Jets as graphs: W tagging with neural message passing

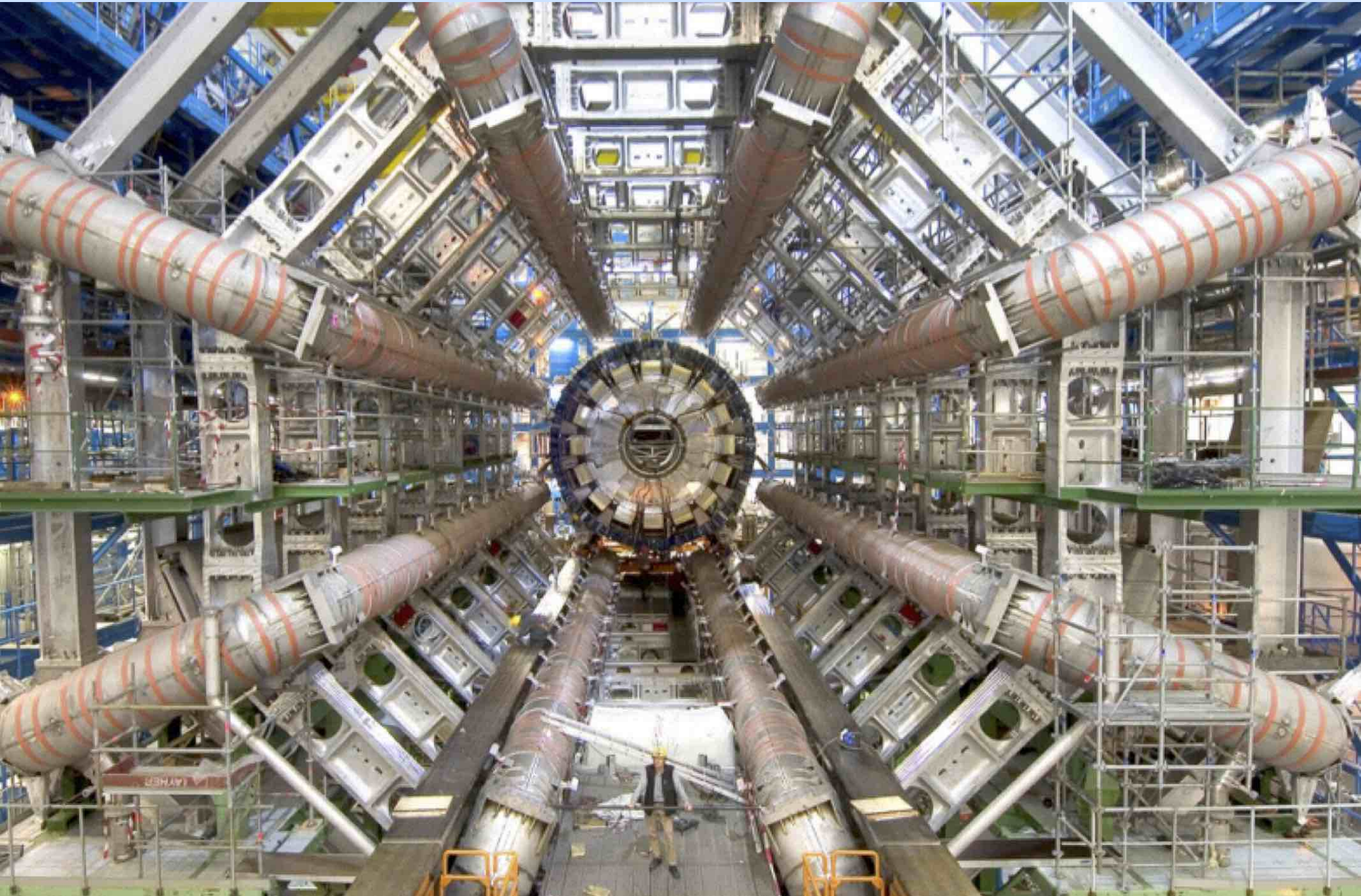
Isaac Henrion, Johann Brehmer, Joan Bruna, Kyunghyun Cho, Kyle Cranmer, Gilles Louppe, Gaspar Rochette

Courant Institute & Center for Data Science

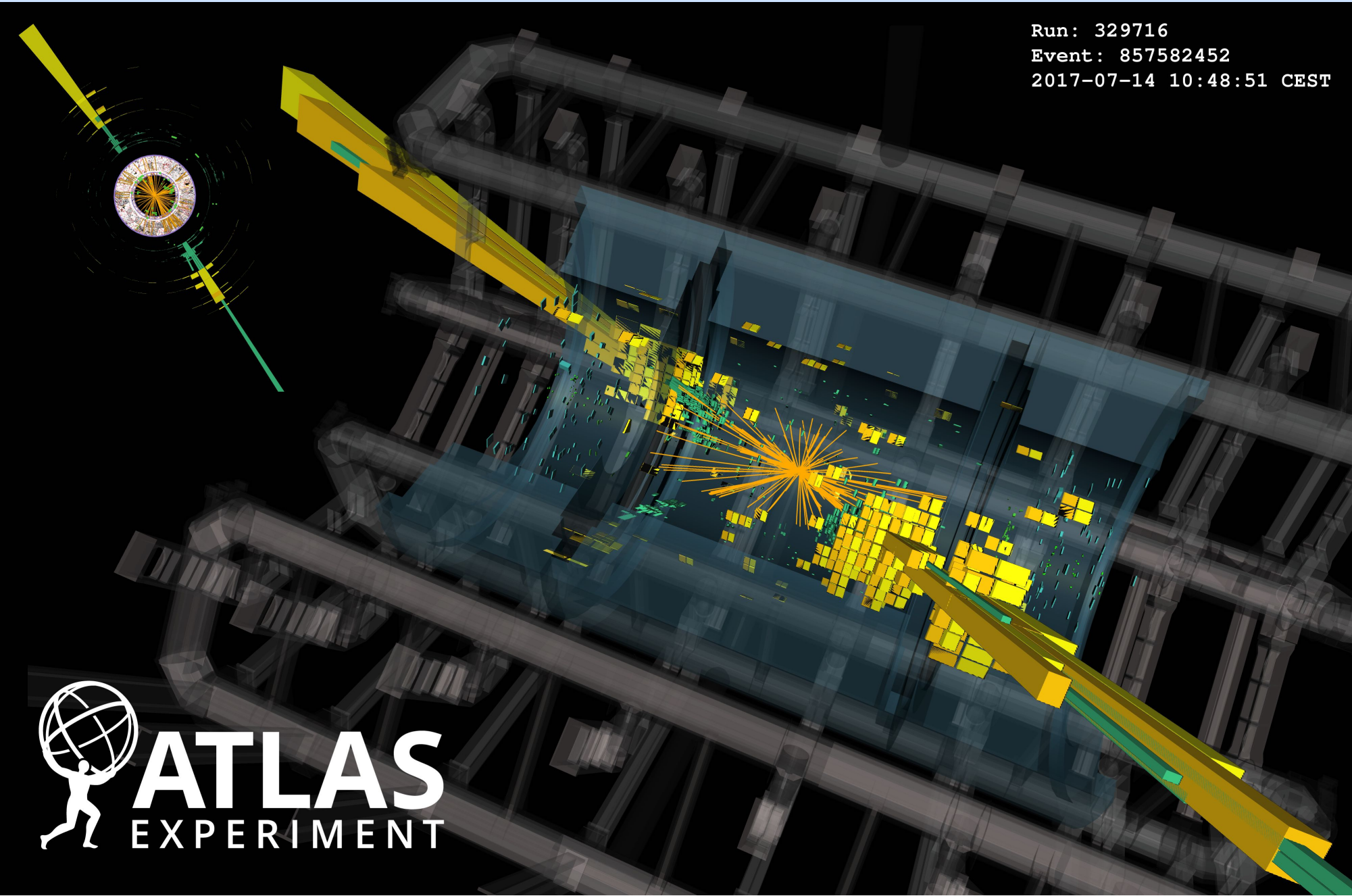
Disclaimer: I am not a physicist!

Jet physics

Large Hadron Collider



ATLAS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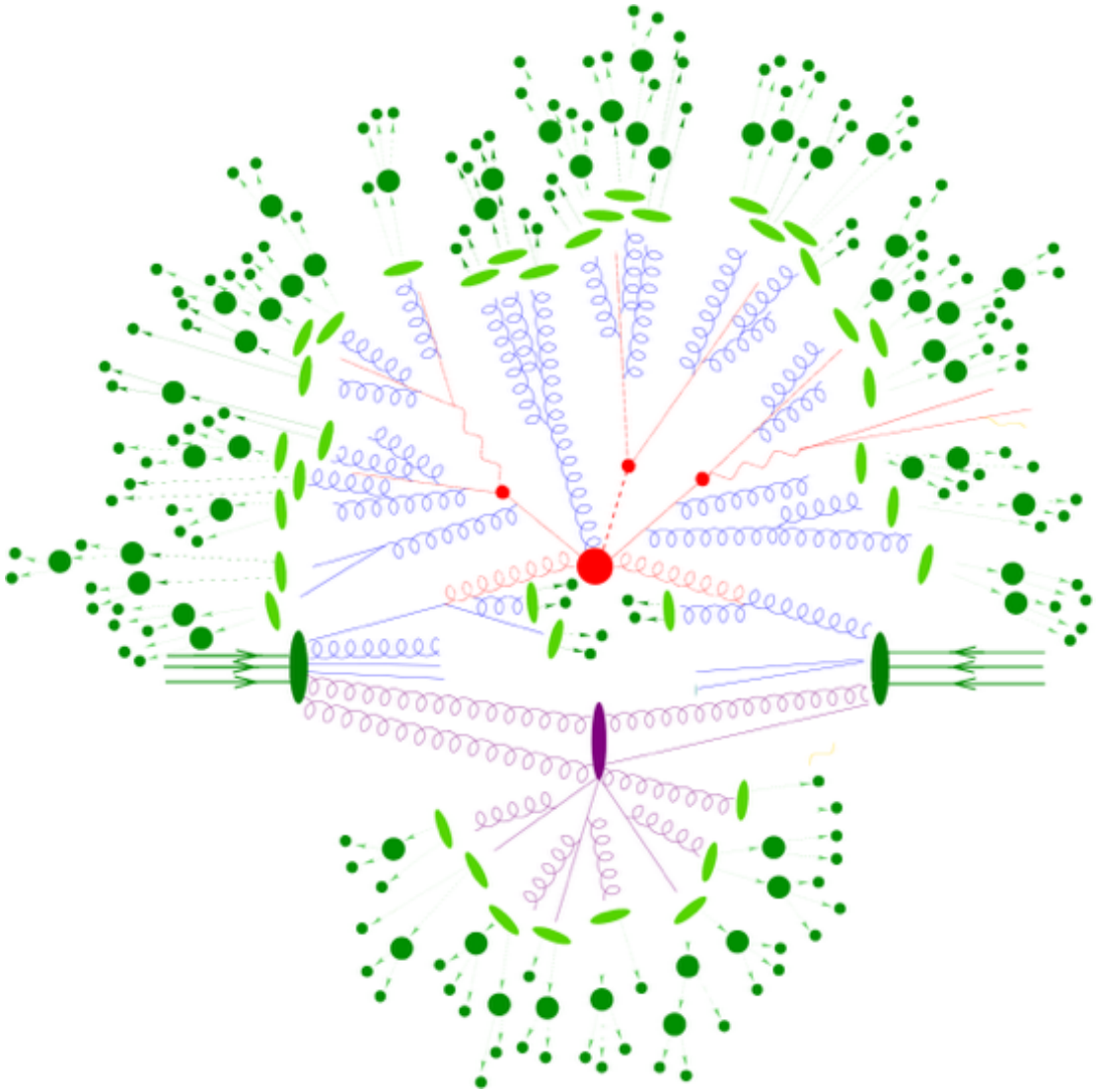
Event: 857582452
2017-07-14 10:48:51 CEST
ATLAS
EXPERIMENT

