

Measurement of the SM Higgs properties at the LHC

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Based on arXiv:2209.03898

Based on arXiv:2303.HOPESoon

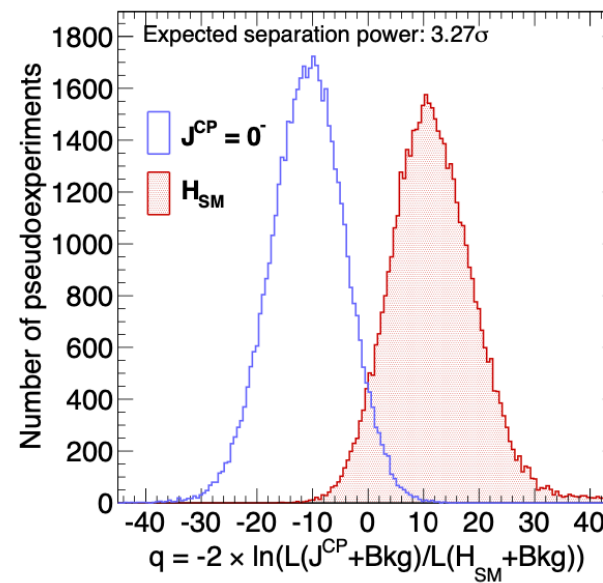
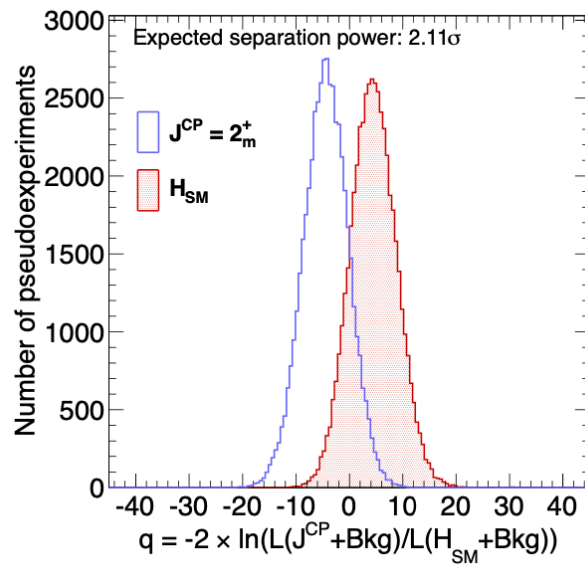
2023 CAU BSM Workshop

Precision SM Higgs @ LHC

- Confirming Higgs properties
Mass, Width, **Spin, CP-property** : **DONE**
[PRD87\(2013\) 5, 055006](#), [PRD89\(2014\)034002](#)
- Confirming a **breaking electroweak symmetry** : **DONE**
[PRL111\(2013\) 041801](#)
- Confirming Yukawa coupling : **Going well**
- Confirming the **shape of Higgs potential**, up to H^3 : **Going well**
[PRL111\(2013\) 041801](#), [JHEP 1909\(2019\) 047](#)

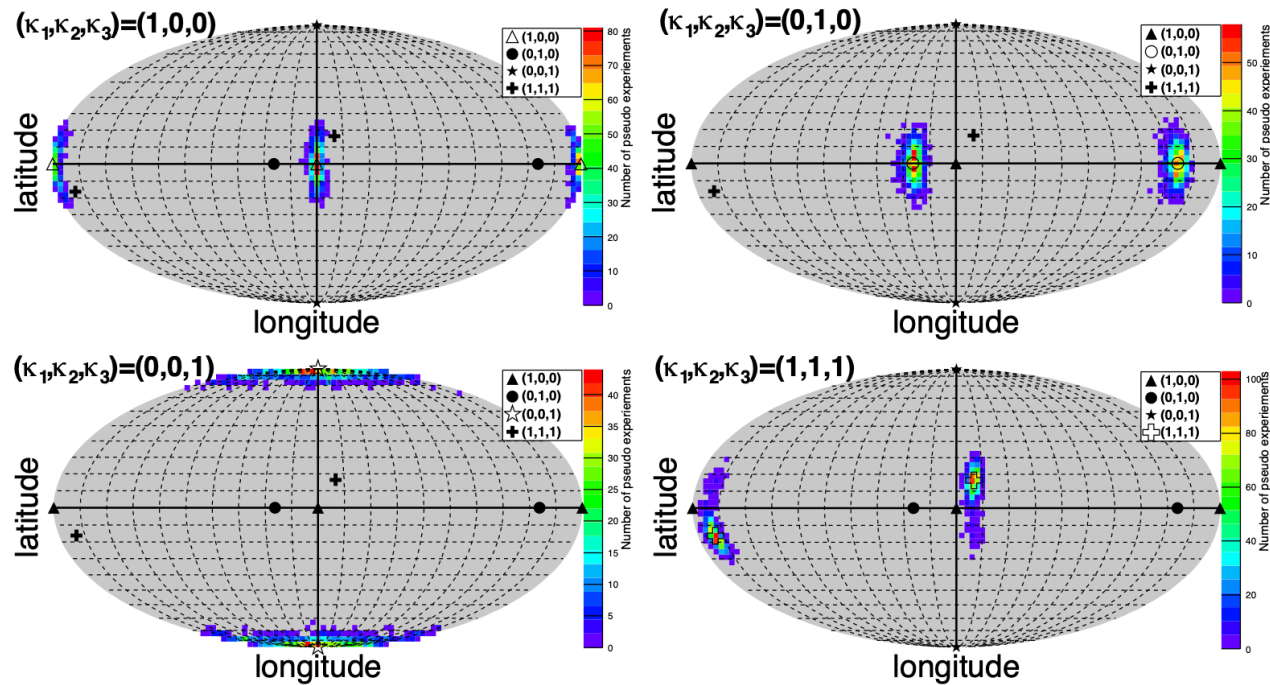
- Spin, CP-property

$$KD(A; B) = \ln \left(\frac{|\mathcal{M}_A(a + b \rightarrow 4\ell)|^2}{|\mathcal{M}_B(a' + b' \rightarrow 4\ell)|^2} \right)$$



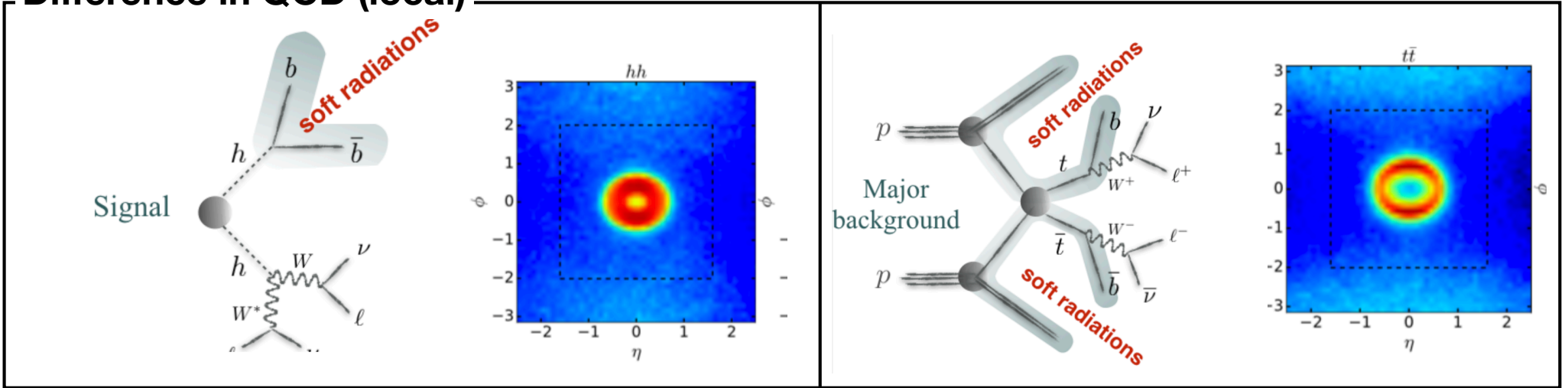
- breaking electroweak symmetry

$$\mathcal{L} = -X \left[\kappa_1 \frac{M_Z^2}{v} Z_\mu Z^\mu + \frac{\kappa_2}{2v} F_{\mu\nu} F^{\mu\nu} + \frac{\kappa_3}{2v} F_{\mu\nu} \tilde{F}^{\mu\nu} \right]$$

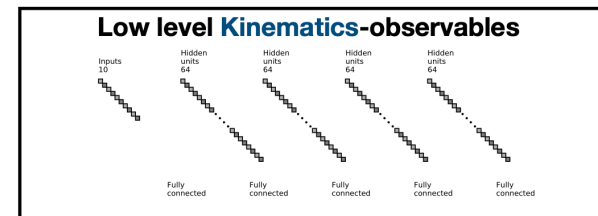
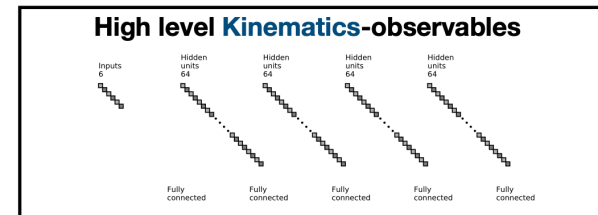
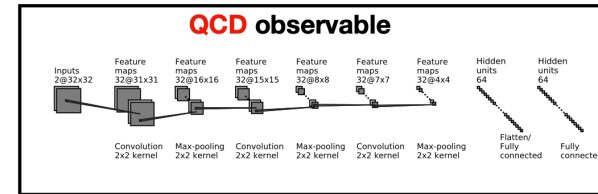
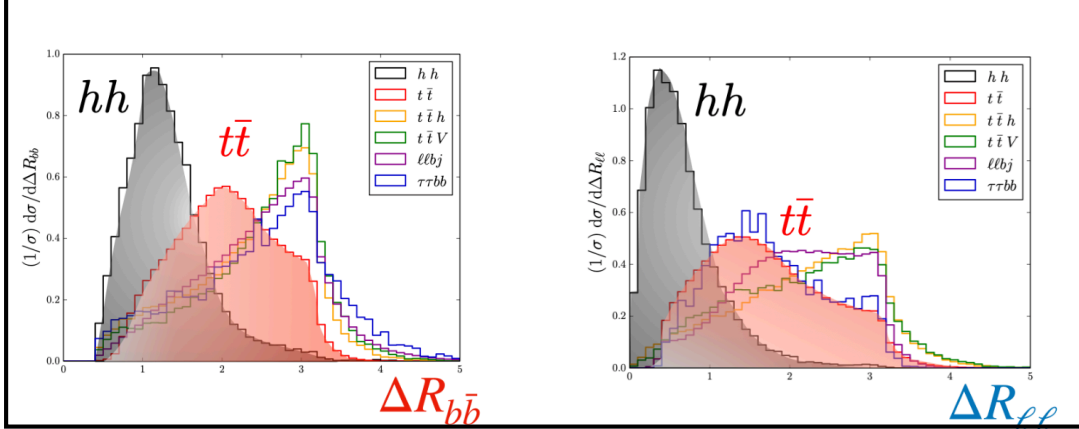


