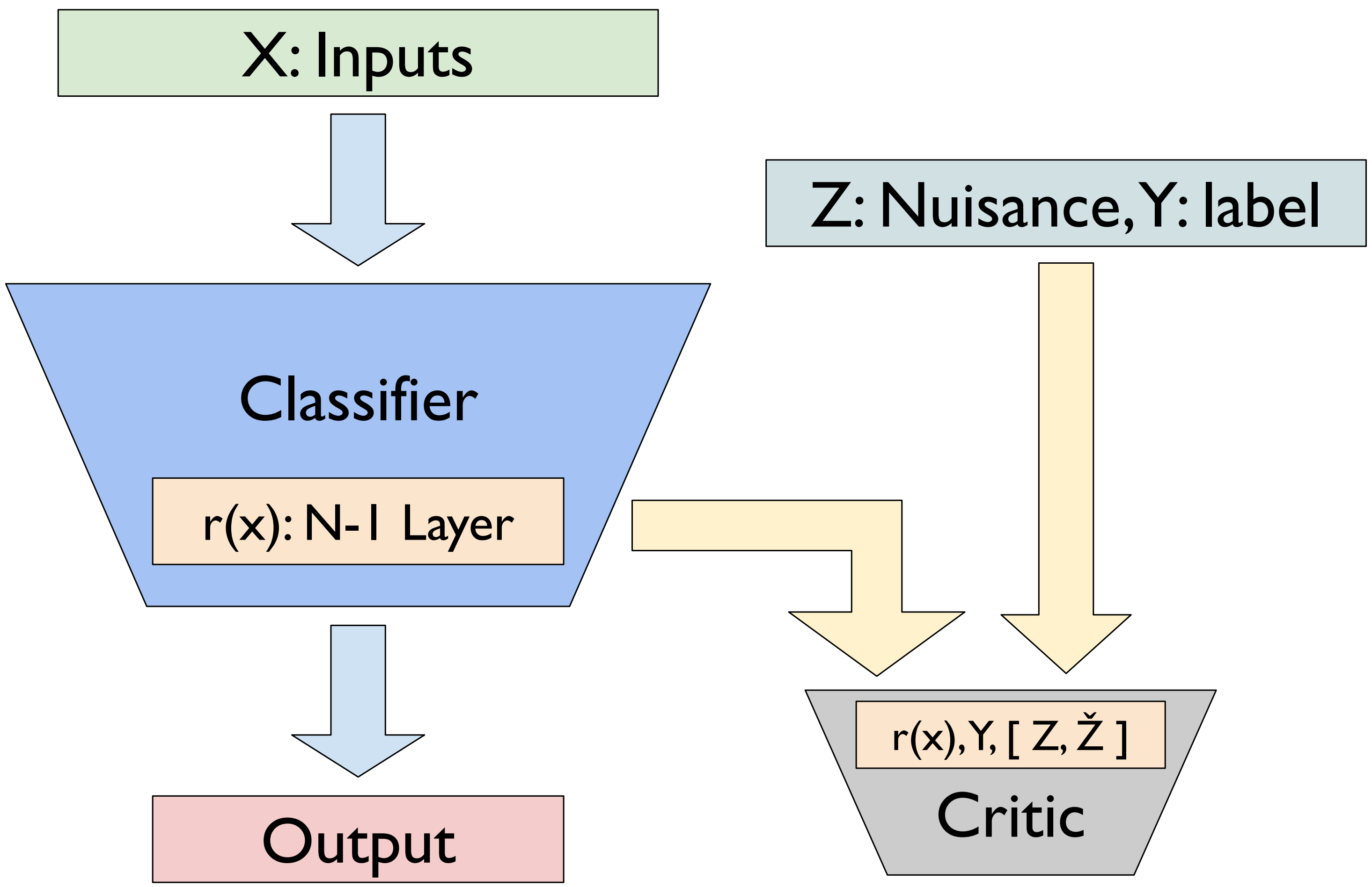
Nuisance Randomized Distillation

- OOD Detection:
  - Outlier Dataset: Top quarks jets
  - Use representations to build anomaly metrics



$$\mathscr{L} = w\left(CE(Y_{pred}, Y_{true}) - \lambda \log \frac{p_\phi(r_X, Y, [Z, \hat{Z}])}{1 - p_\phi} \right)$$

- Metrics:
  - Calculate the distance from samples in representation space

$$d_A = (r_X - \mu_A)\ \Sigma_A^{-1}\ (r_X - \mu_A)^T$$

(dist. from BKG A)

