Machine and deep learning techniques in heavy-ion collisions with ALICE

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for the ALICE collaboration

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Talk outline

b-jet tagging

Dielectron identification

b-jet tagging

b-jets with the ALICE detector

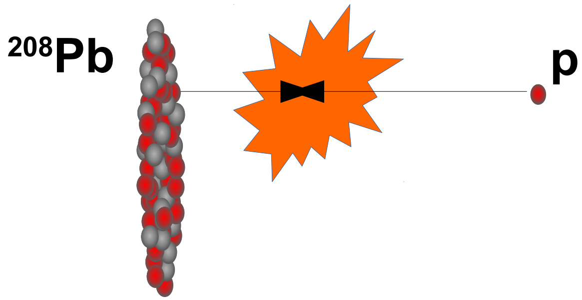
- Main interest of heavy-ion physics: **Quark-Gluon Plasma (QGP)**
- Hot & dense medium, strongly interacting w/ high-energy partons
- Jet measurement with ALICE down to low p_T

- Modification of b-jets different to udsg-jets
  - Larger energy loss for gluons than quarks (color charge)
  - “Dead cone effect”: For massive quarks, gluon bremsstrahlung suppressed at smaller angles w.r.t. parton direction

  → **b-jets interesting probe for the QGP**

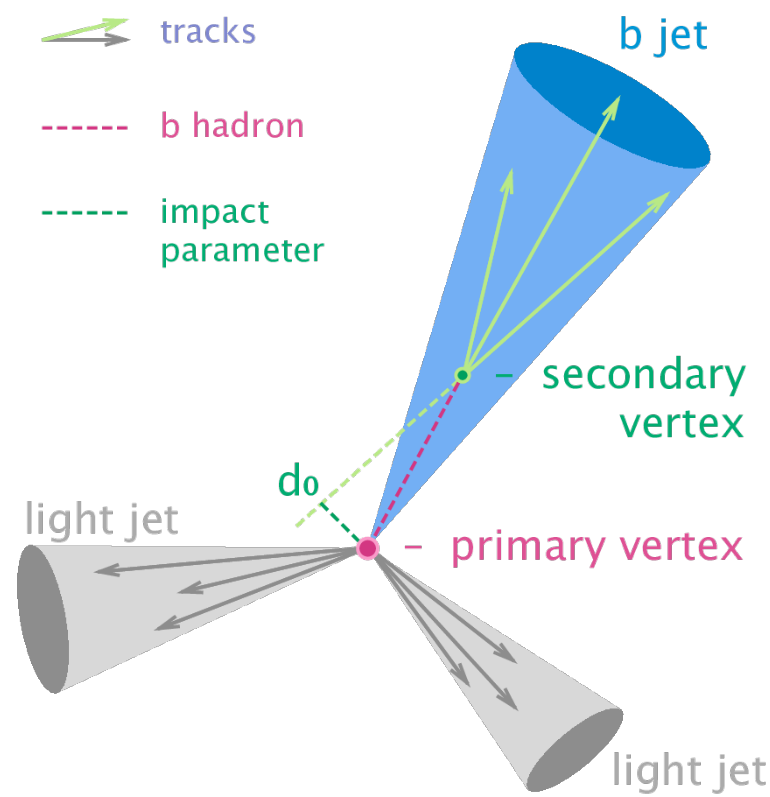
Goal: Investigate parton energy loss mechanisms

- Here: Evaluation for p-Pb collisions as first step towards Pb-Pb collisions
  - Useful to study cold nuclear matter effects
  - Reference measurement for Pb-Pb collisions



b-jet identification

- B-hadrons decay in the (sub-)millimeter range ($c\tau \sim 500\ \mu$m),
  → displaced from primary vertex
- Common discriminators:
  - Reconstructed secondary vertices
  - Track impact parameters
- Secondary vertex reconstruction:
  - Here: All three-track combinations considered (3-prong vertices)



http://bartosik.pp.ua/hep_sketches/btagging

“Conventional” approach:
Application of rectangular cuts on properties of most displaced vertices

Ansatz here: Apply ML techniques to several low-level inputs: Constituents, secondary vertices, track impact parameters

Model design & input features

- Binary classification problem: b-jet *tagging*
- General design: **Multibranched**, **multilayered** neural network
  - Multiple subnetworks on several features:
    1D convolutional networks (**CNNs**)
  - Merged output fed to multilayered fully-connected network
  - Keras[1] has been used for model creation & training
- Tested many different networks on different features

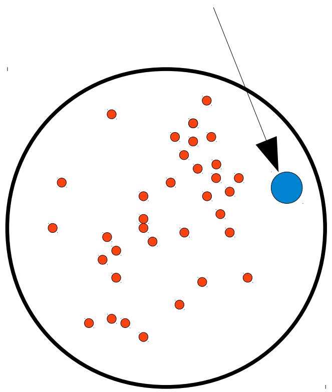
Features

- Array of secondary vertices, each:
  - (x, y, z) rel. to primary vertex
  - Transverse plane distance & uncertainty: L_{xy}, σ_{xy}
  - Vertex track dispersion σ_{vtx}, fit quality χ^2
- Array of constituents: η, φ, r (relative to jet axis),
  track impact parameters D, Z, and j_T

