Learning the language of QCD jets with transformers

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together with

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Outline

Learning the language of QCD jets with transformers

- Data
  - QCD and top jets
  - Turning particle and jets into words and sentences

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- Density estimation
  - on low level data
  - using transformers as in NLP

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  - using transformers as in NLP
- Quality assessment
  - use transformer as generative model
  - classifier tests

Data

standard benchmark data set:

- QCD and top jets: "Top Quark Tagging Reference Dataset"
  https://zenodo.org/records/2603256
- 600k jets each
- $p_T \in [550, 650]$ GeV $\rightarrow$ boosted top jets
- up to 200 constituent four-momenta $\Rightarrow$ low-level data

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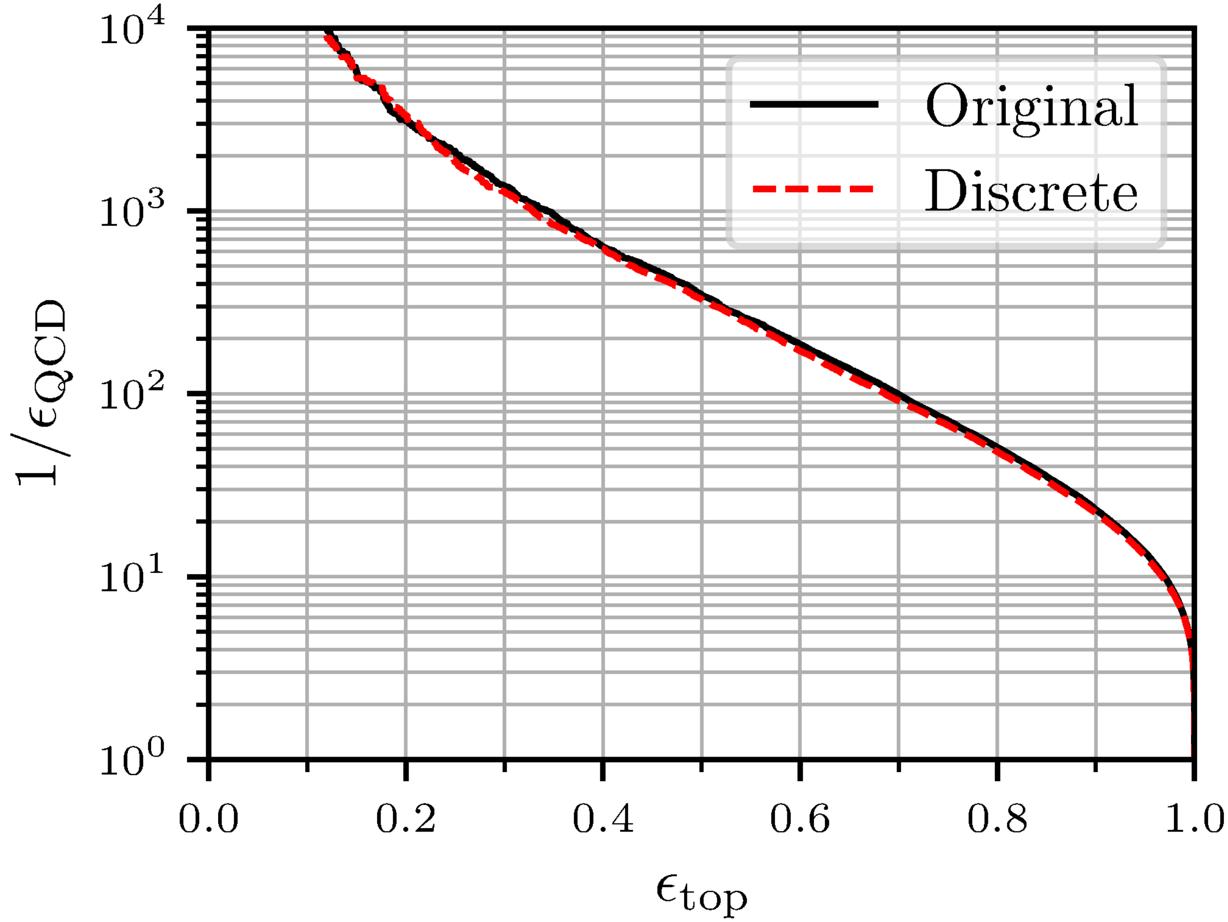
special preprocessing:

