Energy-weighted Message-passing Networks -- An IRC safe prescription for Jets



Anomalies 2021, IITH

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Based on: <u>arxiv: 2109.14636</u> (Partha Konar, VN, Michael Spannowsky)

Outline

- Jet-substructure & IRC safe observables
- Graphs and message-passing neural networks(MPNNs)
- Energy-Weighted Message-passing
 - Building an IRC safe graph
 - IRC safe message-passing
- Results and discussions



EW scale particle : decaying to quarks (dijet like signature) ⇒ Merged large-radius-jet in boosted regime

Jet Substructure at LHC



Infra-red and Collinear (IRC) Safe observables

For an observable \mathcal{O}_n defined on n particles. $|\mathcal{O}_{n+1}(p_a,.\,,p_b, {p_r}, {p_s}, p_c,.\,)
ightarrow \mathcal{O}_n(p_a,.\,,p_b, {p_q}, p_c,.\,)$ In the infra-red $(z_r
ightarrow 0 ext{ or } z_s
ightarrow 0)$ or collinear limits $(\Delta_{rs}
ightarrow 0)$ $p_q = (z_q, \hat{p_a})$ $p_r = (z_r, \hat{p_r})$ For a splitting: $q \rightarrow r + s$ **Calculable in pQCD!!** $p_s = (z_s, \hat{p_s})$ $p_q = p_r + p_s$

Infra-red and Collinear (IRC) Safe observables



Graphs: Compact efficient data structures

 $\mathcal{S} = \{a, b, i, q, \dots \}$

Node Set: all particles within a jet \boldsymbol{a}

 $\mathcal{E} = \{ (i, a), (i, q), (d, c), \dots \}$

Edge set

A graph $G(\mathcal{S},\mathcal{E})$ defined on a set \mathcal{S} , with edge-set \mathcal{E}

Node-features: $\{\mathbf{h}_a, \mathbf{h}_b, \mathbf{h}_c, \dots\}$

Four-momenta, charge, etc,

Edge-features: $\{\mathbf{e}_{ia}, \mathbf{e}_{iq}, \mathbf{e}_{dc}, \dots\}$

 $m_{ia}, \Delta R_{ia} etc,$

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Message-passing neural networks(Graph Neural Networks)

 $\mathcal{S} = \{a, b, i, q, \dots \}$





Deep-sets vs Message-passing neural networks(MPNN)

Deep-sets per-particle map: $\Phi(p_i)$	MPNNs Message-function: $\Phi(p_i, p_j)$		
Cannot extract inter-particle correlations	Can extract inter-particle correlations		
Only single particle information	Graph construction algorithm controls information extraction at first layer(via node-readout)		
Iterative application has no additional complexity on feature extraction, except functional composition $\Phi'(\Phi(p_i))$	Gradual increase in information in node-features, after each iteration		
No such control	Number of iterations control the scope of information contained in the final node-feature		

Energy Flow Networks(EFNs): IRC safe deep-sets framework

JHEP 01 (2019) 121, Komiske, Metodiev, Thaler

IRC safe jet-graphs







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 $\omega_{i}^{(\mathcal{N}[i])}$









Results

Network Performance





Higher AUC = better discrimination

Examining IRC Safety



Split the hardest constituent in a jet and vary $\, z_r \,$ and $\, \Delta R_{rs} \,$

Network Output: $\mathcal{YS} \quad \mathcal{YS} \quad \mathcal{YS} \quad \mathcal{YR}(z_r, \Delta R_{rs})$

Increasing R_0 decreases stability of network output to additional emissions

Conclusions

- Generalised Energy Flow Networks to extract local correlations via message-passing operations
- Single Energy-weighted message passing improves upon EFNs
- Iterative application does not spoil IRC safety, further room for improvement
- Devised generic graph construction algorithms which give invariant graph structure in the <u>deletion</u> of a soft or collinear vertex
- Possibility to structure graphs and networks with highly intuitive physics input
- General enough to study inclusive event shapes
- Can we understand the extracted features within pQCD?



EMPN: Iterative application







C limit:

$$\mathbf{h}_{q}^{(1)} = \mathbf{h}_{r}^{(1)} = \mathbf{h}_{s}^{(1)}$$

EMPN: Iterative application



C limit: $\mathbf{h}_{q}^{(1)} = \mathbf{h}_{r}^{(1)} = \mathbf{h}_{s}^{(1)}$ $\mathbf{h}_{s}^{(2)} = \sum_{j \in \mathcal{N}[i]} \omega_{j}^{(\mathcal{N}[i])} \hat{\Phi}^{(1)}(\mathbf{h}_{i}^{(1)}, \mathbf{h}_{j}^{(1)})$ IRC Safe!!!

EMPN: Iterative application



EMPN: Graph-readout



L = num. iterations

EMPN: Graph-readout





Graph on \mathcal{S}' contain $\mathbf{h}_r^{(L)}$ and $\mathbf{h}_s^{(L)}$

C limit:

$$\mathbf{h}_q^{(L)} = \mathbf{h}_r^{(L)} = \mathbf{h}_s^{(L)}$$

L = num. iterations

Dataset Details

SI. No	Jet Class	Parton-level	MPI	Detector Simulation	Jet Radius (anti-kT)	Transverse momentum [GeV]	Classification Scenario
1.	Gluon	Pythia8	Yes	No	0.4	[500,550]	Gluon vs Quark
2.	Quark	Pythia8	Yes	No	0.4	[500,550]	Gluon vs Quark
3.	QCD	Pythia8	No	Yes	0.8	[550,650]	QCD vs Top/W
4.	Тор	Pythia8	No	Yes	0.8	[550,650]	QCD vs Top
5.	W	Madgraph5	No	Yes	0.8	[550,650]	QCD vs W

[1-2] Publicly available q/g dataset [Komiske et.al] (used in EFNs) [3,4] Publicly available top tagging dataset [Kasieczka et.al] (used in EFNs)

[5] Generated with same specifications as [3,4]

Energy Flow Networks: A Special case of EMPNs

JHEP 01 (2019) 121, Komiske, Metodiev, Thaler

Per-particle map is a special message function constant for the second argument!

IR limit:
$$z_r = 0 \Rightarrow z_r \; \Phi({\hat p}_r) = 0$$



Jet-graph: k-nearest neighbour



$$egin{aligned} \mathcal{N}(c) &= \{a, b, q\} & \mathcal{N}'(c) &= \{a, r, s\} \ \mathbf{h}_i^{(l+1)} &= & \Box_{j \in \mathcal{N}(i)}^{local}{}^i \mathbf{m}_j & \boxed{\lim_{z_r o 0} \mathbf{h}_c'^{(l+1)}
eq \mathbf{h}_c^{(l+1)}} & = \mathbf{h}_c^{(l+1)} \ \mathbf{h}_c^{(l+1)} & \mathbf{h}_c^{(l+1)} \end{aligned}$$
Similar in the collinear limit