Microscopic picture

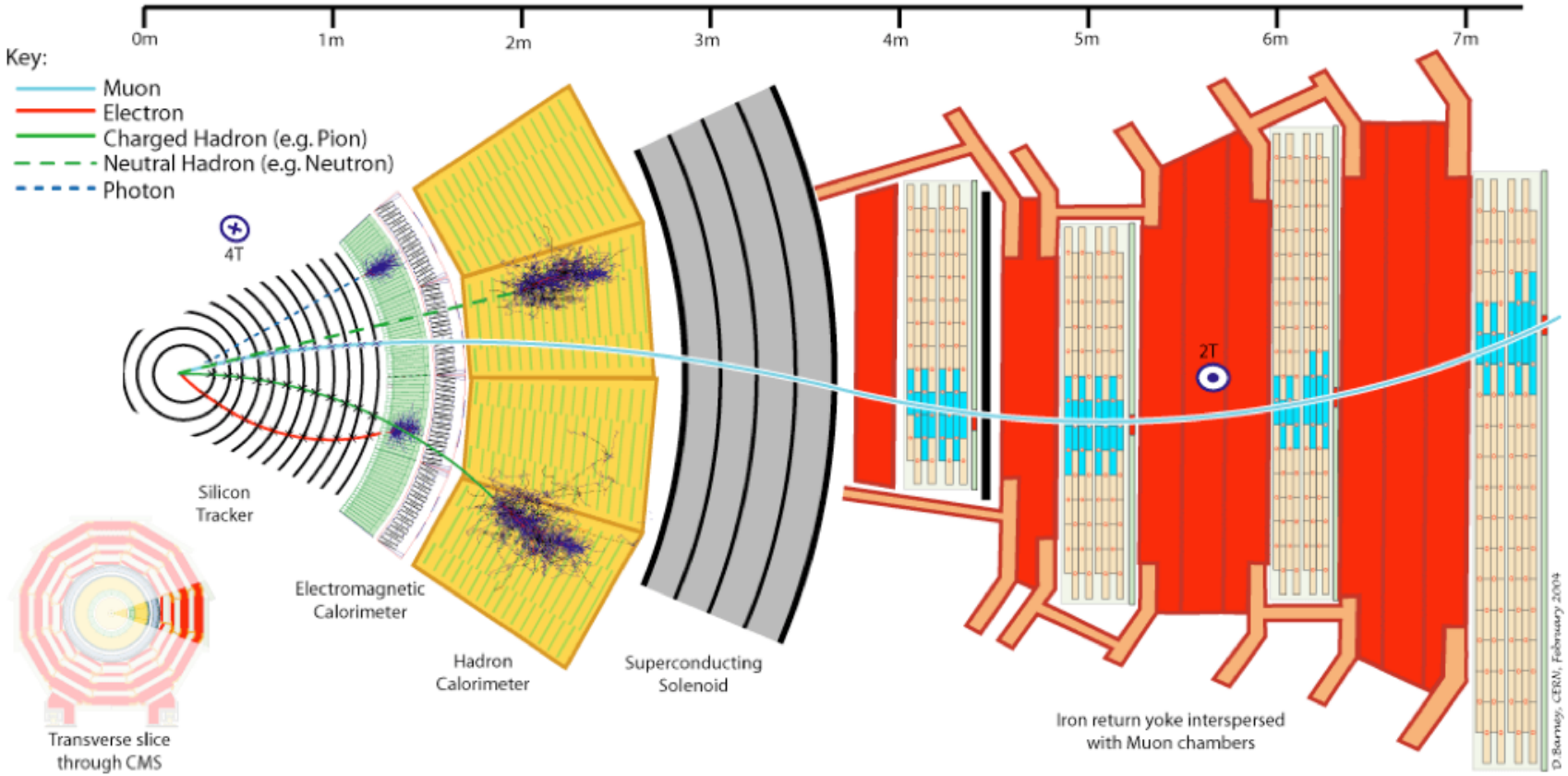


pencil and paper calculable from first principles

controlled approximation of first principles

phenomenological model

Macroscopic picture



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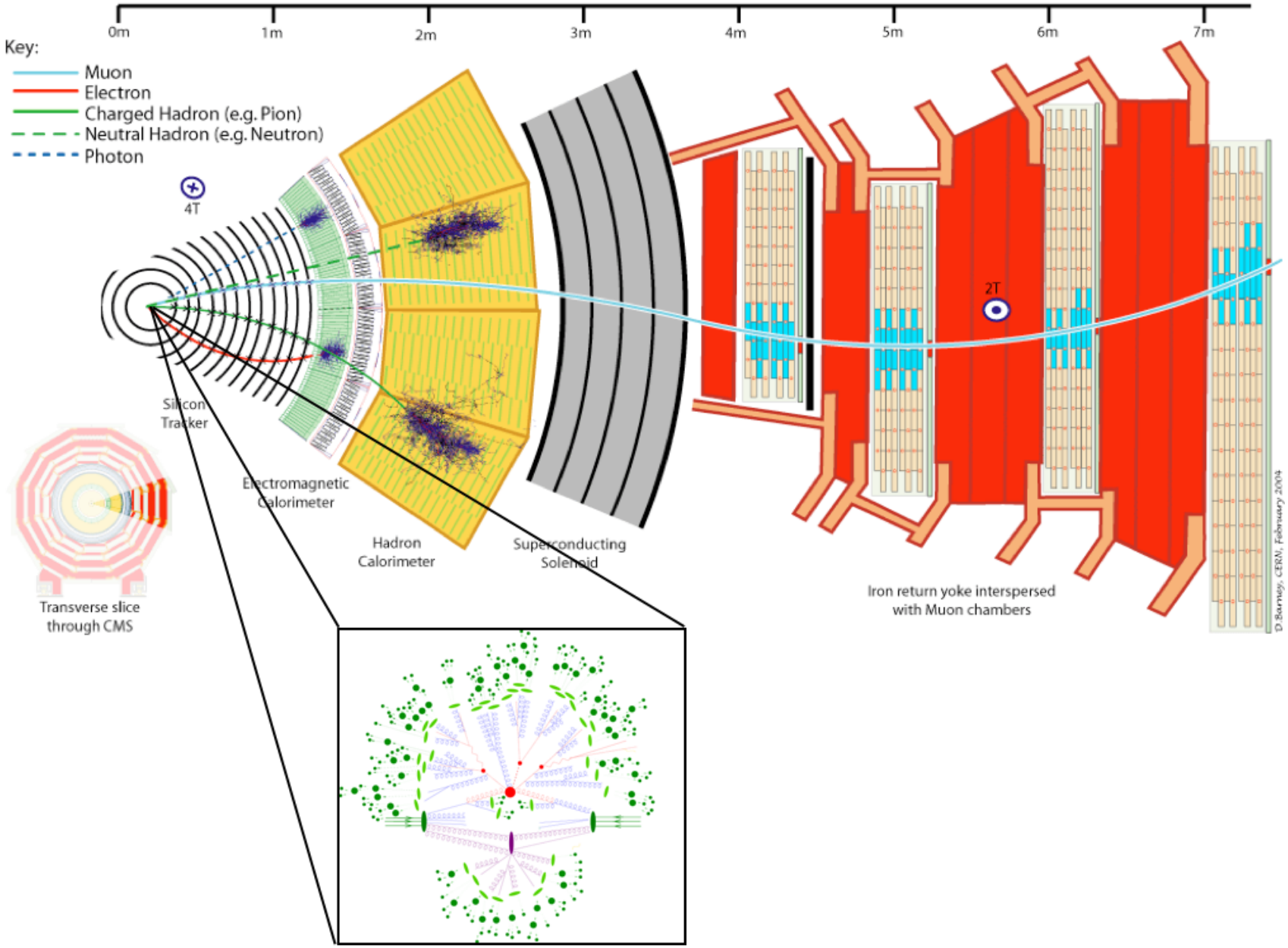

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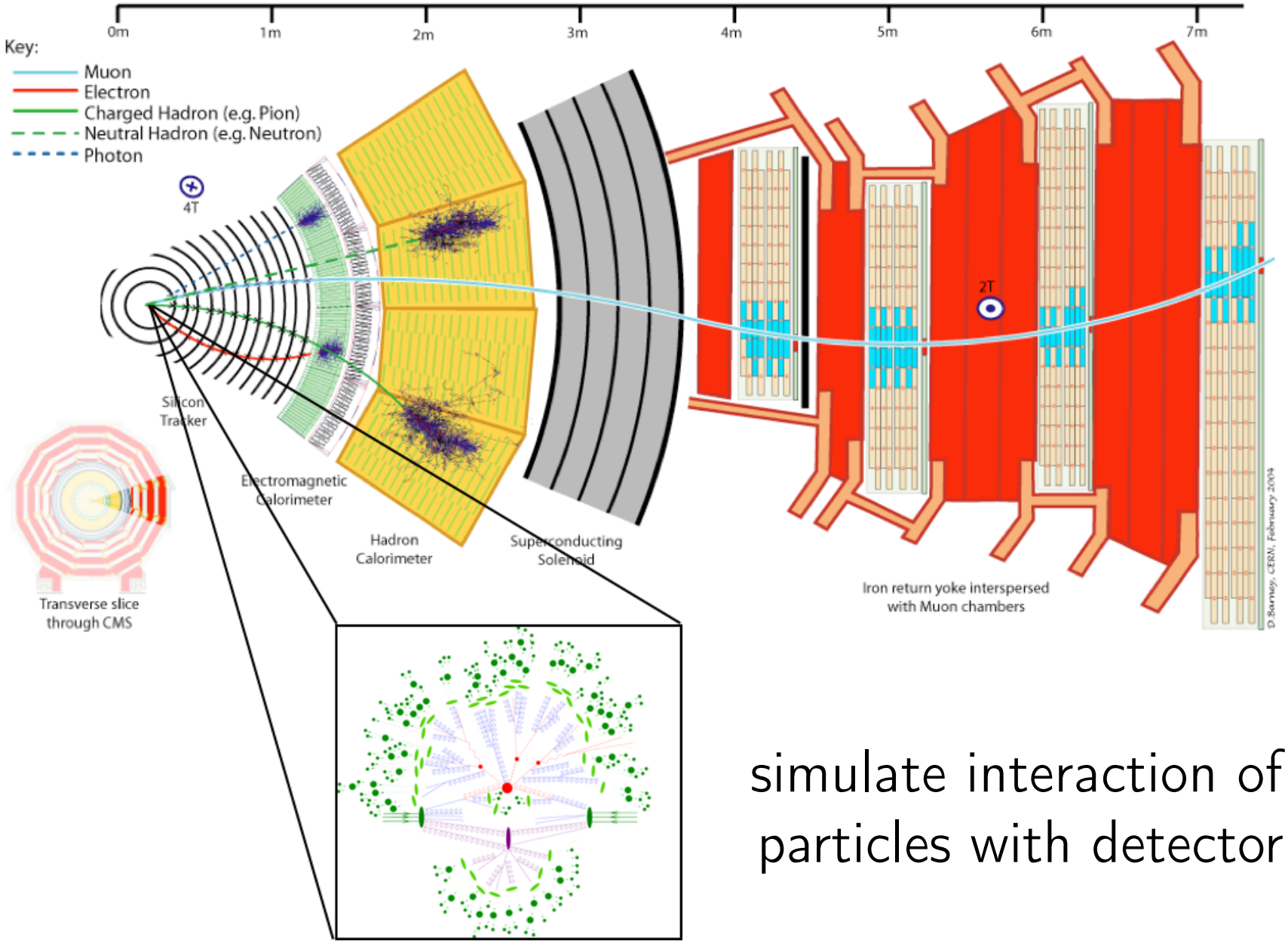