- discretize constituent kinematics by binning:
  $\hat{p}_T \in [0, 40], \quad \Delta\hat{\eta} \in [0, 30], \quad \Delta\hat{\phi} \in [0, 30]$
- $\Rightarrow \sim$ 40k different constituents $\Leftrightarrow$ words in our language
- jets $\Leftrightarrow$ sentences in our language
- loss of information?

Data



⇒ almost no information loss for top tagging with ParticleNet

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Density Estimation

- autoregressive approach:

$$p(\vec{x}) = p(\vec{x}_1)p(\vec{x}_2|\vec{x}_1)\dots p(\vec{x}_n|\vec{x}_1\dots\vec{x}_{n-1})$$

(see also JUNIPR by Andreassen et al., 1804.09720)

- standard transformer architecture as in NLP

(see also Trade by Fakoor et al., 2004.02441)

- simple grammar: order constituents by p_T

(more physics inspired grammar in 1804.09720)

- loss function: categorical cross entropy between

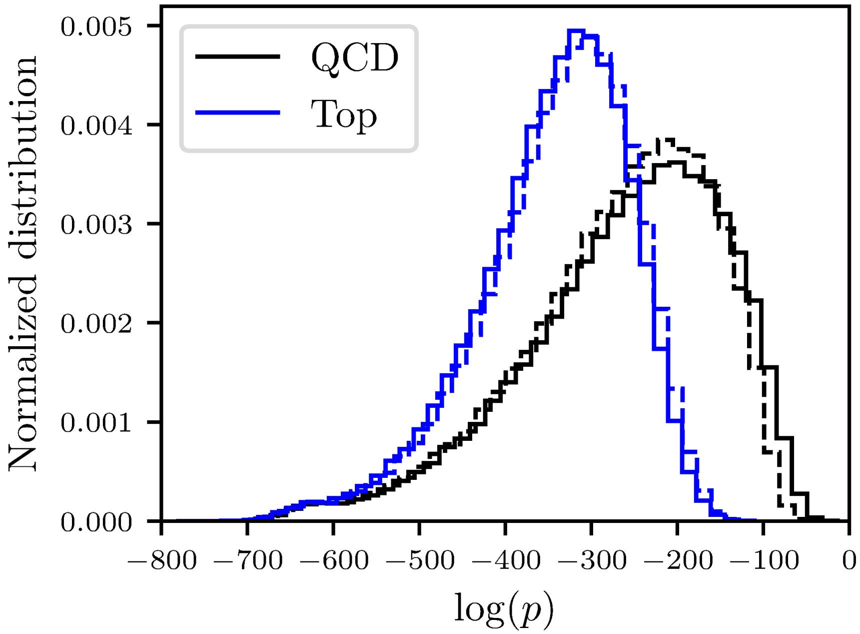
predicted and actual next particle/word

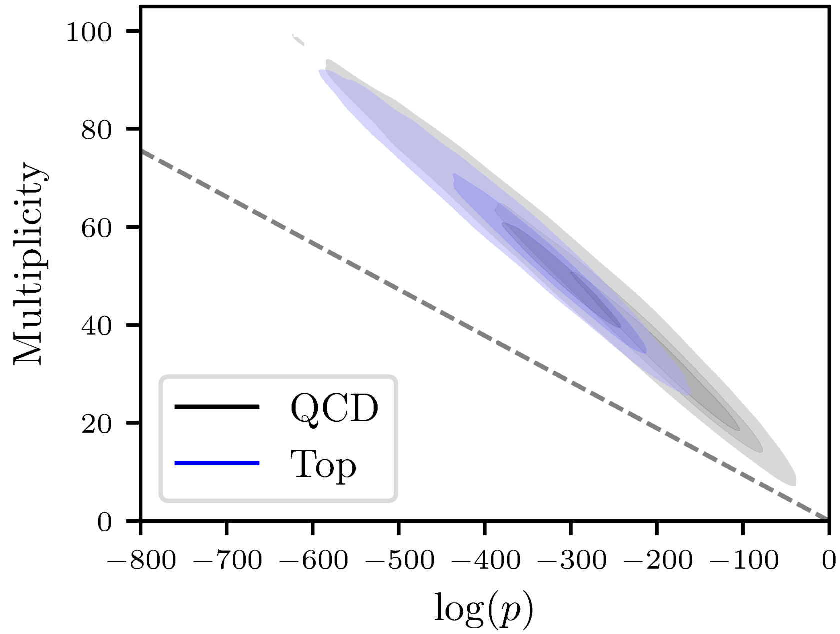
- jet multiplicity: predict stop token to terminate jet

$\Rightarrow$ variable multiplicity

Estimated Density

- probability for QCD and top jets:





solid: trained on QCD jets $\Rightarrow p_{\mathrm{QCD}}(x)$

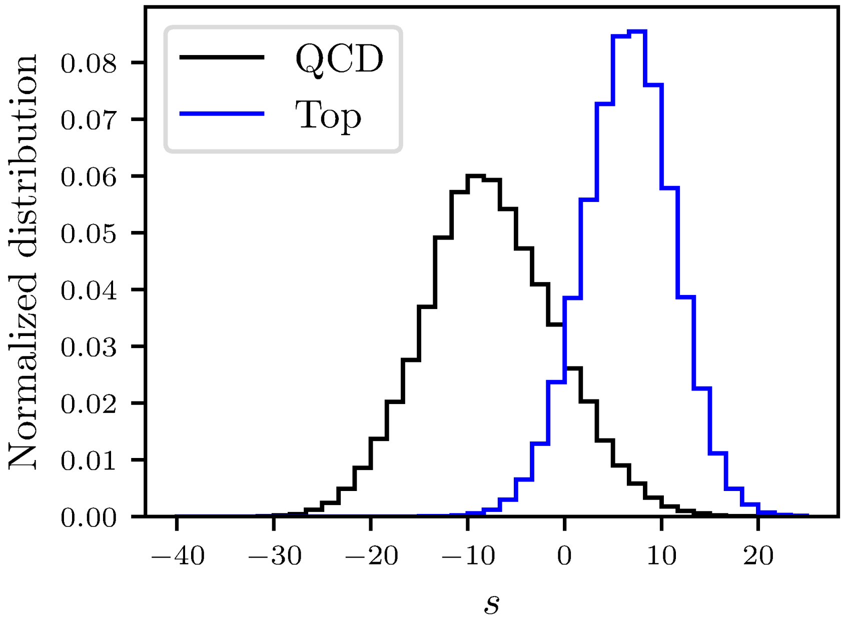
dashed: trained on top jets $\Rightarrow p_{\mathrm{top}}(x)$

