Global Analysis of Higgs Aided by Machine Learning

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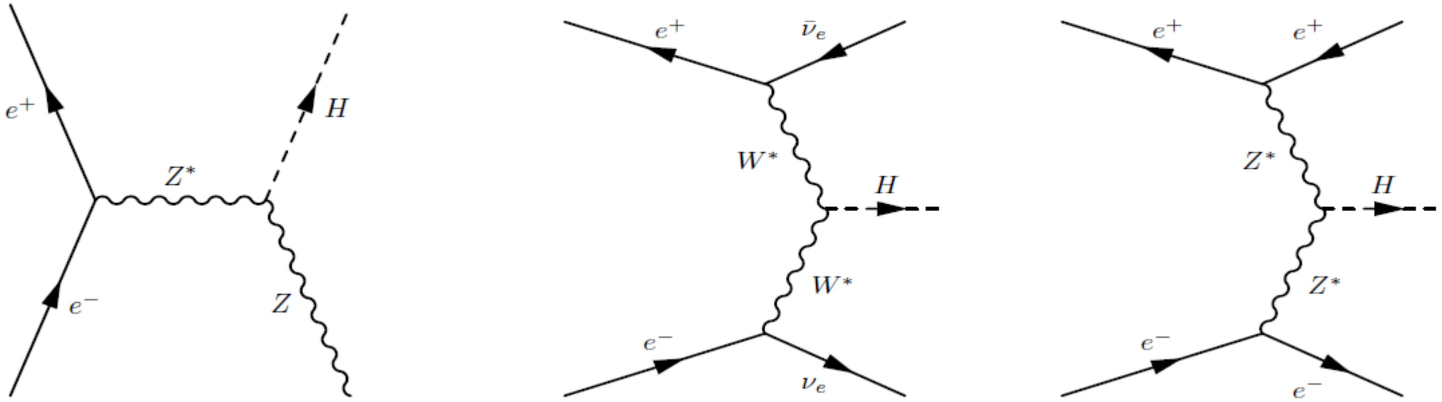
Outline

- Introduction
- Determining efficiency (confusion) matrix with ML
- Preliminary results
- Summary

Introduction

- Higgs decay branching ratios at future Higgs factories can be measured by directly using counting method.

- Events can be categorized into classes using event properties linked to the expected Higgs decay modes. The counts per class are used to fit the Higgs branching ratios in a model independent way.



Introduction

Personal ranking of the difficulty of Higgs analysis at ee colliders

4 x 9 modes in this study, [**5 production and 13 (9) decay** modes in SM]

Prod/decay	cc	bb	μμ	ττ	γγ	gg	WW	ZZ	γZ	ee, uu,dd,ss
eeH (incl. Z fusion)	3	1	5	2	4	1	2	3	5	Not covered yet
μμH	3	1	5	2	4	1	2	3	5	
ττH	3	1	5	2	4	1	2	3	5	
qqH	4	1	2	1	2	5	5	5	3	
ννH (incl. W fusion)	5	1	3	2	3	5	4	2	4	

According to production rate, signal signature, backgrounds, complication of analysis, …

Introduction

Current estimation of Higgs precision

CEPC: 2205.08553

	240 GeV, 20 ab^{-1}		360 GeV, 1 ab^{-1}		
	ZH	vvH	ZH	vvH	eeH
any	0.26%		1.40%	\	\
H→bb	0.14%	1.59%	0.90%	1.10%	4.30%
H→cc	2.02%		8.80%	16%	20%
H→gg	0.81%		3.40%	4.50%	12%
H→WW	0.53%		2.80%	4.40%	6.50%
H→ZZ	4.17%		20%	21%	
$H \to \tau\tau$	0.42%		2.10%	4.20%	7.50%
$H \to \gamma\gamma$	3.02%		11%	16%	
$H \to \mu\mu$	6.36%		41%	57%	
$Br_{upper}(H \to inv.)$	0.07%		\	\	
$H \to Z\gamma$	8.50%		35%	\	
Width	1.65%		1.10%		

