Attention to the strengths of physics interactions

Enhanced Deep Learning Event Classification for Particle Physics Experiments

Polina Moskvitina

Sascha Caron, Clara Nellist, Roberto Ruiz de Austri, Rob Verheyen, Zhongyi Zhang

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Our group

Sascha
(Supervisor,
RU/Nikhef)

Clara
(Co-supervisor,
RU/Nikhef)

Polina
(PhD,
RU/Nikhef)

From DarkMachines :

Zhongyi
(Postdoc,
RU/Nikhef)

Rob
(Postdoc,
UCL)

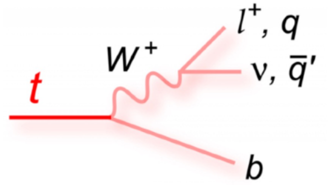
Roberto
(Researcher,
IFIC)

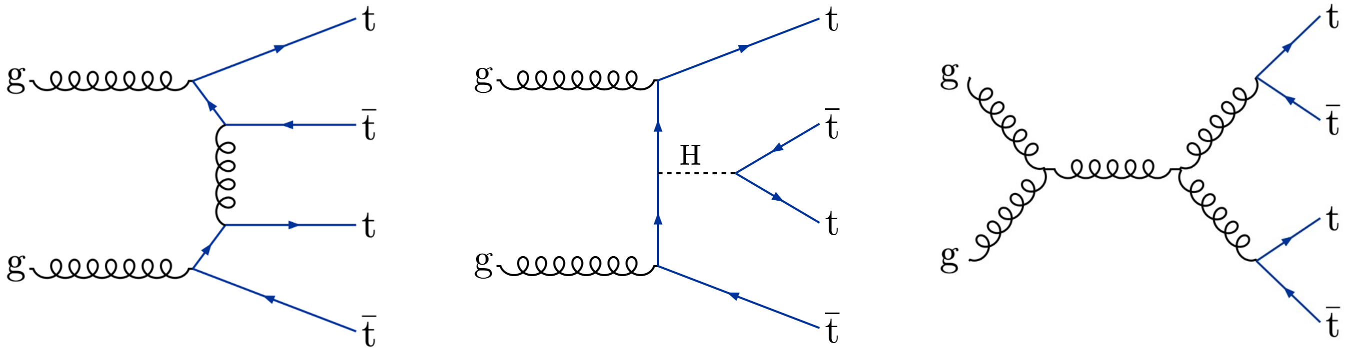
The question was: "**What is *the best event classifier* for the LHC?**"

The four-top-quarks and $t\bar{t}H$ production at LHC

Production of **four top quarks** is very rare

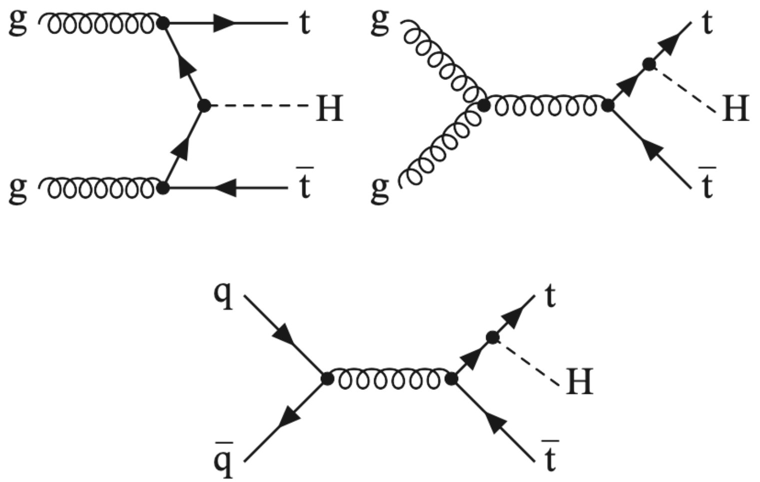
- **NLO QCD:** $\sigma(t\bar{t}t\bar{t}) = 12\ \mathrm{fb} \pm 20\%$ [JHEP02(2018)031]
- **NLO+NLL:** $\sigma(t\bar{t}t\bar{t}) = 13.4\ \mathrm{fb} \pm 11\%$ [arXiv:2212.03259]





Examples of Feynman diagrams for SM $t\bar{t}t\bar{t}$ production at leading order in QCD and via an off-shell Higgs boson mediator

The **Top-top-Higgs**
has a small cross section (1/100 ggF)
$\sigma(t\bar{t}H) \sim 0.507\ \mathrm{pb}$



Example tree-level Feynman diagrams for the pp $\rightarrow t\bar{t}H$

First observation of $t\bar{t}t\bar{t}$ production with an observed (expected) significance of **6.1σ (4.3σ)** with **GNN** by **ATLAS** [Eur. Phys. J. C 83, 496 (2023)]
5.6σ (4.9σ) with **BDT** by **CMS** [Phys. Lett. B 847 (2023) 138290]

Observation of $t\bar{t}H$ production
6.3σ (5.1σ) by **ATLAS** Phys. Lett. B 784 (2018) 173]
5.2σ (4.2σ) by **CMS** [Phys. Rev. Lett. 120, 231801]

The four-top decays and Background composition

Simulated pp Collisions at $\sqrt{S} = 13$ TeV

The most sensitive channel for **four-top** is:

- **Multilepton final state:**
  2 Leptons Same Sign and 3 Leptons (2LSS/3L),
  13% branching ration, highest sensitivity – observation

Signal region:
$\geq$ 6 jets $\geq$ 2b-jets and $\mathbf{H_T}$ $\geq$500 GeV

Signal process:
- $t\bar{t}t\bar{t}$

Physical backgrounds:
- $t\bar{t}Z$, $\boxed{t\bar{t}H,}$ $t\bar{t}W$, $t\bar{t}WW$

$$\text{event ID; process ID; weight; } \not{E}_T;\ \phi_{\not{E}_T};\ \text{obj}_1, E_1, p_{T_1}, \eta_1, \phi_1;\ \text{obj}_2, E_2, p_{T_2}, \eta_2, \phi_2; \ldots$$

- **All other kinematic variables can be calculated from four-vectors**

Later, it is used for a second analysis as a signal (see slide 11)

	jets	b-jets	e^-	e^+	μ^-	μ^+	γ	$N_{\max}$
FCN, BDT	4	4	1	1	1	1		12
CNN, PN, ParT			no limits					18

$N_{\max}$ – the maximum number of objects in an event

Summary of ML model details

arXiv:2211.05143

Variables per particle
E, p_T, η, ϕ, jet$_{\text{tag}}$, b-jet$_{\text{tag}}$, e^-_{tag}, e^+_{tag}, μ^-_{tag}, μ^+_{tag}, γ_{tag}