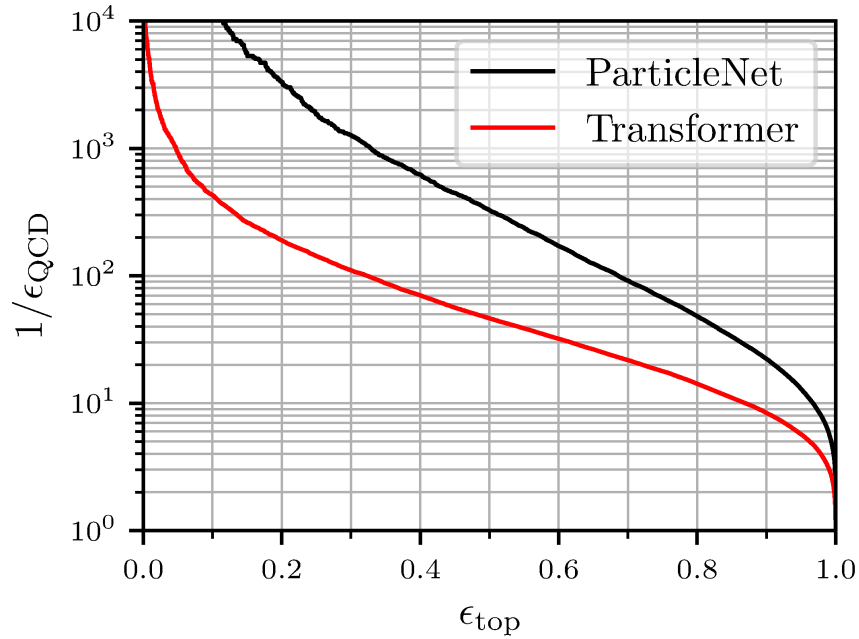
- dominated by particle multiplicity
- indeed depends on specific training data

Quality assessment

- Use density ratio as classifier score:

$$s = \log(p_{\text{top}}(x)) - \log(p_{\text{QCD}}(x))$$





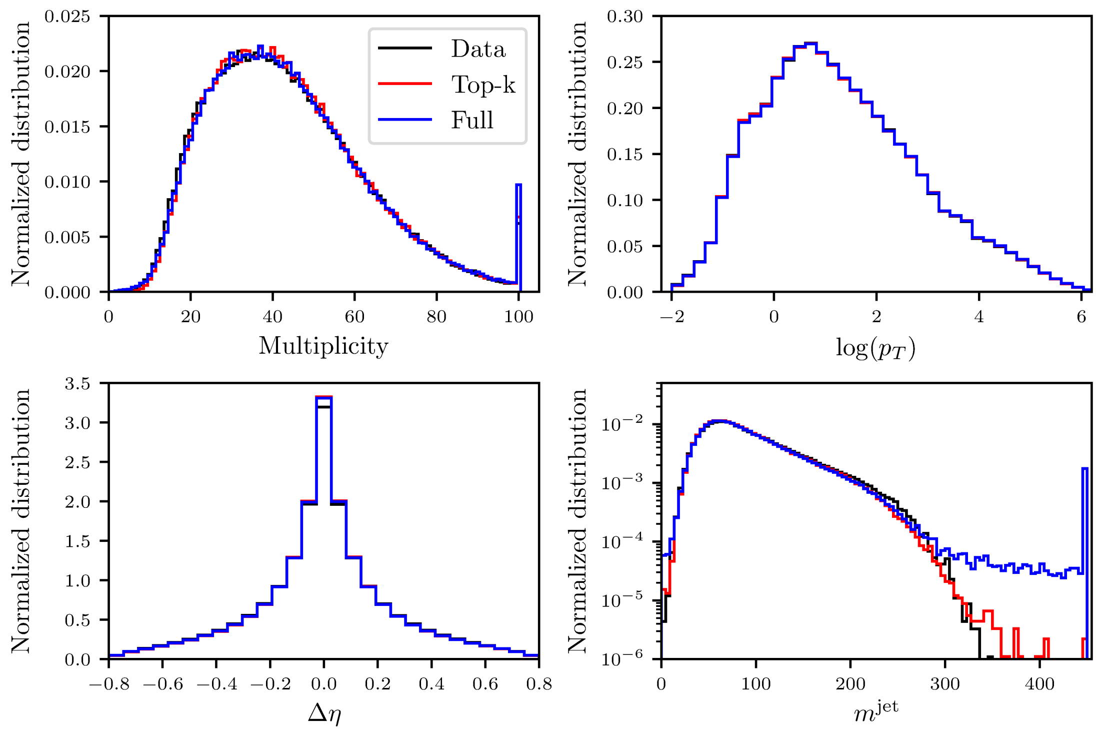
- density provides discrimination power
- room for improvement
- strong overfitting observed

