(Q)ParticleTransformer application in EW coupling of top quark at CEPC

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Outline

- Introduction to the measurement of top quark EW couplings
- Code testing of $t\bar{t}$ jet tagging by ParT/PNet

1.Introduction to the measurement of top quark EW couplings

Project structure

1. **Do the traditional method(cut-base)**
   Select the $t\bar{t}$ case using some traditional variables.
2. **Do the Machine learning method**
   Compared with traditional cut-base ,whether using ML to distinguish $e^{+}e^{-} \rightarrow t\bar{t}$ events in CEPC from the background with the same final state is better?
3. **Add quantum part to step2**
4. **Comparison and Summary**
   Comprehensive comparison of three methods to evaluate the screening results of machine learning and the model after adding quantum part to ttbar

$t\bar{t}$ pair production

1. **Signal process:**$e^+e^- \to \gamma/Z \to t\bar{t}$
2. **Final state:**$l^{\pm}vl^{\mp}\bar{v}b\bar{b}, l^{\pm}vq\bar{q}b\bar{b}$✓$, alljets$
   - t quark related information is largely retained in e/u or b-jet.
   - In the choosen final state, the contribution of MET is much more clear than others due to only one neutrino was produced from the process.
3. **Beam state:** 100% of the particles in a beam have a specific chirality, left-handed electrons and right-handed anti-electrons or right-handed electrons and left-handed anti-electrons
4. **Background:** Any process that have lvqqbb final states.The single top production which is difficult to distinguish $(W^* \to bt)$ and others like: $\mu\bar{\mu}, q\bar{q}, \gamma/Z, WW, ZZ, ZWW, ZZZ$

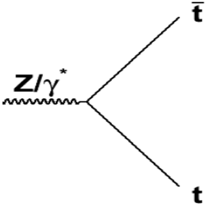

Figure: EW coupling vertax

Observables and Form Factors

- If both y/Z and tt are on-shell, EW coupling can be described by four Form Factors:

$$\Gamma_u^{Vt\bar{t}}(s) = -ie\{\gamma_u[F_{1V}^X(s) + \gamma_5 F_{1A}^X(s)] + \frac{\sigma_{uv}}{2m_t}(q_t + q_{\bar{t}})[i\frac{F_{2V}^X(s)}{2m_t} + \frac{F_{2A}^X(s)}{e}\gamma_5]\}$$

- Obtained σ_L, σ_R(left/right hand cross section) ,θ_L, θ_R(polar angle),$(A_{fb}^t)_L, (A_{fb}^t)_R$(forward backward asymmetry) from the signal process.
  They are the are obeservable which can be measured experimentally.

$$A_{FB}^t = \frac{N(cos\theta > 0) - N(cos\theta < 0)}{N(cos\theta > 0) + N(cos\theta < 0)}$$

- Four Observables($\sigma_L, \sigma_R, (A_{fb}^t)_L, (A_{fb}^t)_R$) can be shown by four Form Factors

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2.Code testing of $t\bar{t}$ jet tagging by ParT/PNet

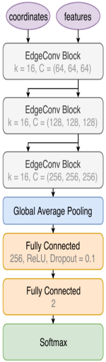
My work

- **My foucs:** Application of machine learning methods in $t\bar{t}$event selection.
- **Current tasks**:Test the application of an existing ParT/ParNet code for jet tagging at CEPC.
- **Simple introduction to ParticleNet/ParticleTransformer:**

1. **ParticleNet** is a model based on GNN architecture that focuses on processing local inter-particle information.

   Features:The interaction relationship between particles within a certain range can be captured through the relationship between points and edges.

   Advantages:Compared with traditional feature engineering and manually defined variables, ParticleNet can automatically learn high-order features of particle injection, improving classification accuracy.