Also receives $\not{E}_T$; $\phi_{\not{E}_T}$

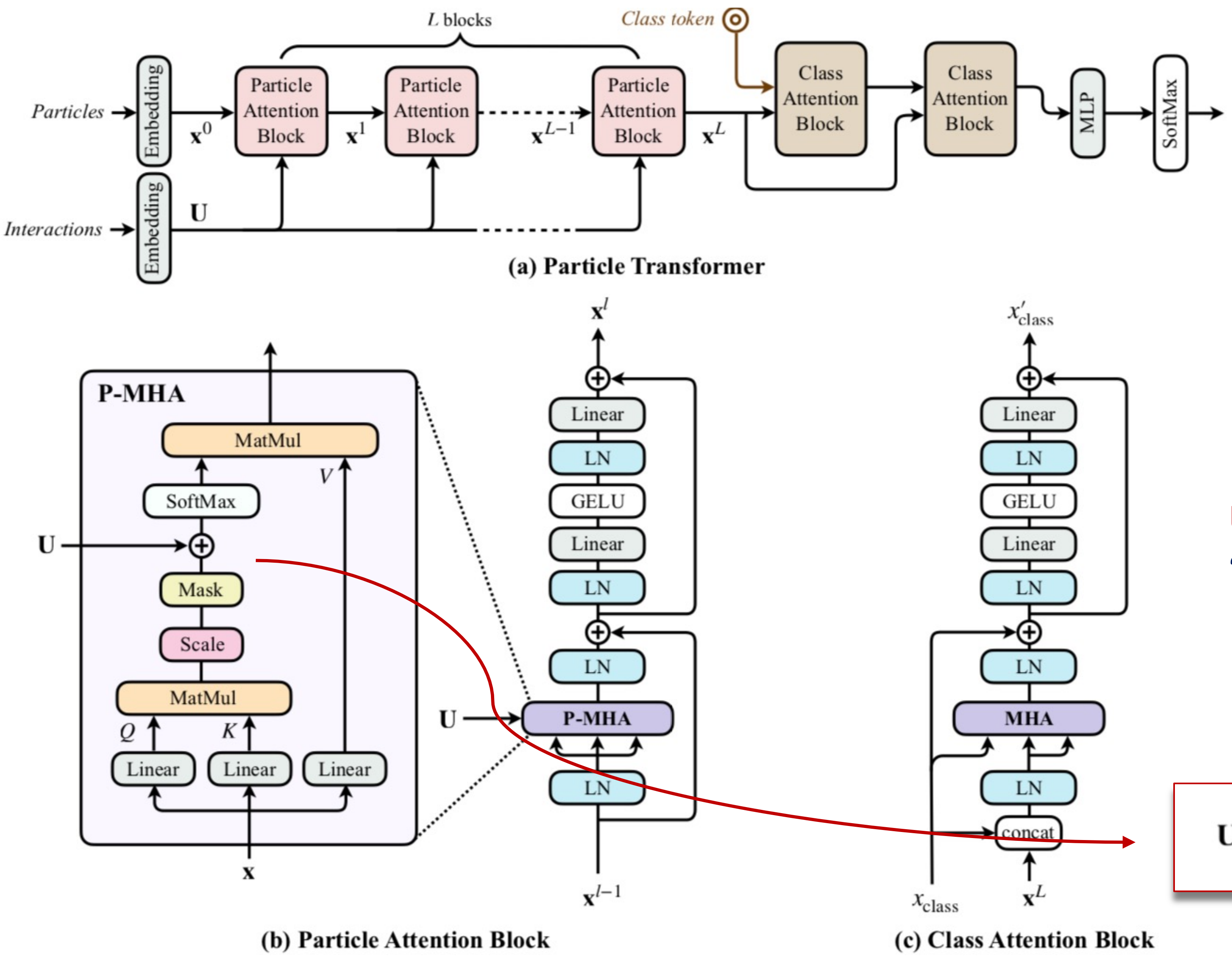
NN structure	Pairwise kinematic features	Loss function
BDT		Cross-entropy
BDT$_{\text{int.}}$	m_{ij}, ΔR_{ij}	
FCN		
CNN		
PN		
PN$_{\text{int.}}$	m_{ij}, ΔR_{ij}	
PN$_{\text{int. SMids}}$	m_{ij}, ΔR_{ij} + SM matrix[1]	
PN$_{\text{int. SM const}}$	m_{ij}, ΔR_{ij} + SM matrix[2]	
PN$_{\text{int. SM}}$	m_{ij}, ΔR_{ij} + SM matrix[3]	
ParT		
ParT$_{\text{int.}}$	m_{ij}, ΔR_{ij}	
ParT$_{\text{int. SM (FL)}}$	m_{ij}, ΔR_{ij} + SM matrix[3]	Focal [$\alpha = 0.75$, $\gamma = 3$]
ParT$_{\text{int. SMids}}$	m_{ij}, ΔR_{ij} + SM matrix[1]	Cross-entropy
ParT$_{\text{int. SM const}}$	m_{ij}, ΔR_{ij} + SM matrix[2]	
ParT$_{\text{int. SM}}$	m_{ij}, ΔR_{ij} + SM matrix[3]	
SetT$_{\text{int. SM}}$	m_{ij}, ΔR_{ij} + SM matrix[3]	

The **particle input** variables and **pairwise kinematic features** that were used in the **NN structures**, each with their respective **loss function**

16 MODELS IN TOTAL!

Transformers

[arXiv:2202.03772](https://arxiv.org/abs/2202.03772)



The architecture of (a) Particle Transformer (b) Particle Attention Block (c) Class Attention Block

Attention Modules

(scaled dot product attention):

- $Attention(Q, K, V) = SoftMax\left(\frac{QK^T}{\sqrt{d}} + \boldsymbol{U}\right)V$
- $Q = queries, K = keys, V = values$
- *Self-attention* $\longrightarrow Q = K = V$

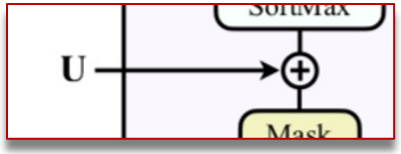
$$\boldsymbol{Q} = \boldsymbol{Q} \times \boldsymbol{W_Q}$$
$$\boldsymbol{K} = \boldsymbol{K} \times \boldsymbol{W_K}$$
$$\boldsymbol{V} = \boldsymbol{V} \times \boldsymbol{W_V}$$

Attention is All You Need!