(for diffusion based results see 2306.03933, Vinicius' talk today at 14.15h)

Quality assessment

- Transformer as generative model: draw jets from $p(\vec{x})$

(see also 2305.10475, Jonas' talk today at 14.30h)



- good agreement for 1D distributions
- multiplicity extrapolation works well (trained only with 50 consituents)
- top-k sampling to suppress low probability bins

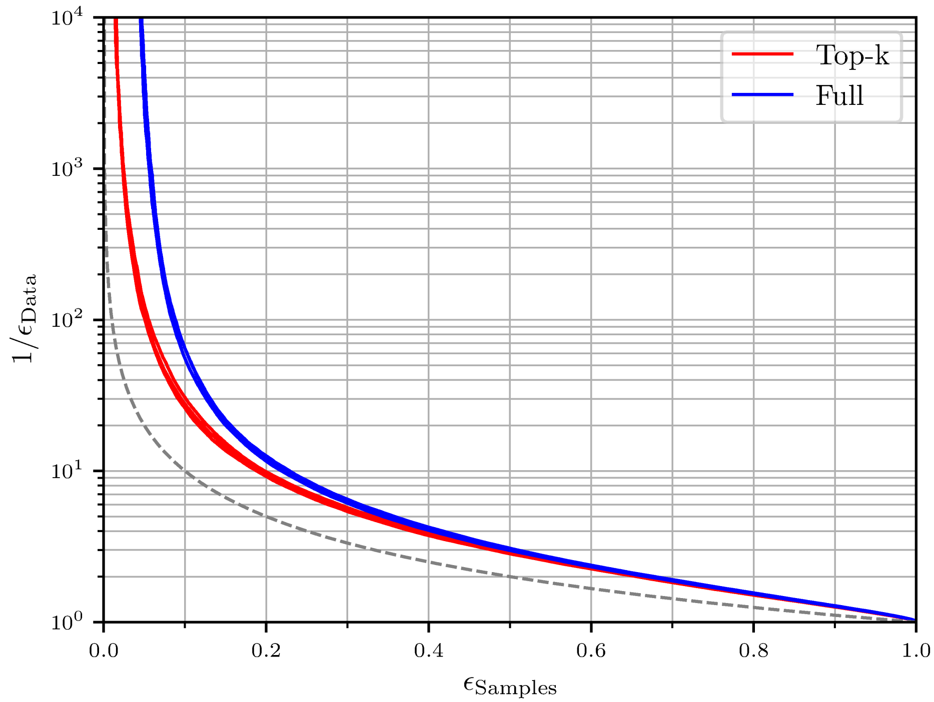
(sample from k=5000 particles with highest probability)

Quality assessment

- Transformer as generative model: draw jets from $p(\vec{x})$

  $\Rightarrow$ use classifier to discriminate samples from data

  (see also 2305.16774, Luigi's talk Thu 11.45h)



- poor classification $\Rightarrow$ good sampling $\Rightarrow$ good density estimate
- Top-k sampling $\Rightarrow$ fewer poor samples

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Conclusion

Density estimation for low-level jet data

- following Natural Language Processing
- works for flexible number of constituents

Promising results

- the transformer can speak QCD with a slight accent
- use classifier to assess quality