My work

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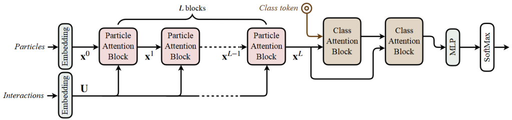
2. **ParticleTransformer** is a deep learning model that combines self-attention mechanism and interaction between particles.

   Features:Ability to flexibly model long-distance dependencies between particles and capture complex relationships between particles and jets.

   Advantages:It can better handle the global dependence of particles, and is more robust in identifying jets and background noise.



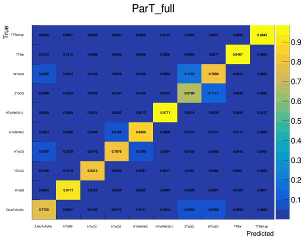
Config of testing

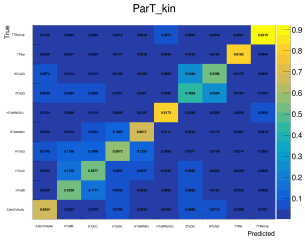
- **Source**(without Quantum part):https://github.com/jet-universe/particle_transformer.
- **input dataset**
  10 processes containing jets: $H \to b\bar{b}, H \to c\bar{c}, H \to gg, H \to 2W \to 4q, H \to 2W \to lvq\bar{q}, t \to bq\bar{q}, t \to blv, W \to q\bar{q}, Z \to q\bar{q}, Z(j)\bar{v}$.(produced by Shudong Wang)
  Each process has 100M in the training set, 20M in the test set, and 5M in the verification set.
  Source:/cefs/higgs/wangshudong/data/JetClass/Pythia
- **features:**
  kin: only kinematic variables

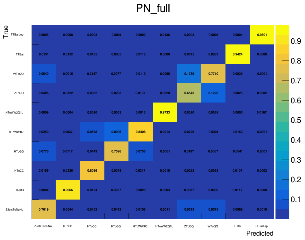
  $$\Delta\eta, \Delta\phi, logp_T, logE, log\frac{p_T}{p_T(jet)}, log\frac{E}{E(jet)}, \Delta R$$

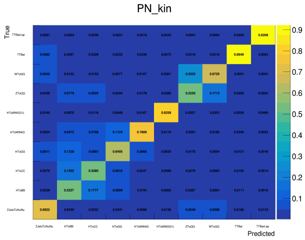
  full : kinematic variables + particle identification + trajectory displacement
- **epochs**:30,**Batch Size**:1024 , **learning rate**:0.01
- **num_heads**:8,**num_lawyer**:8,**num_classlayers**:2
- **activation function**:gelu
- **model**:ParticleNet/ParticleTransformer

Results


ParT_full
True
Predicted


ParT_kin
True
Predicted


PN_full
True
Predicted


PN_kin
True
Predicted

Results

		ParT_full	ParT_kin	PN_full	PN_kin
CEPC	$\overline{AUC}$	>0.95	>0.95	>0.95	>0.95
	$Accuracy$	0.85246	0.74387	0.83939	0.6983
JetClass dataset	$\overline{AUC}$	0.9877		0.9849	
	Accuracy	0.861		0.844	

- $\overline{AUC}$ is the average of AUC values between each two processes.

$$\overline{AUC} = \frac{\sum_{i=1}^{10} \sum_{j=1}^{11-i} AUC_{ij}}{\sum_{i=1}^{10} i}$$

- $Accuracy$ is the accuracy rate of prediction for the entire test dataset

- There is no significant difference compared to the results in the paper, and there is no significant difference between PN and ParT.
- The results using all features are better than using only kin features.

Summary

1. Use ParT/ParNet to do jet tagging on CEPC MC data.It is verified that parNet and parT can be used for subsequent research.
   - The best bjet identification using traditional methods only has an accuracy of 0.7.
   - It is verified that the two models of PN/ParT are equally effective when applied to CEPC data.
2. To do:Apply the model for $t\bar{t}$ selection.