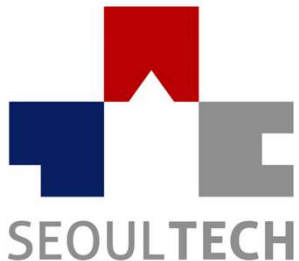


Deep Learning in High Energy Physics

Minho Kim

Based on 1904.08549 and upcoming articles
Collaborated with M. Park, K. C. Kong, J. H. Kim,
and K. T. Matchev

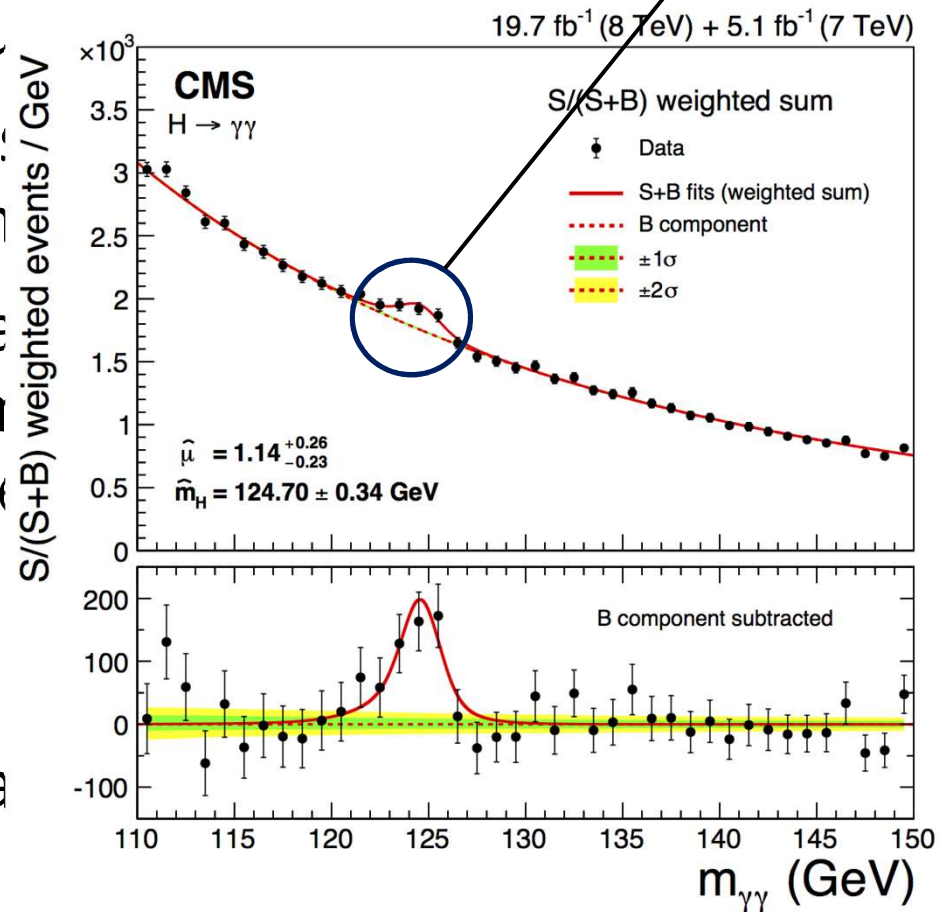


Introduction

- In the high energy physics (HEP), signal is not alone and has a lot of background around it. Thus it is very important to reduce background.
- There are several ways to reduce background. Most of them are based on cut analysis using physical variables.
- People are trying to use all information from data now.
- How can we handle all information?

Introduction

- In the $m_{\gamma\gamma}$ and hadronic channels, the signal is very small
- There are a lot of other variables that can be used to distinguish the signal from the background
- People are working on this now.
- How can we improve the signal-to-background ratio?



Very small signal portion!

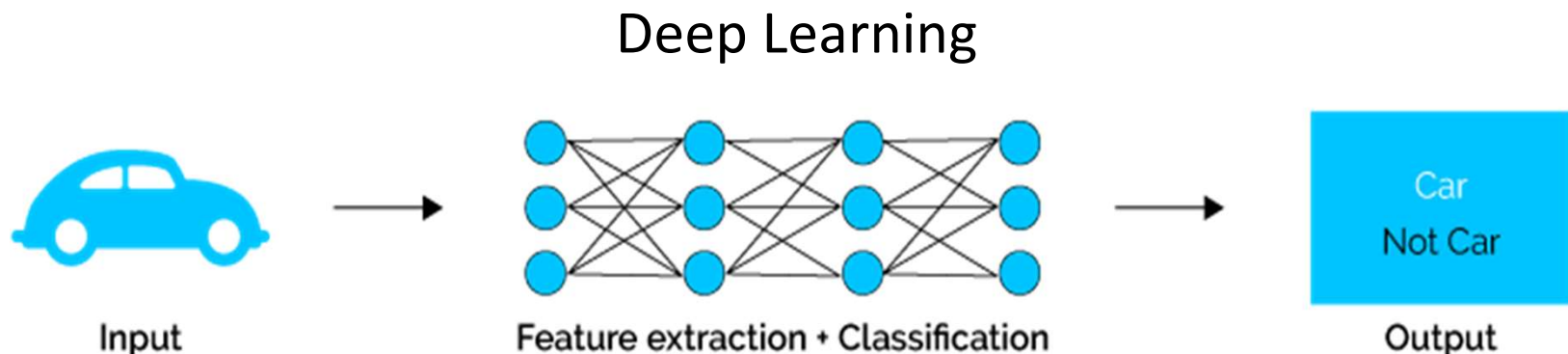
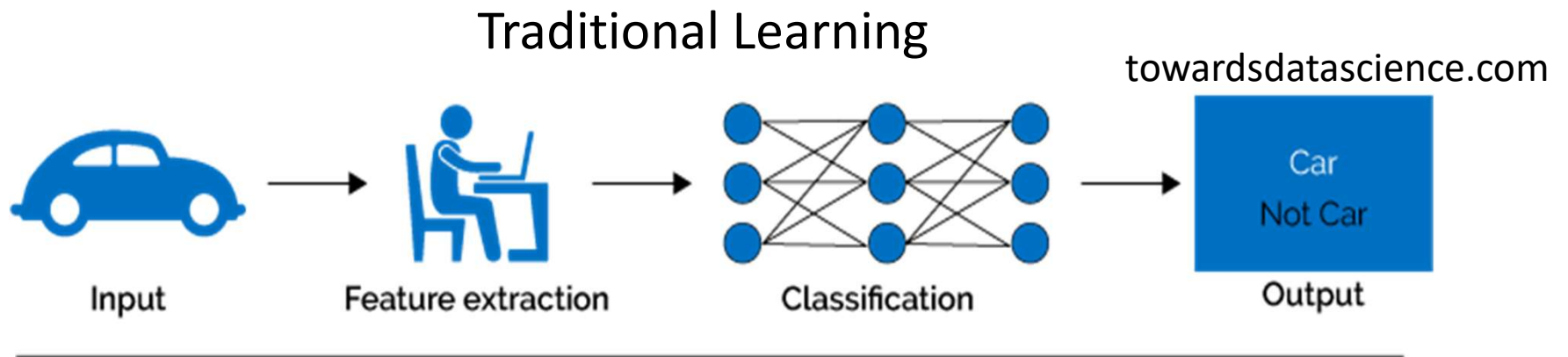
It is not alone
Thus it is