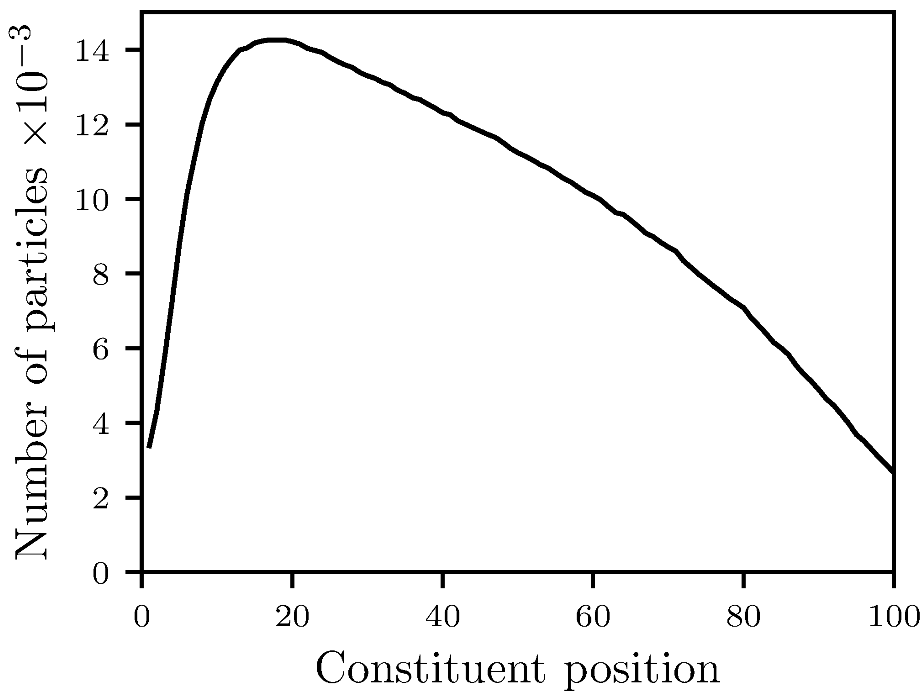
Outlook

- improvements on larger datasets expected
- use in the context of Anode and Cathode

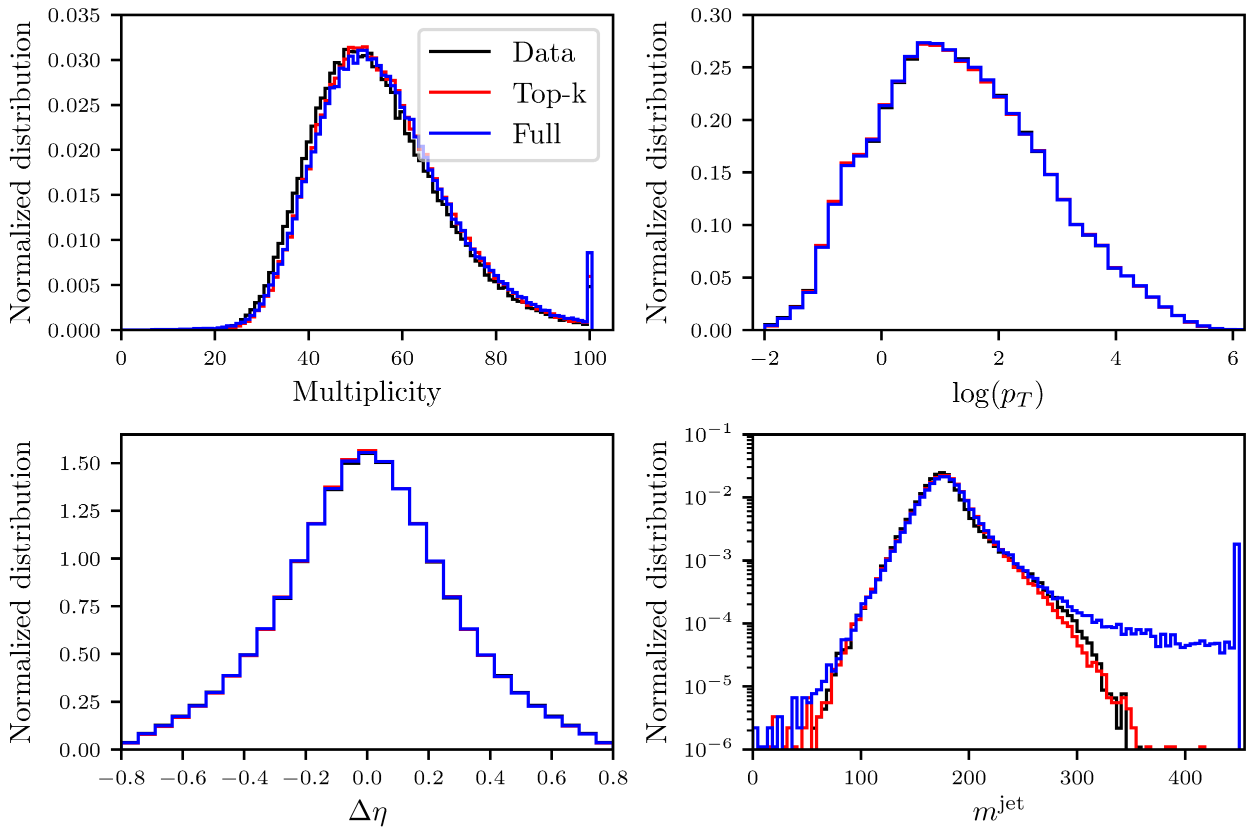
  (see also 2310.06897, talk by Cedric et al. Wed 17.15h)
- general pretraining (see also talk by Matthew)

