SURFing to the fundamental limit of jet tagging

Ian Pang

May 12, 2026

Pheno 2026, Pittsburgh

[2511.15779] **IP,** D. Faroughy, D. Shih , R. Das, G. Kasieczka

ian.pang@physics.rutgers.edu

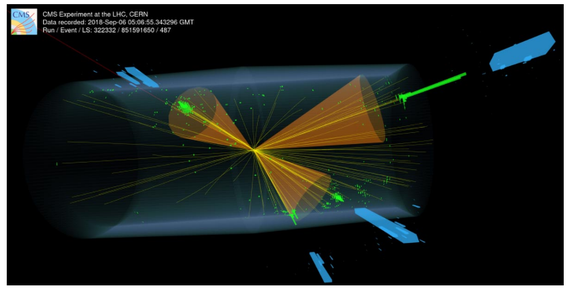
Outline

1. **Generation:** Jet generative models

2. **Inference:** Fundamental limit of jet tagging

3. **Evaluation:** SURF method

Jet generative models



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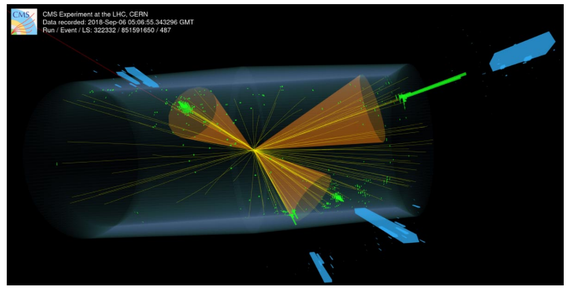

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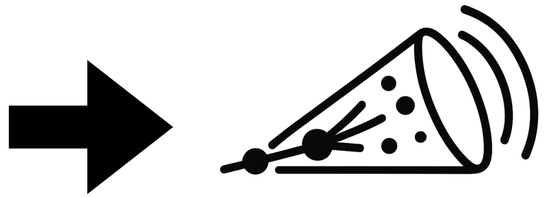
Generation: Generative model 

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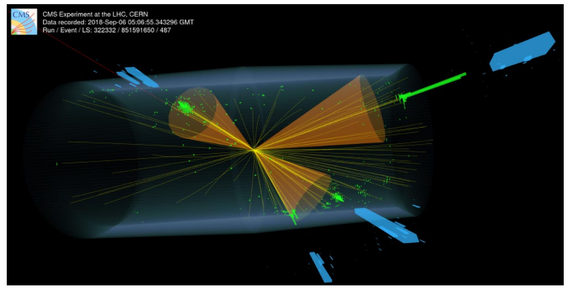

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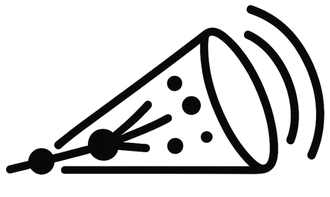
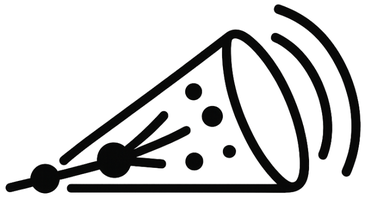
Generation: Generative model → 

Likelihood computation:  → Generative model → Likelihood $p(\text{jet})$

Jet tagging

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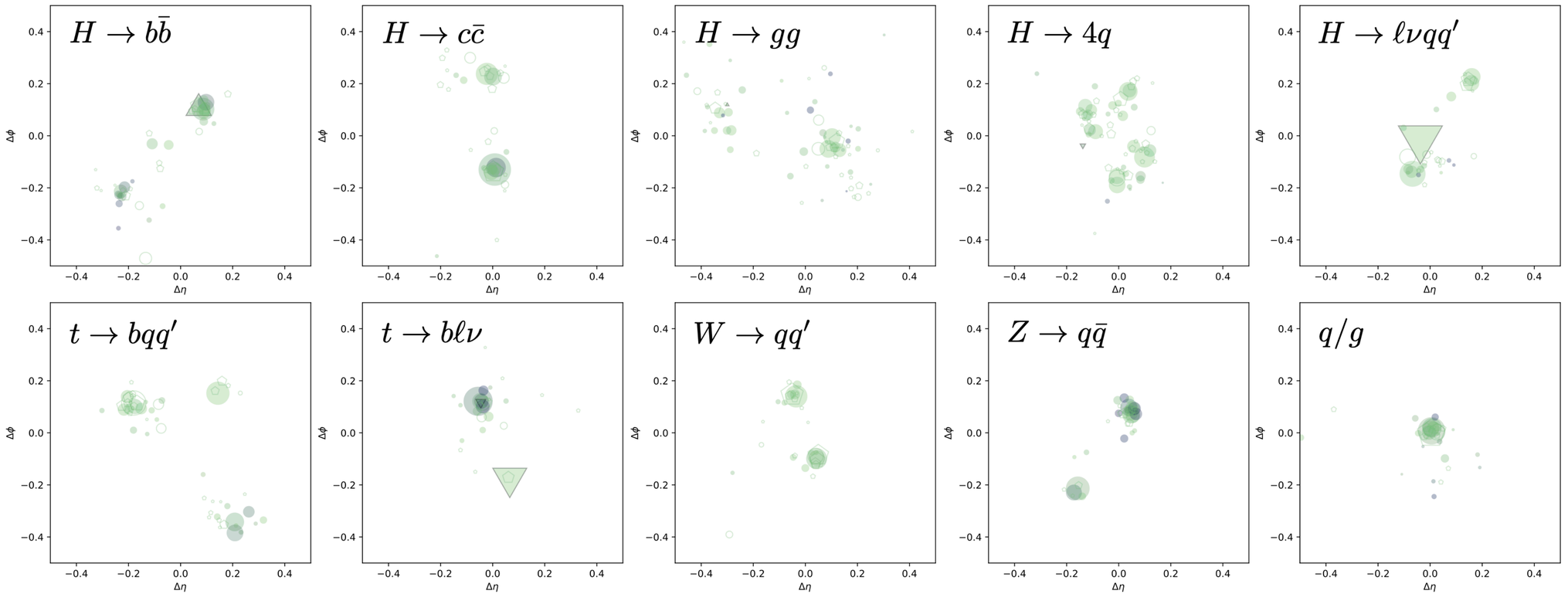

https://github.com/jet-universe/particle_transformer

Jet tagging

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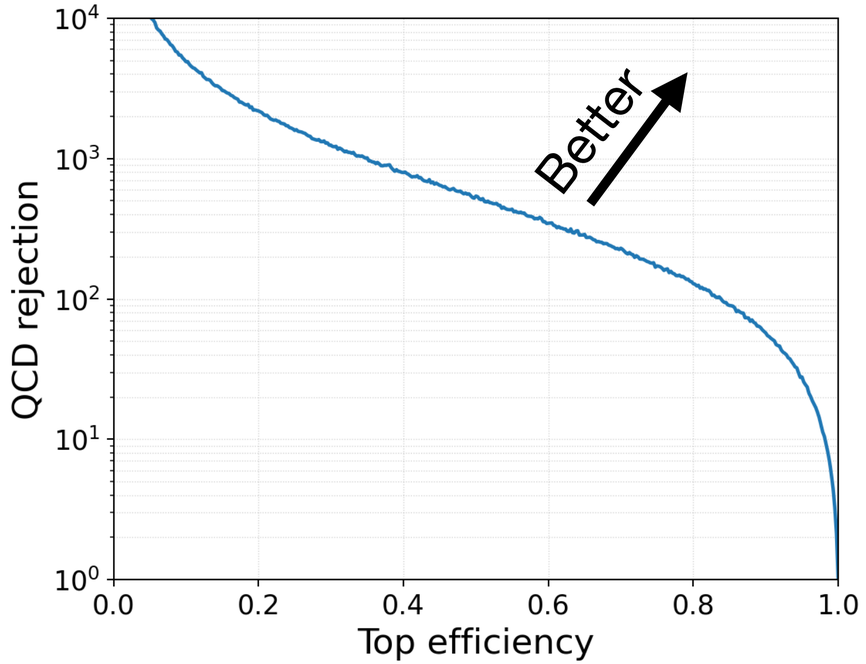
ROC curve:



Background: QCD jets
Signal: Top jets

Fundamental limit of jet tagging (2411.02628)

[2411.02628] J. Geuskens et al.

- **ML jet taggers (classifiers)** are achieving state-of-the-art performance!

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- **Neyman-Pearson Lemma:** Likelihood ratio is the most powerful test statistic for binary classification

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- **Goal:** Determine the optimal achievable performance for jet tagging
- **Neyman-Pearson Lemma:** Likelihood ratio is the most powerful test statistic for binary classification
- **Challenge:** True jet likelihoods are not available **a priori**

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GPT jet generative models trained on JetClass

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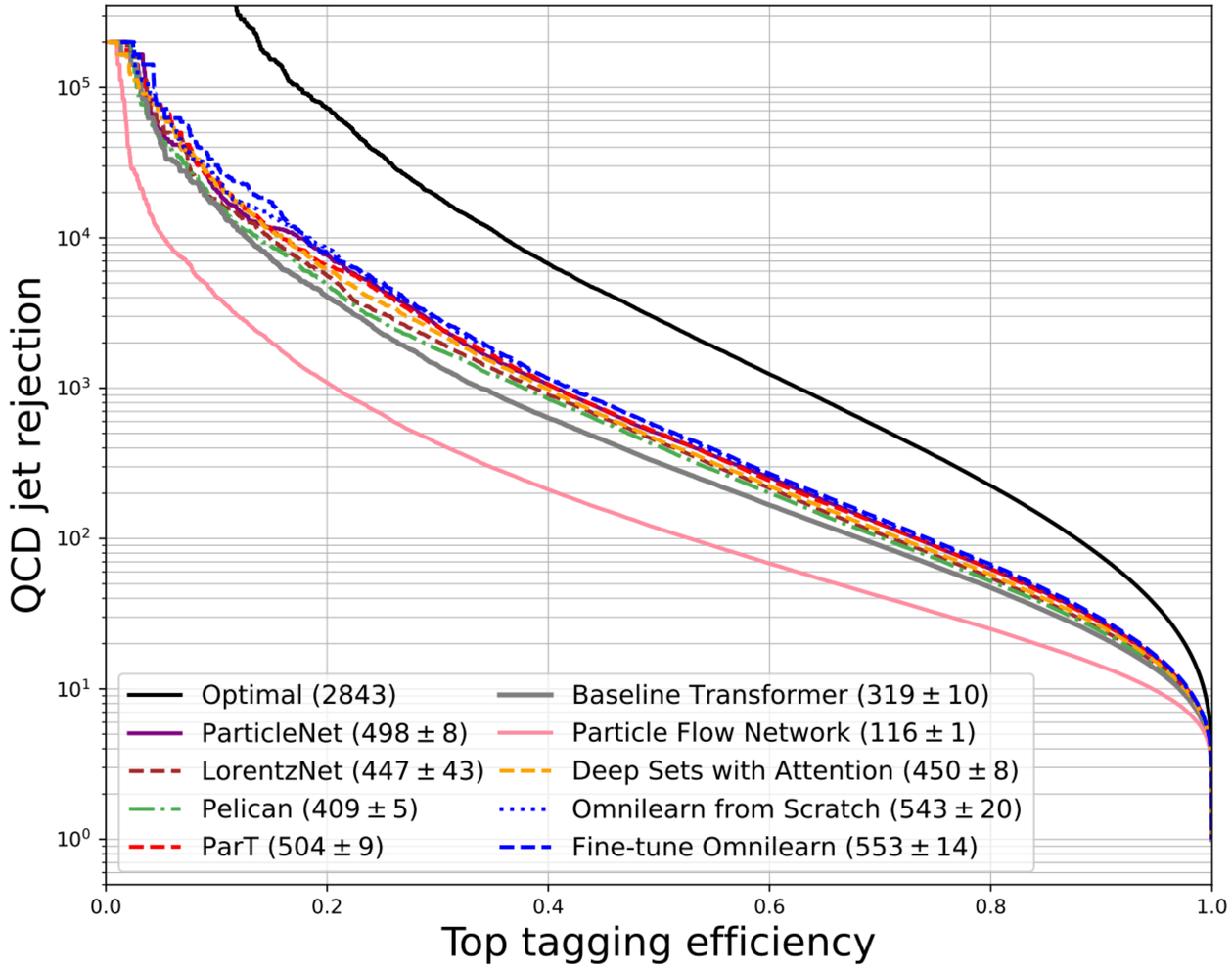

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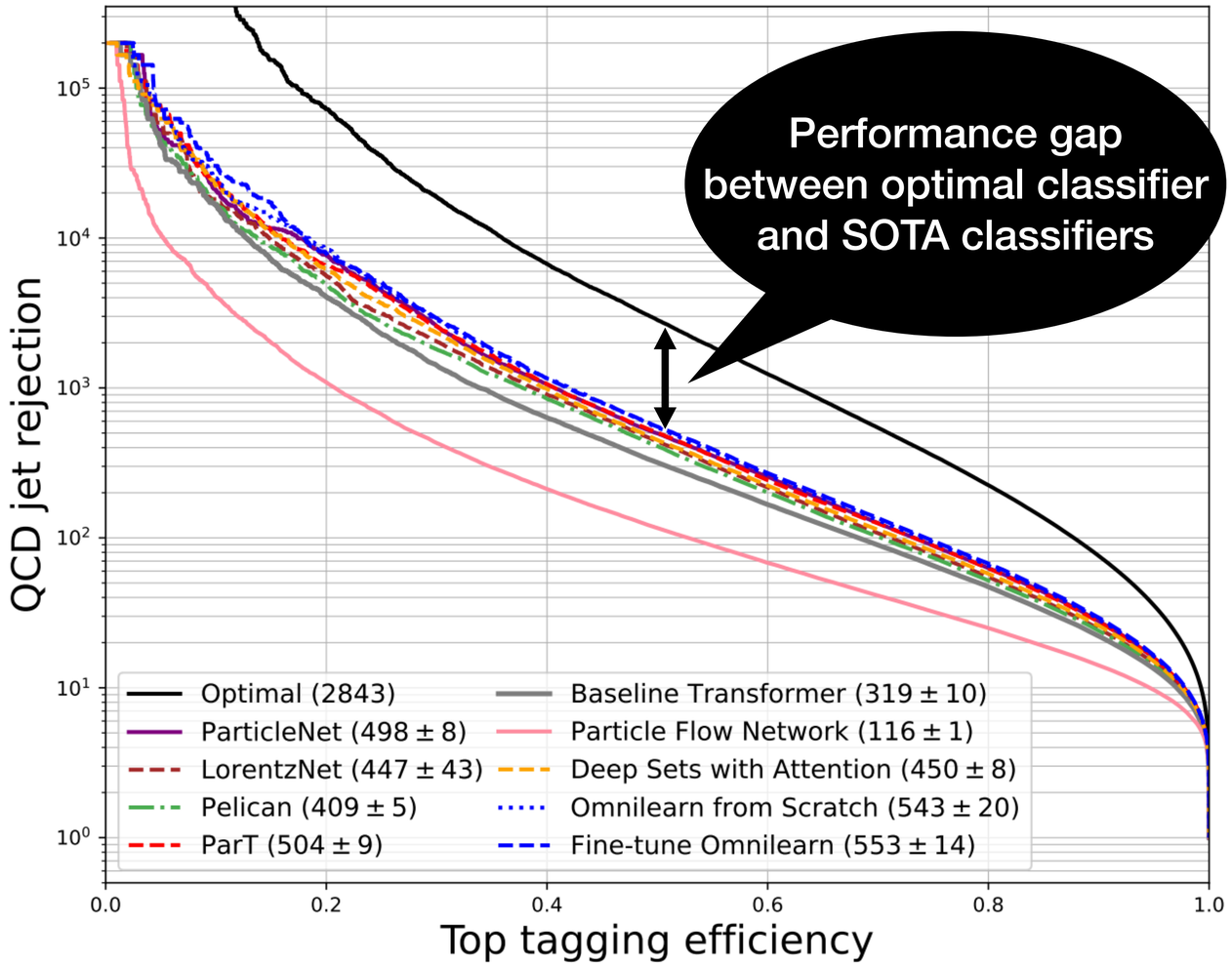

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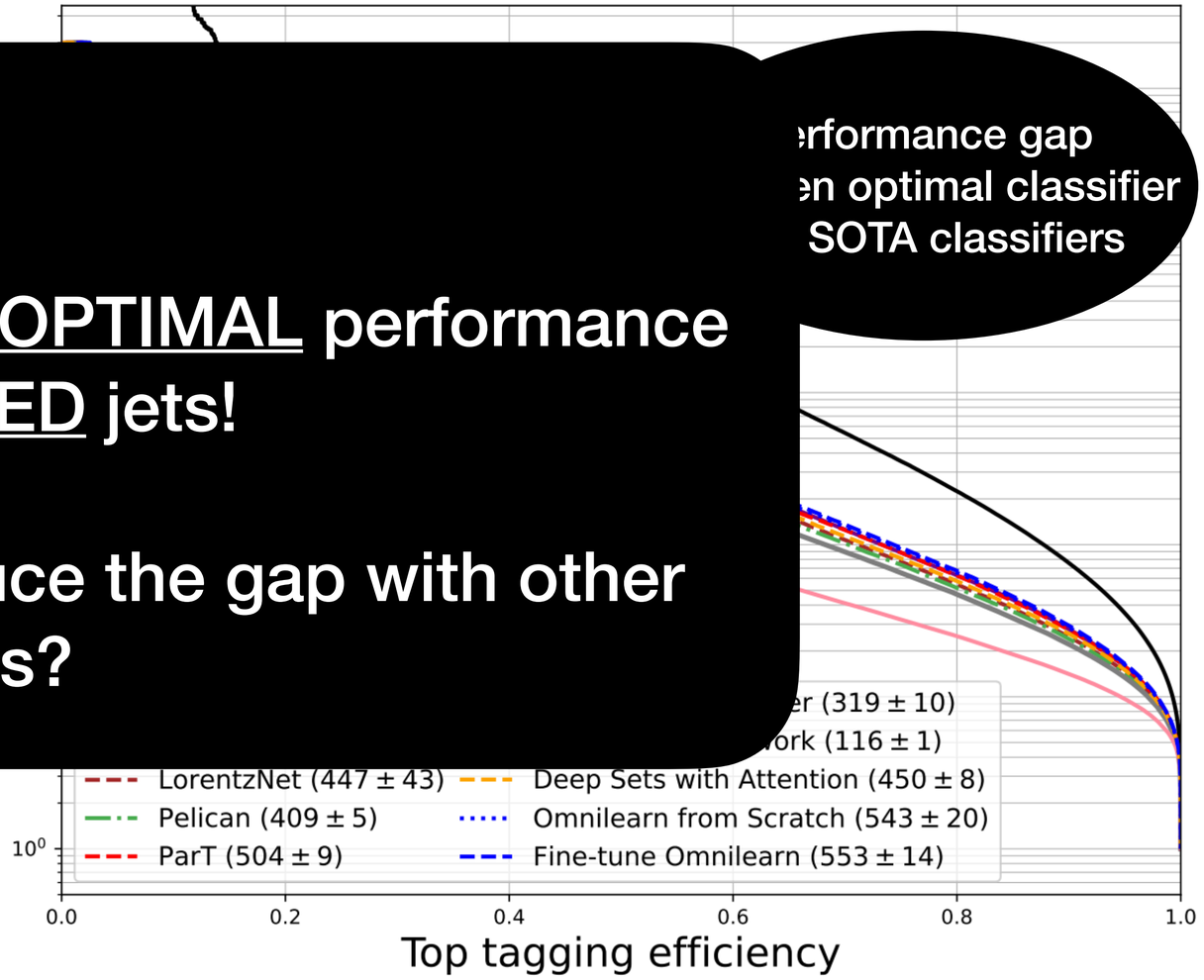
Not so fast…

1. This is only the <u>OPTIMAL</u> performance for the <u>GENERATED</u> jets!

2. Can we reproduce the gap with other generative models?

[2411.02628] J. Geuskens et al.