simulate interaction of particles with detector

Classification of W-bosons

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Input

Momentum estimates of jet constituents

$$\{x_1, \ldots, x_n\}$$

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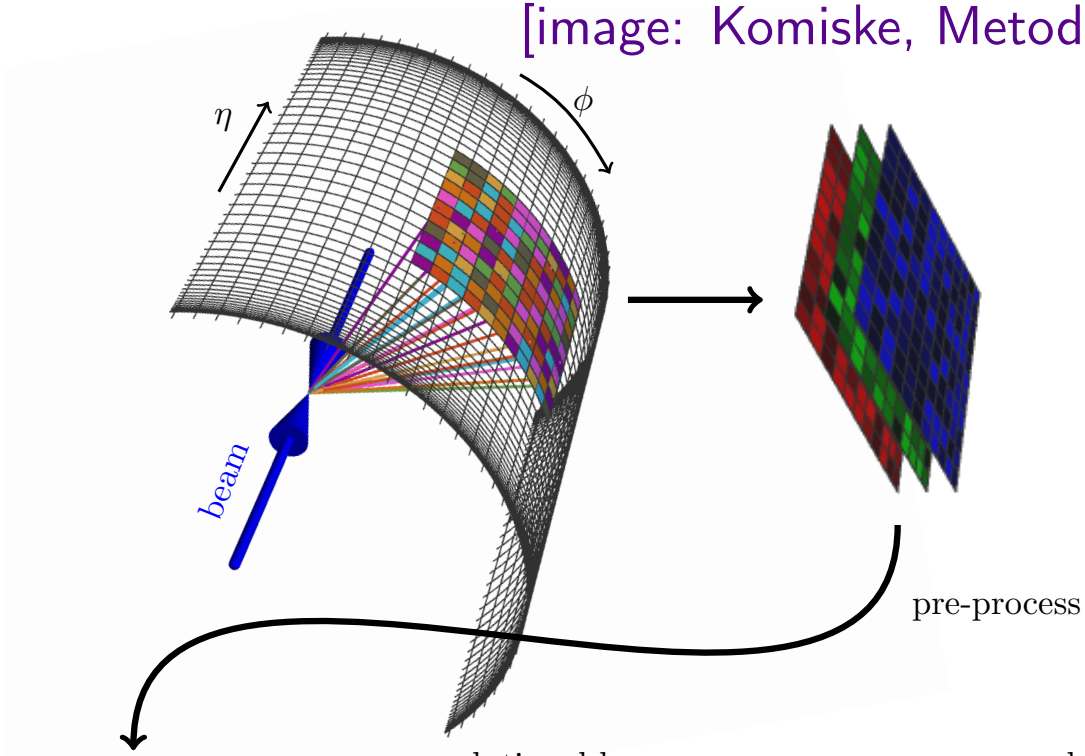
Binary classification problem!

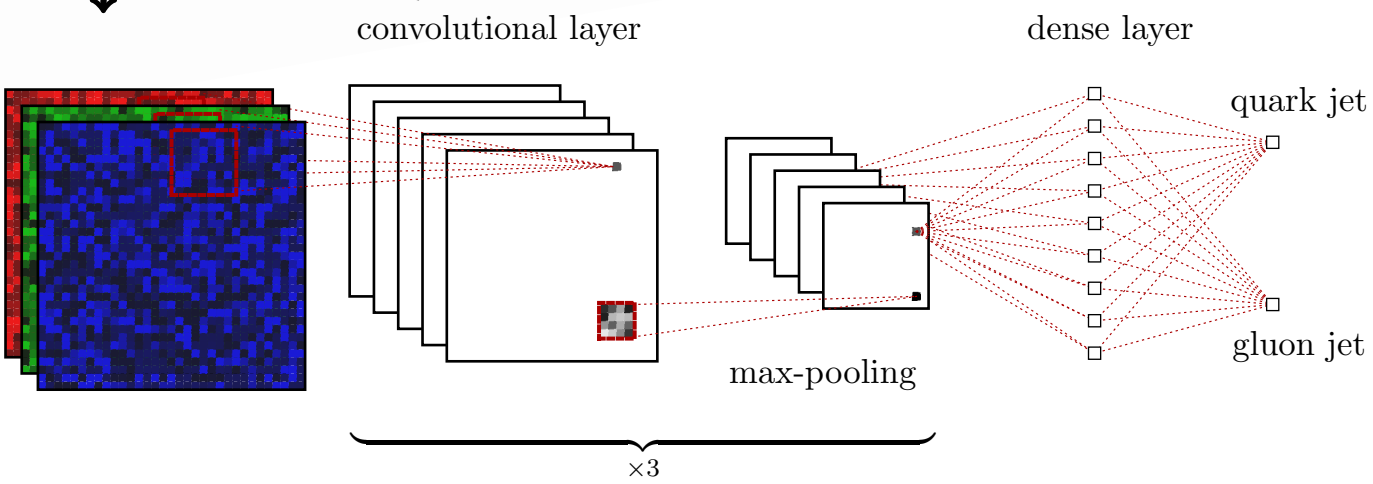
Previous work

Jet images

[image: Komiske, Metodiev, Schwartz arxiv:1612.01551]

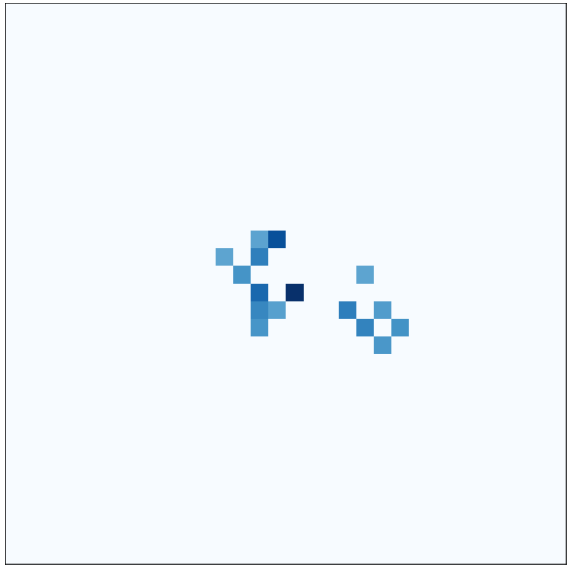


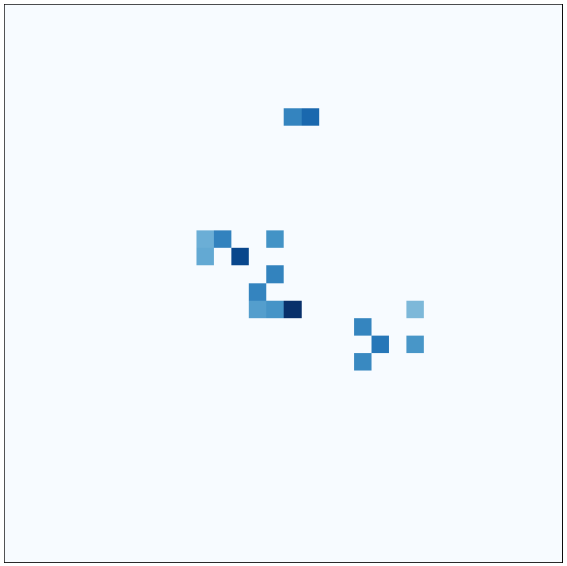
[Oliveira et al arXiv:1511.05190]
[Baldi et al arXiv:1603.09349]
[Barnard et al arXiv:1609.00607]



