Boost-Invariant Polynomials:

an efficient and interpretable approach to jet tagging

ACAT 2022

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Personal Introduction

Christoph Ortner

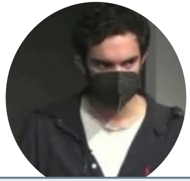
Ilyes Batatia

Jose M Munoz

Personal Introduction

Christoph Ortner

THE UNIVERSITY OF BRITISH COLUMBIA



Ilyes Batatia

UNIVERSITY OF CAMBRIDGE

- Undergrad Physics Student
- ML Engineer at Guane
- Focus on Geometric-DL and ML for HEP
- UBC Intern
- CERN Summer Student

Jose M Munoz

UNIVERSIDAD EIA

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State of the art

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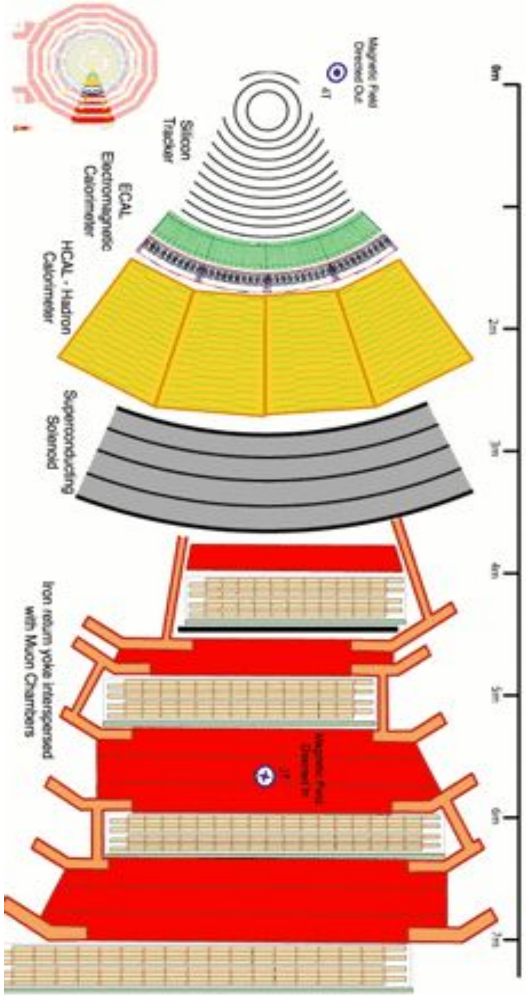
Results 4.
Of the approach

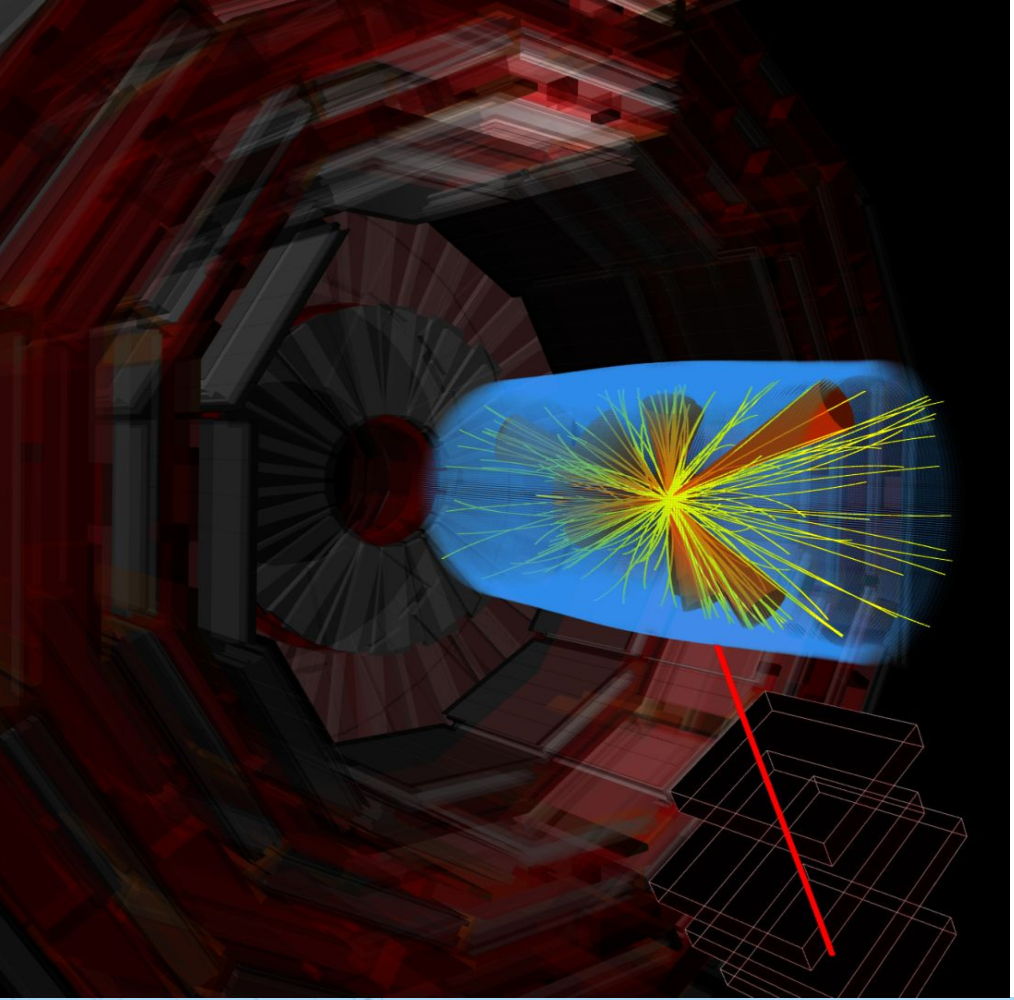
Future Outlook 5.
& Conclusions



1.