FCC-ee

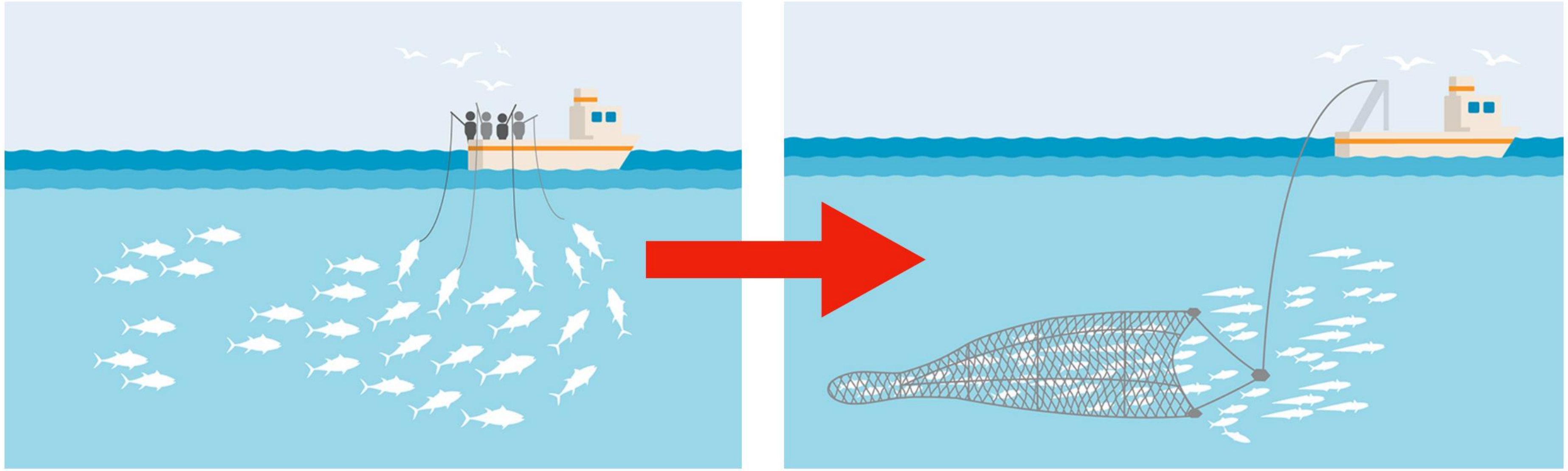
$\sqrt{s}$ (GeV)	240		365	
Luminosity (ab^{-1})	5		1.5	
$\delta(\sigma BR)/\sigma BR$ (%)	HZ	$\nu\bar{\nu}$ H	HZ	$\nu\bar{\nu}$ H
$H \to$ any	± 0.5		± 0.9	
$H \to b\bar{b}$	± 0.3	± 3.1	± 0.5	± 0.9
$H \to c\bar{c}$	± 2.2		± 6.5	± 10
$H \to gg$	± 1.9		± 3.5	± 4.5
$H \to W^+W^-$	± 1.2		± 2.6	± 3.0
$H \to ZZ$	± 4.4		± 12	± 10
$H \to \tau\tau$	± 0.9		± 1.8	± 8
$H \to \gamma\gamma$	± 9.0		± 18	± 22
$H \to \mu^+\mu^-$	± 19		± 40	
$H \to$ invisible	< 0.3		< 0.6	

- **Results of CEPC and FCC-ee based individual analysis**
- **Comparable precision**

A lot of efforts

Introduction

- Signal of an individual analysis is the background of another and vice versa.
- Combine efforts in a global analysis style?



With the help of ML/DL techniques

Introduction

- Individual style

- N_s: signal
- N_b: backgrounds, could be different types, higgs crosstalks and higgs-free events
- Br_s to be measured

$$Br_s = \frac{N_s}{N_s + N_{b_{higgs}}}$$

- Events selection:

$$\begin{pmatrix} n_s \\ n_b \end{pmatrix} = \begin{pmatrix} \epsilon_{ss} & \epsilon_{sb} \\ \epsilon_{bs} & \epsilon_{bb} \end{pmatrix} \times \begin{pmatrix} N_s \\ N_b \end{pmatrix}$$