ground. Most
of physical

is from data

The Solution : Deep Learning

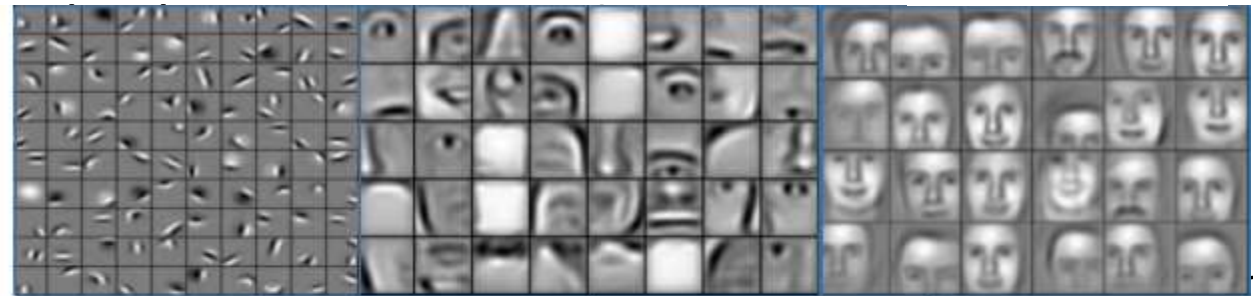
- Deep learning (DL) can be one of the best solution.
- Main difference is use of feature extraction.



The Solution : Deep Learning

rsipvision.com

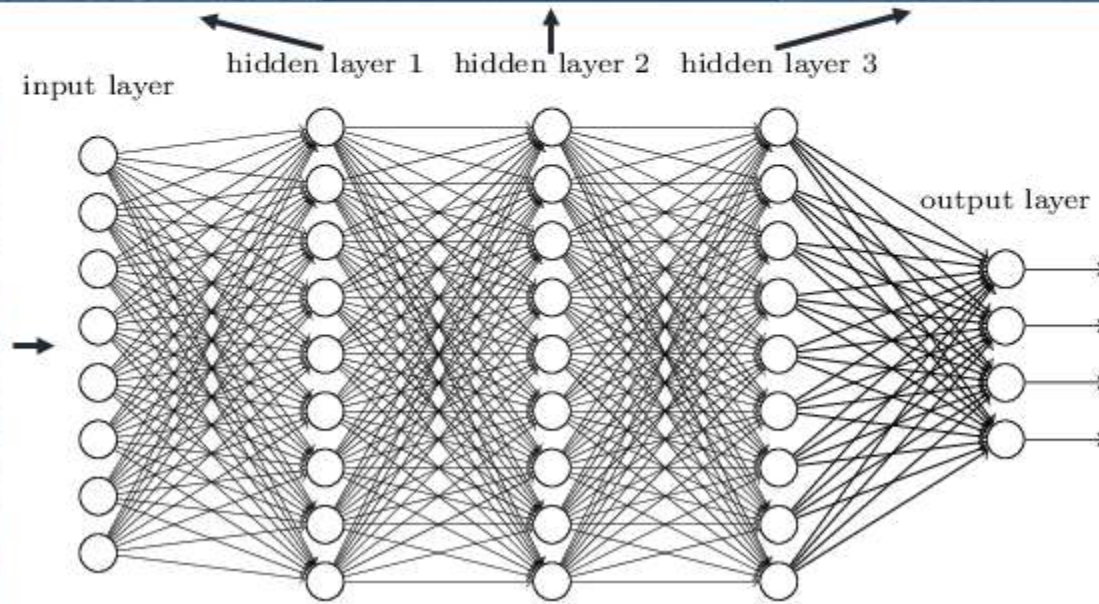
Deep neural networks learn hierarchical feature representations