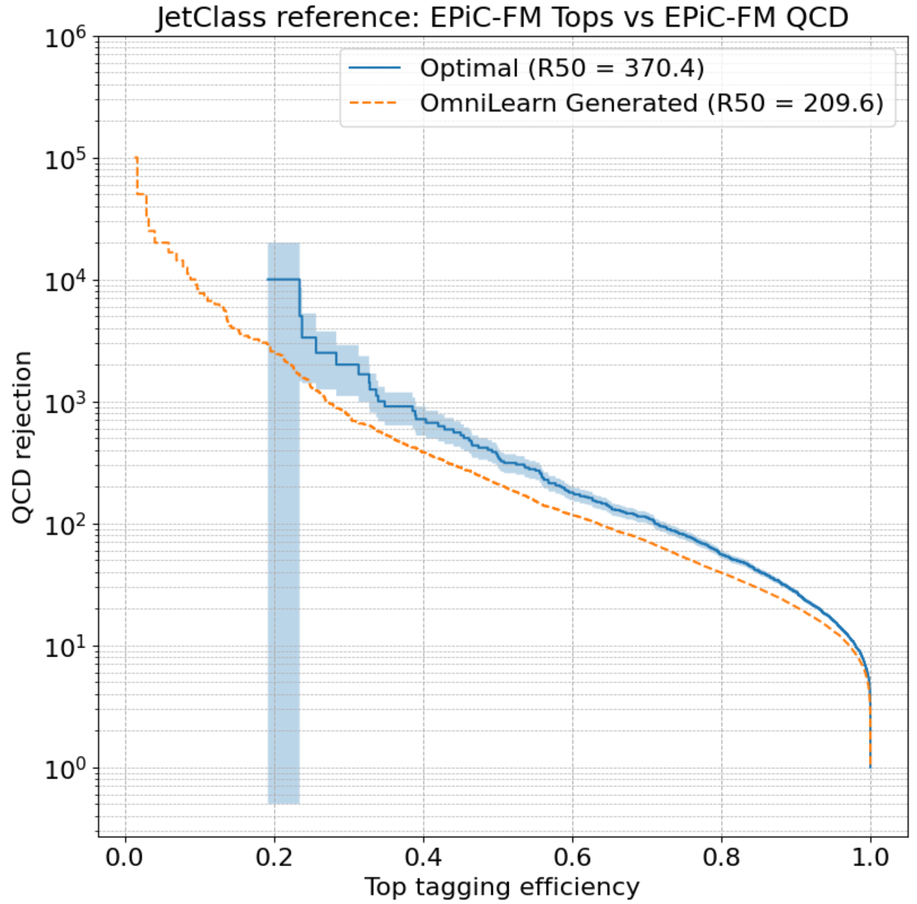
erformance gap
en optimal classifier
SOTA classifiers



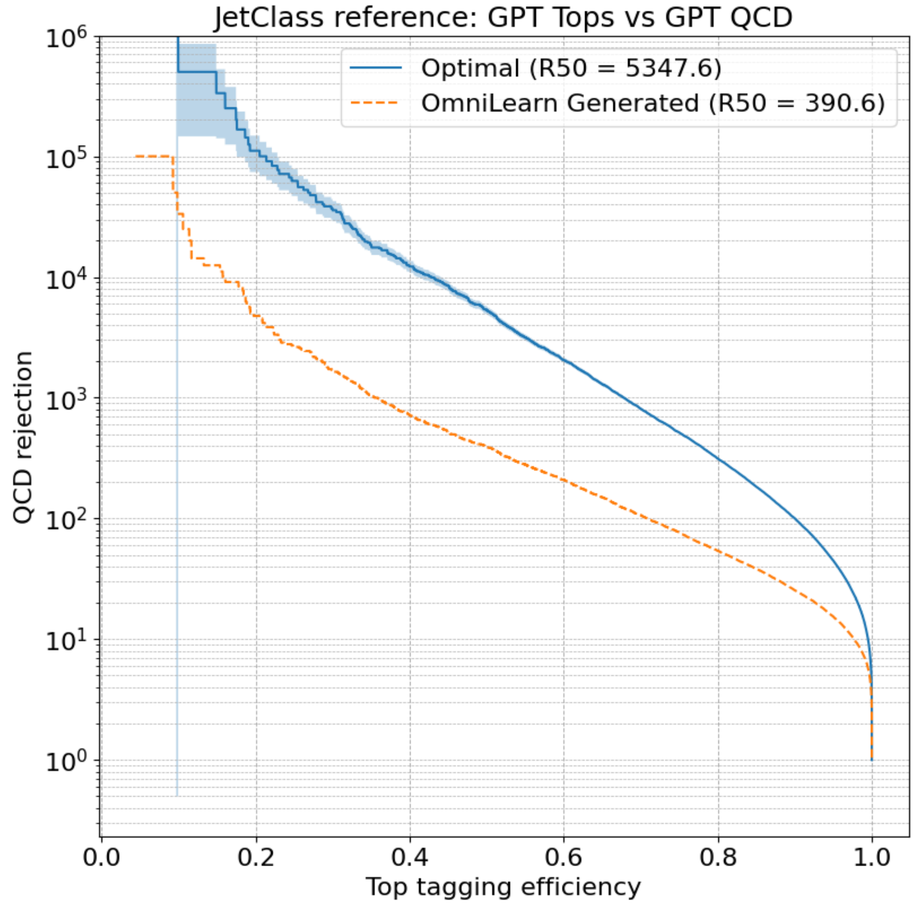
Tops vs QCD

We restricted to up to hardest 40 jet constituents

EPiC-FM results



Rutgers GPT results



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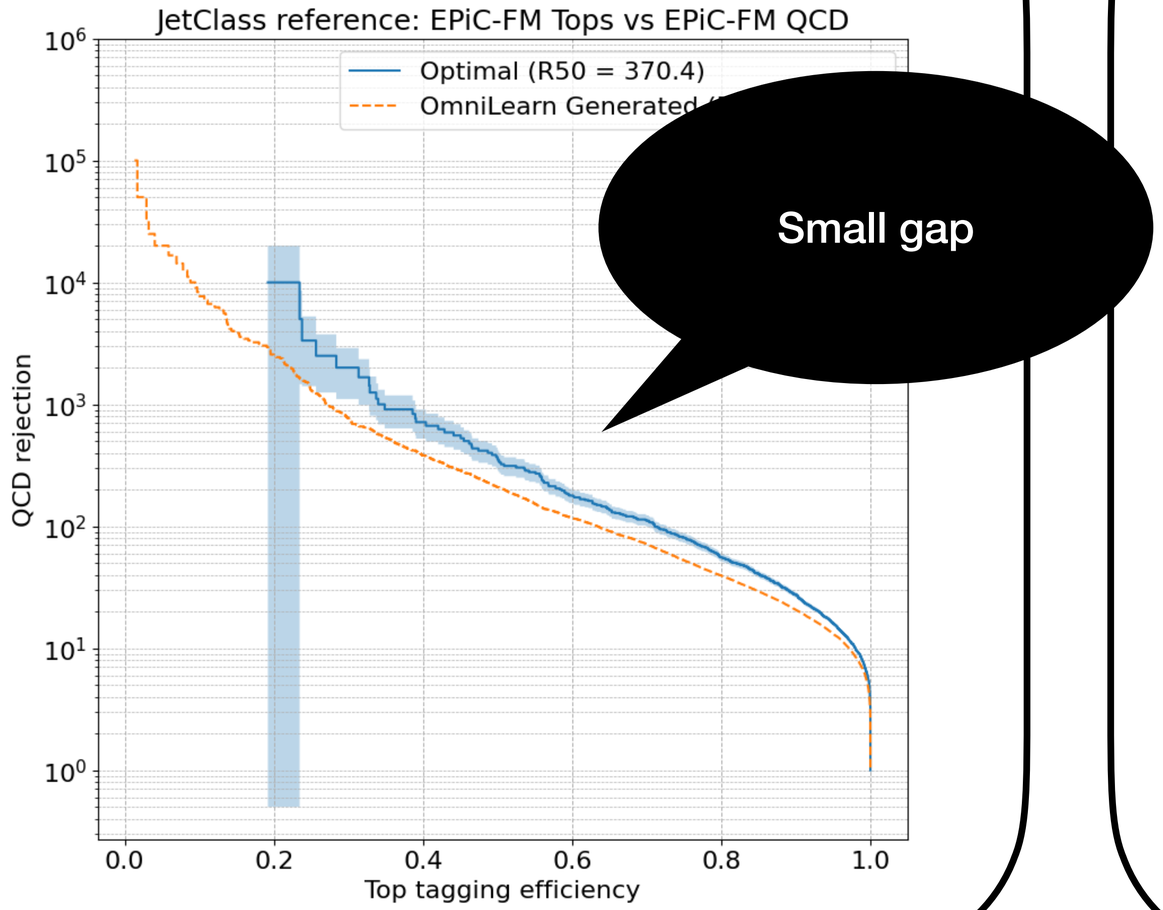

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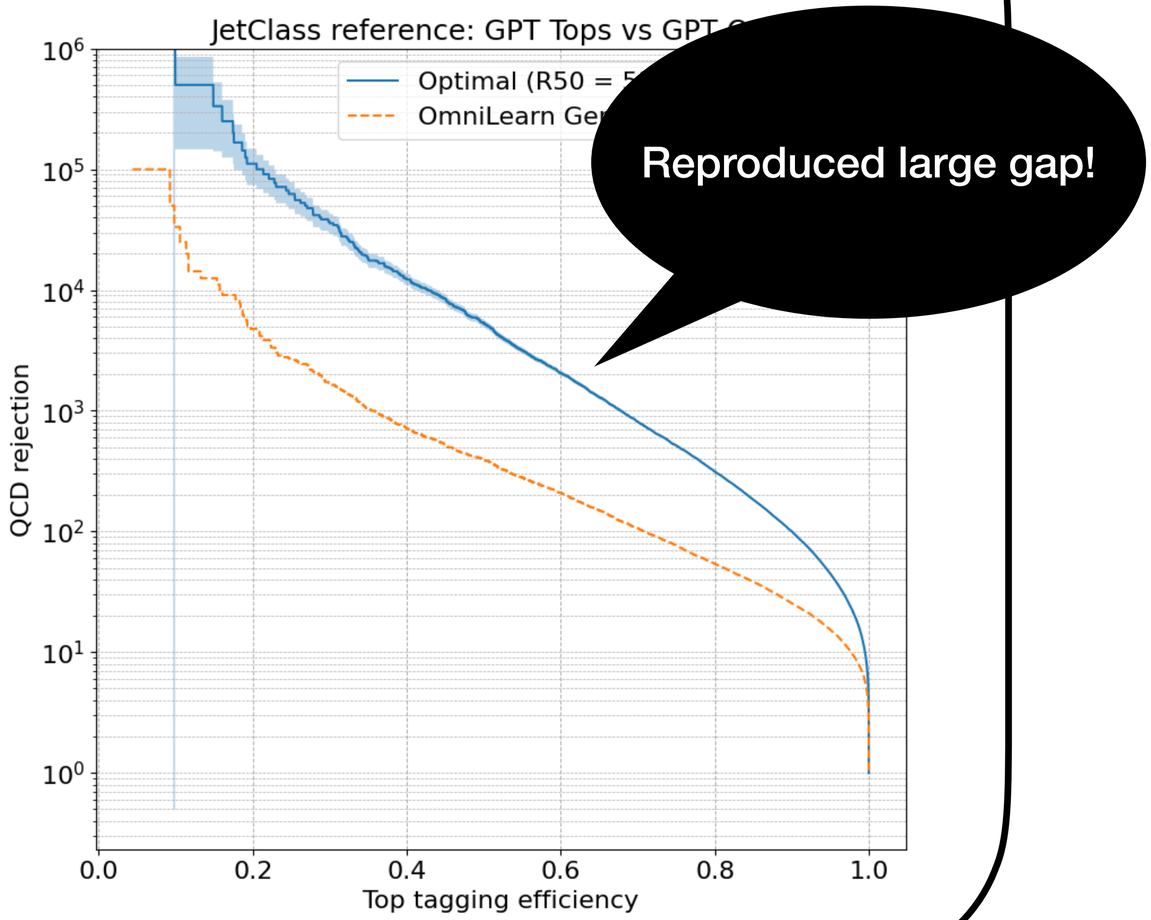

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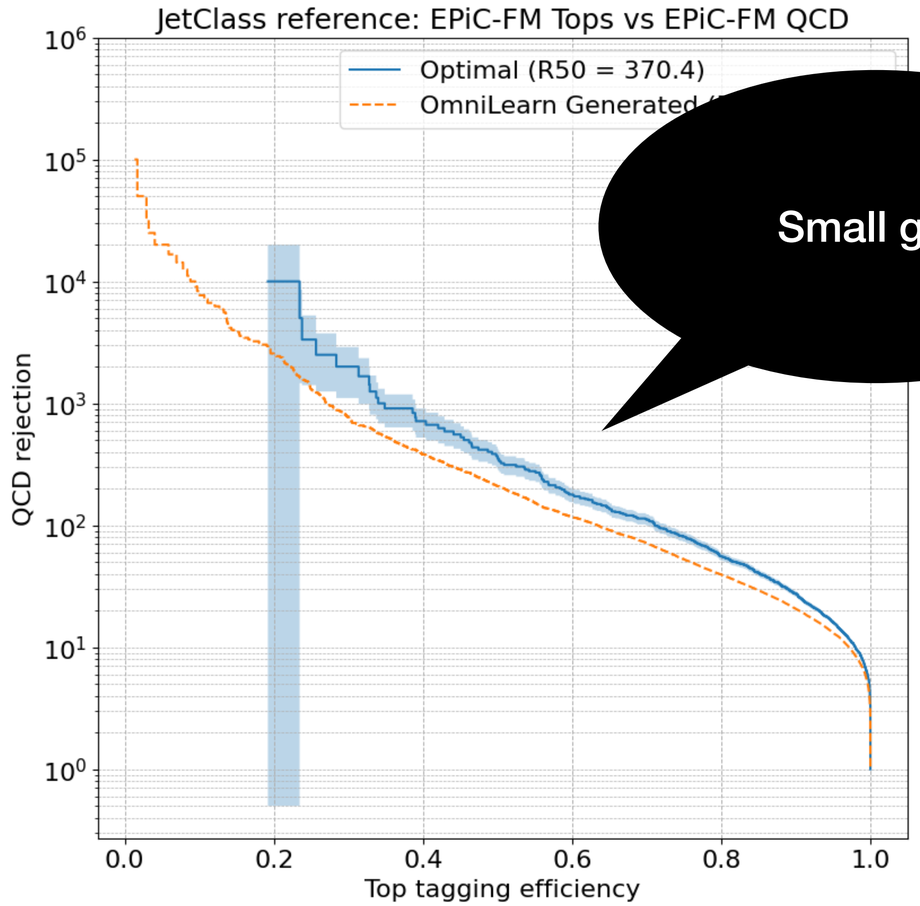
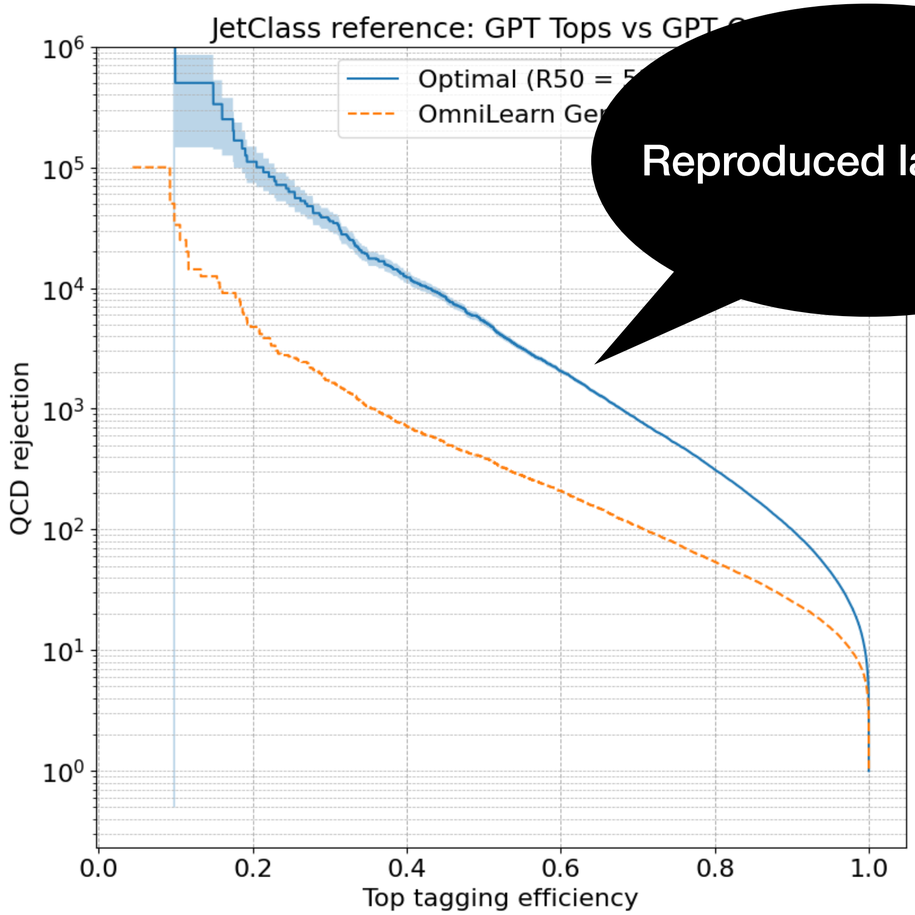
So is there really a gap? If so, which method is correct?

EPiC-FM result



Small gap

s GPT results



Reproduced large gap!

Likelihood of reference?