[arXiv:1706.03762](https://arxiv.org/abs/1706.03762)

U —> Attention matrix —> correlation of "data sequence with data sequence"

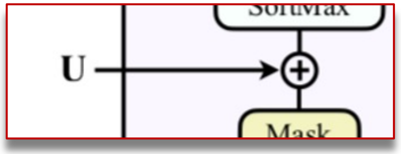
***U* ->** **Pairwise Features + SM interaction matrix** (attention matrix)



To show the interaction strength based on the SM coupling constants

Adding Pairwise features

Include pairwise features in **Par**ticle **T**ransformer through a trainable embedding $\boldsymbol{U_{ij}}$ for particles i and j



Pairwise Features +
SM interaction matrix
(attention matrix)

Attention Modules

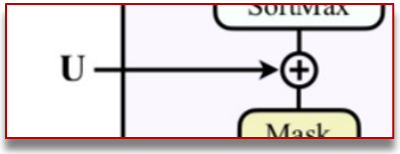
$$Attention(Q,K,T) = SoftMax\left(\frac{QK^T}{\sqrt{d}} + \boldsymbol{U}\right)V$$

Features from the paper [arXiv:2202.03772]

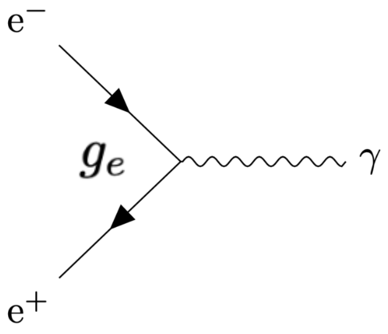
- **ParT** uses high level features for better performance
  1. $\Delta = \sqrt{(y_a - y_b)^2 + (\phi_a + \phi_b)^2}$
  2. $k_t = min(p_{T,a}, p_{T,b})\Delta$
  3. $z = min(p_{T,a}, p_{T,b})/(p_{T,a}, p_{T,b})$
  4. $m^2 = (E_a + E_b)^2 - \|p_a + p_b\|^2$
- These were also tested in **LightGBM**

What we end up using :
$\boldsymbol{m_{ij}}, \Delta\, \boldsymbol{R_{ij}}$ and dynamically calculated **coupling constants** of interaction terms (i.e. a feature that is coupling constant when i and j are components of a **SM** current, and 0 otherwise)

Interaction Matrices



Pairwise Features +
SM interaction matrix
(attention matrix)



Matrix [1] – SM ids

```
#   -   j   jb  e-  e+  m-  m+  g
([[0,  0,  0,  0,  0,  0,  0,  0],   # -
  [0,  1,  1,  0,  0,  0,  0,  1],   # j
  [0,  1,  1,  0,  0,  0,  0,  1],   # jb
  [0,  0,  0,  0,  1,  0,  0,  1],   # e-
  [0,  0,  0,  1,  0,  0,  0,  1],   # e+
  [0,  0,  0,  0,  0,  0,  1,  1],   # m-
  [0,  0,  0,  0,  0,  1,  0,  1],   # m+
  [0,  1,  1,  1,  1,  1,  1,  0]])  # g
```

Matrix [2] – SM const

```
#  -     j       bjet    e-    e+    m-    m+    g(photon)
([[0,    0,      0,      0,    0,    0,    0,    0     ],  # -
  [0,    g_s,    g_s,    0,    0,    0,    0,    g_e/2],   # j
  [0,    g_s,    g_s,    0,    0,    0,    0,    g_e/3],   # bjet
  [0,    0,      0,      0,    g_z,  0,    0,    g_e   ],  # e-
  [0,    0,      0,      g_z,  0,    0,    0,    g_e   ],  # e+
  [0,    0,      0,      0,    0,    0,    g_z,  g_e   ],  # m-
  [0,    0,      0,      0,    0,    g_z,  0,    g_e   ],  # m+
  [0,    g_e/2,  g_e/3,  g_e,  g_e,  g_e,  g_e,  0]    ])  # g
```

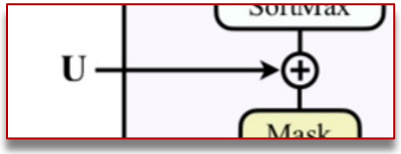
- '1' indicates an interaction possible at **LO** in the **SM**
- '0' indicates interactions that only appear at higher orders

- $g_Z = 0.758$ for the weak force for leptons
- $g_s = 1.22$ for the strong force in jet interactions
- $g_e = 0.31$ for the electromagnetic force in photon interactions

The energy dependence of the coupling constants

Matrix [3] – SM

```
#  -      j       bjet     e-     e+     m-     m+     g(photon)
([[0,     0,      0,       0,     0,     0,     0,     0      ],  # -
  [0,     g_s,    g_s,     0,     0,     0,     0,     g_e/2],  # j
  [0,     g_s,    g_s,     0,     0,     0,     0,     g_e/3],  # bjet
  [0,     0,      0,       0,     g_z,   0,     0,     g_e  ],  # e-
  [0,     0,      0,       g_z,   0,     0,     0,     g_e  ],  # e+
  [0,     0,      0,       0,     0,     0,     g_z,   g_e  ],  # m-
  [0,     0,      0,       0,     0,     g_z,   0,     g_e  ],  # m+
  [0,     g_e/2,  g_e/3,   g_e,   g_e,   g_e,   g_e,   0]   ])  # g
```



Pairwise Features + SM interaction matrix (attention matrix)

Dynamically calculated **coupling constants** of interaction terms !

α is the running coupling constant

$$(*)\quad \alpha(Q^2) = \frac{\alpha(\mu_0^2)}{1 - \frac{n\alpha(\mu_0^2)}{3\pi} \cdot \ln\left(\frac{Q^2}{\mu_0^2}\right)},$$

$$g_e = \sqrt{4\pi\alpha}$$

$$\alpha_s(Q^2) = \frac{\alpha_s(\mu_0^2)}{1 + \frac{\alpha_s(\mu_0^2)(33-2n_f)}{12\pi} \ln\left(\frac{Q^2}{\mu_0^2}\right)},$$

$$g_s = \sqrt{4\pi\alpha_s}$$

n_f – number of quark flavors that are active

Where $\mu_0 = 91.1876$ GeV, $\alpha(\mu_0) = \frac{1}{127.5}$, $\alpha_s(\mu_0) = 0.118$, $n_f = 6$

$$Q^2 = \bar{p}_t^2 = \left(\frac{p_t^i + p_t^j}{2}\right)^2$$

energy scale

(*) Considered only leptons

$\boldsymbol{n = 3}$ – approximates the contribution of the different particles in the loop