- Global style

$$\mathbf{n} = \mathbf{EN}$$

$$\begin{pmatrix} n_1 \\ n_2 \\ \vdots \\ n_9 \end{pmatrix} = \begin{pmatrix} \epsilon_{11} & \epsilon_{12} & \cdots & \epsilon_{19} \\ \epsilon_{21} & \epsilon_{22} & \cdots & \epsilon_{29} \\ \vdots & \vdots & \ddots & \vdots \\ \epsilon_{91} & \epsilon_{92} & \cdots & \epsilon_{99} \end{pmatrix} \begin{pmatrix} N_1 \\ N_2 \\ \vdots \\ N_9 \end{pmatrix}$$

$$\begin{matrix} n_{b_1} & \vdots & \cdots & \vdots & N_{b_1} \\ n_{b_2} & \vdots & \ddots & \vdots & N_{b_2} \\ \vdots & \vdots & \cdots & \vdots & \vdots \end{matrix}$$

$$Br_i = \frac{N_i}{N_1 + N_2 + \cdots + N_9}$$

A “one-stop” approach:
measure all branching ratios simultaneously, more efficient and hopefully better precision

Introduction

Key ingredient: efficiency matrix ($\boldsymbol{E}$) also challenging

$$\begin{pmatrix} \epsilon_{11} & \epsilon_{12} & \cdots & \epsilon_{19} \\ \epsilon_{21} & \epsilon_{22} & \cdots & \epsilon_{29} \\ \vdots & \vdots & \ddots & \vdots \\ \epsilon_{91} & \epsilon_{92} & \cdots & \epsilon_{99} \end{pmatrix}$$

A multiple classification problem

In 2020s, try machine learning?

Determining efficiency (confusion) matrix with ML

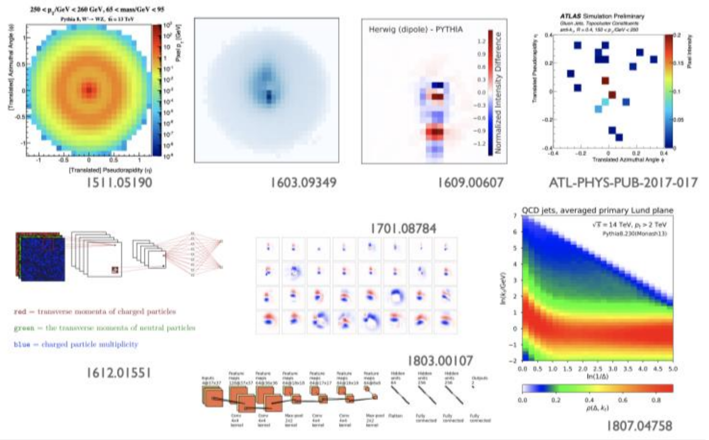
- **From jet tagging to event tagging**

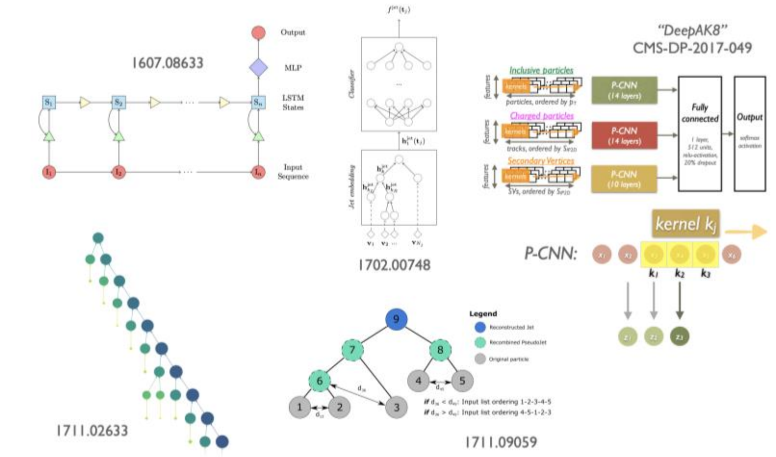
- Jets are important physics objects, >90% of ZH events contain jets

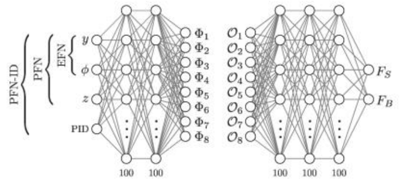
- Jet tagging with BDT: feature engineering
  - Lots of works