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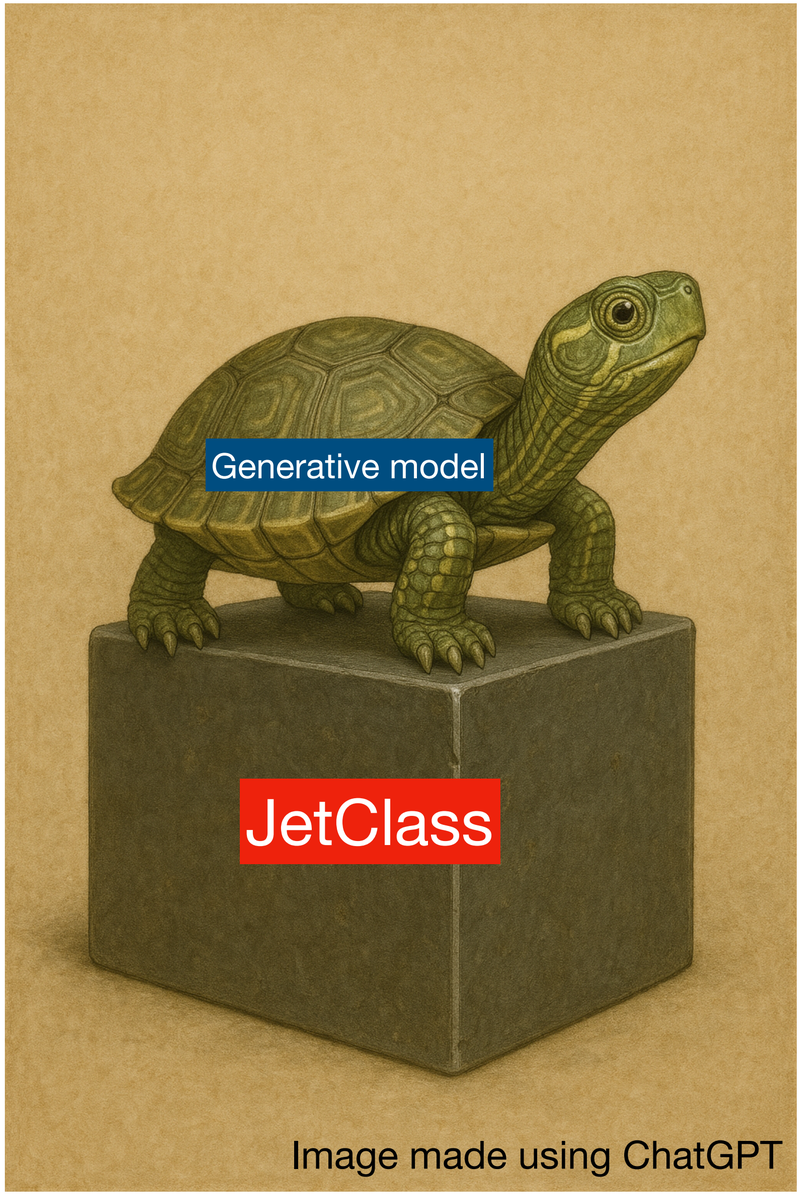
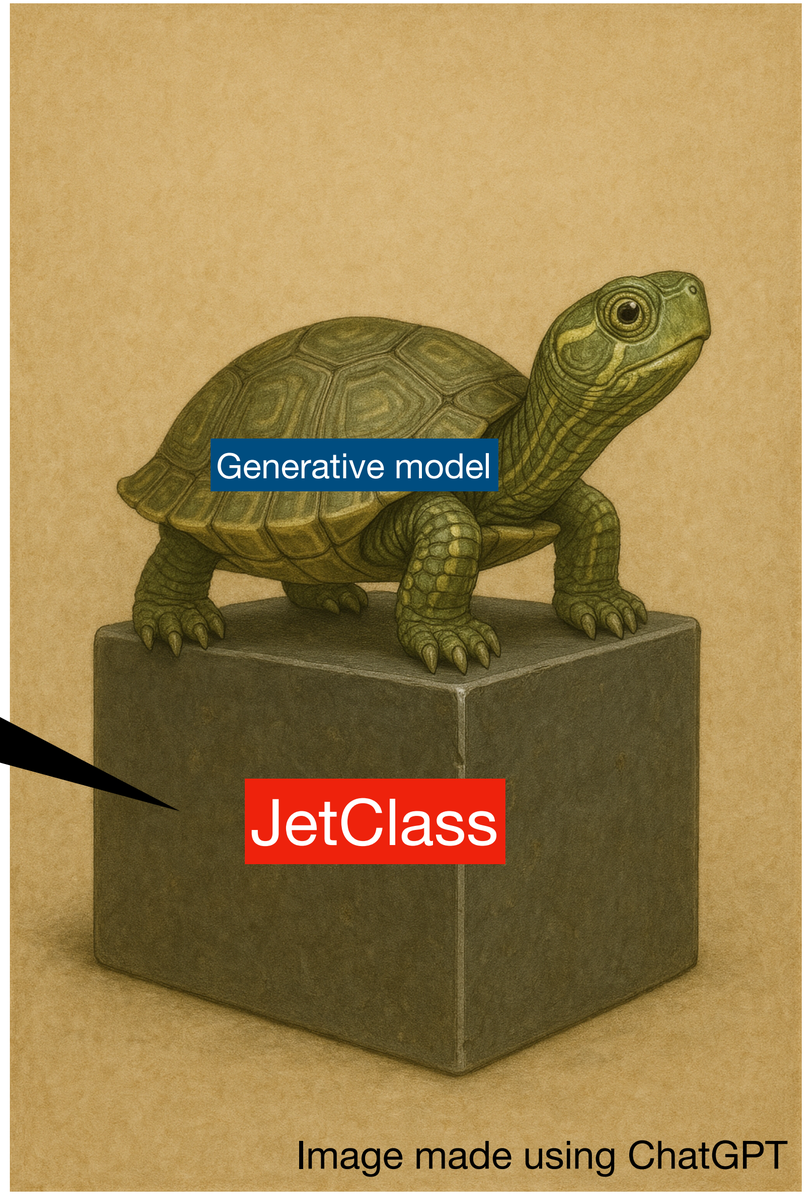


Image made using ChatGPT

Likelihood of reference?

Don’t have likelihood of reference jets :(



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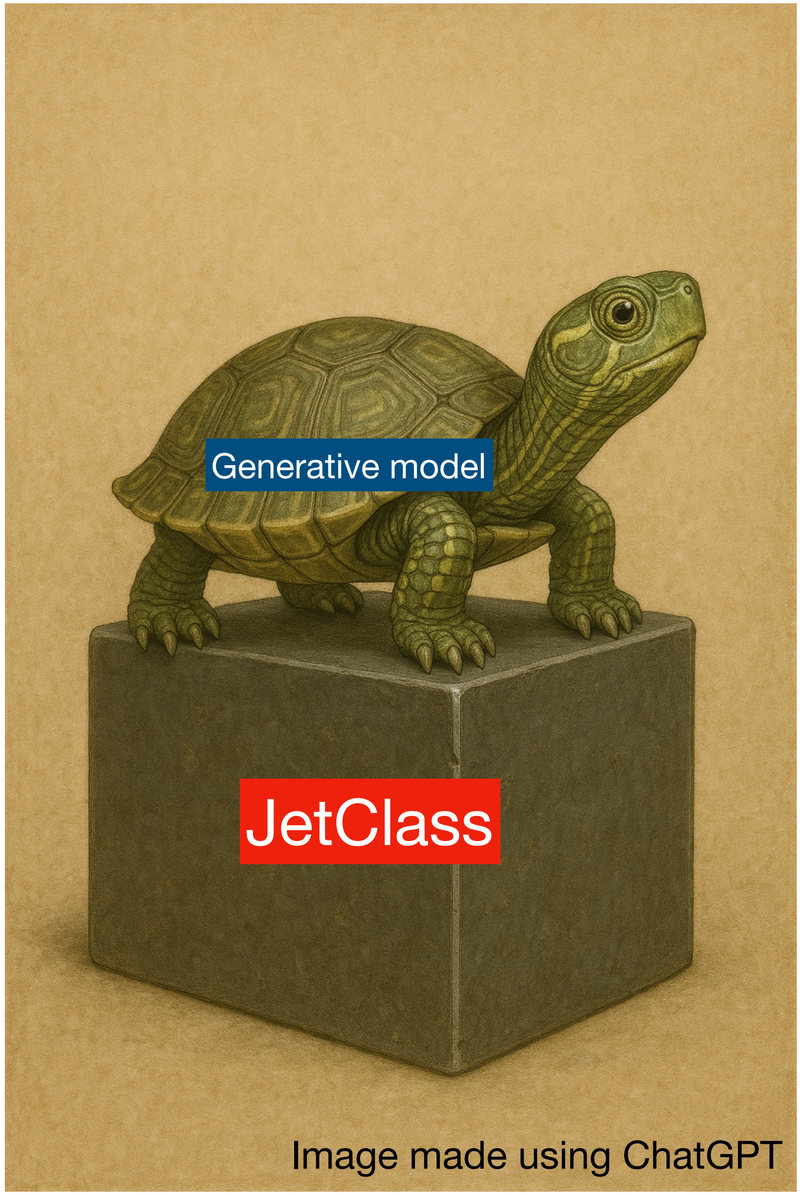

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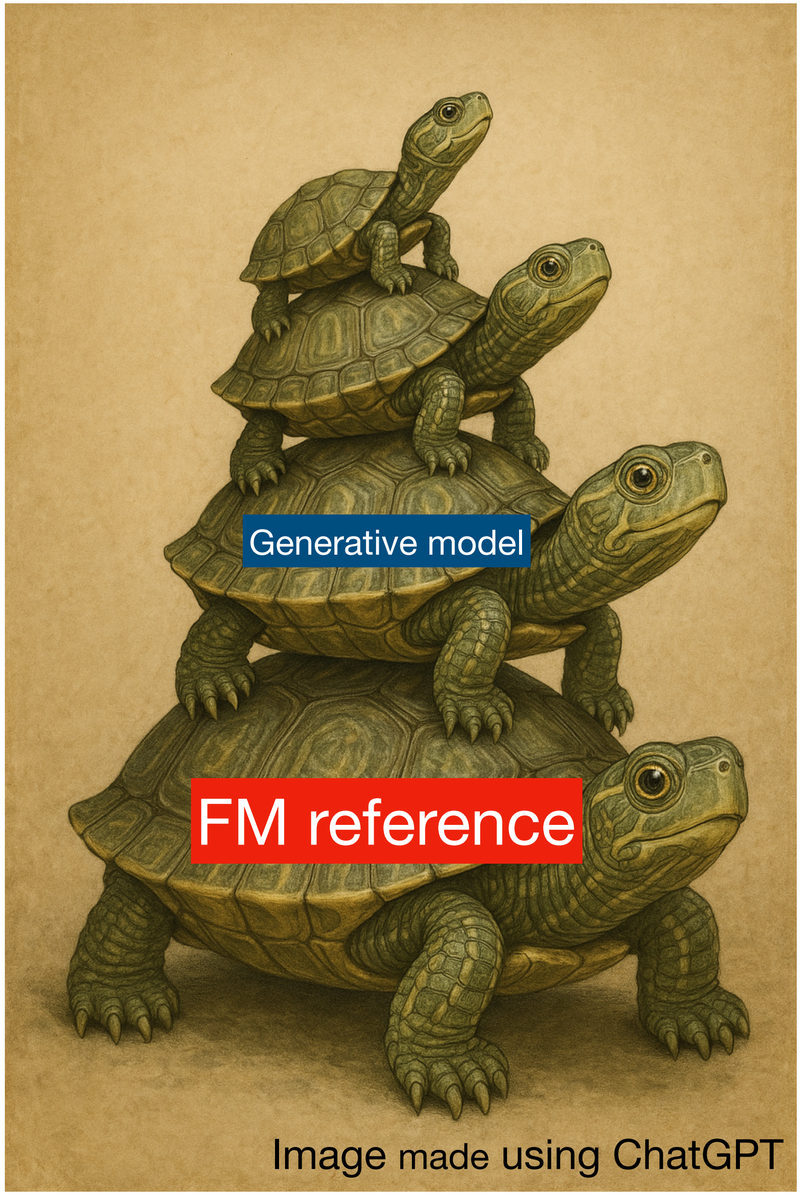
- **Use generated EPiC-FM jets as reference:**

SUrrogate ReFerence (SURF) method



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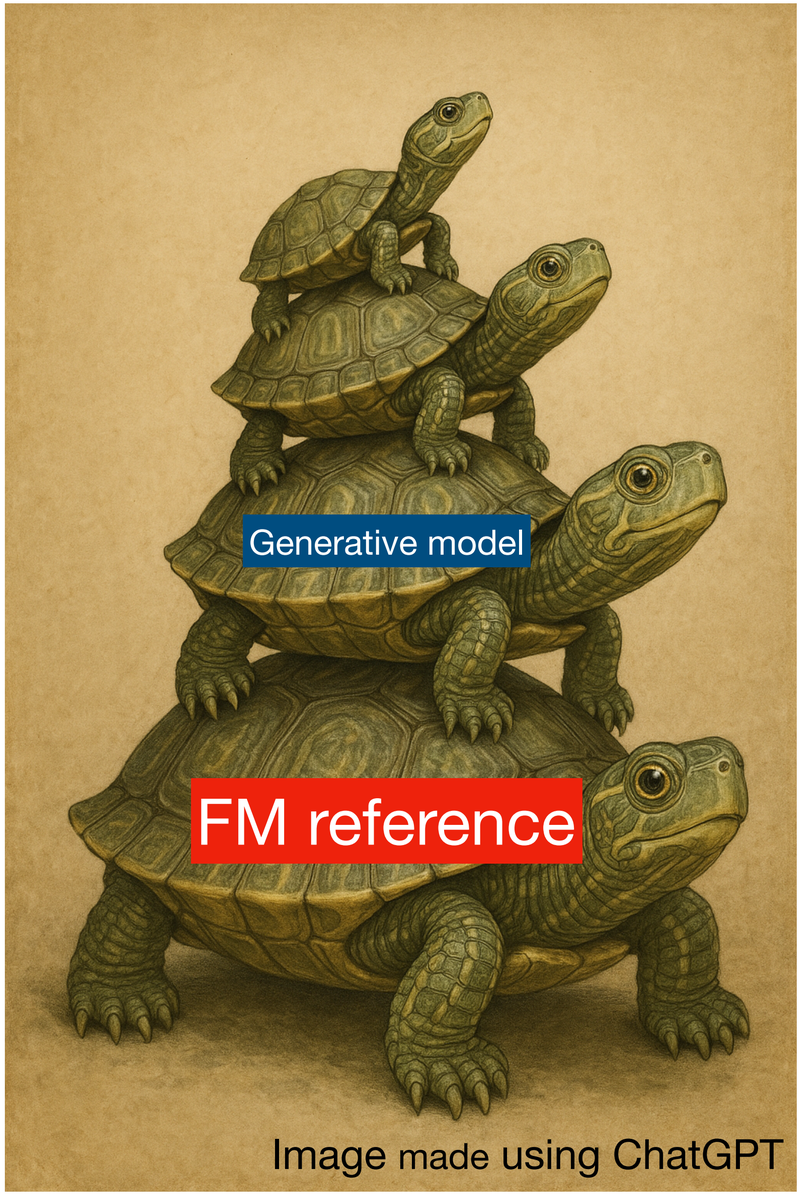

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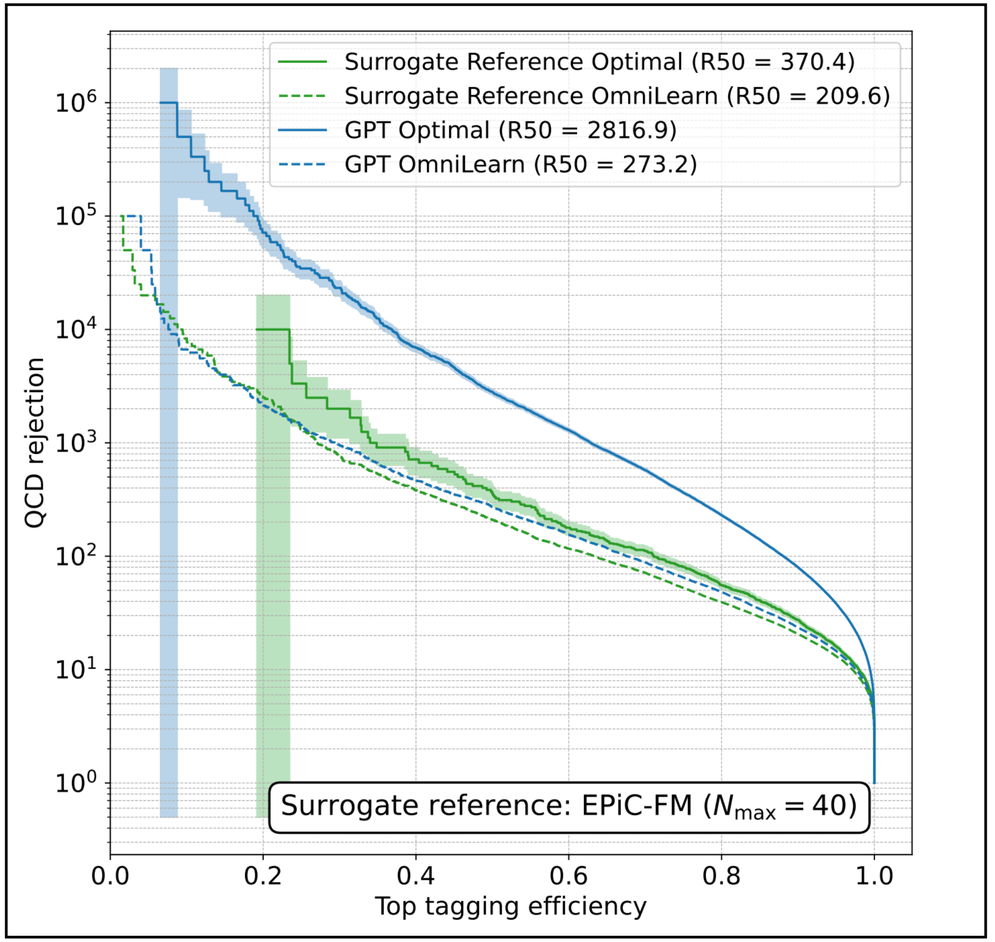