com



Input



Feature extraction + Classification

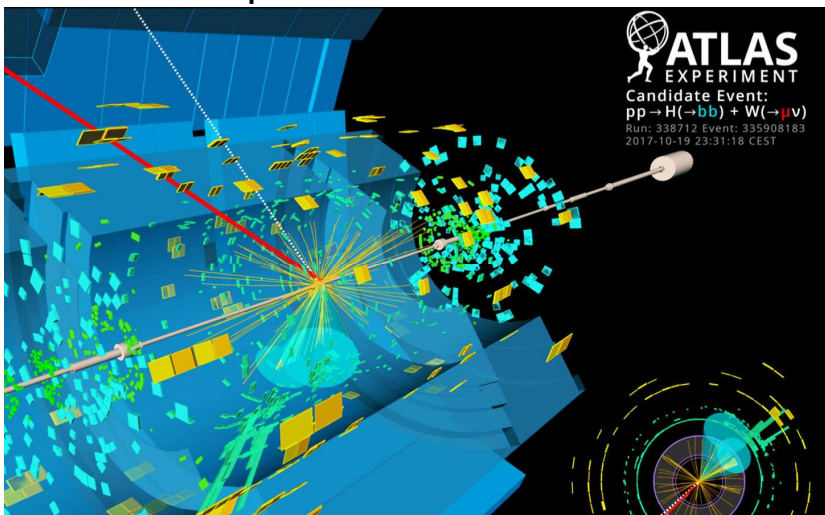
Not Car

Output

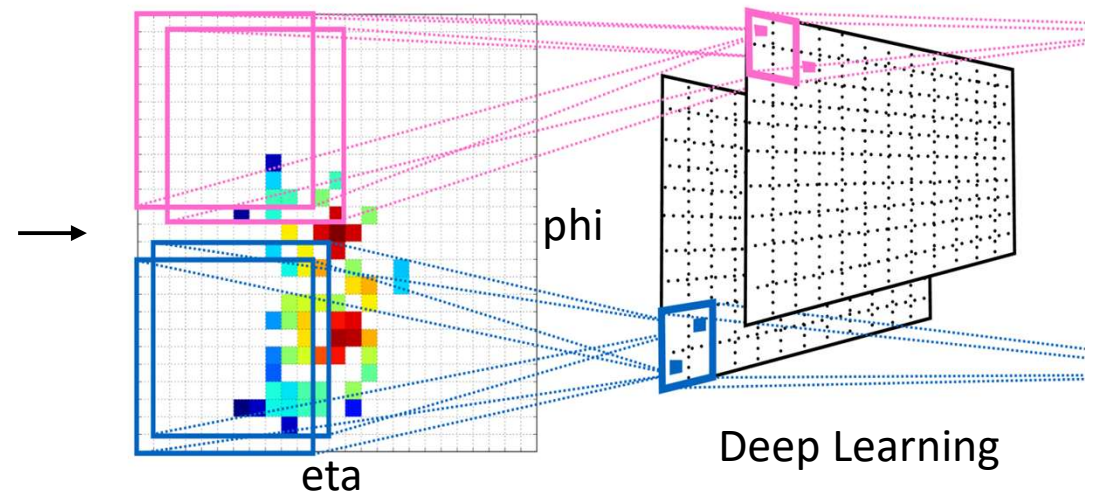
The Solution : Deep Learning

- Deep learning allows you to use all physics information from data.
- One of the successful approach is making LHC data as (jet) image and feed them to deep learning.

Experiment Data

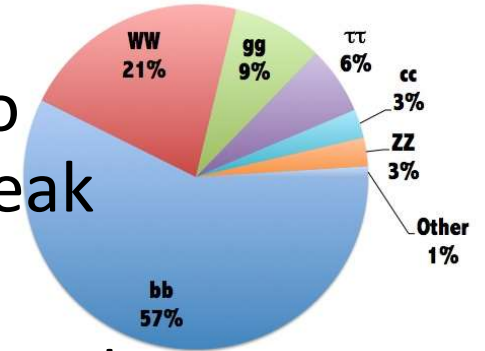


Jet Image

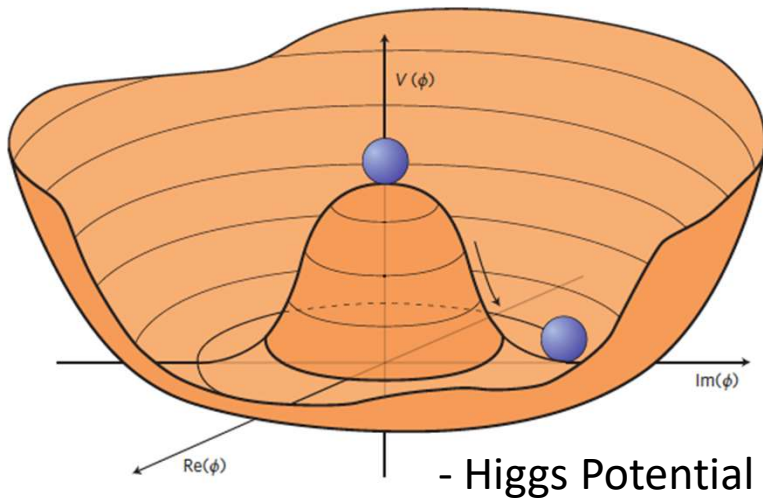


Applications on LHC : Higgs Pair Production

Higgs decays at $m_H=125\text{GeV}$



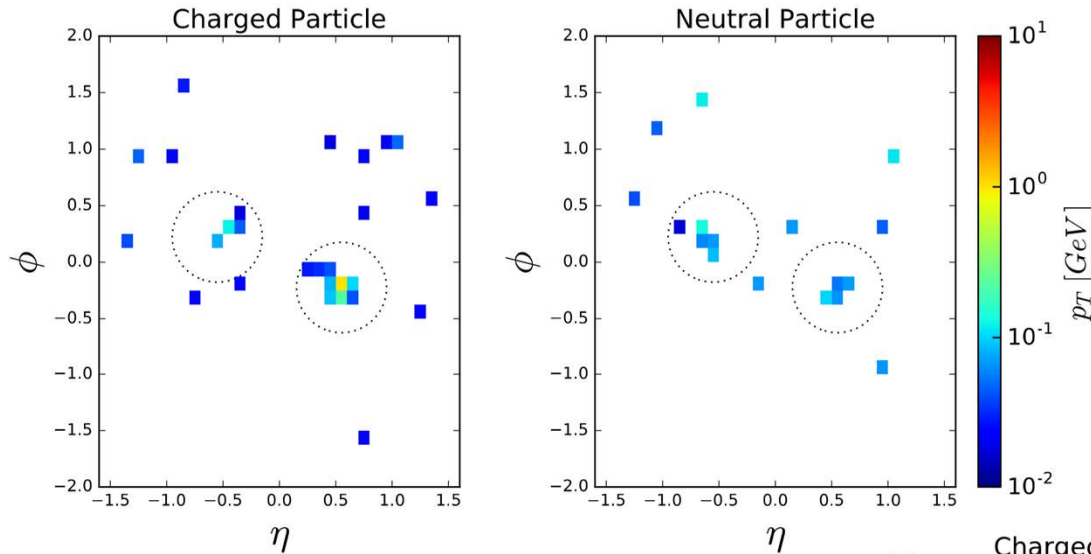
- Higgs pair production is very important to understand Higgs potential and electroweak symmetry breaking of SM.
- Because major decay processes of Higgs are b quarks pair and W boson pair, it suffers from enormous QCD background.