$$g_Z = 0.758$$

Results for the $t\bar{t}t\bar{t}$ signal

arXiv:2211.05143

		BDT	$\text{BDT}_{\text{int.}}$	FCN	CNN
$t\bar{t}+h$	AUC	0.825(0)	0.831(0)	0.821(2)	0.778(6)
	$\epsilon_B(\epsilon_S=0.7)$	0.206(0)	0.192(0)	0.203(1)	0.272(11)
	$\epsilon_B(\epsilon_S=0.3)$	0.026(1)	0.026(0)	0.026(1)	0.037(1)
$t\bar{t}+W$	AUC	0.891(0)	0.895(0)	0.887(0)	0.867(5)
	$\epsilon_B(\epsilon_S=0.7)$	0.099(0)	0.092(0)	0.103(1)	0.125(8)
	$\epsilon_B(\epsilon_S=0.3)$	0.011(0)	0.011(0)	0.010(0)	0.011(1)
$t\bar{t}+WW$	AUC	0.740(0)	0.746(0)	0.737(1)	0.745(2)
	$\epsilon_B(\epsilon_S=0.7)$	0.347(0)	0.339(0)	0.342(5)	0.335(3)
	$\epsilon_B(\epsilon_S=0.3)$	0.050(0)	0.051(0)	0.054(0)	0.051(0)
$t\bar{t}+Z$	AUC	0.833(0)	0.856(0)	0.836(0)	0.839(1)
	$\epsilon_B(\epsilon_S=0.7)$	0.191(0)	0.163(0)	0.192(0)	0.190(4)
	$\epsilon_B(\epsilon_S=0.3)$	0.026(0)	0.019(0)	0.023(0)	0.021(1)
		PN	$\text{PN}_{\text{int.}}$	$\text{PN}_{\text{int. SM}}$	$\text{ParT}_{\text{int. SM (FL)}}$
$t\bar{t}+h$	AUC	0.824(0)	0.842(1)	**0.846(1)**	0.844(1)
	$\epsilon_B(\epsilon_S=0.7)$	0.199(0)	0.176(3)	**0.171(2)**	0.176(2)
	$\epsilon_B(\epsilon_S=0.3)$	0.025(0)	**0.019(1)**	0.020(1)	0.020(1)
$t\bar{t}+W$	AUC	0.887(0)	0.895(2)	0.900(1)	**0.902(4)**
	$\epsilon_B(\epsilon_S=0.7)$	0.102(1)	0.097(1)	**0.091(1)**	**0.091(5)**
	$\epsilon_B(\epsilon_S=0.3)$	0.011(0)	0.011(0)	**0.010(0)**	0.011(0)
$t\bar{t}+WW$	AUC	0.742(0)	0.760(1)	0.765(0)	0.768(3)
	$\epsilon_B(\epsilon_S=0.7)$	0.335(2)	0.311(1)	0.297(2)	0.294(7)
	$\epsilon_B(\epsilon_S=0.3)$	0.051(0)	0.044(1)	**0.044(1)**	0.044(1)
$t\bar{t}+Z$	AUC	0.851(0)	0.879(1)	**0.887(1)**	0.892(0)
	$\epsilon_B(\epsilon_S=0.7)$	0.168(4)	0.136(1)	**0.126(2)**	0.119(4)
	$\epsilon_B(\epsilon_S=0.3)$	0.020(0)	0.016(1)	0.016(0)	0.016(0)
		ParT	$\text{ParT}_{\text{int.}}$	$\text{ParT}_{\text{int. SM}}$	$\text{SetT}_{\text{int. SM}}$
$t\bar{t}+h$	AUC	0.824(0)	0.837(2)	**0.846(1)**	0.845(1)
	$\epsilon_B(\epsilon_S=0.7)$	0.197(3)	0.179(6)	0.174(1)	0.176(3)
	$\epsilon_B(\epsilon_S=0.3)$	0.023(0)	0.020(0)	0.020(0)	0.020(0)
$t\bar{t}+W$	AUC	0.896(1)	0.899(1)	**0.905(2)**	0.898(1)
	$\epsilon_B(\epsilon_S=0.7)$	0.097(2)	0.090(1)	**0.089(3)**	0.094(2)
	$\epsilon_B(\epsilon_S=0.3)$	0.010(0)	0.010(0)	**0.009(0)**	0.011(0)
$t\bar{t}+WW$	AUC	0.737(0)	0.767(1)	**0.769(0)**	0.763(1)
	$\epsilon_B(\epsilon_S=0.7)$	0.354(3)	0.295(5)	**0.288(2)**	0.301(5)
	$\epsilon_B(\epsilon_S=0.3)$	0.050(1)	0.040(0)	**0.042(0)**	0.047(1)
$t\bar{t}+Z$	AUC	0.839(1)	0.885(0)	**0.891(1)**	0.886(2)
	$\epsilon_B(\epsilon_S=0.7)$	0.182(2)	0.130(1)	**0.119(3)**	0.129(4)
	$\epsilon_B(\epsilon_S=0.3)$	0.021(1)	0.016(0)	**0.015(0)**	**0.014(0)**

The areas under the ROC curve and the **background efficiencies**, at **signal efficiencies of** 70% and 30% respectively

- Quoted uncertainties are extracted from three independent runs for each network architecture
- Numbers in bold indicate the best performance

Let's zoom in →

Results for the $t\bar{t}t\bar{t}$ and $t\bar{t}H$ signals

arXiv:2211.05143

The AUC for both 4 top and top-top-Higgs signal detection

		PN	$\mathrm{PN}_{\mathrm{int.}}$	$\mathrm{PN}_{\mathrm{int.\,SMids}}$	$\mathrm{PN}_{\mathrm{int.\,SM\,const}}$	$\mathrm{PN}_{\mathrm{int.\,SM}}$
$t\bar{t}t\bar{t}$	AUC	0.8471(1)	0.8729(0)	0.8725(0)	0.8727(0)	**0.8739(0)**
	$\epsilon_B(\epsilon_S = 0.7)$	0.1758(3)	0.1387(1)	0.1377(0)	0.1384(0)	**0.1369(1)**
	$\epsilon_B(\epsilon_S = 0.3)$	0.0207(0)	0.0182(0)	0.0178(0)	0.0178(0)	**0.0176(0)**
		ParT	$\mathrm{ParT}_{\mathrm{int.}}$	$\mathrm{ParT}_{\mathrm{int.\,SMids}}$	$\mathrm{ParT}_{\mathrm{int.\,SM\,const}}$	$\mathrm{ParT}_{\mathrm{int.\,SM}}$
$t\bar{t}t\bar{t}$	AUC	0.8404(0)	0.8708(0)	0.8715(0)	0.8717(0)	**0.8732(0)**
	$\epsilon_B(\epsilon_S = 0.7)$	0.1842(3)	0.1394(0)	0.1389(2)	0.1372(1)	**0.1366(0)**
	$\epsilon_B(\epsilon_S = 0.3)$	0.0230(0)	0.0172(0)	0.0180(0)	**0.0167(0)**	0.0169(0)

The models containing both the **pairwise features** and the **SM interaction matrix** performs **best**

		PN	$\mathrm{PN}_{\mathrm{int.}}$	$\mathrm{PN}_{\mathrm{int.\,SMids}}$	$\mathrm{PN}_{\mathrm{int.\,SM\,const}}$	$\mathrm{PN}_{\mathrm{int.\,SM}}$
$t\bar{t}+h$	AUC	0.8146(2)	0.8505(0)	0.8489(1)	0.8505(0)	**0.8523(0)**
	$\epsilon_B(\epsilon_S = 0.7)$	0.2292(1)	0.1787(0)	0.1785(1)	0.1764(3)	**0.1733(1)**
	$\epsilon_B(\epsilon_S = 0.3)$	0.0471(1)	0.0345(0)	0.0343(1)	0.0350(0)	**0.0340(0)**
		ParT	$\mathrm{ParT}_{\mathrm{int.}}$	$\mathrm{ParT}_{\mathrm{int.\,SMids}}$	$\mathrm{ParT}_{\mathrm{int.\,SM\,const}}$	$\mathrm{ParT}_{\mathrm{int.\,SM}}$
$t\bar{t}+h$	AUC	0.8058(1)	0.8507(0)	0.8473(0)	0.8497(0)	**0.8532(0)**
	$\epsilon_B(\epsilon_S = 0.7)$	0.2399(2)	0.1794(1)	0.1836(3)	0.1801(1)	**0.1748(1)**
	$\epsilon_B(\epsilon_S = 0.3)$	0.0502(0)	0.0357(0)	0.0355(1)	0.0367(0)	**0.0351(0)**