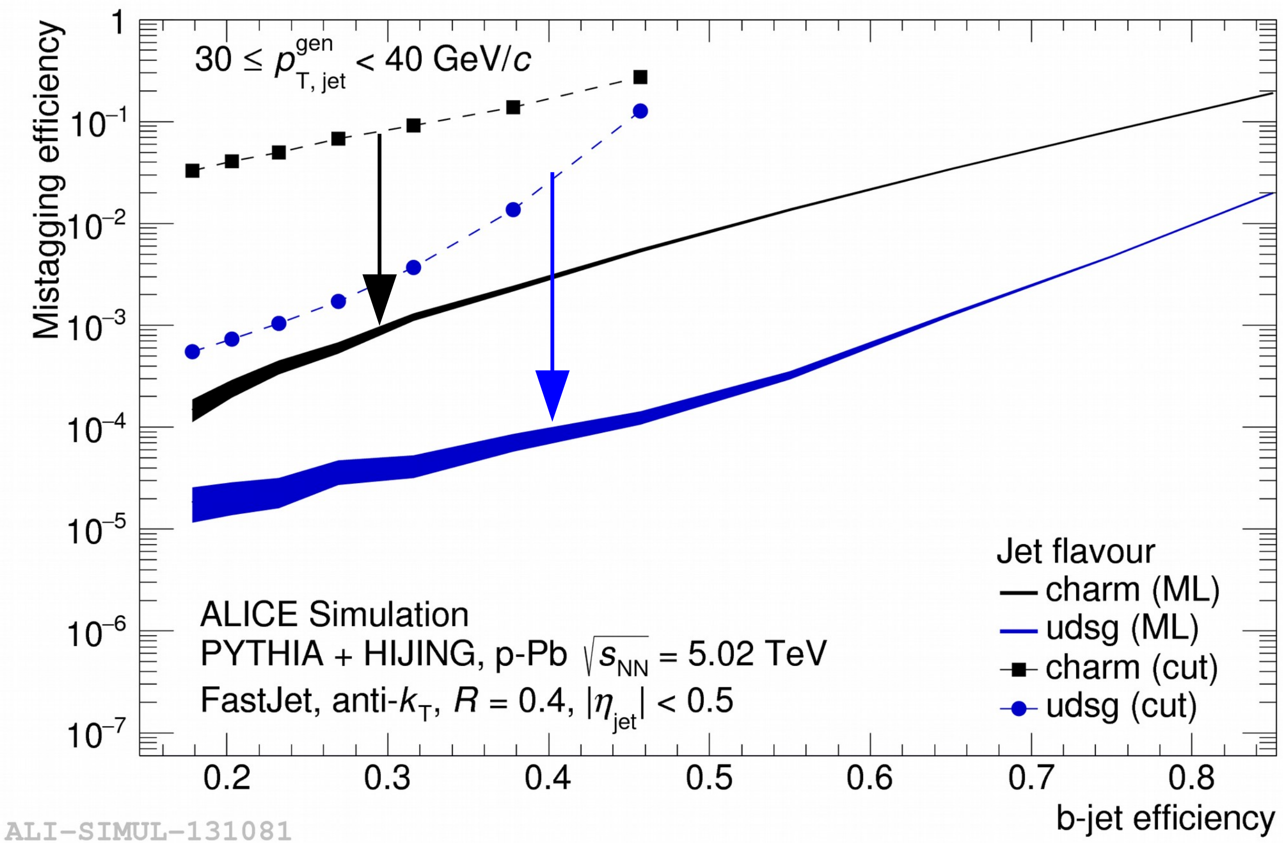
[1] F. Chollet et al., https://github.com/fchollet/keras

Simulation dataset

- p-Pb $\sqrt{s_{NN}}$ = 5.02 TeV, PYTHIA6 + HIJING
- FastJet anti-k_T jets, R = 0.4, tracks only, bgrd. corr.
- 200k training, 50k validation samples
- True jet type set with particle level information:
  - **B-hadron within *R* = 0.4:**
    → b-jet
  - **If instead, C-hadron within *R* = 0.4:**
    → c-jet
  - **Else:**
    → light-flavor jet