nvtx=0	trk1d0sig trk2d0sig trk1z0sig trk2z0sig trk1pt_jete trk2pt_jete jprobr5sigma jprobz5sigma d0bprob d0cprob d0qprob z0bprob z0cprob z0qprob nmuon nelectron trkmass(17)
nvtx=1&&nvtxall=1	trk1d0sig trk2d0sig trk1z0sig trk2z0sig trk1pt_jete trk2pt_jete jprobr jprobz vtxlen1_jete vtxsig1_jete vtxdirang1_jete vtxmom1_jete vtxmass1 vtxmult1 vtxmasspc vtxprob d0bprob d0cprob d0qprob z0bprob z0cprob z0qprob trkmass nelectron nmuon(25)
nvtx=1&&nvtxall=2	trk1d0sig trk2d0sig trk1z0sig trk2z0sig trk1pt_jete trk2pt_jete jprobr jprobz vtxlen1_jete vtxsig1_jete vtxdirang1_jete vtxmom1_jete vtxmass1 vtxmult1 vtxmasspc vtxprob 1vtxprob vtxlen12all_jete vtxmassall (19)
Nvtx>=2	trk1d0sig trk2d0sig trk1z0sig trk2z0sig trk1pt_jete trk2pt_jete jprobr jprobz vtxlen1_jete vtxsig1_jete vtxdirang1_jete vtxmom1_jete vtxmass1 vtxmult1 vtxmasspc vtxprob vtxlen2_jete vtxsig2_jete vtxdirang2_jete vtxmom2_jete vtxmass2 vtxmult2 vtxlen12_jete vtxsig12_jete vtxdirang12_jete vtxmom_jete vtxmass vtxmult 1vtxprob(29)

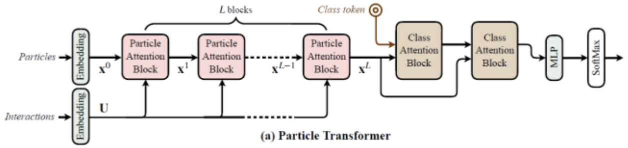
- Novel ML/DL algorithms: jets treated as images, sequences, sets/point clouds
  - Performance boost, less human labor



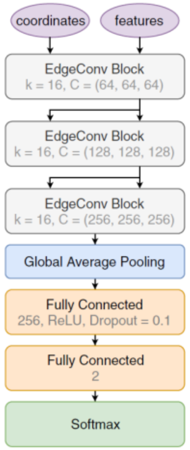




EFN/PFN: JHEP01(2019)121



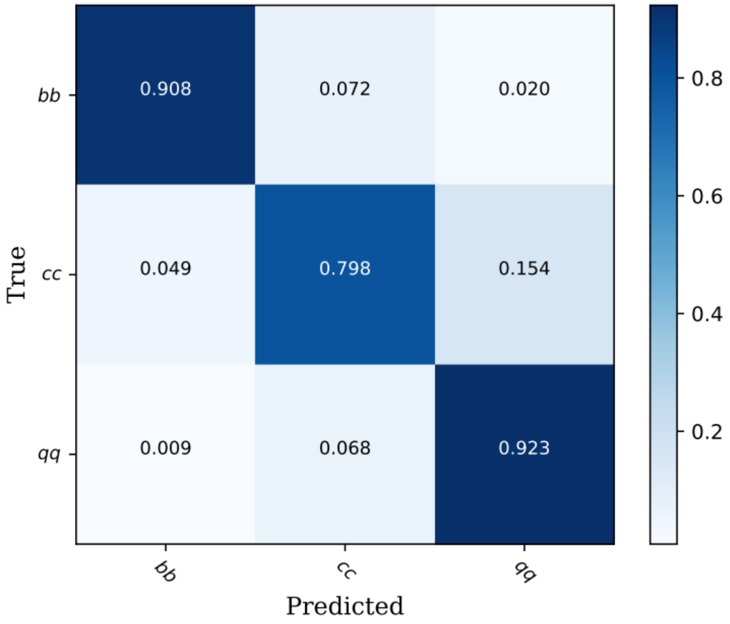
ParticleTransformer: 2202.03772



ParticleNet: Phys.Rev.D 101 (2020) 5, 056019

Determining efficiency (confusion) matrix with ML

- **From jet tagging to event tagging**
- Novel ML/DL algorithms:
  - Performance on jet flavor tagging in a realistic scenario (CEPC fullsim) is pretty good