Jet Tagging

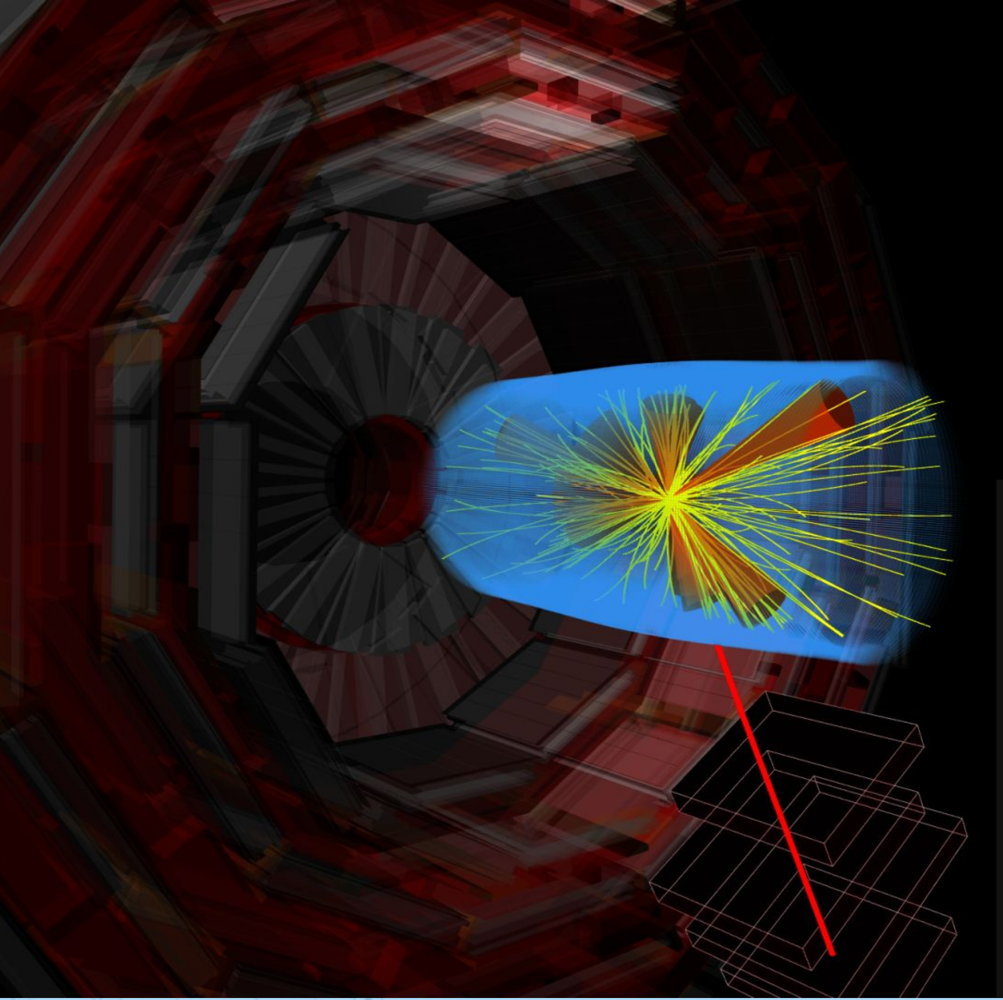
A Brief Introduction



Jet Tagging

Identify signal vs background in particles coming from different processes

The particles are detected and reconstructed as point clouds



Jet Tagging

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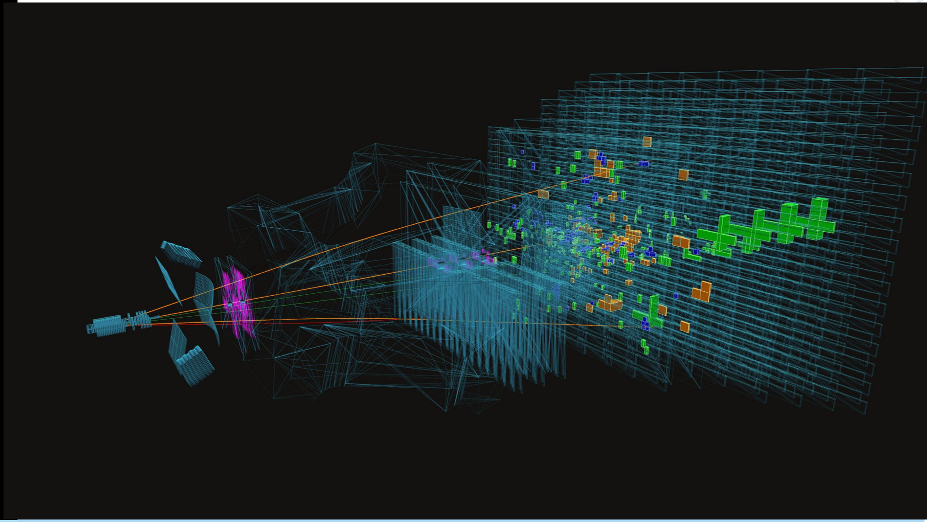
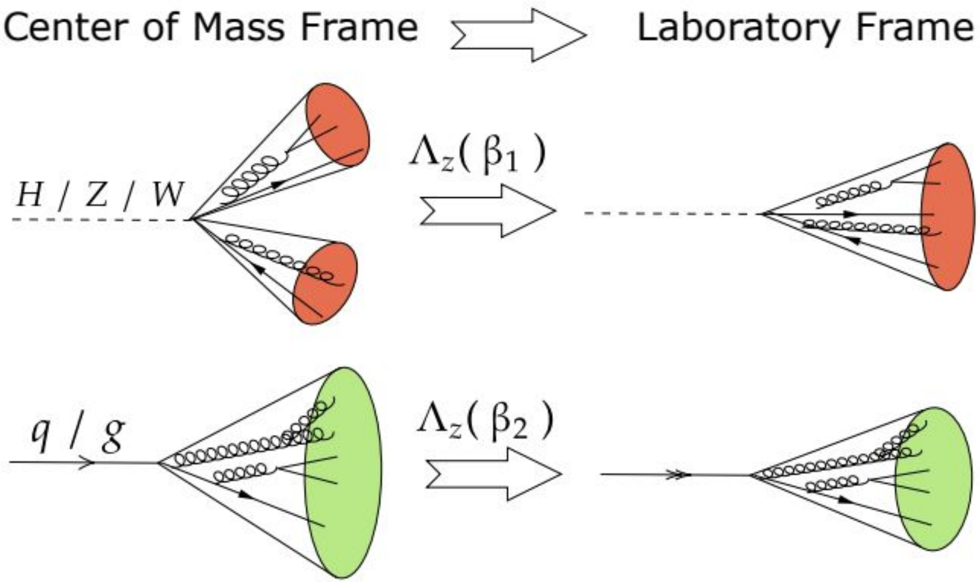


The issue of Boosted Jet Tagging

The angular resolution depends on the pT of the jets…



arXiv:2207.08272v2

2.

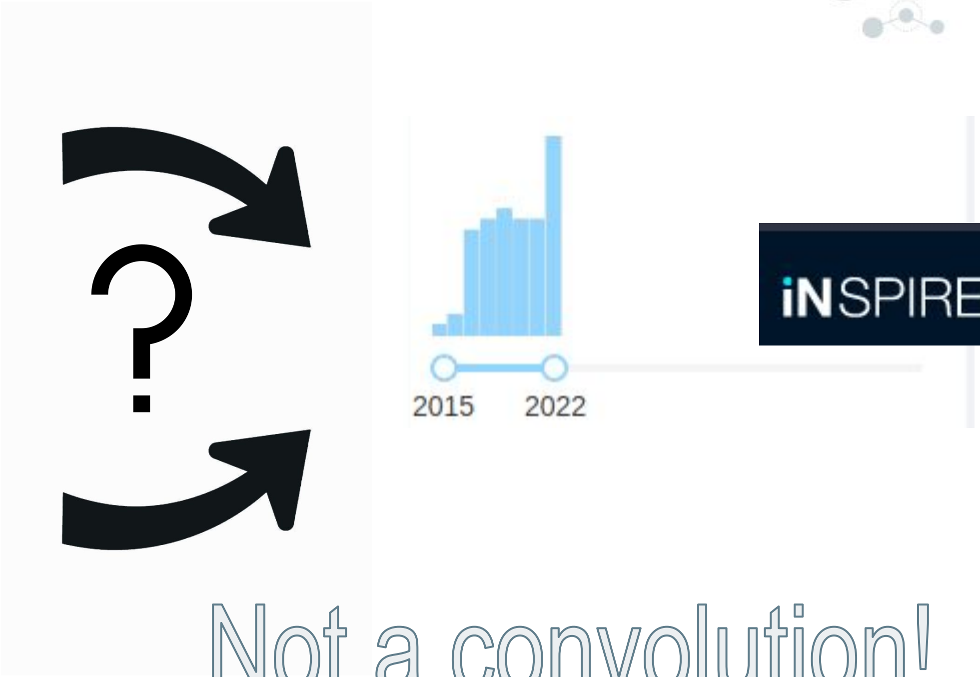
ML for Jet Tagging

A Brief Introduction

Why Machine Learning?

Jet-Tagging Papers:

ML papers:



Not a convolution!

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The model size is a determining factor

In other fields: (LLMs)

Particle physics

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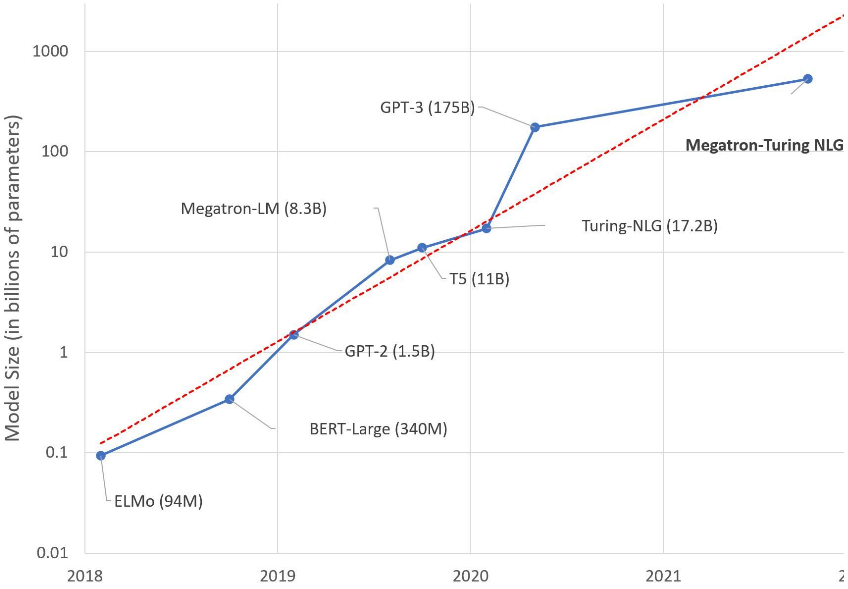
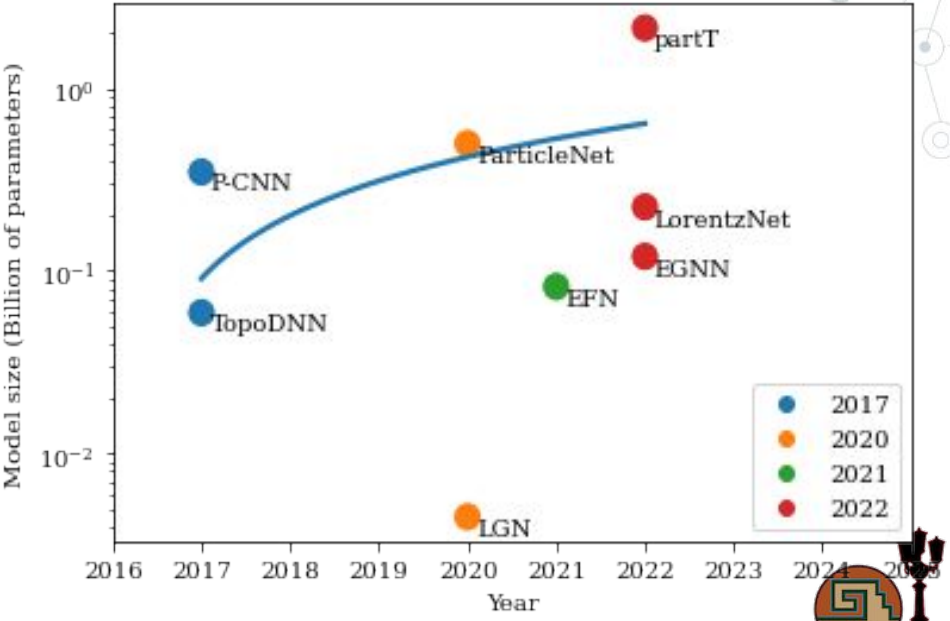


https://huggingface.co/blog/large-language-models



What information should we give the models?