Results: Mistagging vs. b-jet efficiency

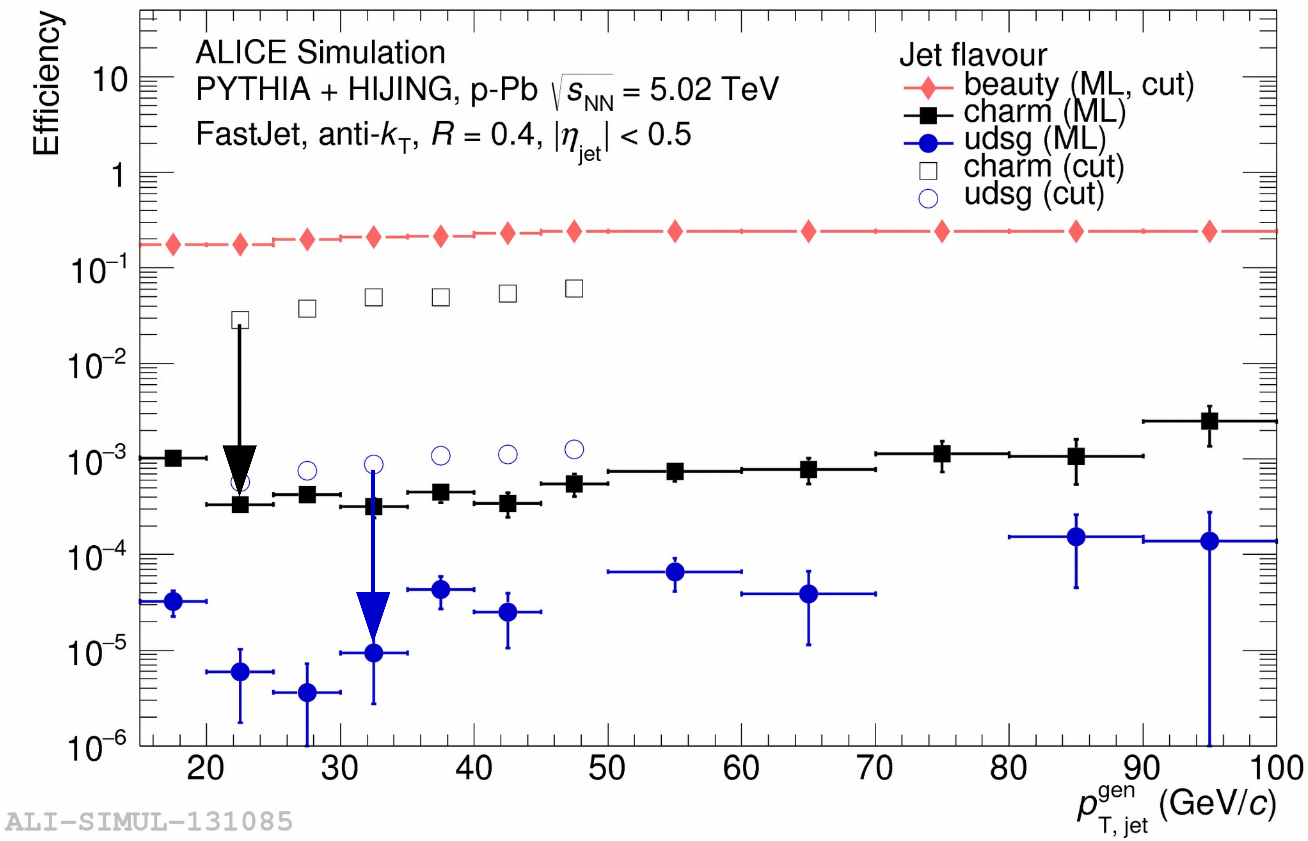


- **Solid lines:** ML-based method (statistical uncertainty only)
- **Dashed lines:** Conventional, cut-based method[1]

- ML-assisted tagging method very promising
- Mistagging efficiency much lower for c- and udsg-jets

[1] cf. arXiv:1605.00143

Results: Mistagging efficiency vs. jet p_T



- **Solid symbols:** ML-based method (statistical uncertainty only)
- **Open symbols:** Conventional, cut-based method[1]
- b-jet efficiency fixed (red)

- Also here: ML-assisted tagging method very promising

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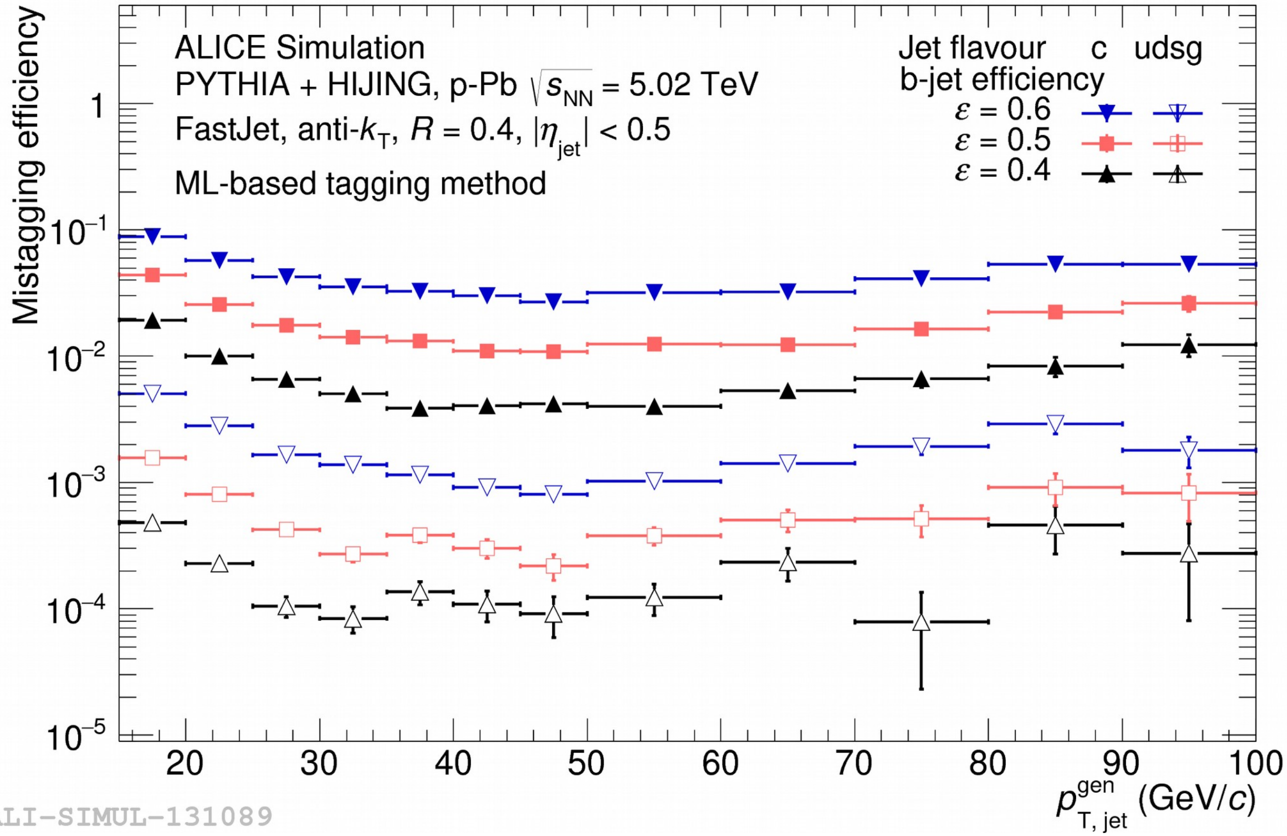
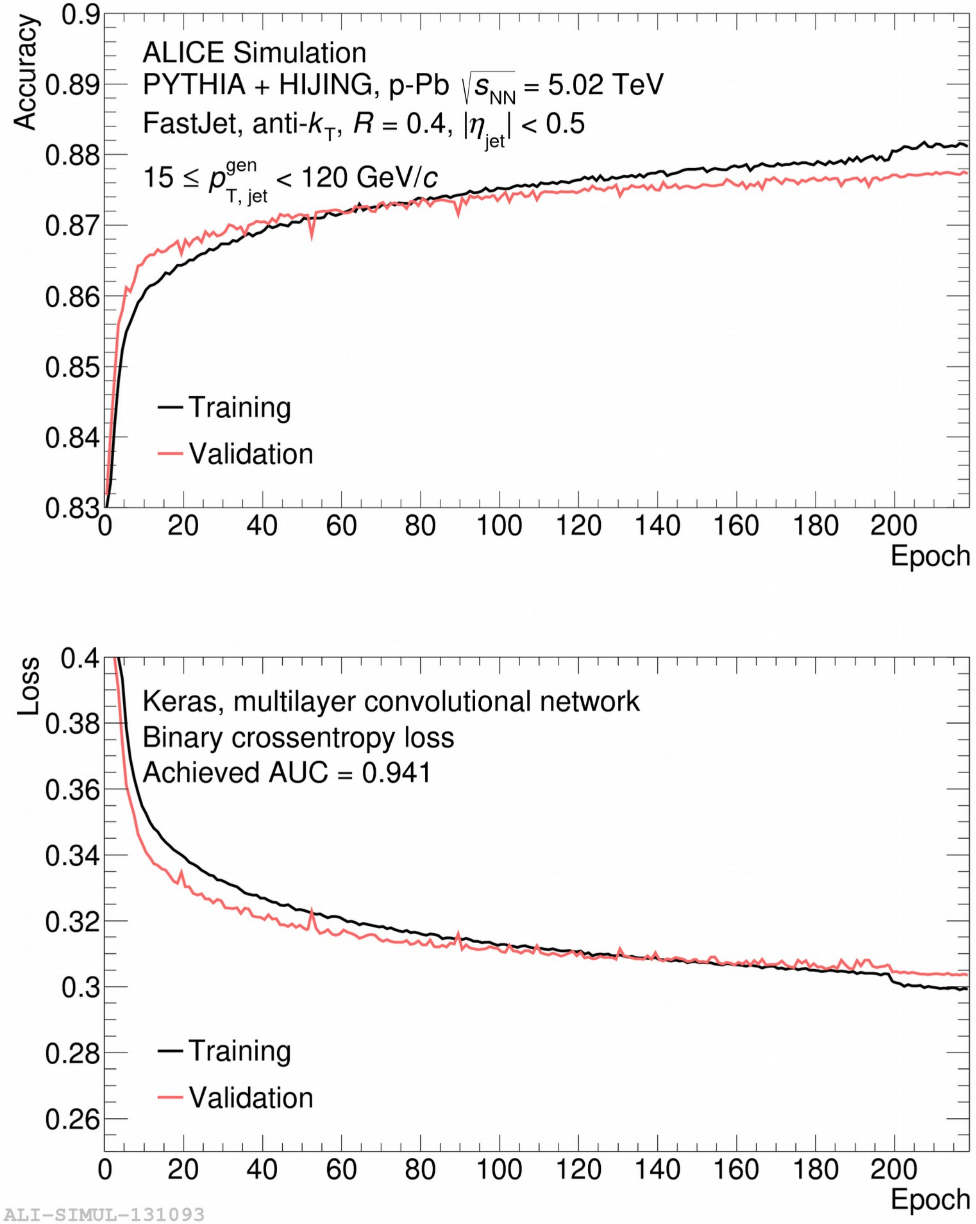
Results: Mistagging efficiency vs. jet p_T



- Mistagging efficiency for higher b-jet efficiency
- **Solid symbols:** c-efficiency
- **Open symbols:** udsg-efficiency

- Sample mostly udsg. About 90% udsg-, 5% c-jets
  → udsg efficiency should be below 0.5-1%
  → c efficiency should be below a 5-10%
- Higher b-jet efficiencies possible

Training control plots



- Accuracy, loss good control parameters
- Model shows slow learning up to high epoch counts
- Learning rate parameter has been lowered after 200 epochs:
  $[10^{-4}, 10^{-5}]$
- Not much to gain with longer training

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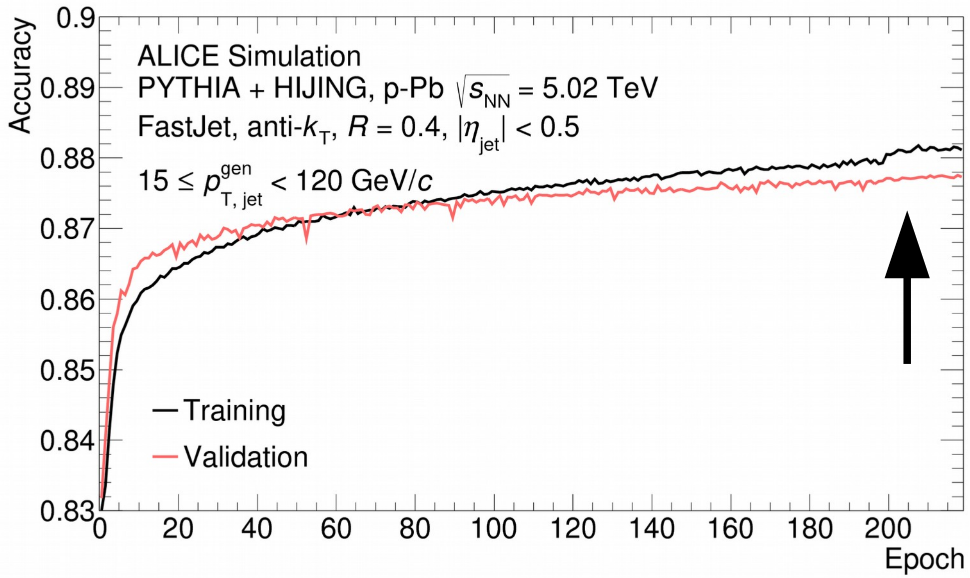

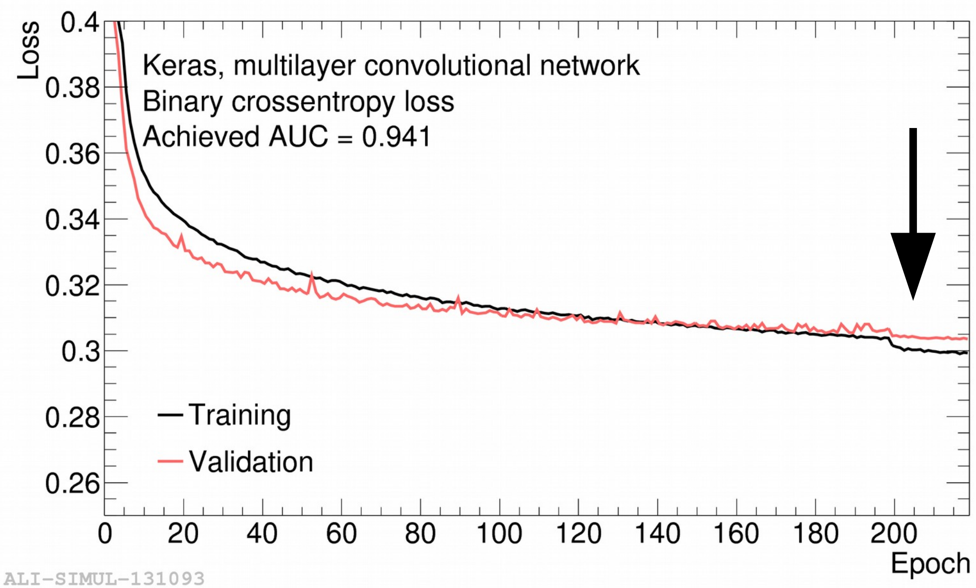

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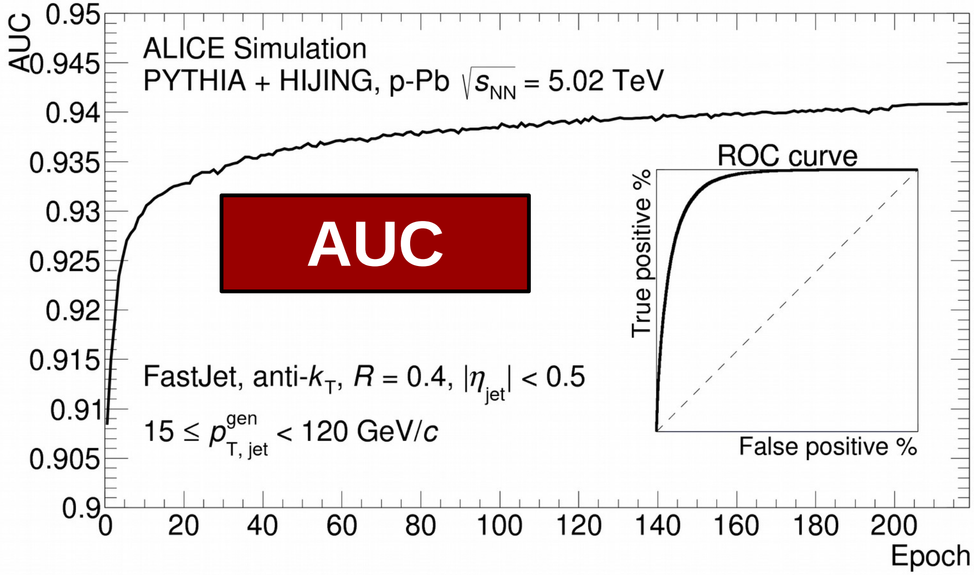

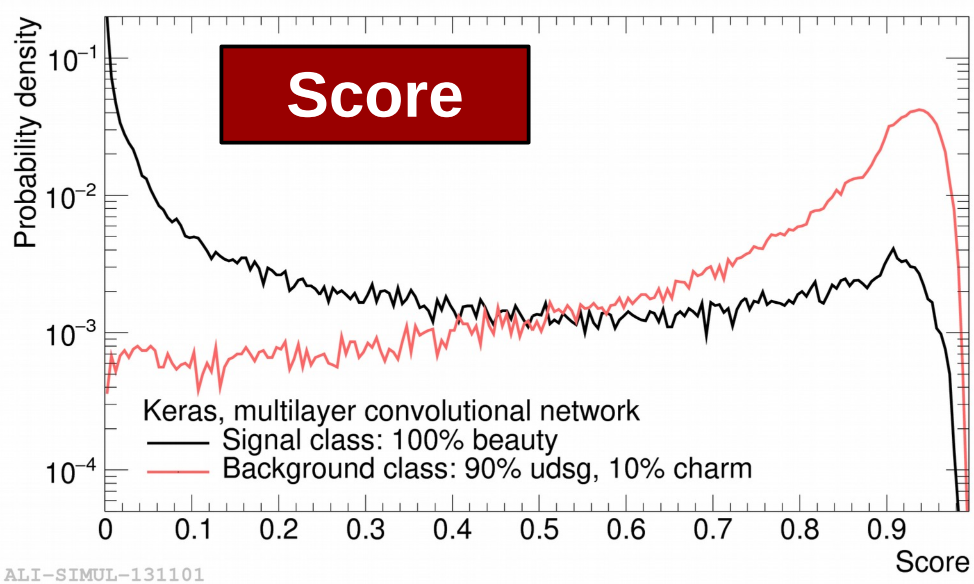

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- Learning rate parameter has been lowered after 200 epochs:
  $[10^{-4}, 10^{-5}]$
- Not much to gain with longer training
- AUC = **A**rea **U**nder ROC **C**urve
- AUC reveals slow, but constant learning up to 220 epochs
- Clearly separated score distribution

Dielectrons

Dielectron classification

- Dielectrons created at all stages of collision
- Negligible interaction after creation

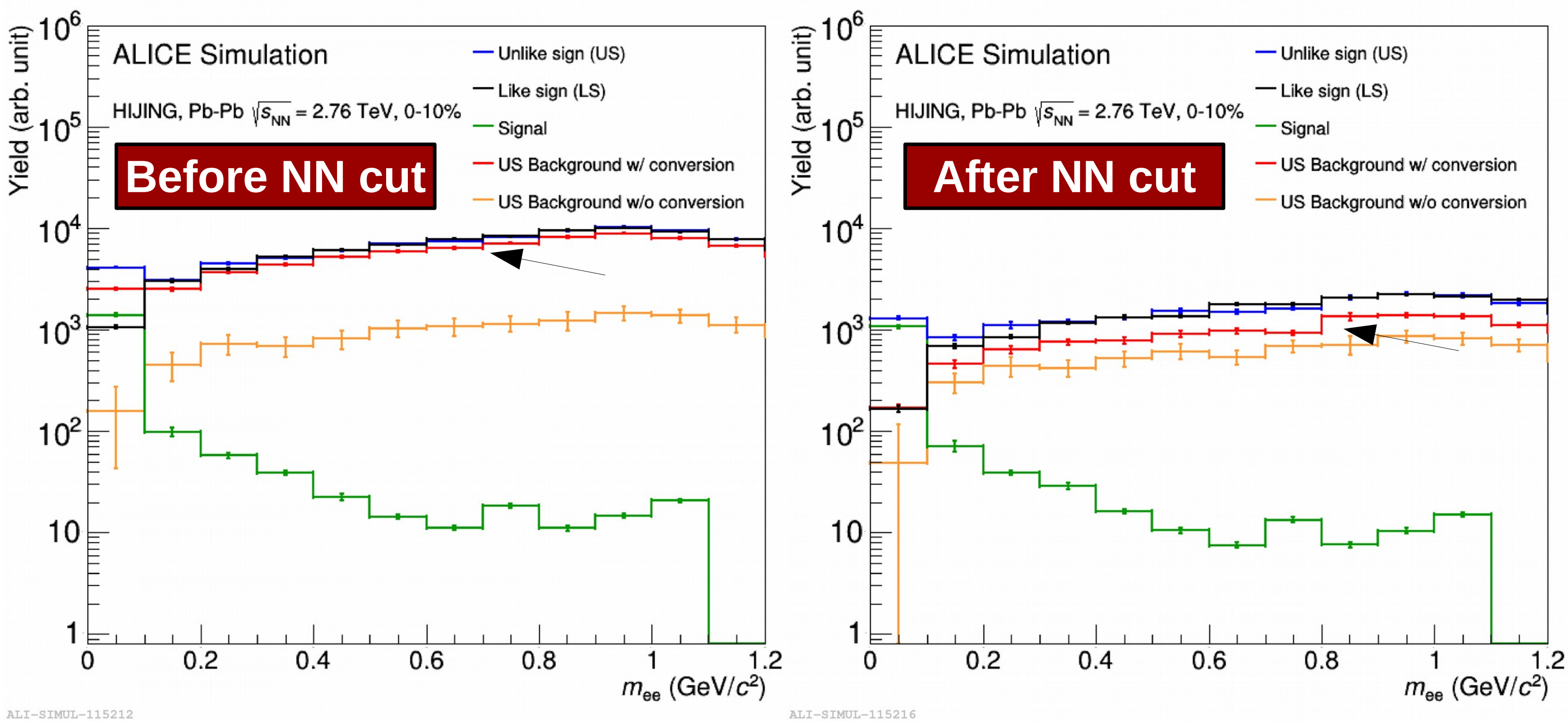
Interesting probe for QGP

- Here: Focus on low-mass e^+e^- identification
- Main goal of dielectron classification analysis:

Reject background efficiently

Dielectron classification

- Sample is contaminated w/ combinatorial & γ-conversion pairs
- Use two neural networks to classify background
  (1) Pairs from conversion
  (2) Pairs with one electron from photon conversion
  Fully-connected, multilayered networks
- Cut such that signal is most significant



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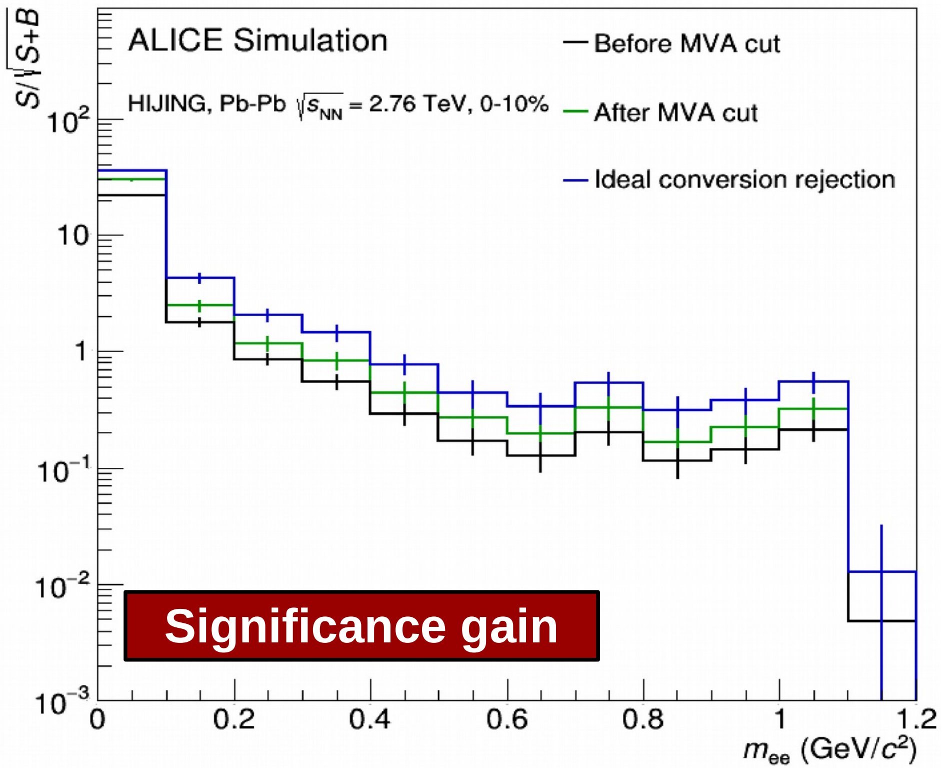
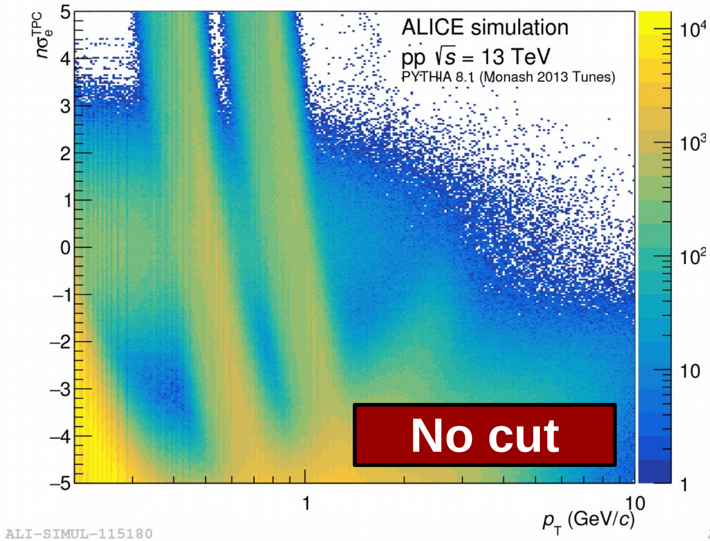


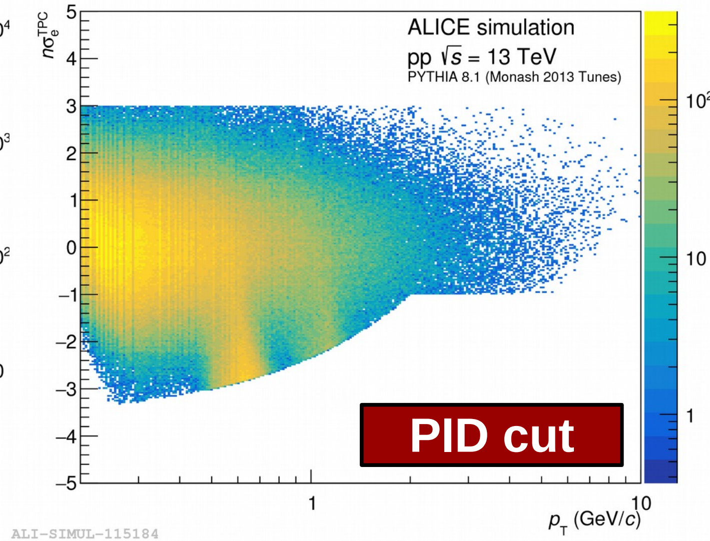
Very promising gain in significance

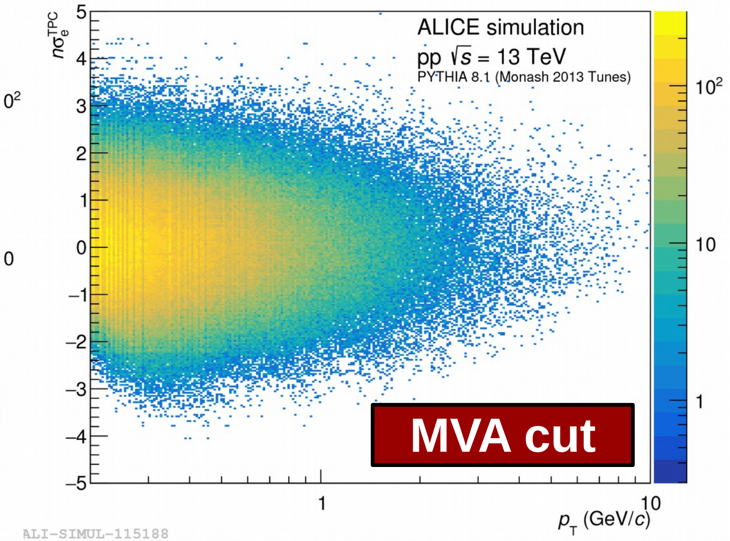
On top: Improved electron identification

- Electron identification using several subdetectors in ALICE
  Measurement of *nσ's:* How many standard deviations away from mean expected value
- MVA approach:
  Use Boosted Decision Tree (BDT) on *nσ* values, track properties
- Performance evaluated in pp. Soon: PbPb

nσ distribution for electrons TPC:







Summary

Summary

b-jet tagging

- Deep learning tagging method has been developed
- Performance evaluated in p-Pb MC simulations and compared to cut-based method
- Results are very promising
  - Tagging method allows much higher b-jet efficiencies
  - Lower mistagging rates

- Application on p-Pb data ongoing → promising results
- In addition: c-jet tagging to be explored

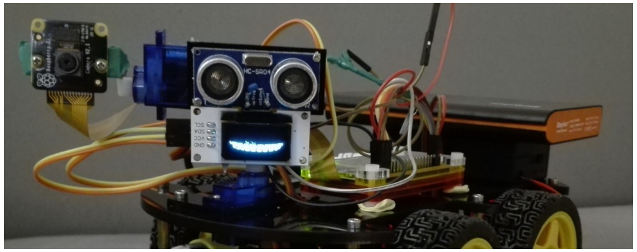
Summary

Low-mass dielectron classification

- Applied BDT to electron identification in pp, soon Pb-Pb
- Applied NN to classify dielectron background in Pb-Pb
- Very promising performance in MC simulations
- Electron identification in PbPb
- Application on pp, p-Pb, and Pb-Pb LHC Run 2 data