ATL-PHYS-PUB-2017-001 CMS-FTR-15-002-PAS 3 ab^{-1} (14 TeV)

		$N(hh)_{SM}$	N_{BKG}	S/\sqrt{B}
ATLAS	$bb\gamma\gamma$	8.4	47.1	1.2
CMS	$bb\gamma\gamma$	9	26.9	1.7
	$bb\tau\tau$ (fully-hadronic)	4.9	30.3	0.89
	$bb\tau\tau$ (semi-leptonic)	6.1	122	0.55
	$bbWW^*$ (di-leptonic)	37.1	3875	0.60

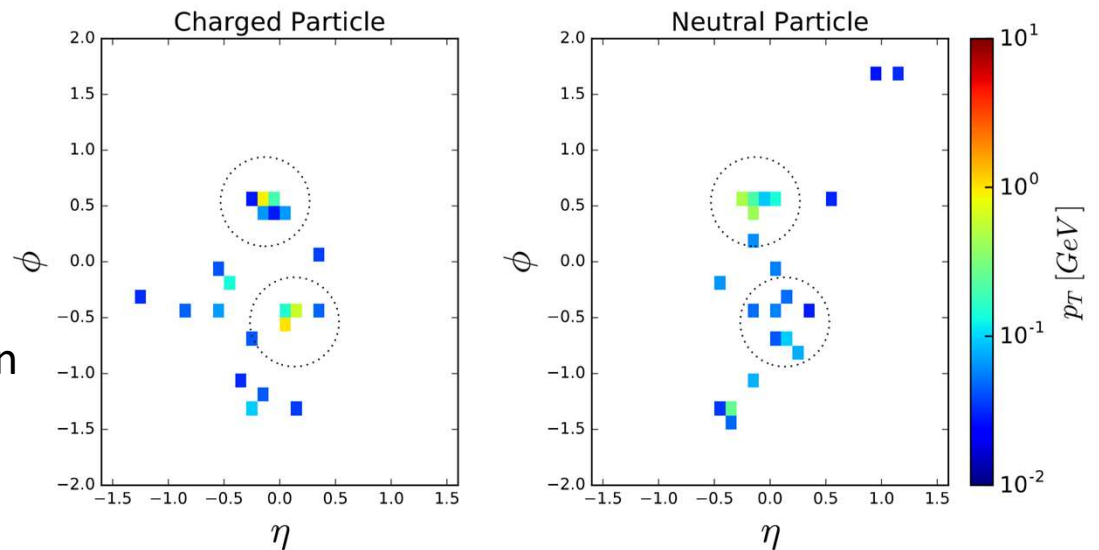
Applications on LHC : Higgs Pair Production



Jet image of signal and background

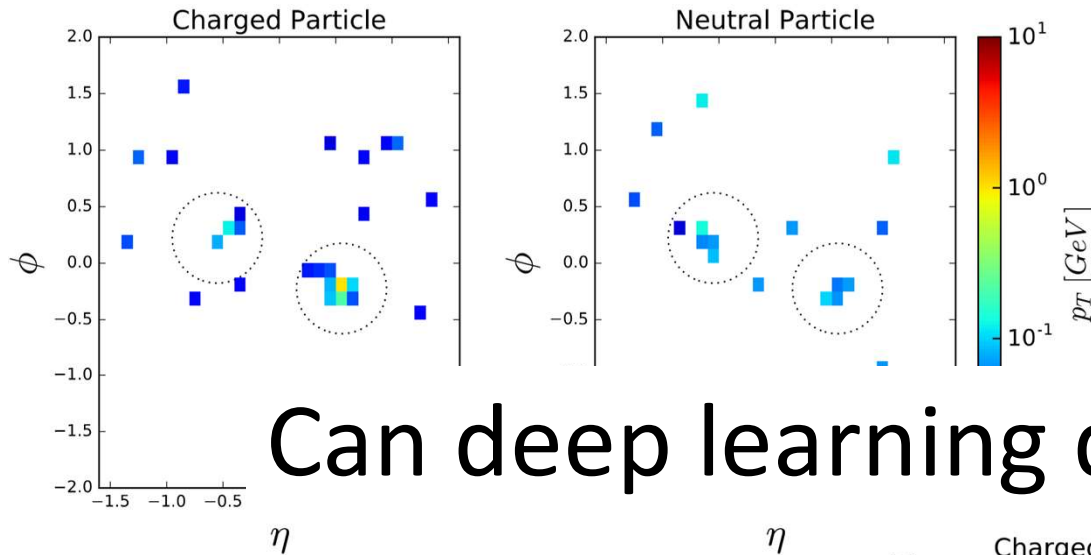
- Higgs pair production
($h h > b b \sim w^- w^+$)

- Top pair production
($t t \sim b b \sim w^- w^+$)



Applications on LHC : Higgs Pair Production

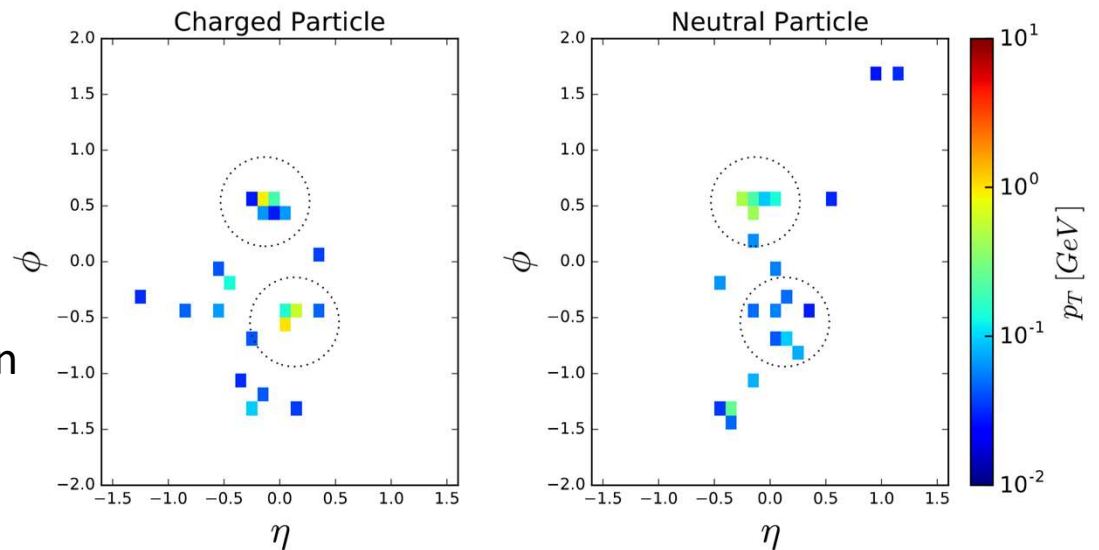
9



Jet image of signal and background

Can deep learning distinguish this?