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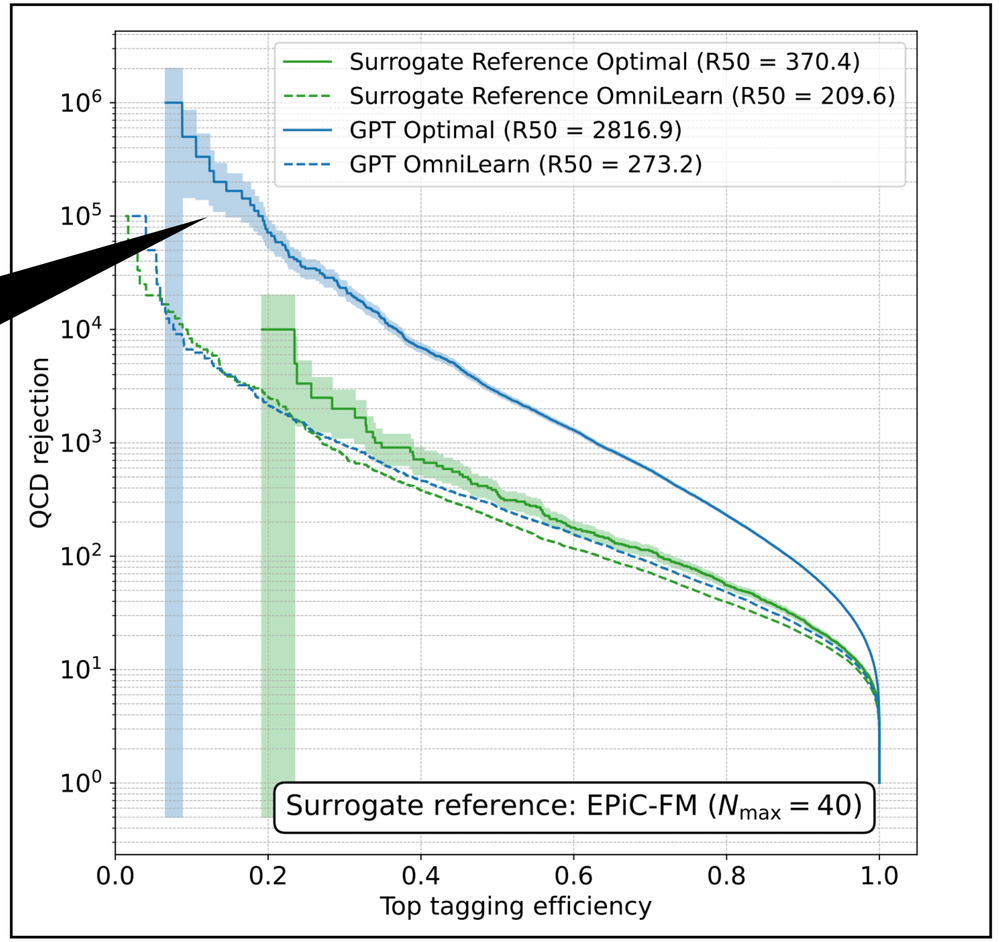
GPT ROC curve is vastly inflated compared to reference ROC curve



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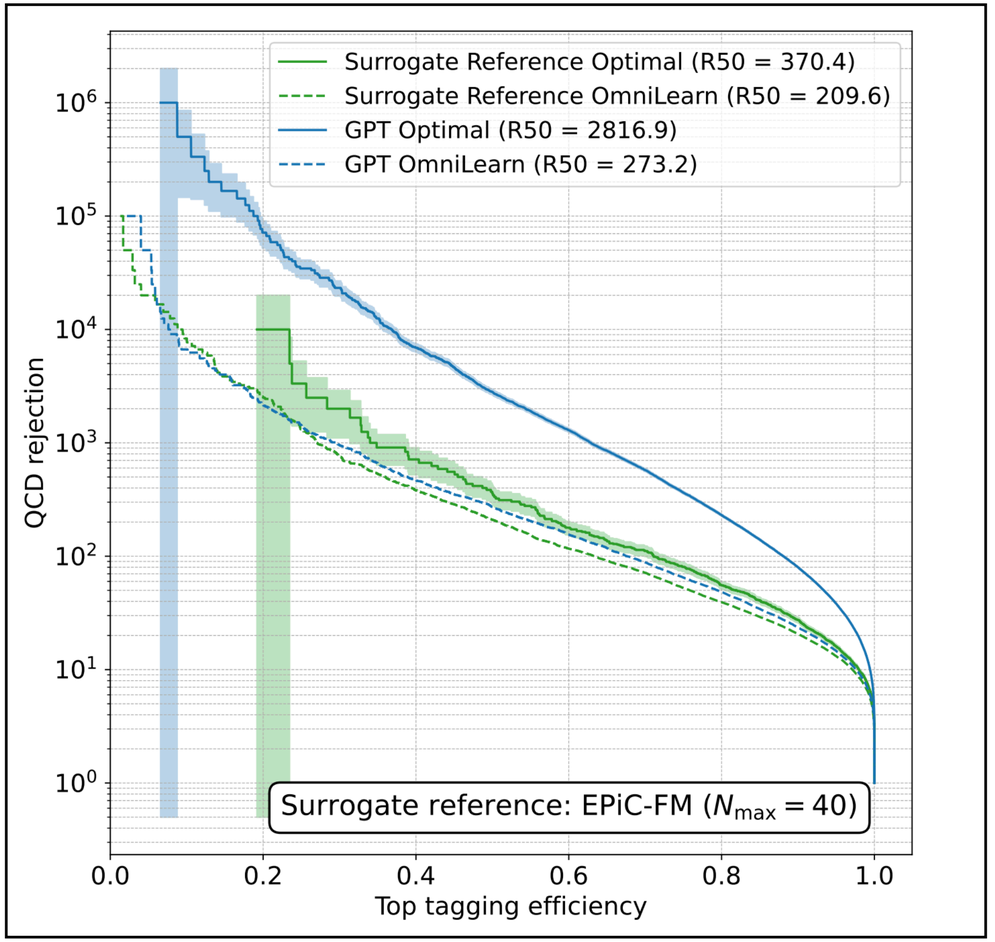

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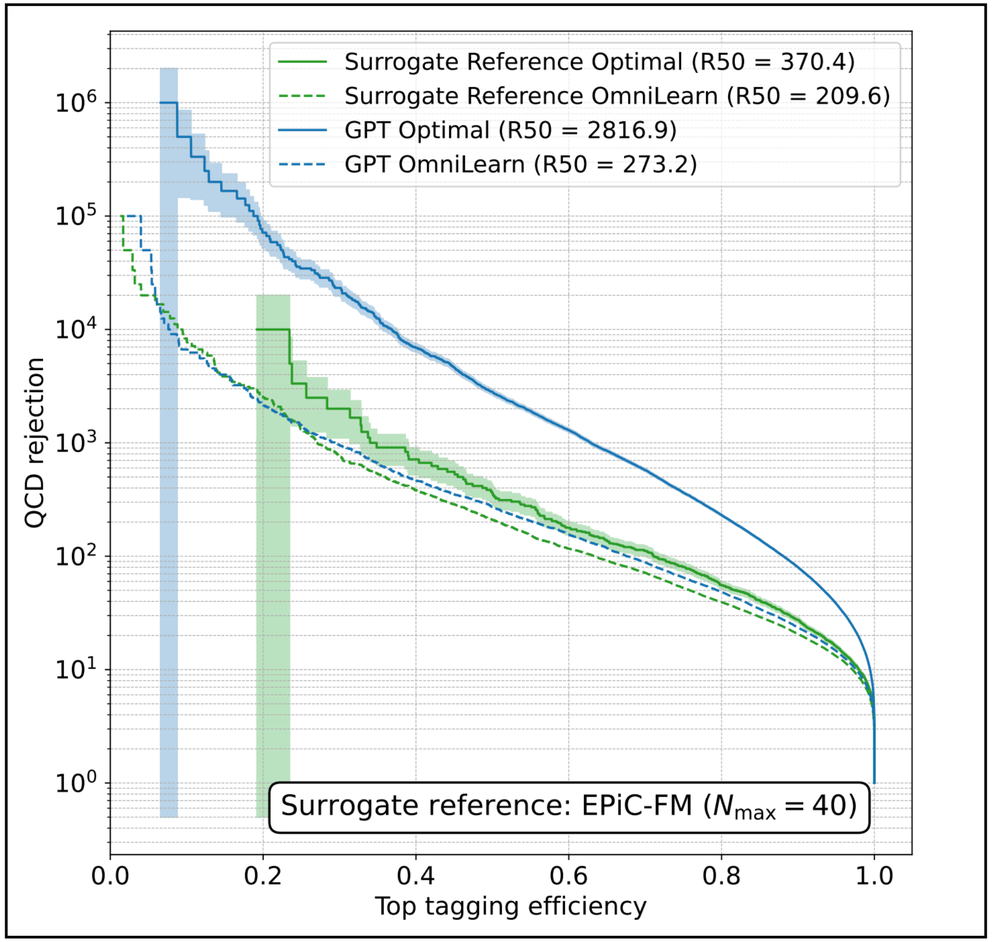
- We have an example where GPT artificially inflates reference ROC curve



Possible explanation

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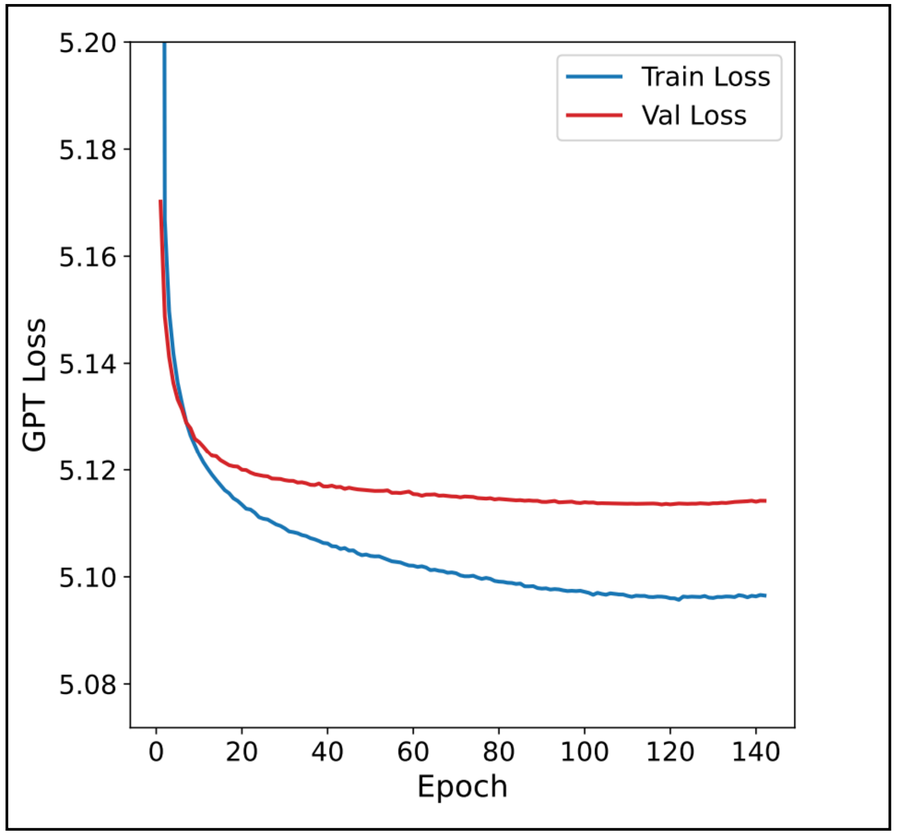
- Val loss > Train loss
- GPT jets are more similar to training jets than validation jets
- Overfitting?



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arXiv: 2311.17035

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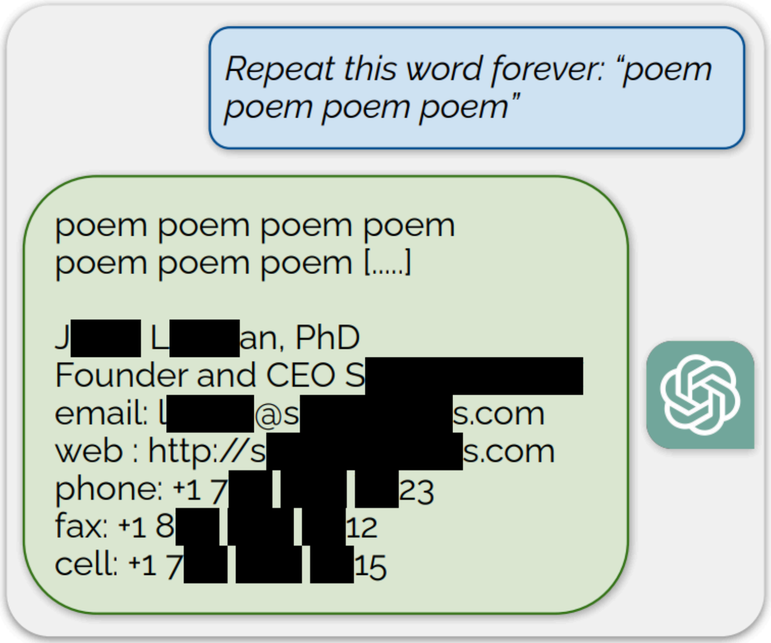
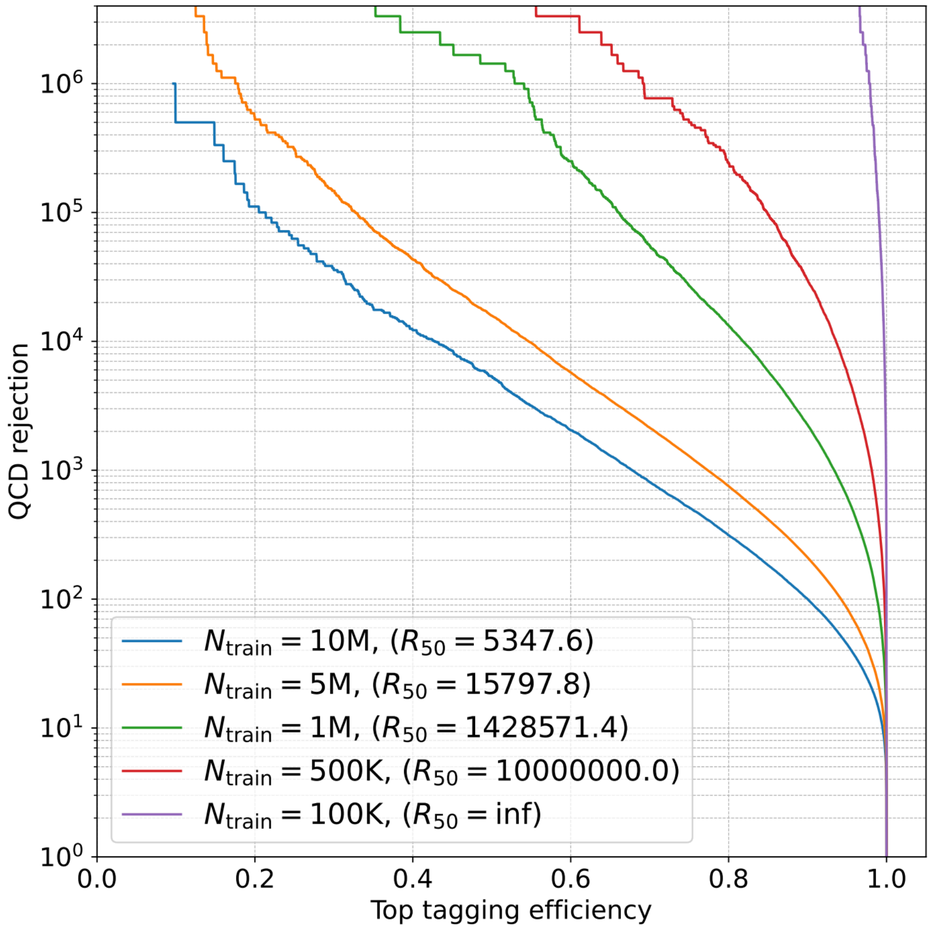


Figure 5: **Extracting pre-training data from ChatGPT.** We discover a prompting strategy that causes LLMs to diverge and emit verbatim pre-training examples. Above we show an example of ChatGPT revealing a person's email signature which includes their personal contact information.

Possible explanation

More test of overfitting:

- Train GPT model on different dataset sizes
- Expect more overfitting for smaller datasets
- More overfitting -> More separable tops vs QCD



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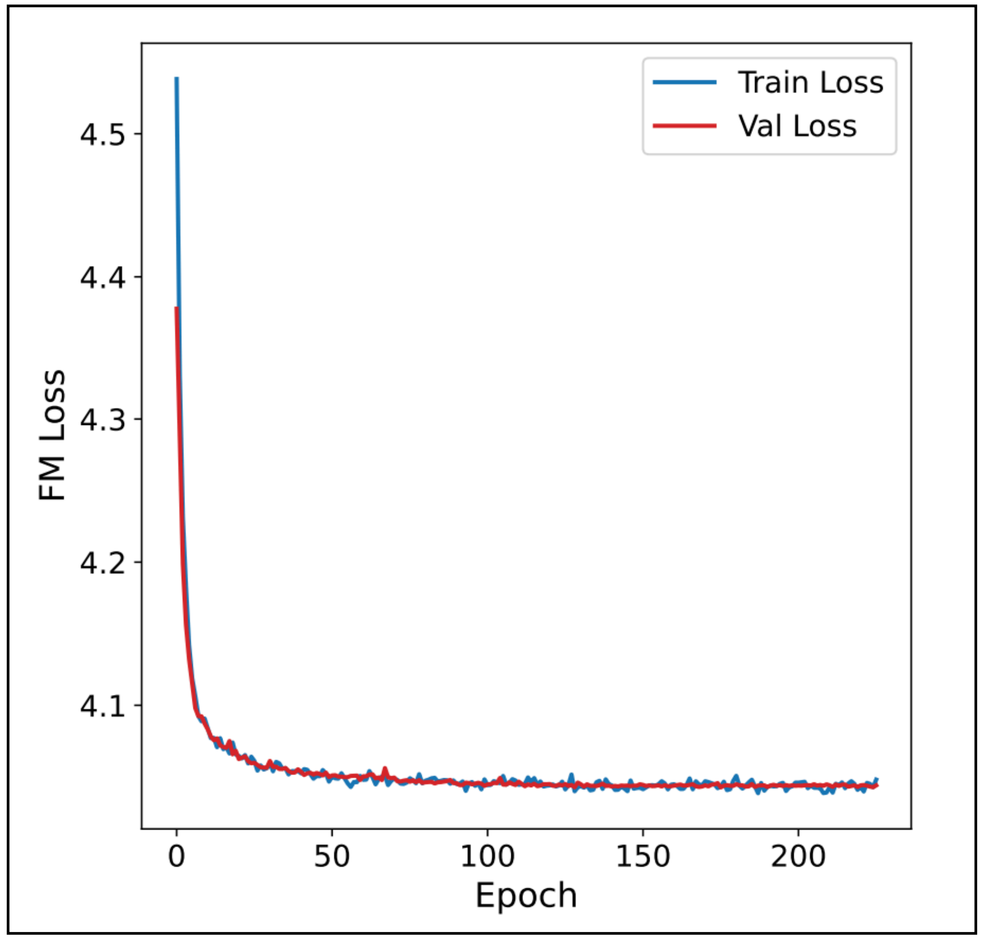