- shape of Higgs potential, up to H^3

Difference in QCD (local)

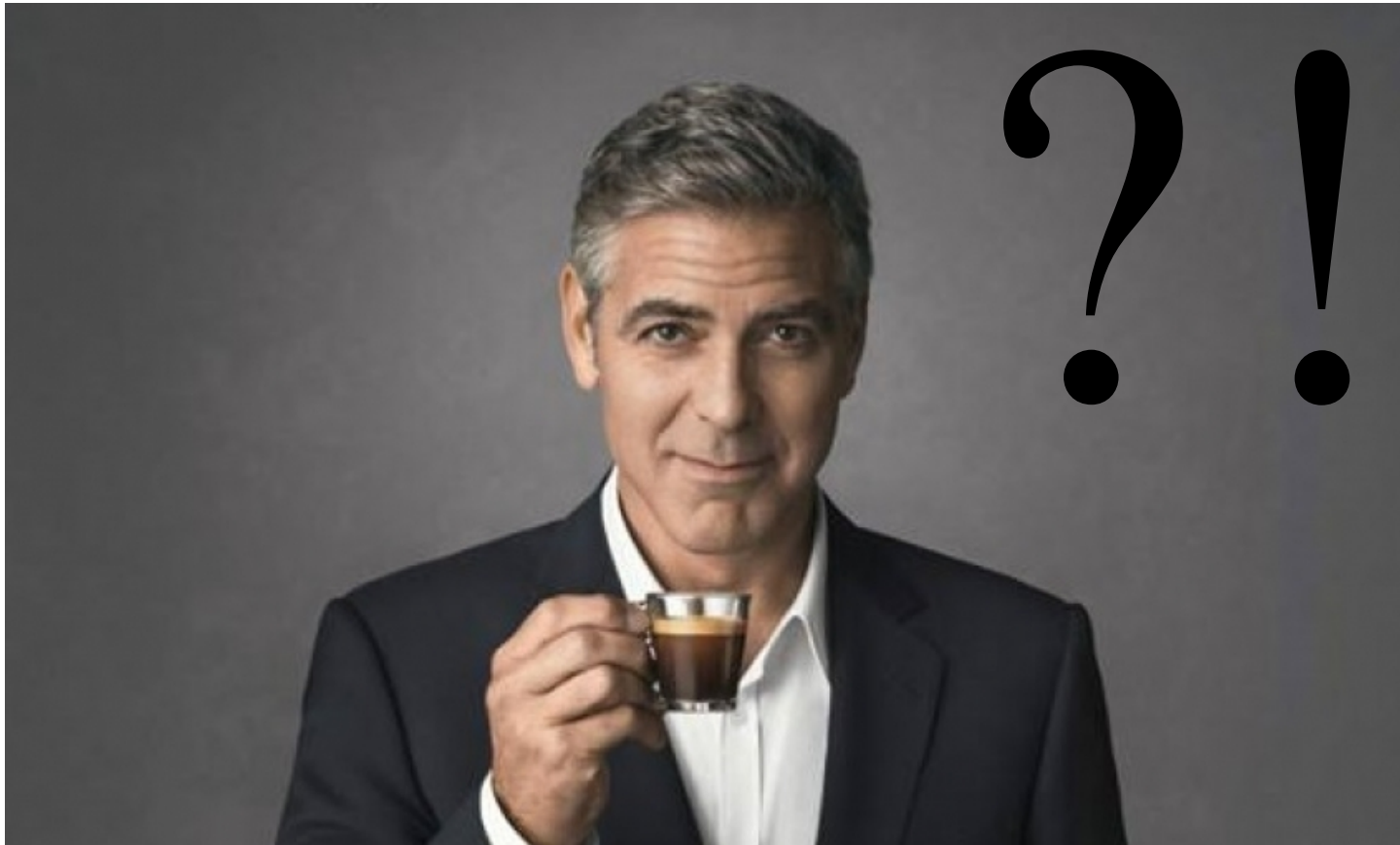


Difference in a phase space (global)



α
 β
 γ
Deep Learning Score
Separation

What else?



Color charge of Higgs ?

- Everybody knows SM **Higgs is colorless !**

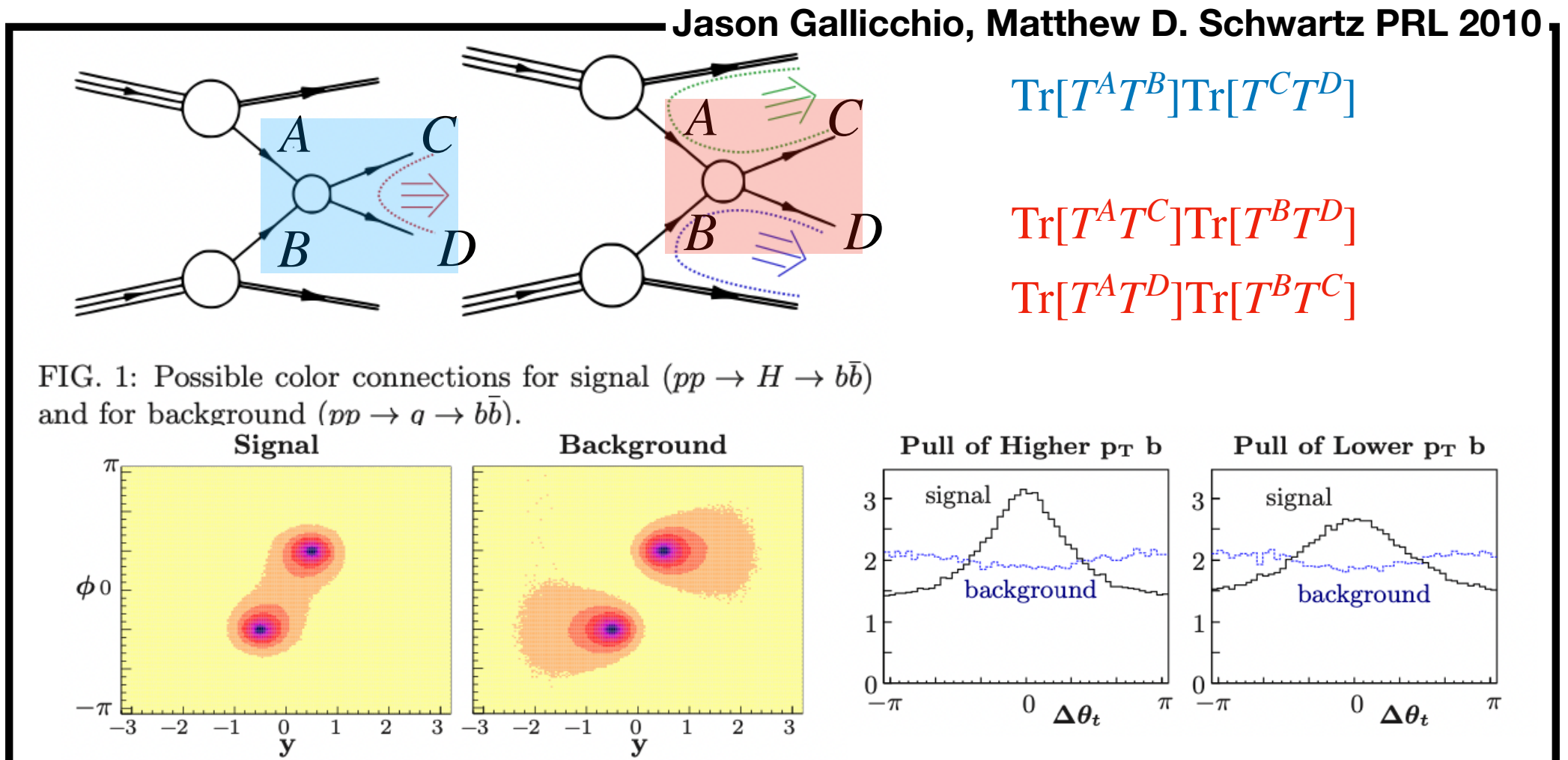
- But, I decided to check

"how can we **directly** measure the color charge of the **Higgs**" @ the LHC ?