- Top pair production
($t \bar{t} > b \bar{b} w^- w^+$)



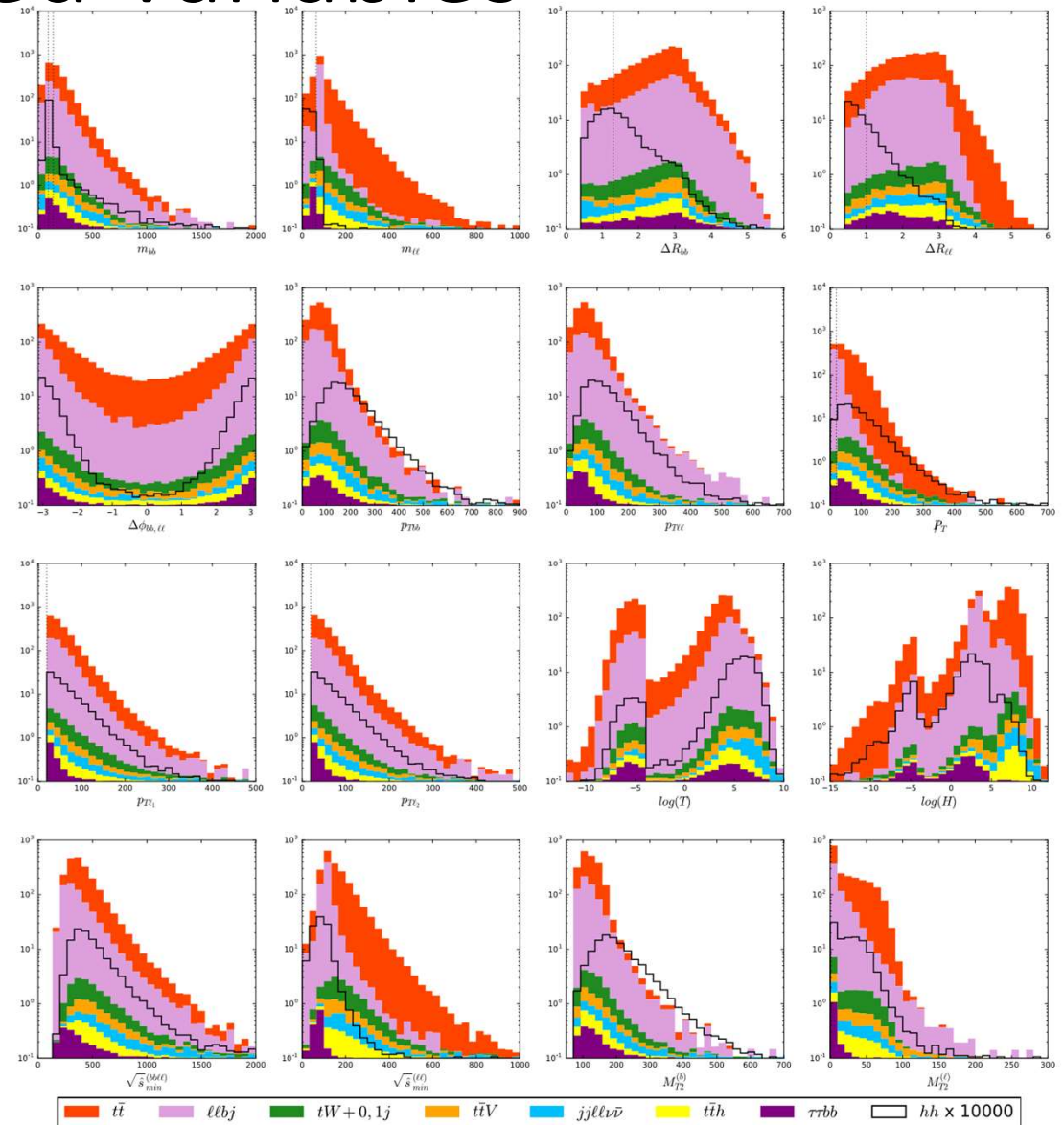
1904.08549

Note : Data Limitation

- Unfortunately, deep learning performance highly depends on the number of data to learn.
- In high energy physics, it is very difficult to generate a lot of data.
- We can enhance DL performance as follows:
 - By using featured variables,
 - By utilizing optimized DL architecture.

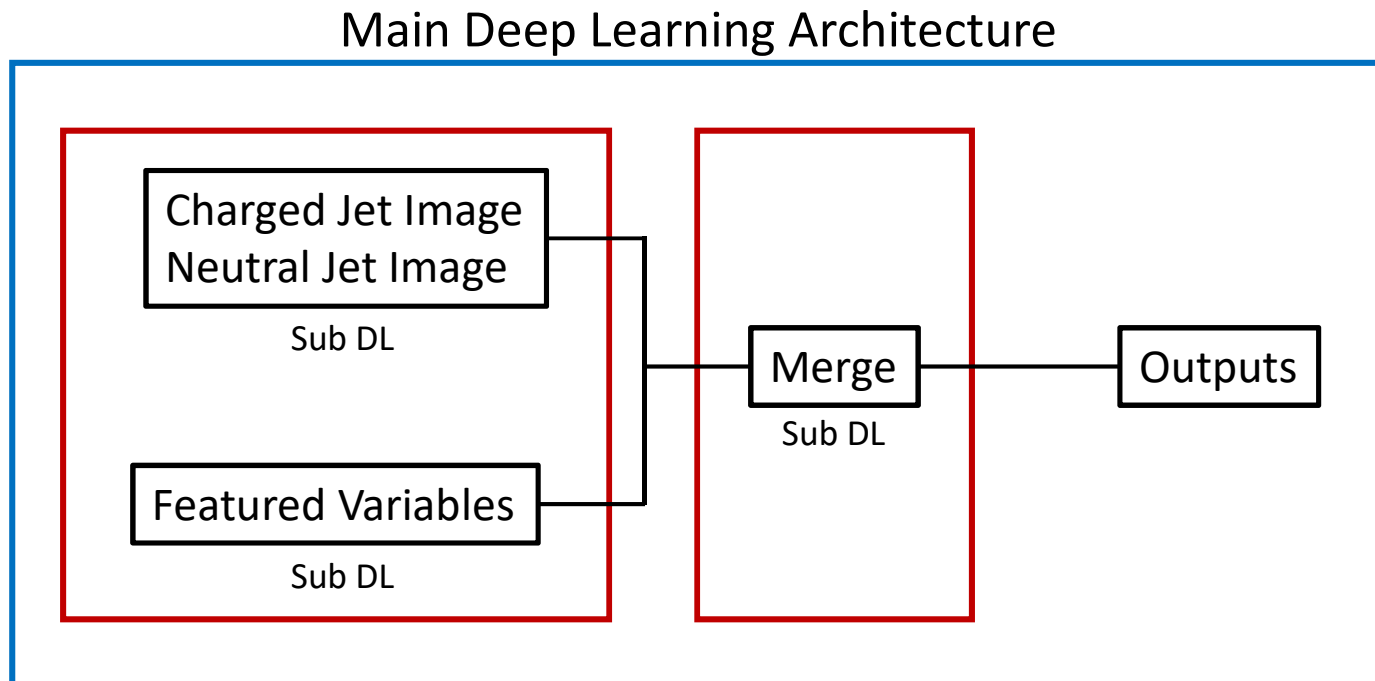
Use of Featured Variables

- We can extract good physical variables from data.
- Its effect is similar to reducing dimensions.