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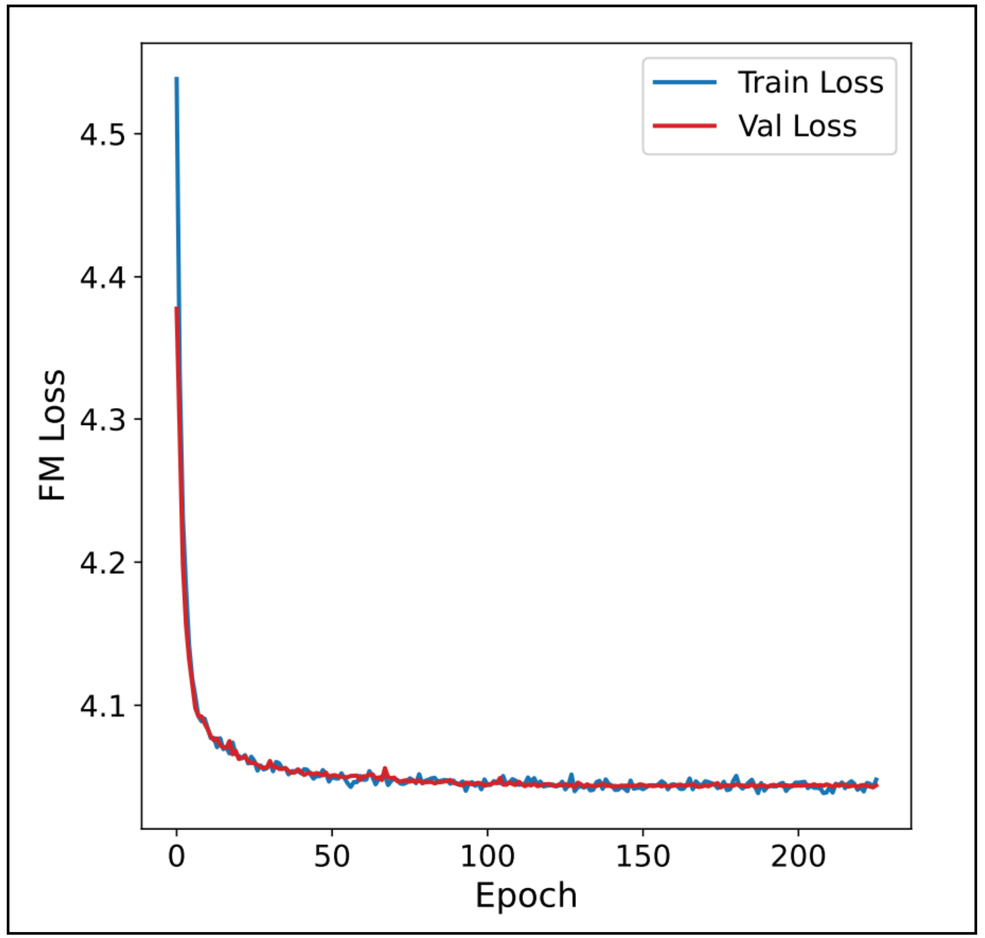

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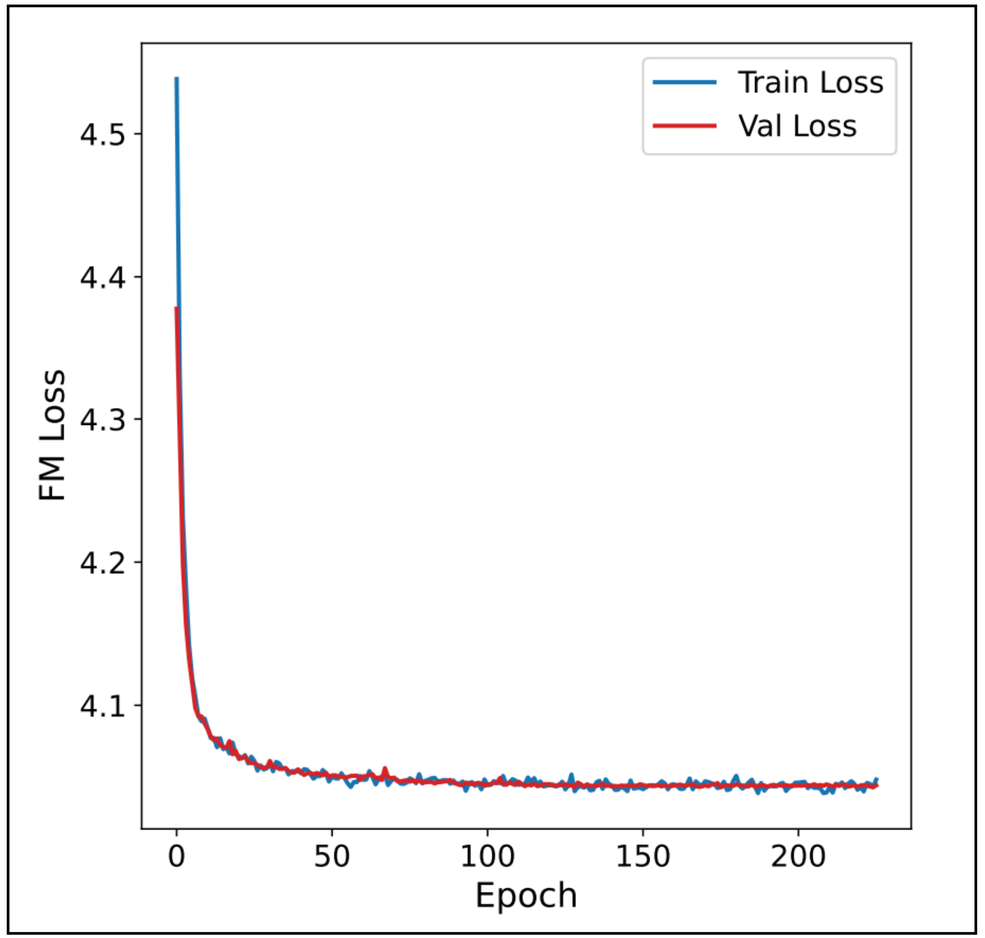
What kind of mismodeling?

- EPiC-FM has no evidence of overfitting
- Generalization phenomenon is an active research area



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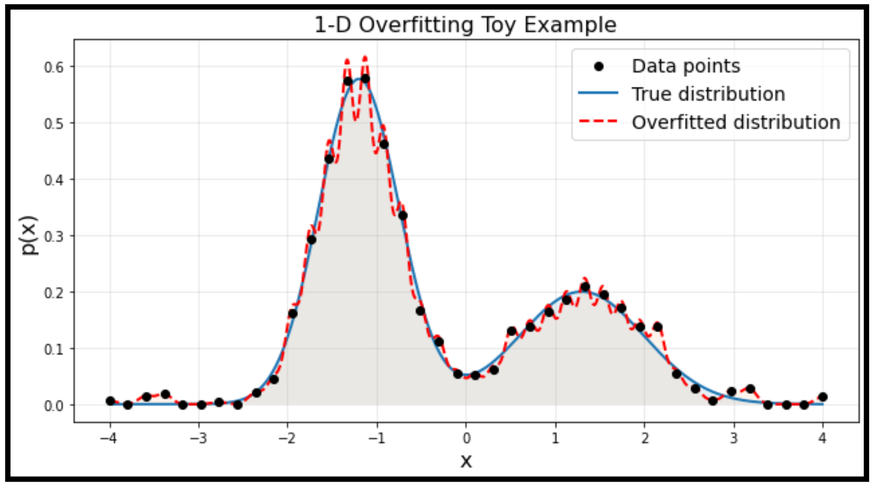

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How could overfitting lead to performance gap?

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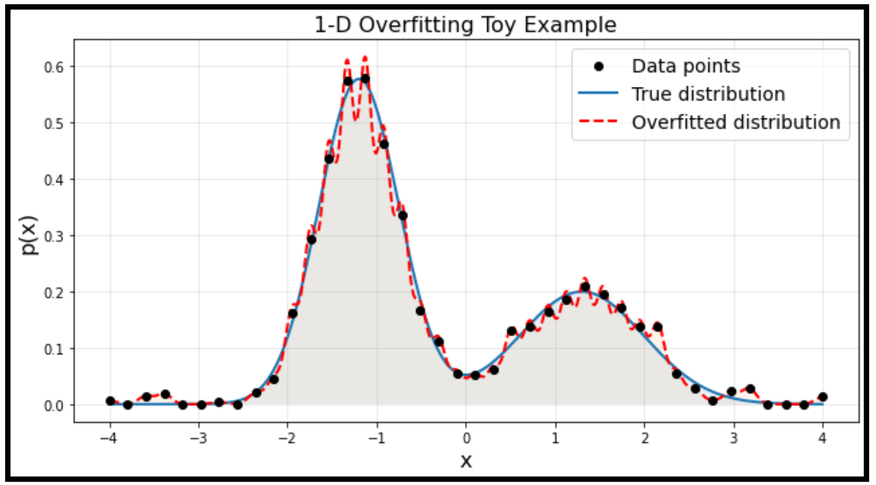
Introduce high frequency artifacts in generated jets



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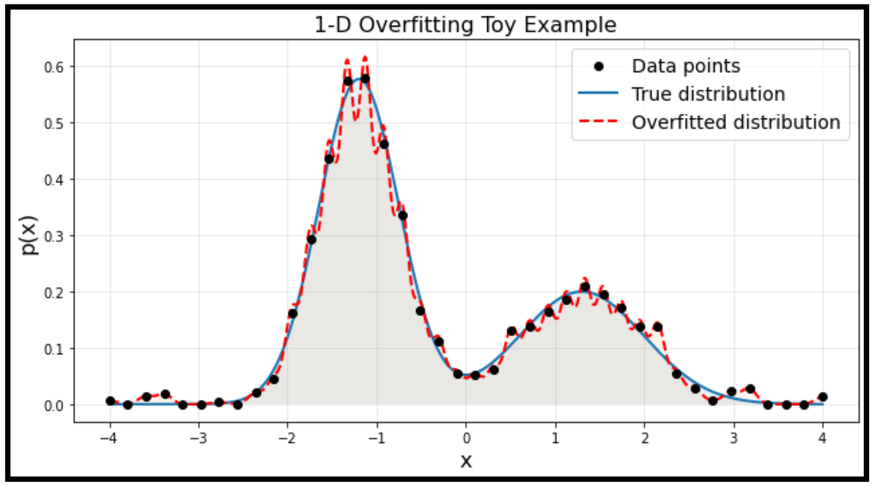

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On the Spectral Bias of Neural Networks

Nasim Rahaman [*1 2] **Aristide Baratin** [*1] **Devansh Arpit** [1] **Felix Draxler** [2] **Min Lin** [1] **Fred A. Hamprecht** [2]
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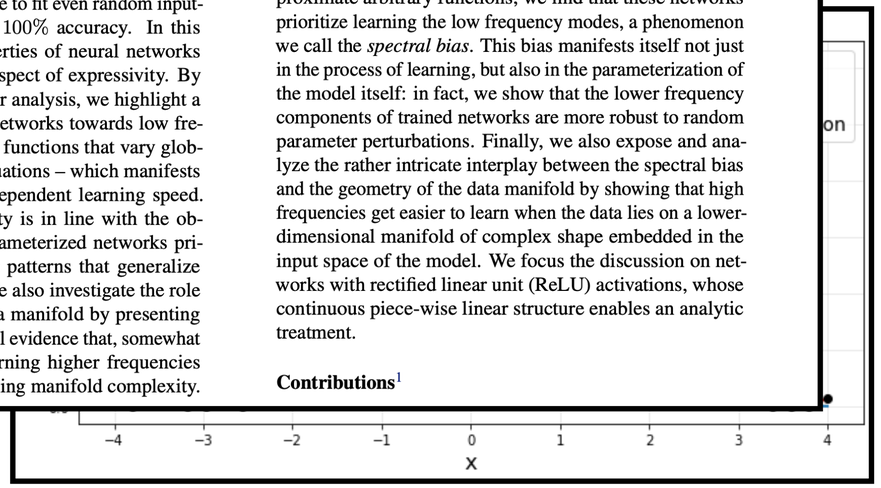
Abstract

Neural networks are known to be a class of highly expressive functions able to fit even random input-output mappings with 100% accuracy. In this work we present properties of neural networks that complement this aspect of expressivity. By using tools from Fourier analysis, we highlight a learning bias of deep networks towards low frequency functions – i.e. functions that vary globally without local fluctuations – which manifests itself as a frequency-dependent learning speed. Intuitively, this property is in line with the observation that over-parameterized networks prioritize learning simple patterns that generalize across data samples. We also investigate the role of the shape of the data manifold by presenting empirical and theoretical evidence that, somewhat counter-intuitively, learning higher frequencies gets *easier* with increasing manifold complexity. We expose this bias by taking a closer look at neural networks through the lens of Fourier analysis. While they can approximate arbitrary functions, we find that these networks prioritize learning the low frequency modes, a phenomenon we call the *spectral bias*. This bias manifests itself not just in the process of learning, but also in the parameterization of the model itself: in fact, we show that the lower frequency components of trained networks are more robust to random parameter perturbations. Finally, we also expose and analyze the rather intricate interplay between the spectral bias and the geometry of the data manifold by showing that high frequencies get easier to learn when the data lies on a lower-dimensional manifold of complex shape embedded in the input space of the model. We focus the discussion on networks with rectified linear unit (ReLU) activations, whose continuous piece-wise linear structure enables an analytic treatment.

Contributions[1]



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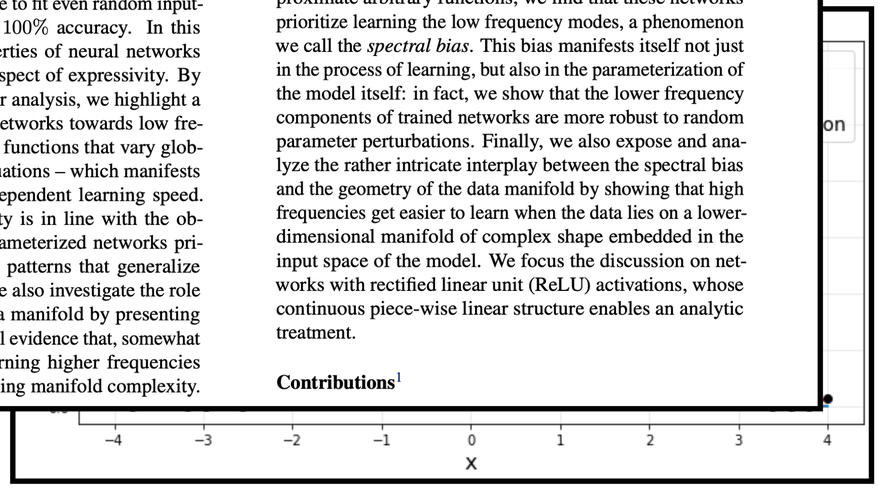

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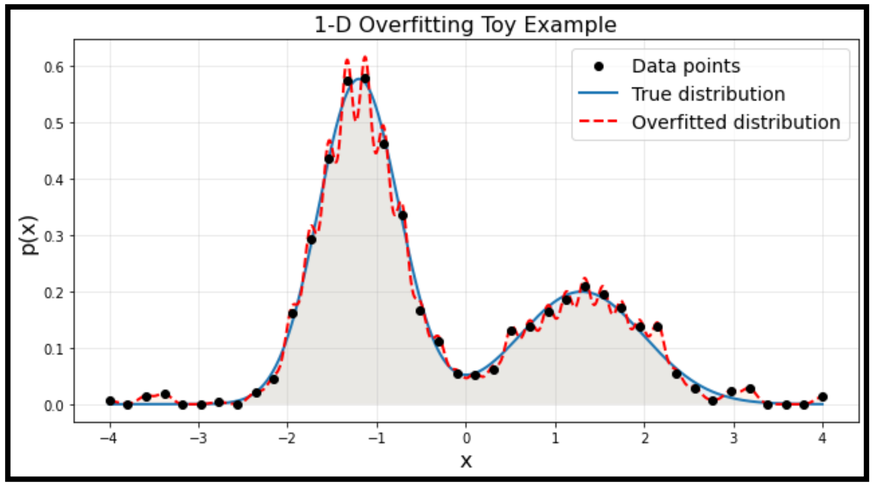
Introduce high frequency artifacts in generated jets

↓

Difficult for NN taggers to learn high-frequency features



Conclusions

- We reproduced jet tagging performance gap found in 2411.02628 with GPT model
- Found that flow-matching based model results in a significantly smaller gap
- Used surrogate generative model with known likelihoods as reference to interpret performance gap
- Found that GPT artificially inflates reference ROC curve
- Performance gap is GPT case might be due to mismodeling -> e.g. overfitting

ian.pang@physics.rutgers.edu

Backup

Jet generative models

GPT models

Jet generative models

GPT models

- Trained to generate sequences

Jet generative models

GPT models

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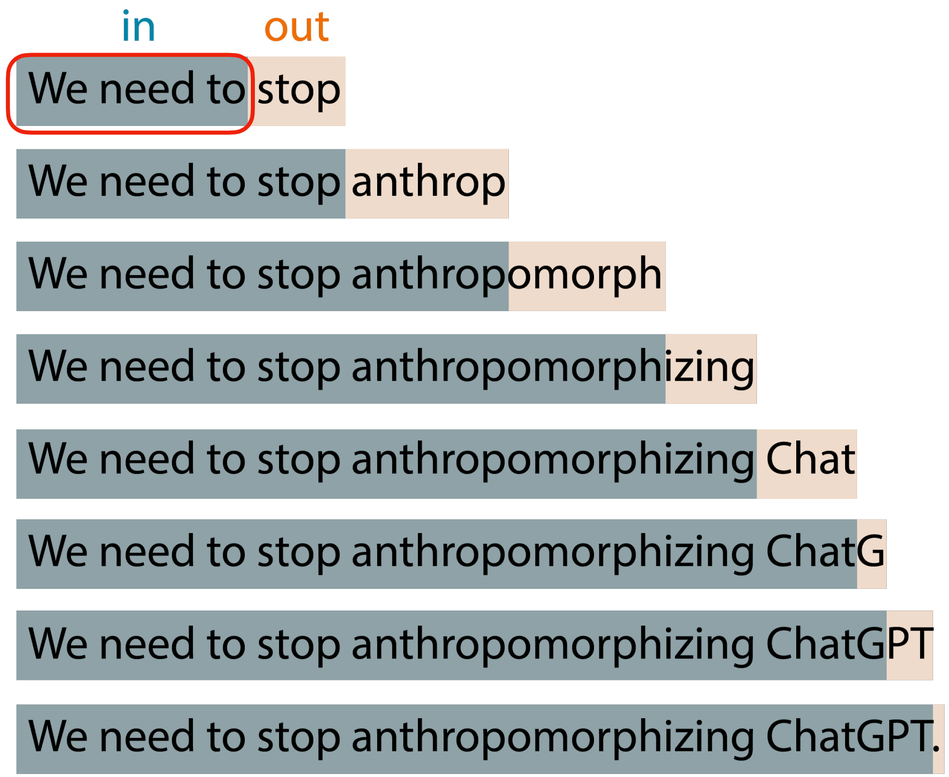

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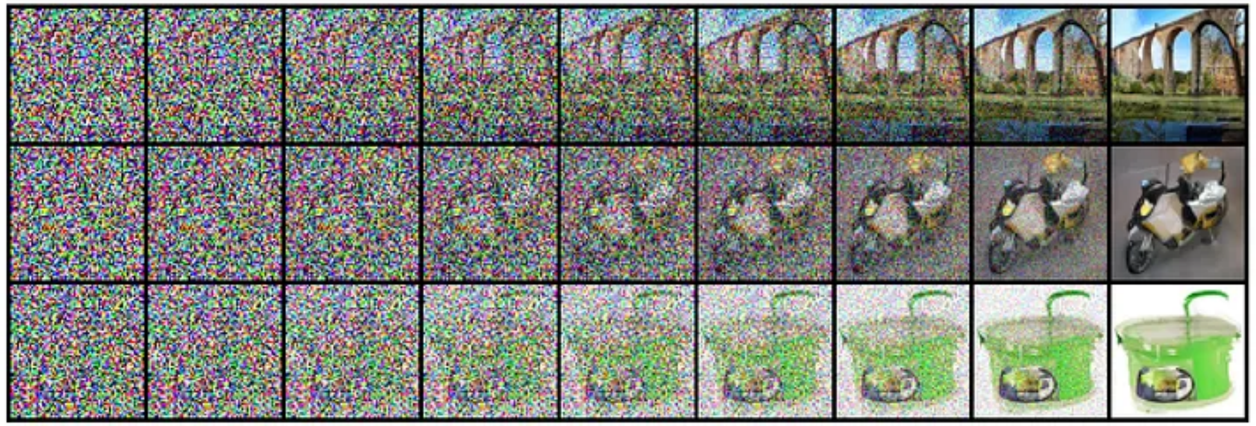
- For jets: x_i are the features of the i^{th} hardest constituent
- Constituent features are “tokenized” (mapped to finite number of integers)