2208.13503

Determining efficiency (confusion) matrix with ML

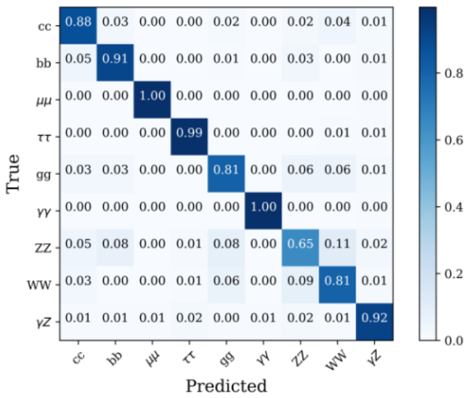
- **From jet tagging to event tagging**
- Number of particles
  - Jets: $O(10)\sim O(100)$
  - Events on a ee collider: $O(10)\sim O(100)$
- Classify events (event tagging) using ML algorithms?
  - Most important objective : $e^+e^- \rightarrow ZH$
  - 4 *Z* decay modes

    $ee, \mu\mu, \tau\tau, q\bar{q}$
  - 9 Higgs decay modes

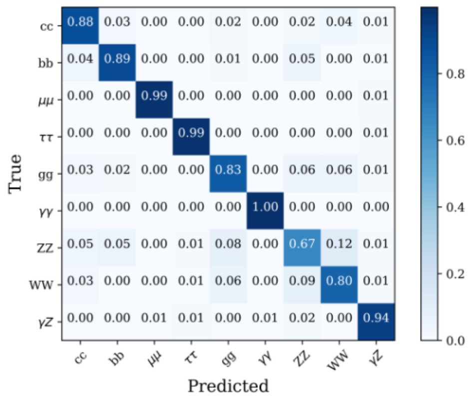
    $c\bar{c}, b\bar{b}, \mu^+\mu^-, \tau^+\tau^-, \gamma\gamma, gg, WW^*, ZZ^*, \gamma Z$
  - 36 in total
  - 9 background processes: $\nu\nu H, l^+l^-, q\bar{q}, W^+W_l^-, W^+W_{sl}^-, W^+W_h^-, ZZ_l, ZZ_{sl}, ZZ_h$
  - 400k events for each class, DELPHES fast simulation
  - Particle level information as input

Determining efficiency (confusion) matrix with ML

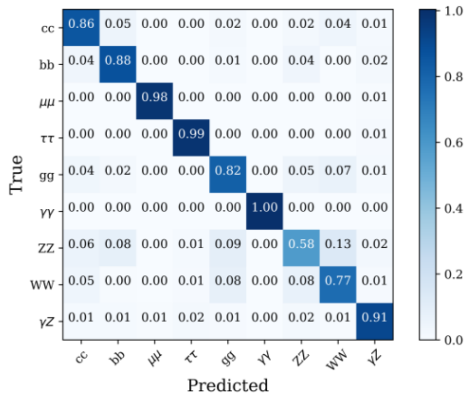
- **From jet tagging to event tagging**
- First attempt: classify higgs decay (9-category classification) using ParticleNet