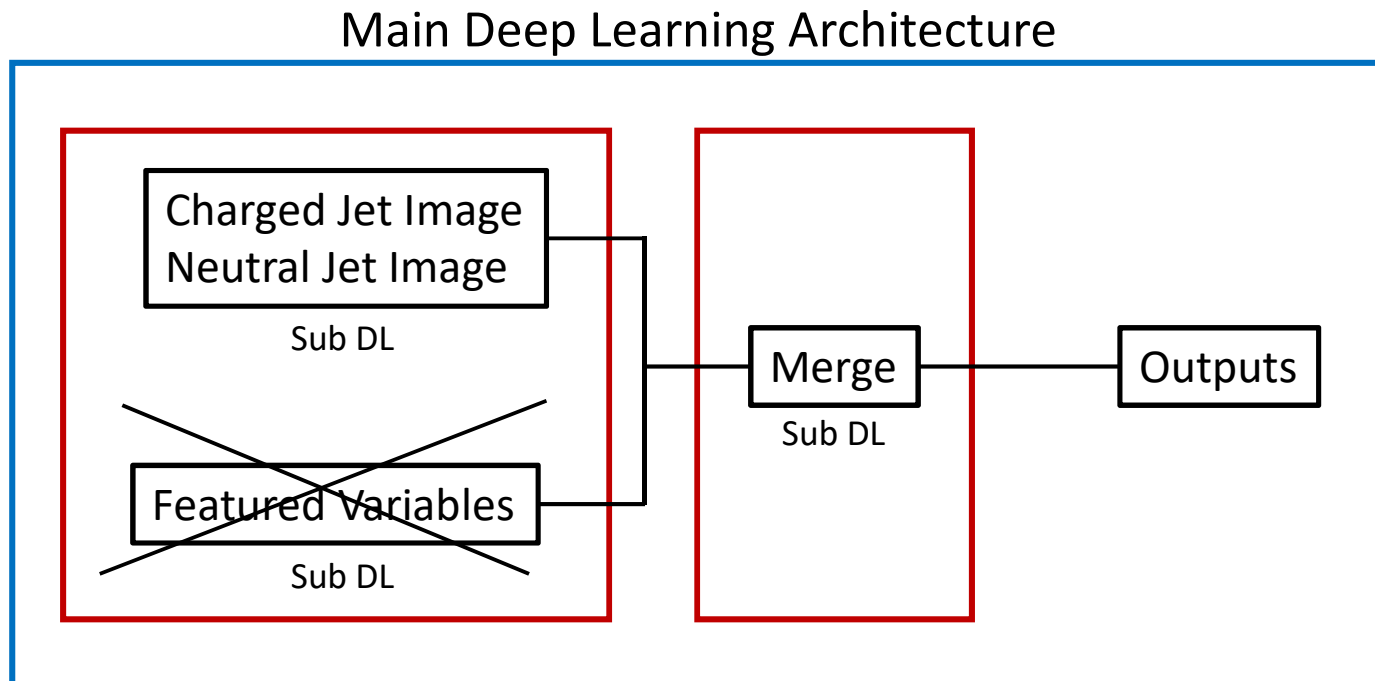
Use of Featured Variables

- We can use jet image and featured variables simultaneously :



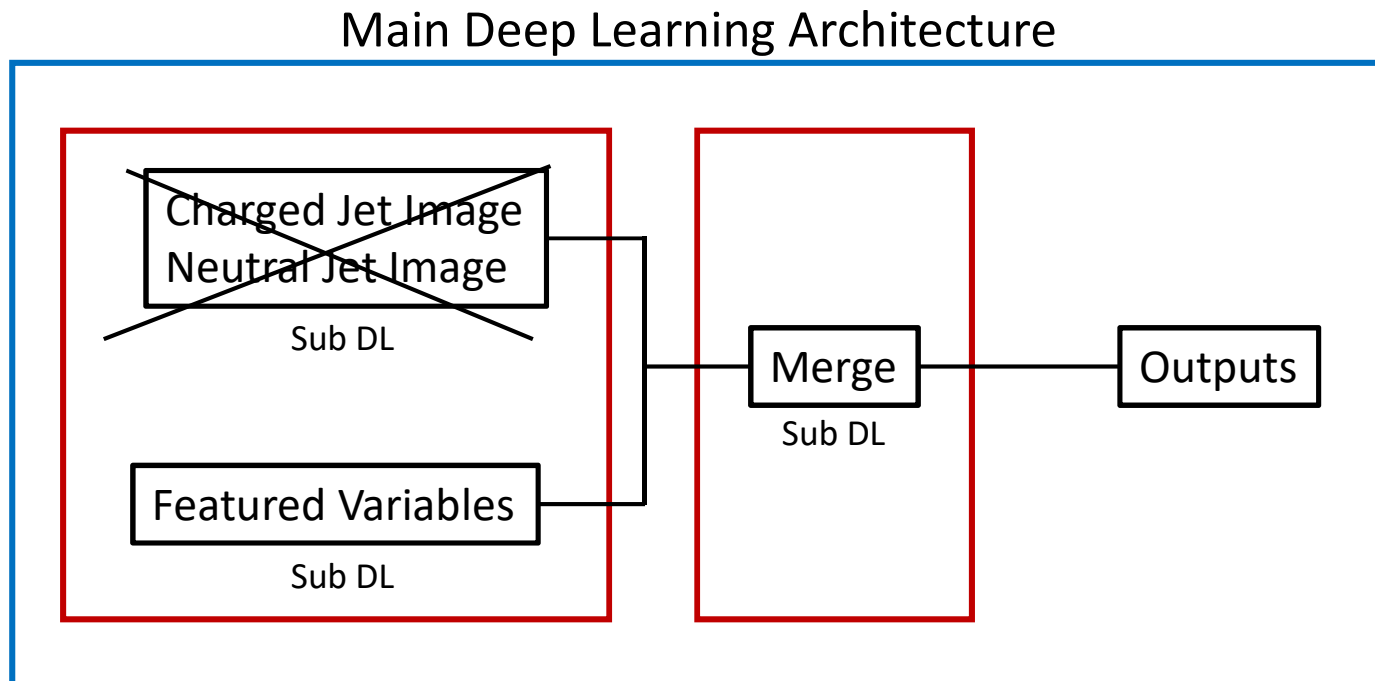
Use of Featured Variables

- We can use jet image and featured variables simultaneously :