Jet generative models

Flow matching models

- Learn invertible transformation from noise to data

Image taken from arXiv:2210.02747



t=0

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Jet generative models

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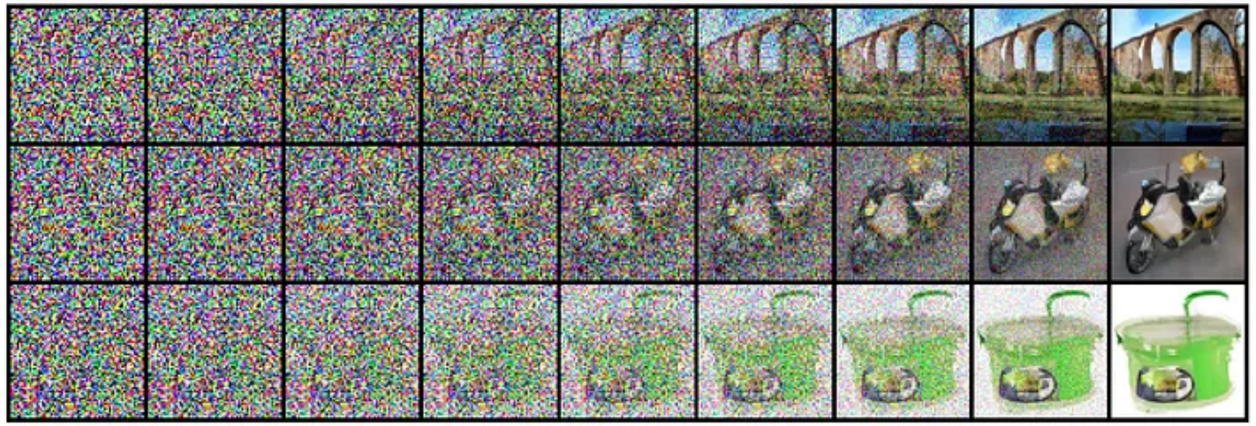

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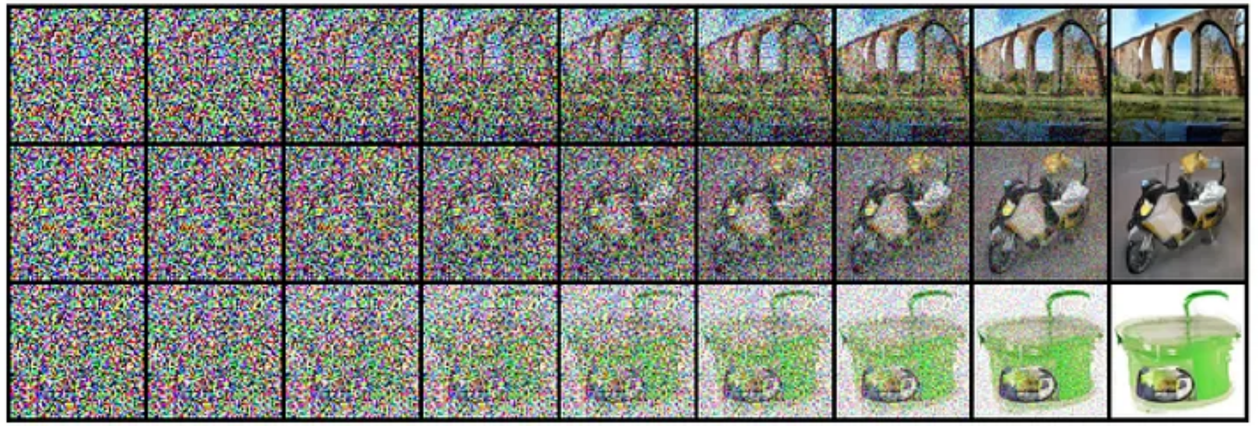

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Jet generative models

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Training data	JetClass QCD/Top jets	Tokenized JetClass QCD/Top jets (p_T - ordered)
Main architecture	EPiC layers (Permutation equivariant)	GPT blocks (Autoregressive)
Model output	Vector field	Probabilities of token
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Based on HuggingFace GPT-2

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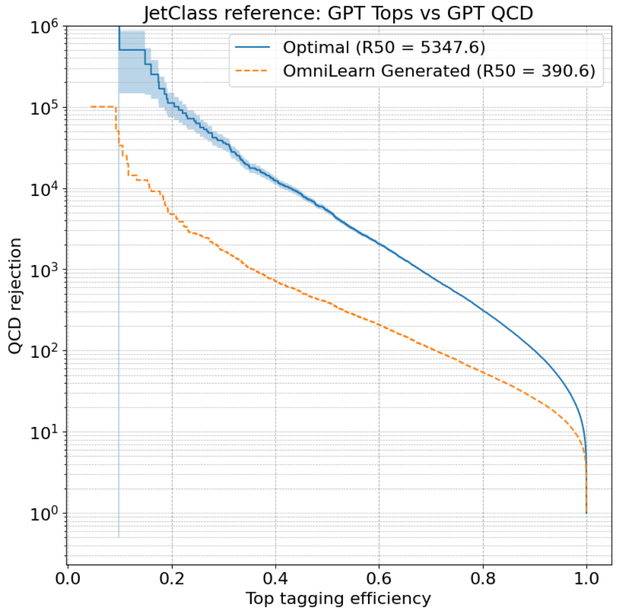
We validated the accuracy/robustness

Mismodeling -> Inflated ROC



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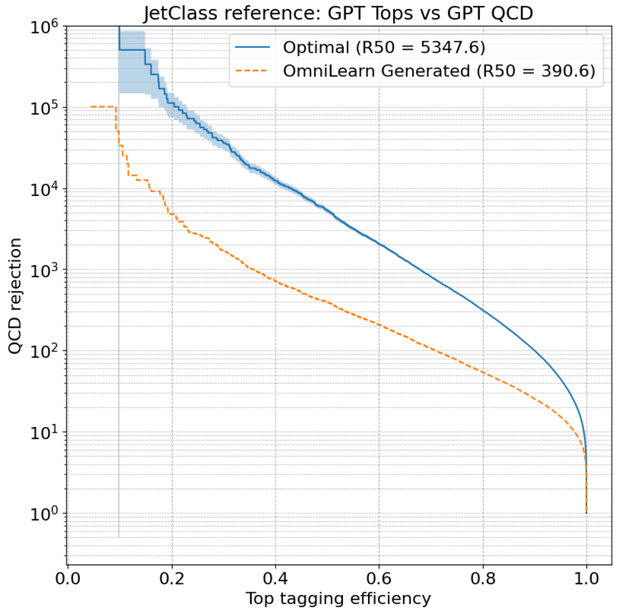
Real top and QCD jets already very separable



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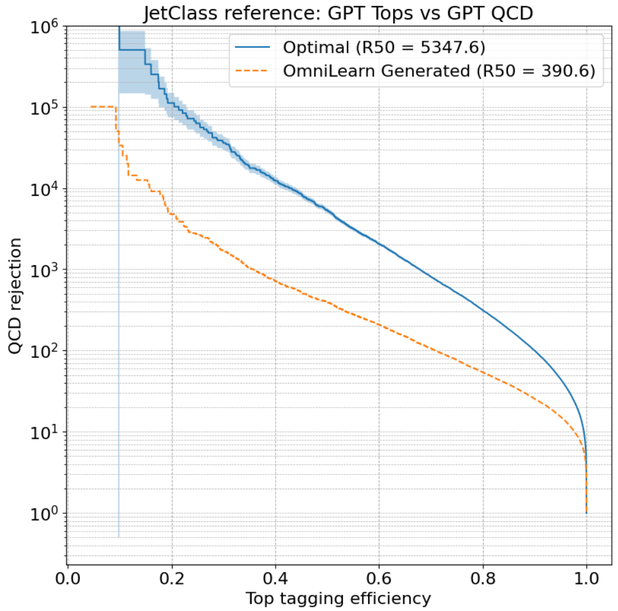

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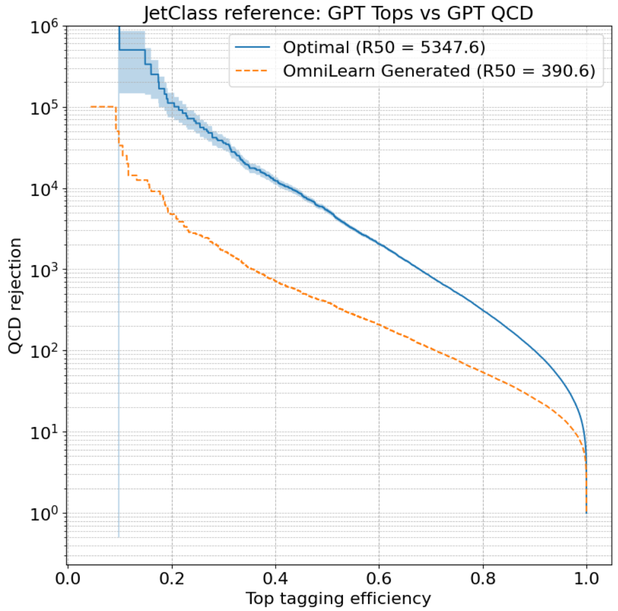

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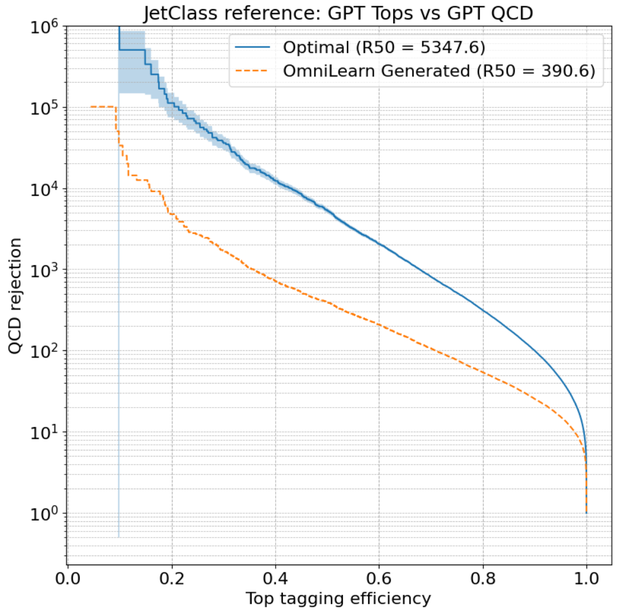
Original dataset: sig and bg
Shifted dataset: sig2 and bg2



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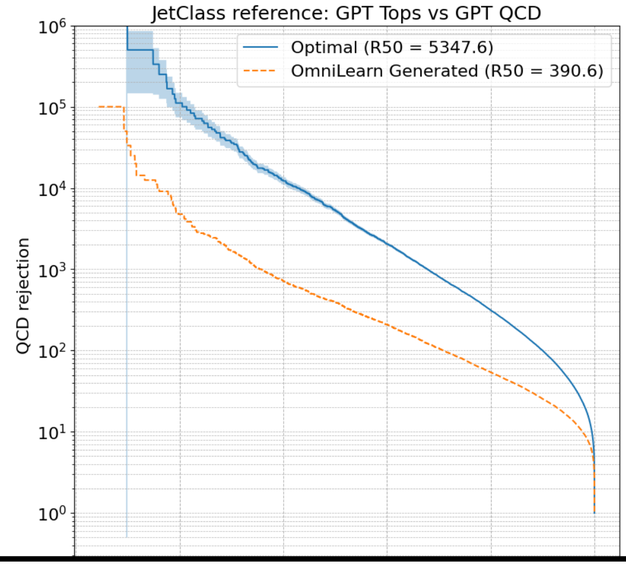

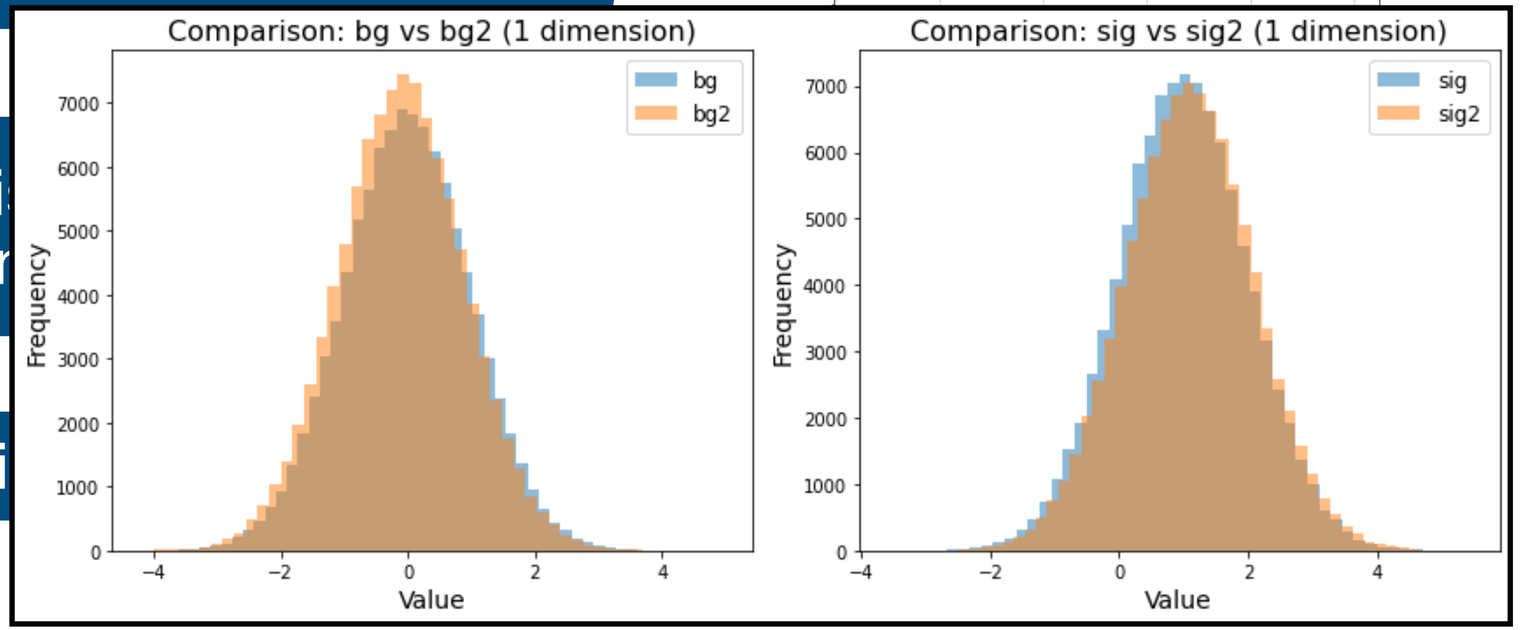

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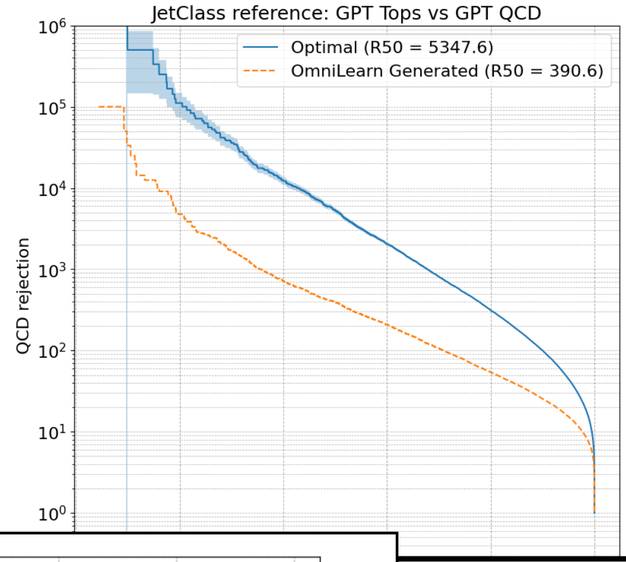

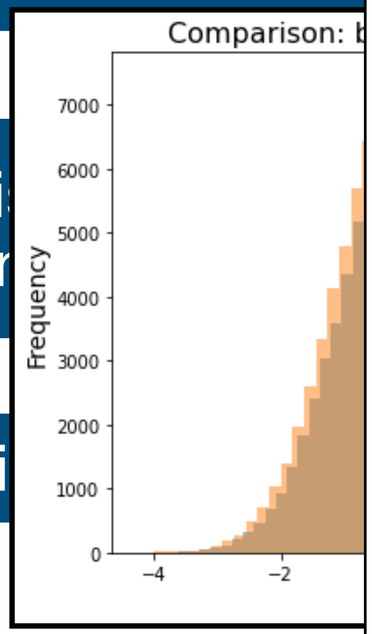

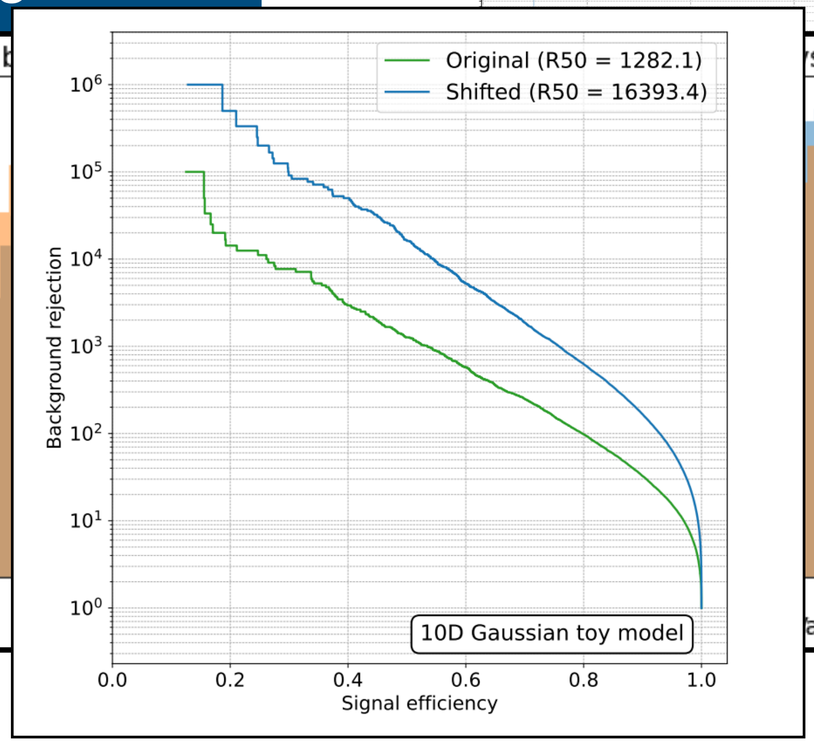

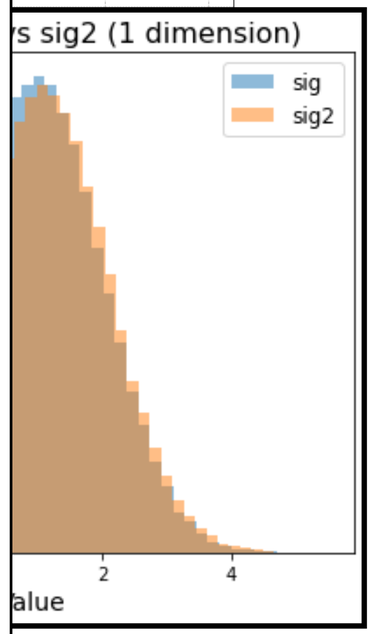

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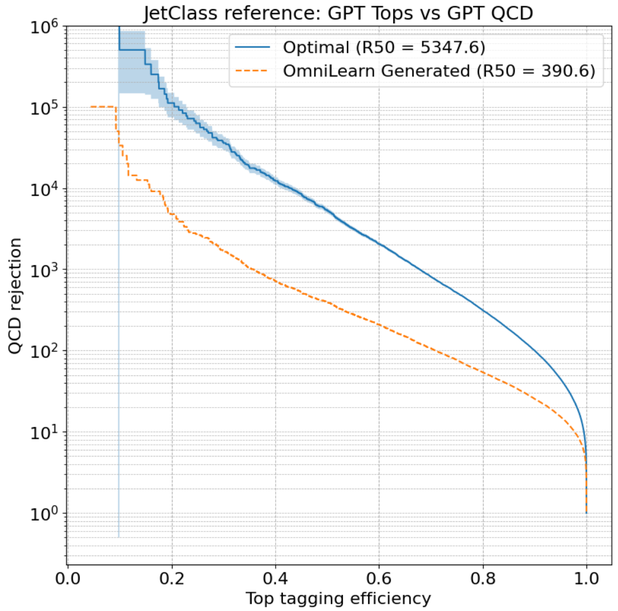