  - Obtain distance from all BKG samples
    - Here: $[d_{QCD}, d_{WZ}]$
  - Use this to find anomalies

Nuisance Randomized Distillation

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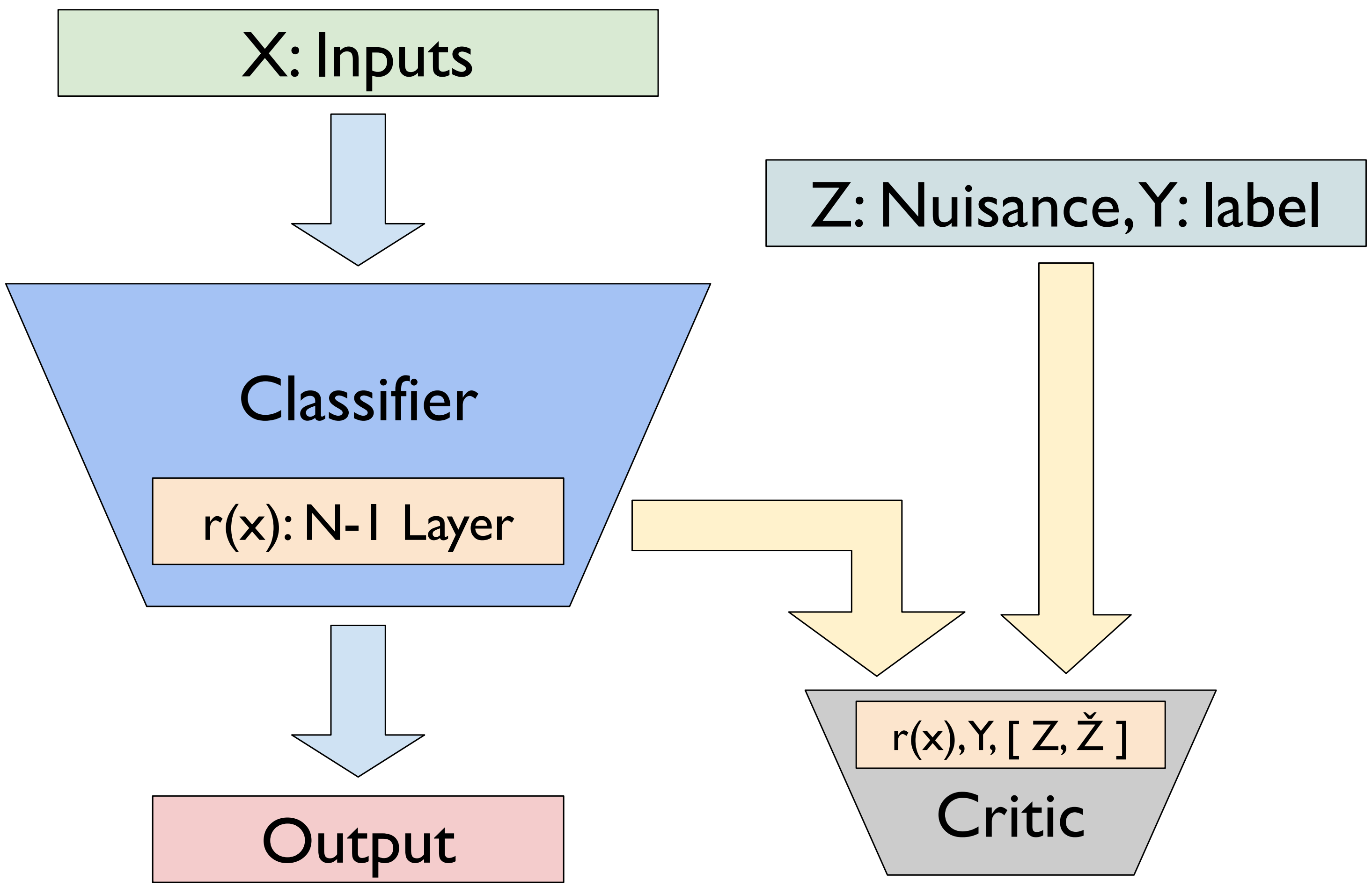

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- Metrics:
  - Obtain distance d_A from all BKG samples
    - Here: $[d_{QCD}, d_{WZ}]$
- Alternative Metrics:
  - Max(Logits) also serves as a OOD Score
  - Max $_{\text{Logits}}$ (OOD) < Max $_{\text{Logits}}$ (BKG)