Jet images

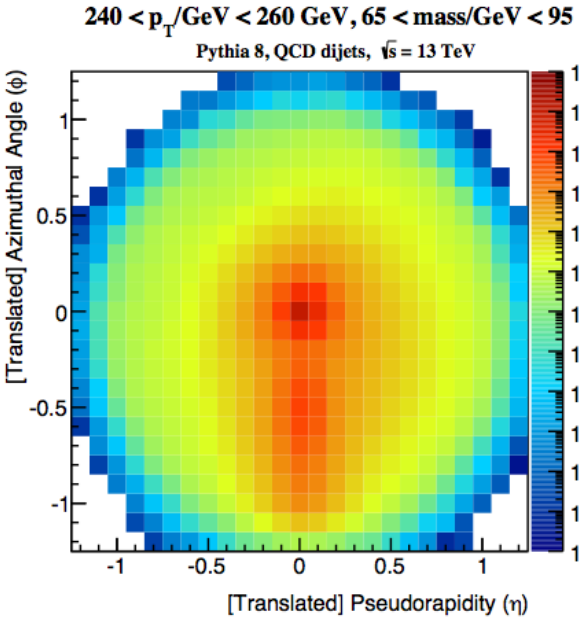
Single QCD jet

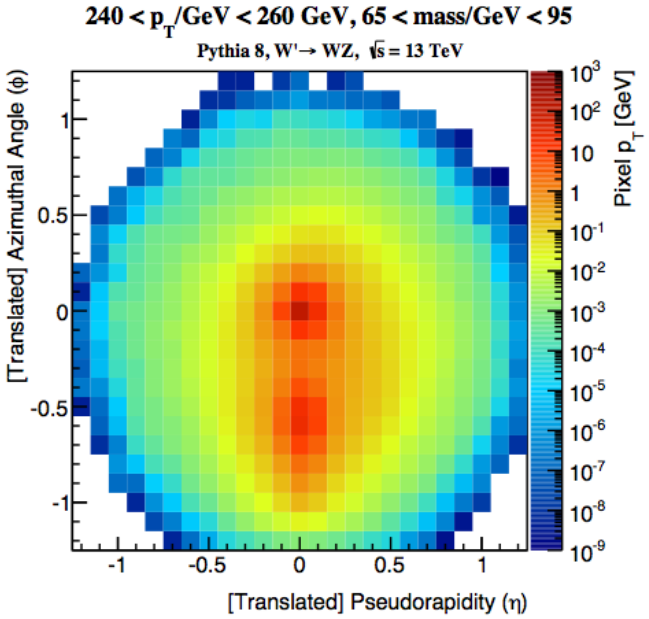




Single *W* jet

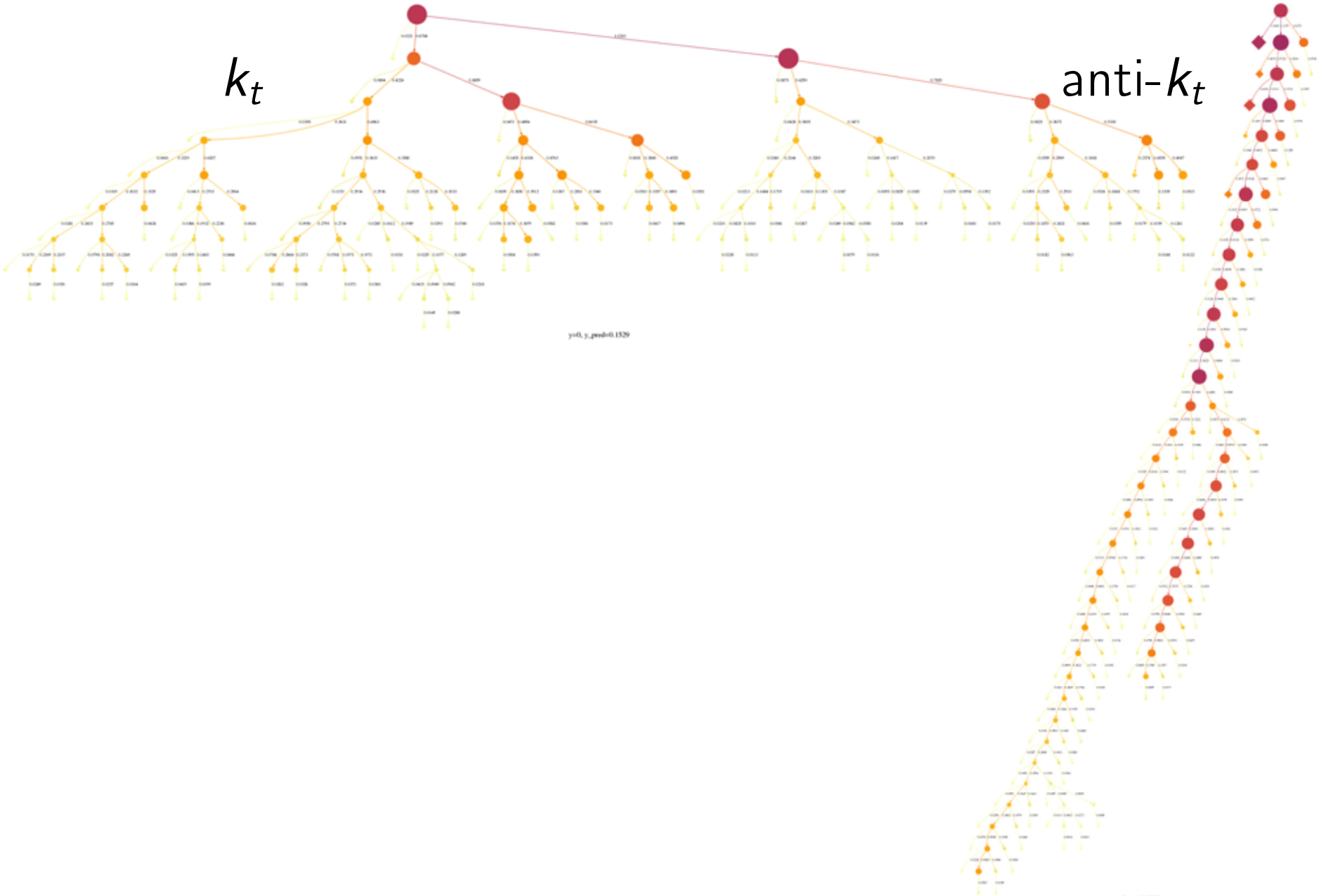
Average QCD jet





Average *W* jet

Jet parse trees



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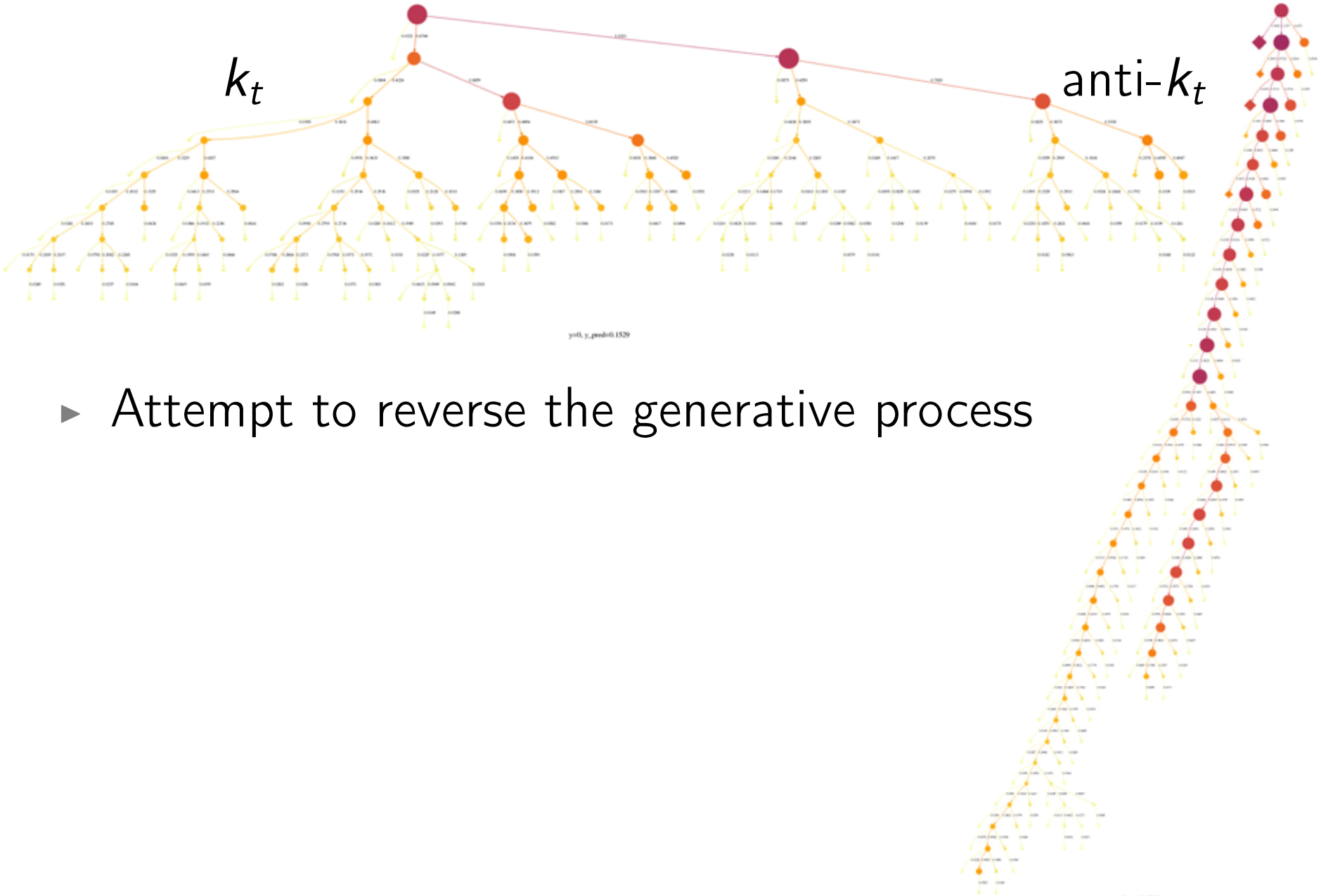
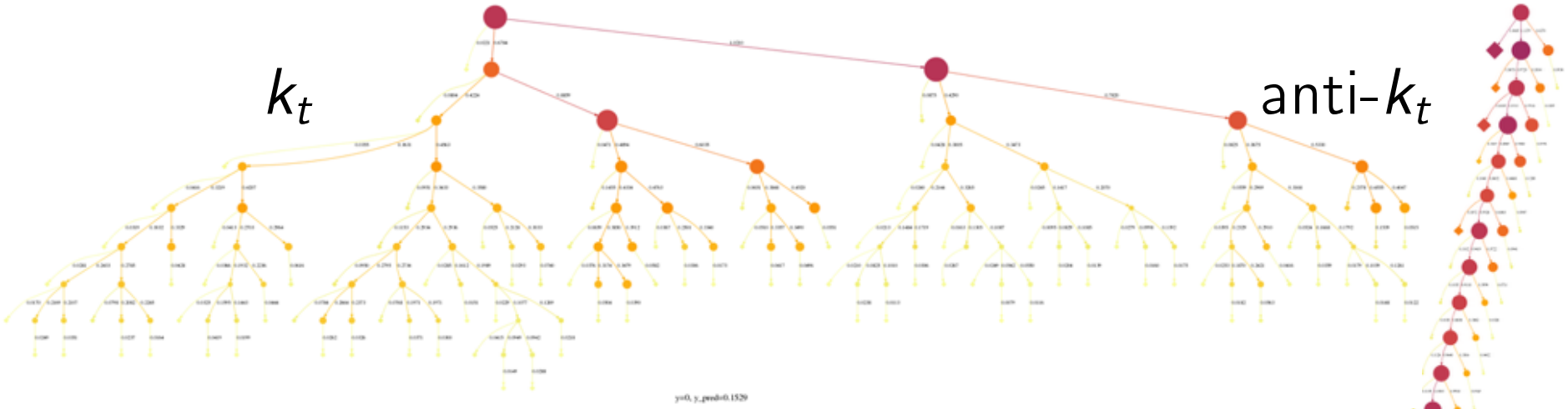