The **background** can be significantly **reduced** by about **30%** compared to a **PN (GNN)**

Significance

arXiv:2211.05143

Highlights the **enhanced performance** of **ParT int. SM** models over baseline **PN (GNN)** (neglecting sys err) for 4top signal

$$\sigma = \frac{s}{\sqrt{b}} \qquad \sigma_{\delta_{sys}=0.2} = \frac{s}{\sqrt{b_{sys}}}$$

$$\mathrm{b}_{sys} = b + (b \cdot \delta_{sys})^2$$

- At $\epsilon_S = 0.7$: significance boost from **2.21** to **2.98** $\boldsymbol{\sigma}$ with **ParT int. SM** => **PN** requires **82%** more luminosity !
- At $\epsilon_S = 0.3$: significance boost from **8.29** to **9.88** $\boldsymbol{\sigma}$ with **ParT int. SM** => **PN** needs **42%** more luminosity !
- At $\epsilon_S = 0.3$: significance boost from **8.29** to **10.48** $\boldsymbol{\sigma}$ with **ParT int. SM (FL)** => **PN** needs **60%** more luminosity !

Significance table (calculations assume L = 100 fb^{-1})

		σ	$\sigma_{\delta sys} = 0.2$
BDT	$\epsilon_S = 0.3$	20.77	6.79
	$\epsilon_S = 0.7$	16.82	2.01
$\mathrm{BDT_{int.}}$	$\epsilon_S = 0.3$	21.93	7.53
	$\epsilon_S = 0.7$	17.51	2.17
FCN	$\epsilon_S = 0.3$	20.31	6.51
	$\epsilon_S = 0.7$	16.67	1.97
CNN	$\epsilon_S = 0.3$	20.88	6.86
	$\epsilon_S = 0.7$	16.73	1.98
PN	$\epsilon_S = 0.3$	23.09	8.29
	$\epsilon_S = 0.7$	17.68	2.21
$\mathrm{PN_{int.}}$	$\epsilon_S = 0.3$	25.30	9.83
	$\epsilon_S = 0.7$	**20.51**	**2.97**
$\mathrm{PN_{int.\,SM}}$	$\epsilon_S = 0.3$	**25.65**	**10.09**
	$\epsilon_S = 0.7$	**20.50**	**2.97**
ParT	$\epsilon_S = 0.3$	22.37	7.82
	$\epsilon_S = 0.7$	17.72	2.23
$\mathrm{ParT_{int.}}$	$\epsilon_S = 0.3$	24.54	9.29
	$\epsilon_S = 0.7$	20.21	2.89
$\mathrm{ParT_{int.\,SM}}$	$\epsilon_S = 0.3$	25.36	9.88
	$\epsilon_S = 0.7$	**20.53**	**2.98**
$\mathrm{ParT_{int.\,SM\,(FL)}}$	$\epsilon_S = 0.3$	**26.19**	**10.48**
	$\epsilon_S = 0.7$	20.28	2.91
$\mathrm{SetT_{int.\,SM}}$	$\epsilon_S = 0.3$	**25.58**	**10.03**
	$\epsilon_S = 0.7$	20.18	2.88

Results

arXiv:2211.05143

We asked the question: → "**Do the models saturate ?**"

PN and ParT Models (with the pairwise features + the SM coupling constants)

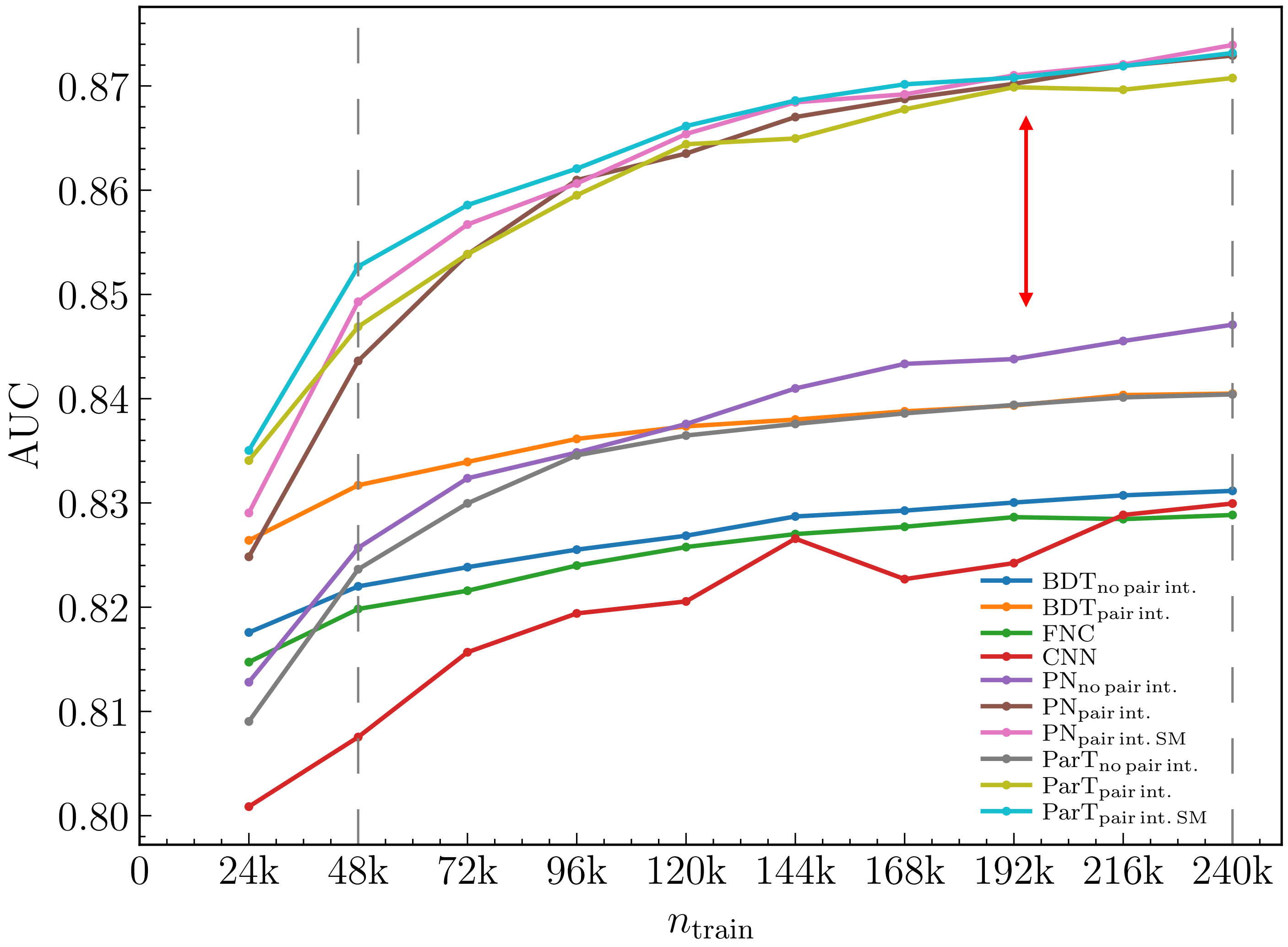
- Shows a steeper increase in **AUC** with fewer data
- Indicate higher data efficiency → less data needed for strong performance