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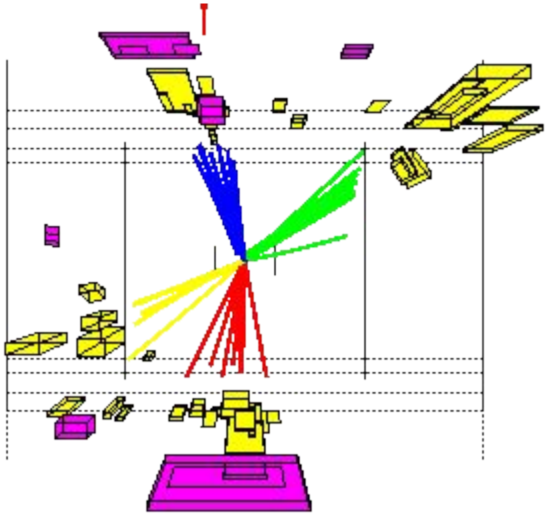
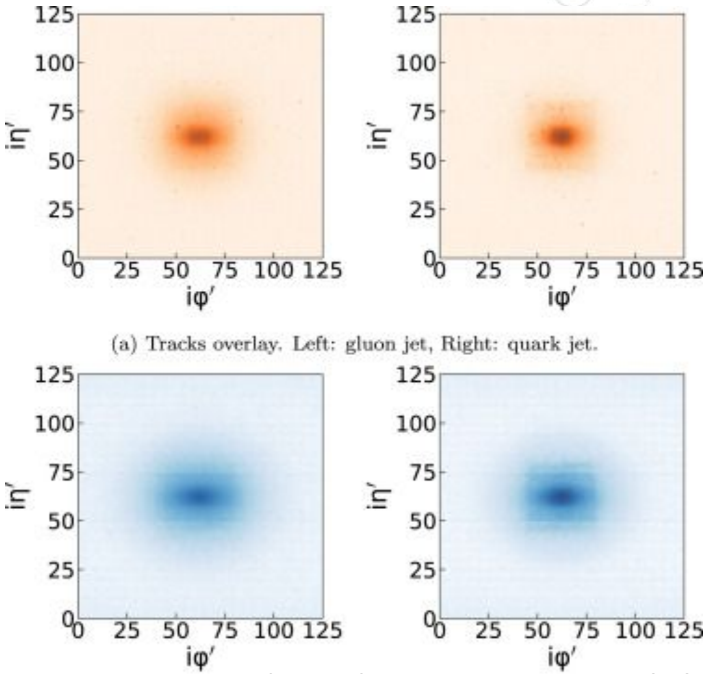
Low level variables

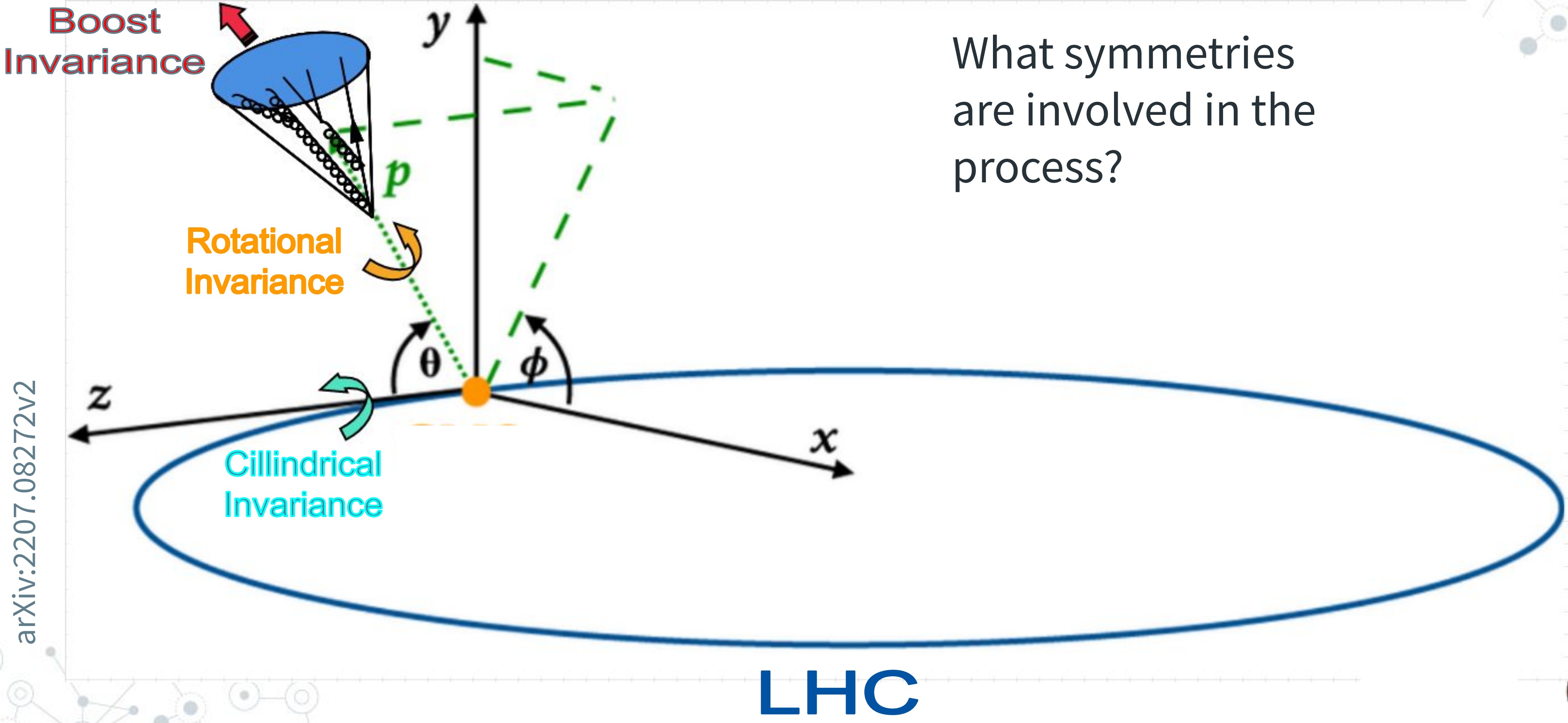


High Level variables



End-to-end jet classification of quarks and gluons with the CMS Open Data. Andrew et Al.

What about inductive biases?



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What symmetries are involved in the process?

What Lorentz group equivariant message passing networks achieve?

Equivariant Energy Flow Networks for jet tagging

Matthew J. Dolan[1,*] and Ayodele Ore[1,†]
[1] *ARC Centre of Excellence for Dark Matter Particle Physics, School of Physics, The University of Melbourne, Victoria 3010, Australia*

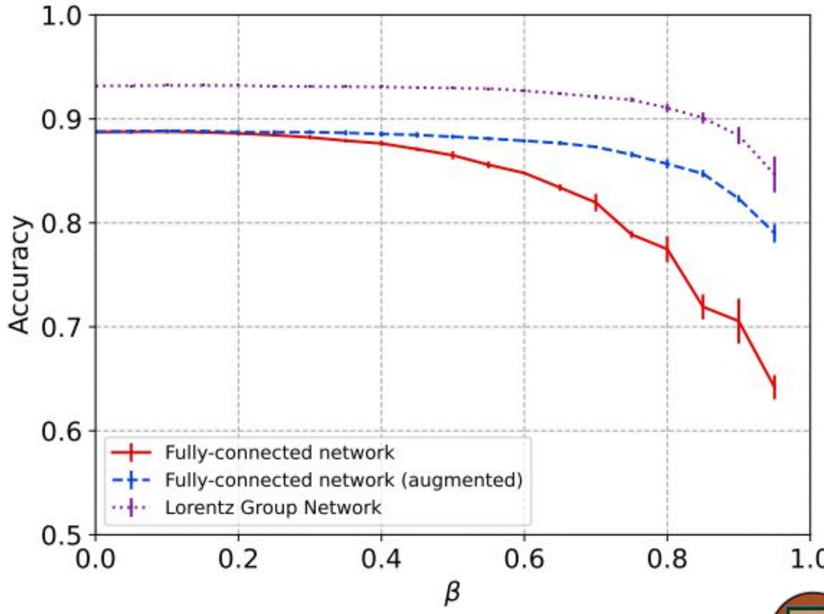
An Efficient Lorentz Equivariant Graph Neural Network for Jet Tagging