Backup

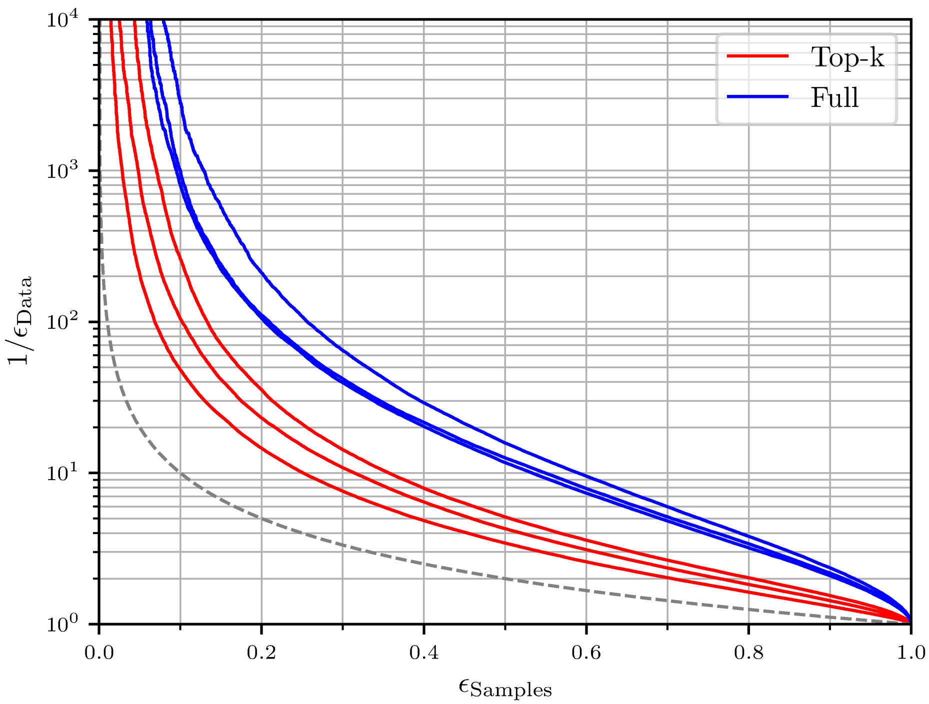
How many different particle types are in the data set?



Training on and sampling top jets: 1D distributions



Training on and sampling top jets: Classifier test



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Sampling speed: