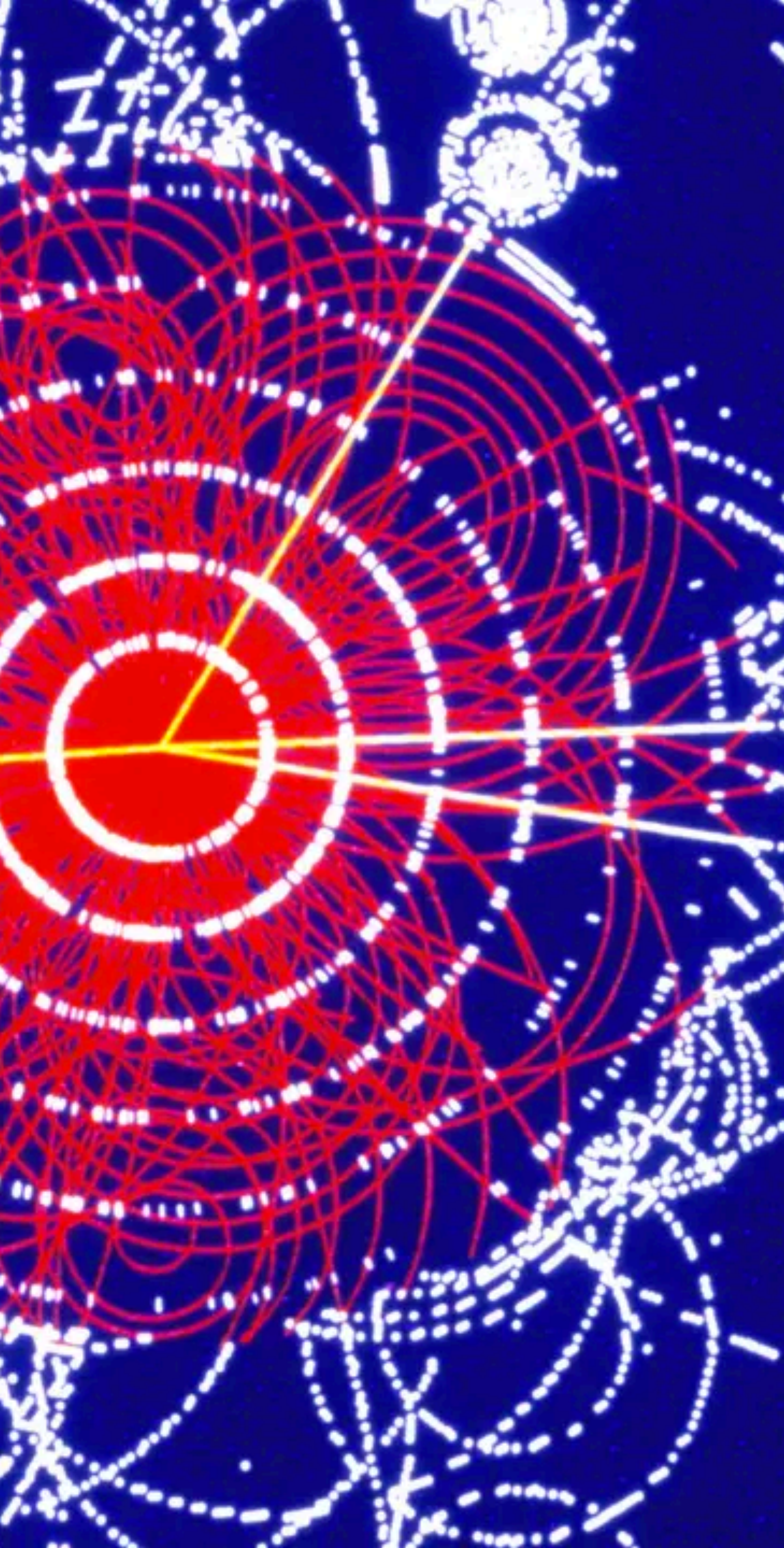




Machine Learning Electroweakino Production

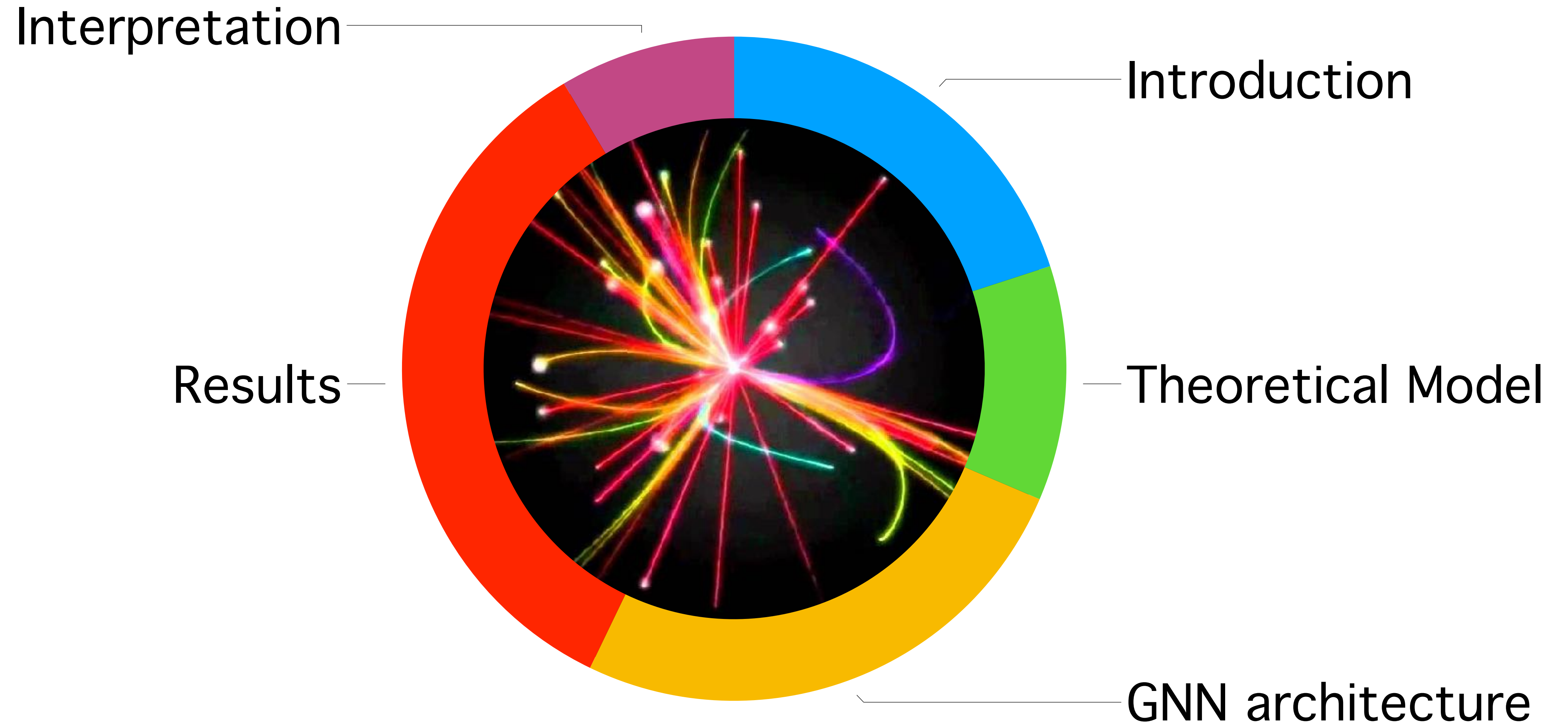
Rafał Masełek

in collaboration with K. Sakurai and M. Nojiri

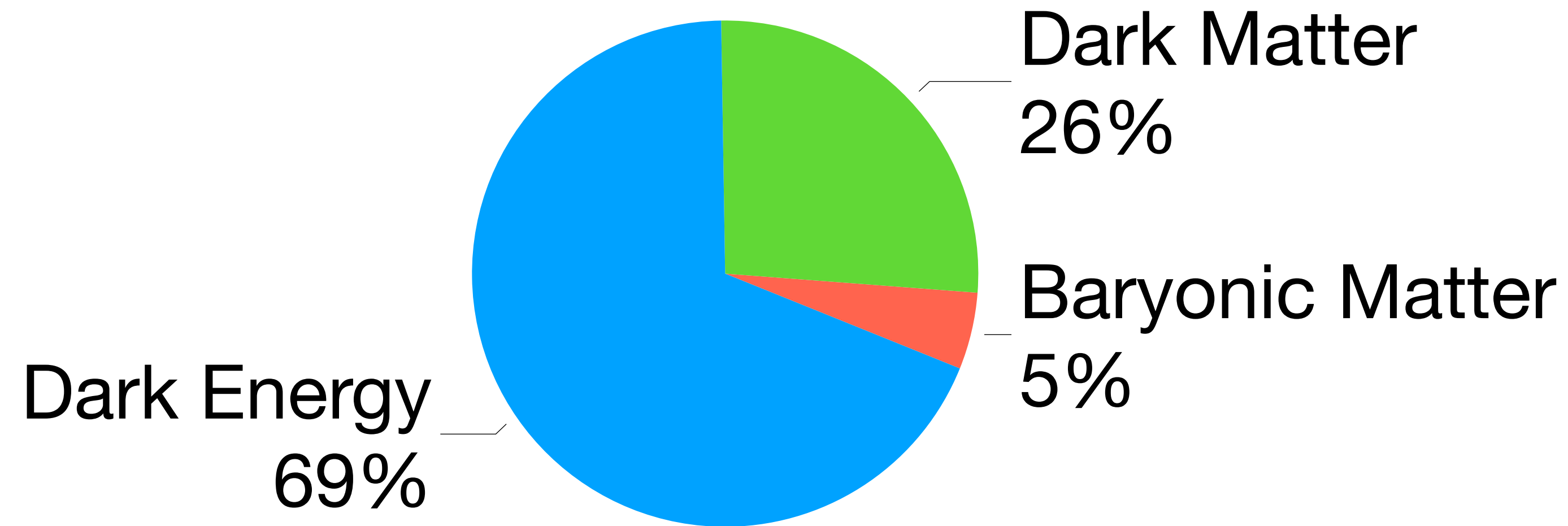
Based on [arXiv: 2411.00093 \[hep-ph\]](https://arxiv.org/abs/2411.00093)

ML coffee 17-01-2025

Presentation plan



Dark Matter

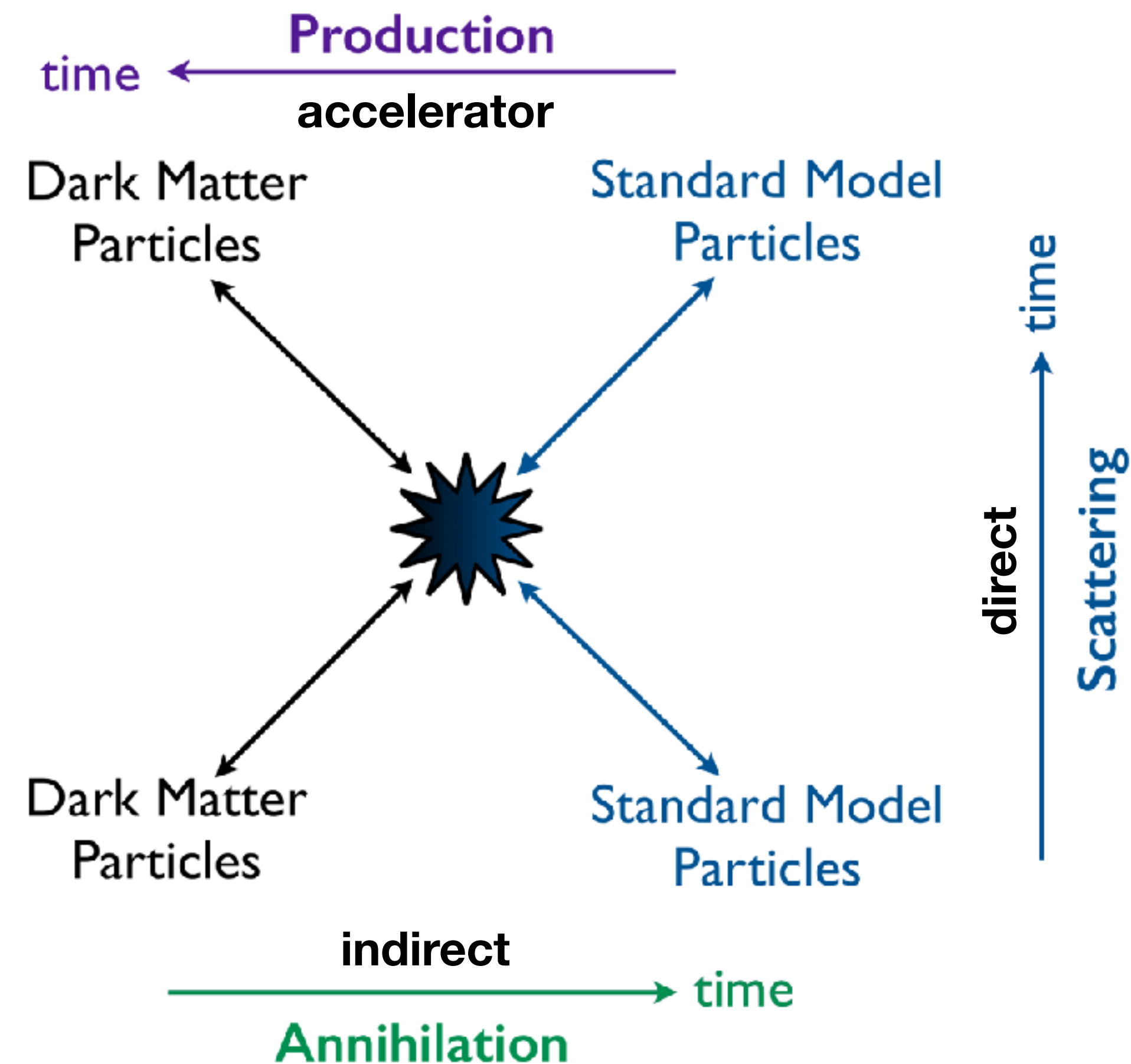


- ⦿ long-lived over the age of the Universe

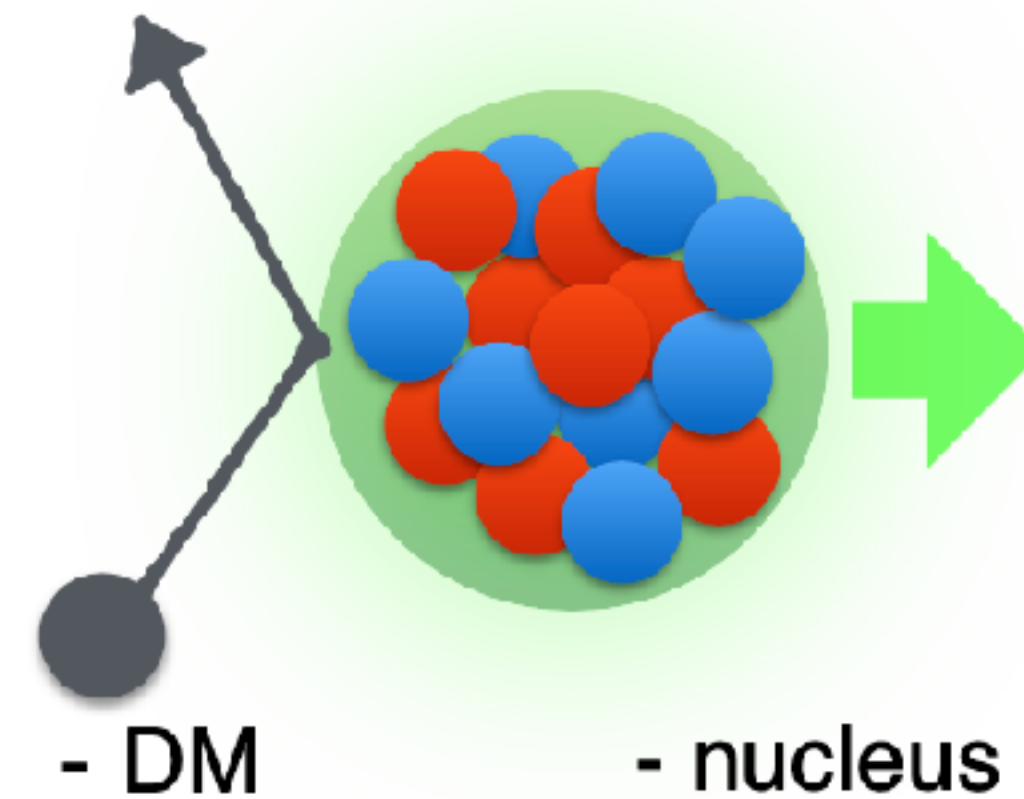
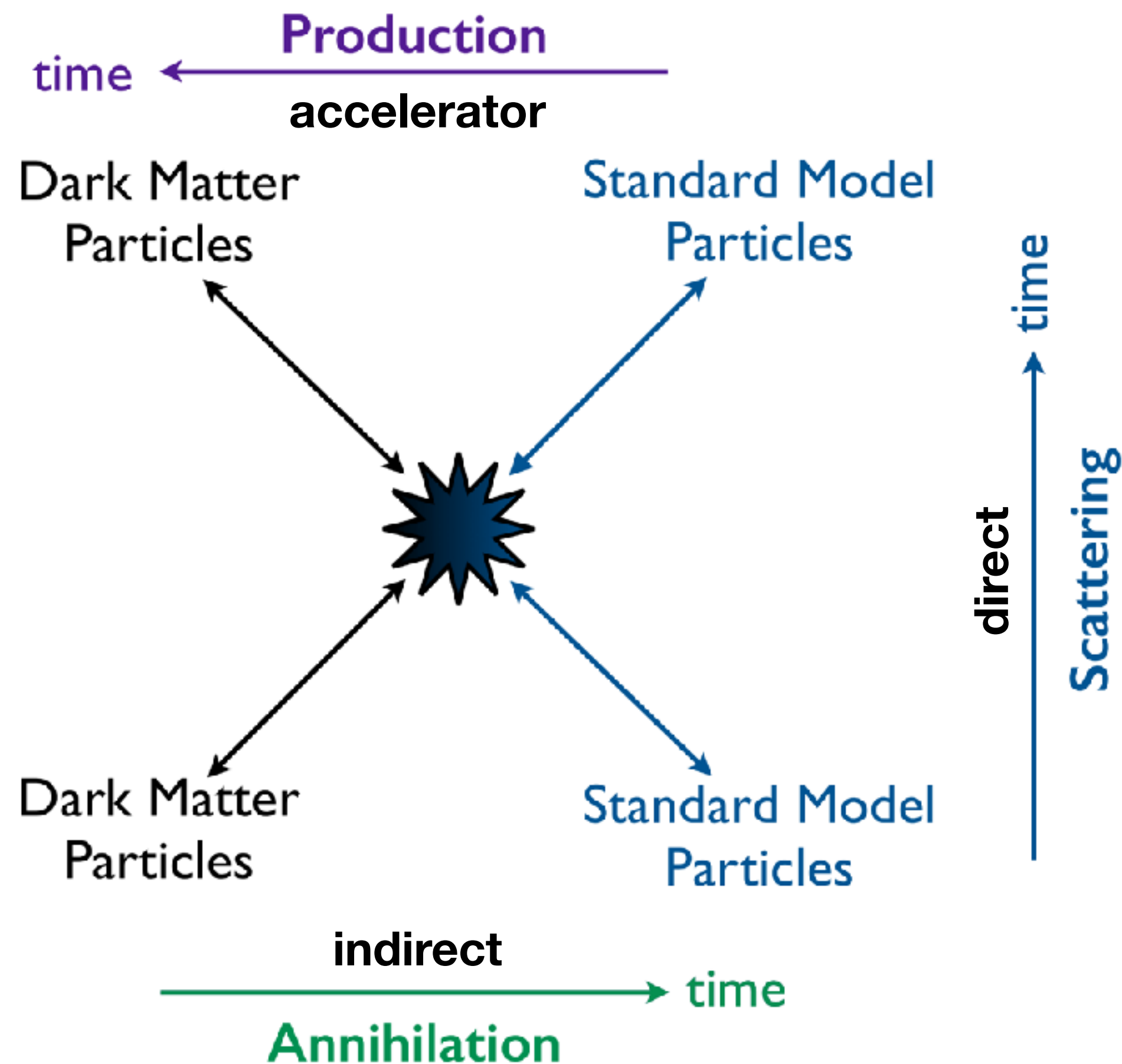
- ⦿ feebly-interacting with photons and baryons

- ⦿ not too hot

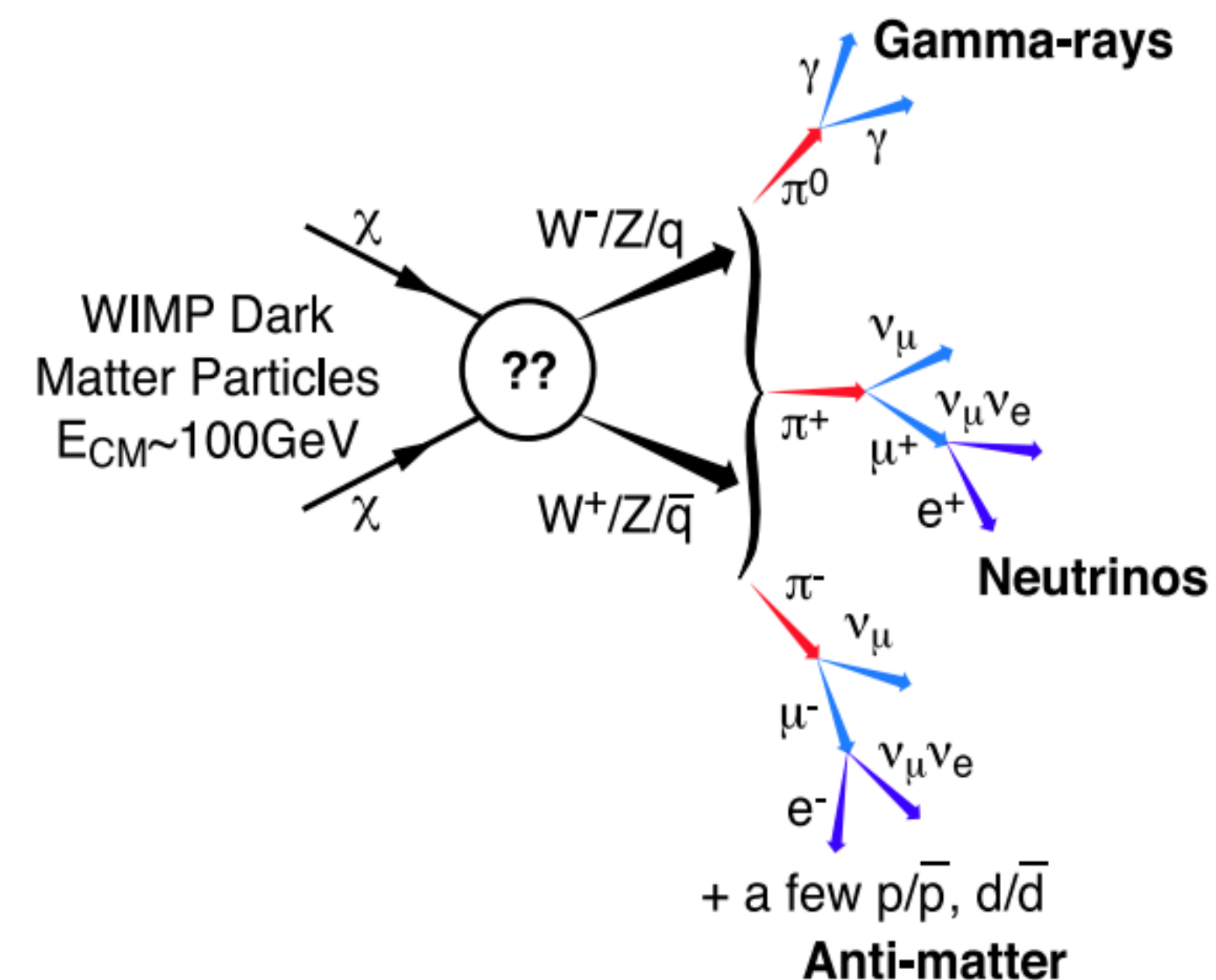
Dark Matter



Dark Matter



Direct



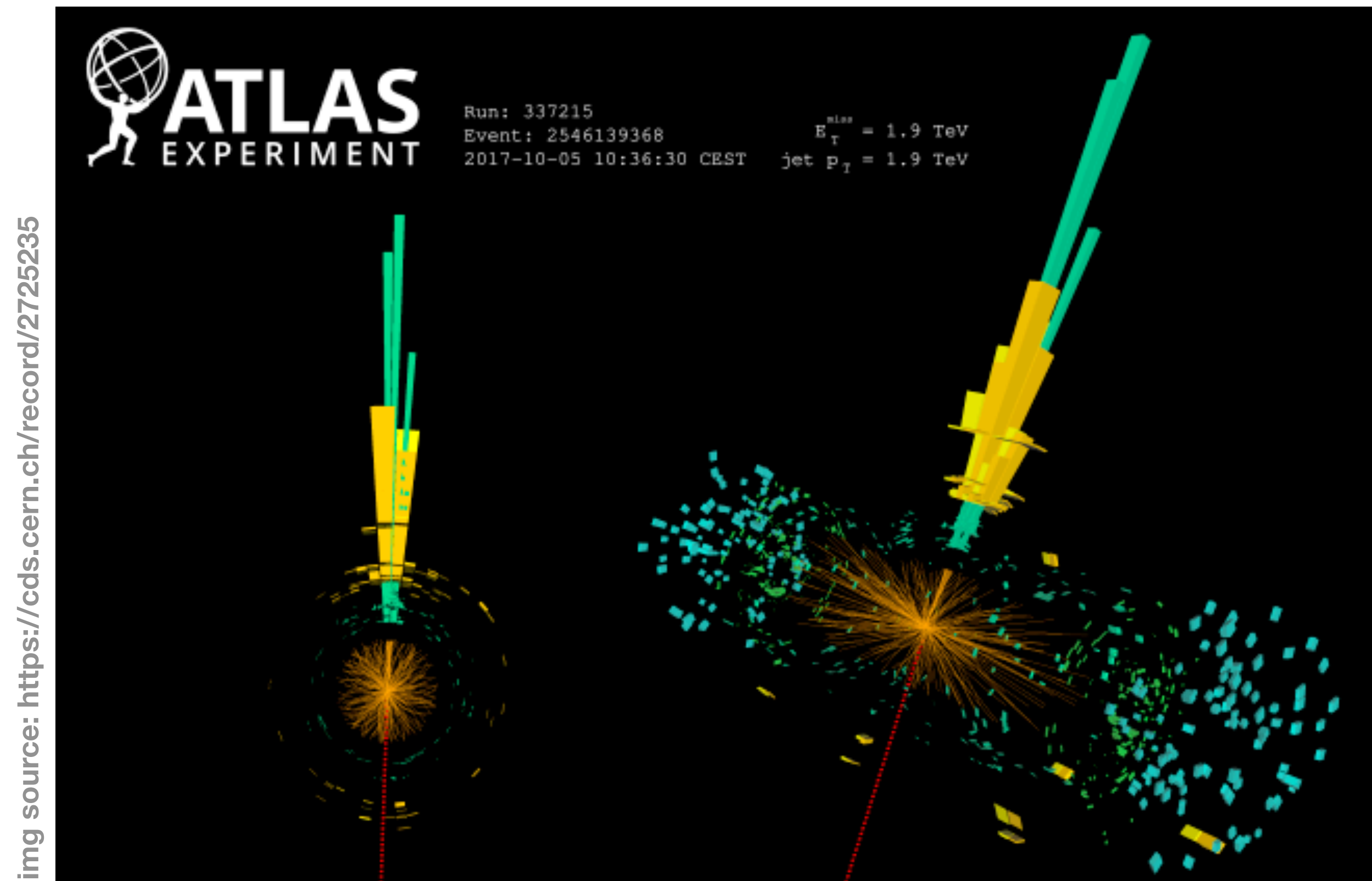
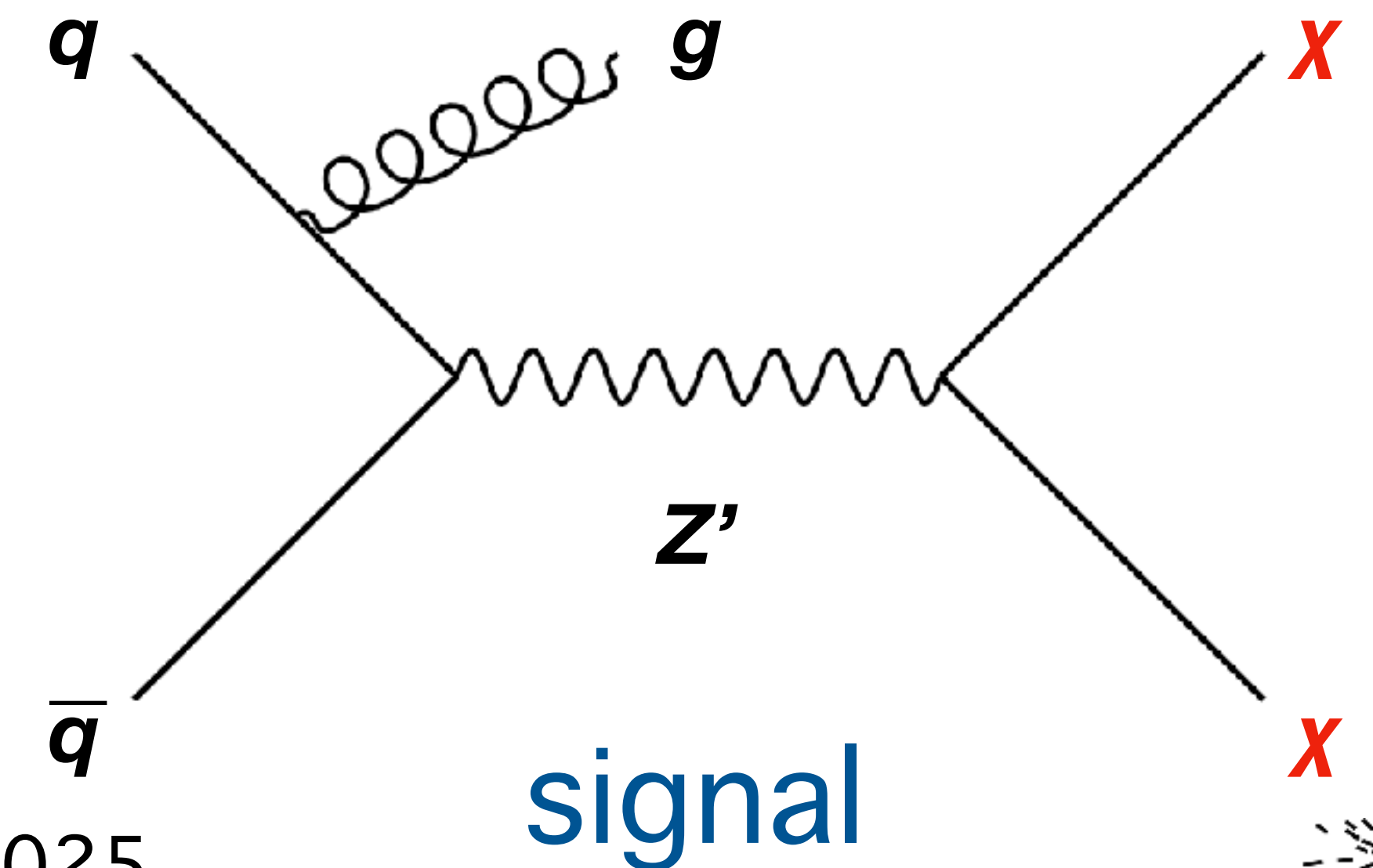
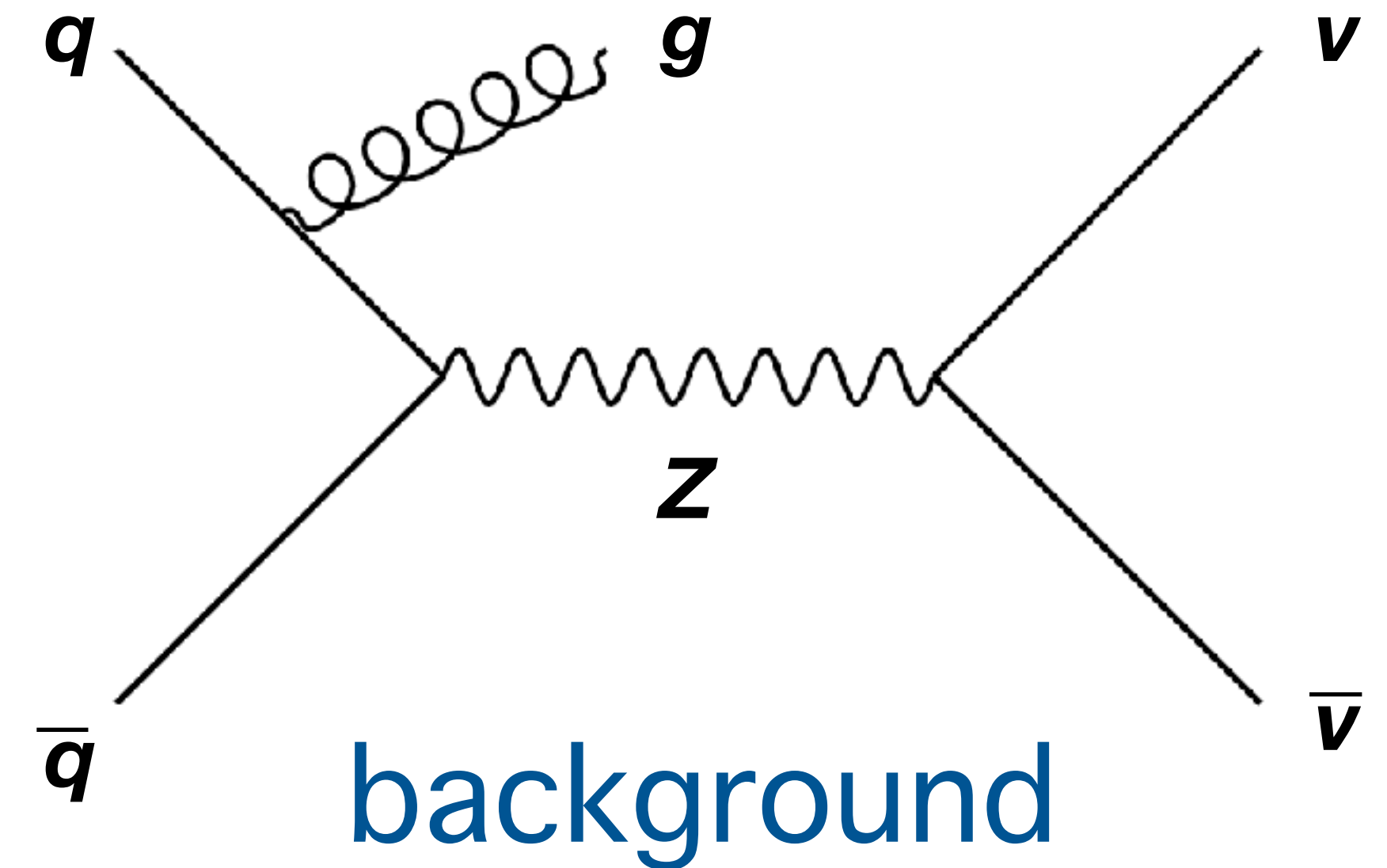
Indirect



THERE IS ANOTHER

DM searches @ LHC — Monojet

Monojet channel = 1 or more hard jets recoiling against a missing transverse momentum and no isolated leptons



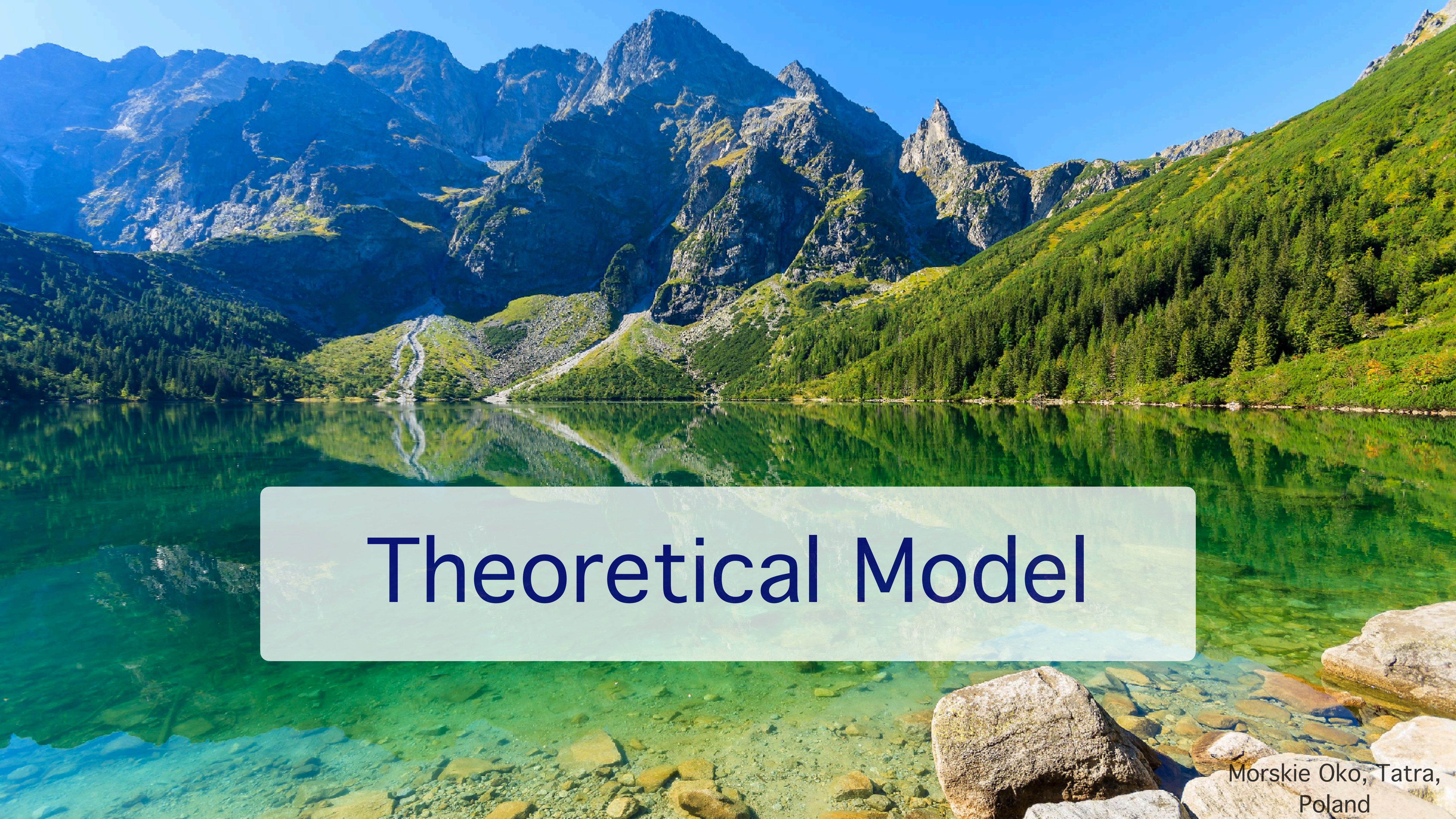
img source: <https://cds.cern.ch/record/2725235>

The idea

- ⚛️ One of the challenges for the Monojet searches is that we observe very similar jets for both signal and background
- ⚛️ Analysis of jet substructure is needed
- ⚛️ With Machine Learning we can effectively analyse low-level data
- ⚛️ ML can learn both local and global correlations
- ⚛️ **GOAL: Design new analysis using ML**

GOAL: Design new analysis using ML

- ⊛ We want approach that can be applied (with retraining):
 - ⊛ to real data
 - ⊛ to many BSM models
- ⊛ We want to combine low-level and high-level information
- ⊛ We want to include soft activity
- ⊛ We want robustness againsts:
 - ⊛ changing masses of BSM particles in a reasonable range
 - ⊛ changing other model parameters, e.g. mixings
- ⊛ We want to quantify the uncertainty of our method



Theoretical Model

Morskie Oko, Tatra,
Poland

Dark Matter candidates

⊛ Weakly Interacting Massive Particles (WIMPs)

⊛ Strongly Interacting Massive Particles (SIMPs)

⊛ Axions and axion-like particles

⊛ Dark photons

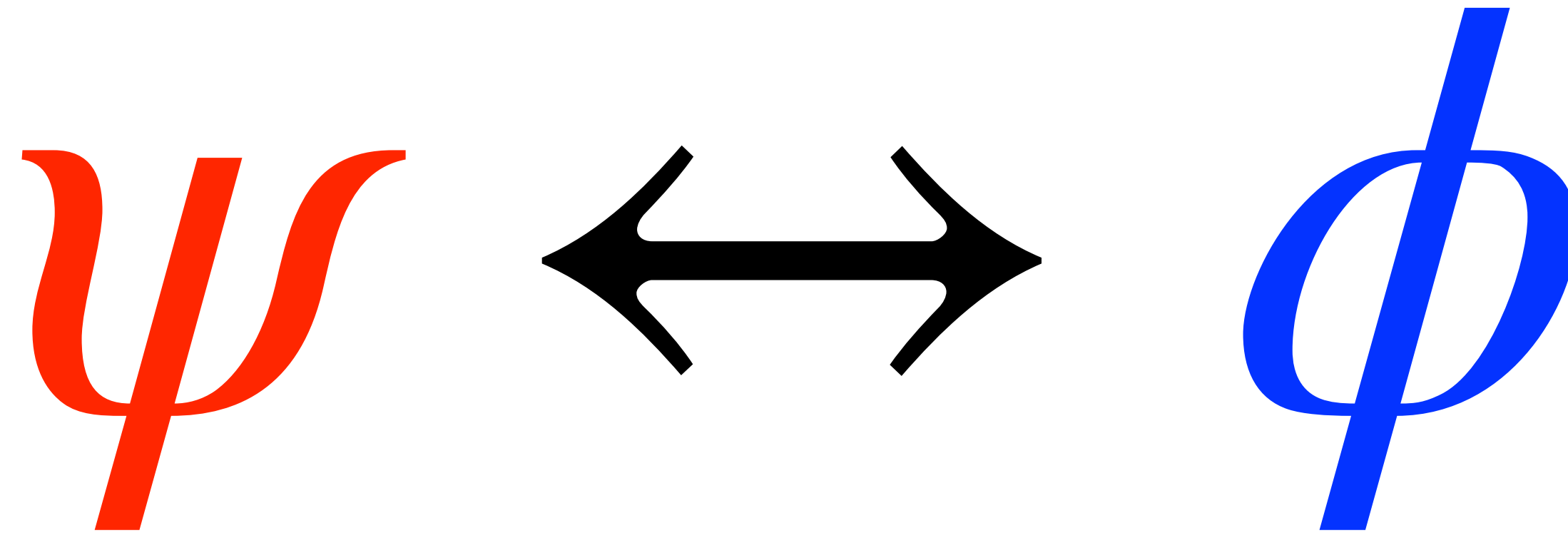
⊛ Sterile neutrinos

⊛ Primordial Black Holes

⊛ ...

Supersymmetry

symmetry relating **fermions** and **bosons**



quark (up, down, ...) $\leftrightarrow$ **squark** (sup, sdown, ..)

lepton (electron, muon, tau) $\leftrightarrow$ **slepton** (selectron, smuon, stau)

neutrino $\leftrightarrow$ **sneutrino**

gluon $\leftrightarrow$ **gluino**

B/W boson $\leftrightarrow$ **bino/wino**

Higgs (2!) $\leftrightarrow$ **2 higgsinos**

mixing

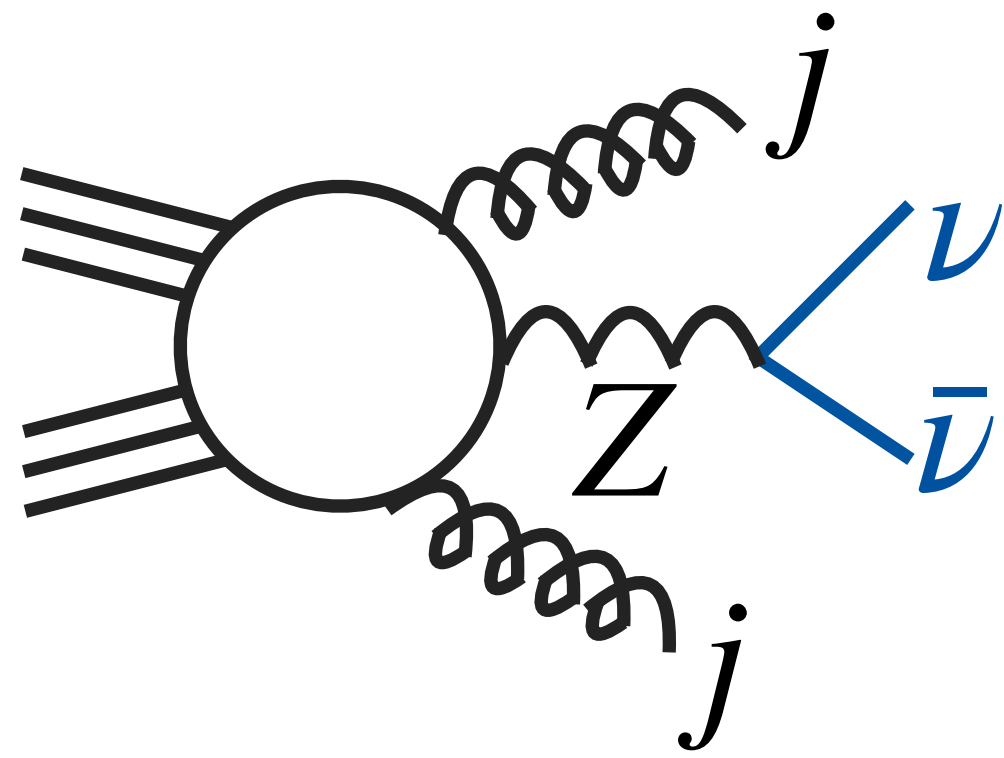
Electroweakinos

neutralinos $(\tilde{\chi}_1^0, \tilde{\chi}_2^0, \tilde{\chi}_3^0, \tilde{\chi}_4^0)$

charginos $(\tilde{\chi}_1^\pm, \tilde{\chi}_2^\pm)$

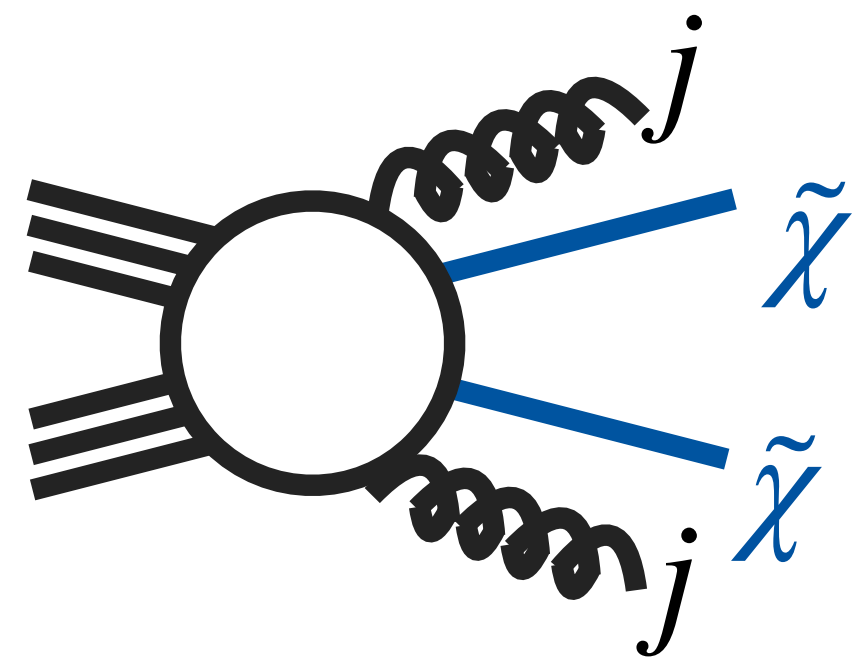
Benchmark model

SM background



$(Z \rightarrow \nu\bar{\nu}) + \text{jets}$

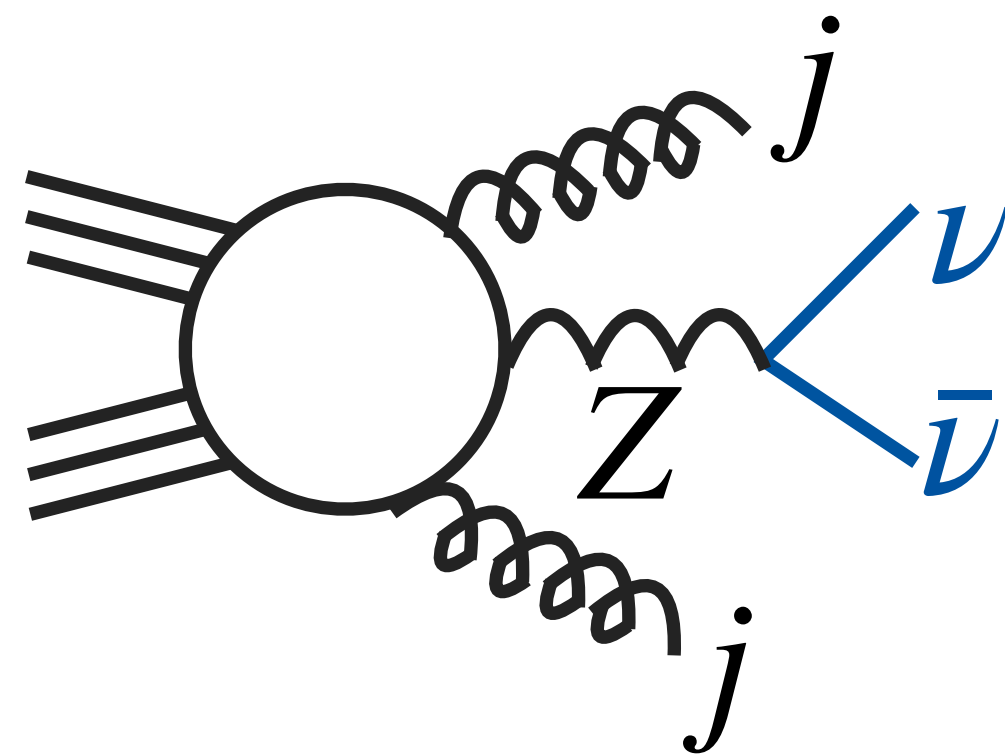
Contributing signal process



EWKino-EWKino

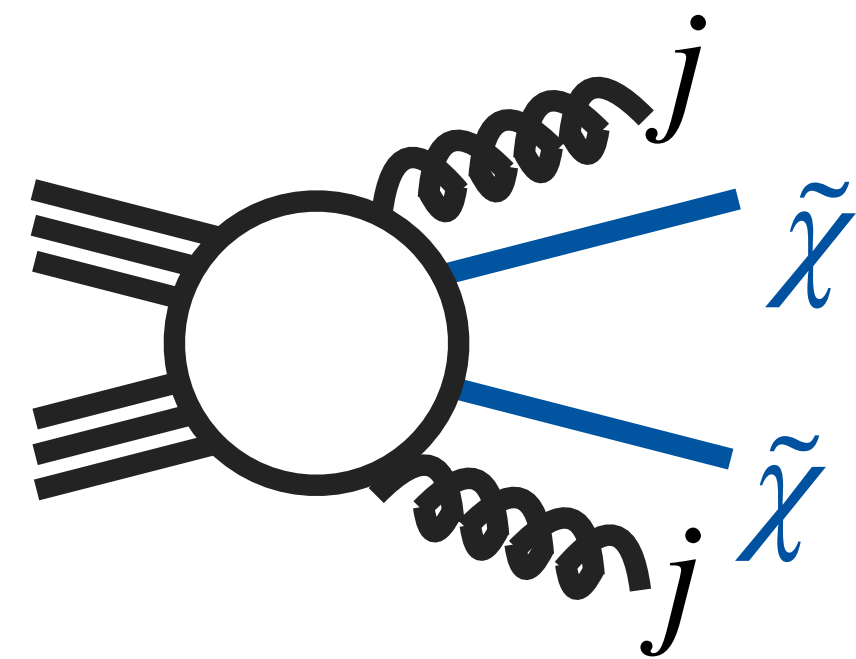
Benchmark model

SM background

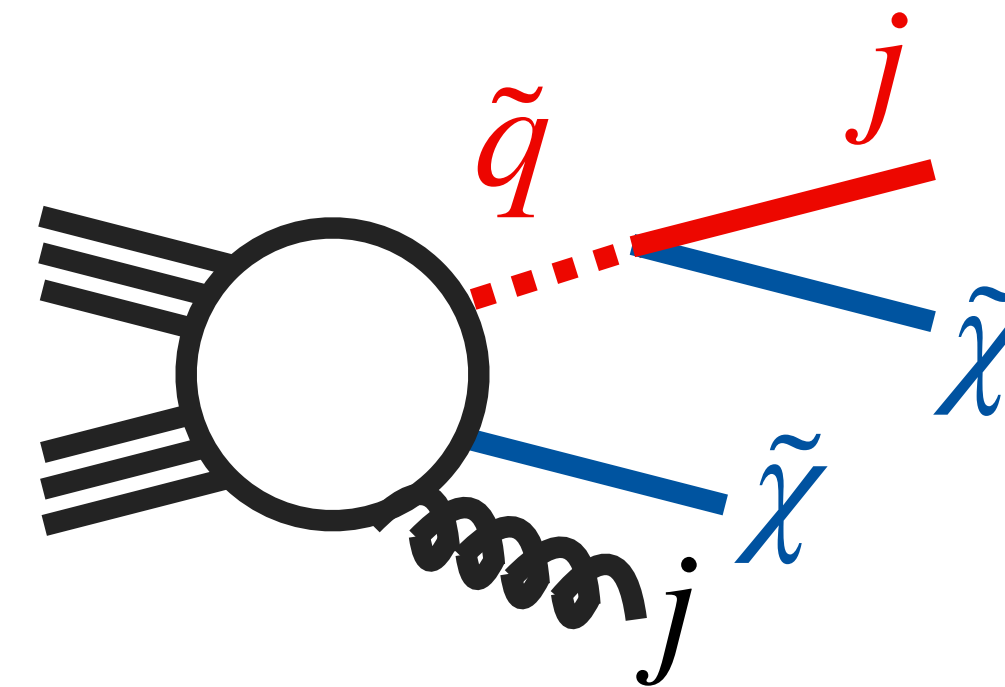


$(Z \rightarrow \nu\bar{\nu}) + \text{jets}$

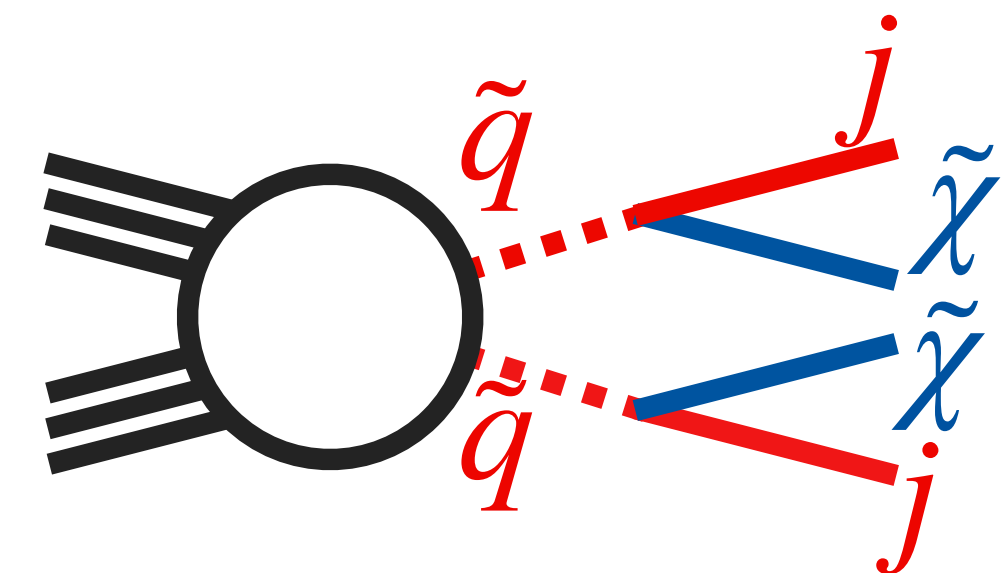
Contributing signal processes



EWKino-EWKino



EWKino-squark



squark-squark

$$m_{\tilde{\chi}} \in \{200, 300, 500, 700, 900, 1100\} \text{ GeV}$$

$$m_{\tilde{q}} \in \{2.0, 2.2, 2.3, 2.7, 3.0\} \text{ TeV}$$

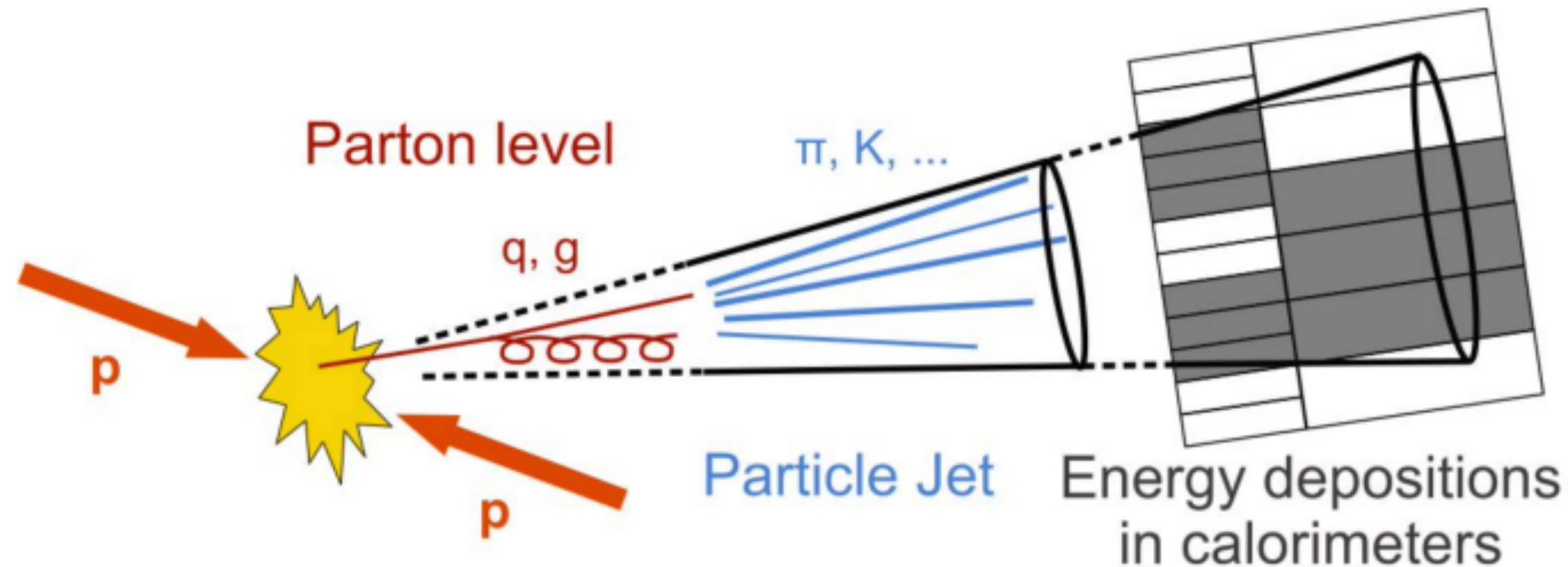
$$m_{\tilde{g}} = 10 \text{ TeV}$$



Neural Network architecture

Malbork Castle, Poland
photo from museum's FB page

Jets and jet tagging



Naive definition:

Collimated bunch of hadrons flying in roughly the same direction

Proper definition:

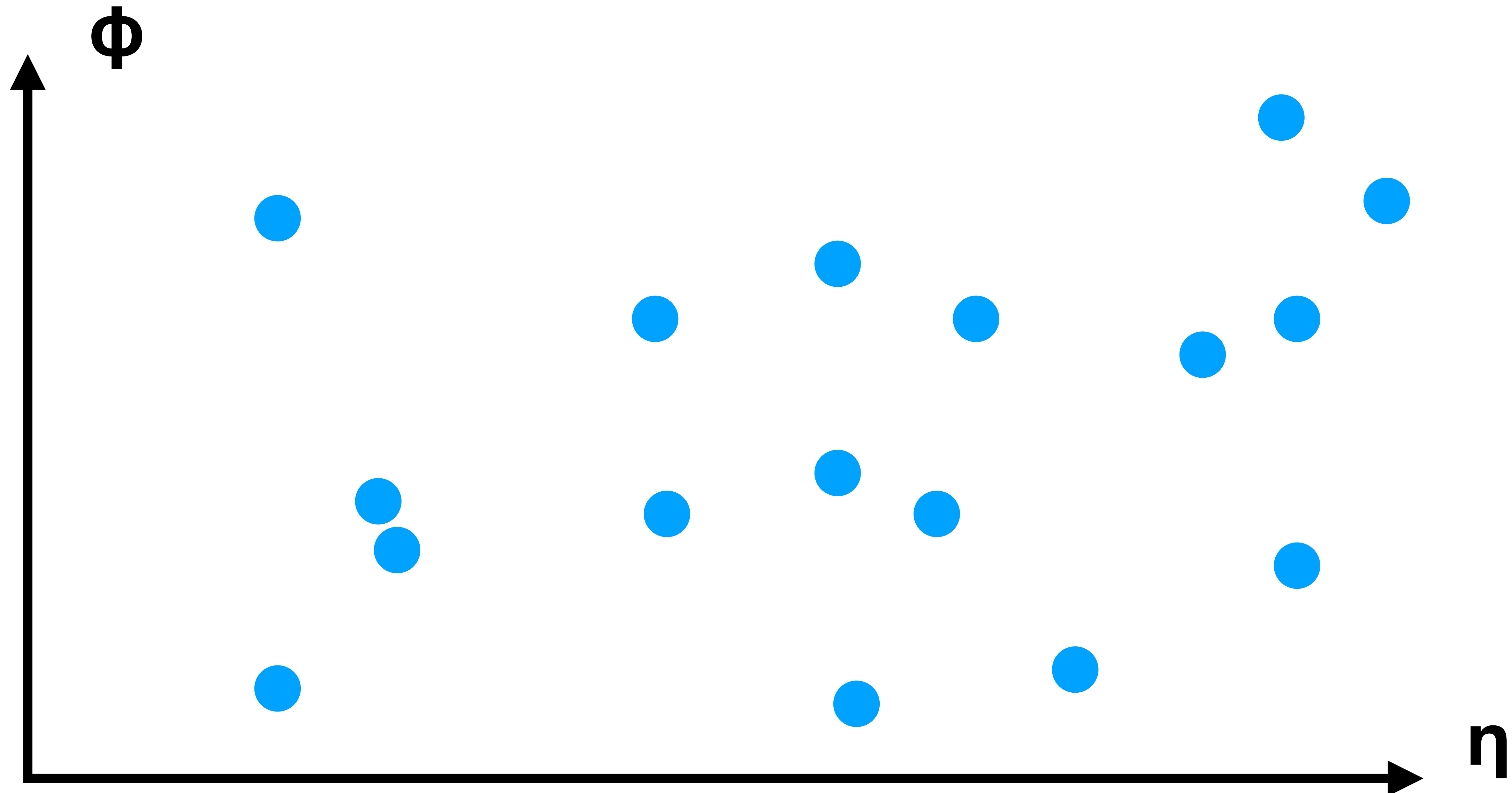
Collection of hadrons defined with a jet algorithm

ParticleNet

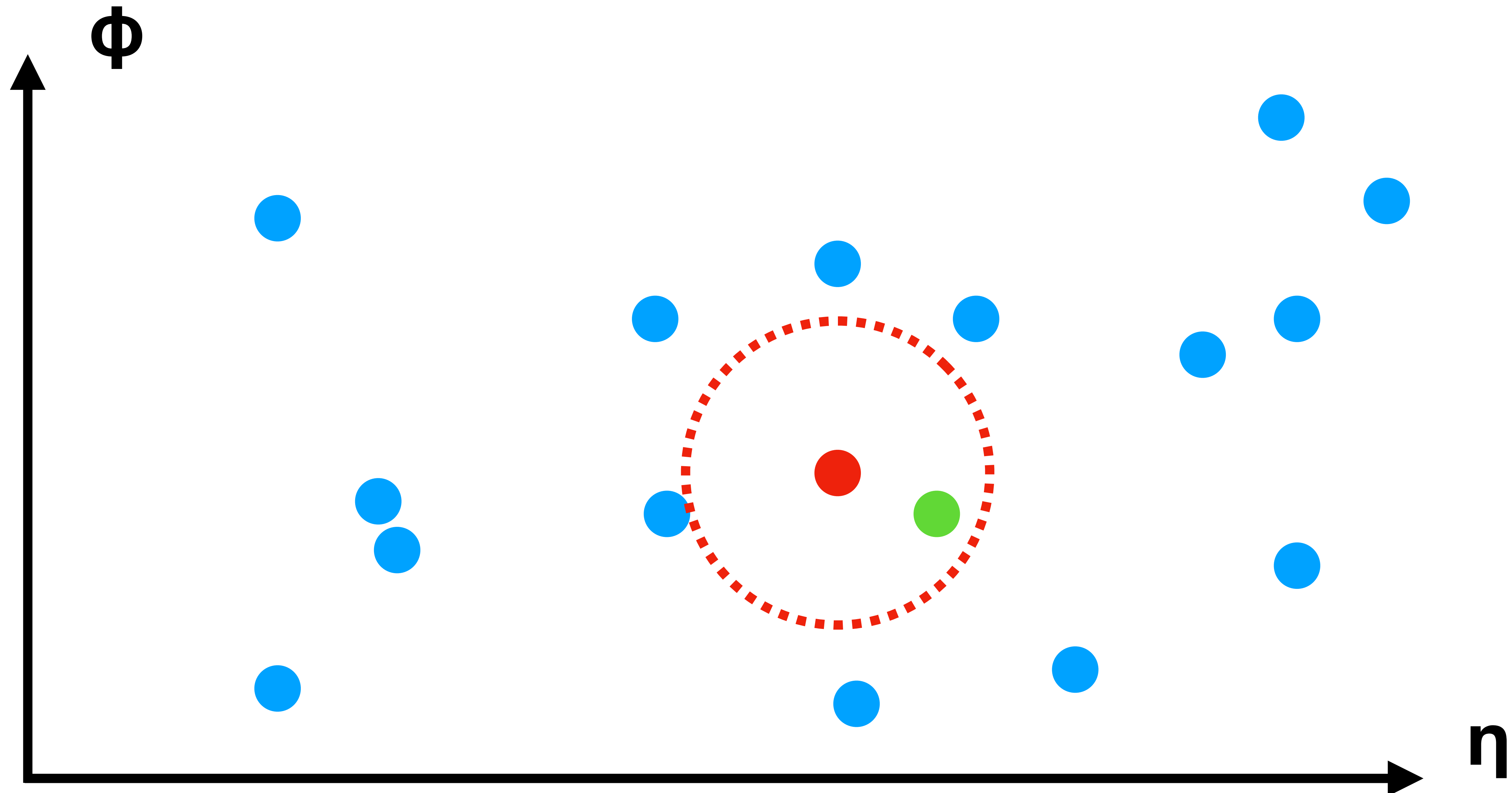
Model	Accuracy	AUC
TopoDNN [49]	0.916	0.972
LoLa [16]	0.929	0.980
P-CNN [1]	0.930	0.9803
<i>N</i> -subjettiness [62]	0.929	0.981
PFN [51]	0.932	0.9819
TreeNiN [58]	0.933	0.982
ParticleNet [64]	0.940	0.9858
ParT [65]	0.940	0.9858
LorentzNet* [42]	0.942	0.9868
CGENN* [68]	0.942	0.9869
PELICAN* [10]	0.9426 ± 0.0002	0.9870 ± 0.0001
L-GATr (ours)*	0.9423 ± 0.0002	0.9870 ± 0.0001

Table from: <https://arxiv.org/pdf/2405.14806>

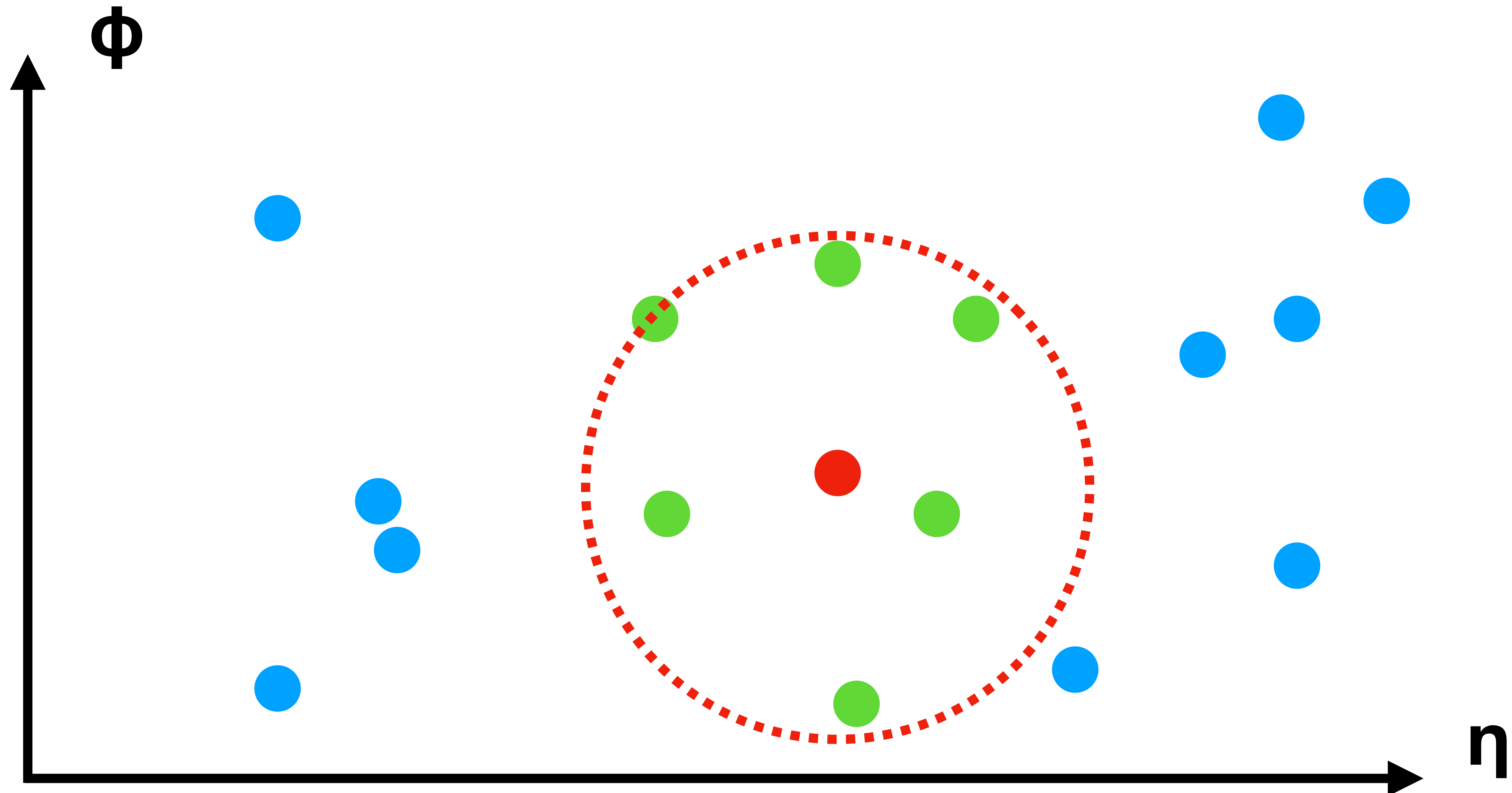
ParticleNet—edge convolutions



ParticleNet—edge convolutions

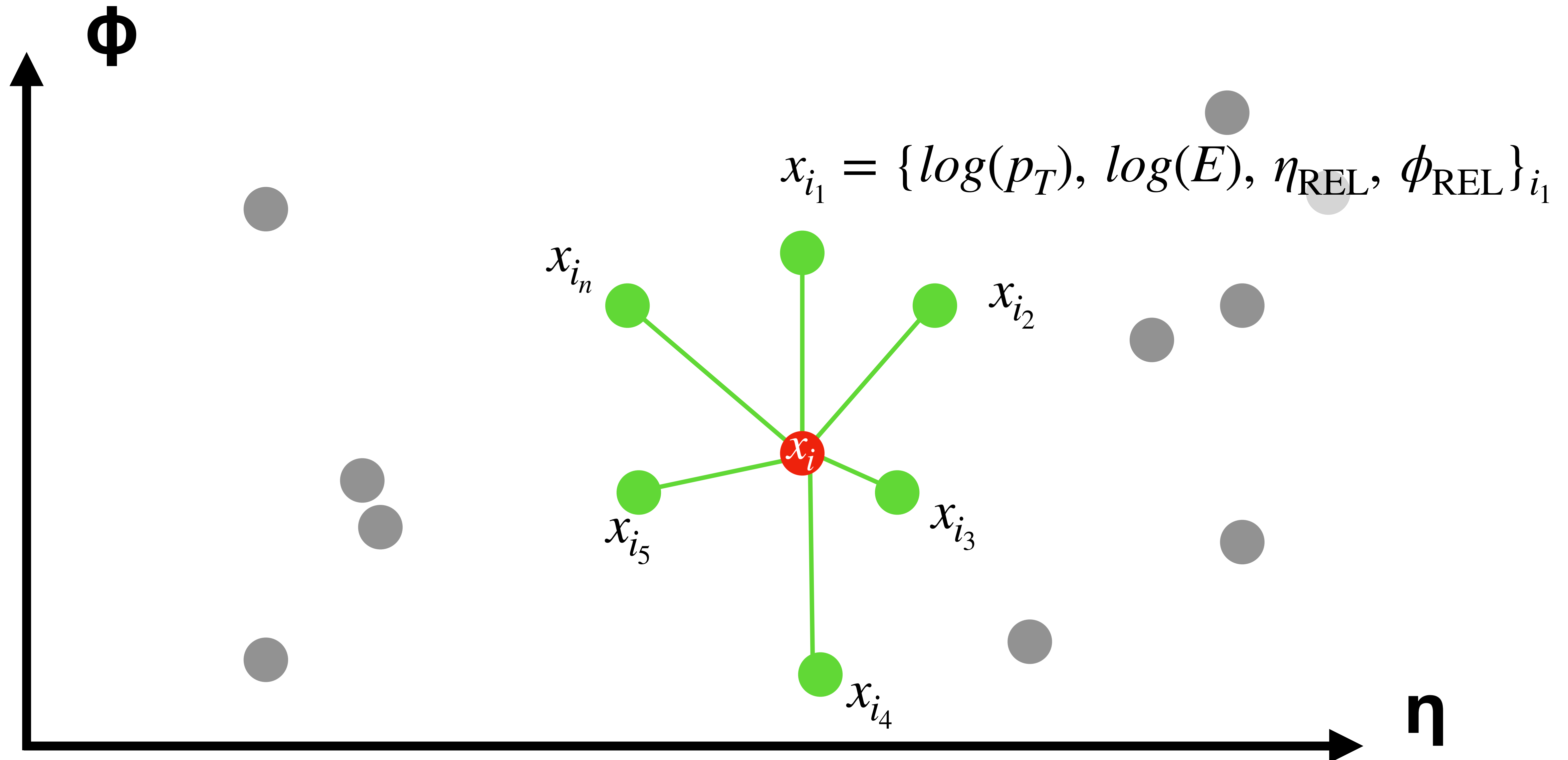


ParticleNet—edge convolutions



R. Masełek ML coffee 17-01-2025

ParticleNet—edge convolutions



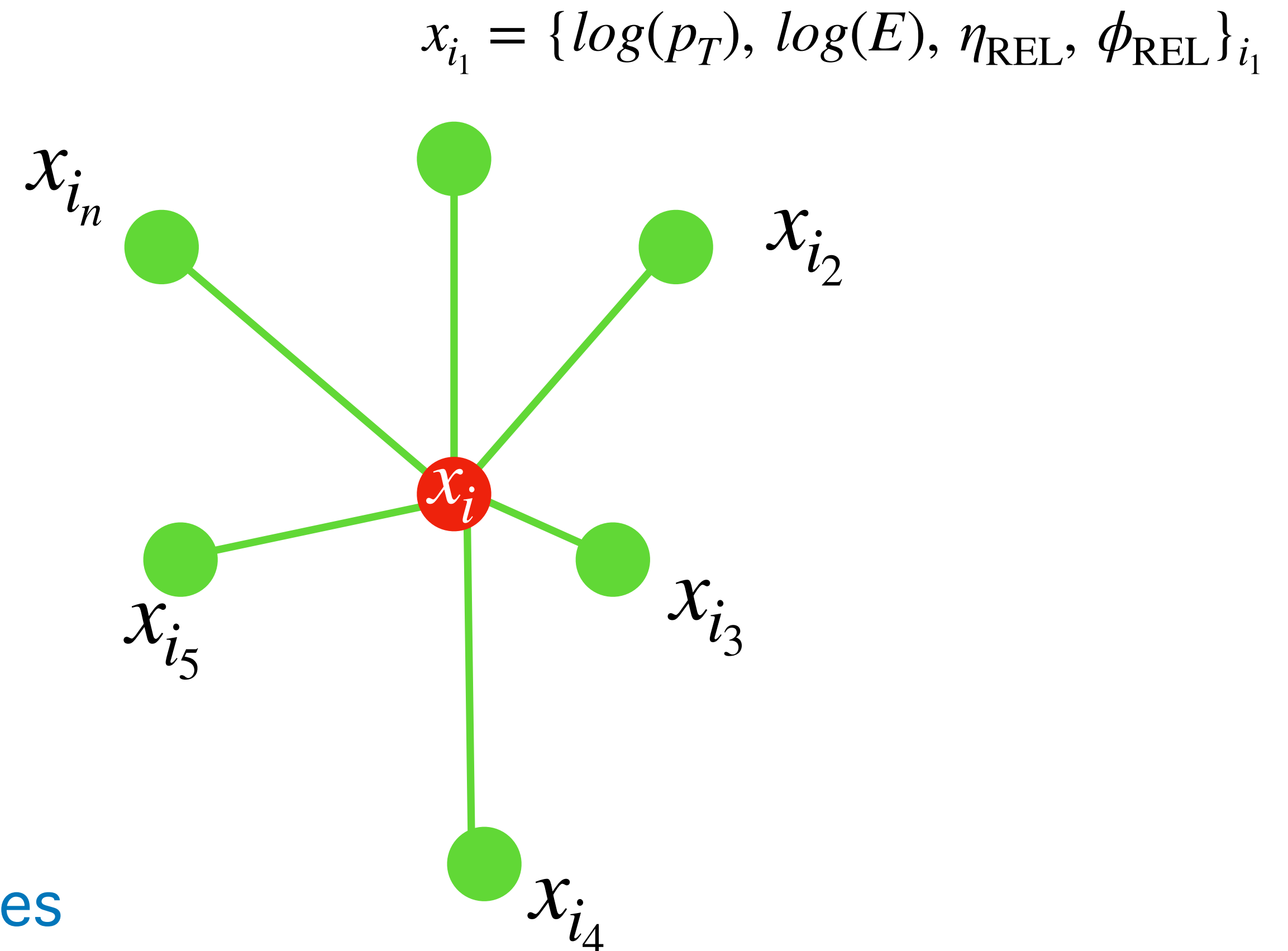
ParticleNet—edge convolutions

representation
in a new space

sum over k
nearest neighbours

$$x'_i = \frac{1}{k} \sum_{j=1}^k \text{MLP}_{\Theta}(x_i, x_{i_j} - x_i)$$

Multi Layer Perceptron
with trainable weights Θ shared among all edges



ParticleNet (lite)

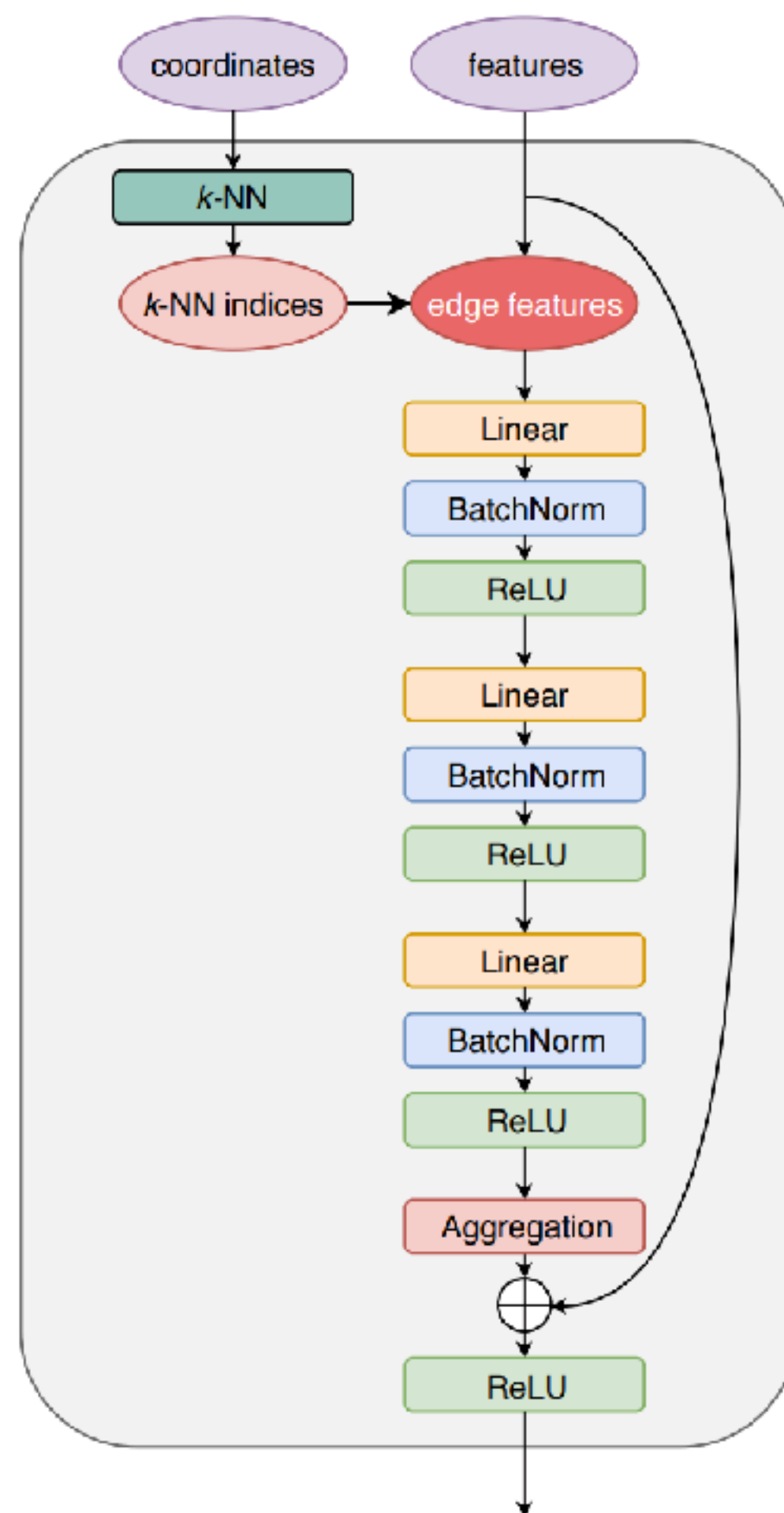
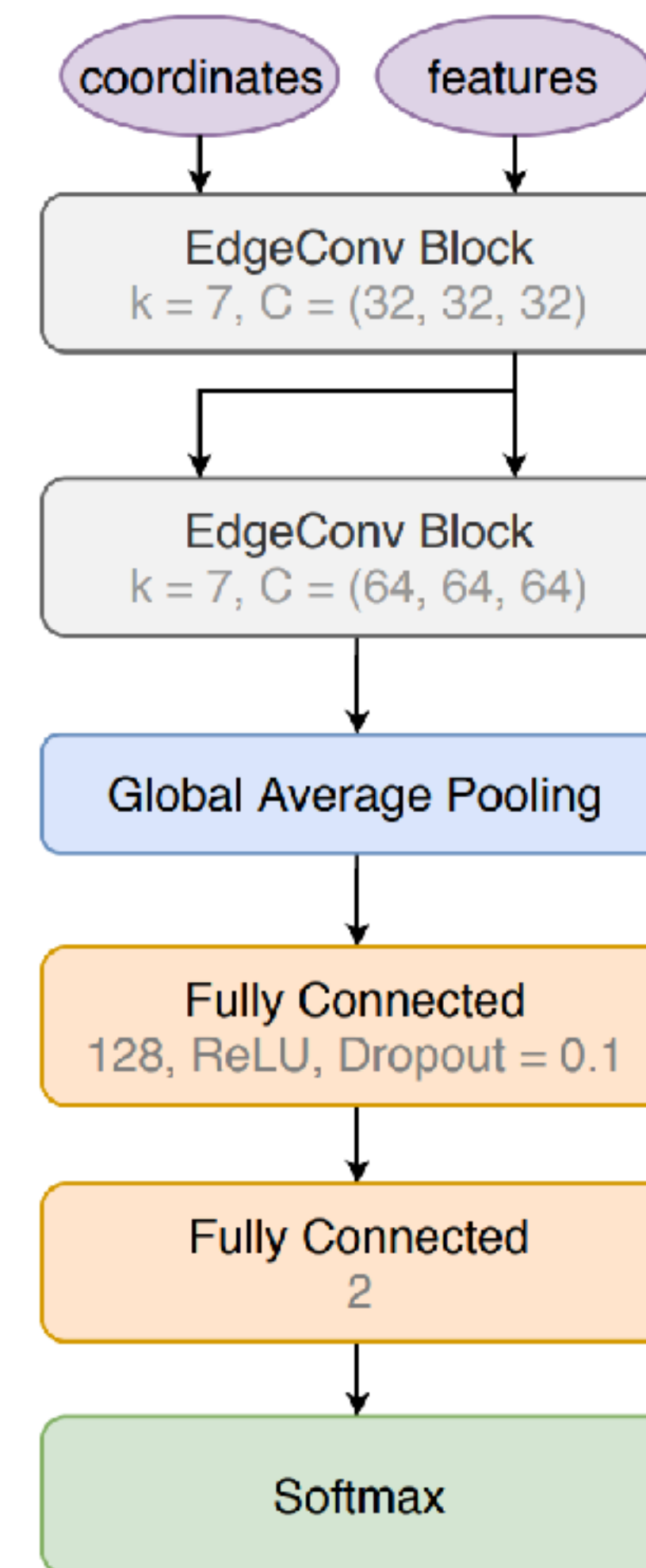


FIG. 1: The structure of the EdgeConv block.



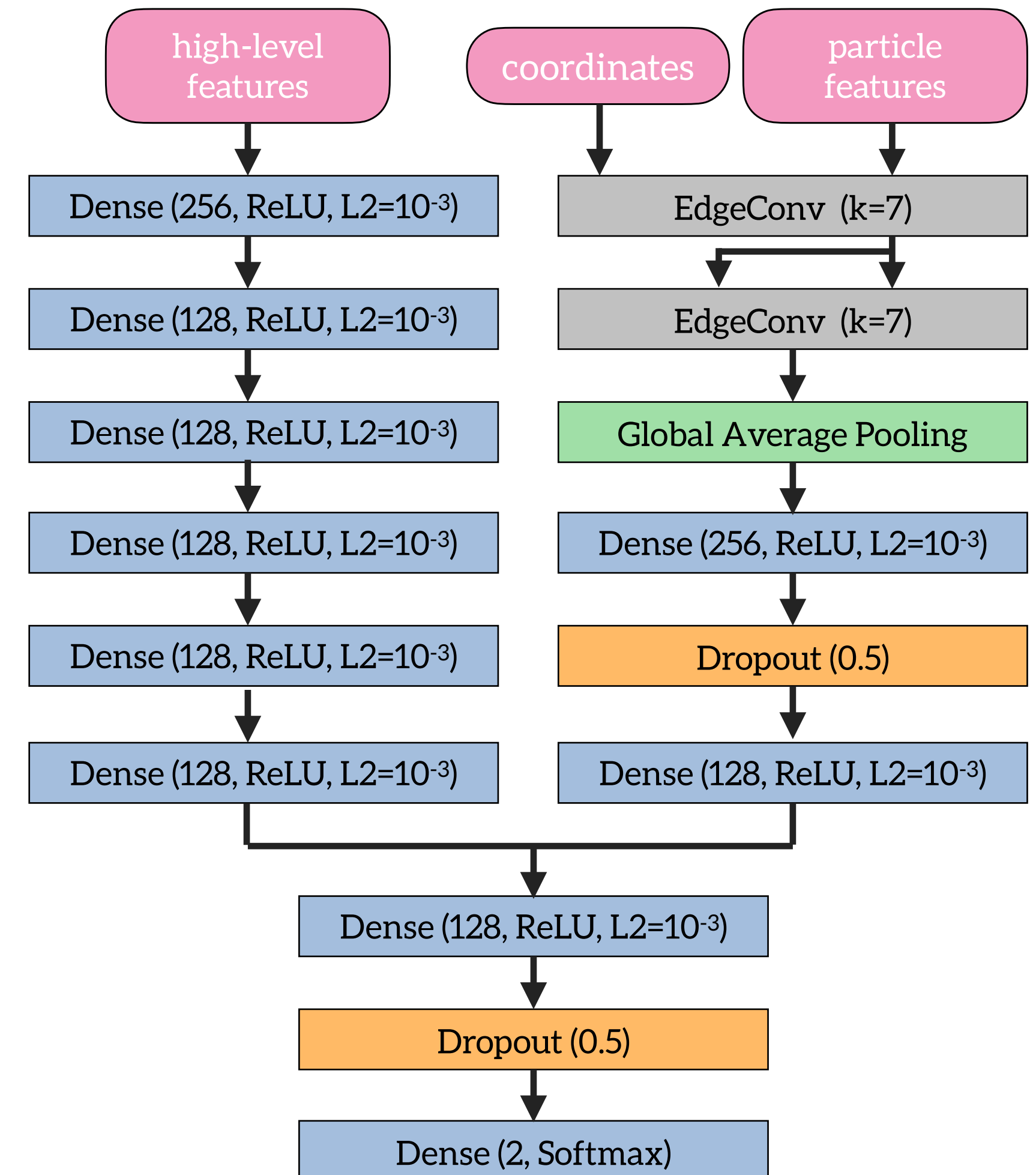
(b) ParticleNet-Lite

Analysis

Preanalysis

- $4 \geq \#jets \geq 2$
- $p_T^{1j} > 520 \text{ GeV}$
- $\eta^{1j} < 2.0$
- $p_T^{2j} > 320 \text{ GeV}$
- $\eta^{2j} < 2.0$
- $MET > 820 \text{ GeV}$
- lepton veto
- $\Delta\phi(j^{1,2,3}, p_T^{\text{miss}}) > 0.8$
- $\Delta\phi(j^4, p_T^{\text{miss}}) > 0.4$
- $MET/\sqrt{H_T} > 16 \sqrt{\text{GeV}}$
- $M_{\text{eff}} > 1600 \text{ GeV}$
- **particle $p_T > 1 \text{ GeV}$**

GNN model



A wide-angle photograph of a beach at sunset. Two yellow fishing boats with multiple flags are beached in the foreground. The sun is a bright, glowing orb on the horizon, casting a long, shimmering reflection across the wet sand and the ocean's surface. The sky is a deep orange, and the water shows gentle waves. In the distance, a few small figures of people are walking along the shoreline. A semi-transparent white box with rounded corners is centered in the lower half of the image, containing the word "results" in a dark blue, sans-serif font.

results

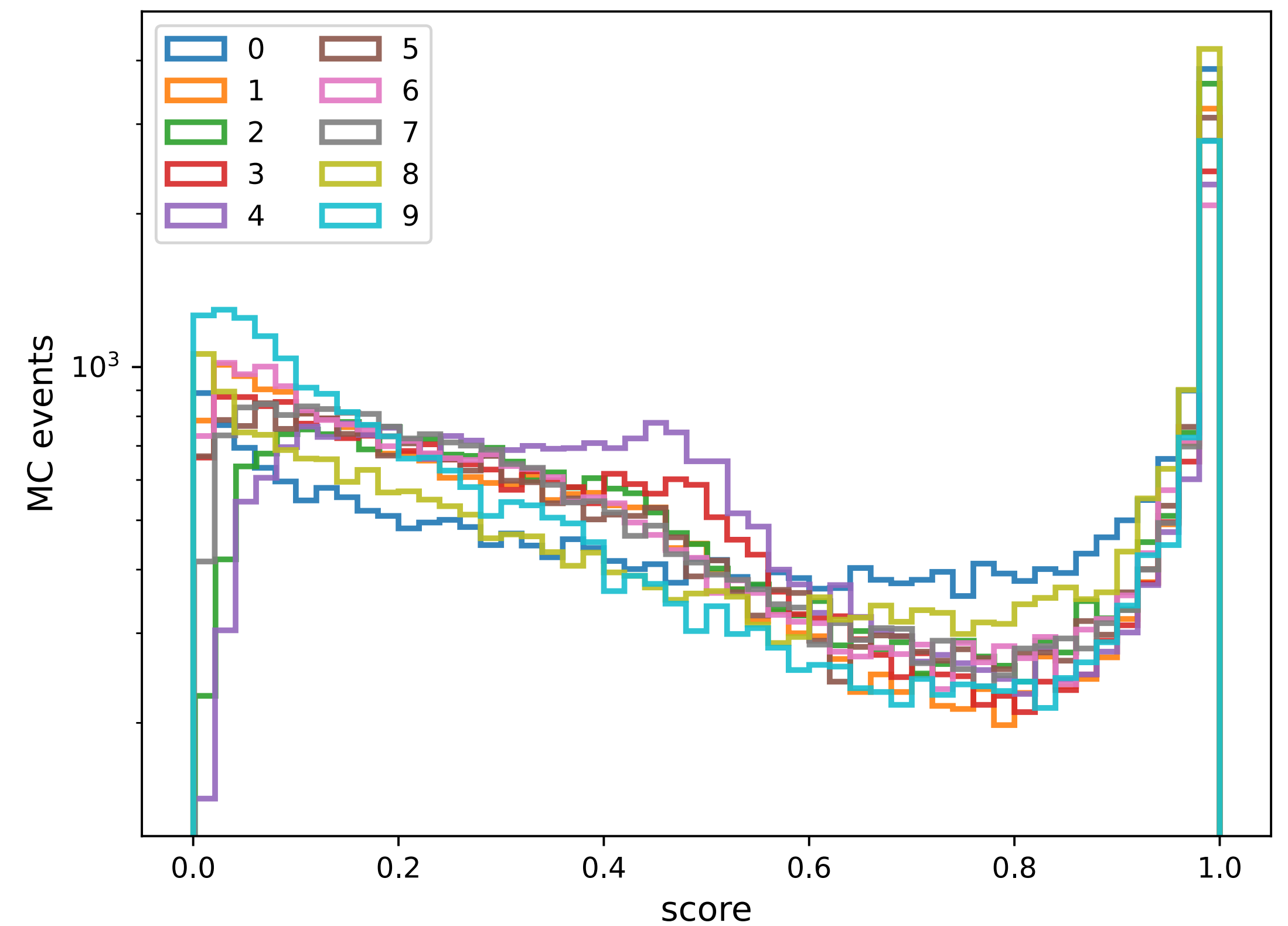
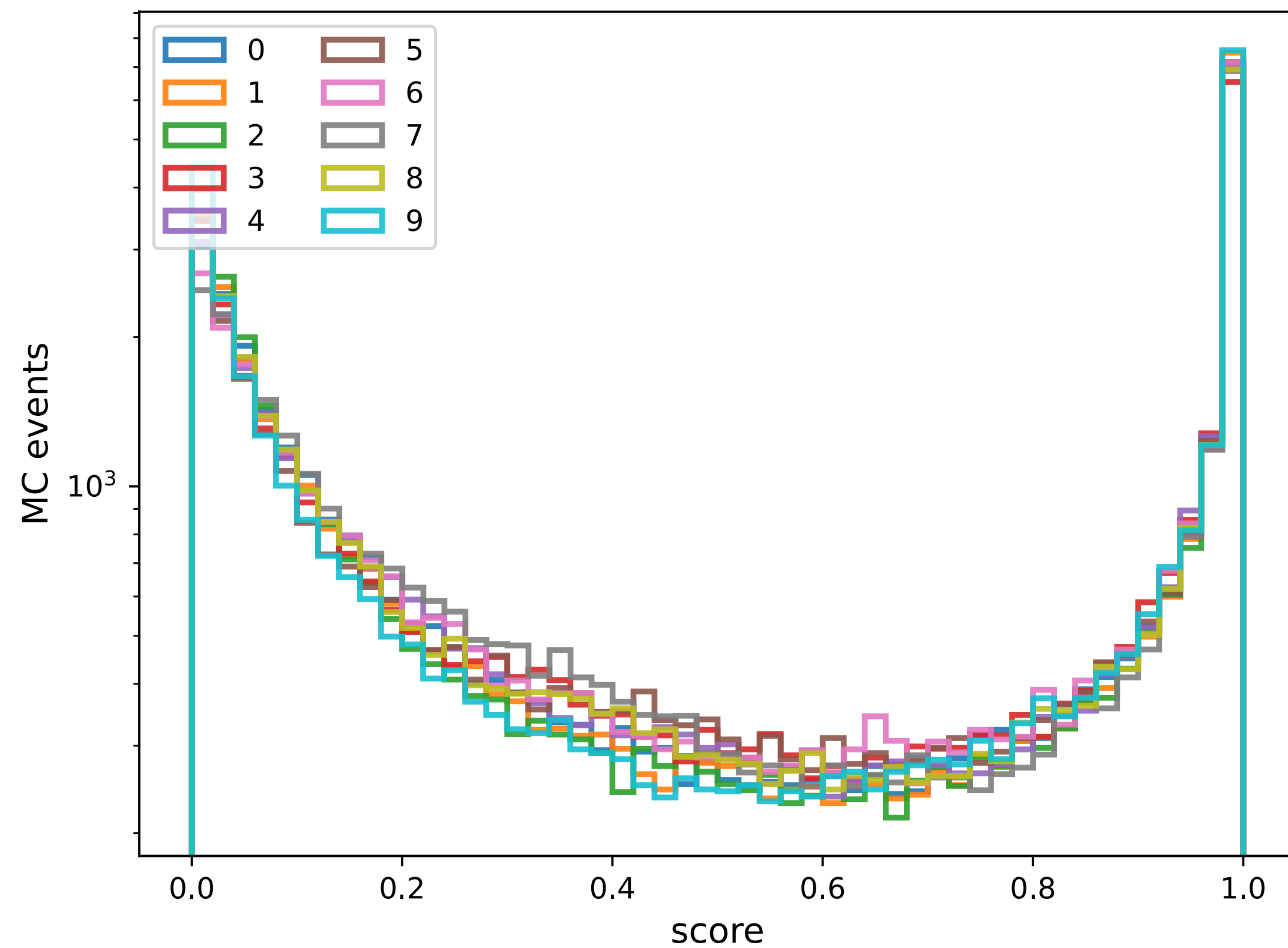
Beach in Dębki, Poland

Ensemble training

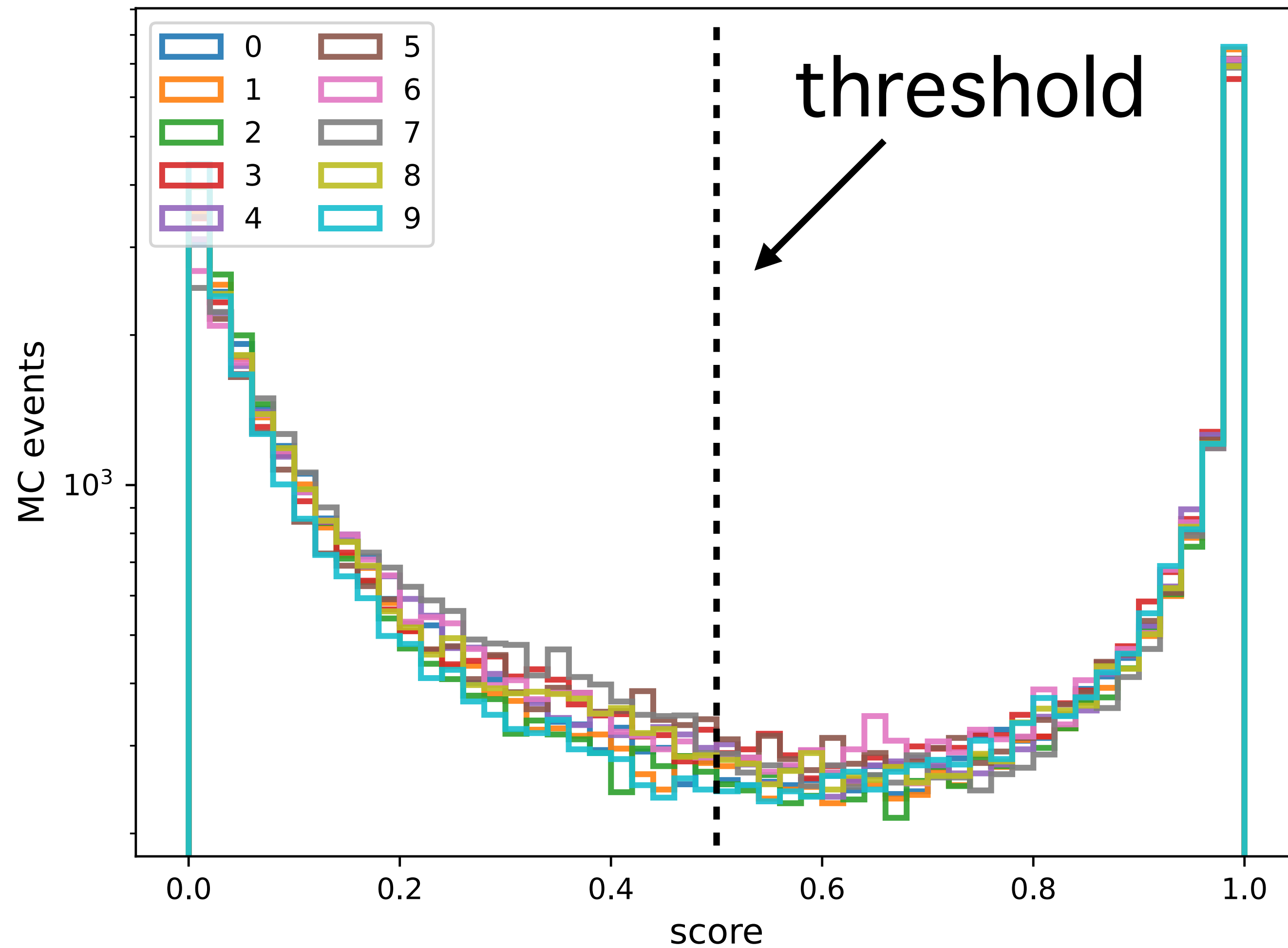
$$m_{\tilde{\chi}} = 300 \text{ GeV}, m_{\tilde{q}} = 2.2 \text{ TeV}$$

higgsinos

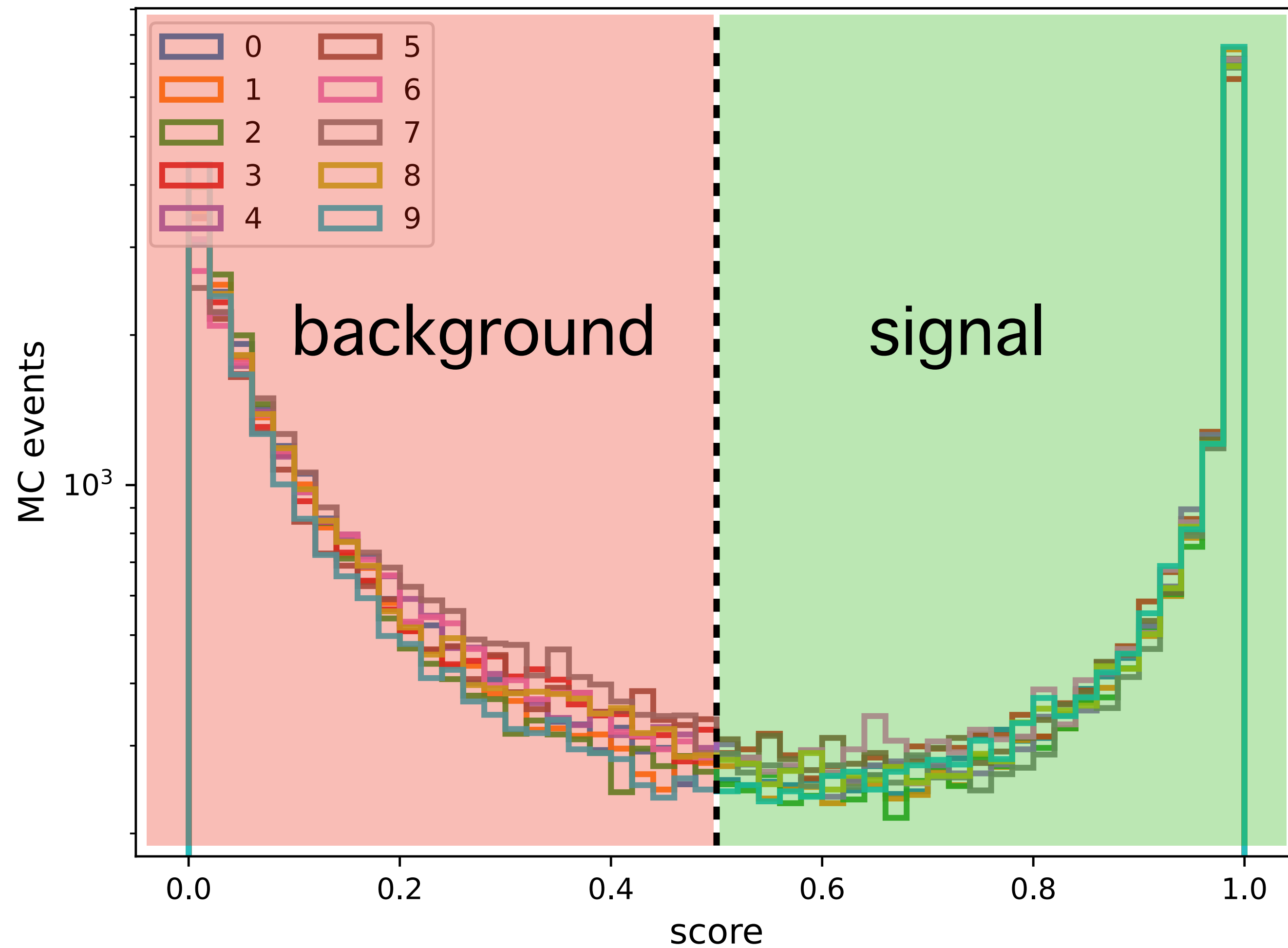
winos



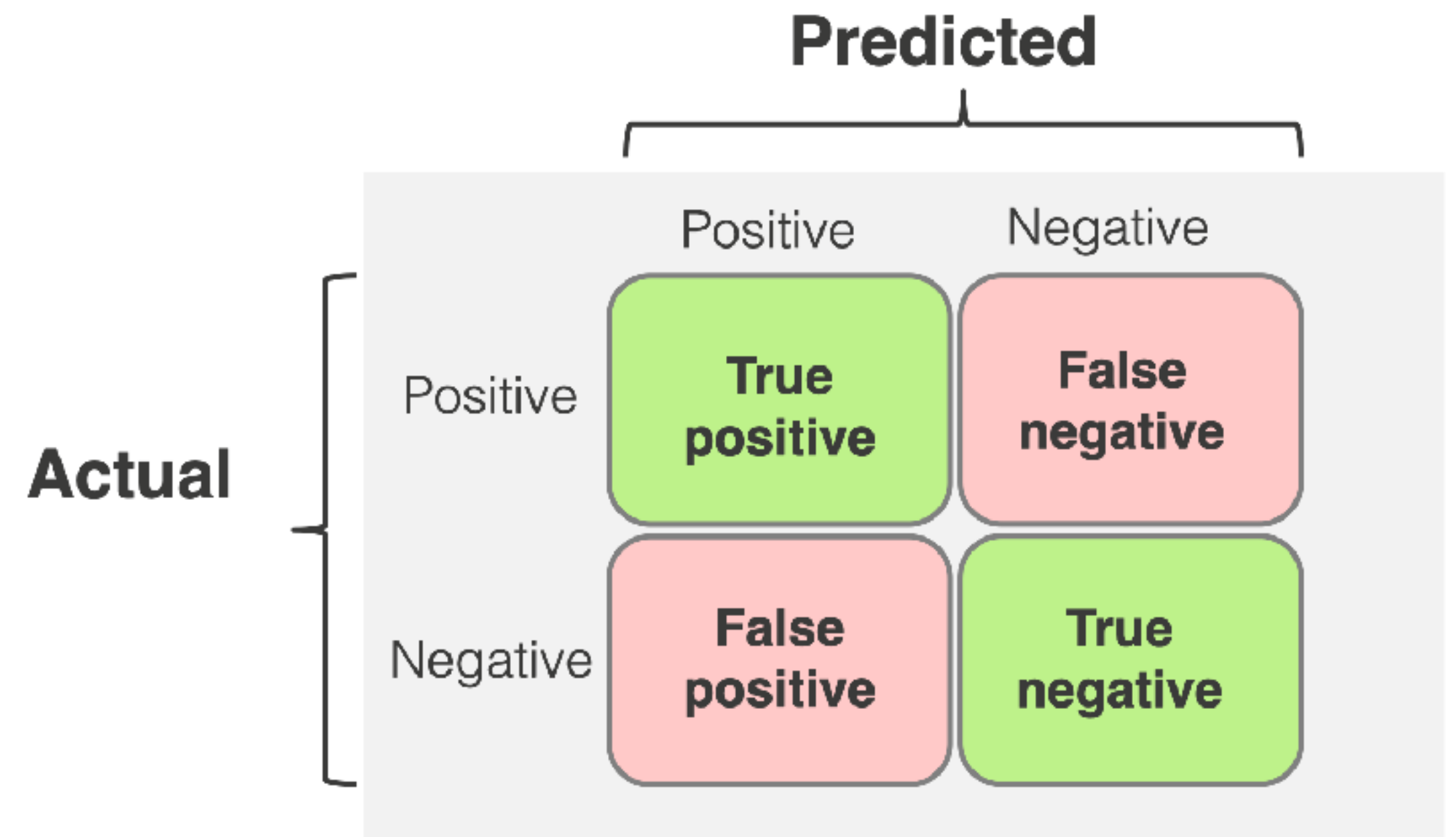
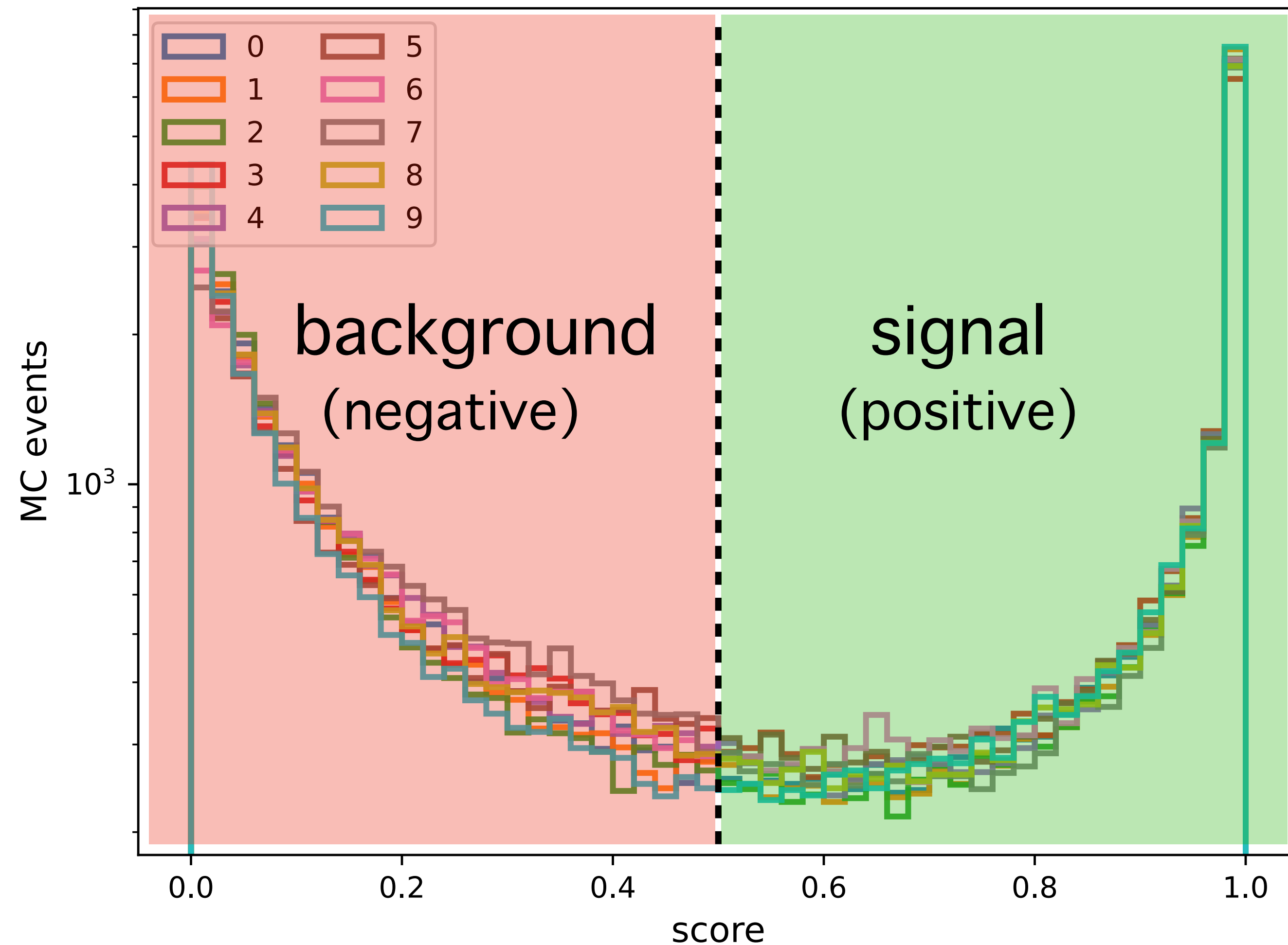
Binary classification



Binary classification



Binary classification



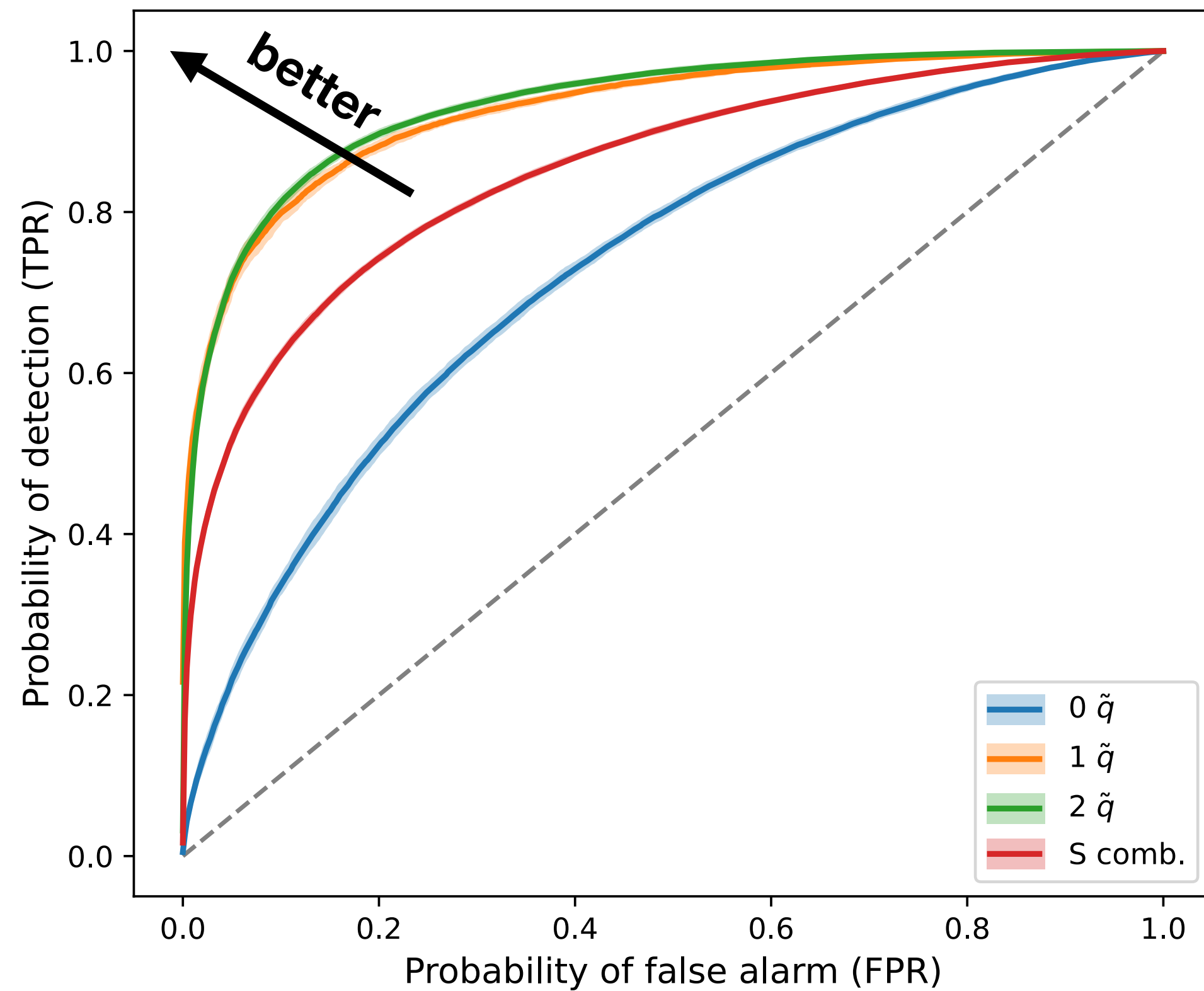
$$\text{TPR} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{FPR} = \text{FP} / (\text{FP} + \text{TN})$$

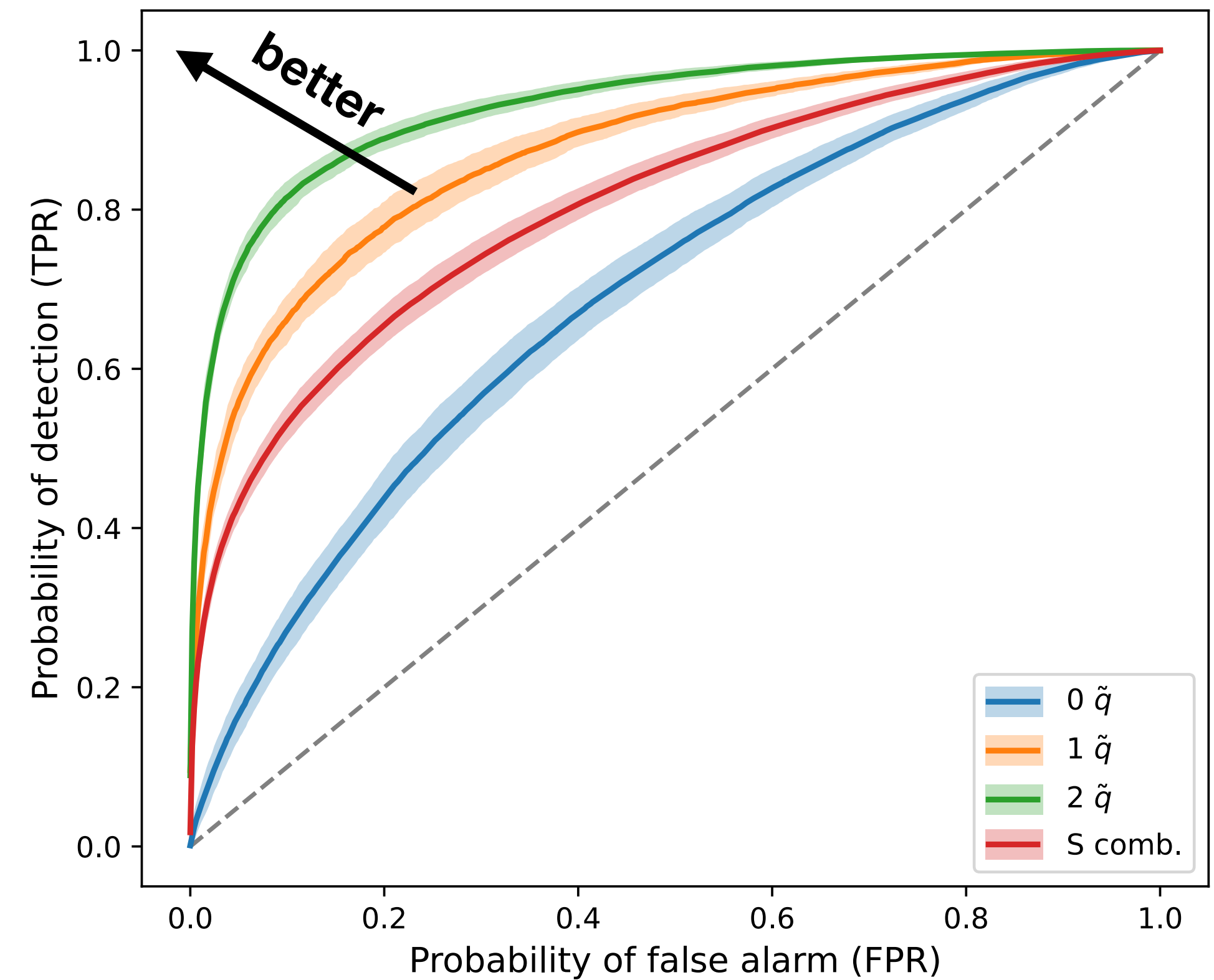
Evaluation

$$m_{\tilde{\chi}} = 300 \text{ GeV}, m_{\tilde{q}} = 2.2 \text{ TeV}$$

higgsinos



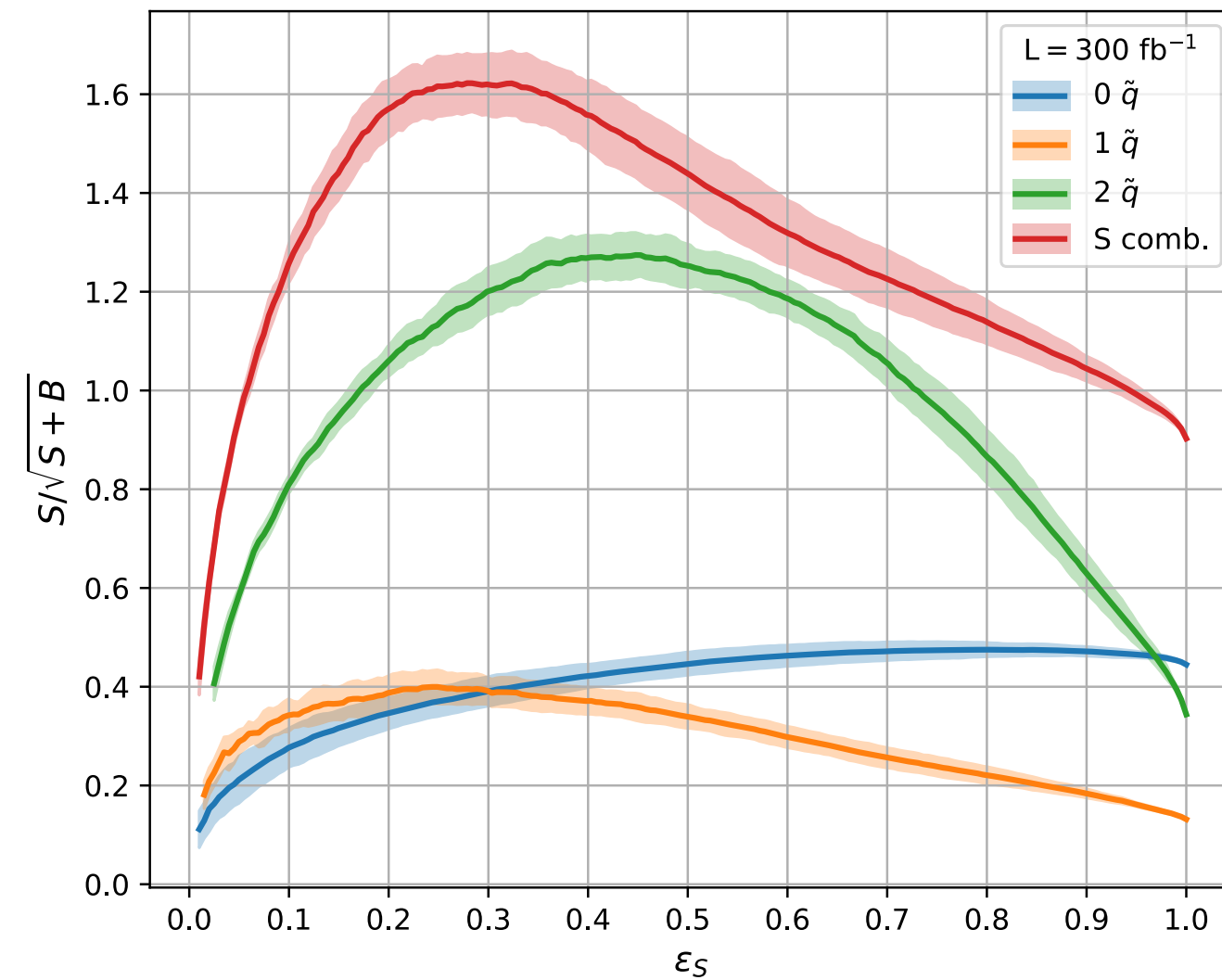
winos



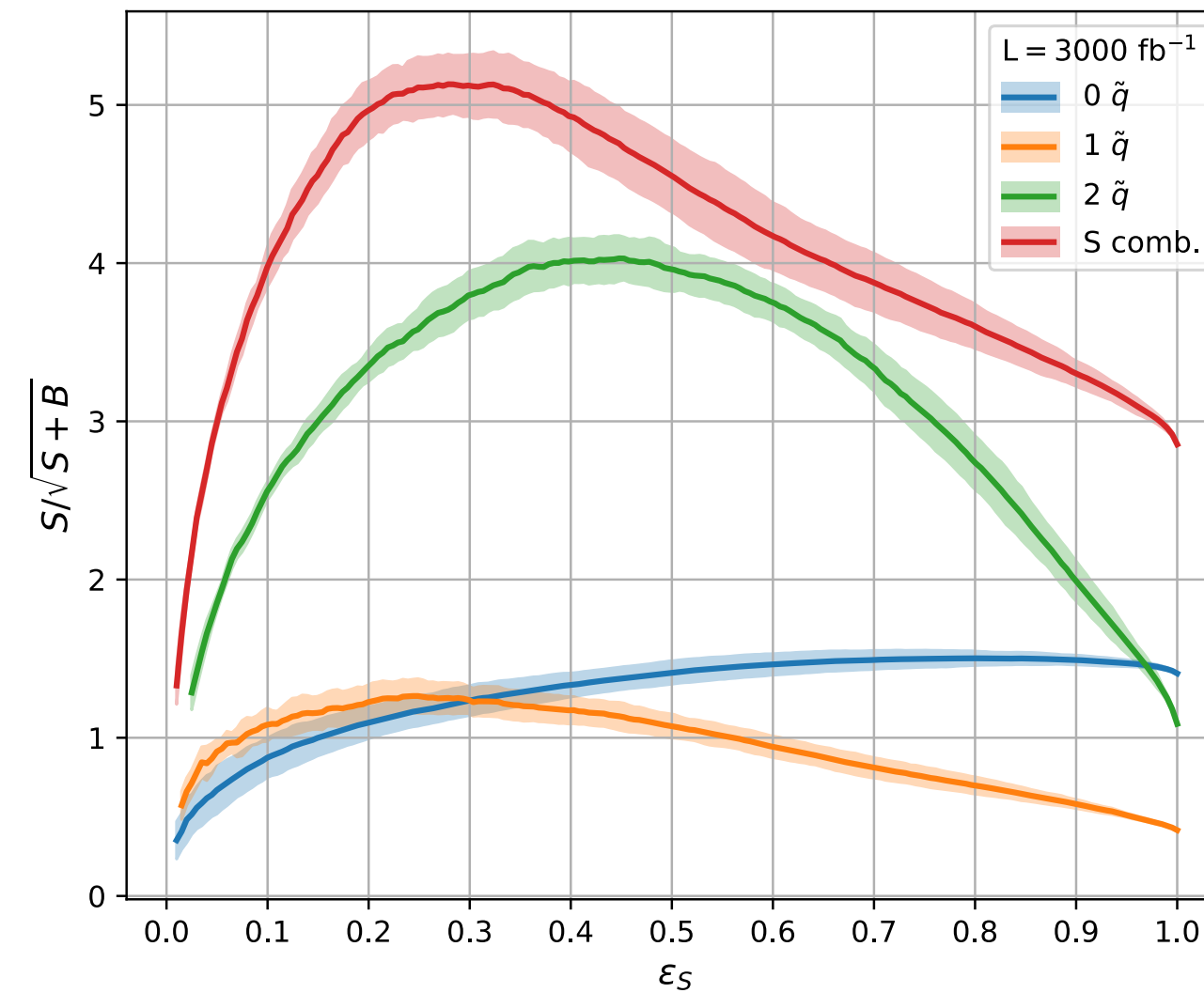
Signal efficiency vs. naive significance

winos

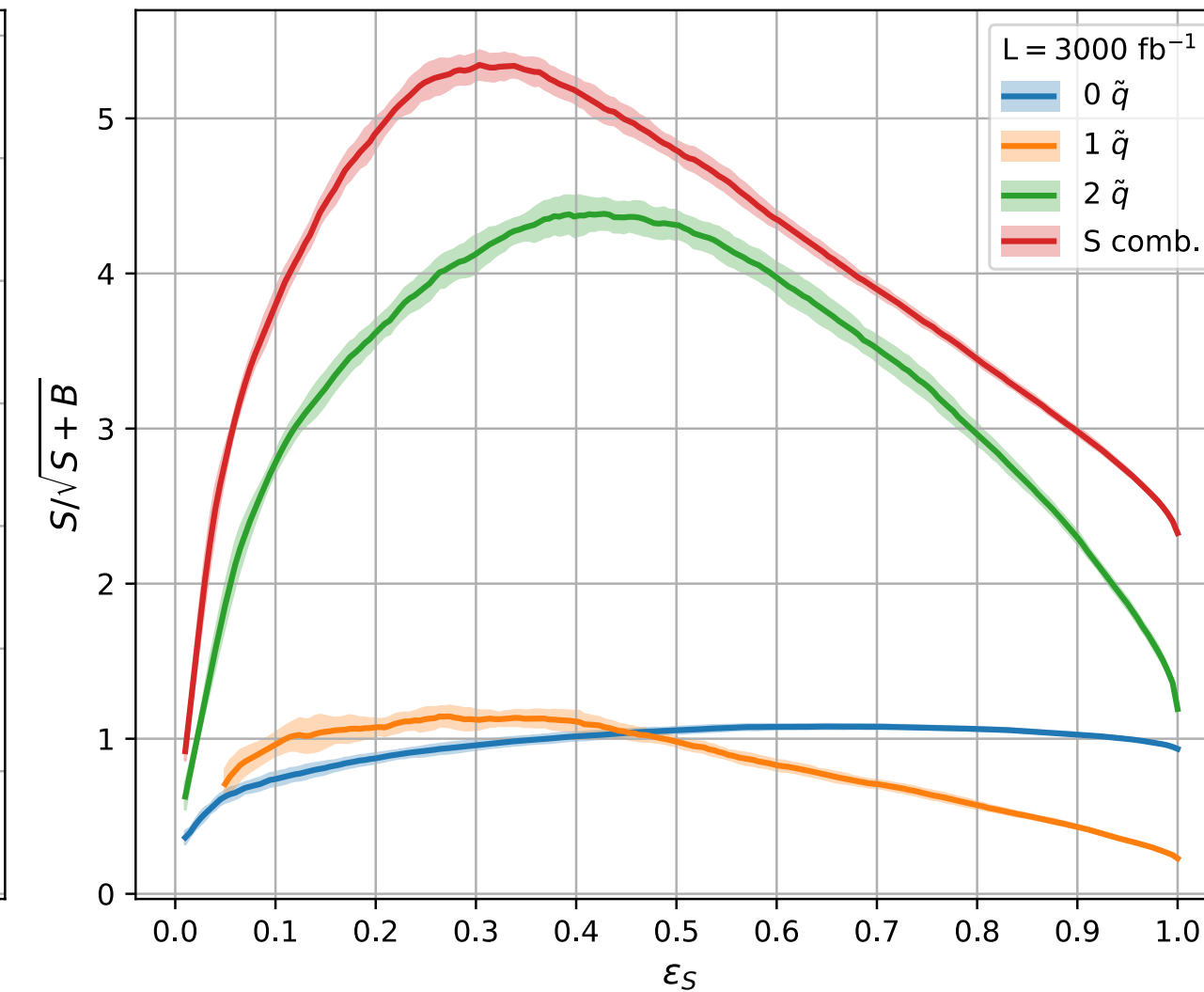
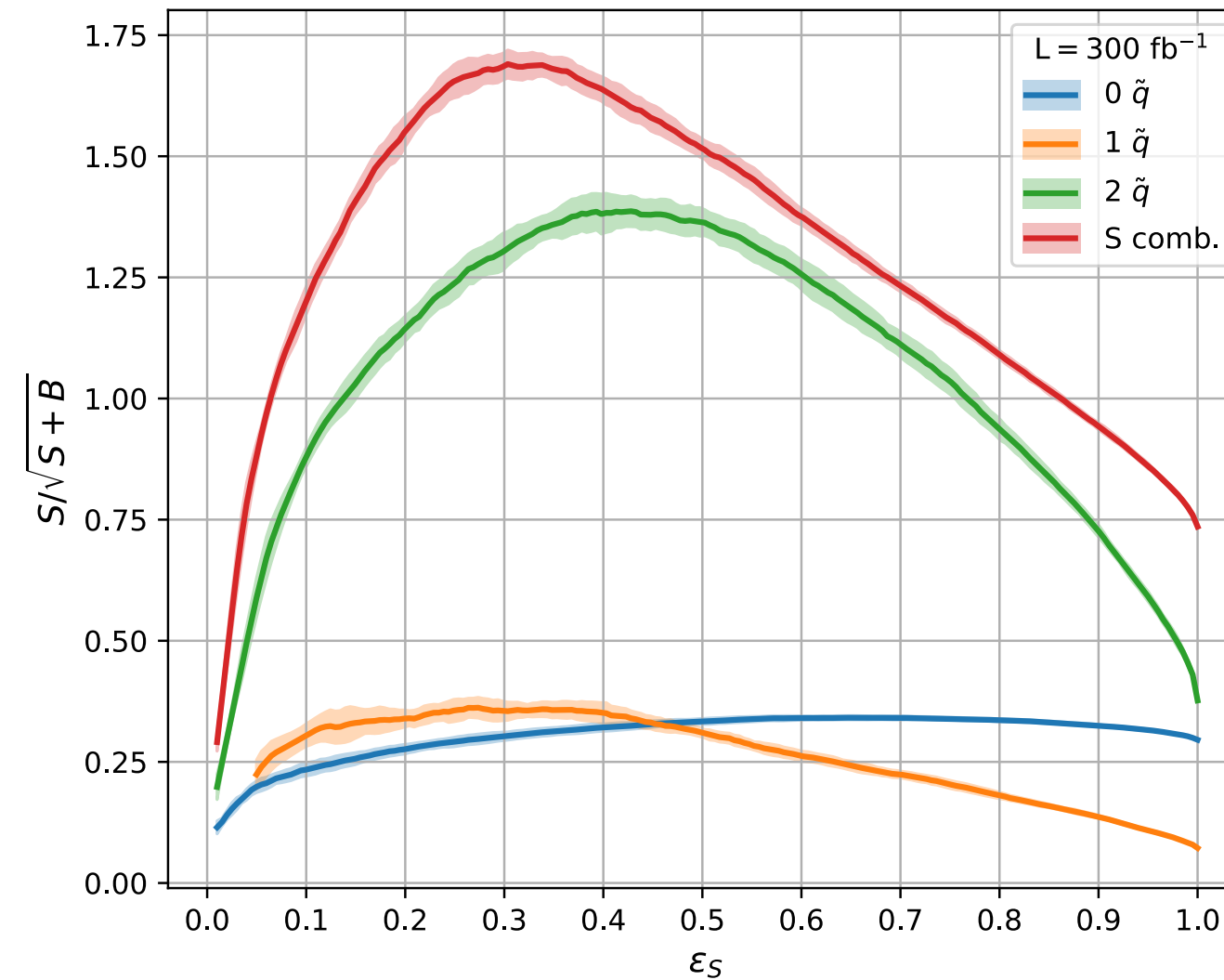
Run-3



HL-LHC



higgsinos

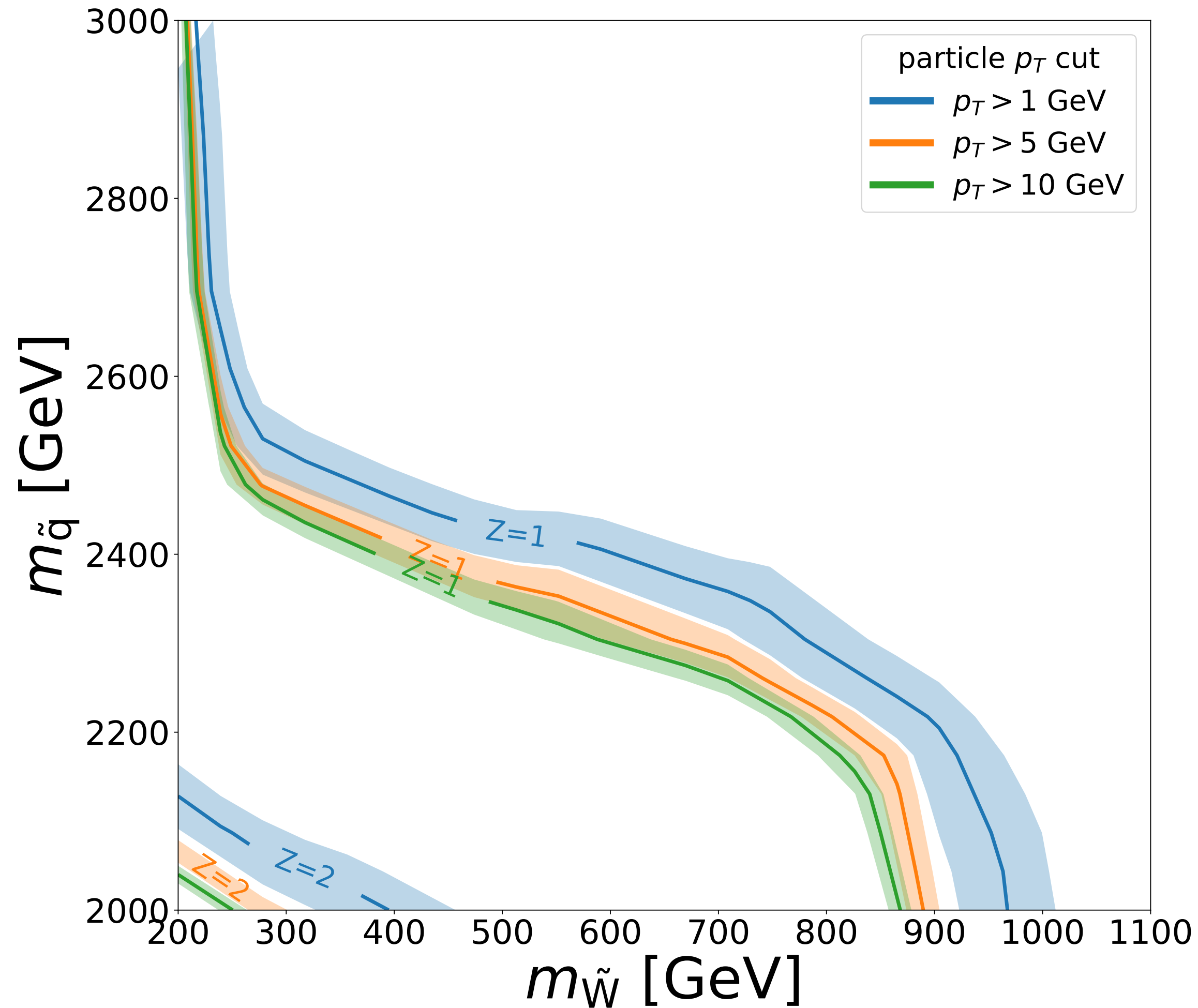


$$Z = S/\sqrt{S+B}$$

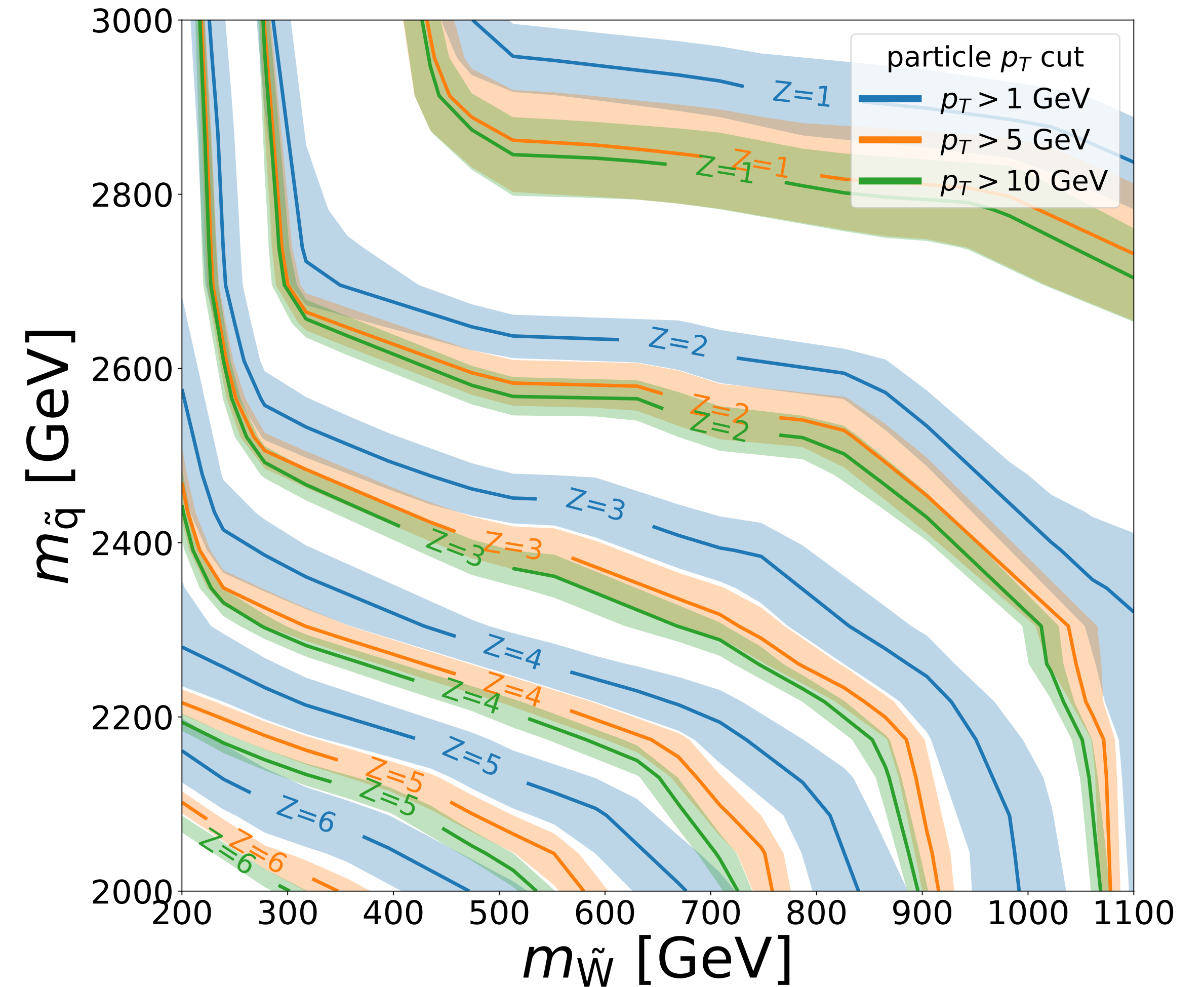
$$m_{\tilde{\chi}} = 300 \text{ GeV}, m_{\tilde{q}} = 2.2 \text{ TeV}$$

Limits for winos

Run-3

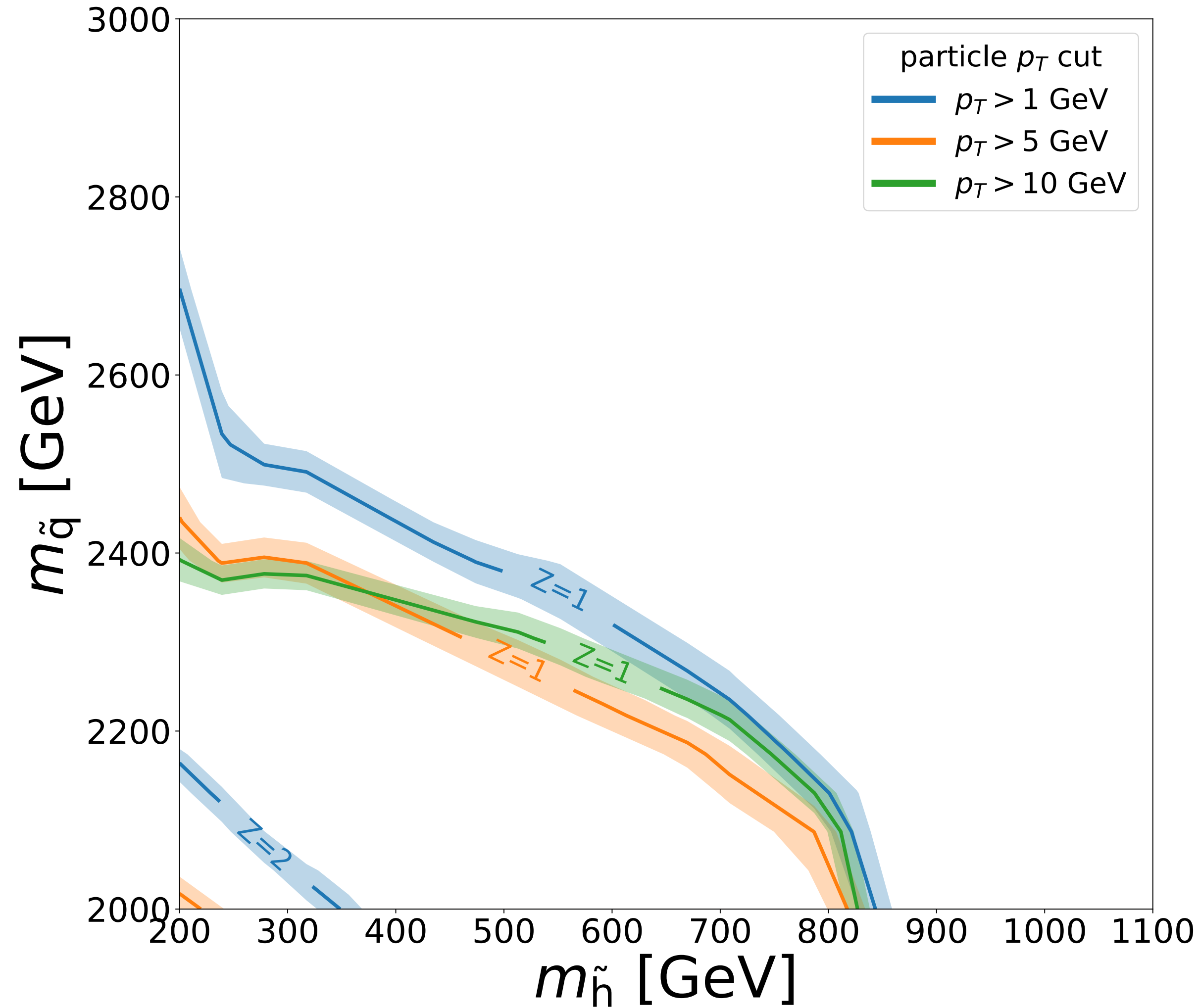


HL-LHC

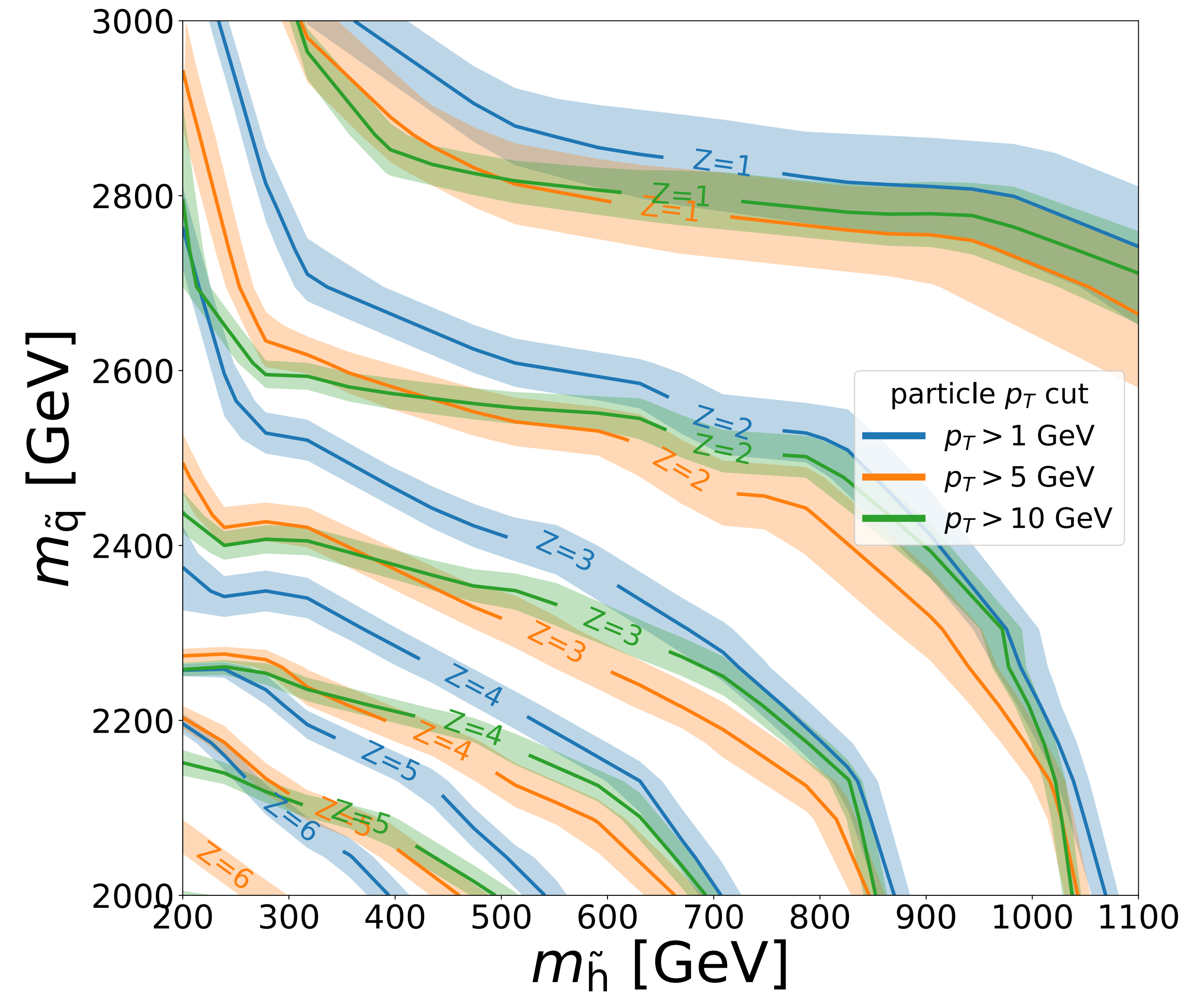


Limits for higgsinos

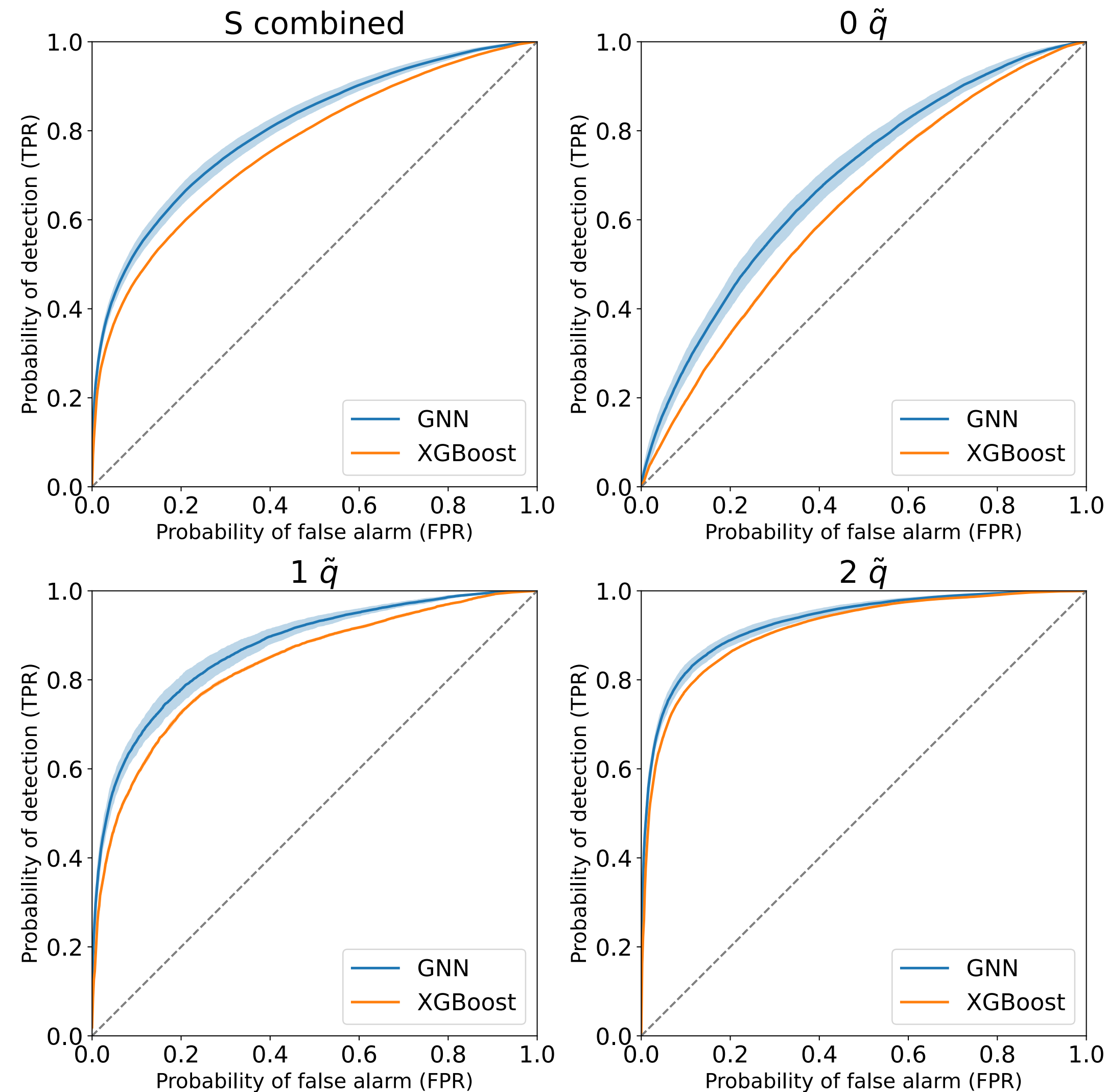
Run-3



HL-LHC

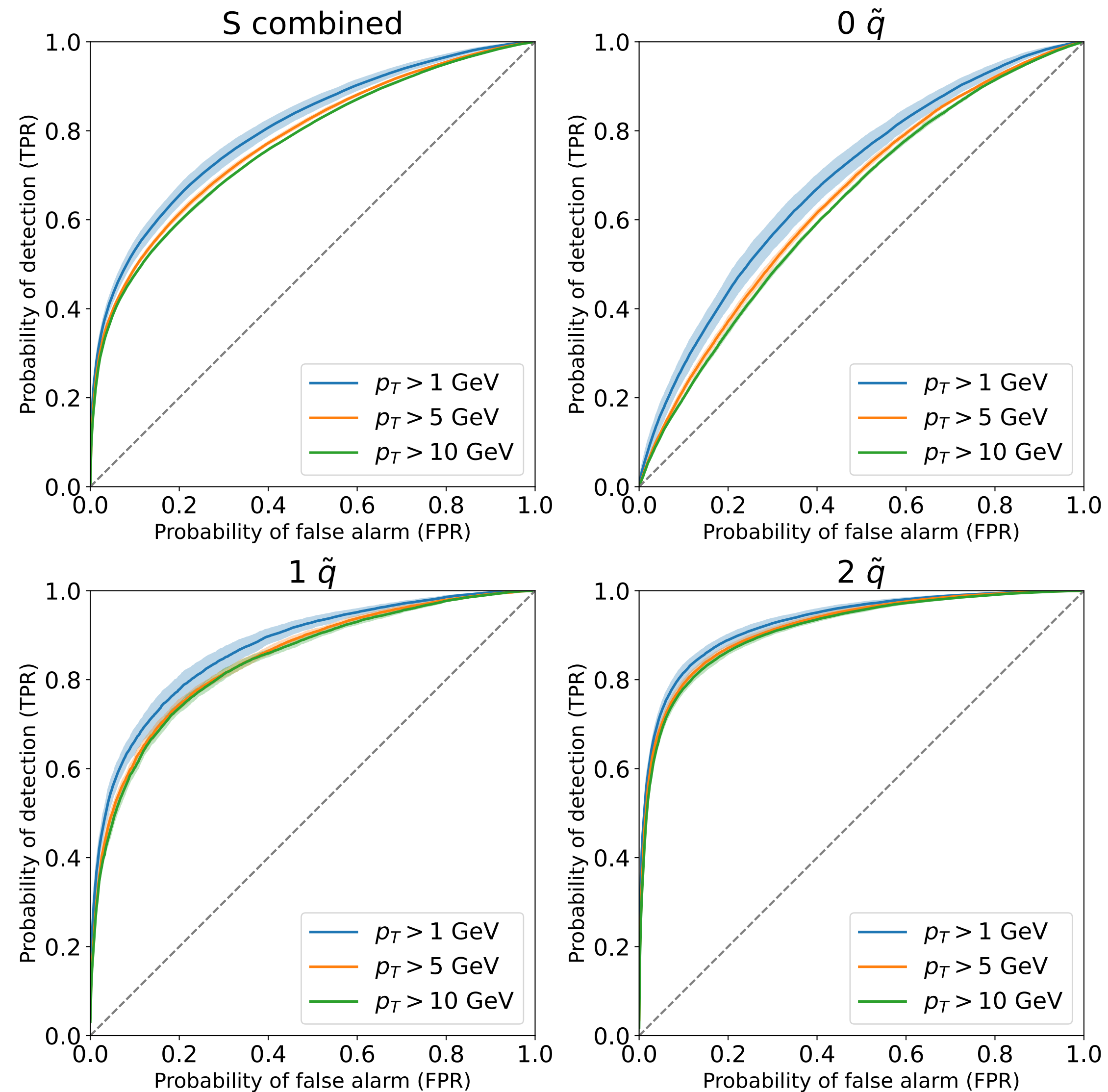


Comparison with BDTs (winos)

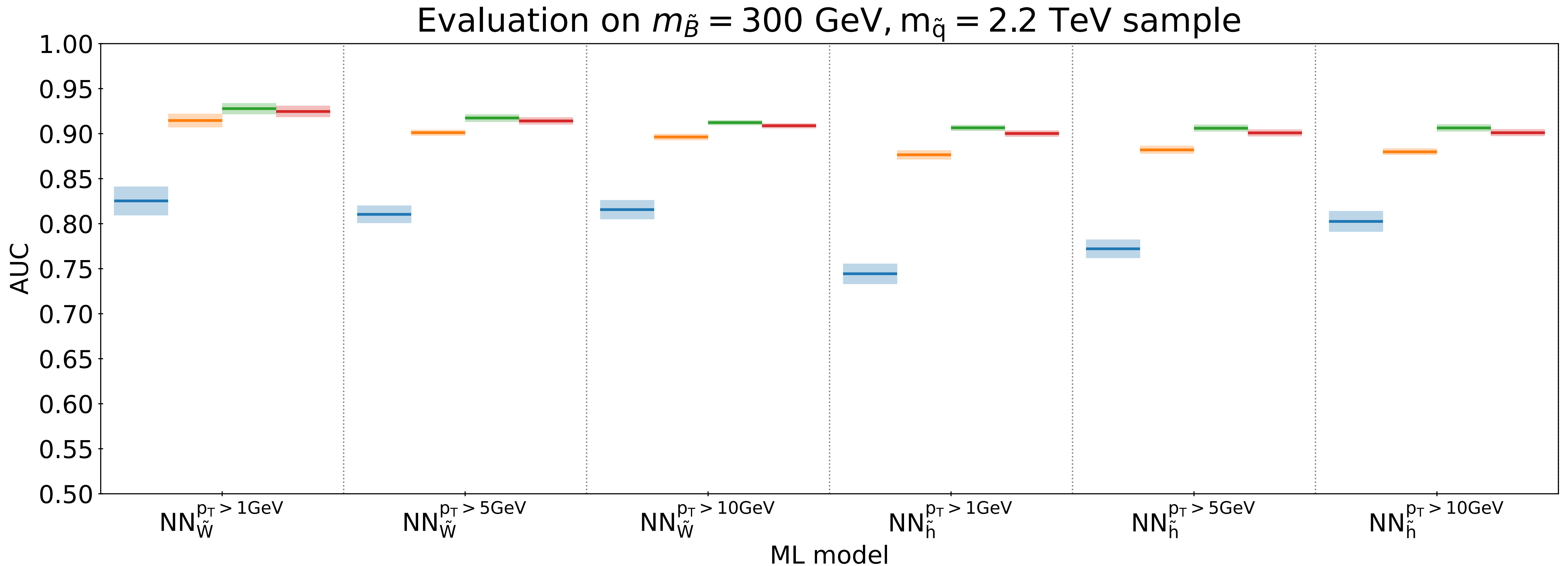


=

Impact of the p_T cut (winos)

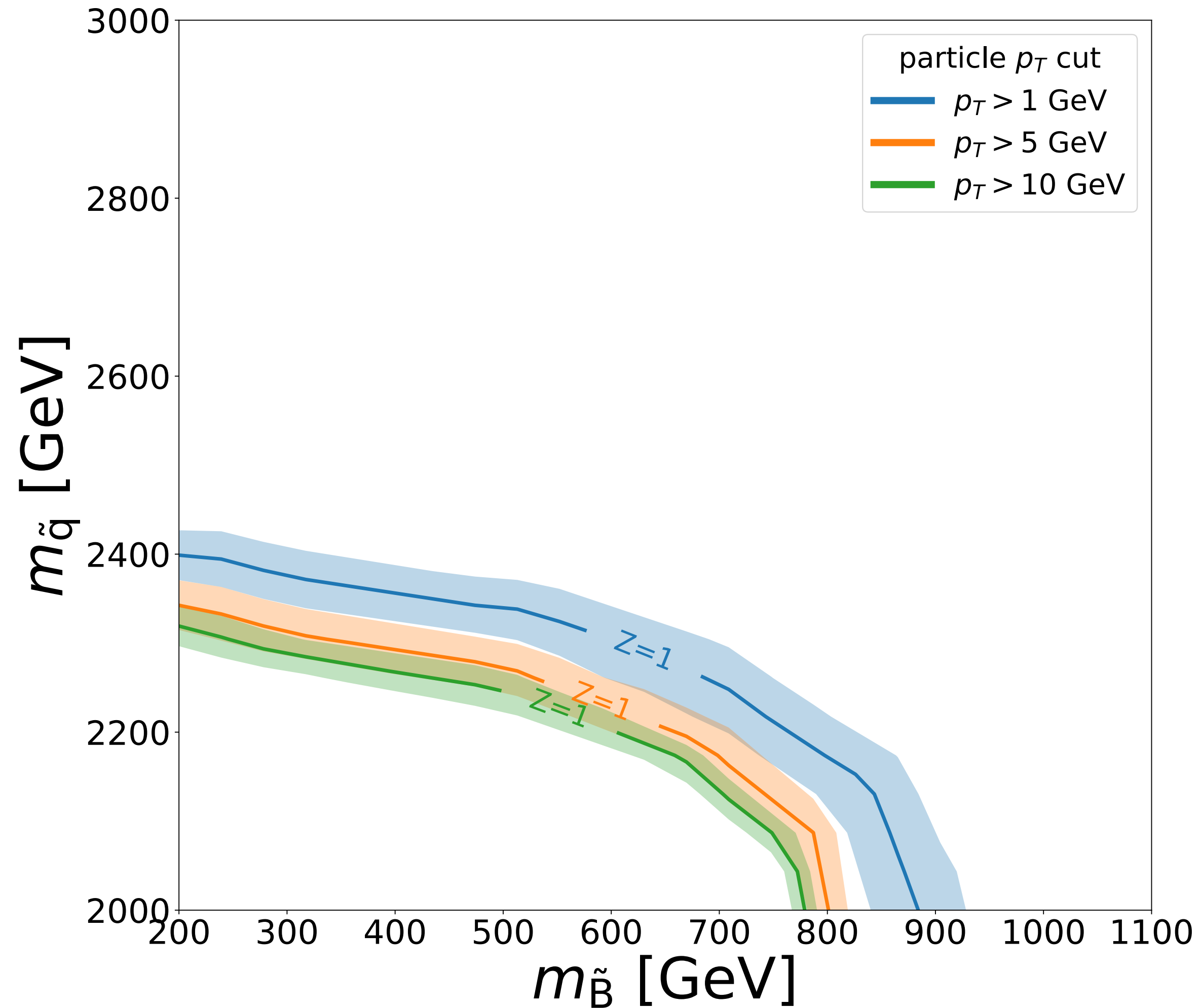


Cross evaluation for binos

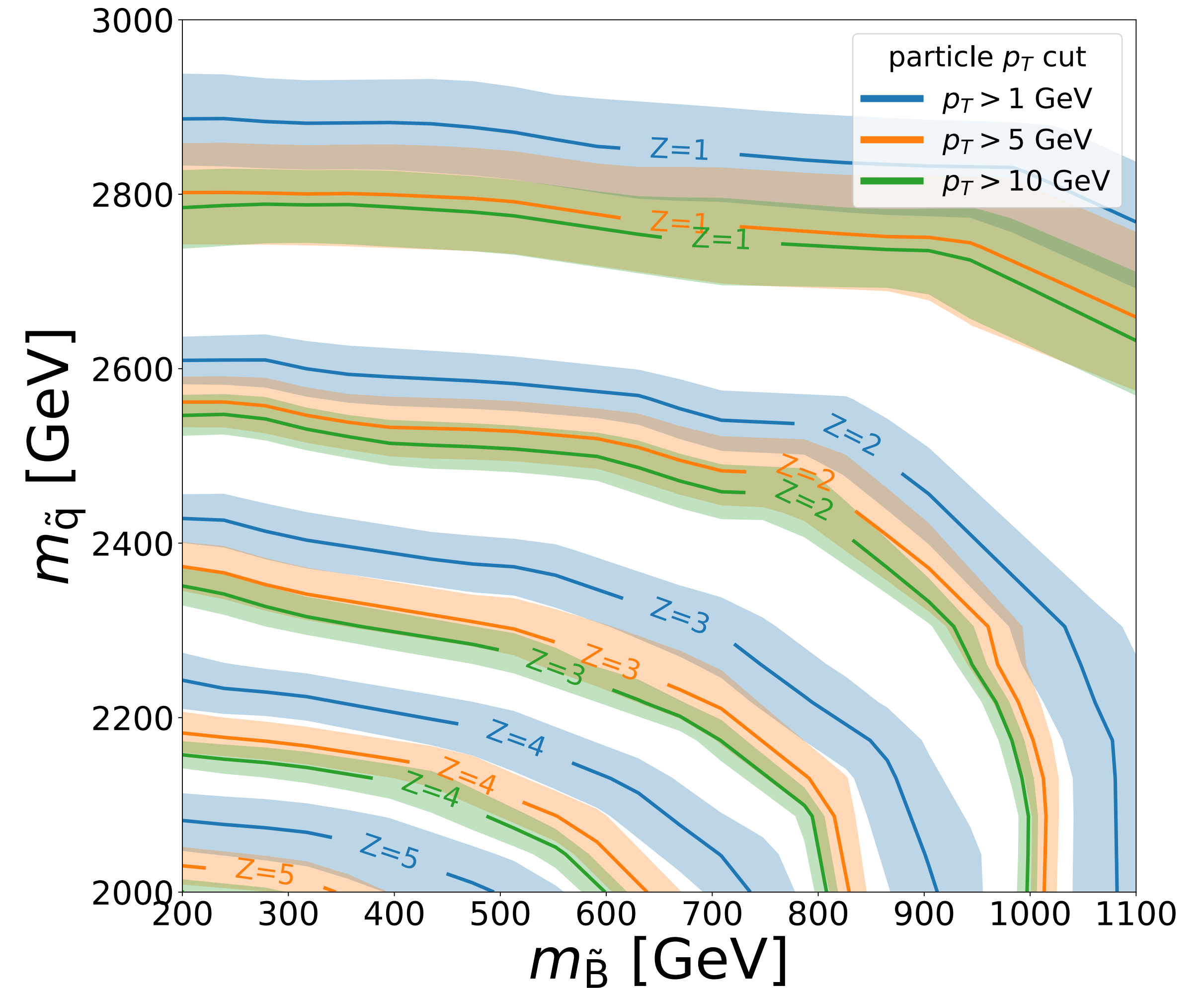


Limits for binos

Run-3



HL-LHC



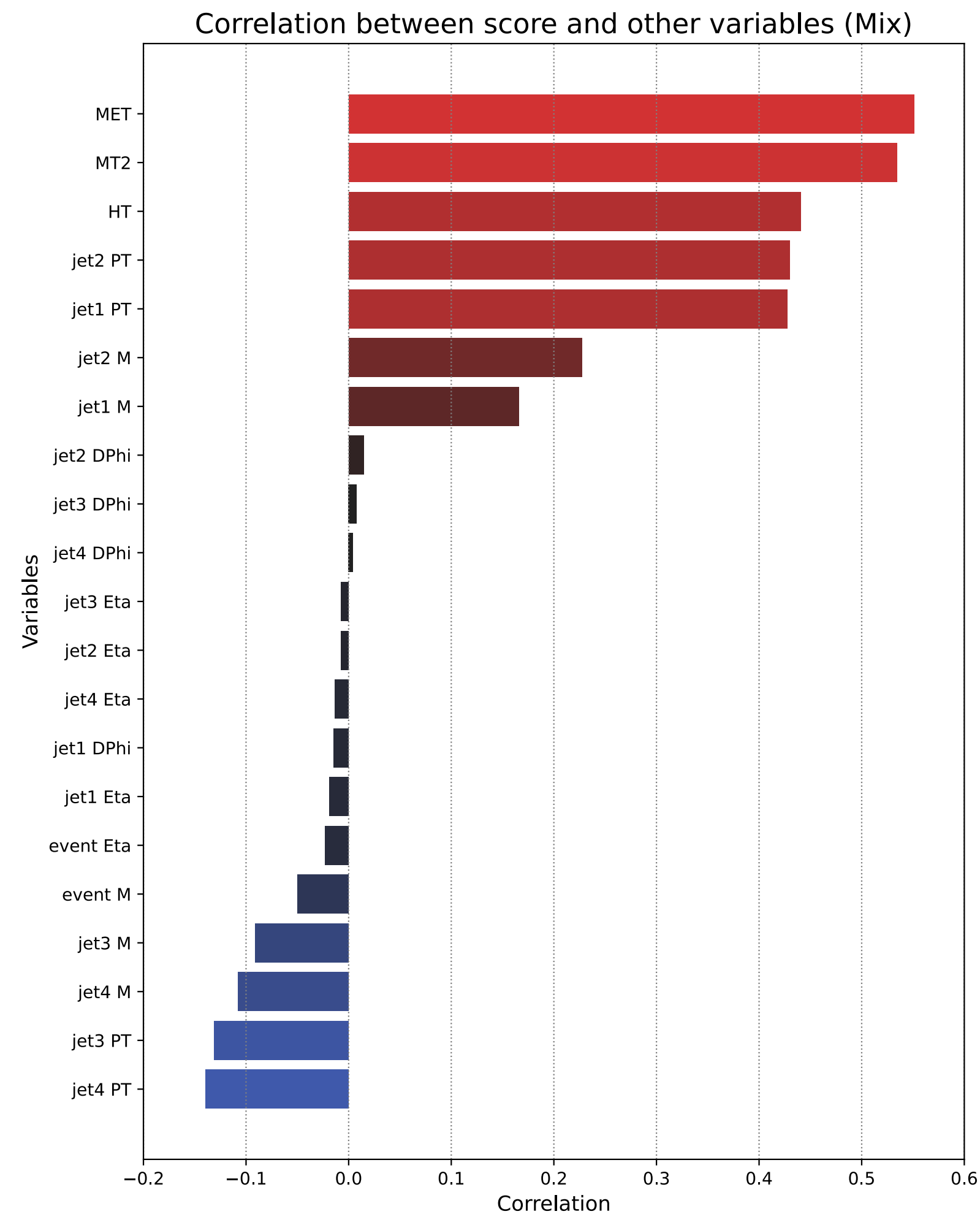
A full-page background image showing a dramatic landscape. In the foreground, a gnarled pine tree stands on a rocky, uneven surface. The middle ground is filled with a thick layer of mist or fog, obscuring the lower parts of the mountains. In the background, several mountain ranges are visible under a sky with vibrant orange, red, and purple hues from the setting or rising sun. The overall mood is serene and majestic.

Interpretation

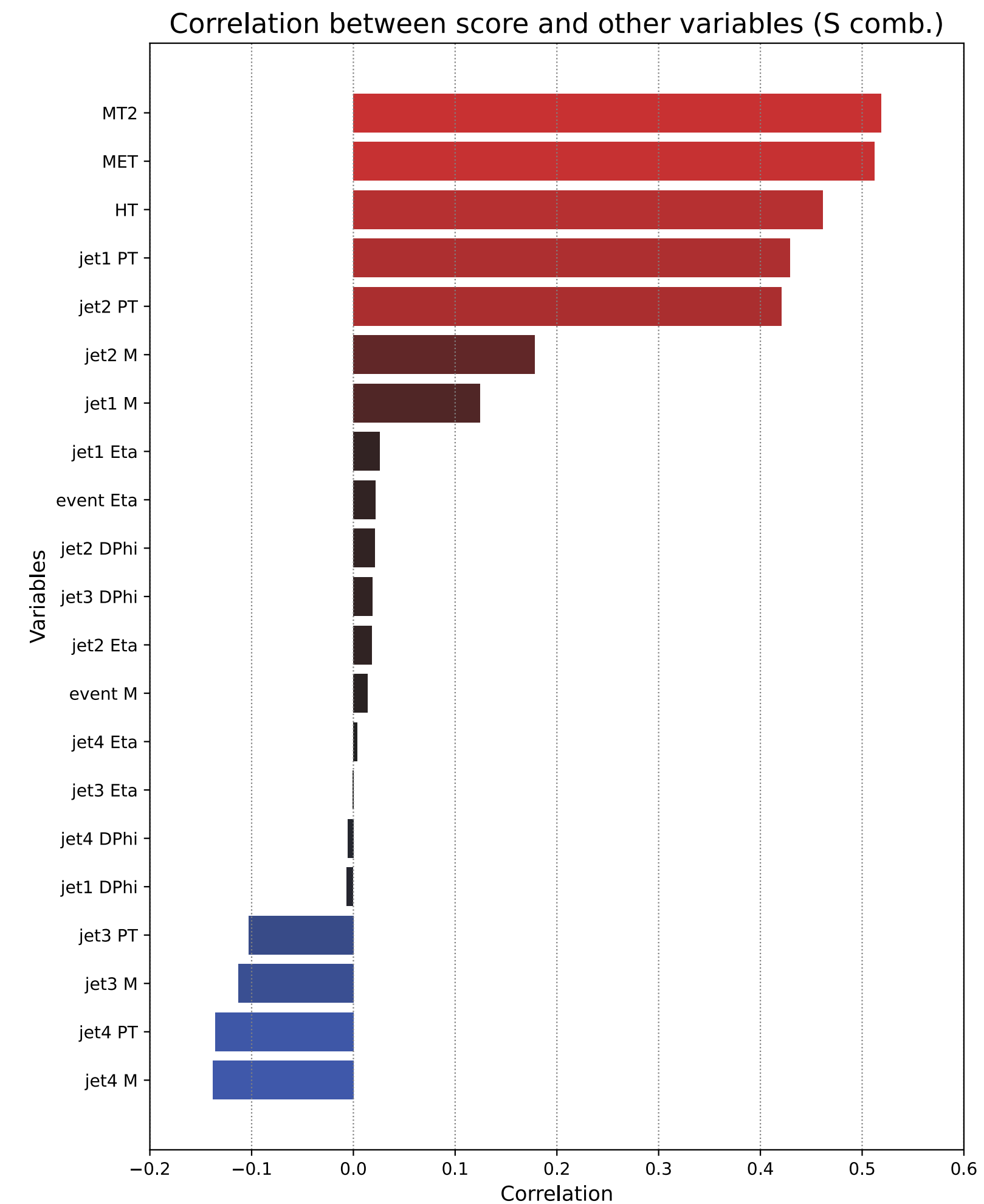
Sokolica peak, Poland

Input-output correlation

winos



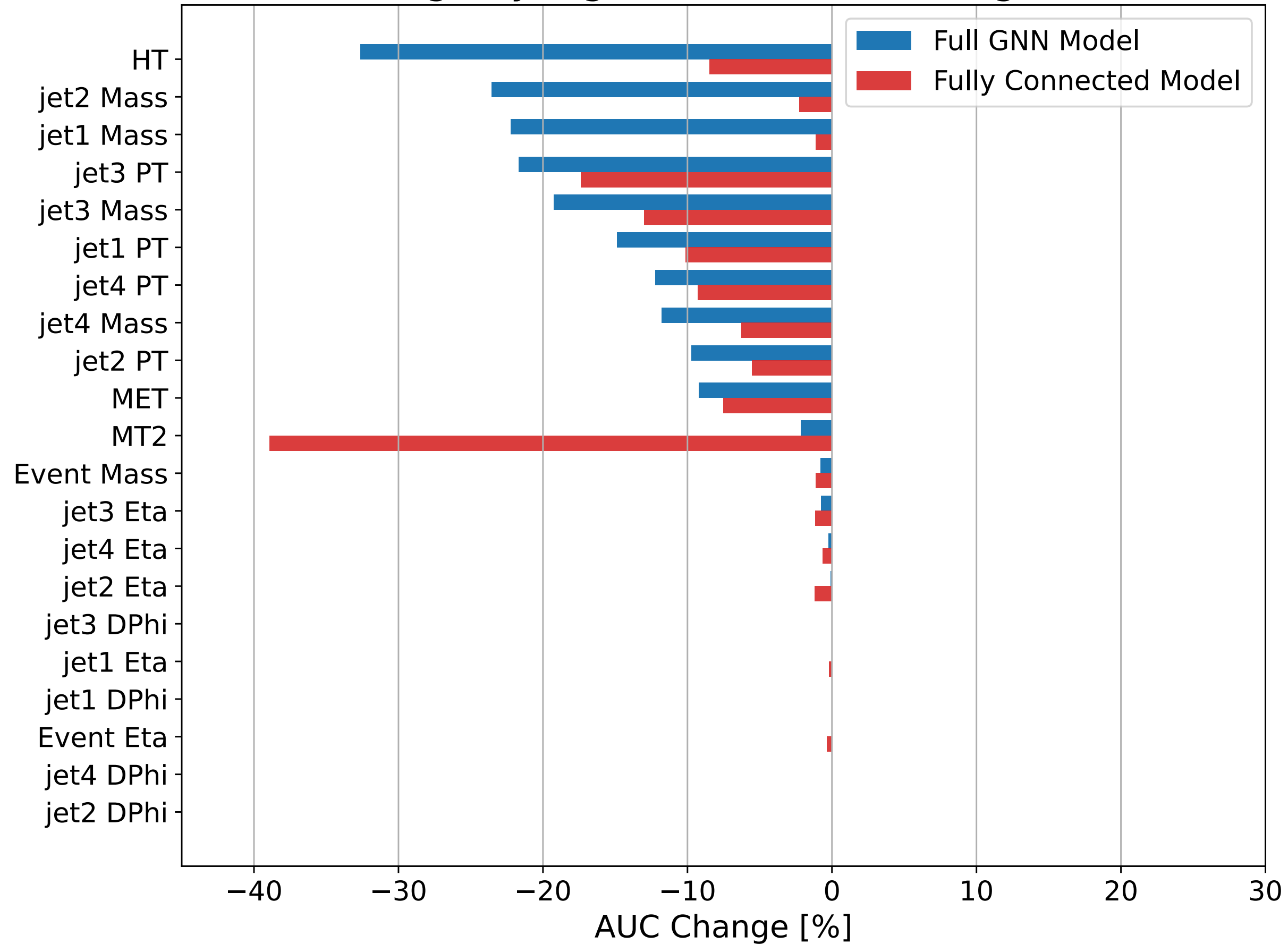
higgsinos



Variable shuffling

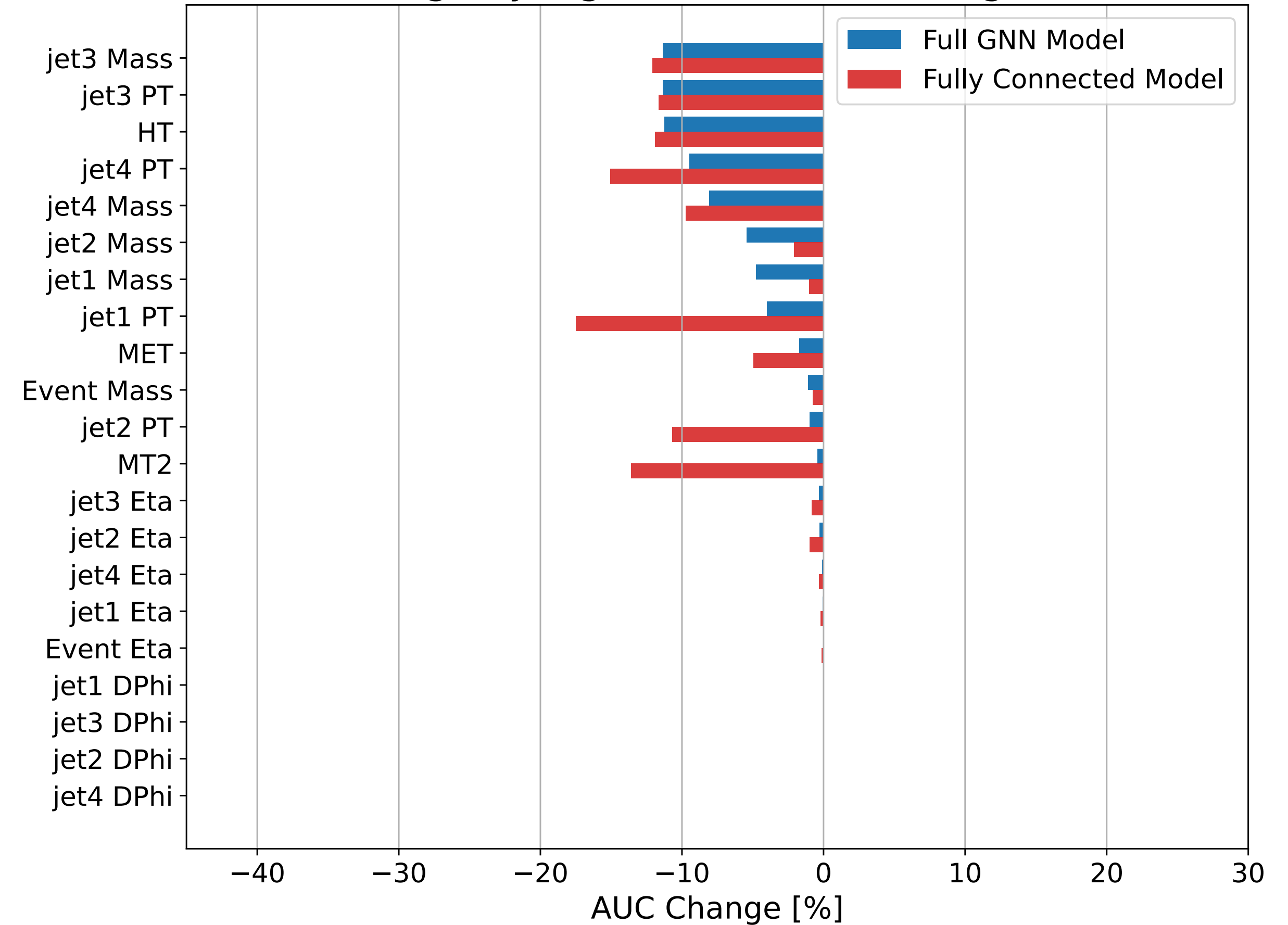
winos

AUC Change by high-level data shuffling (S comb.)

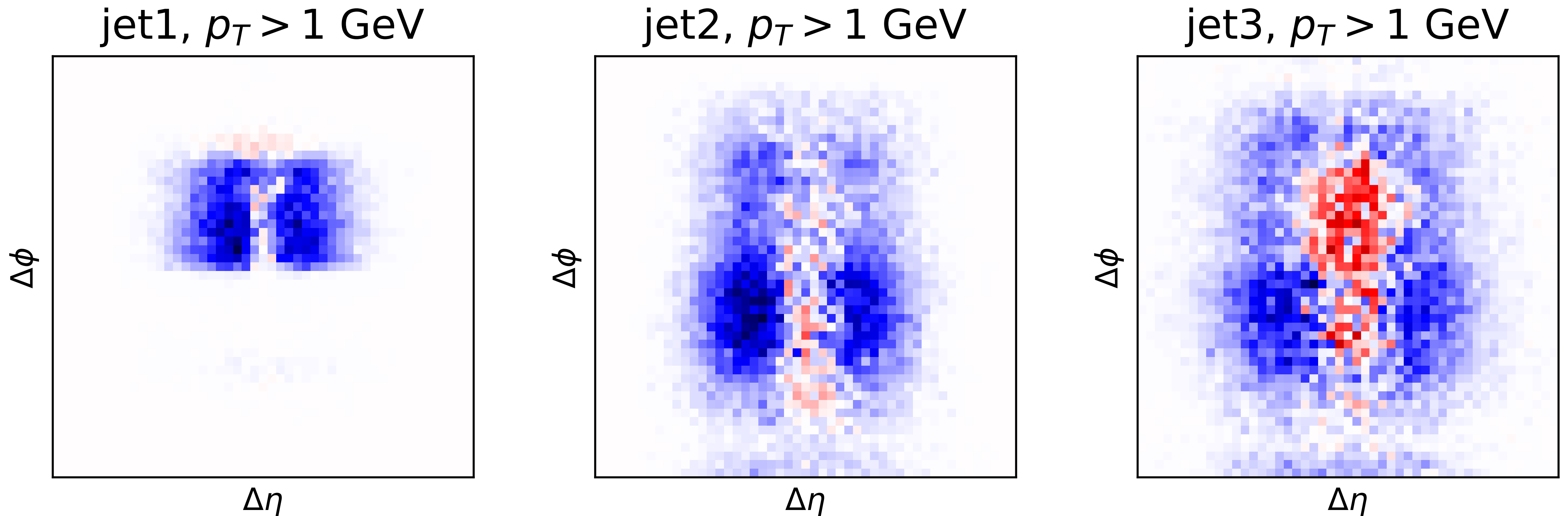


higgsinos

AUC Change by high-level data shuffling (S comb.)



Jet images (winos)



BLUE -> higher activity for background
RED -> higher activity for signal

Summary

- ⊛ Dark Matter can be searched @ LHC
- ⊛ We introduce a new analysis based on GNN
- ⊛ SUSY as benchmark model:
 - ⊛ EWKino pair production
 - ⊛ EWKino-squark associated production
 - ⊛ squark-pair production
- ⊛ We evaluate our model:
 - ⊛ sample composition is crucial: the more squarks the easier the classification
 - ⊛ high robustness against a change of the EWKino type
 - ⊛ high robustness against the change of the masses of sparticles
- ⊛ We derive the limits
- ⊛ Our approach is better than BDTs
- ⊛ Soft activity is used, but can simulation be trusted?
- ⊛ We interpret the network's behavior

Machine Learning Electroweakino Production

Rafał Masełek^(a,b), Mihoko M. Nojiri^(c,d,e) and Kazuki Sakurai^(b)

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^(b) *Institute of Theoretical Physics, Faculty of Physics, University of Warsaw, Pasteura 5, 02-093, Warsaw, Poland*

^(c) *Theory Center, IPNS, KEK, 1-1 Oho, Tsukuba, Ibaraki 305-0801, Japan*

^(d) *The Graduate University of Advanced Studies (Sokendai), 1-1 Oho, Tsukuba, Ibaraki 305-0801, Japan*

^(e) *Kavli IPMU (WPI), University of Tokyo, 5-1-5 Kashiwanoha, Kashiwa, Chiba 277-8583, Japan*

Abstract

The system of light electroweakinos and heavy squarks gives rise to one of the most challenging signatures to detect at the LHC. It consists of missing transverse energy recoiled against a few hadronic jets originating either from QCD radiation or squark decays. The analysis generally suffers from the large irreducible $Z + \text{jets}$ ($Z \rightarrow \nu\bar{\nu}$) background. In this study, we explore Machine Learning (ML) methods for efficient signal/background discrimination. Our best attempt uses both reconstructed (jets, missing transverse energy, etc.) and low-level (particle-flow) objects. We find that the discrimination performance improves as the p_T threshold for soft particles is lowered from 10 GeV to 1 GeV, at the expense of larger systematic uncertainty. In many cases, the ML method provides a factor two enhancement in $S/\sqrt{S+B}$ from a simple kinematical selection. The sensitivity on the squark-electroweakino mass plane is derived with this method, assuming the Run-3 and HL-LHC luminosities. Moreover, we investigate the relations between input features and the network's classification performance to reveal the physical information used in the background/signal discrimination process.

<https://arxiv.org/abs/2411.00093>



Thank you for attention!

rafal.maselek@lpssc.in2p3.fr

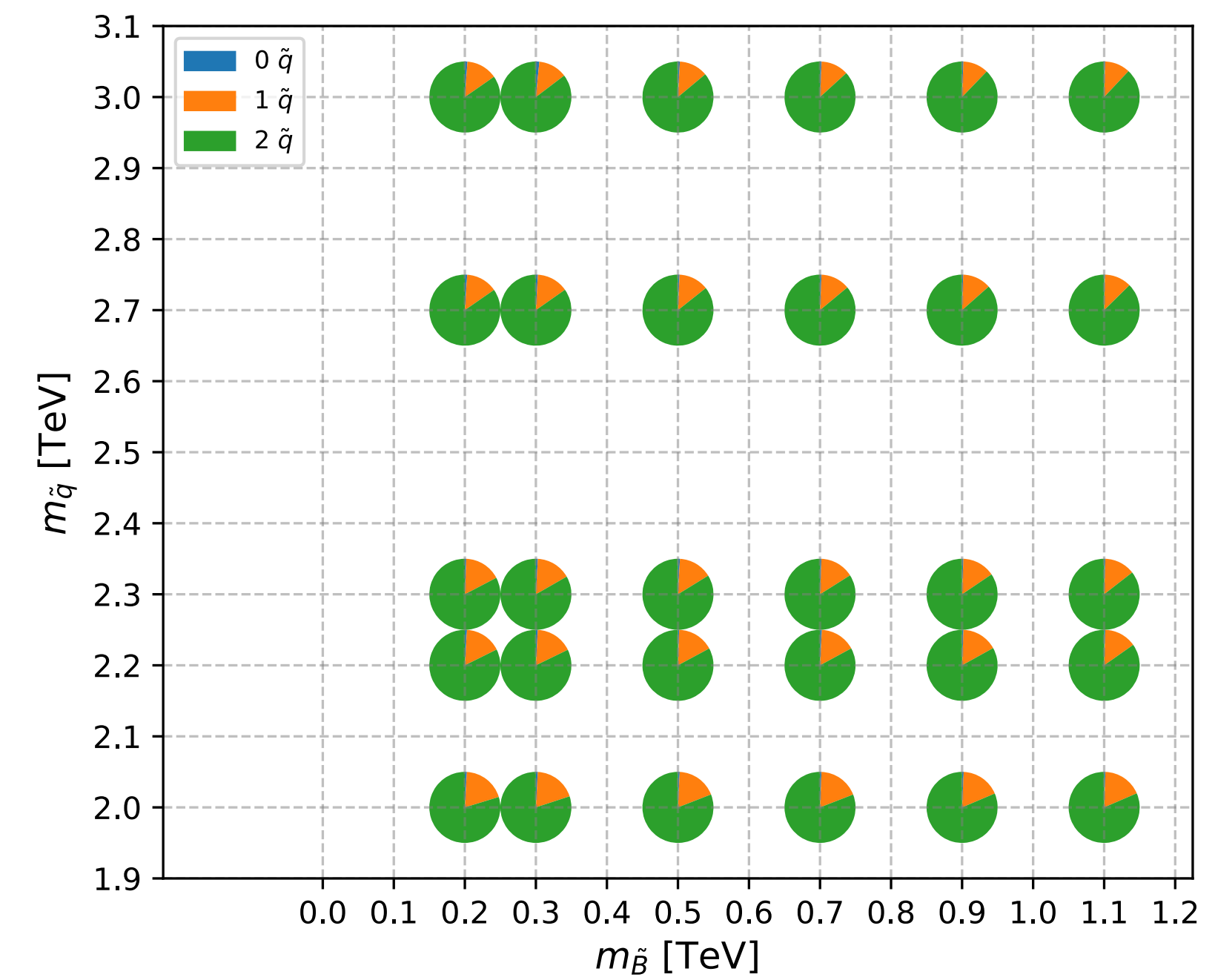
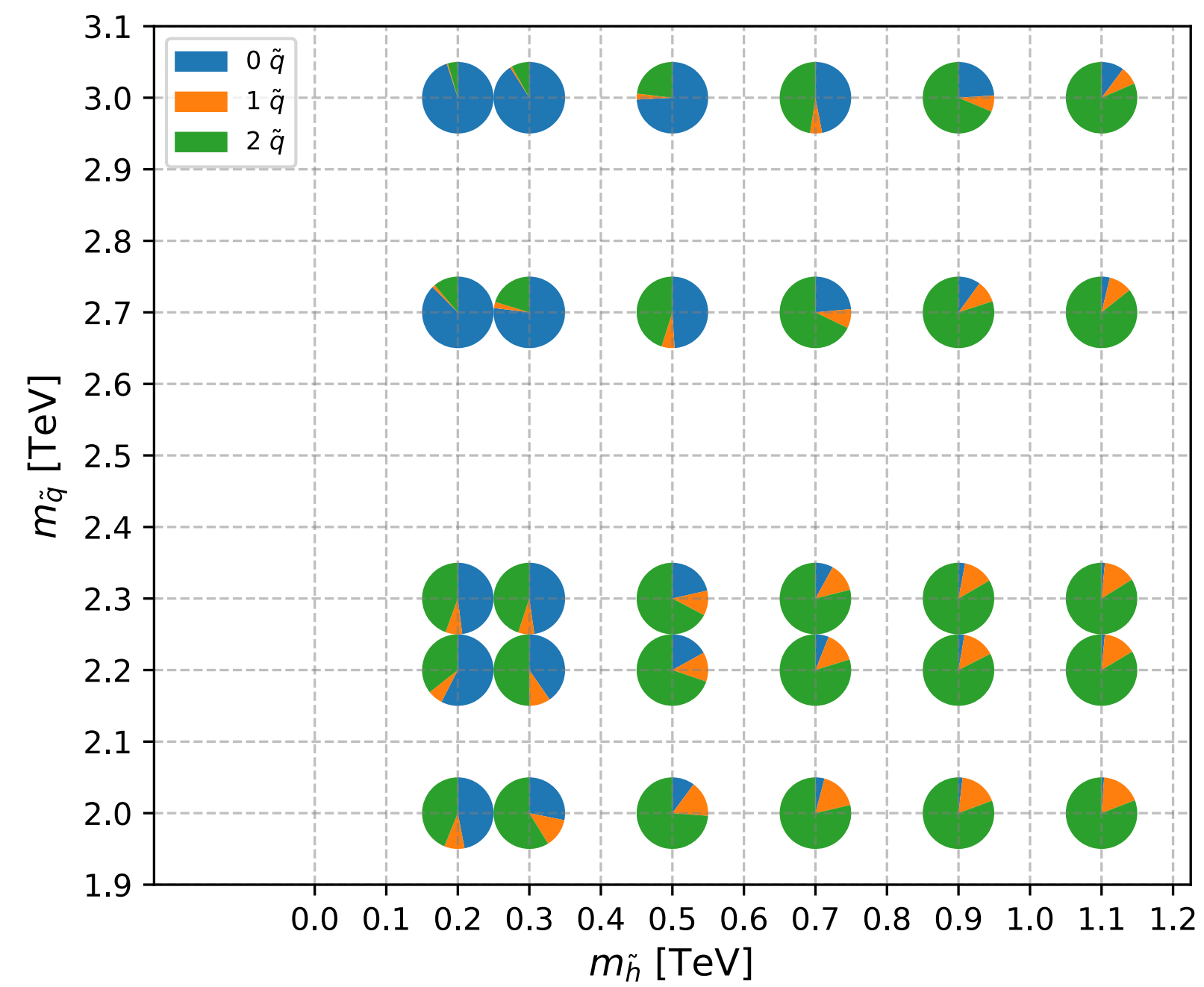
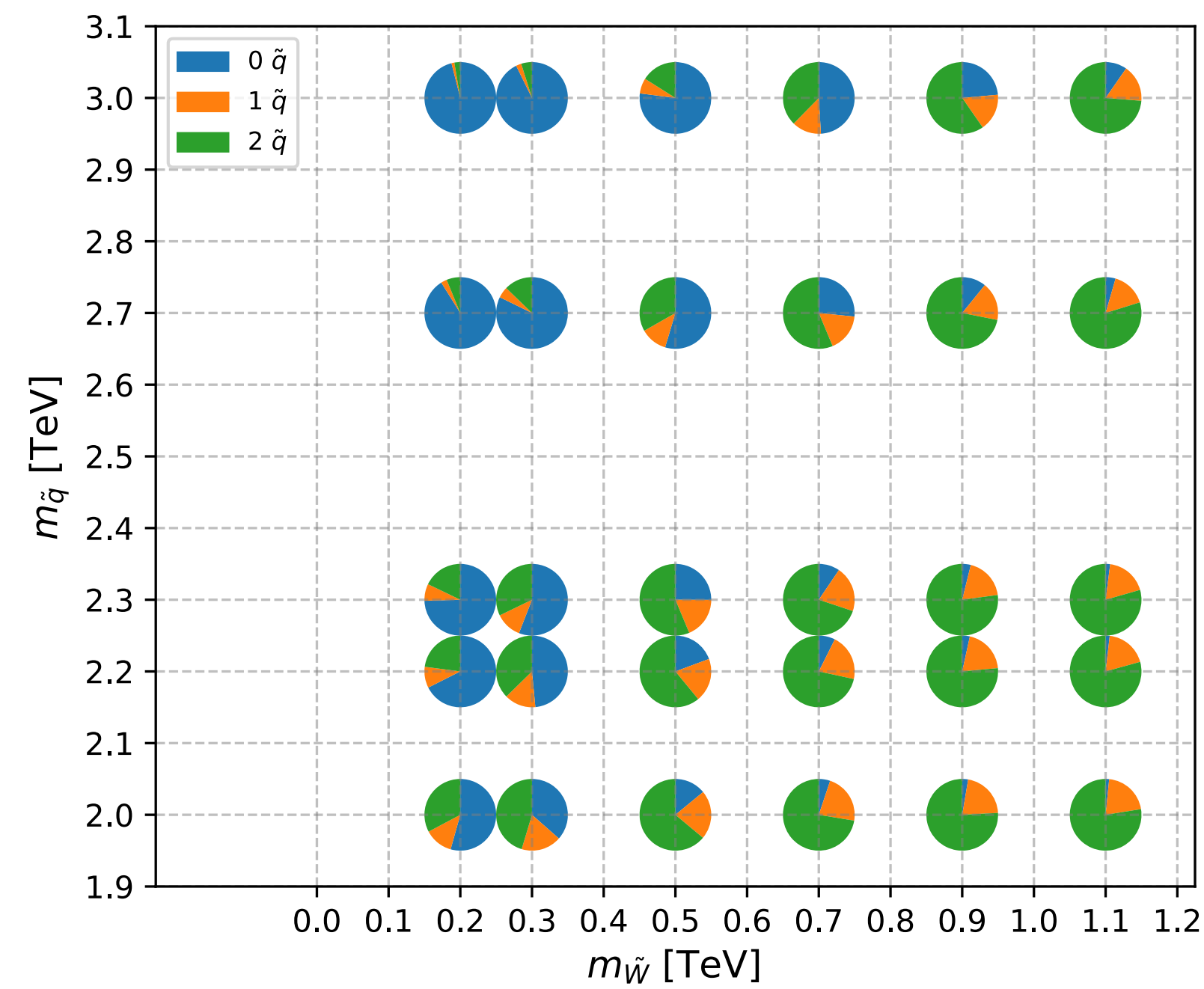
Dolina Chochołowska, Poland
photo by Piotr Kałuża