- Attempt to reverse the generative process

Jet parse trees



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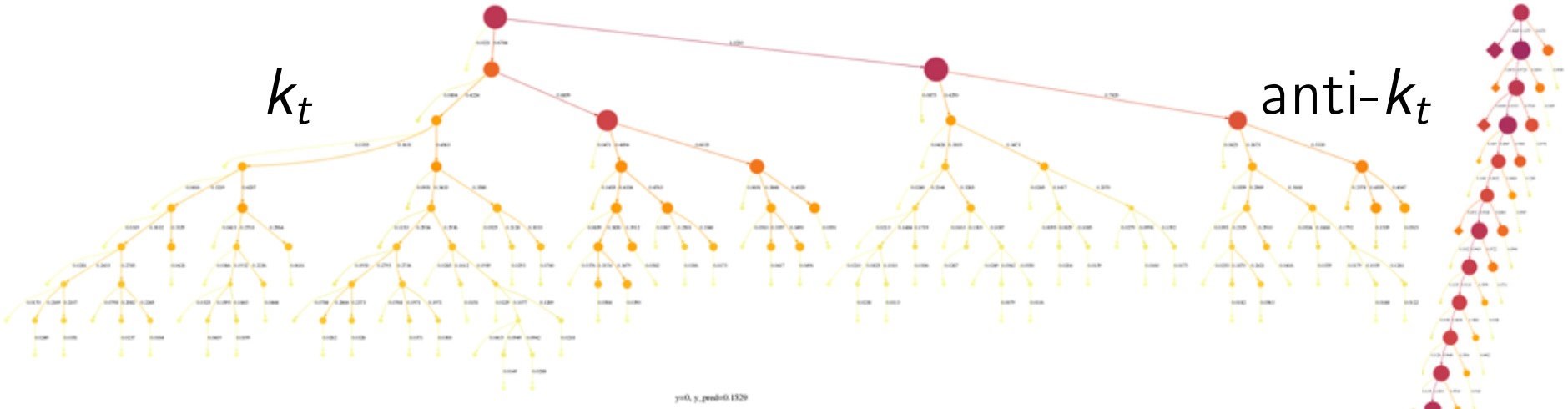

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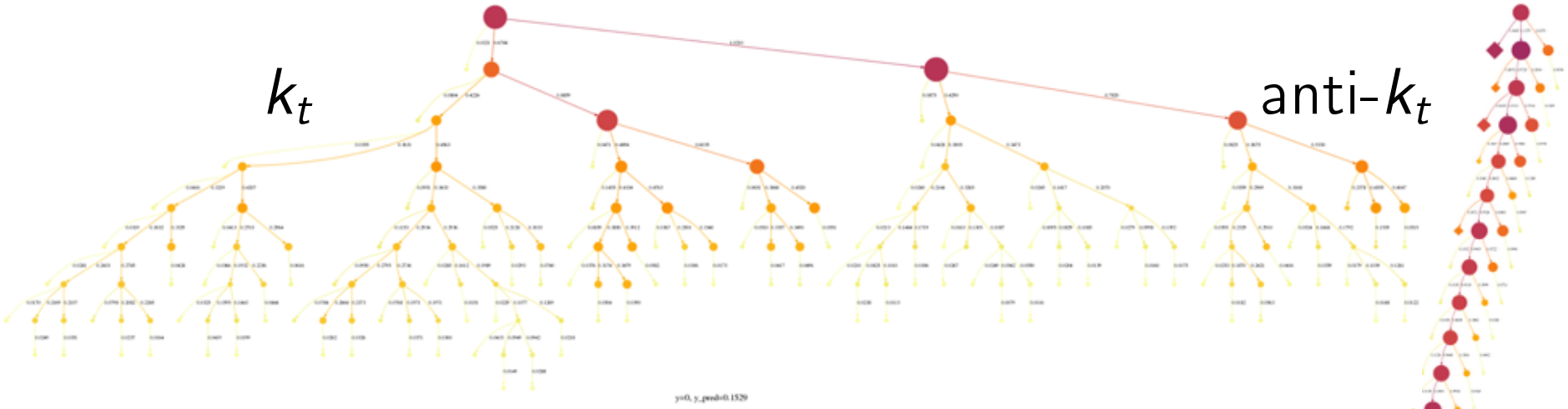

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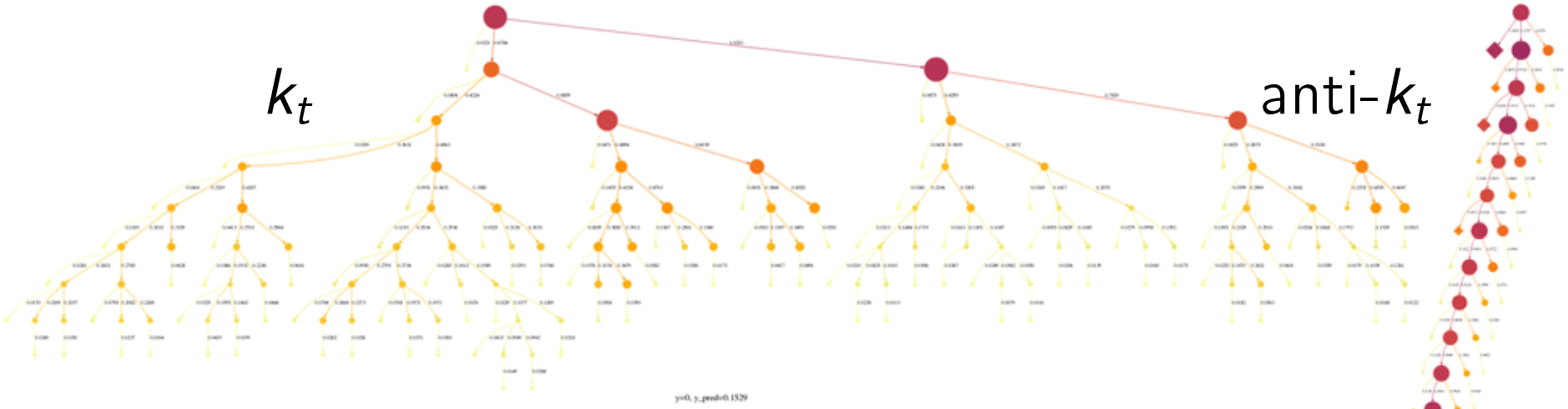
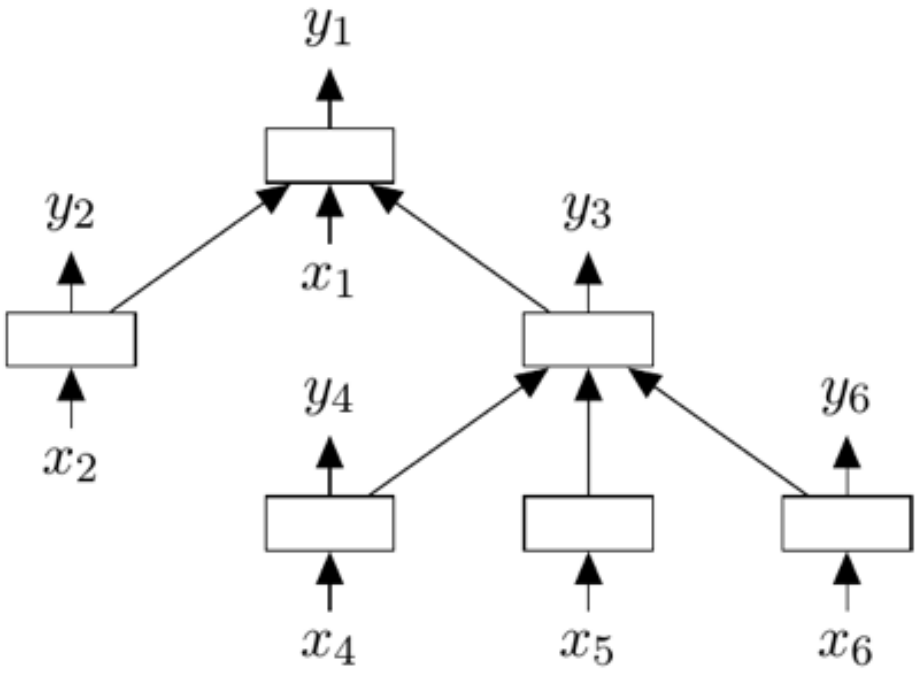


- Attempt to reverse the generative process
- Sequential recombination algorithms
- Cambridge-Aachen, k_t, anti-k_t
- Binary tree representation
- NLP methods for parse trees

Recursive neural network

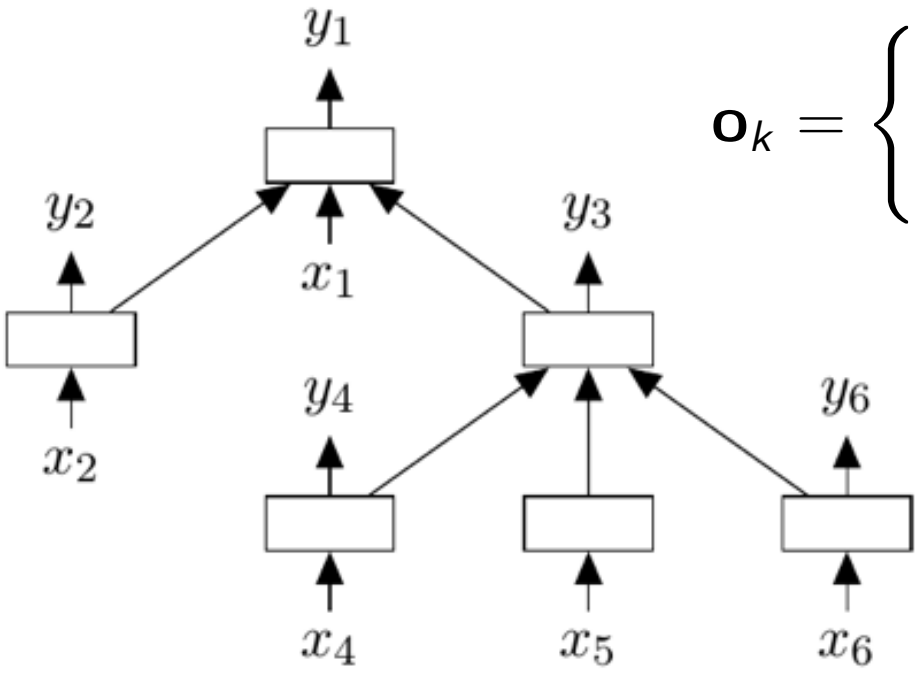


Recursive neural network

$$\mathbf{y}_k = \begin{cases} \mathbf{u}_k & \text{if } k \text{ a leaf} \\ \sigma\left(W_h \begin{bmatrix} \mathbf{y}_{k_L} \\ \mathbf{y}_{k_R} \\ \mathbf{u}_k \end{bmatrix} + \mathbf{b}_h\right) & \text{otherwise} \end{cases}$$