Shiqi Gong[a,e,1] Qi Meng[b] Jue Zhang[b] Huilin Qu[c] Congqiao Li[d] Sitian Qian[d] Weitao Du[a] Zhi-Ming Ma[a] Tie-Yan Liu[b]

arXiv:2207.08272v2

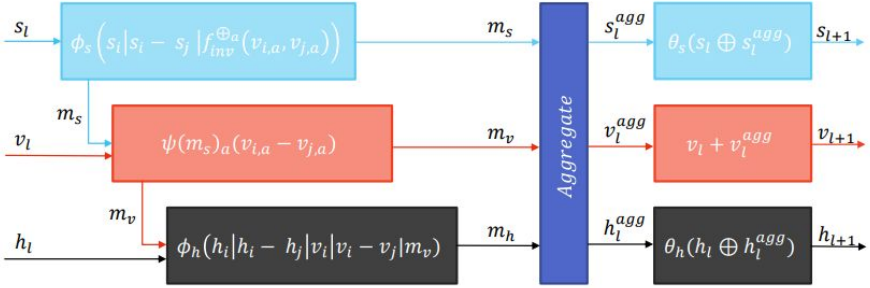
Semi-Equivariant GNN Architectures for Jet Tagging

Daniel Murnane[1], Savannah Thais[2], Jason Wong[3]

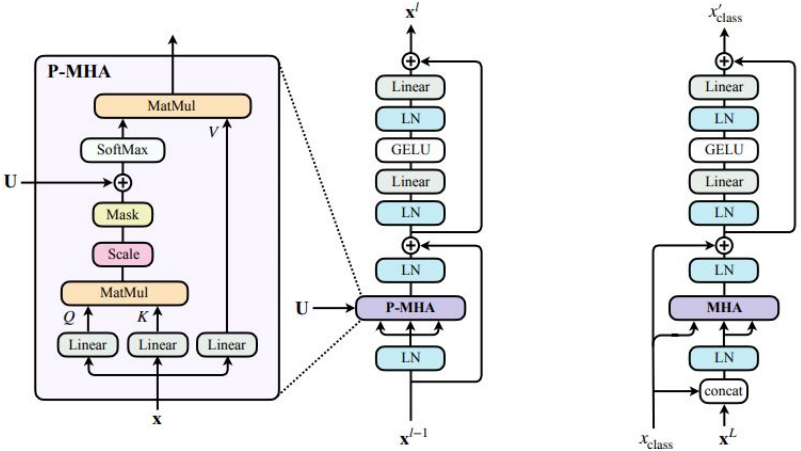


Bogatskiy et al.

A problem...

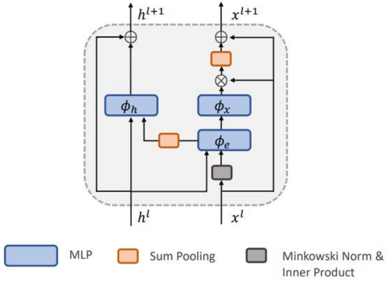


Murnane et al.

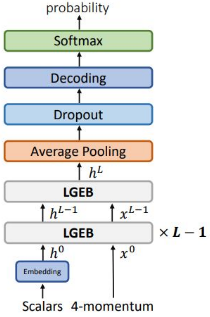


Qu et al.

arXiv:2207.08272v2



Lorentz Group Equivariant Block (LGEB)



LorentzNet

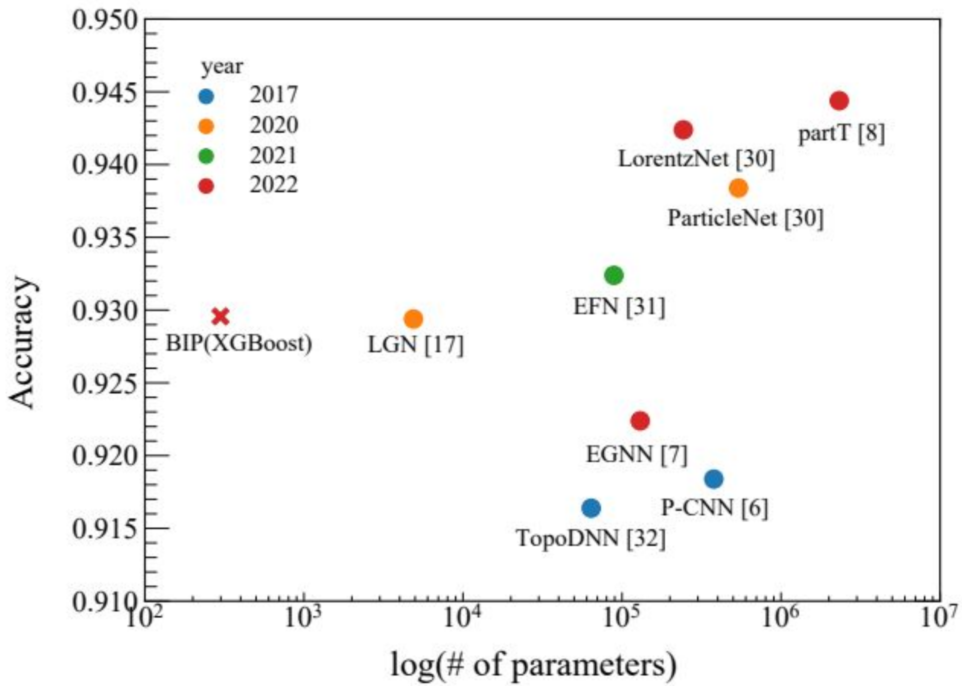
Very expensive tensorial computation

3.

The Boost Invariant Polynomials

A Brief Introduction

SOTA Accuracy with a fraction of the parameters



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A basis change

$$y_i = \frac{1}{2}\log\left(\frac{\delta_1 + E_i + p_{\|i}}{\delta_1 + E_i - p_{\|,i}}\right)$$

$$p_\perp$$

$$E_{\perp,i} = \sqrt{m_i^2 + p_{\perp,i}^2}$$

$$\varphi_i$$

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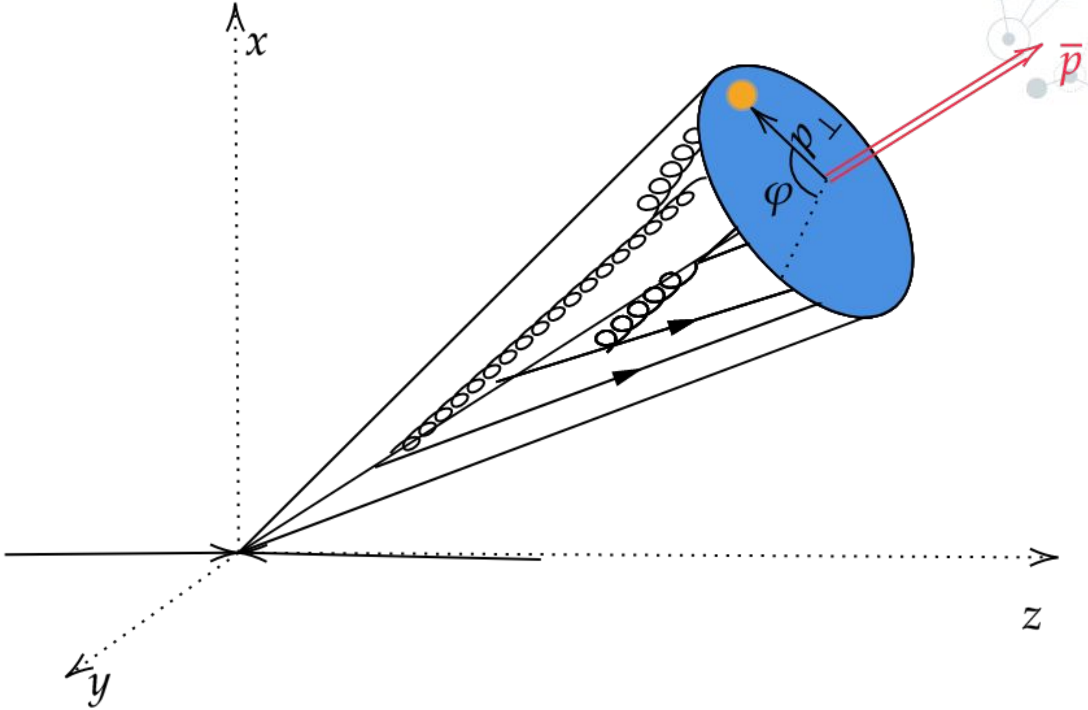