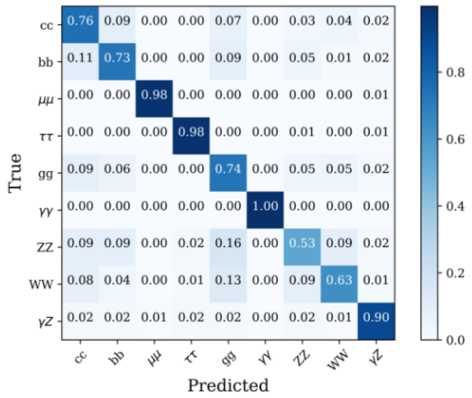
eeH



$\mu\mu$H



$\tau\tau$H



$q\bar{q}$H

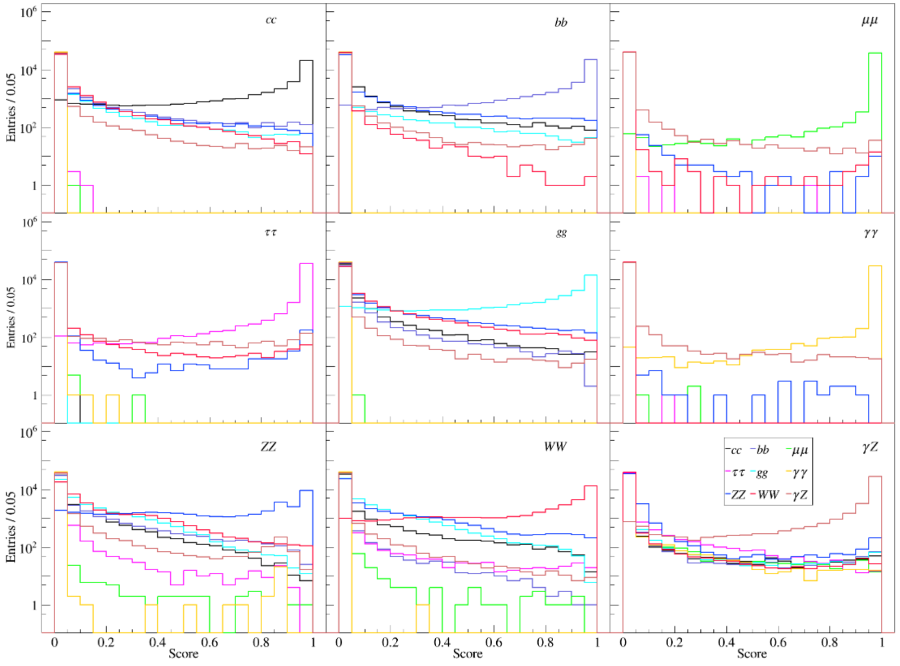
- Sufficiently good performance
- Average Accuracy ~ 87%

  (11% for random guess)

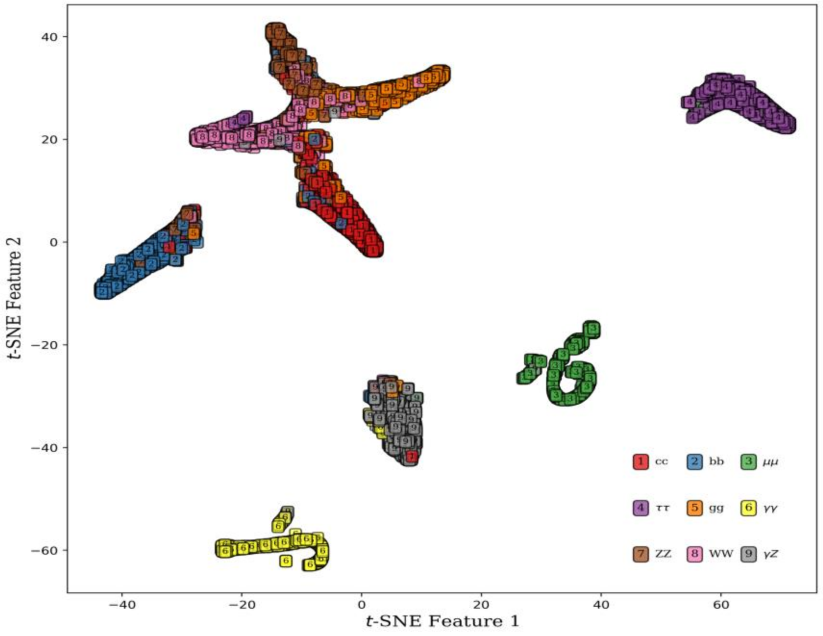
Determining efficiency (confusion) matrix with ML

- **From jet tagging to event tagging**
- First attempt: classify higgs decay (9-category classification) using ParticleNet