$$\mathbf{u}_k = \sigma\left(W_u g(\mathbf{o}_k) + \mathbf{b}_u\right)$$

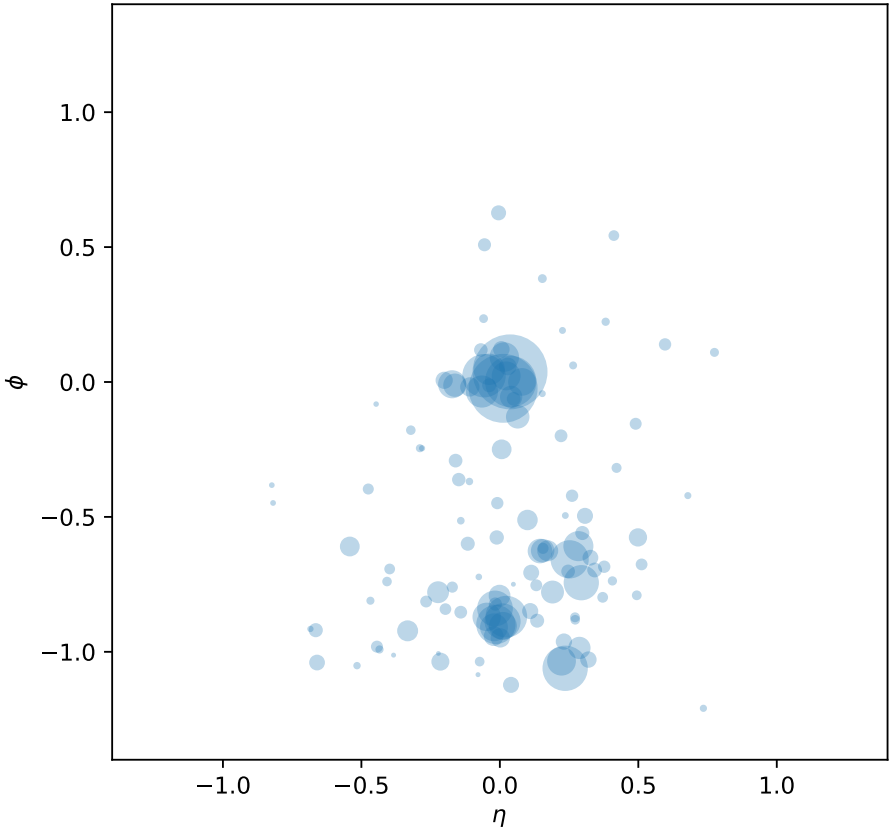
$$\mathbf{o}_k = \begin{cases} \mathbf{x}_{i(k)} & \text{if } k \text{ a leaf} \\ \mathbf{o}_{k_L} + \mathbf{o}_{k_r} & \text{otherwise} \end{cases}$$



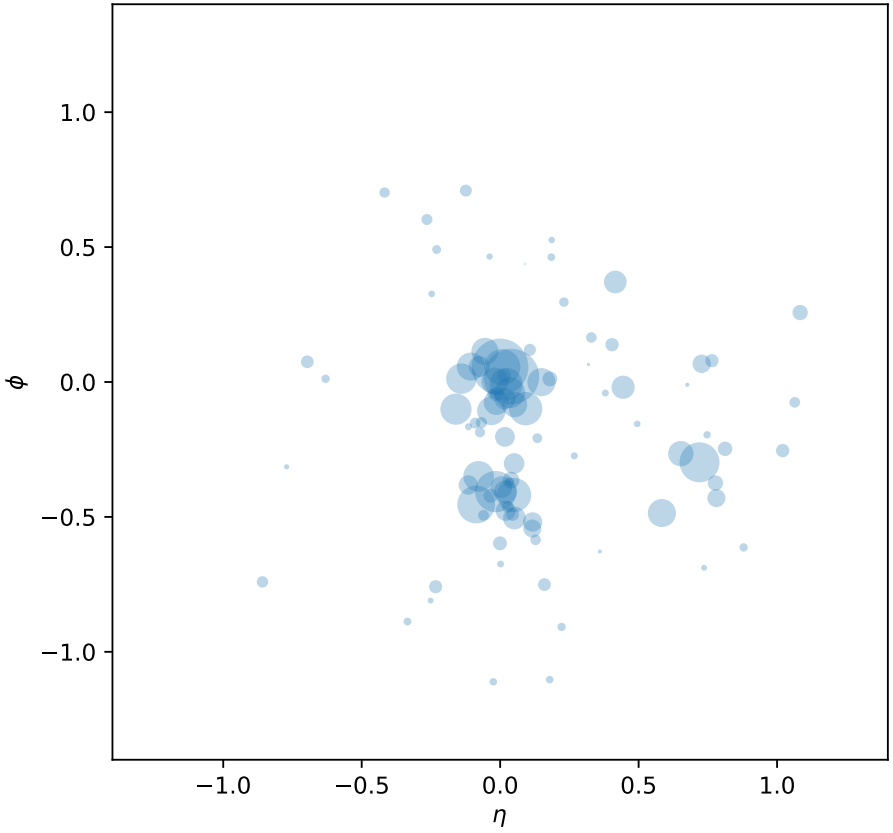
[Louppe et al. 2017]

Our work

Jet graphs

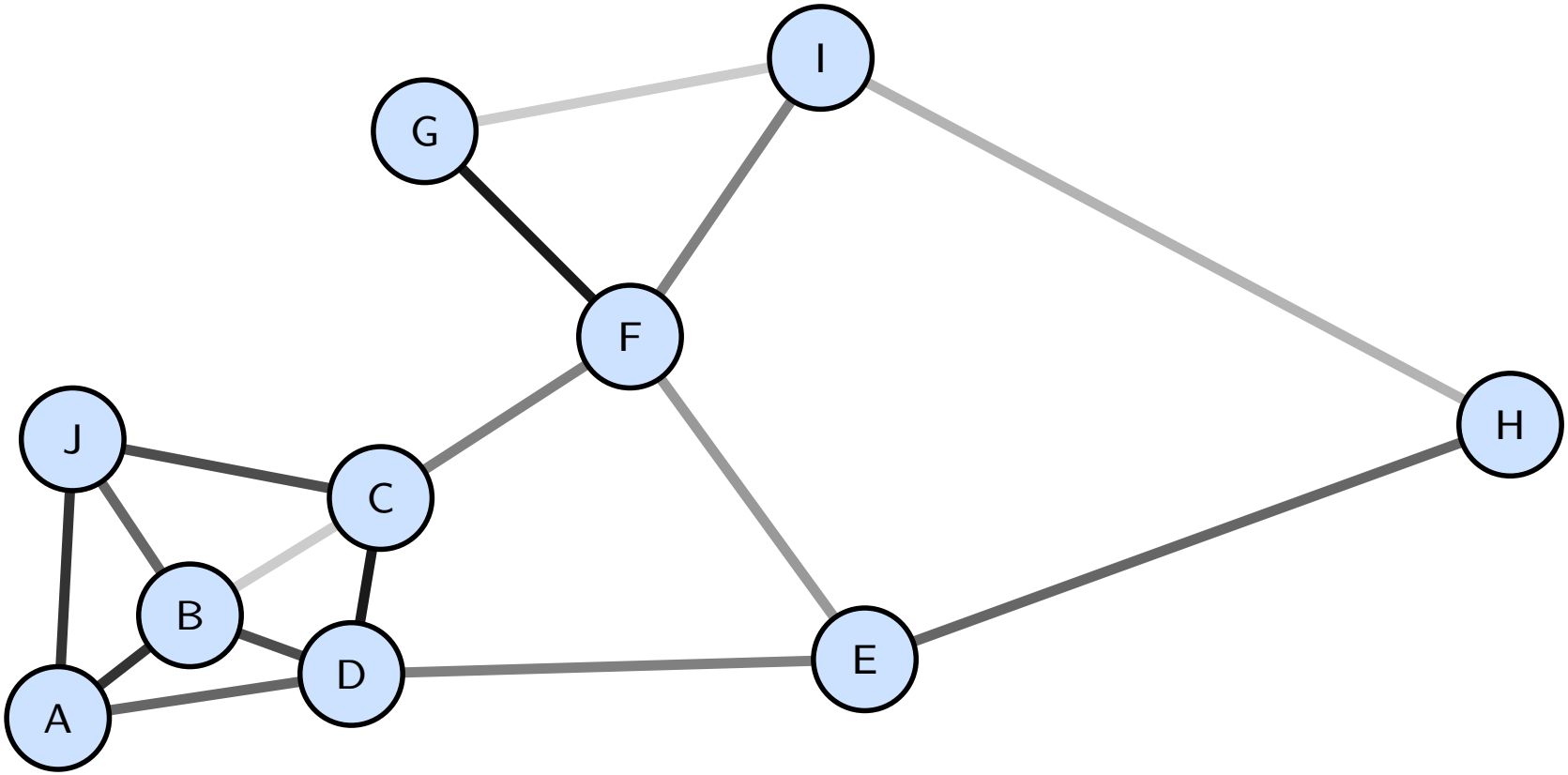


QCD jet



W jet

Graph neural networks



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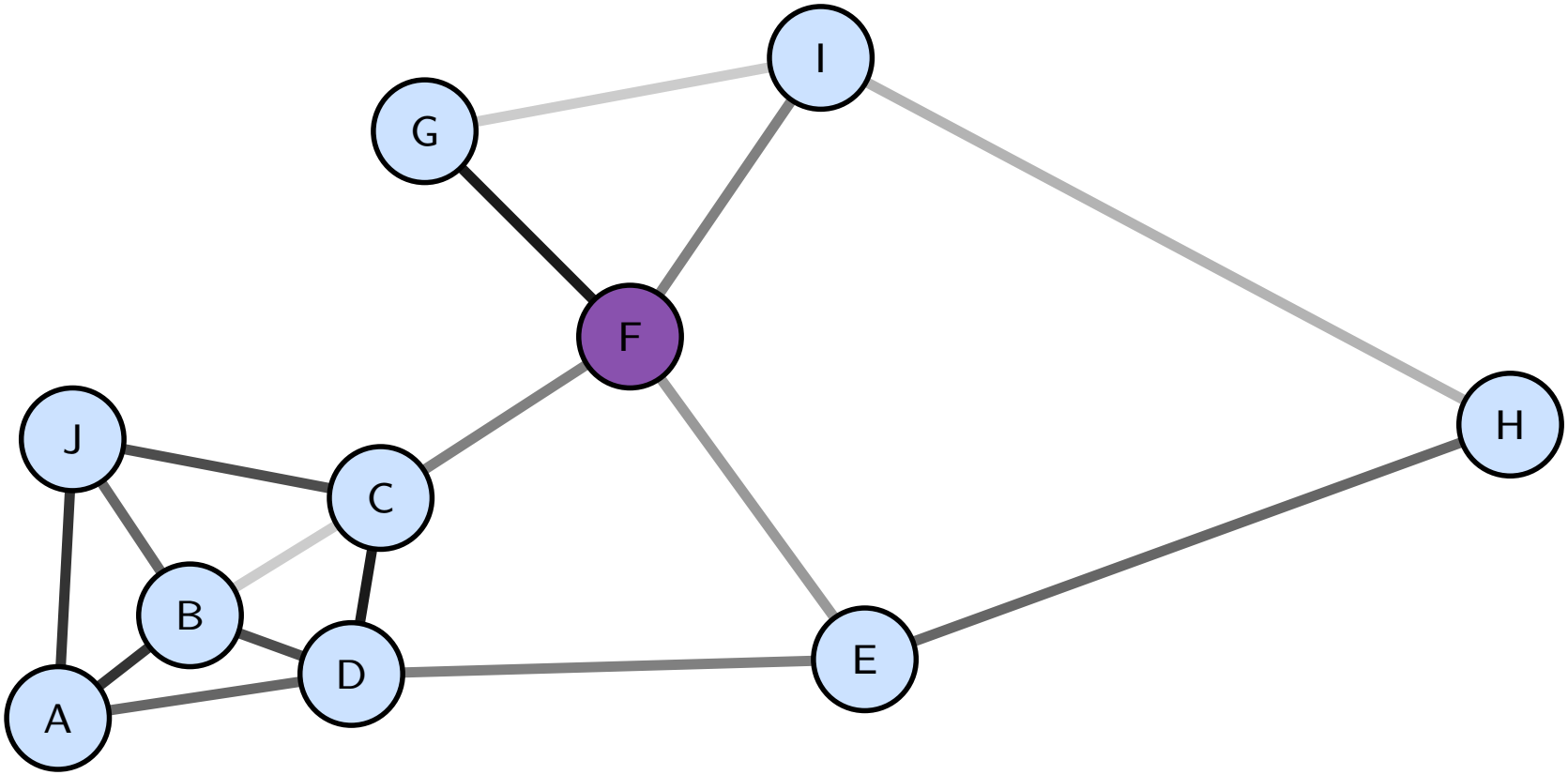