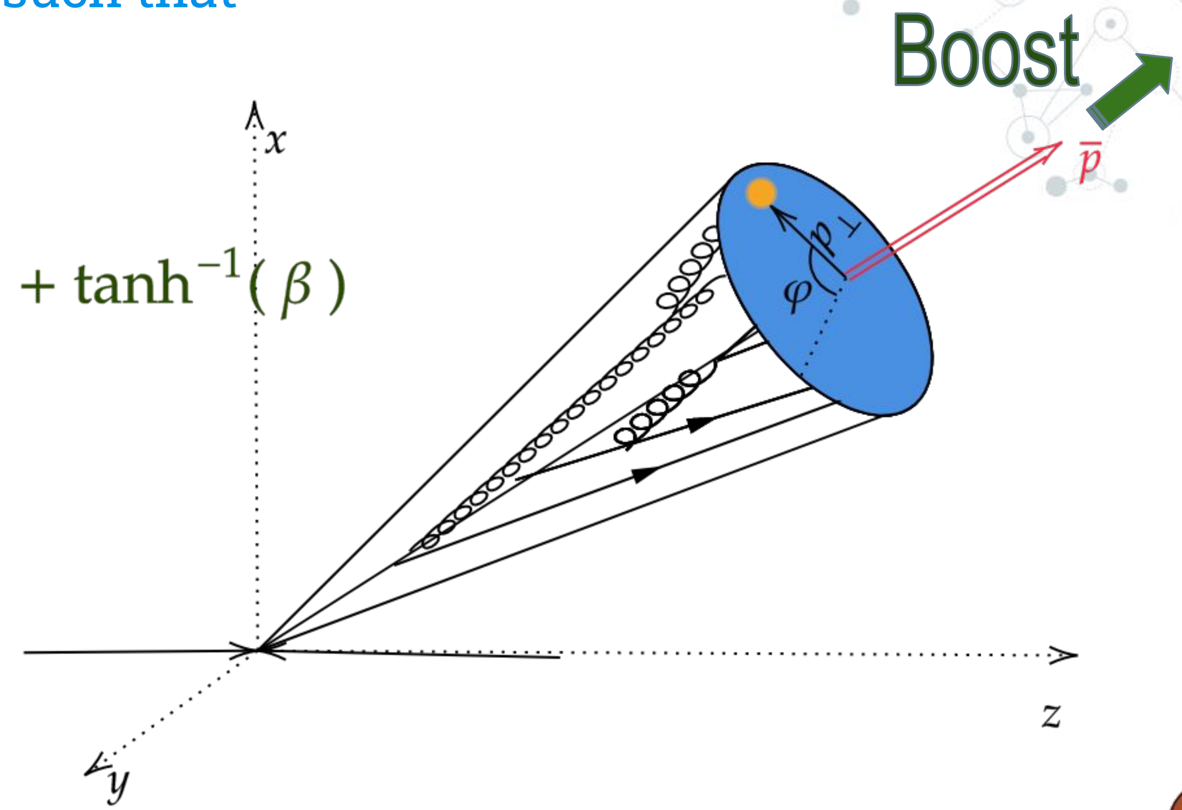
A basis change… such that

$$y_i = \frac{1}{2}\log\left(\frac{\delta_1 + E_i + p_{\|i}}{\delta_1 + E_i - p_{\|,i}}\right) + \tanh^{-1}(\,\beta\,)$$

$$p_\perp$$

$$E_{\perp,i} = \sqrt{m_i^2 + p_{\perp,i}^2}$$

$$\varphi_i$$



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A basis change… such that

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$$E_{\perp,i} = \sqrt{m_i^2 + p_{\perp,i}^2}$$

$$\varphi_i \quad + \Delta\varphi$$

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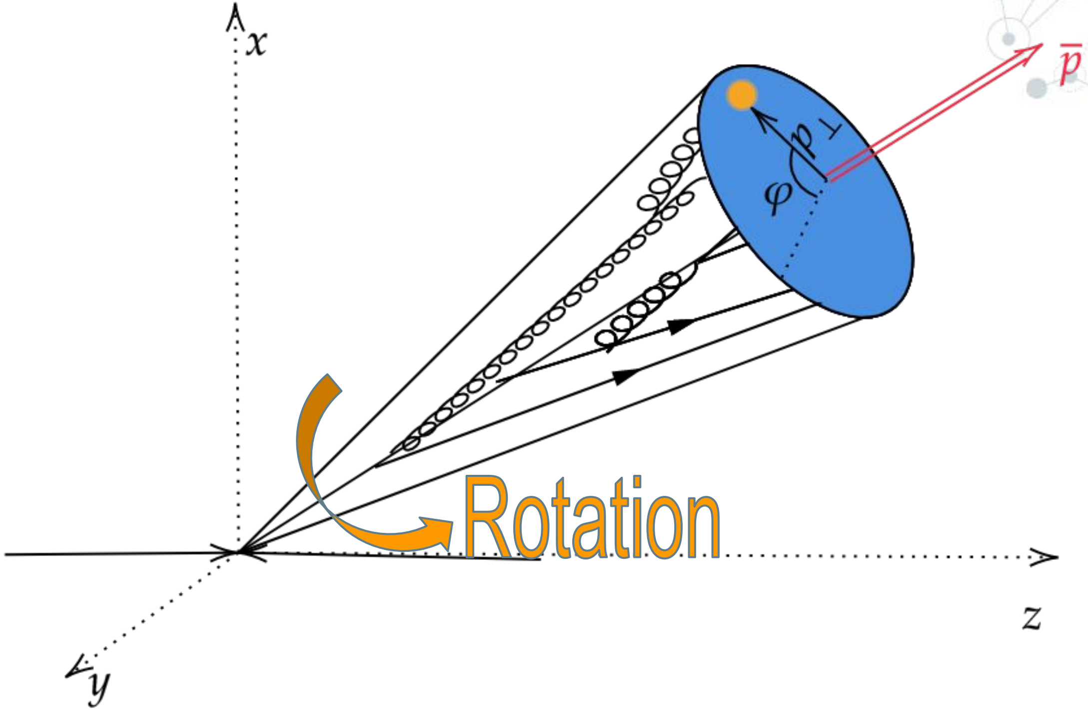

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$$\varphi_i$$

Invariant

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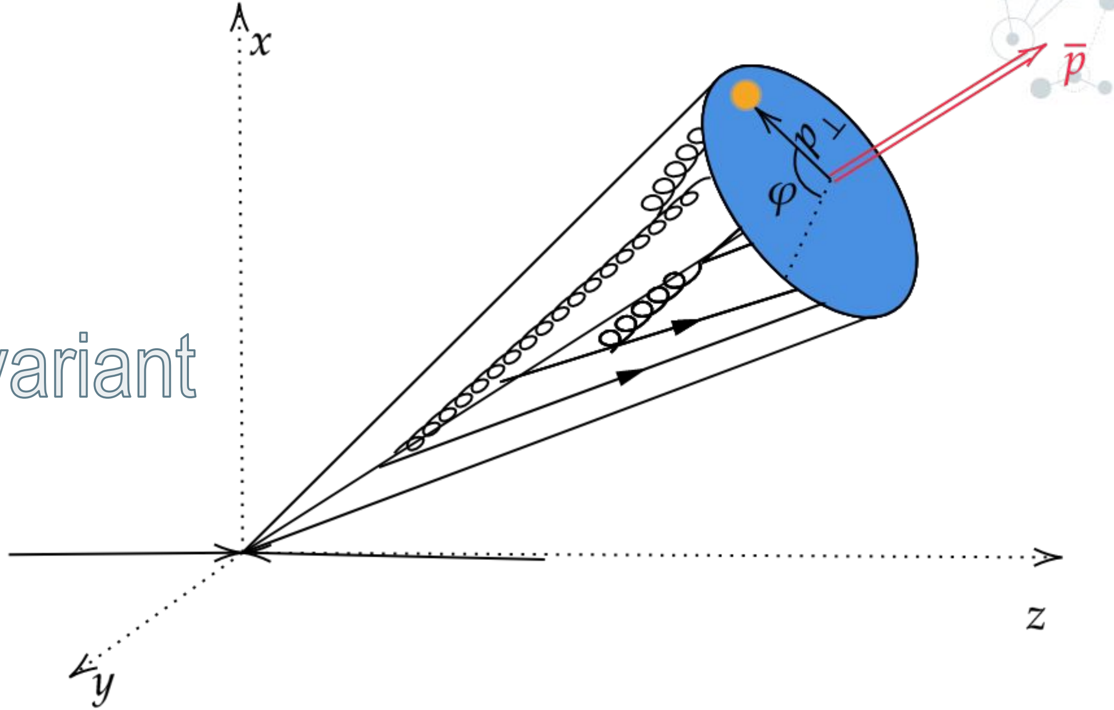

The Atomic Cluster Expansion Recipe:

1. Build a one particle basis:

$$A_{nlk} = \sum_{i=1}^{N} Q_n(p_{\perp,i}, E_{\perp,i}, \xi_i) e^{il\varphi_i} e^{-\lambda k y_i}$$

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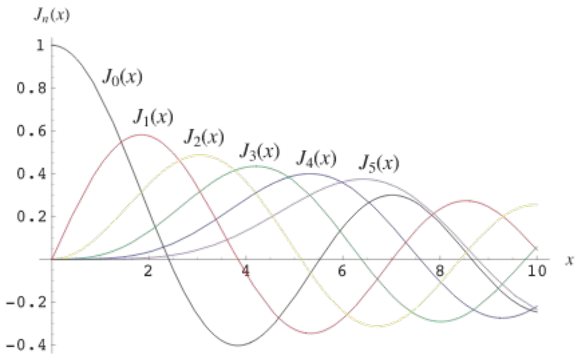

A general basis allows to introduce additional features… e.g

$$Q_n(E_{\perp,i}, p_{\perp,i}) = B_n(\tilde{p}_{\perp,i}) \log(1 + E_{\perp,i})$$

Bessel polynomials

The Atomic Cluster Expansion Recipe:

1. Build a one particle basis:

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Decoupled generators
(rotations + boosts)

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The Atomic Cluster Expansion Recipe:

1. Build a one particle basis:

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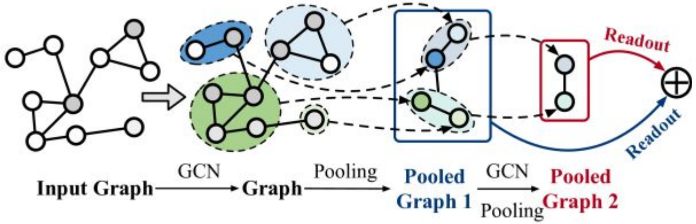

Liu et al.