- We can use this method to separate $H \rightarrow b\bar{b}$
from $g \rightarrow b\bar{b}$

Basic guide line

- Soft radiations along the color flow



Good news

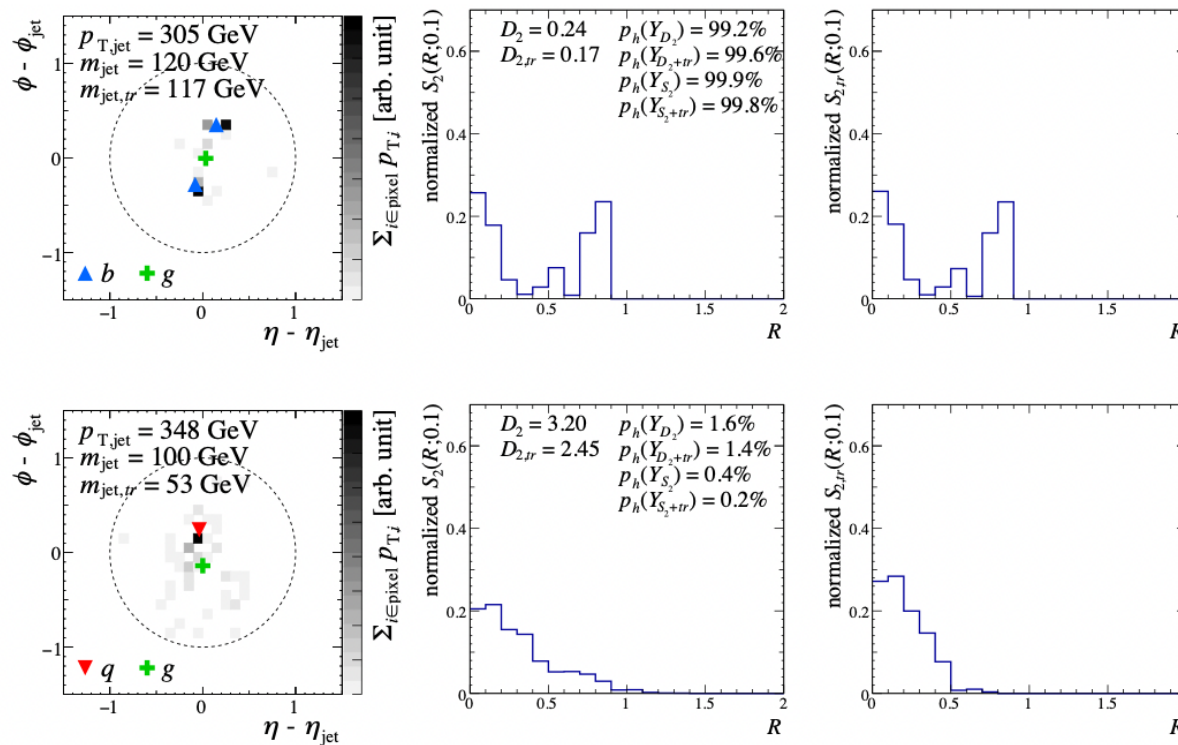
- There have been very good theoretical studies, but

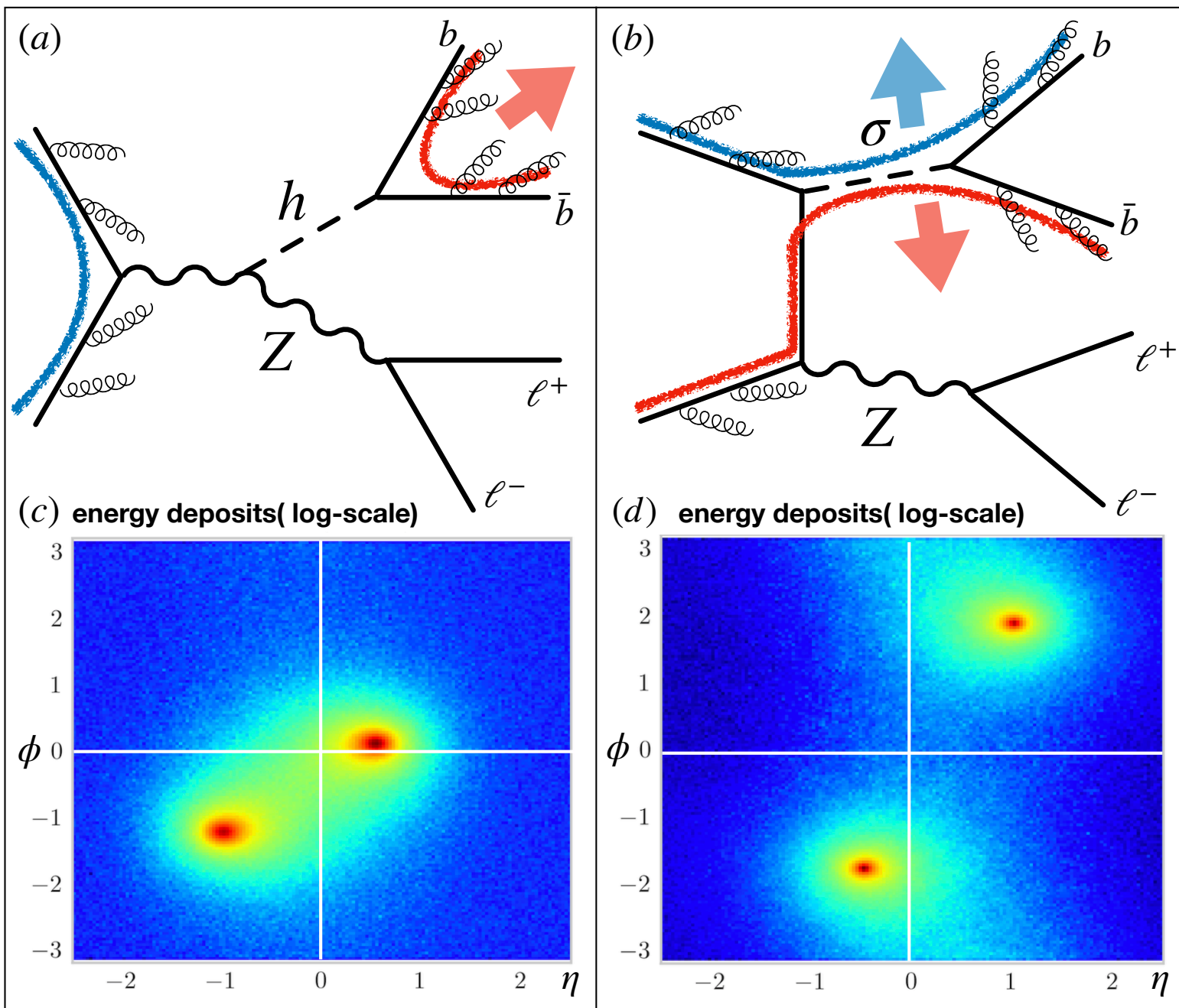
No consideration about the **"finite" LHC statistics** (up to HL-LHC)

- **Armed with "DEEP and complicated" Neural Network,**
there have been lots of studies on "jet-tagging" with ML

- Based on "spectral function", $S_2(R, \Delta R) = \frac{1}{\Delta R} \sum_{R_{ij} \in [R, R+\Delta R]} p_{T,i} p_{T,j}$

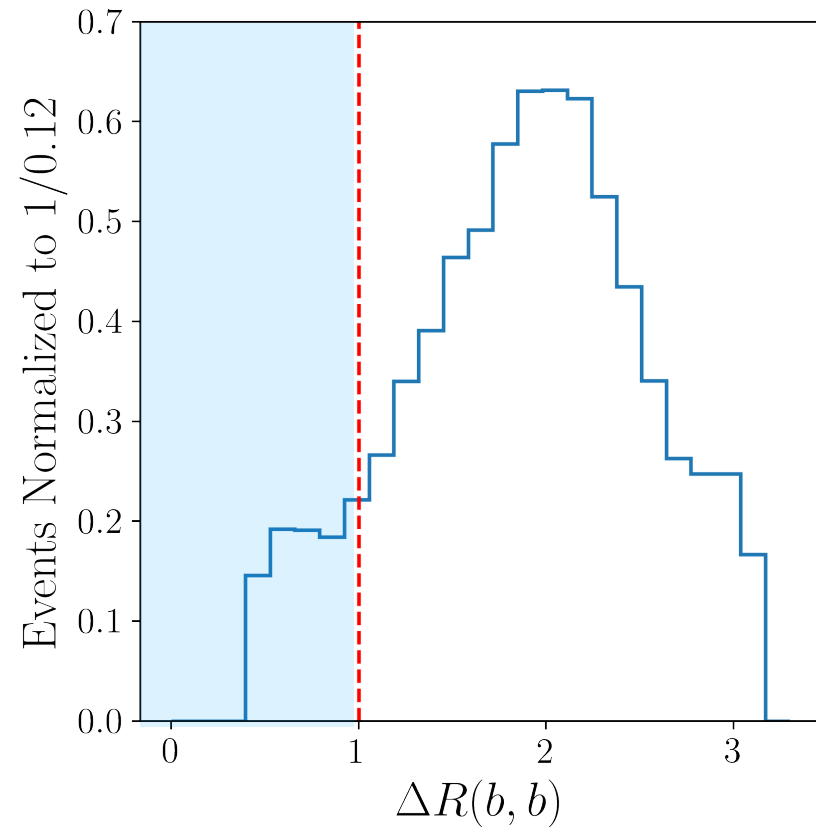
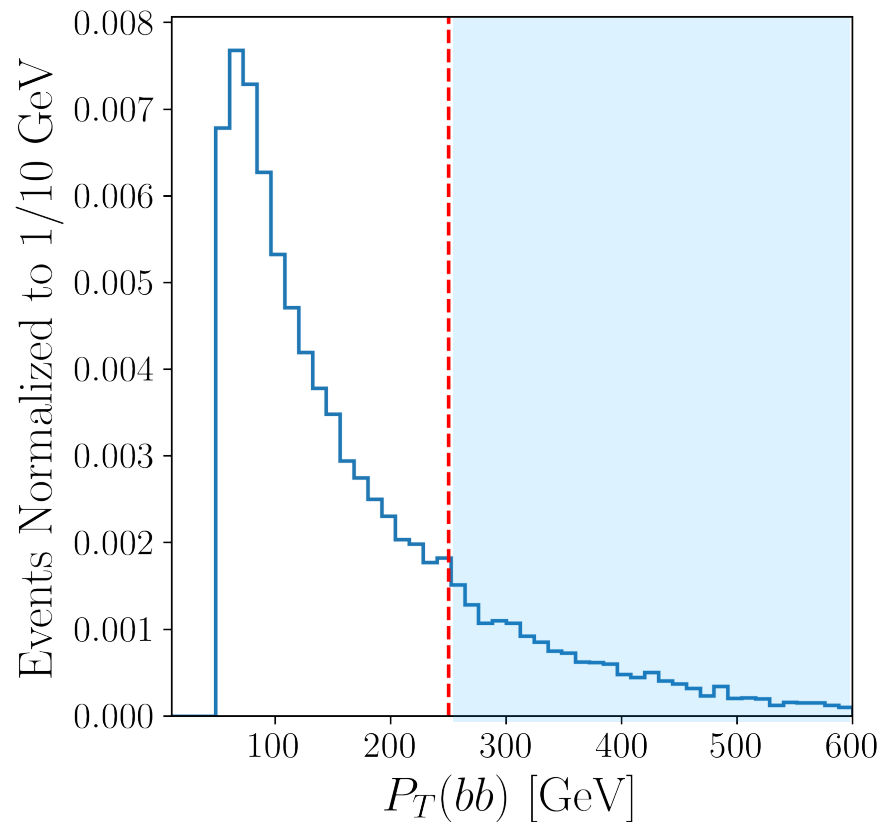
achieved an "**Understandable**" neural network and get **better performance**...
but in the **BOOSTED region**