Distribution of score



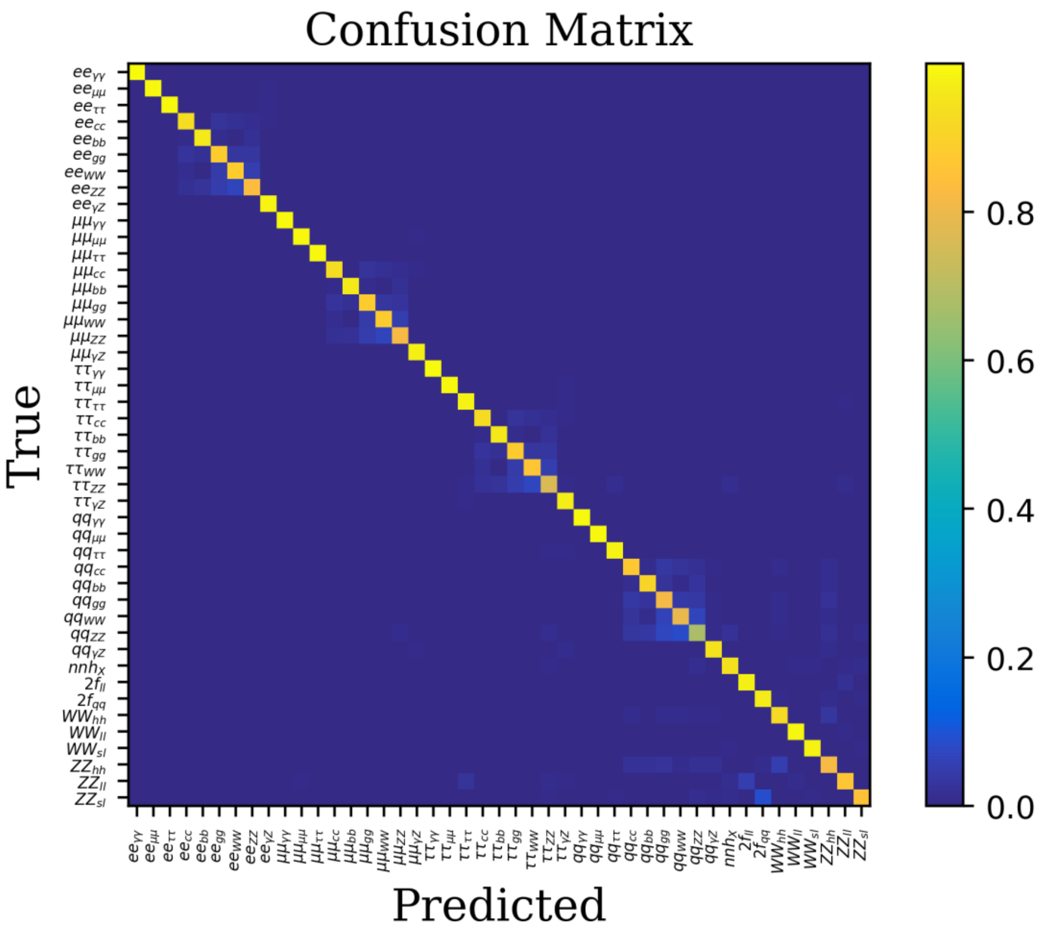
Dimensionality reduction (t-SNE)



- ✓ μμ, γγ, ττ well classified as expected
- ✓ bb and γZ also good
- ✓ cc, gg, WW, and ZZ fake each other, but under control

Determining efficiency (confusion) matrix with ML

- **From jet tagging to event tagging**
- More ambitious: classify 36 signals + 9 bkgs using ParticleTransformer