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The Atomic Cluster Expansion Recipe:

1. Build a one particle basis:

$$A_{nlk} = \sum_{i=1}^{N} Q_n(p_{\perp,i}, E_{\perp,i}, \xi_i) e^{il\varphi_i} e^{-\lambda k y_i}$$

NOT an Invariant jet descriptor

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The Atomic Cluster Expansion Recipe:

1. Build a one particle basis.

2. Symmetrize the basis:

$$\boldsymbol{A_{nlk}} = \prod_{t=1}^{\nu} A_{n_t l_t k_t}$$

$$(n_1 l_1 k_1,\ \dots,\ n_\nu l_\nu k_\nu)$$

The Atomic Cluster Expansion Recipe:

1. Build a one particle basis.

2. Symmetrize the basis.

3. Keep Invariant features:

$$\boldsymbol{A_{nlk}} = \prod_{t=1}^{\nu} \sum_{i=1}^{N} Q_n(p_{\perp,i}, E_{\perp,i}, \xi_i) e^{\mathrm{i} l \varphi_i} e^{-\lambda k y_i} \Rightarrow \begin{array}{l} \sum_t l_t = \sum_t k_t = 0 \\ \sum_{t=1}^{\nu} |l_t| + |k_t| + n_t \leq \Gamma \end{array}$$

The Atomic Cluster Expansion Recipe:

1. Build a one particle basis.
2. Symmetrize the basis.
3. Keep Invariant features.

et Voilà

A highly expressive and invariant jet representation

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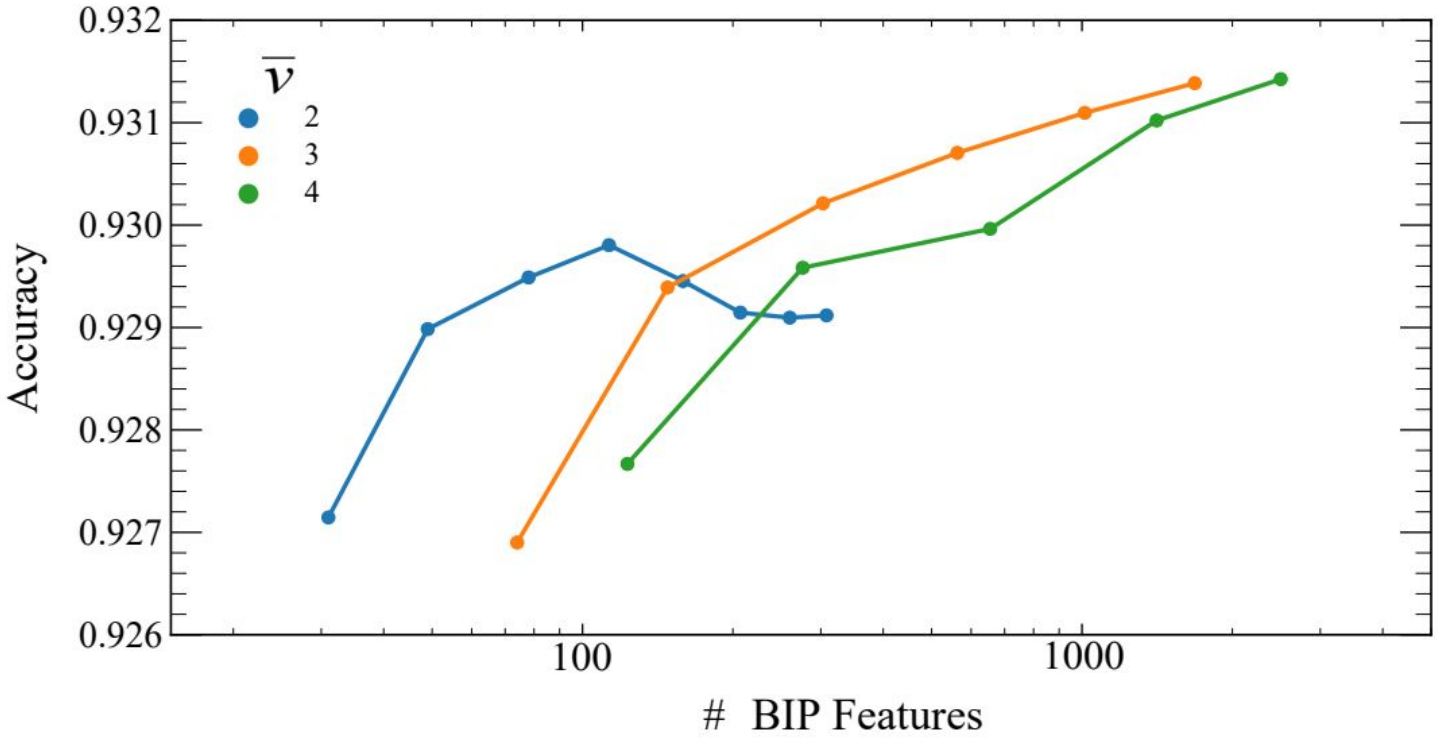
4.

Results

Of the approach

Versatility on the basis size



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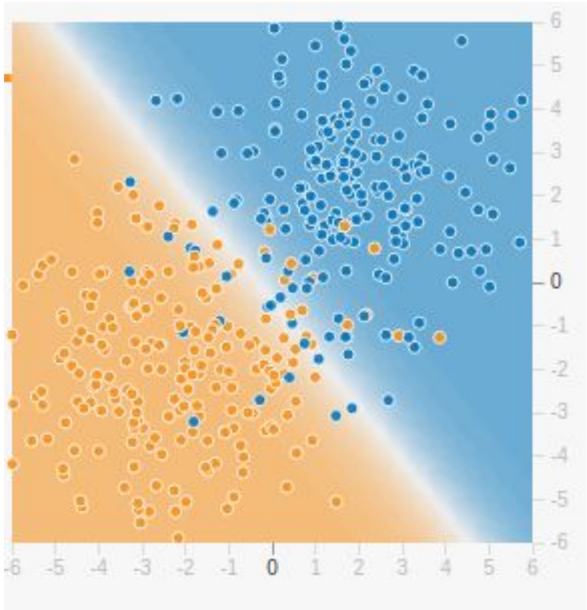
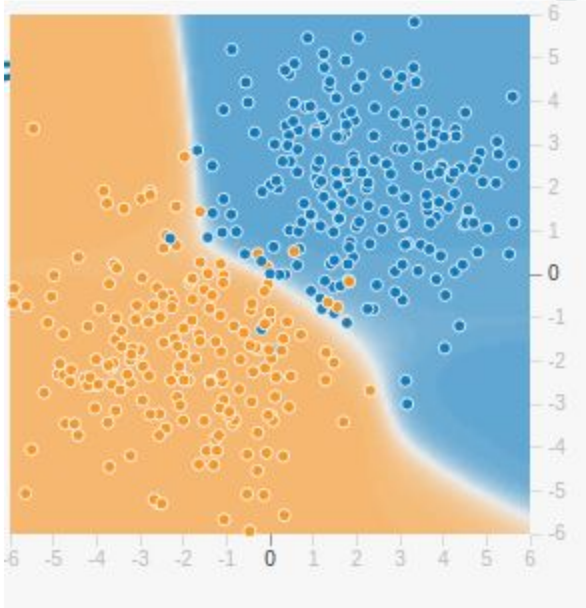
Versatility on the classifier algorithm

From logistic regressions



To DL and GBT



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Versatility on the classifier algorithm

Architecture	#Param	Accuracy	AUC
***partT (2022)**[8]	2.14M	0.944	0.988
EGNN (2022)[7]	120k	0.922	0.970
PCT (2021)[30]	139.3k	0.940	0.986
EFN (2021)[31]	82k	0.927	0.979
ParticleNet (2020)[30]	498k	0.938	0.985
LGN (2020)[17]	4.5k	0.929	0.964
P-CNN (2017)[6]	348k	0.918	0.980
TopoDNN (2017)[32]	59k	0.916	0.972
Supervised			
BIP(3, 6, MLP)	4k	0.931	0.981
BIP(3, 6, XGBoost)	300	0.929	0.978
BIP(3, 6, LogReg)	300	0.927	0.977
BIP(3, 6, SVM)	300	0.927	0.976