Other Models

- **AUC** scores improve more gradually
- Suggest a requirement for larger datasets to match **PN** and **ParT** performance

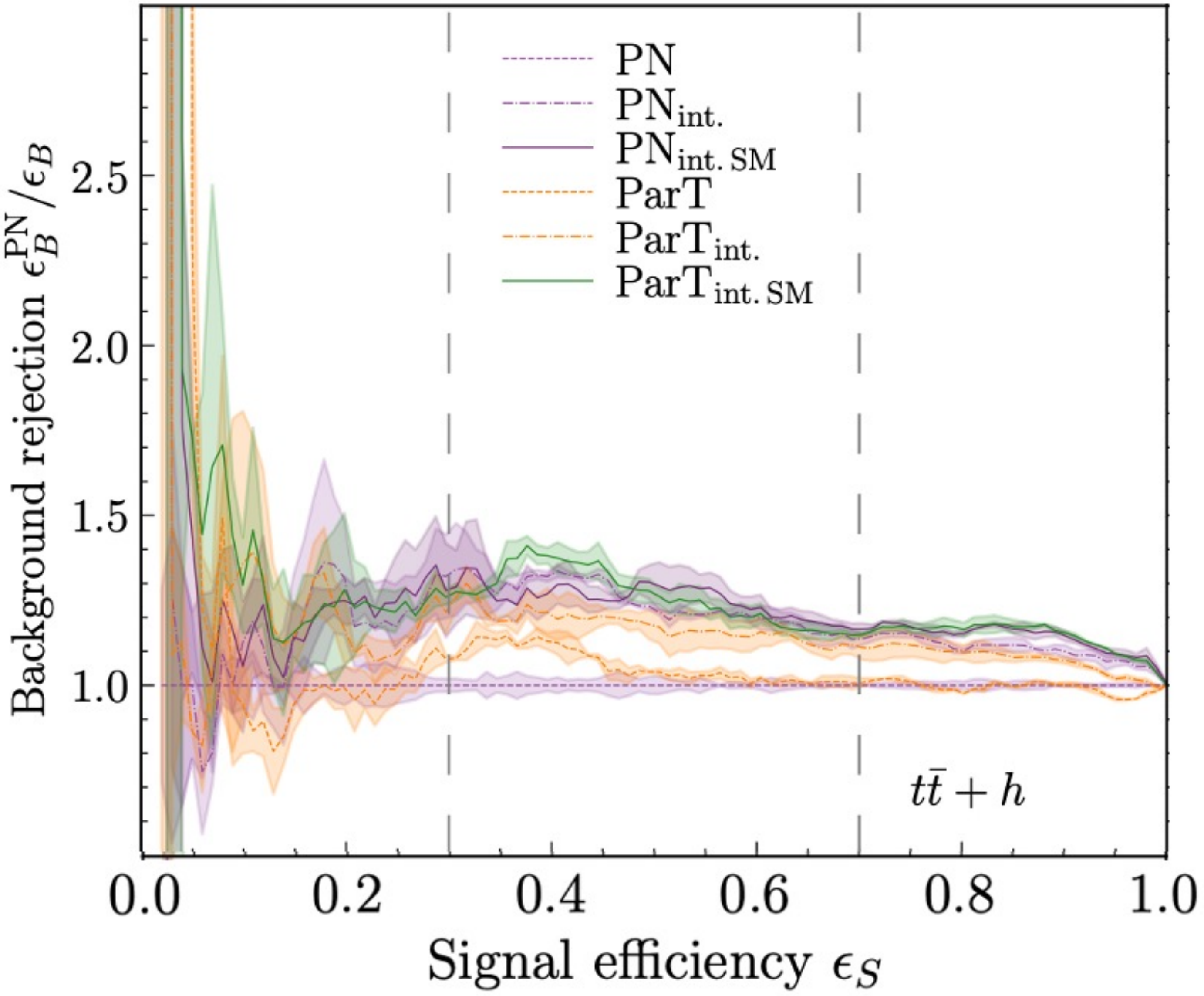
PN and ParT models could be preferable in data-scarce cases

The AUC scores as a function of training size



Results

arXiv:2211.05143



A plot with signal efficiency VS background rejection

*compared to the **ParticleNet (GNN)**

Models with integrated **pairwise features + SM interactions** exhibit up to a 40% higher background rejection

Demonstrates the strength of **SM interaction matrix** as a powerful inductive bias in learning

X-axis – the signal efficiency
Y-axis – the background rejection

Summary

⭐ **Integration of energy-dependent SM interactions into ML models**

- Embedding pairwise features and energy-dependent **SM** interactions into **ML** architectures significantly boosts event classification accuracy and efficiency:

  - Enhanced background suppression by **10-40%** compared to baseline **PN** (**GNN**) models

  - Approximately **10%** of this improvement is due to the **SM interaction matrix**

  - ML models show up to **30%** increase in significance vs. baseline

  - Achieving similar significance via increased luminosity would require **~70%** more data (compare to the baseline model)

Transformers, when supplemented with **pairwise features** and **SM couplings**, show potential as a **powerful tool** for collider physics challenges!

CAN WE TURN CLASSIFIERS INTO ANOMALY DETECTORS ?

⭐ It has been observed that, ***on average***,
the top-performing classifiers serve as best anomaly detectors
(**with the SM interactions**)

For further details, refer to Adrian's [talk]

Thank you for your attention!

Back up

Math Behind the Attention Mechanism

Attention Modules
(scaled dot product attention):

- $Attention(Q, K, V) = SoftMax\left(\frac{QK^T}{\sqrt{d}} + \boldsymbol{U}\right)V$
- $Q = queries, K = keys, V = values$
- *Self-attention* $\longrightarrow Q = K = V$

How Particles Inform Each Other ?