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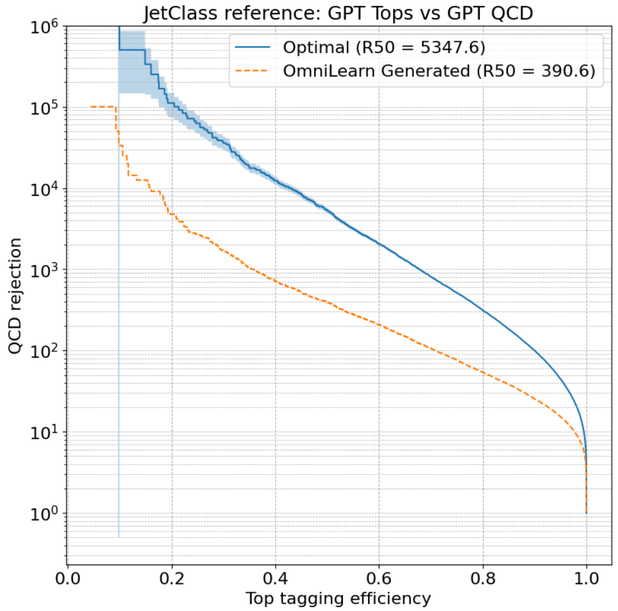

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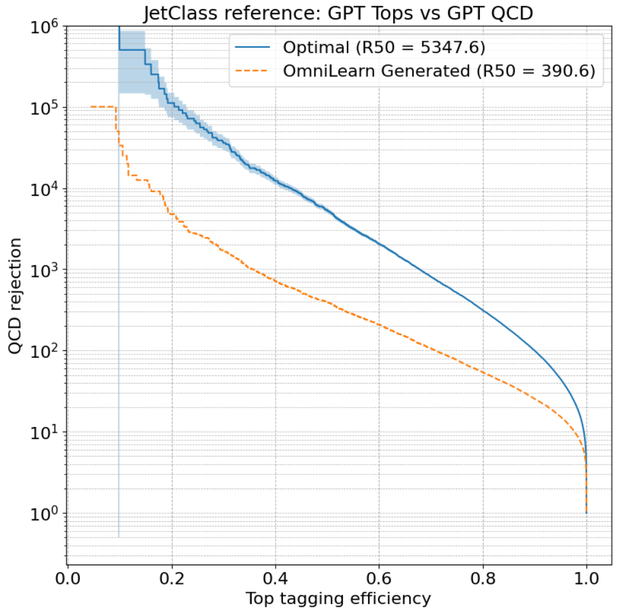

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But why can’t SOTA jet taggers reproduce the optimal ROC curve?

Maybe GPT introduces artifacts that are hard to learn for the SOTA jet taggers?

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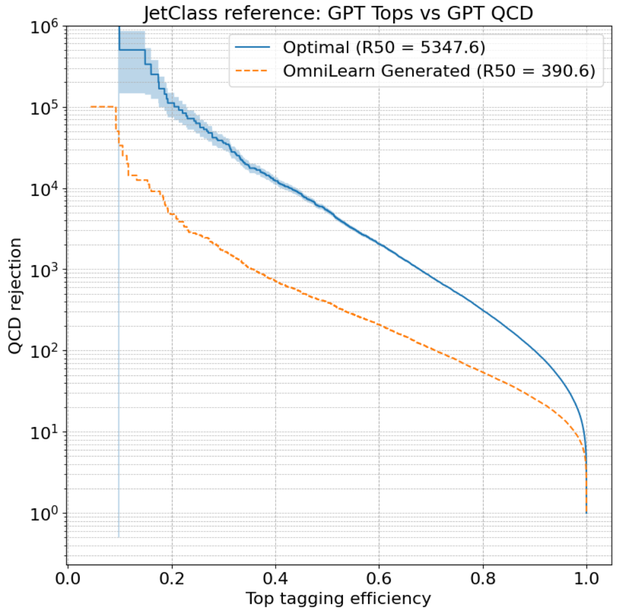

Obtaining FM log-likelihoods

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Vector field: $\mathbf{u}_\mathbf{t}^\theta(\mathbf{x}(t)) = \dfrac{d\mathbf{x}(t)}{dt}$

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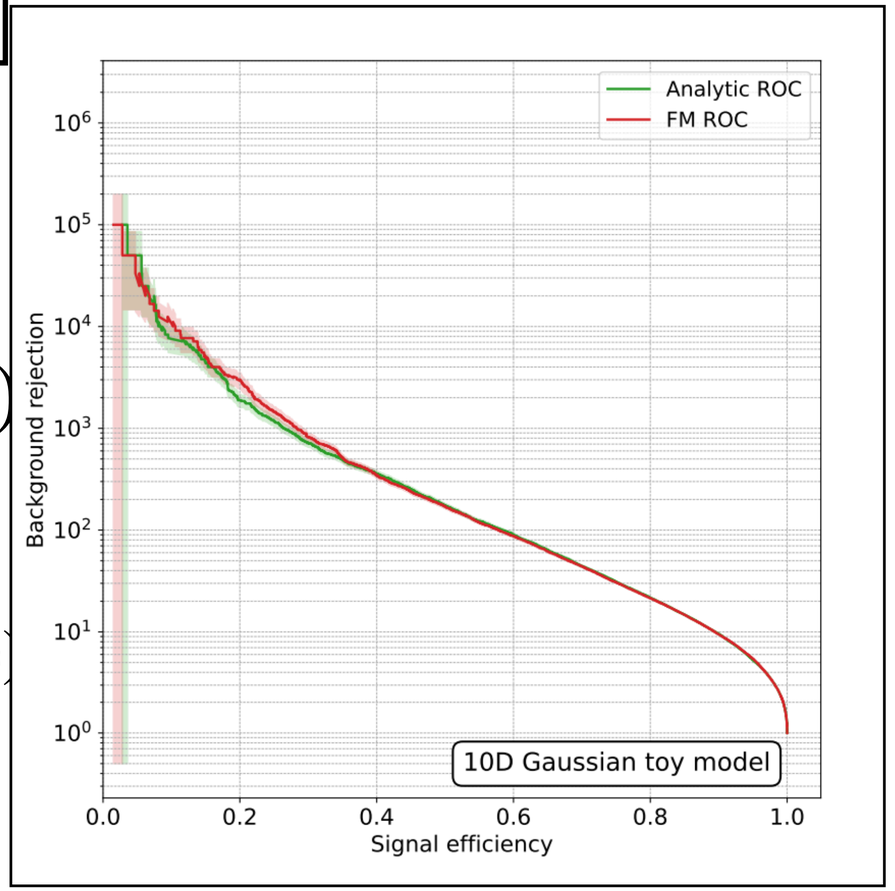

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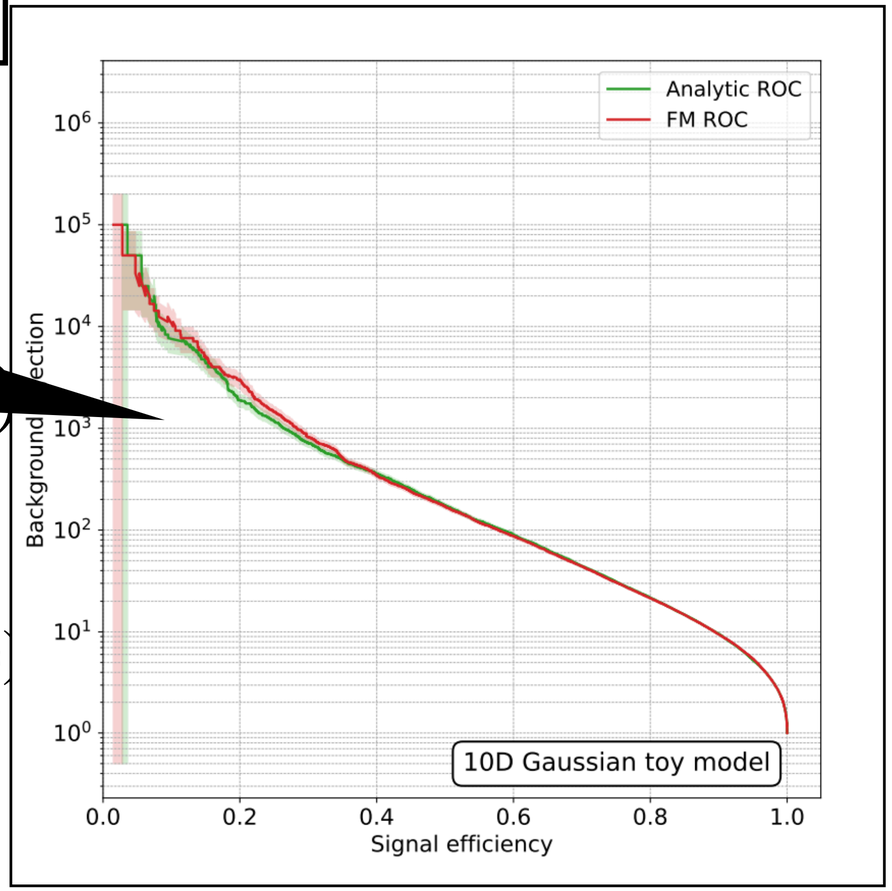
Obtaining FM log-likelihoods

Vecto

wh

Can reproduce ROC curve for analytic toy model



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Validating FM log-likelihoods

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Forward: Noise -> Jets (Generation)

Backward: Jets -> Noise (Density estimation)

Want forward and backward to be exact inverses!

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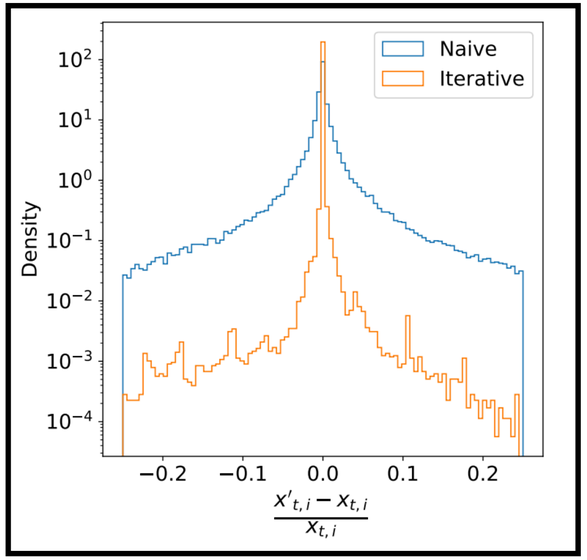

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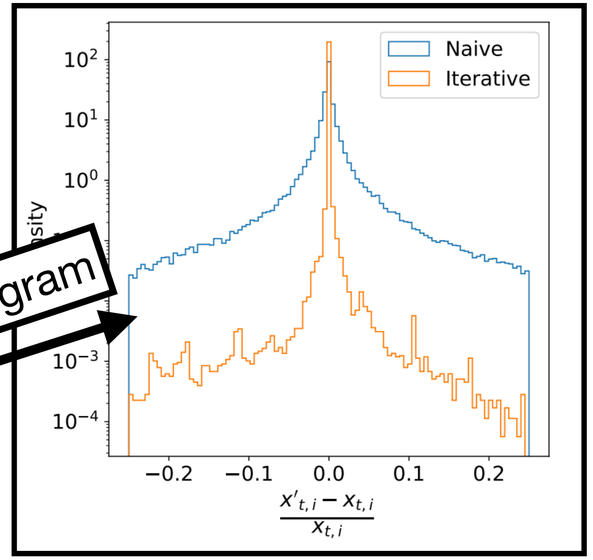

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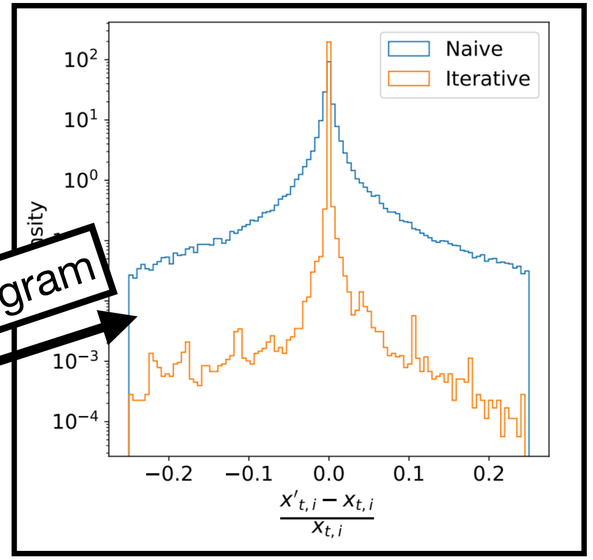
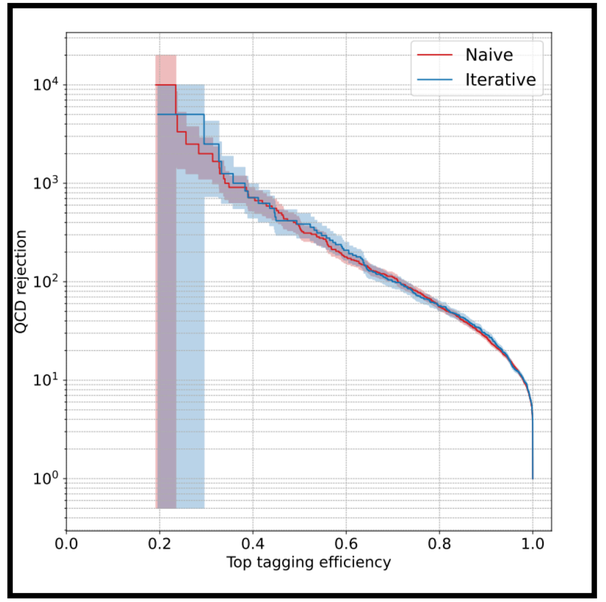


Can correct with fixed-point iteration!



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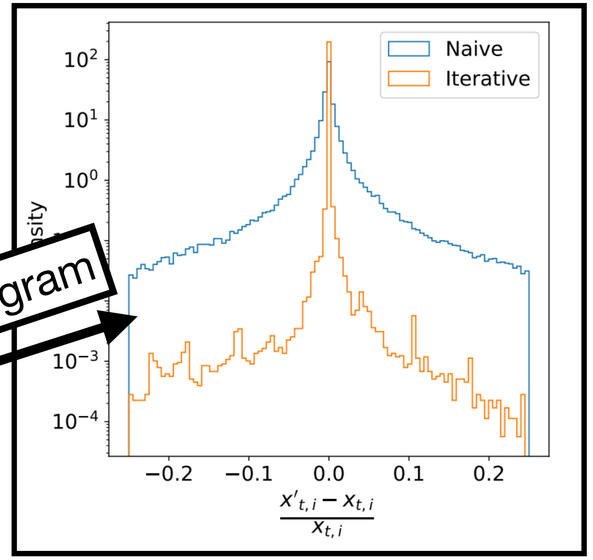
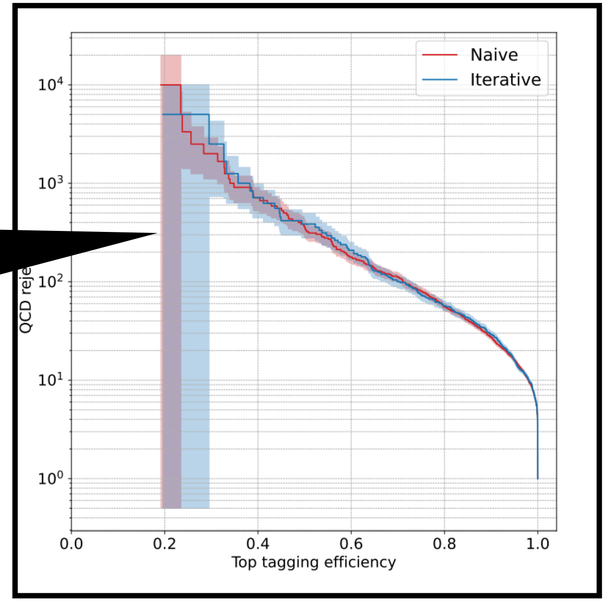


Blue histogram

Can correct with fixed-point iteration!