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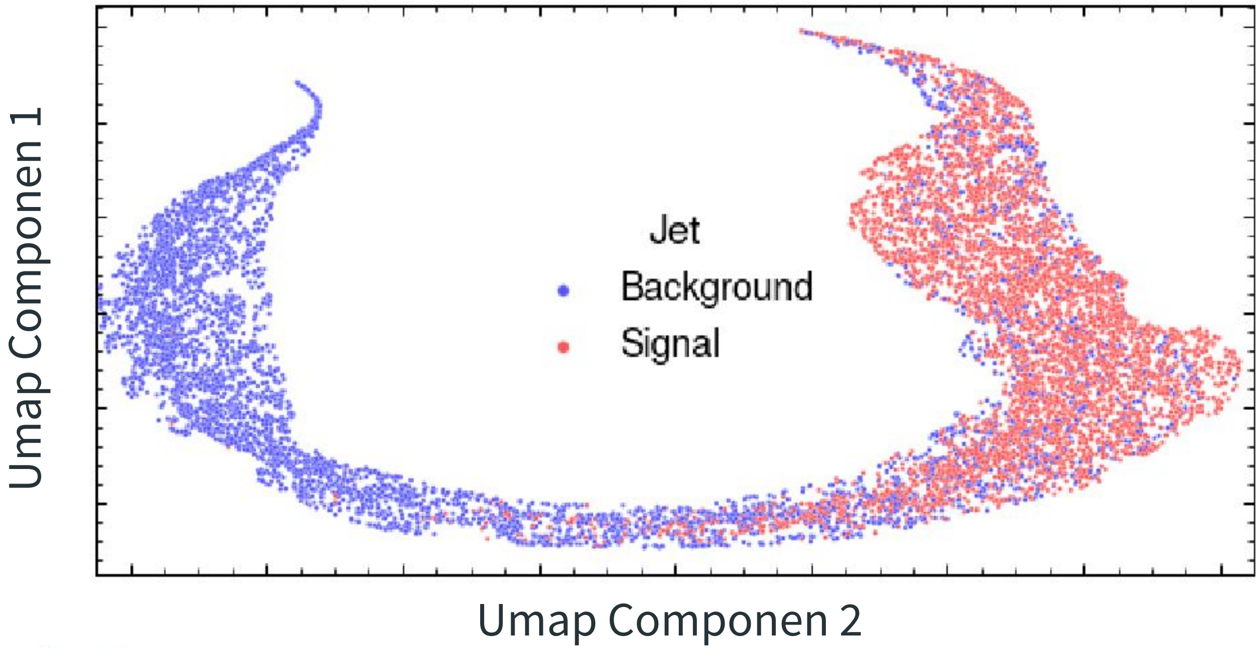
Expressive representation



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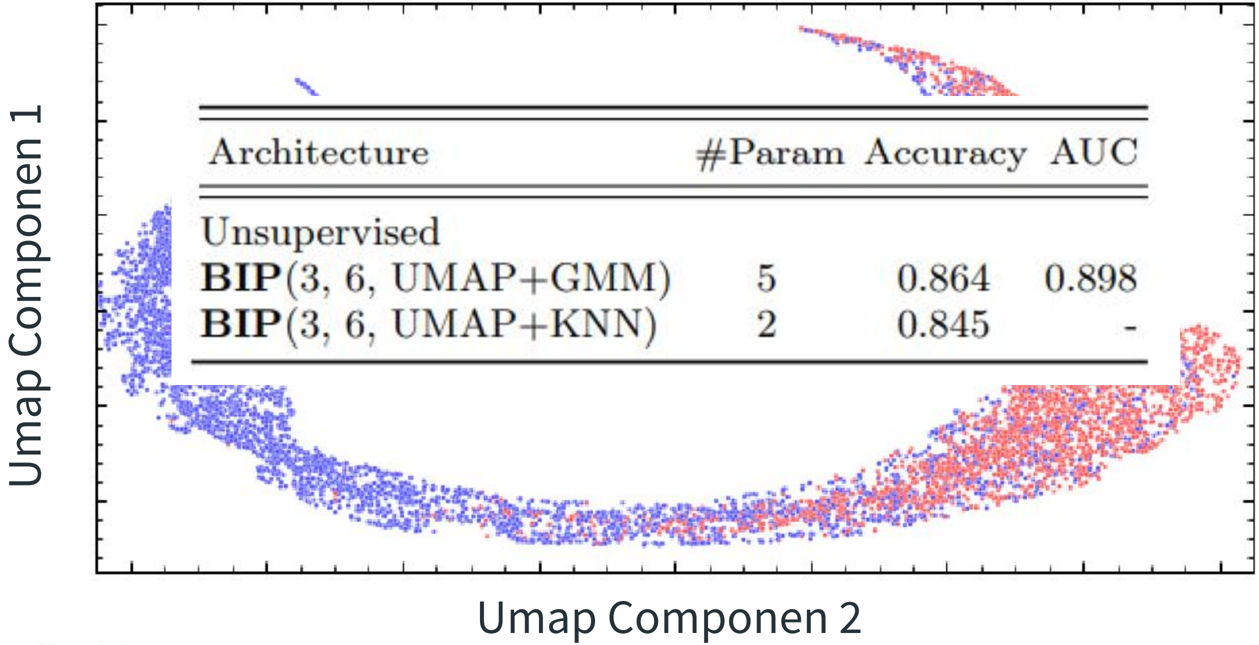
Expressive representation



Architecture	#Param	Accuracy	AUC
Unsupervised			
BIP(3, 6, UMAP+GMM)	5	0.864	0.898
BIP(3, 6, UMAP+KNN)	2	0.845	-

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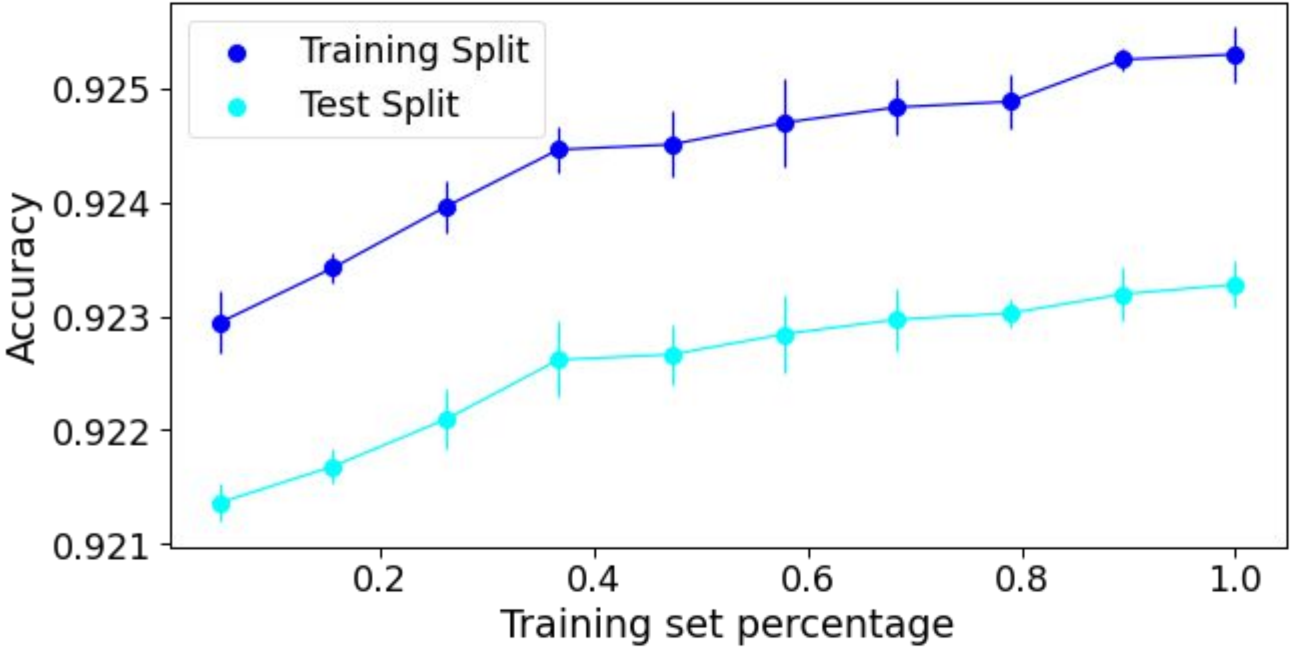
Data Efficiency