- **Calculating Interaction Scores:**
  - **Attention Score** $(\boldsymbol{Q}, \boldsymbol{K}) = \frac{\boldsymbol{QK^T}}{\sqrt{\boldsymbol{d}}}$

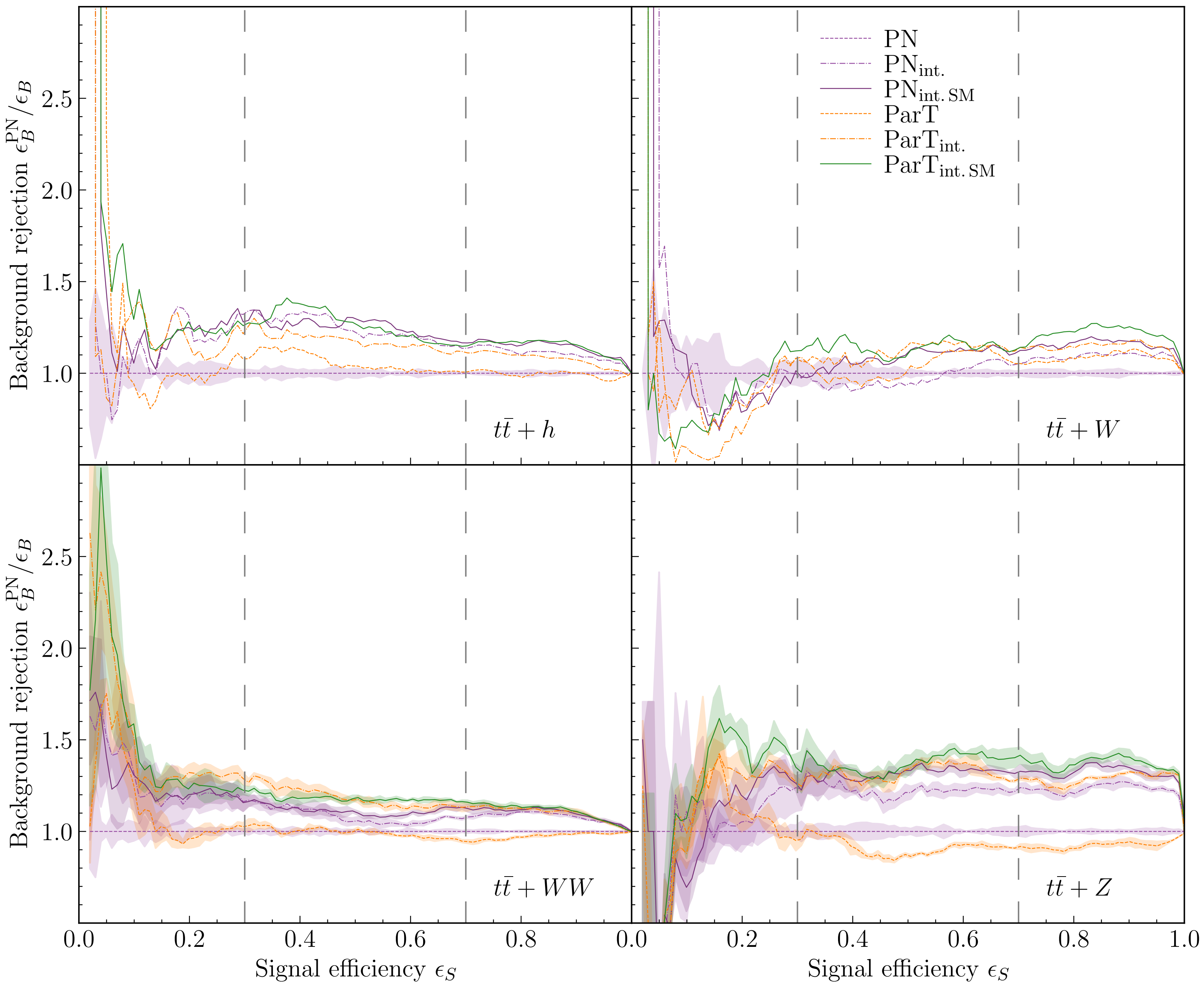
    where $\sqrt{d}$ is the dimentionality of the key vector, used to scale the dot product
- **Normalizing Scores to Probabilities:**
  - **Attention Weighs** $=$ $\boldsymbol{SoftMax}$***(Attention Score)***

    normalizes the scores to ensure they sum up to 1, acting as probabilities
- **Particle Representation:**
  - **Output** $=$ ***Attention Wights*** $*\ \boldsymbol{V}$

    each particle's output is a combination of all particles' information, weighted by their computed relevance