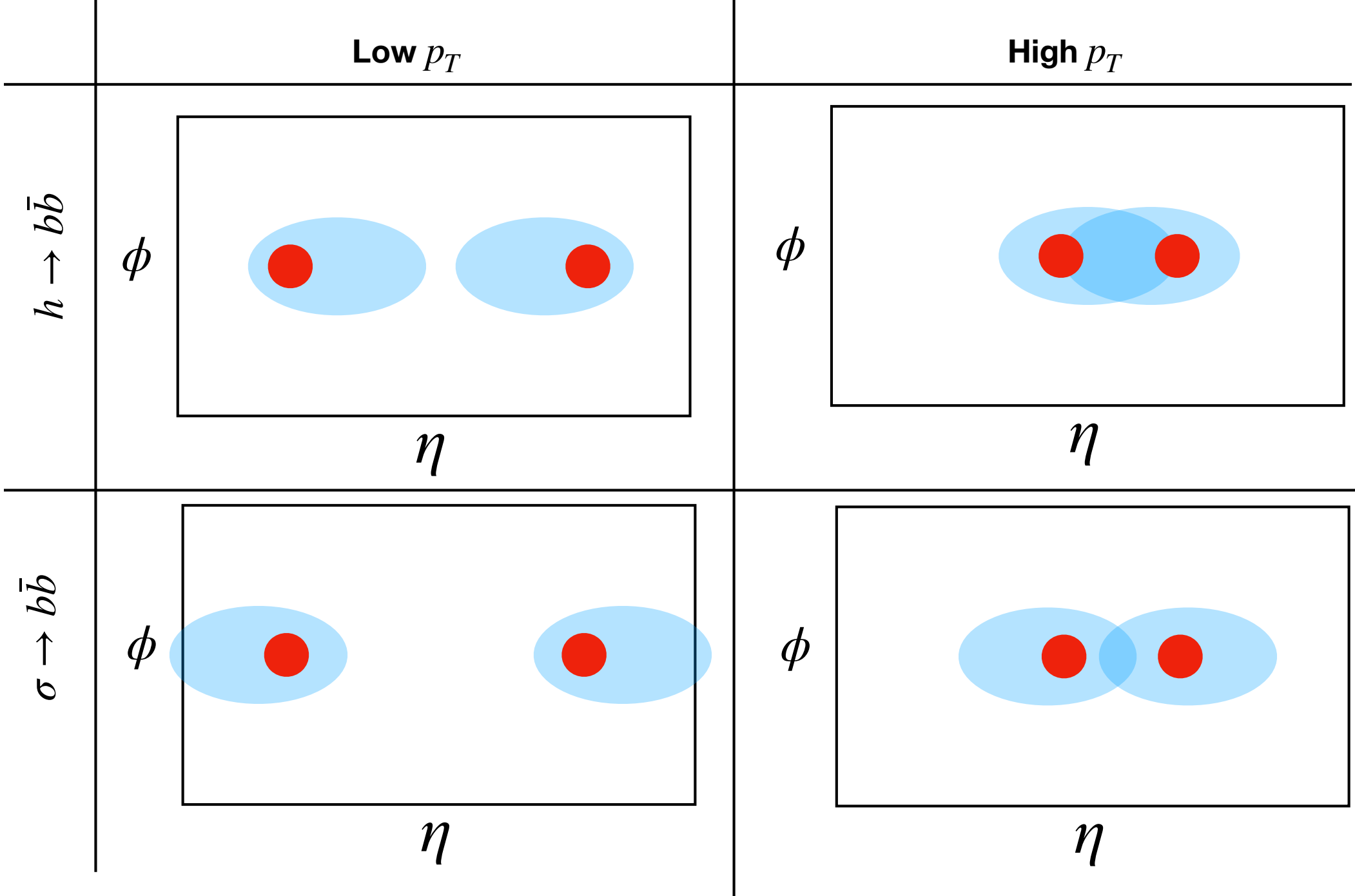


NOT boosted Higgs?

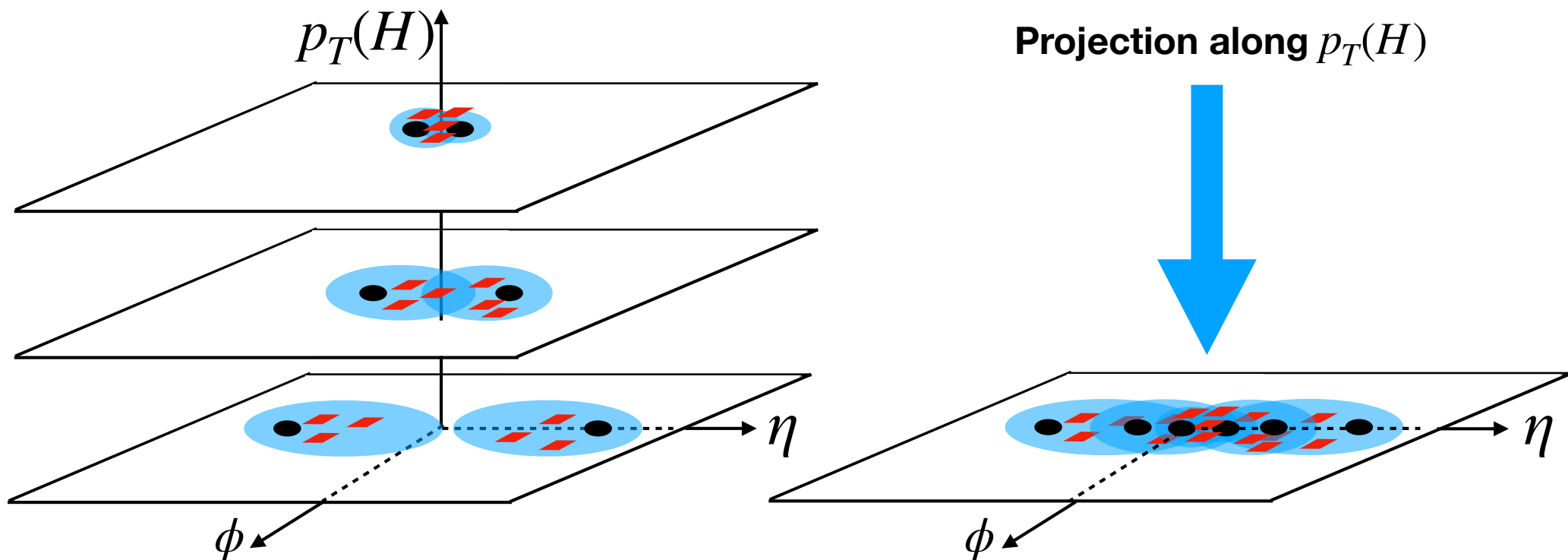
$pp \rightarrow HZ @ 13\text{TeV LHC}$



- Of course, we loose STATISTICS



- Due to the **softness of radiations**, everyone (even ML) get focused on **hot cores (b/\bar{b})**

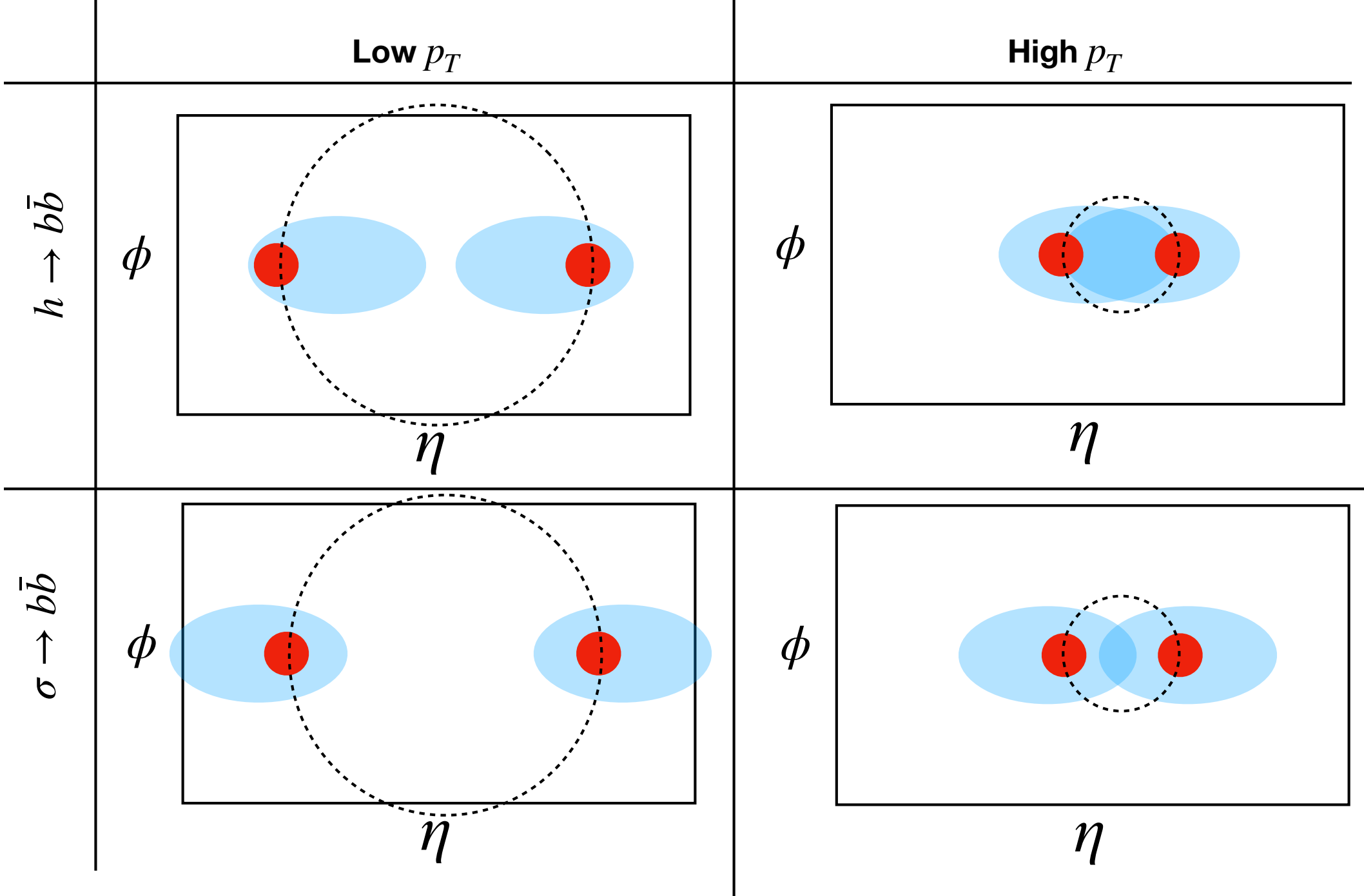


- If one tries to study various $p_T(H)$ ranges, even ML will not give a good performance.

How can we use

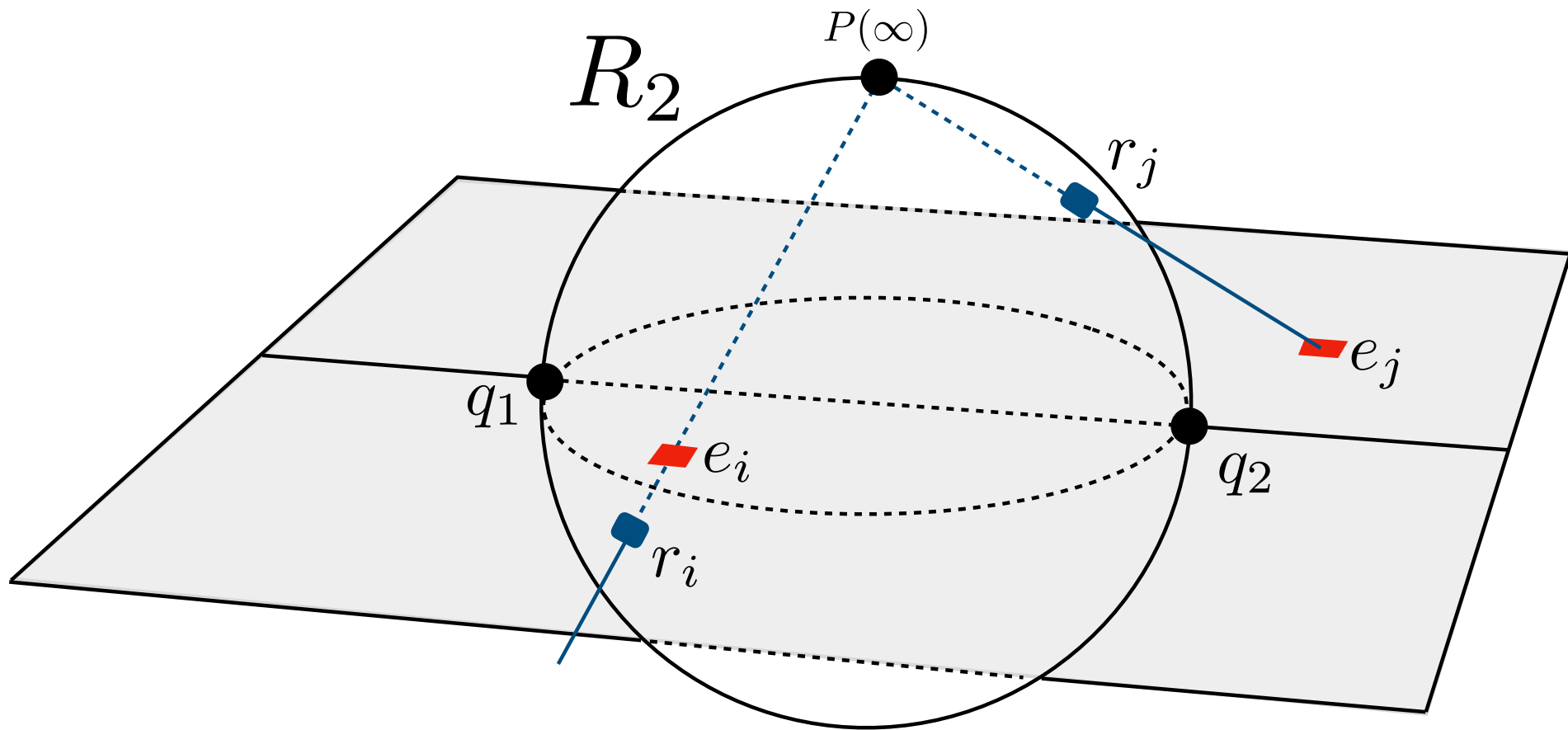
"full p_T range" of "Higgs"?

- for the actual LHC test

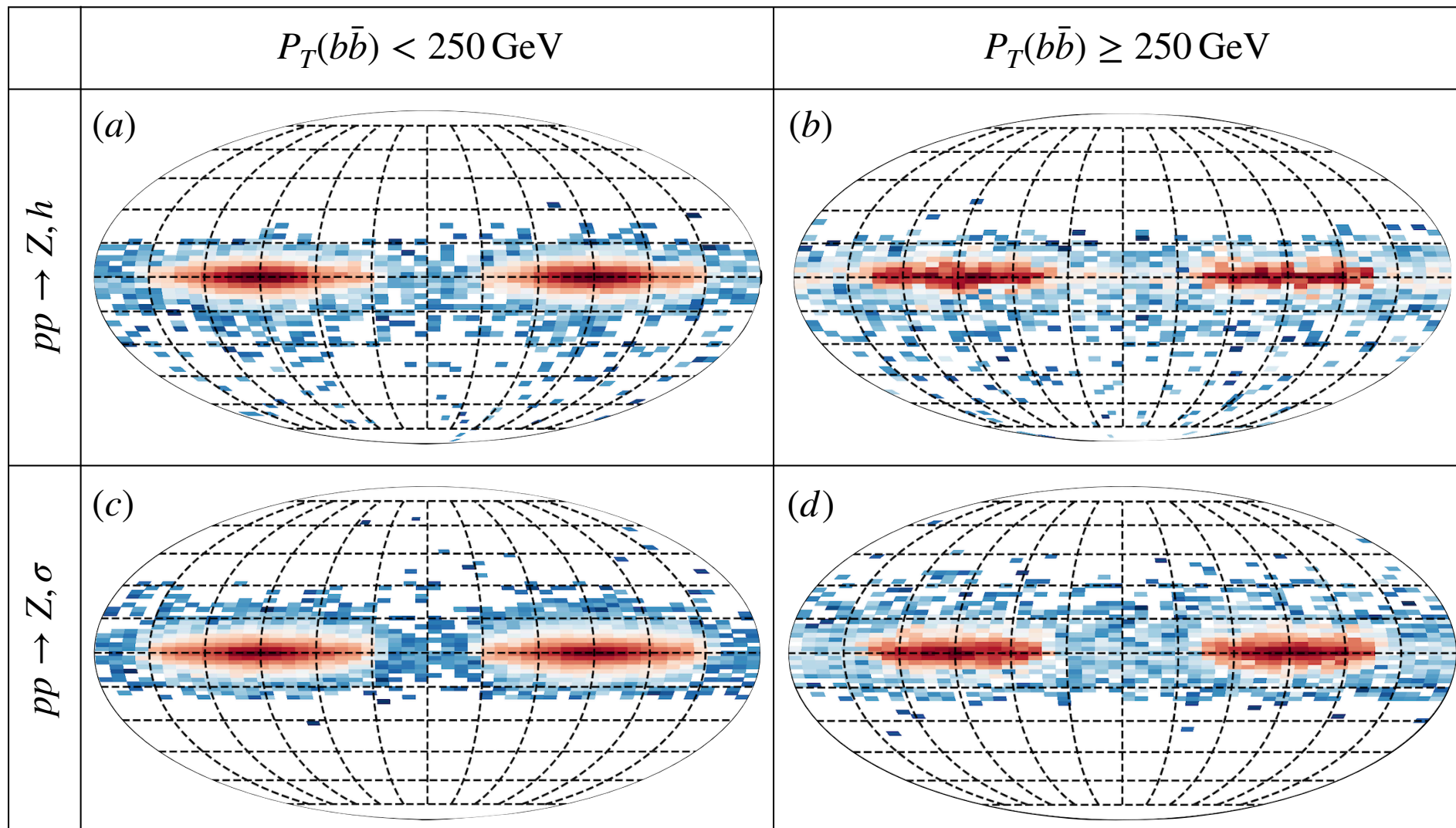


- A binary problem, either "**inside**" or "**outside**" a circle.

Inverse stereographic projection

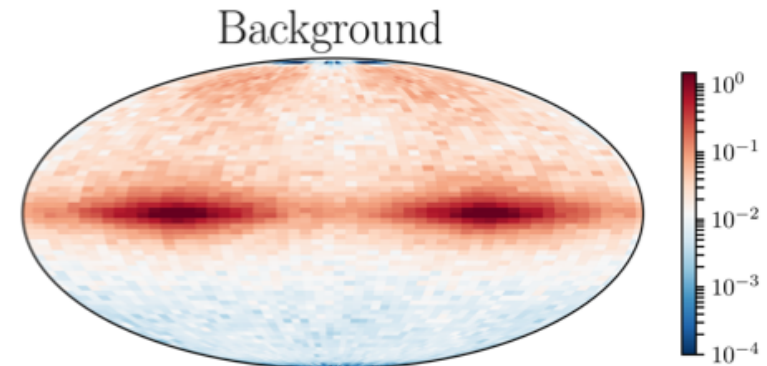
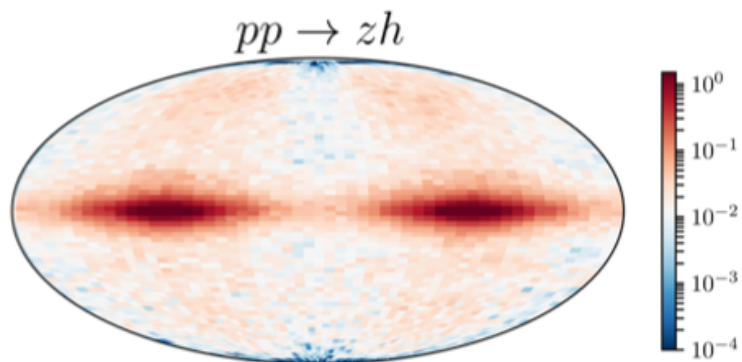


- Soft radiations which are
inside of a circle \rightarrow Southern hemisphere (H)
outside of a circle \rightarrow North hemisphere (σ)

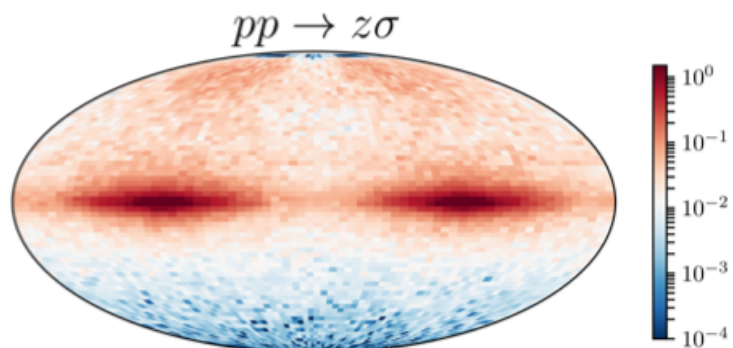


Landscape of Color activity

- Accumulated 5000 events shot

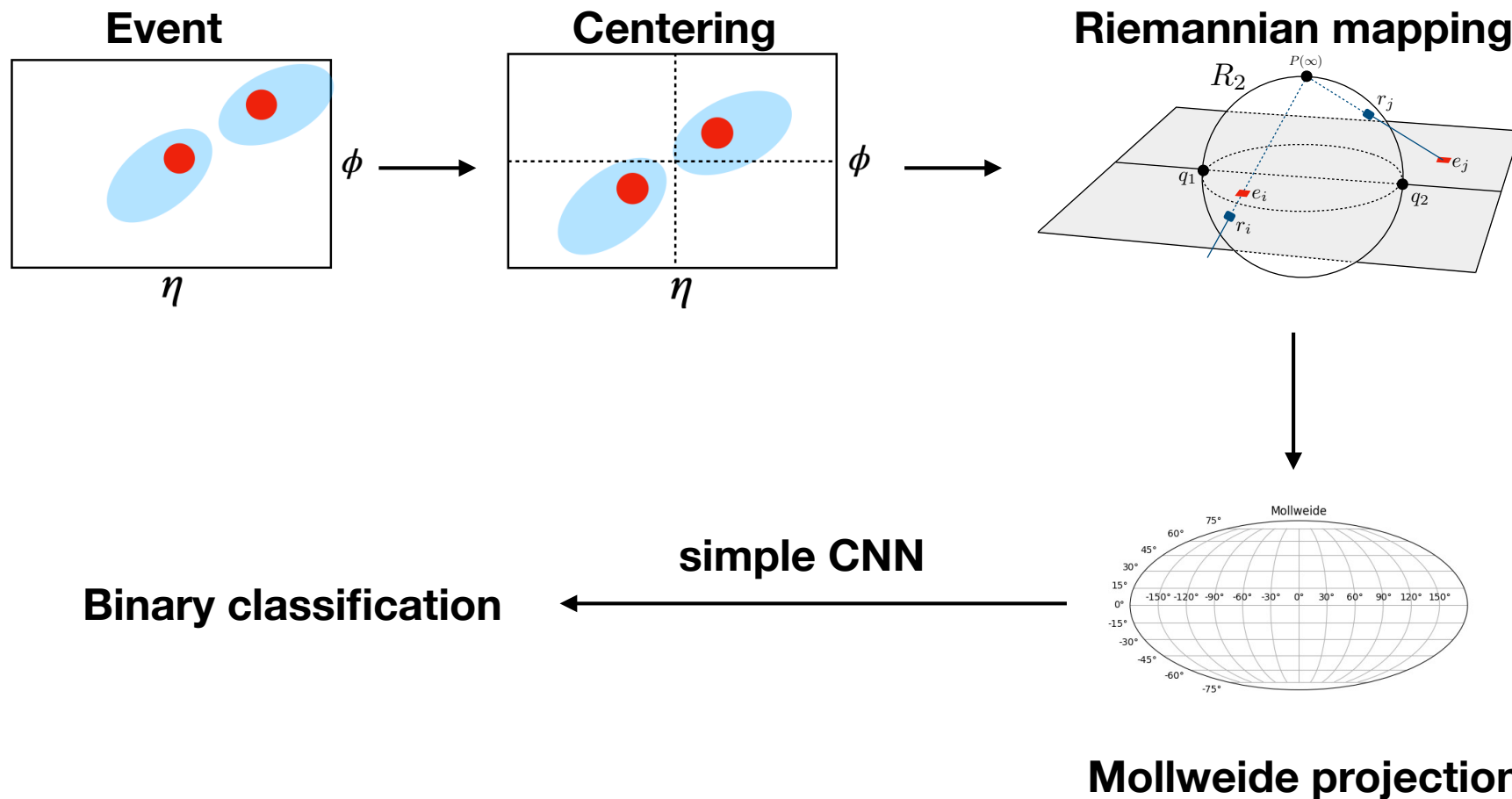


$(V + js, t\bar{t}, t(\bar{t}), VV, \dots)$

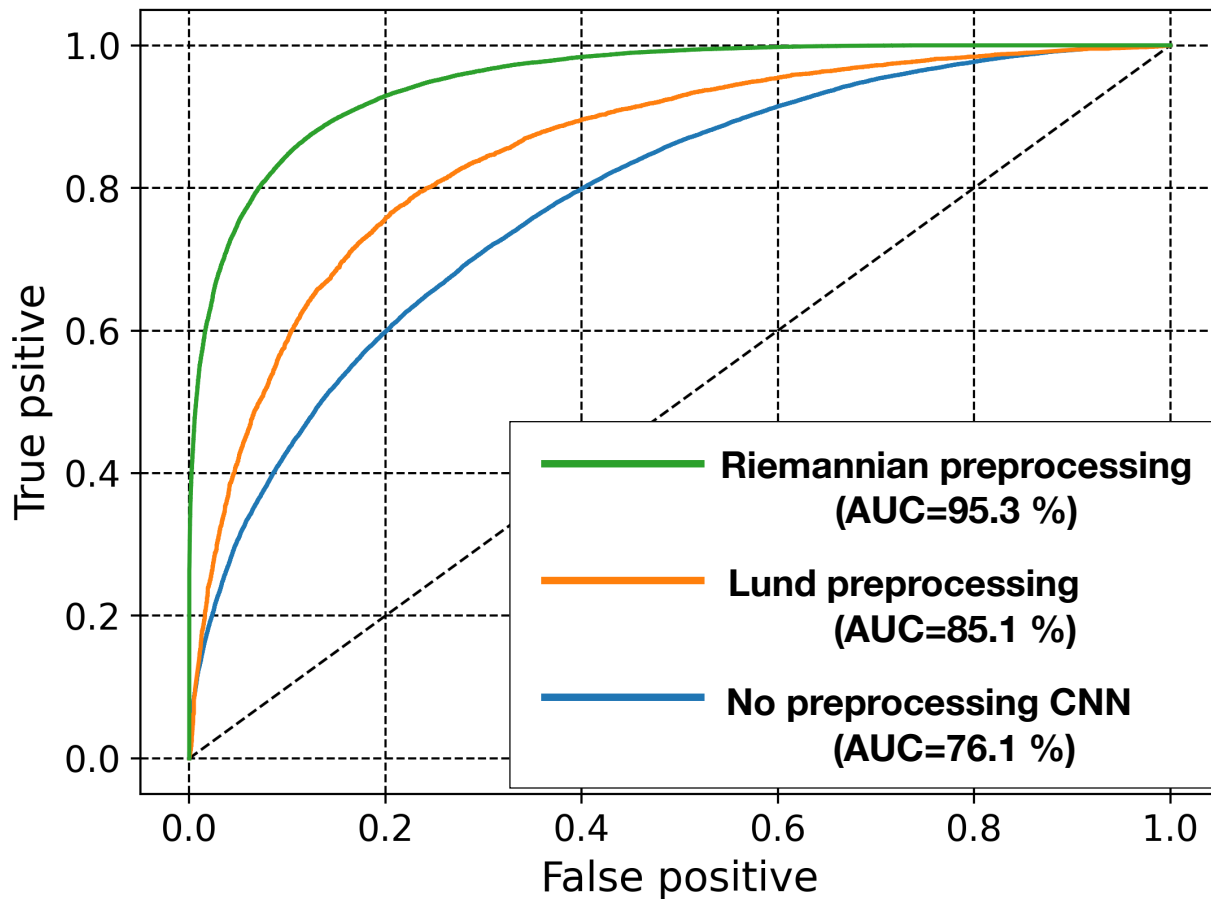


- Corruptions in North hemisphere are from ISR / MPI QCD activities.
- We may utilize this image for SIG / BKG separation too.

Riemannian preprocessing with CNN

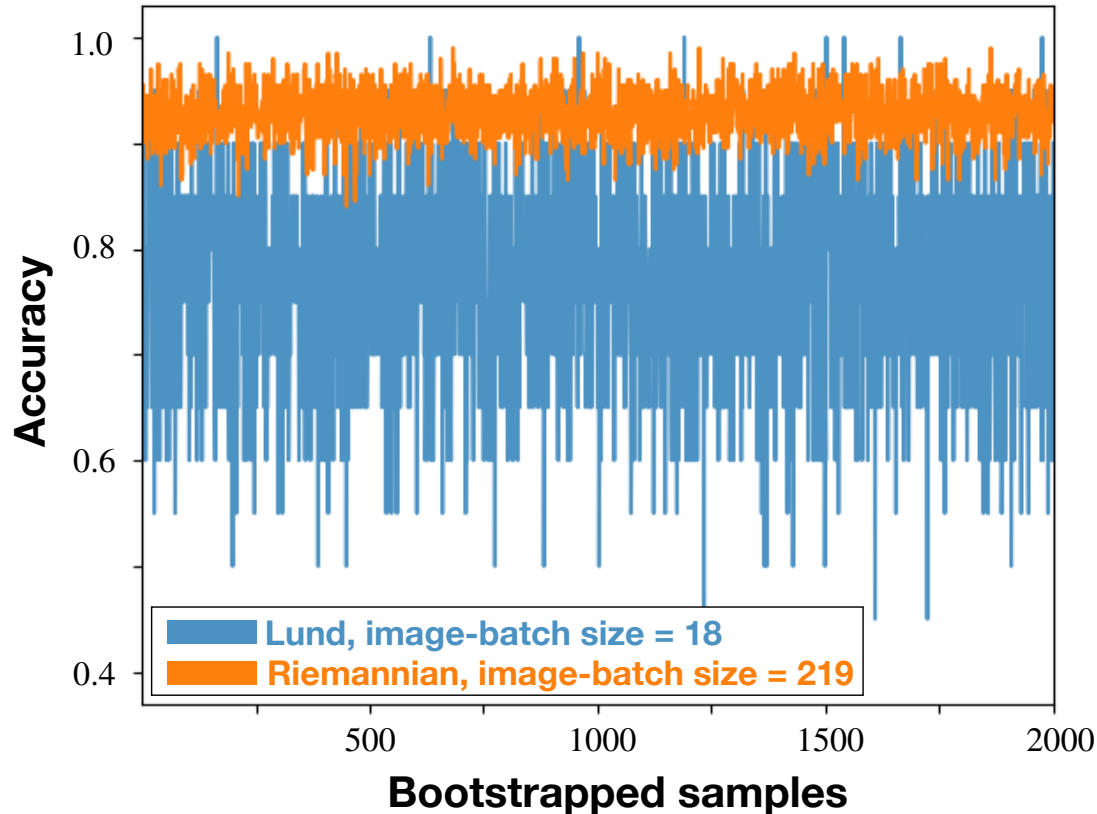


Performance test



- With 100,000 MC data sample each for (1) whole p_T range and for (2) boosted p_T (60% training, 20% validation, 20% test), Riemannian preprocessing has a outperformance.
- Lund preprocessing ("double-logarithmic plane") is from [arXiv:2105.03989] for a boosted Higgs (Data preprocessing with selected QCD features)

Applying NN to the LHC

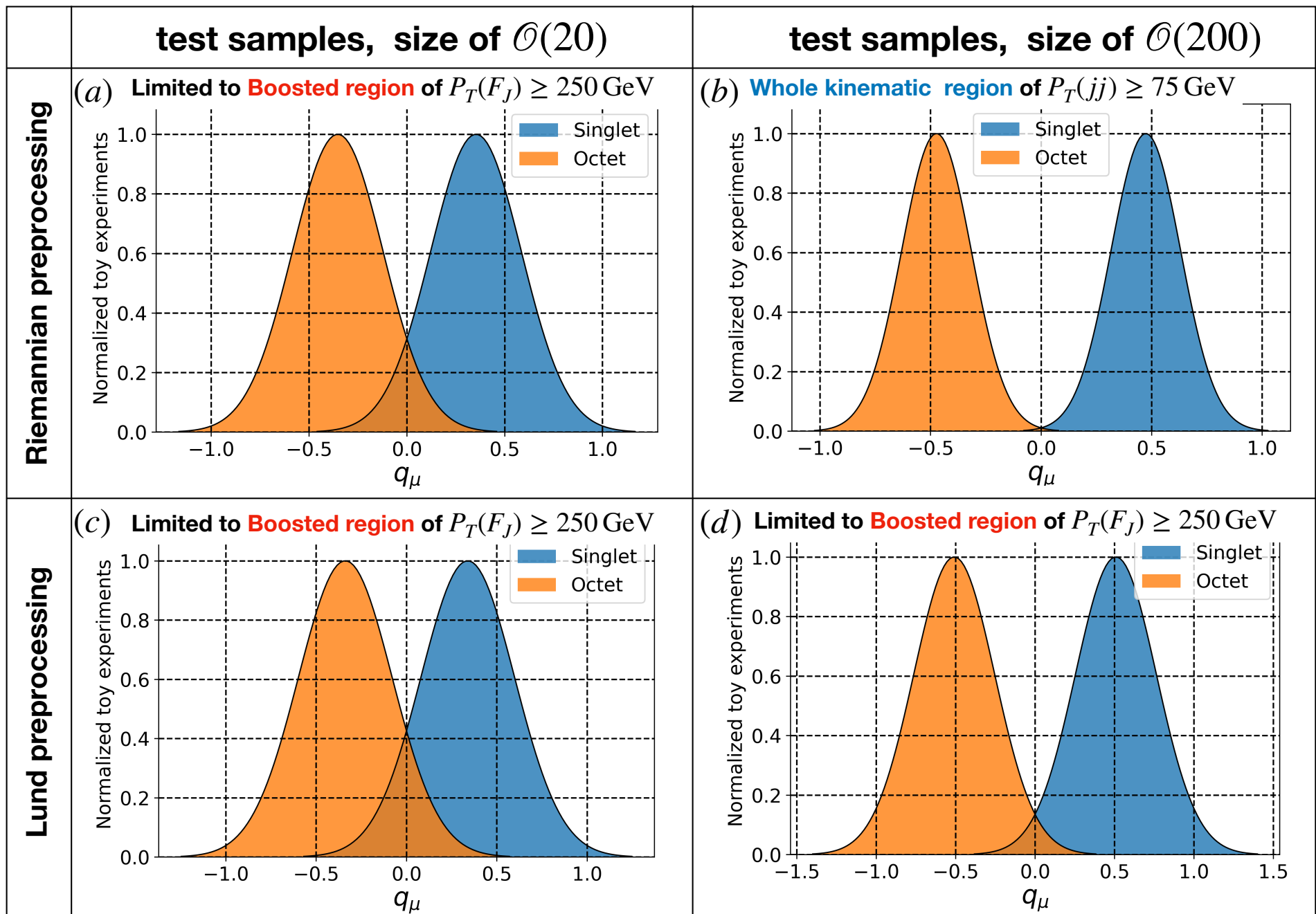


- Based on the ATLAS work (Measurement of WH/ZH in $H \rightarrow b\bar{b}$, 13TeV with 139fb^{-1} : arXiv:2007.02873)

Number of Higgs samples after selection cuts : 219

Number of Higgs samples in the boosted region ($p_T > 250\text{GeV}$) : 18

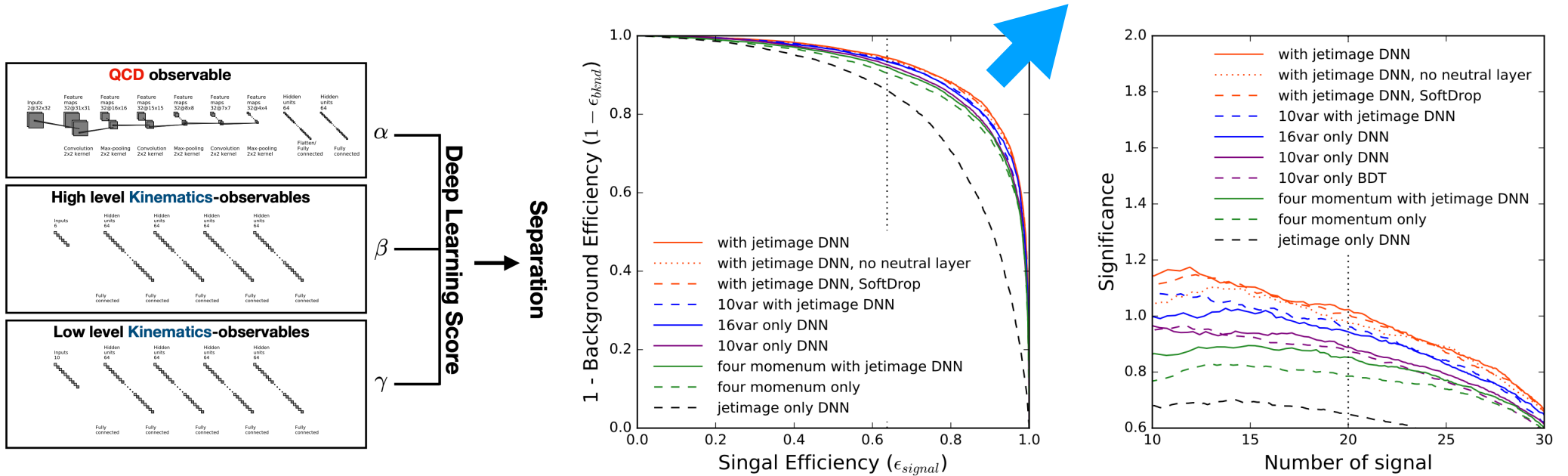
- With well-trained Neural Network, we may suffer from **"statistical fluctuation"** in the real battle of the LHC.
- Thus, the method with wide range of $p_T(h)$ would be better



- Our simple mapping is better even with the same statistics.

Further studies?