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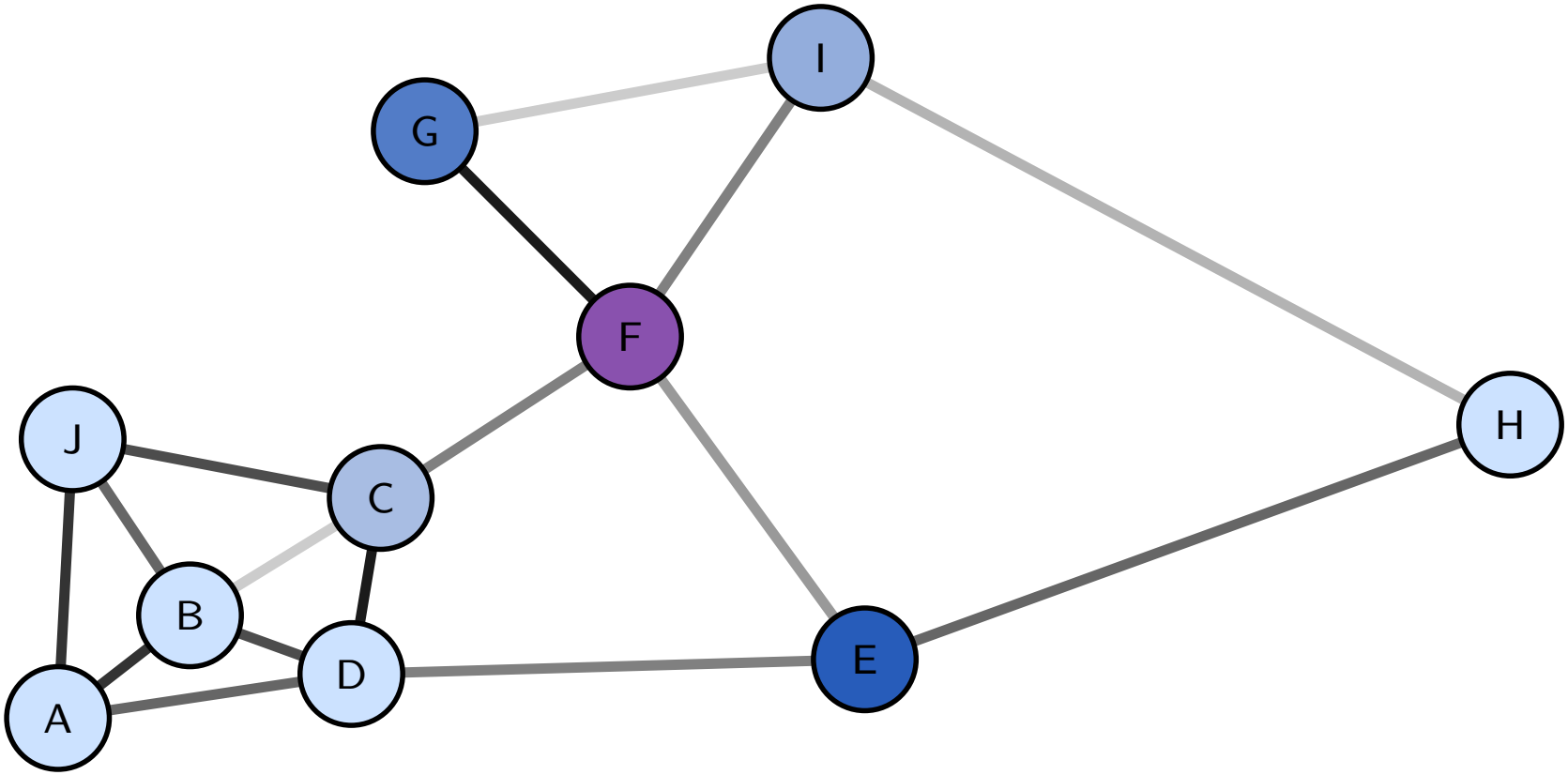

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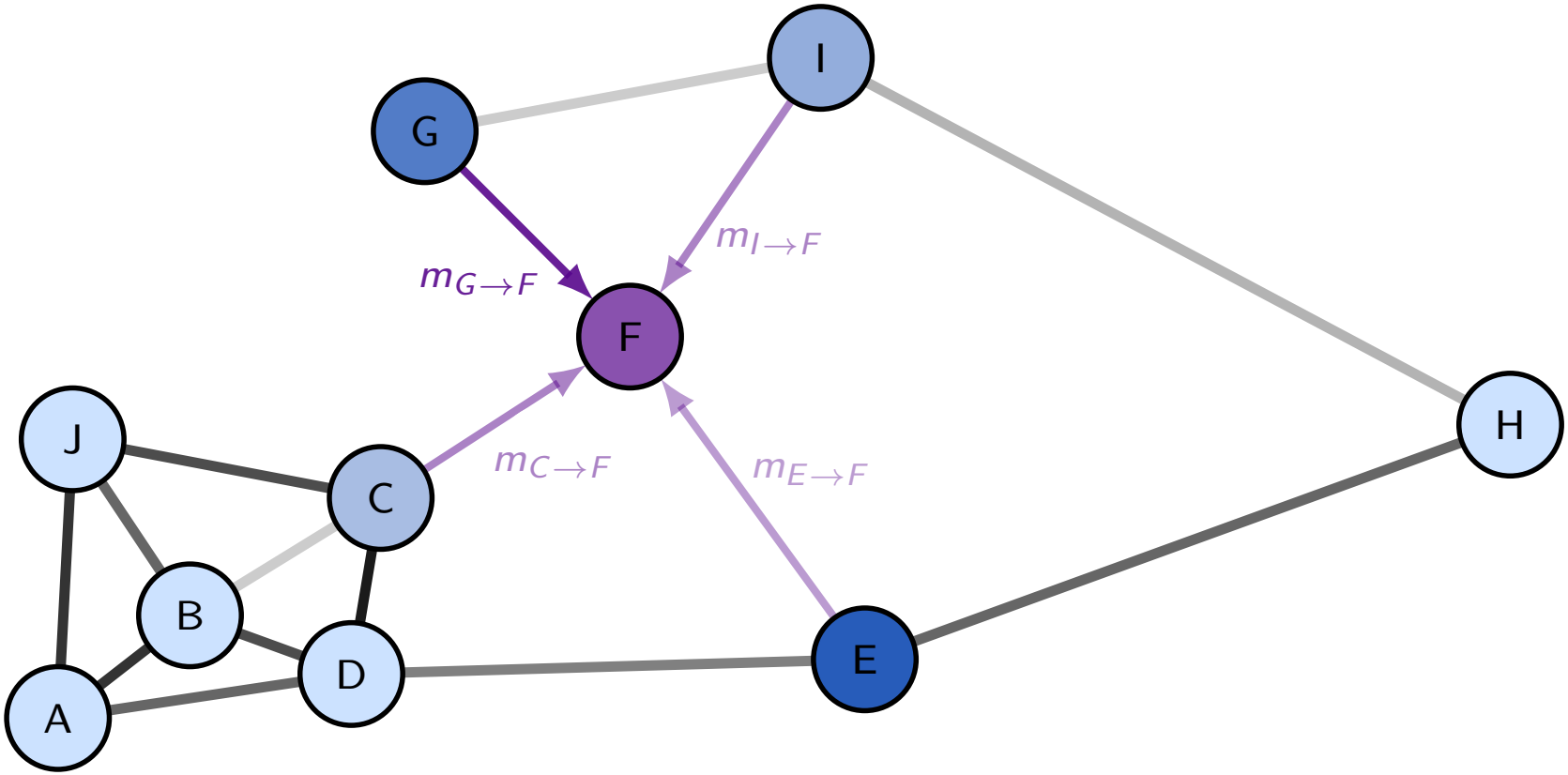