Result: captures the dynamic interactions between particles

A plot with signal efficiency VS background rejection



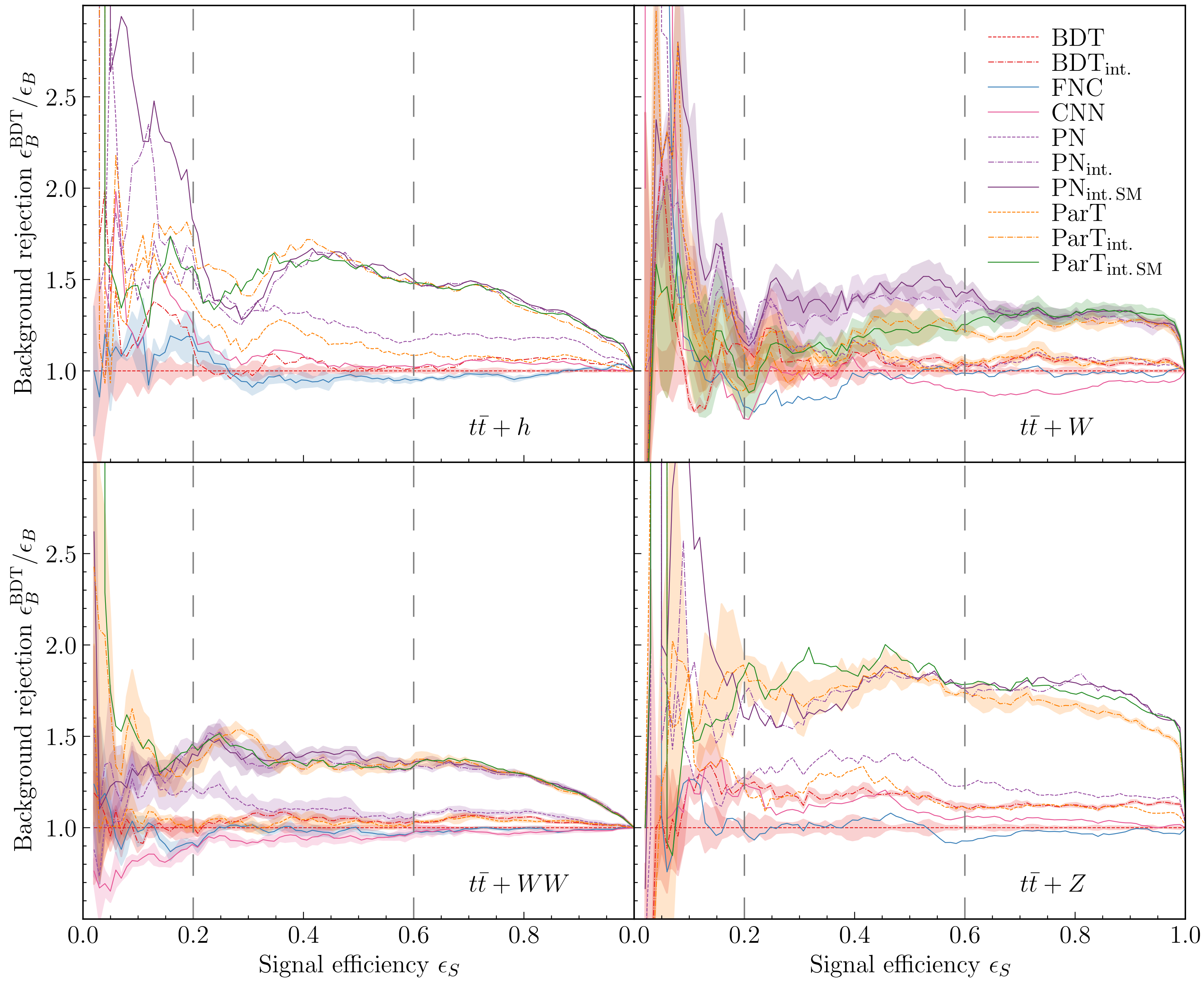
arXiv:2211.05143

compared to the **ParticleNet (GNN)**

We can achieve a **10-40% higher background rejection** for signal efficiencies between 30-90% by switching from **GNN** to **models with the pairwise features + the SM coupling constants**

X-axis – the signal efficiency
Y-axis – the background rejection

A plot with signal efficiency VS background rejection



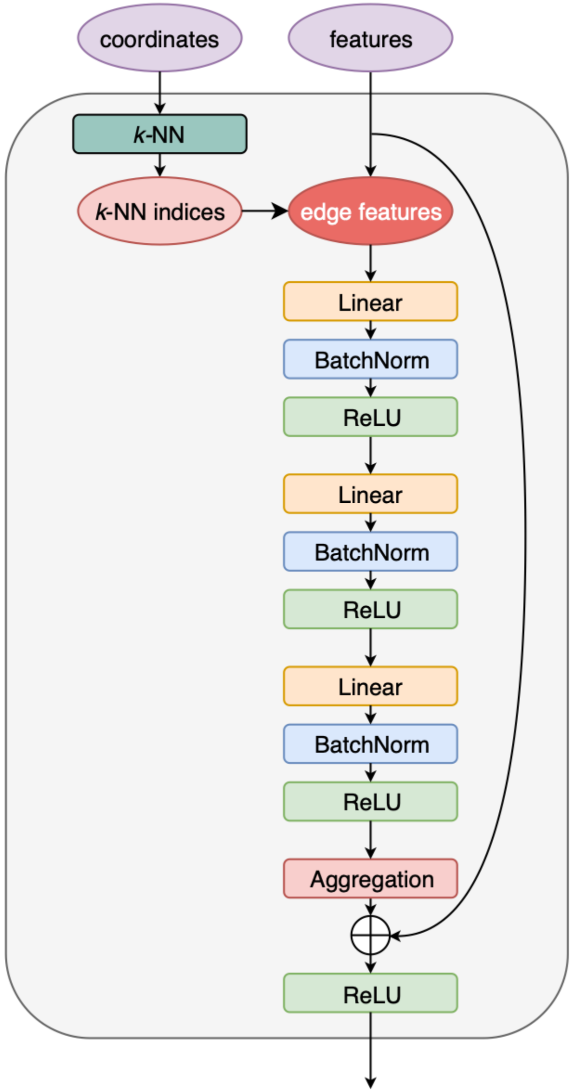
arXiv:2211.05143

Compared to the **BDT** for full size of the dataset

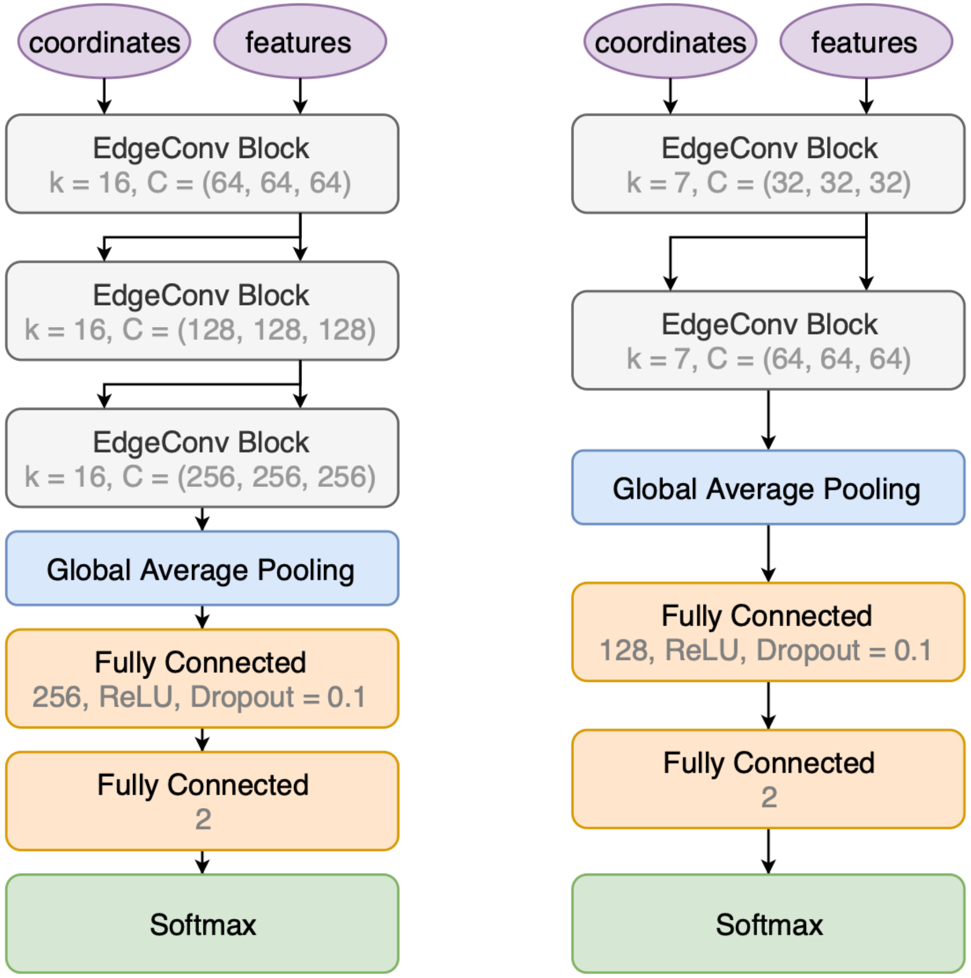
X-axis – the signal efficiency
Y-axis – the background rejection

EdgeConv and ParticleNet

arXiv:1902.08570



The structure of the EdgeConv block



(a) ParticleNet (b) ParticleNet-Lite

The architectures of the ParticleNet and the ParticleNet-Lite networks

1D CNN

arXiv:2011.13466

- Input is a **Particle List**
- **LRP** is a backpropagation method