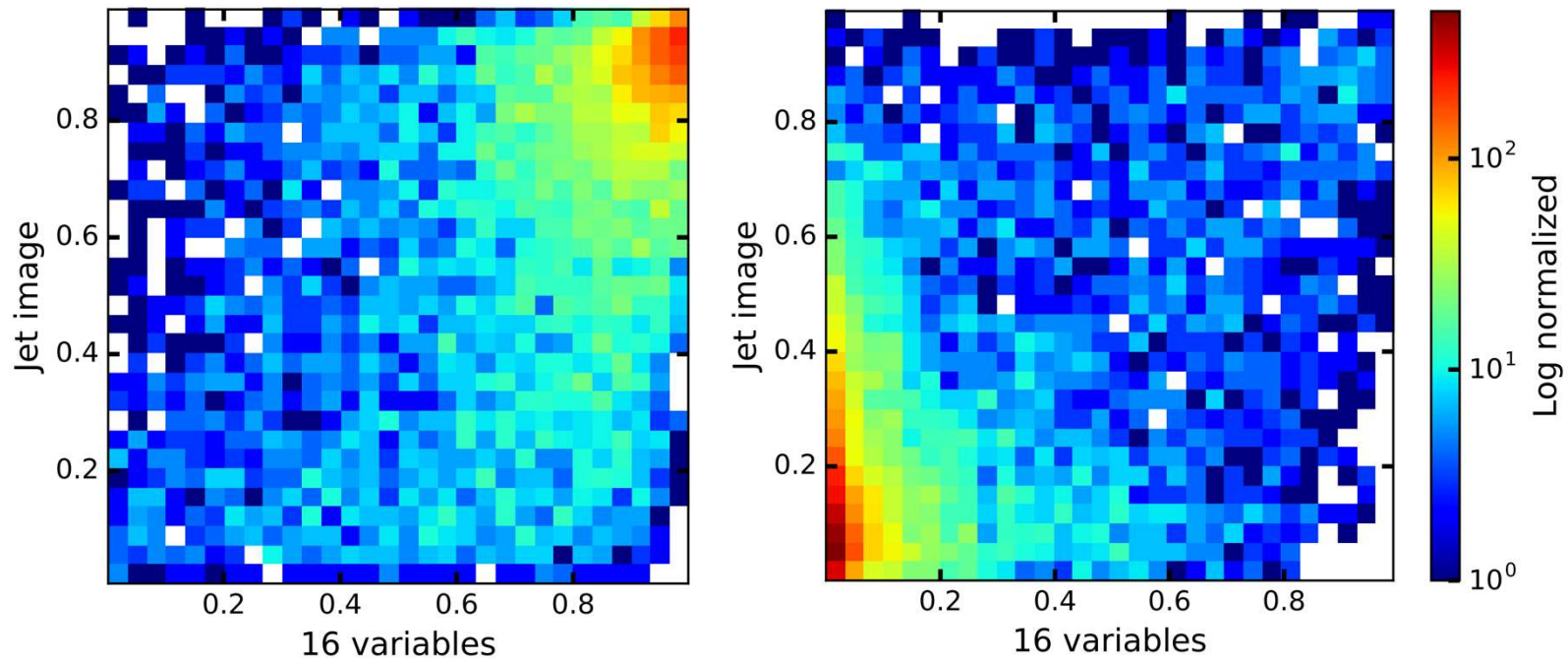
Use of Featured Variables

- We can use jet image and featured variables simultaneously :



Use of Featured Variables

- The correlation between jet image only DL and featured variables only DL clearly shows that there is uncorrelated information!



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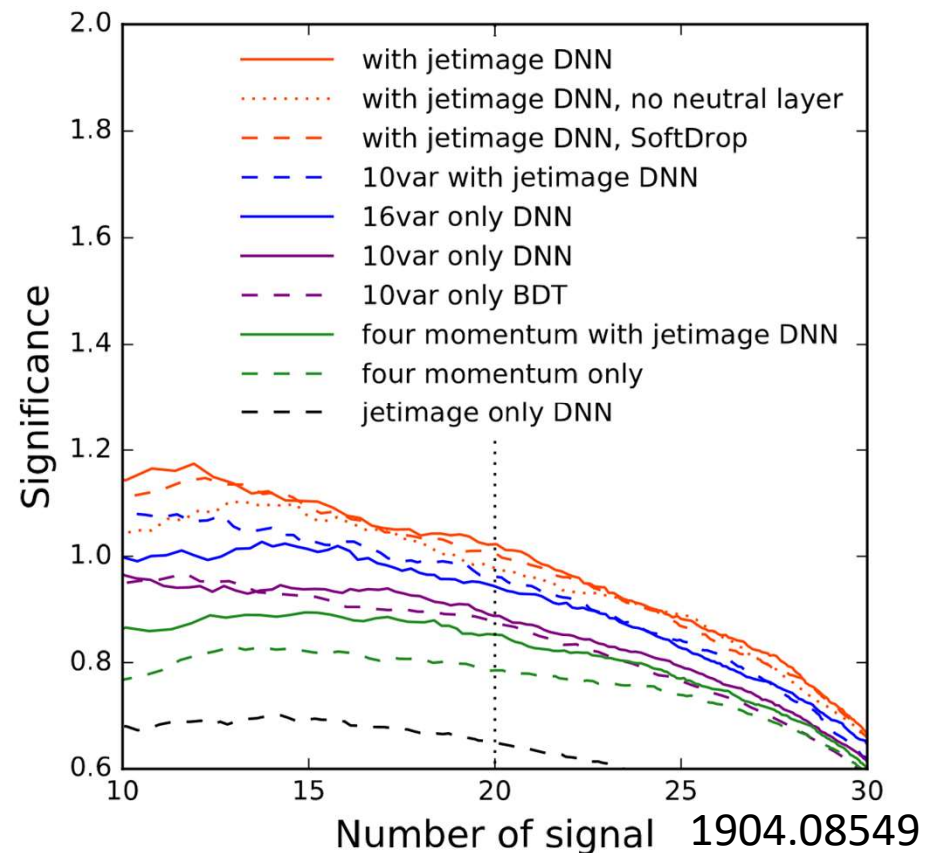
Signal

Background

Use of Featured Variables

- Then deep learning can distinguish signal and background with better performance.