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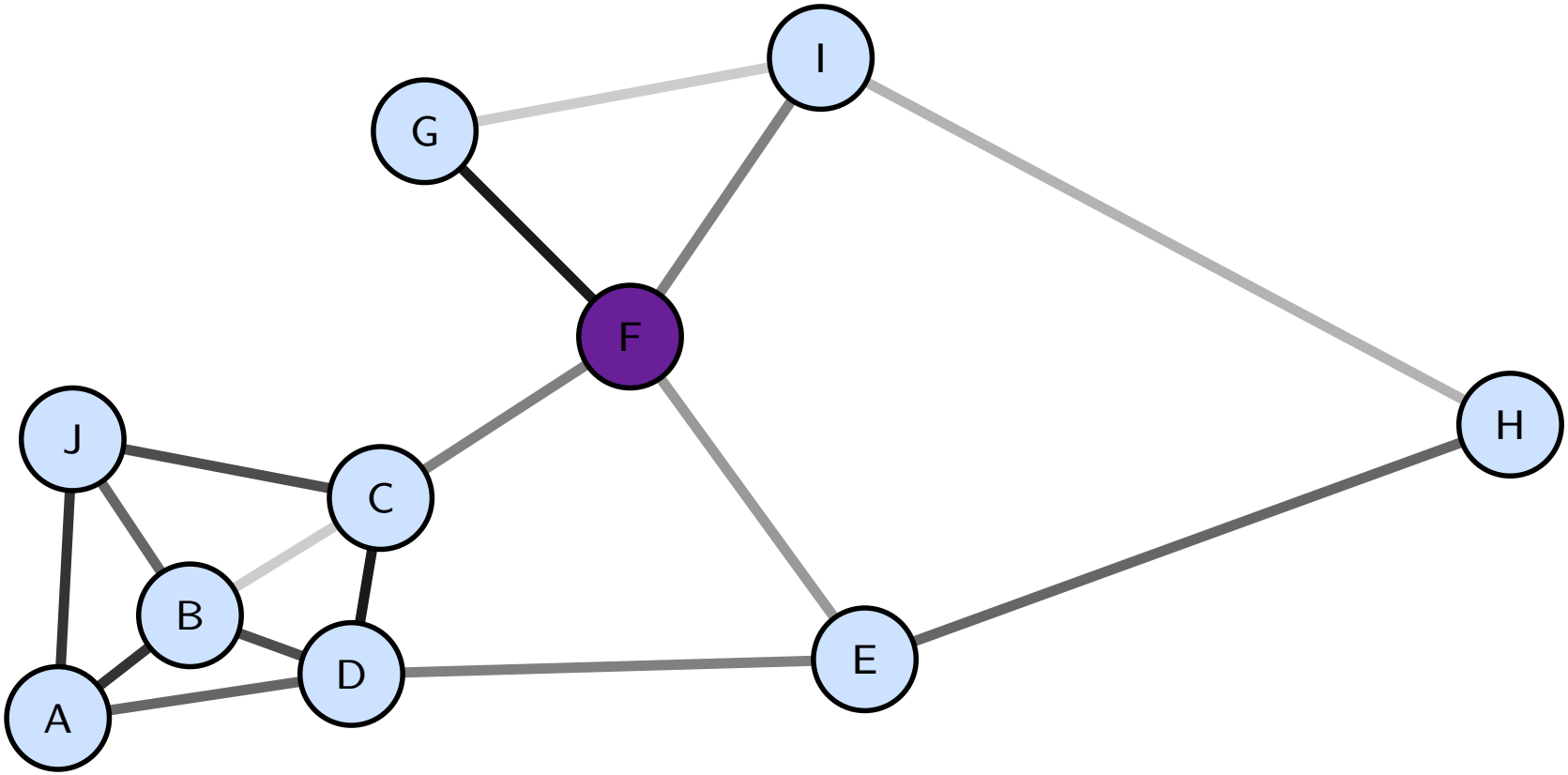

$$\tilde{m}_j^t = f(h_j^{t-1})$$
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Message Passing Neural Network

Algorithm 1 Message passing neural network

Require: $N \times D$ nodes $\mathbf{x}$, adjacency matrix A

$\mathbf{h} \leftarrow$Embed($\mathbf{x}$)

for $t = 1, \ldots, T$ **do**

  $\mathbf{m} \leftarrow$ Message($A, \mathbf{h}$)

  $\mathbf{h} \leftarrow$ VertexUpdate($\mathbf{h}, \mathbf{m}$)

end for

$\mathbf{r} =$ Readout($\mathbf{h}$)

return Classify($\mathbf{r}$)

A problem with the adjacency matrix

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Question

Where does adjacency matrix come from?

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Answer 1

Use a physics-inspired adjacency matrix.

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Learn the adjacency matrix from the data.
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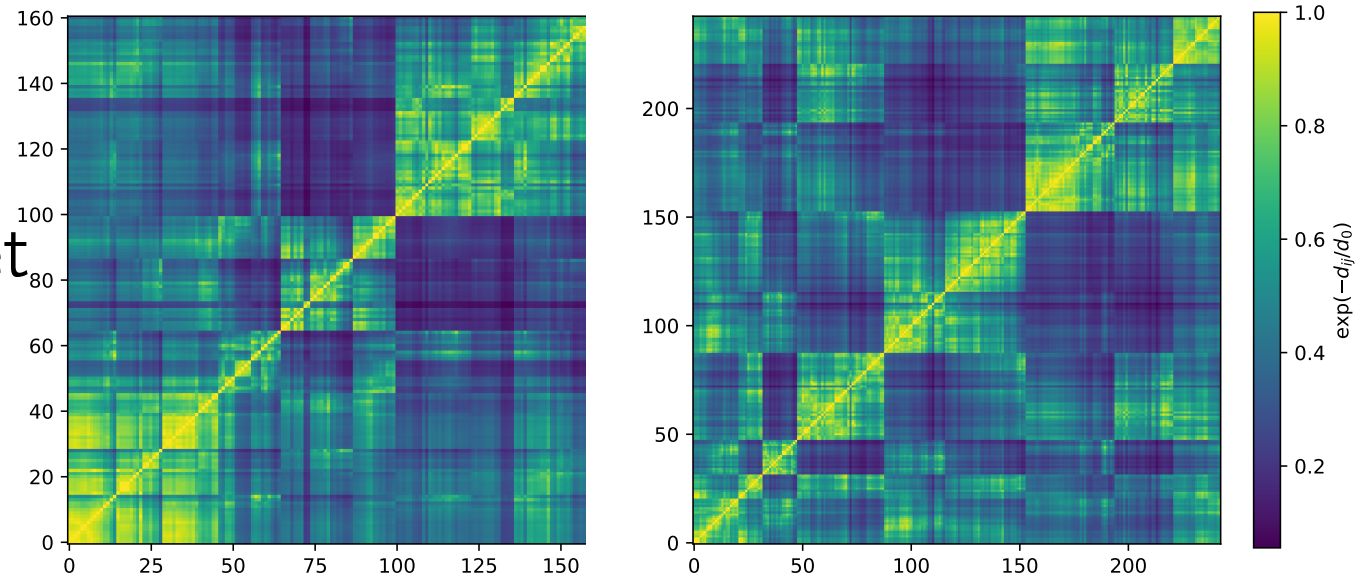
Jet images

Single QCD jet



Single W jet

Learning the adjacency matrix

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$$A_{\text{sym}} = \frac{1}{2}\left(A + A^\top\right) \qquad \text{(undirected)}$$

Message Passing Neural Network

Algorithm 2 Message passing neural network

Require: $N \times D$ array of jet constituents $\mathbf{x}$

$\mathbf{h} \leftarrow \text{Embed}(\mathbf{x})$

for $t = 1, \ldots, T$ **do**

$A \leftarrow \text{AdjacencyMatrix}_t(\mathbf{h})$

$\mathbf{m} \leftarrow \text{Message}_t(A, \mathbf{h})$

$\mathbf{h} \leftarrow \text{VertexUpdate}_t(\mathbf{h}, \mathbf{m})$

end for

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Experiments

Dataset and metric

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- Binary cross-entropy loss

Classification results

Model	Iterations	$R_{\epsilon=50\%}$
Rec-NN (no gating)	1	70.4 ± 3.6
Rec-NN (gating)	1	$\mathbf{83.3 \pm 3.1}$
MPNN (directed)	1	89.4 ± 3.5
MPNN (directed)	2	$\mathbf{98.3 \pm 4.3}$
MPNN (directed)	3	85.9 ± 8.5
MPNN (identity)	3	74.5 ± 5.2
Relation Network	1	67.7 ± 6.8

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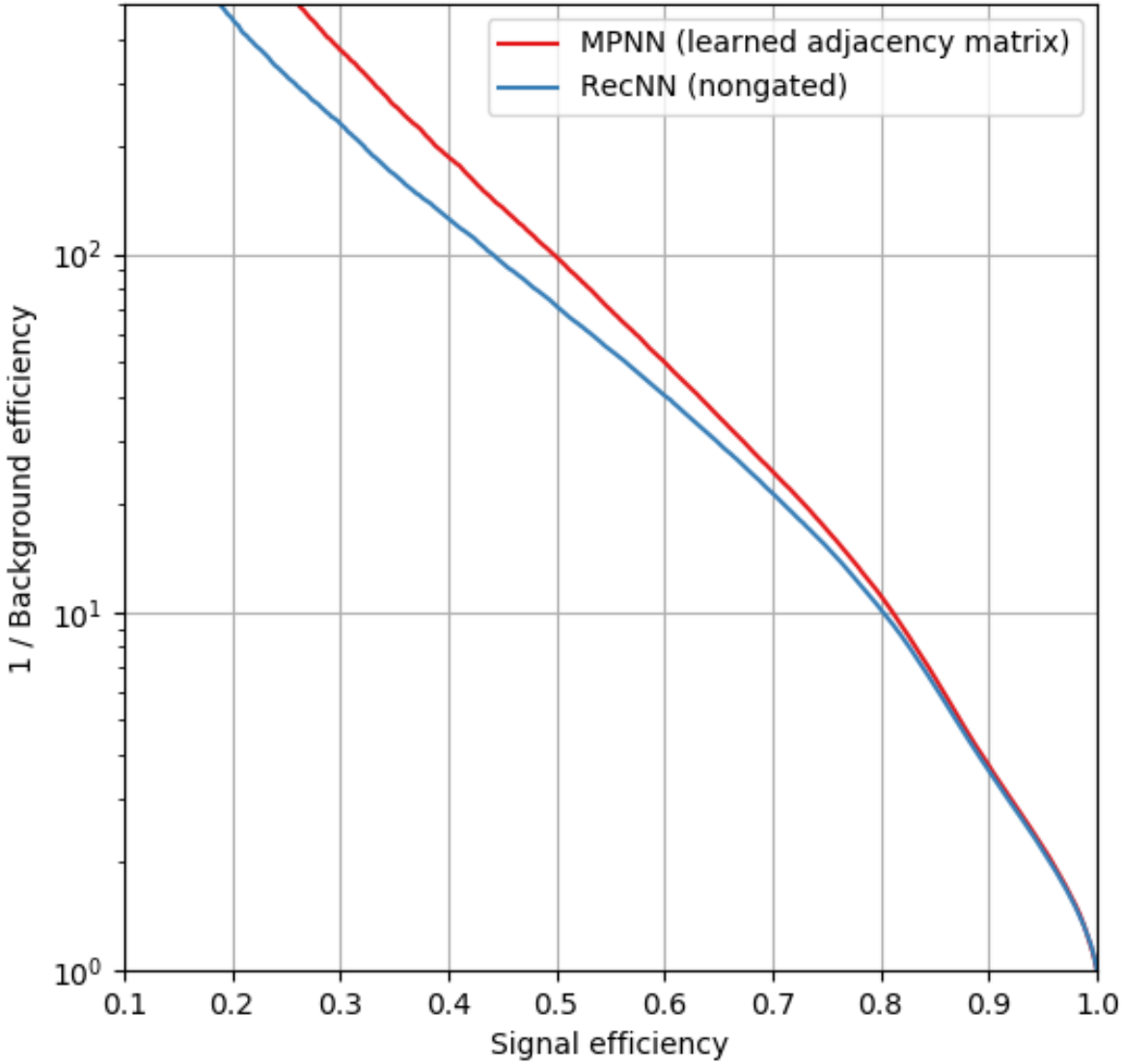
MPNN (learned adjacency matrix)
RecNN (nongated)
1 / Background efficiency
10^2
10^1
10^0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Signal efficiency

Conclusions

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- Several different analogies we can use to represent jets:

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- We can learn a "metric" directly from particles
- MPNN attains $O(10^2)$ background rejection at TPR = 50%

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- Use QCD-inspired adjacency matrix for message passing.
- Export adjacency matrix for sequential recombination jet algorithms?

Thank you!