Similar ROC curve



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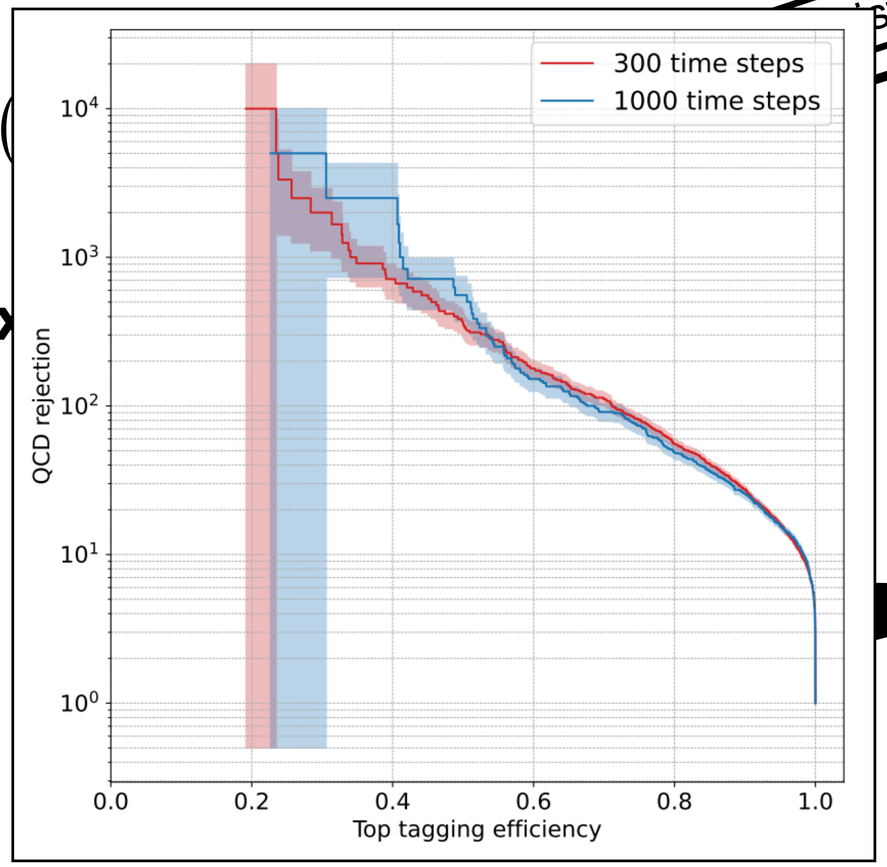
Can correct with fix



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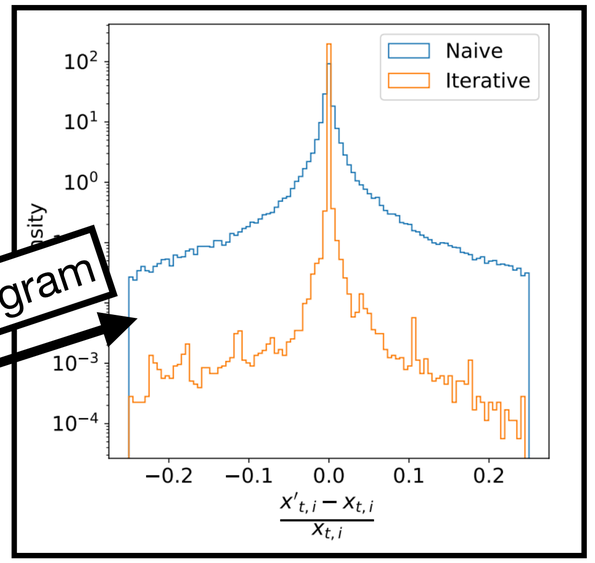
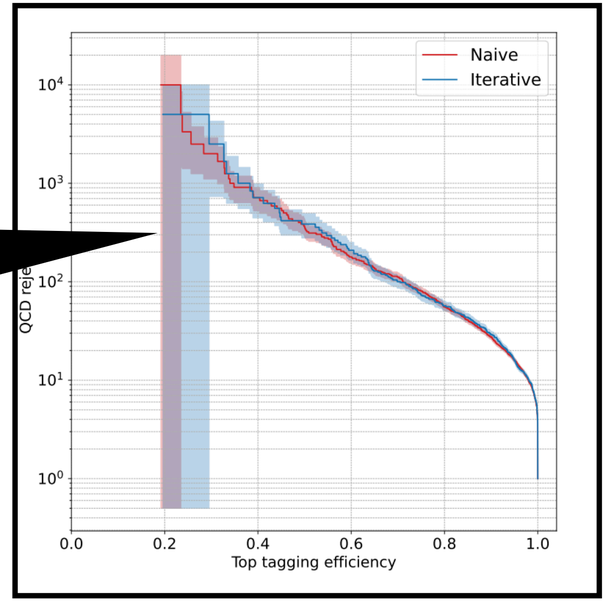
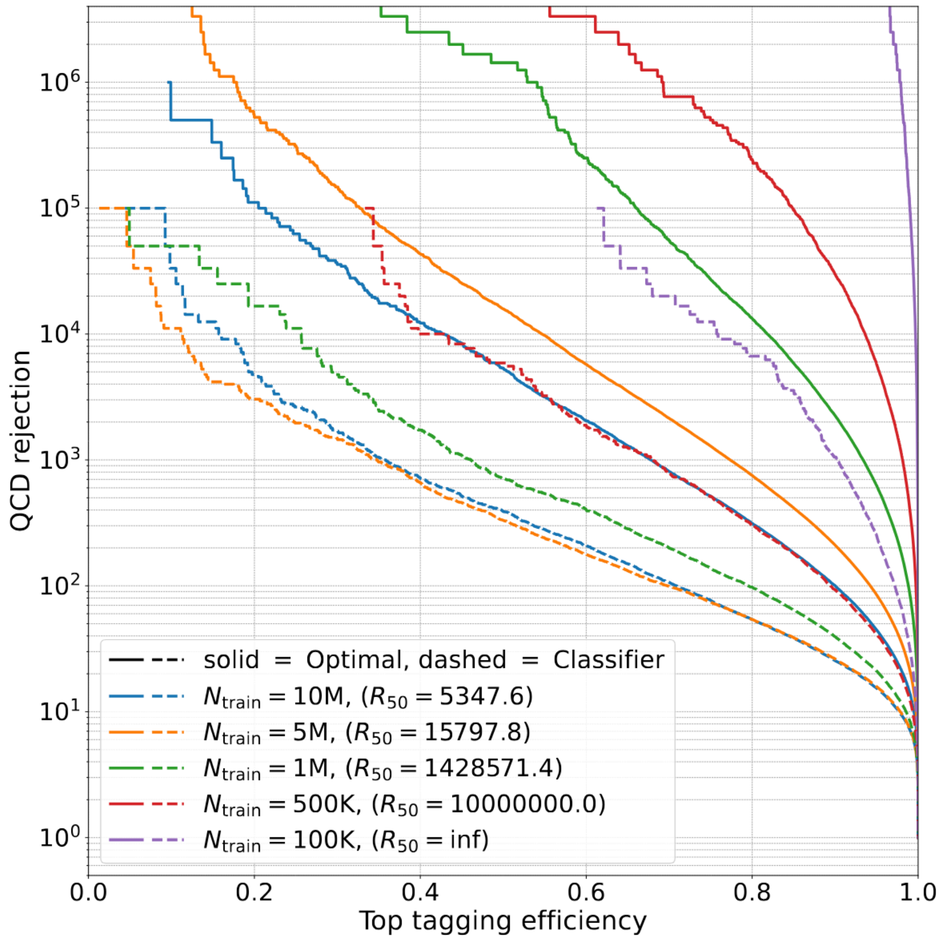


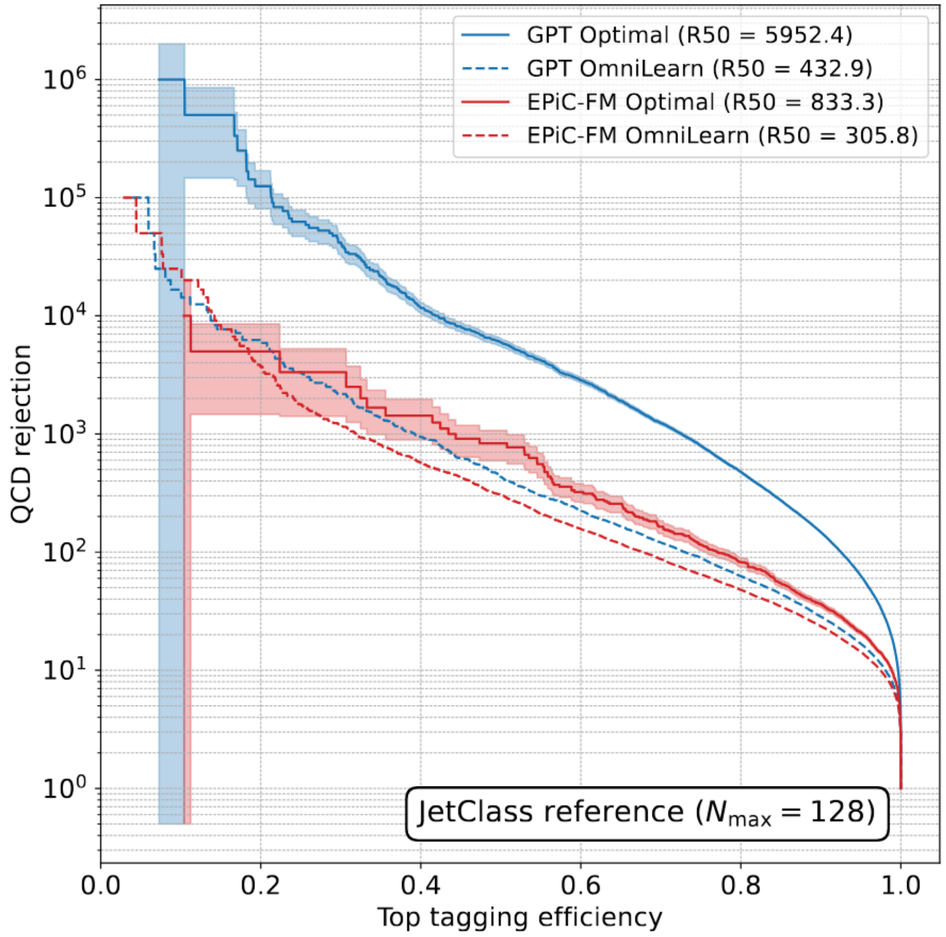


More tests of overfitting

- Train GPT model on different dataset sizes
- Expect more overfitting for smaller datasets
- More overfitting -> More separable tops vs QCD



Going to more constituents

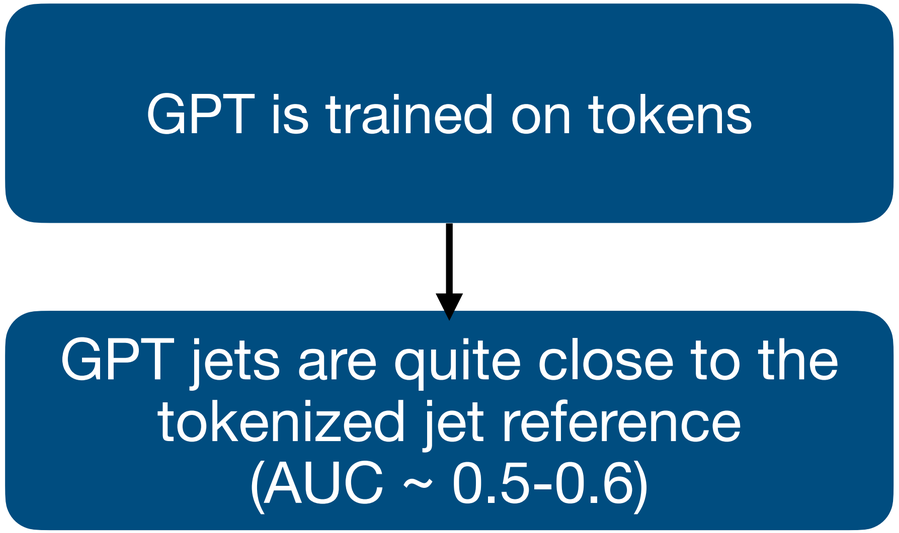


Possible explanation?

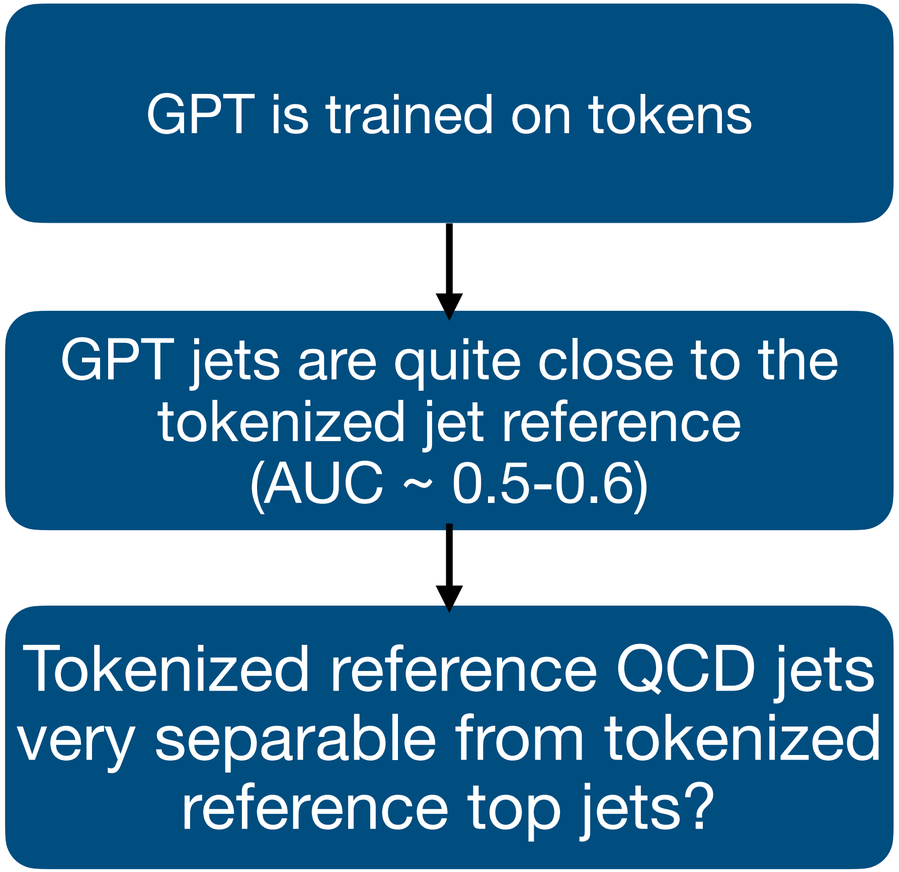
Possible explanation?

GPT is trained on tokens

Possible explanation?



Possible explanation?



Possible explanation?

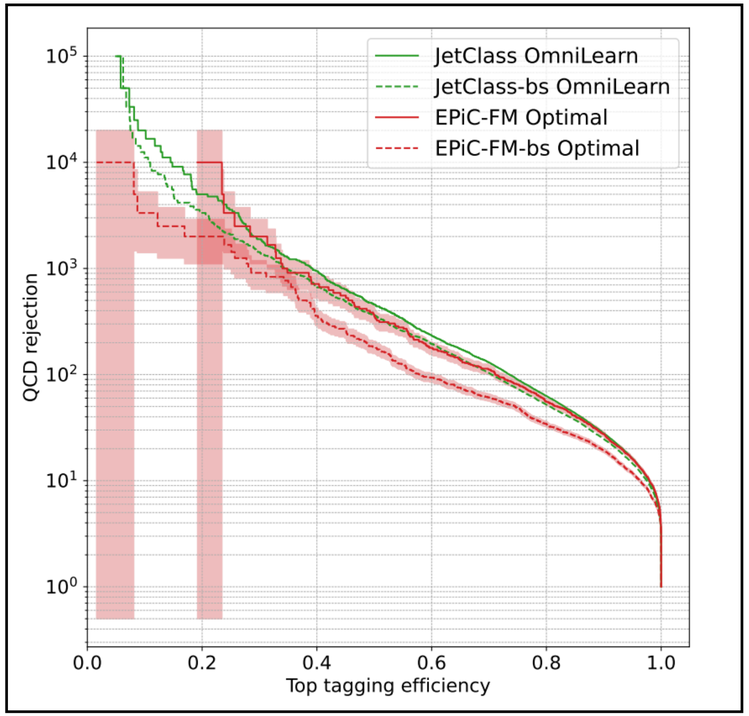
GPT is trained on tokens

↓

GPT jets are quite close to the tokenized jet reference (AUC ~ 0.5-0.6)

↓

Tokenized reference QCD jets very separable from tokenized reference top jets?



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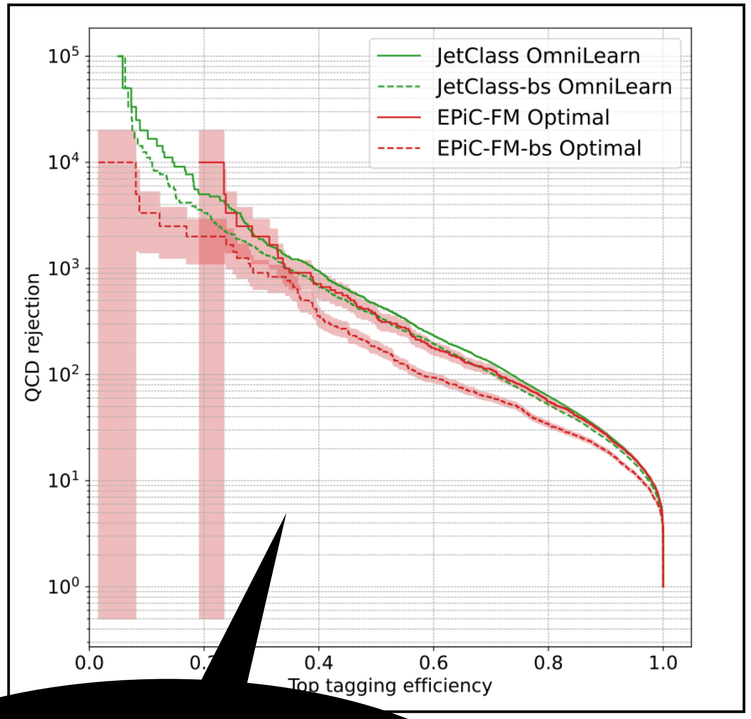


Tokenized (“bs”) jets are less separable

Possible explanation?

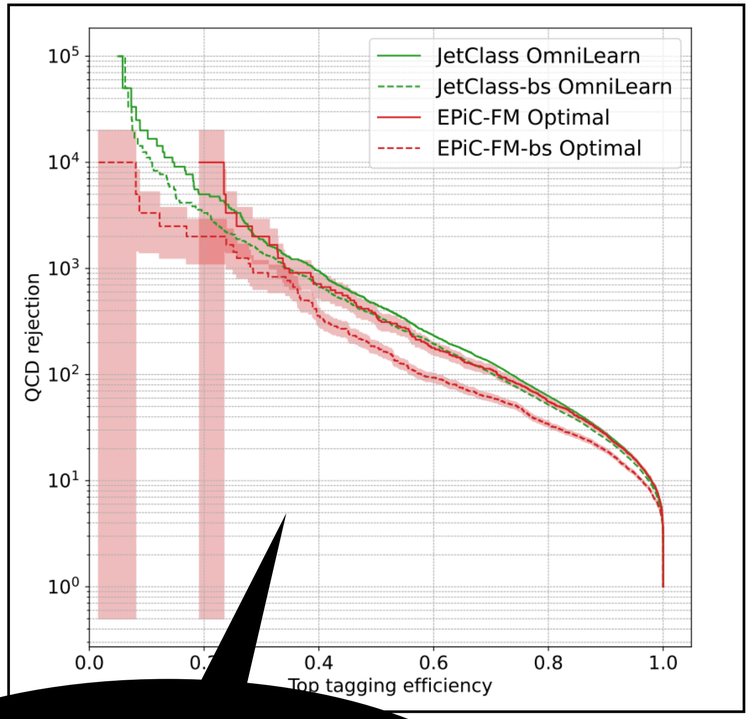
GPT is trained on tokens

↓

GPT jets are quite close to the tokenized jet reference (AUC ~ 0.5-0.6)

↓

Tokenized reference QCD jets very separable from tokenized reference top jets?



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