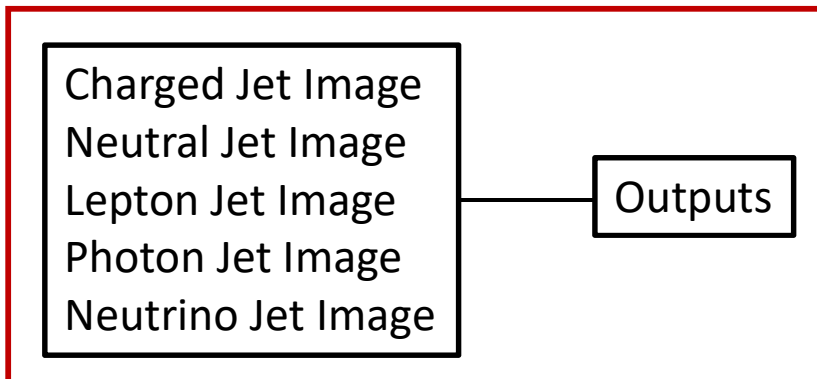
- Signal and (all) background discrimination performance of Higgs pair production with tight cut



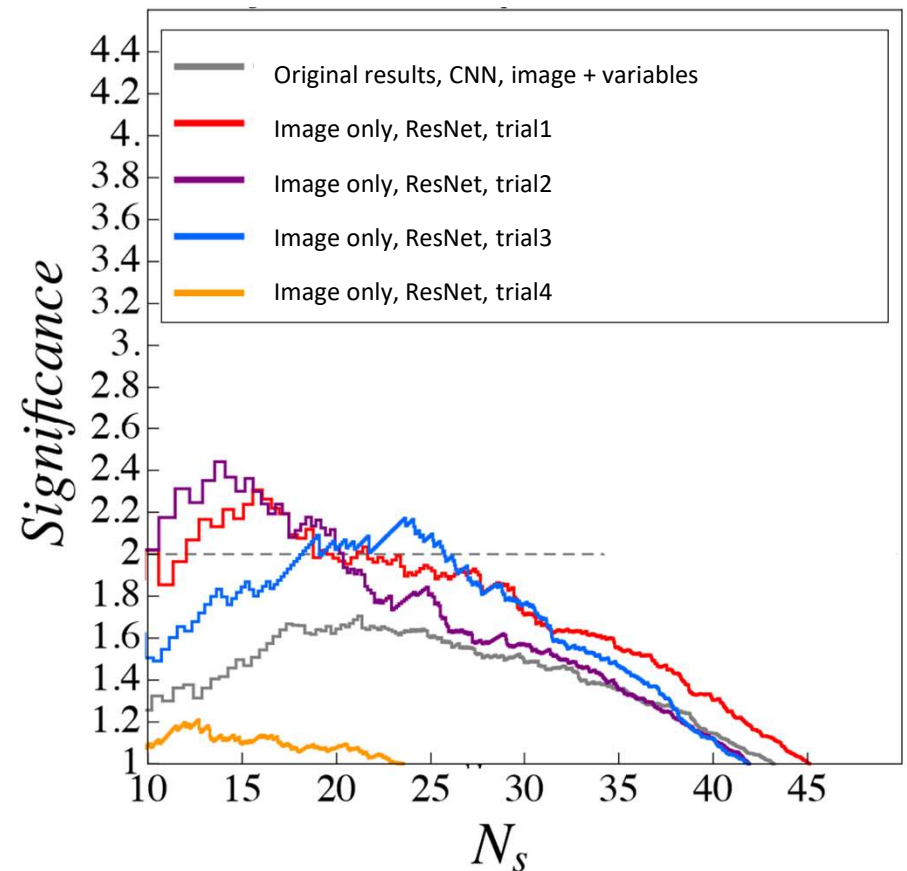
Optimized Deep Learning Architecture

- Appropriate deep learning algorithm can also give us overwhelming performance without featured variables.

Main Deep Learning Architecture



- Preliminary, signal and background (ttbar only) discrimination performance with loose cut



Conclusion

- It is very hard to obtain best performance using traditional analysis method in the HEP.
- Deep learning can be the breakthrough.
- It is showing outstanding performance in various high energy physics problems.

Thanks

Back Up

Higgsness, Topness

- Higgsness and Topness examine how many specific kinematic resembles Higgs or Top quarks.
- We can use momentum which minimize Higgsness or Topness as neutrino momentum.

Higgsness

$$H \equiv \min \left[\frac{(m_{\ell^+\ell^-\nu\bar{\nu}}^2 - m_h^2)^2}{\sigma_{h\ell}^4} + \frac{(m_{\nu\bar{\nu}}^2 - m_{\nu\bar{\nu},peak}^2)^2}{\sigma_\nu^4} \right. \\ \left. + \min \left(\frac{(m_{\ell^+\nu}^2 - m_W^2)^2}{\sigma_W^4} + \frac{(m_{\ell^-\bar{\nu}}^2 - m_{W^*,peak}^2)^2}{\sigma_{W^*}^4}, \right. \right. \\ \left. \left. \frac{(m_{\ell^-\bar{\nu}}^2 - m_W^2)^2}{\sigma_W^4} + \frac{(m_{\ell^+\nu}^2 - m_{W^*,peak}^2)^2}{\sigma_{W^*}^4} \right) \right],$$

Topness

$$T \equiv \min(\chi_{12}^2, \chi_{21}^2) . \\ \chi_{ij}^2 \equiv \min_{\vec{p}_T = \vec{p}_{\nu T} + \vec{p}_{\bar{\nu} T}} \left[\frac{(m_{b_i\ell^+\nu}^2 - m_t^2)^2}{\sigma_t^4} + \frac{(m_{\ell^+\nu}^2 - m_W^2)^2}{\sigma_W^4} \right. \\ \left. + \frac{(m_{b_j\ell^-\bar{\nu}}^2 - m_t^2)^2}{\sigma_t^4} + \frac{(m_{\ell^-\bar{\nu}}^2 - m_W^2)^2}{\sigma_W^4} \right],$$

ResNet

- Residual network (ResNet) uses operation jumping which prevents gradient vanishing problem.

residual learning