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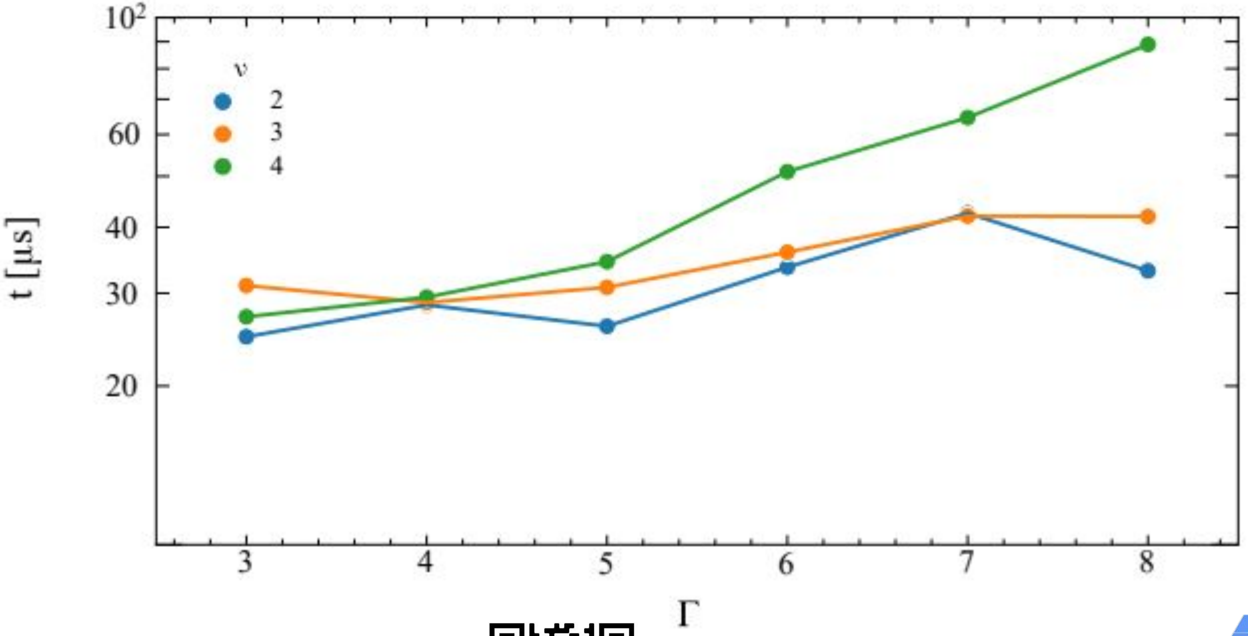
High efficiency



Also on…

same performance

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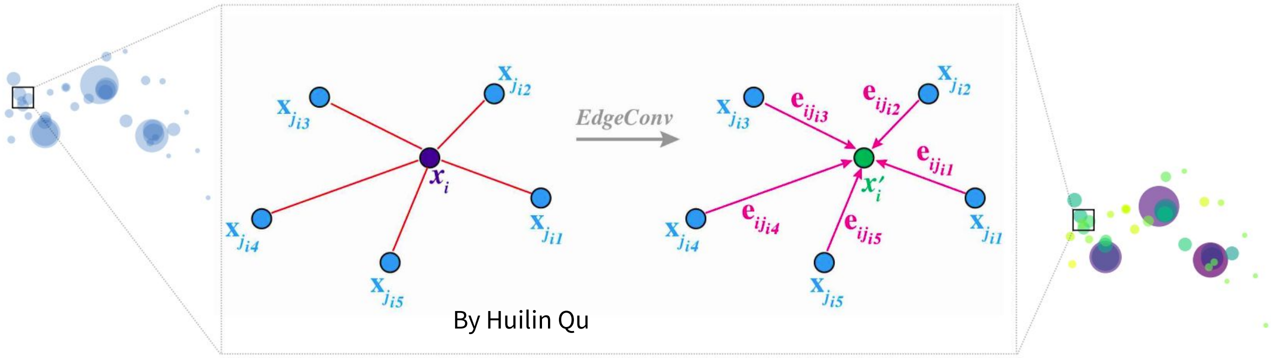
5.

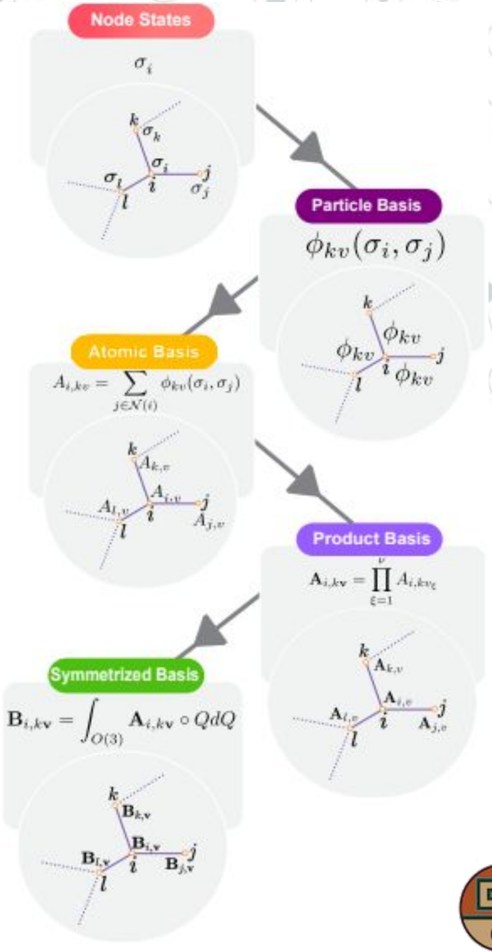
Outlooks

& Conclussions

Now... go deep



By Huilin Qu



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+ Learnable embeddings

Batatia et. al

Play with the model

Paper

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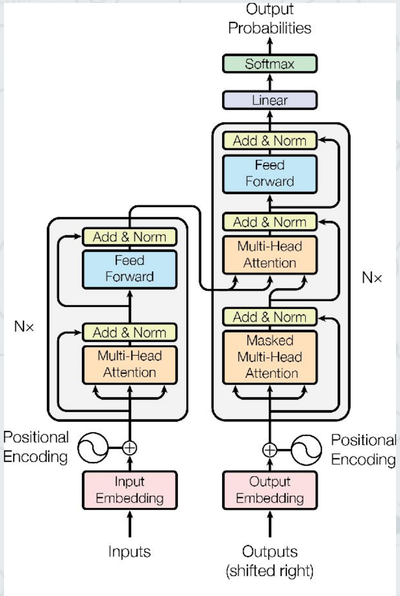
Thanks for the ~~attention~~!

profile

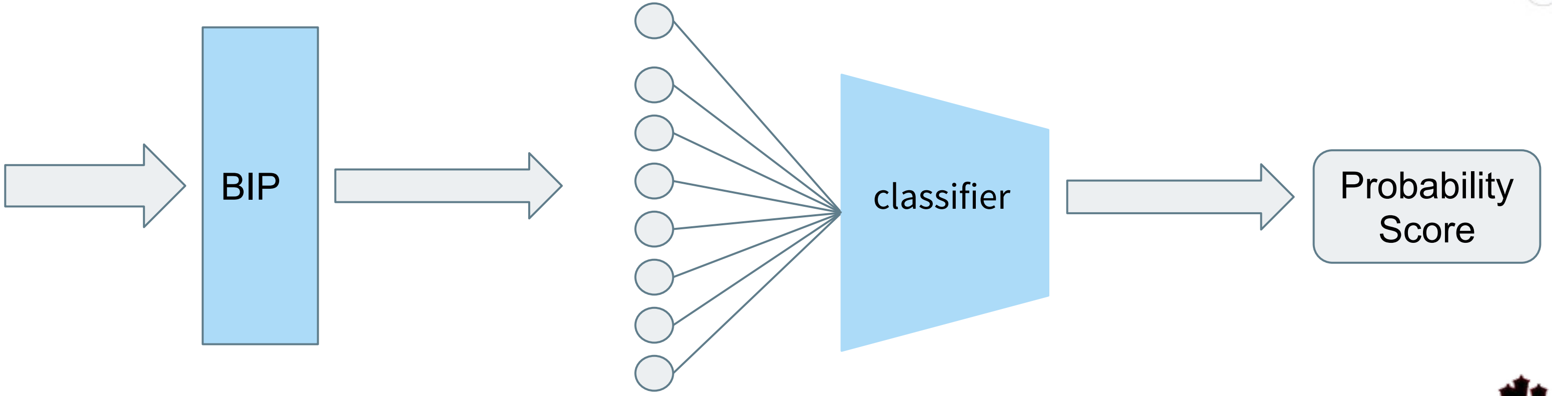
Please contact me for anything related




BACKUP

The classifier setup:

$$f(\{E_i, \boldsymbol{p}_i, \xi_i\}_i) = \sum_{\boldsymbol{nlk}} w_{\boldsymbol{nlk}} \boldsymbol{A}_{\boldsymbol{nlk}},$$



Jet representation

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A many body expansion

$$f(\{x_i\}_i) = f_0 + \sum_i f_1(x_i) + \sum_{i_1,i_2} f_2(x_{i_1}, x_{i_2}) + \cdots + \sum_{i_1,\ldots,i_{\bar{\nu}}} f_{\bar{\nu}}(x_{i_1}, \ldots, x_{i_{\bar{\nu}}}).$$

Or a density

$$\rho(x) = \sum_{i=1}^{N} \delta(x - x_i)$$

$$A_v = \langle Q_n(p_\perp, E_\perp, \xi) e^{il\varphi} e^{-ky} \mid \rho \rangle$$

$$\langle \phi_{v_1} \otimes \cdots \otimes \phi_{v_\nu} \mid \rho \otimes \cdots \otimes \rho \rangle = \prod_t \langle \phi_{v_t} \mid \rho \rangle = \prod_t A_{v_t} = \boldsymbol{A}_{\boldsymbol{v}},$$

arXiv:2207.08272v2