1. Combining two regions (local and global)



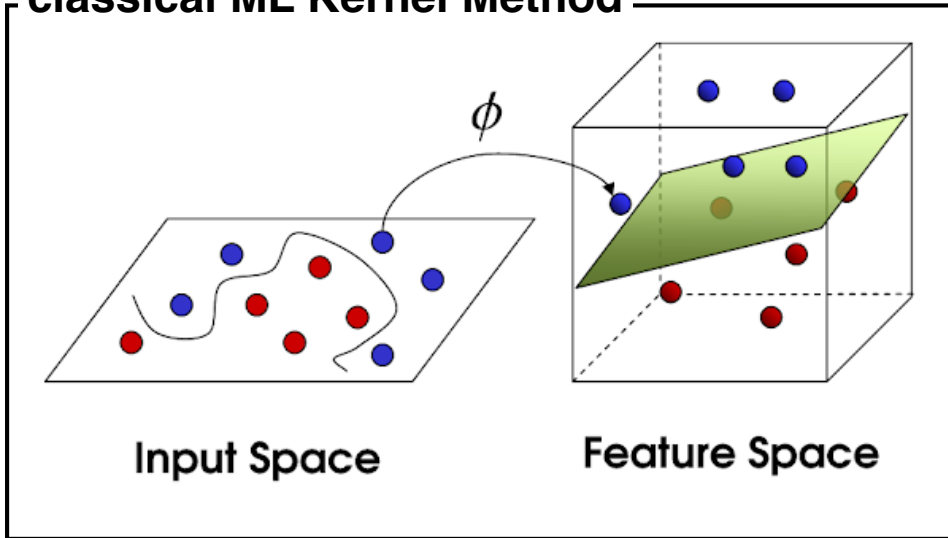
- Combining QCD observable with kinematics **does not** provide a BIG improvement... **why???**

2. ML with a few training data

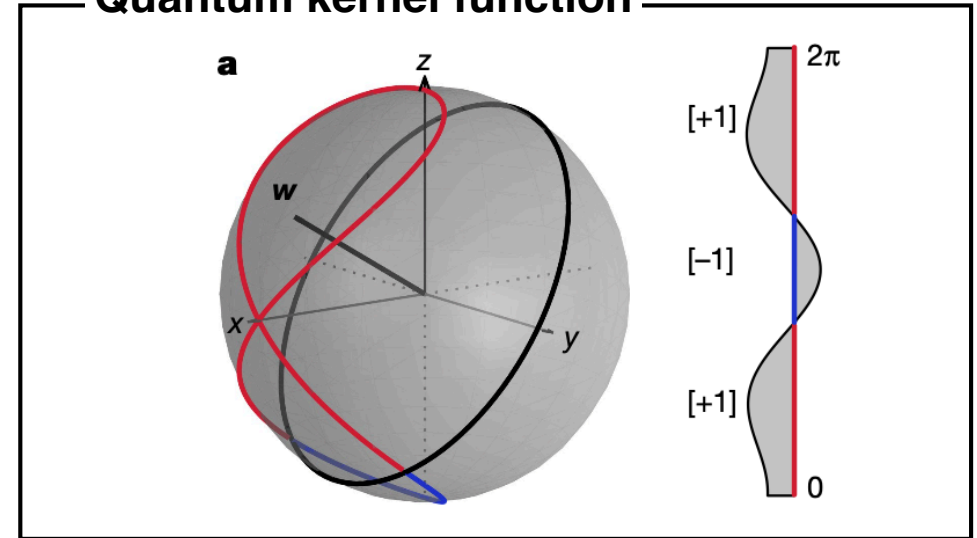
- Current ML technologies require "Big DATA" to train the "sophisticated" neural network.
 - Big data from MC simulations...
 - With a few data, we can "augment" existing data :self-supervised
- Algorithm based on Quantum Information can do this job !

Quantum Hilbert space

classical ML Kernel Method



Quantum kernel function

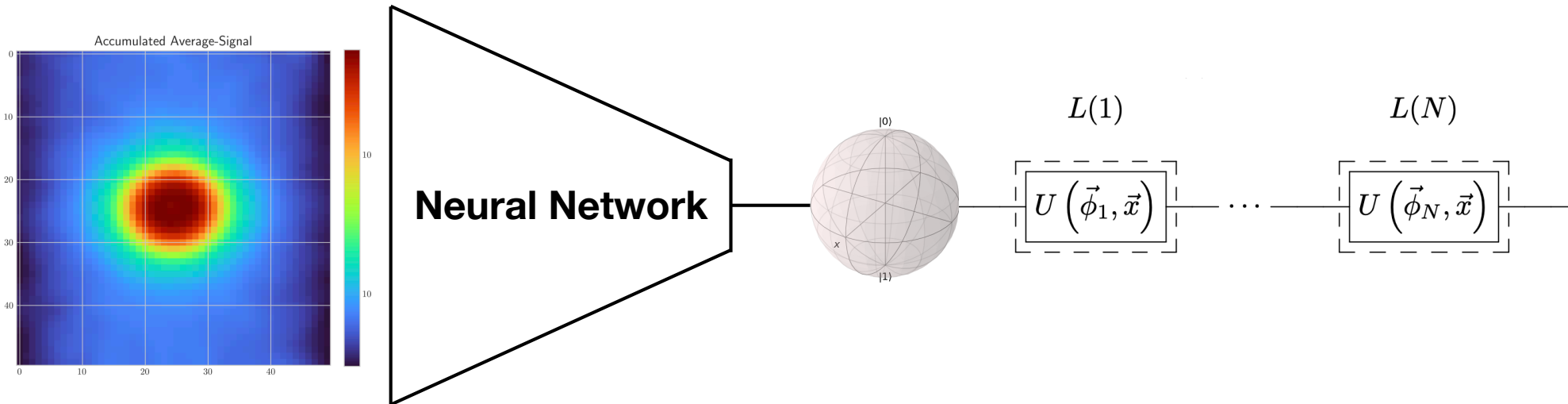


$$|\Psi\rangle = \sum a_{i_1 i_2 \dots i_n} \begin{array}{c} |0\rangle \\ \text{Bloch Sphere} \\ |1\rangle \end{array} \otimes \begin{array}{c} |0\rangle \\ \text{Bloch Sphere} \\ |1\rangle \end{array} \dots \otimes \begin{array}{c} |0\rangle \\ \text{Bloch Sphere} \\ |1\rangle \end{array}$$

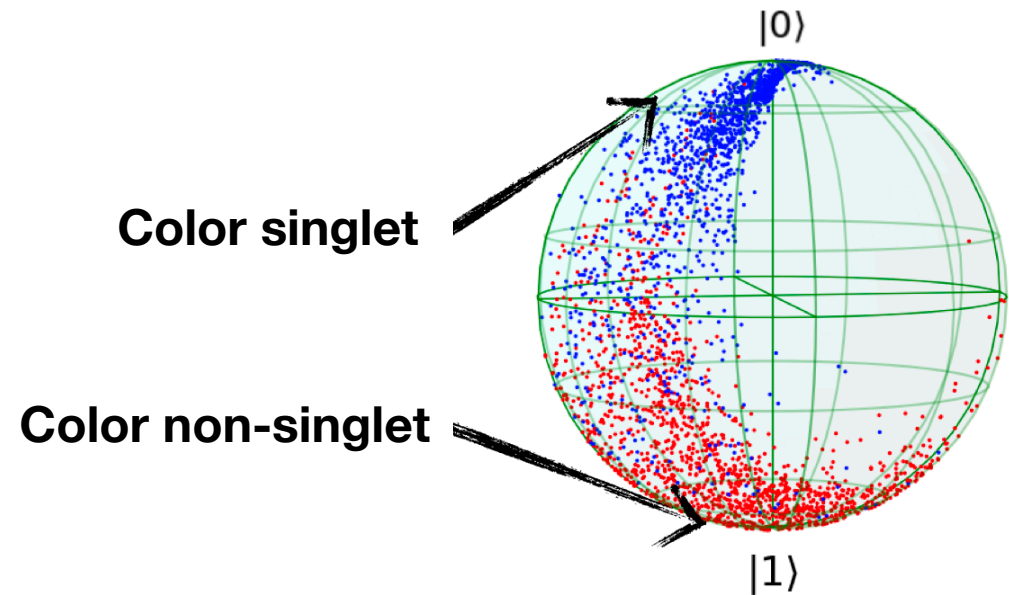
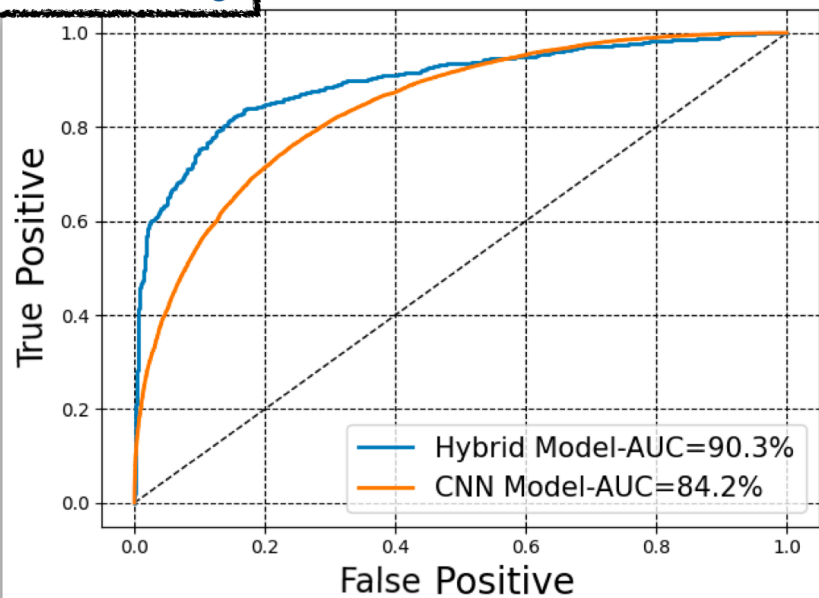
- Expressing and manipulating input data in an **exponentially large** (2^n) and "compact" Quantum Hilbert Space.
- We can **linearly separate** different objects with a "kernel method"

- With one qubit,

Dimensional Reduction



Preliminary



Conclusion

- The Standard Model Higgs precision requires advanced computing methods.
- Thanks to the LHC, we have improved the physics of QCD dramatically.
 - Precision physics with soft patterns armed with ML
 - But current focuses are in the boosted analyses.
- Here, I present how we can utilize (local) QCD features in "non-boosted" region: Need to resolve effects from different kinematics

TO DO

1. Efficient way to combine local (QCD) and global (Kinematics)
2. Utilize Quantum Information in Machine Learning algorithms.