Backup slides

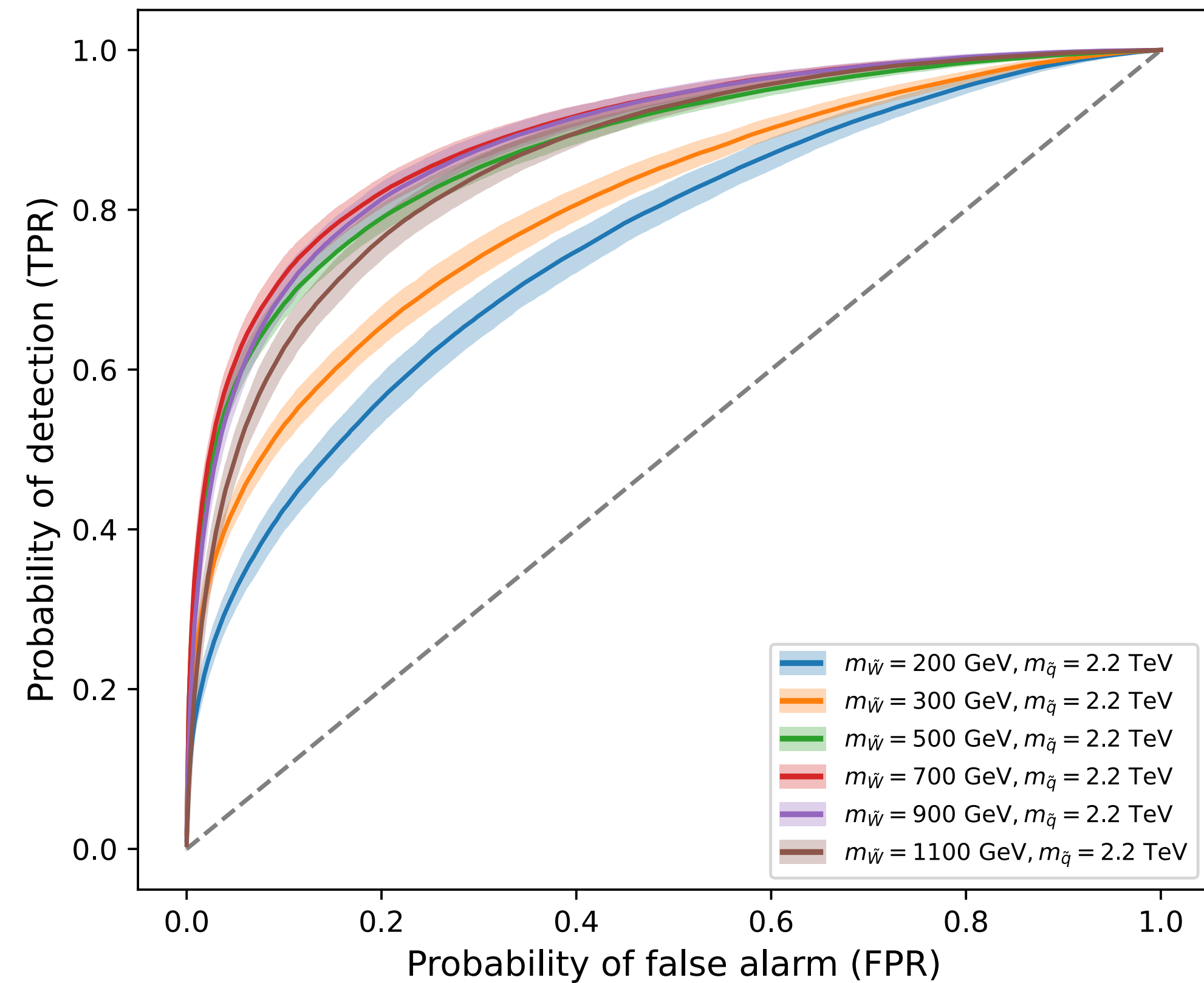
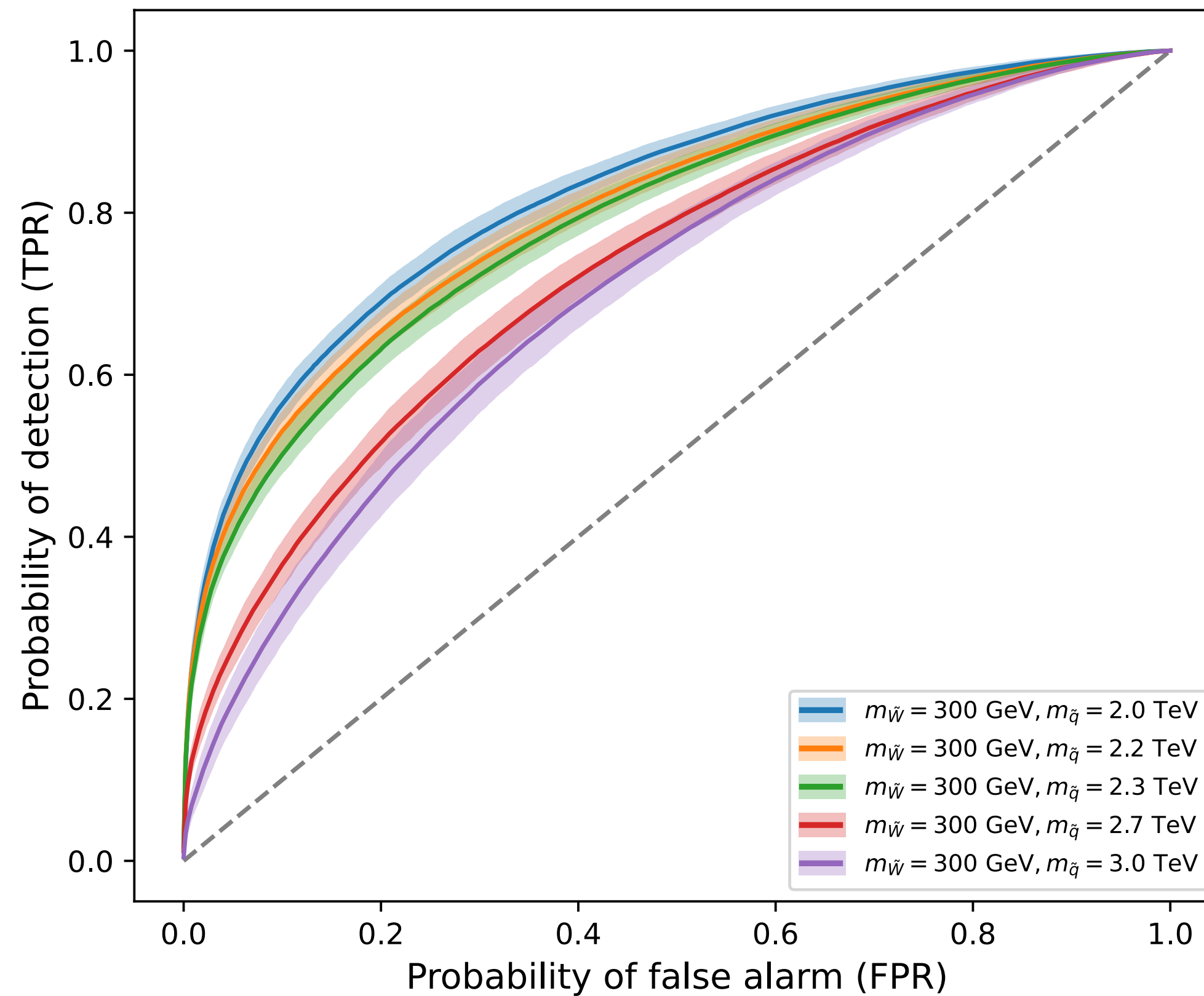
Rafał Masełek

R. Masełek ML coffee 17-01-2025

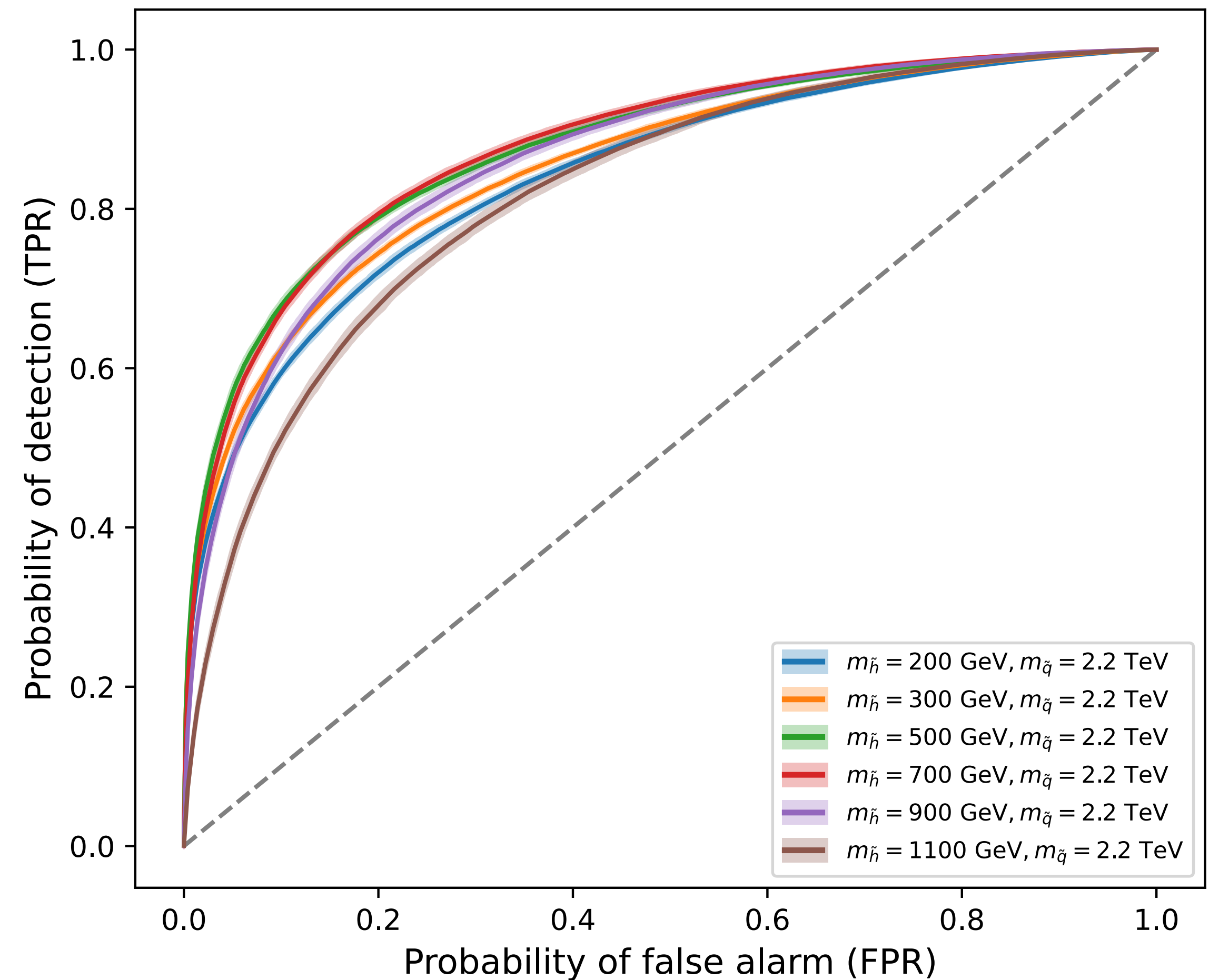
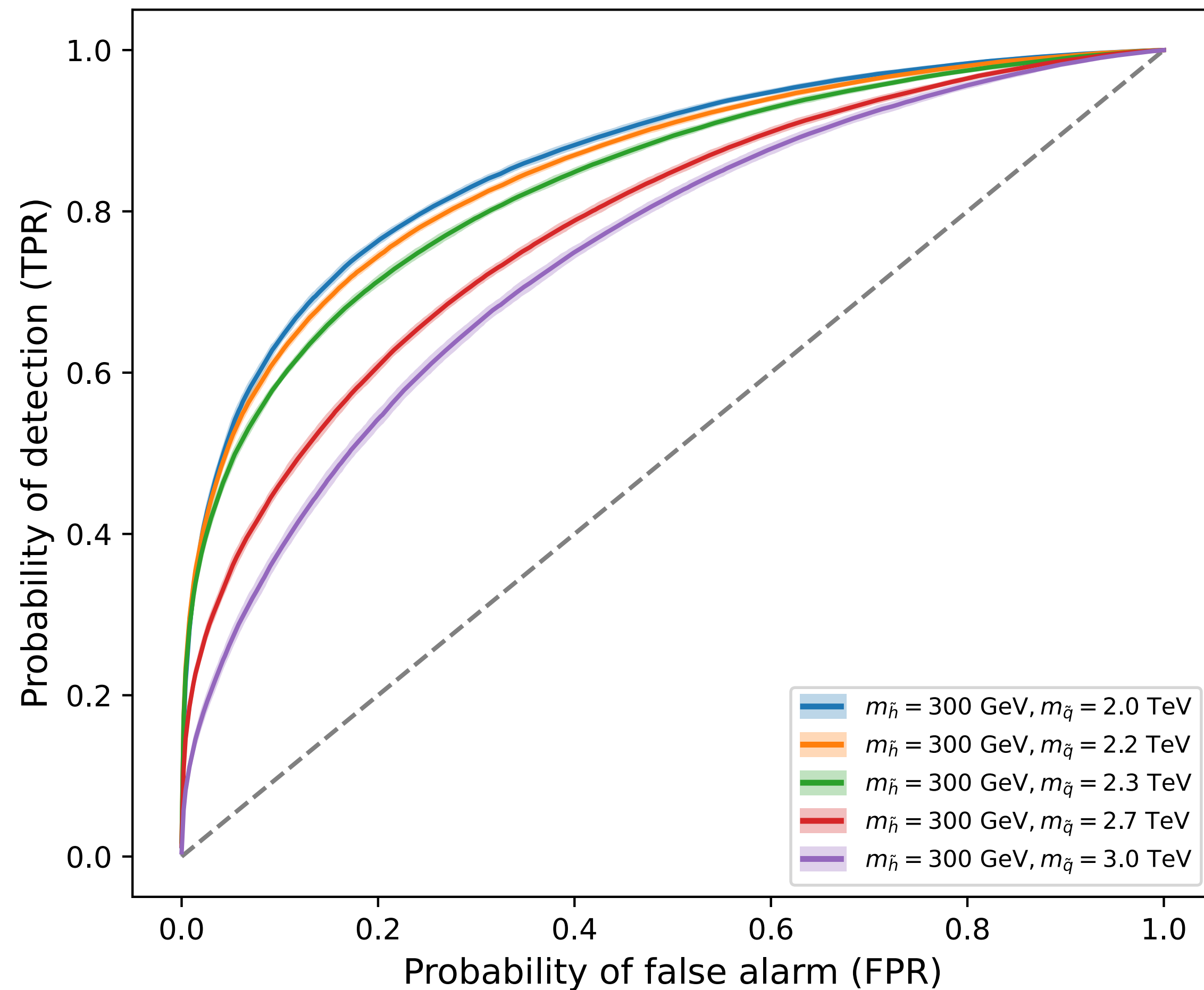
Sample composition



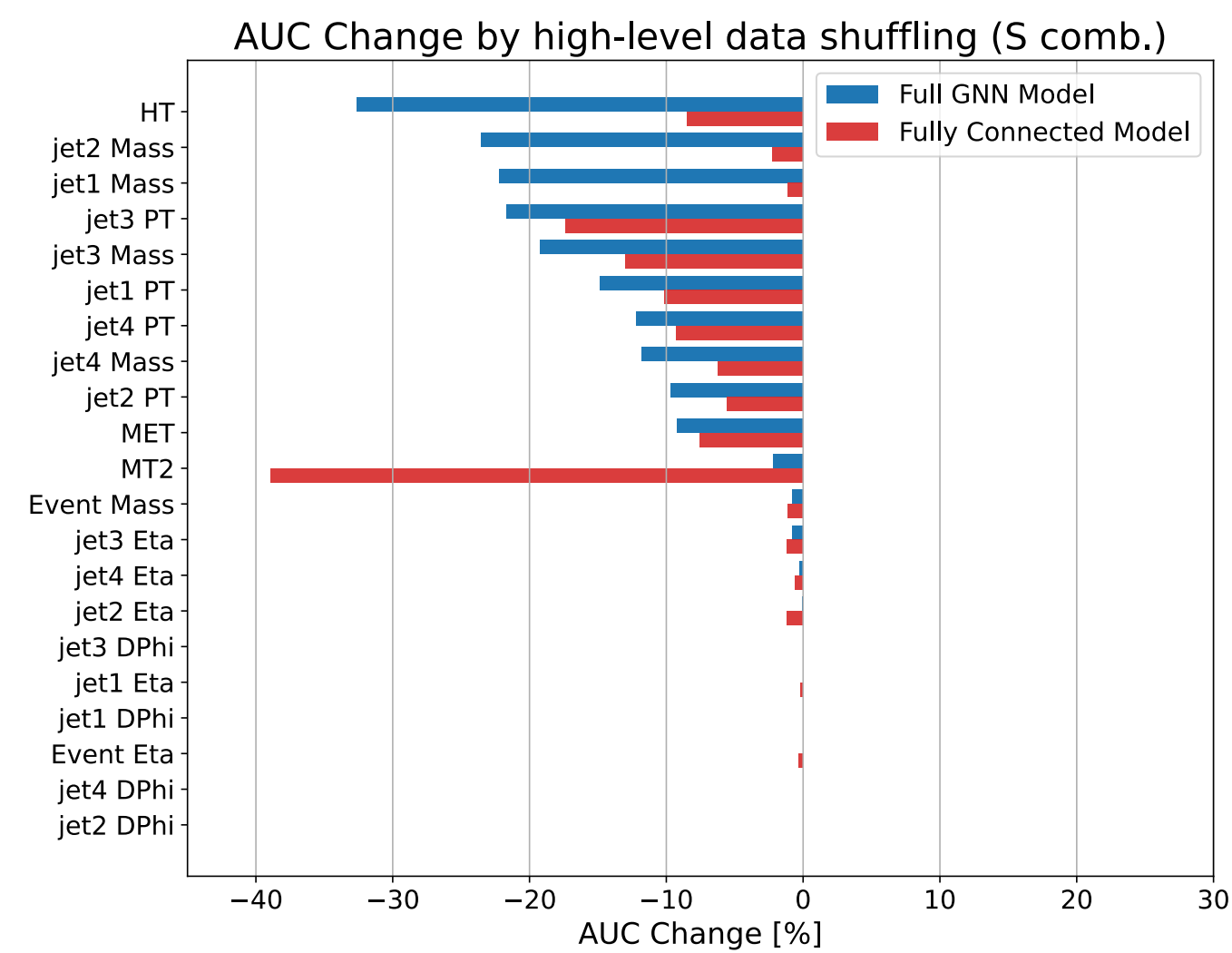
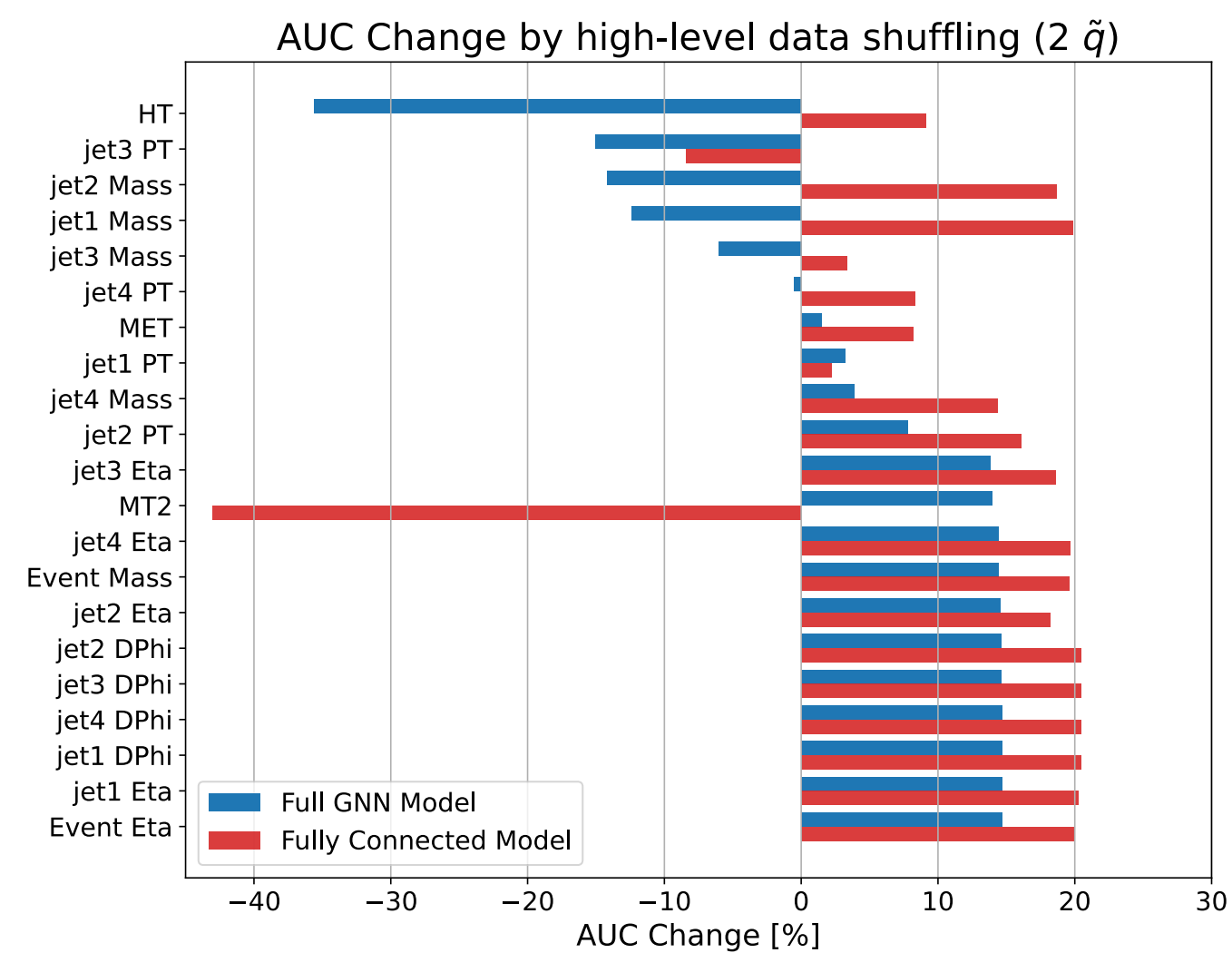
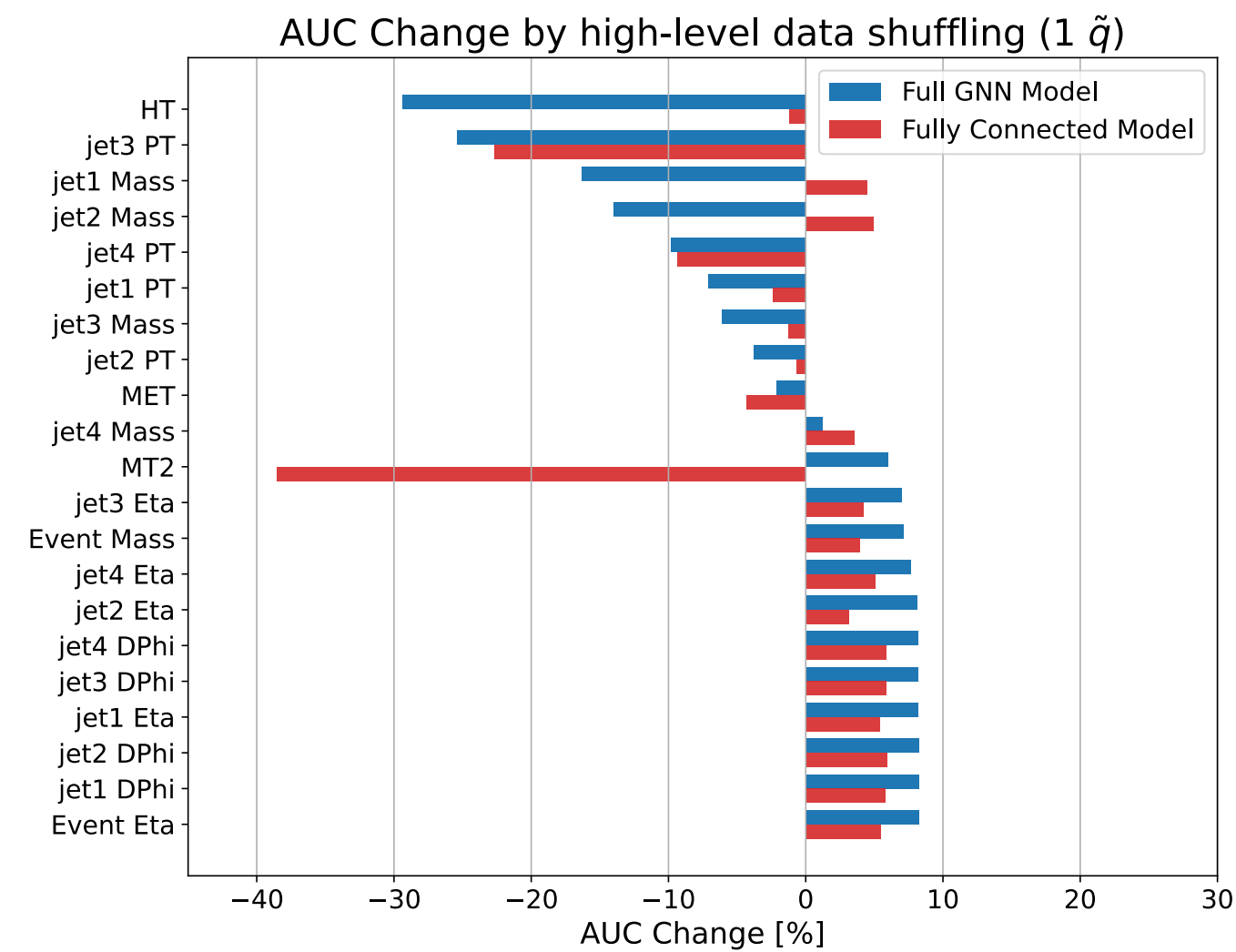
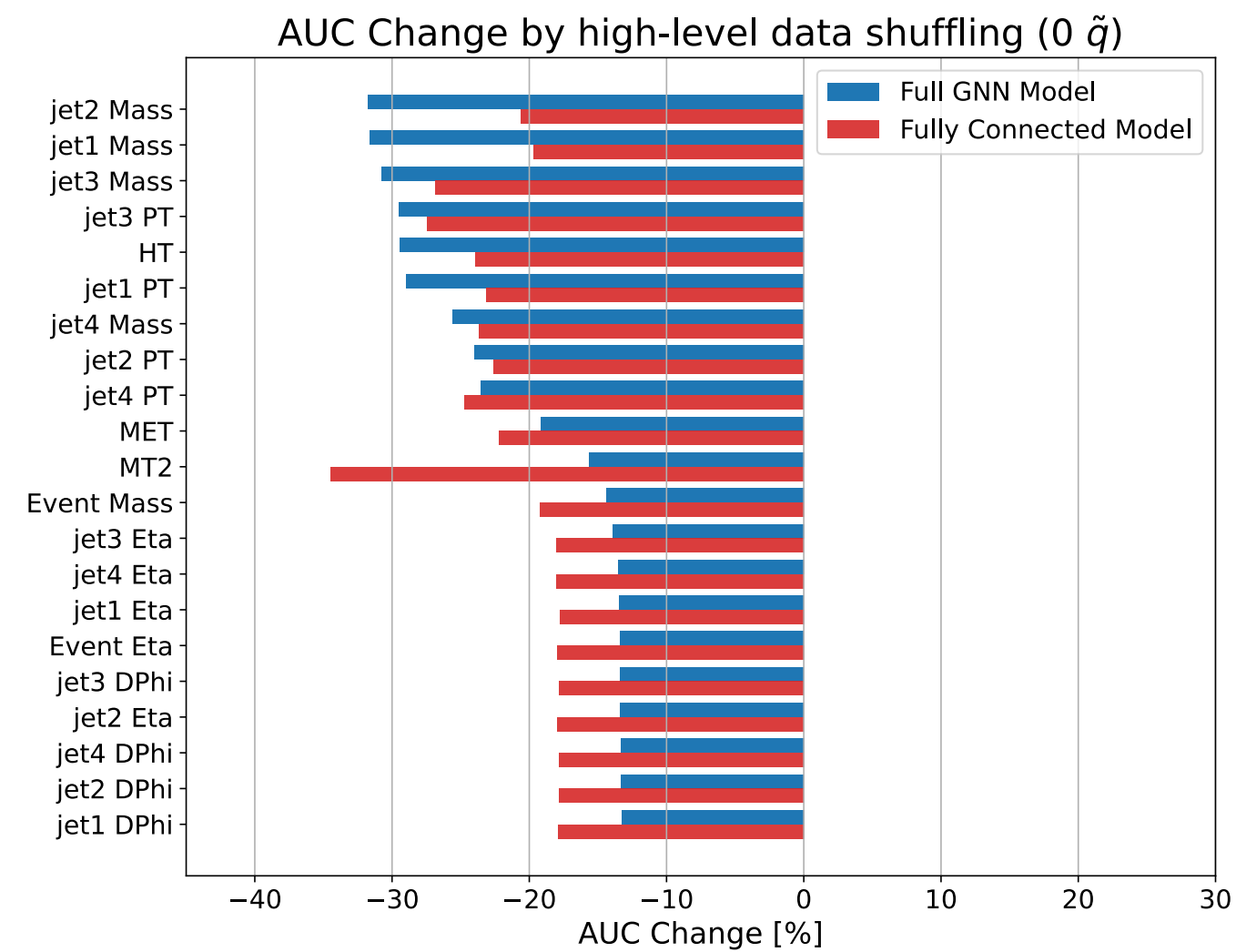
Mass dependence (winos)



Mass dependence (higgsinos)



Variable importance (winos)



Variable importance (higgsinos)