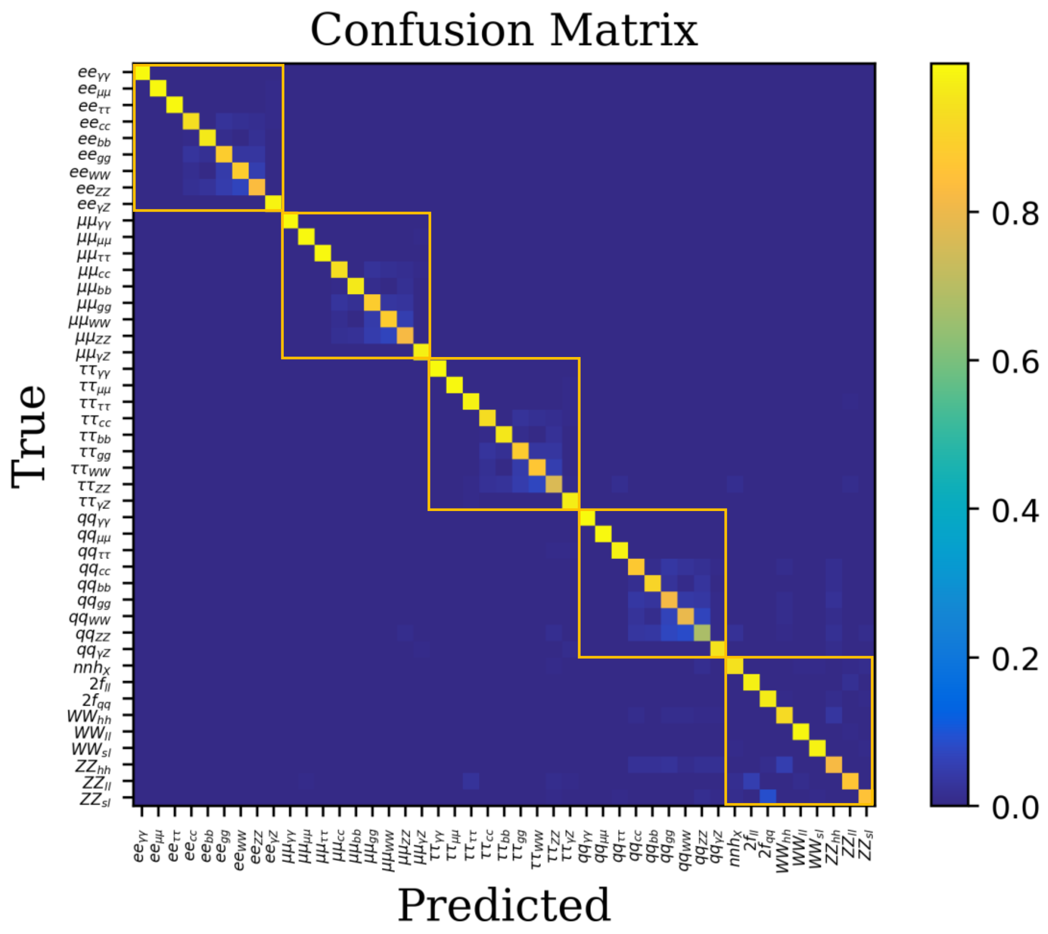


- Average Accuracy ~ 92%
- Appealing performance
- Use this for global analysis…

1M events for each class

Determining efficiency (confusion) matrix with ML

- **From jet tagging to event tagging**
- More ambitious: classify 36 signals + 9 bkgs using ParticleTransformer



- Average Accuracy ~ 92%
- Appealing performance
- Use this for global analysis…

1M events for each class

Preliminary results

- Extract *Br*s and their uncertainties using toy method.
  - Integrated luminosity: 20 ab^{-1}
- Minimizing $\chi^2 = \sum \frac{(N_{obs}-N_{exp})^2}{N_{exp}} + N_{ZH} * (\sum_i Br_i - 1)^2$

  (assuming Higgs have and only have the 9 decay modes we studied)
- Hope to improve the uncertainties of higgs decay branching ratios, but… ☹

Decay Mode	Rel.Unc.
$H \to c\bar{c}$	1.63%
$H \to b\bar{b}$	0.16%
$H \to \mu^+\mu^-$	19.53%
$H \to \tau^+\tau^-$	0.37%
$H \to gg$	0.73%
$H \to \gamma\gamma$	28.45%
$H \to ZZ$	2.7%
$H \to W^+W^-$	0.28%
$H \to \gamma Z$	38.5%

🤔

- Uncertainties of some branching ratios are even worse than results in CDR (5.6 ab^{-1})
- The branching ratios of those decay modes are relatively small
- Contaminated by backgrounds, even if the proportion is small, the cross-section of the backgrounds are large -> large contamination, large uncertainty

Preliminary results

- Hope to improve the uncertainties of higgs decay branching ratios, but… ☹

- No much pre-selection before events classification.
  - Only require #Particles > 2, E_{vis} >20 GeV
  - Too optimistic, too radical? 🤔

Decay Mode	Rel.Unc.
$H \to c\bar{c}$	1.63%
$H \to b\bar{b}$	0.16%
$H \to \mu^+\mu^-$	19.53%
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$H \to \gamma\gamma$	28.45%
$H \to ZZ$	2.7%
$H \to W^+W^-$	0.28%
$H \to \gamma Z$	38.5%

- **Next step:** 🤔
  - Fall back to a classical style, try to add few more pre-selections.
    - Problem solved, precision improved?

or

    - Worsen the performance of classifier? The loss outweighs the gain.

Still in progress…

Summary

- Higgs physics is the top priority in future Higgs factories.
- Feasibility study shows that novel ML/DL algorithms could classify events to a very good extent.

- A new analysis paradigm
  - Multi-classification: accurate enough and fast enough.
  - Only particle level information as input, no dependence on jet algorithm, … less software work.
  - Preliminary results not as good as expected, need more study.
  - Systematics will be very challenging, need more study.