Several other ML-based analyses in ALICE …

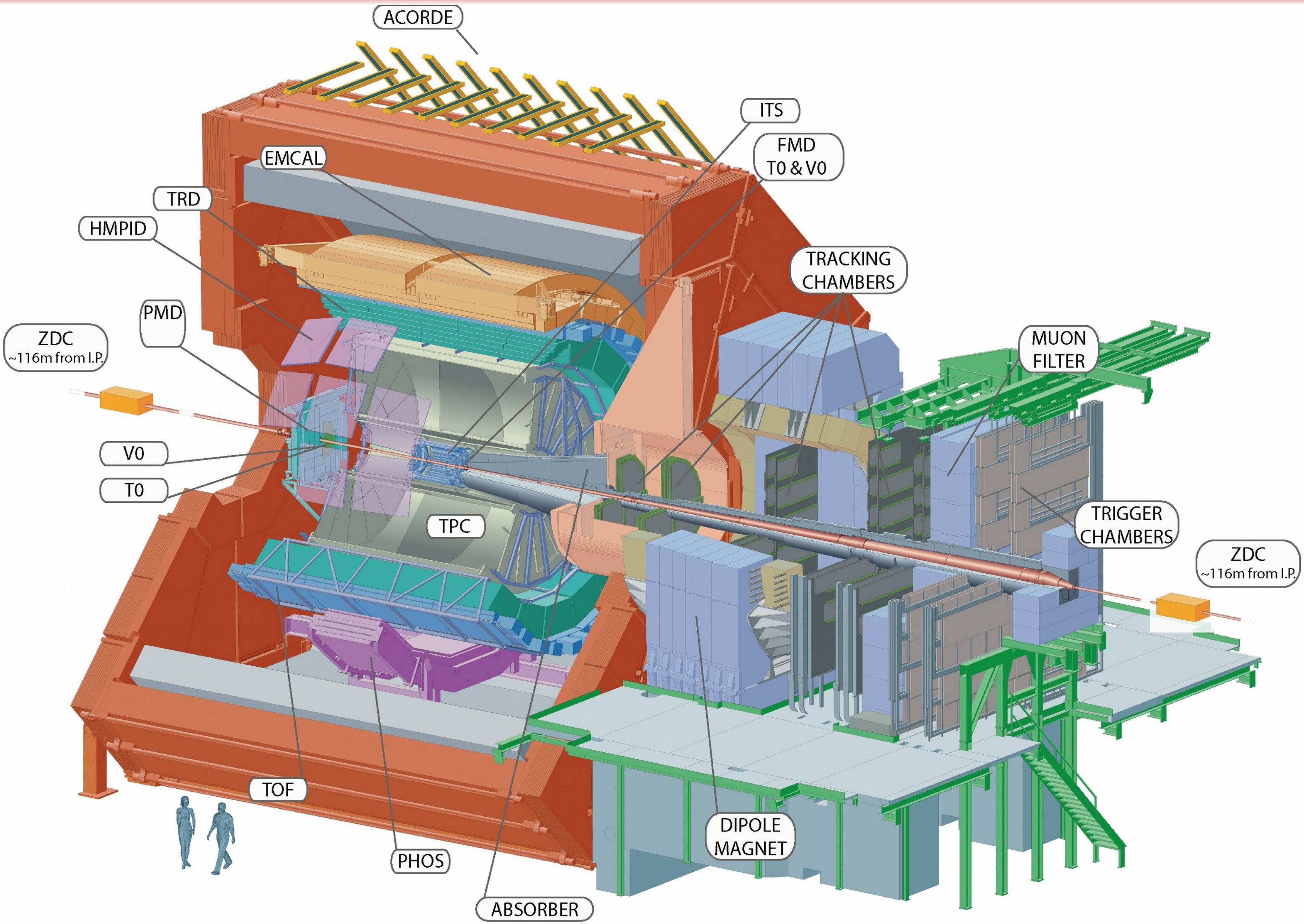
- For example, this morning at EPS-HEP:
  Charmed mesons & baryons pp & pPb (A. De Caro)



Thank you for your attention!

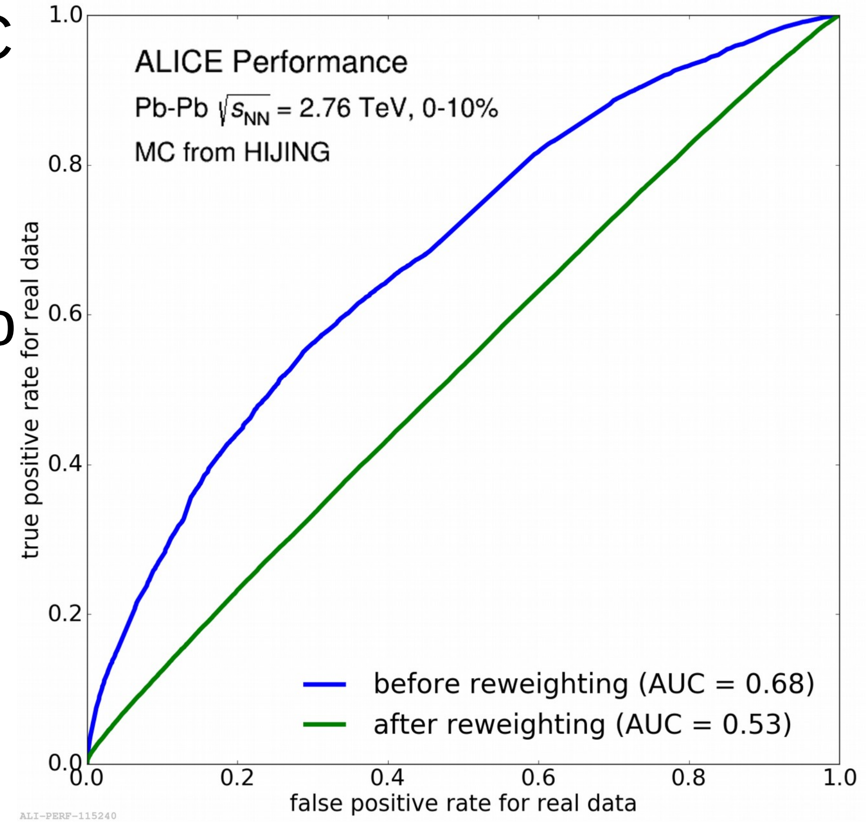
Backup

The ALICE detector



MC-data adaption

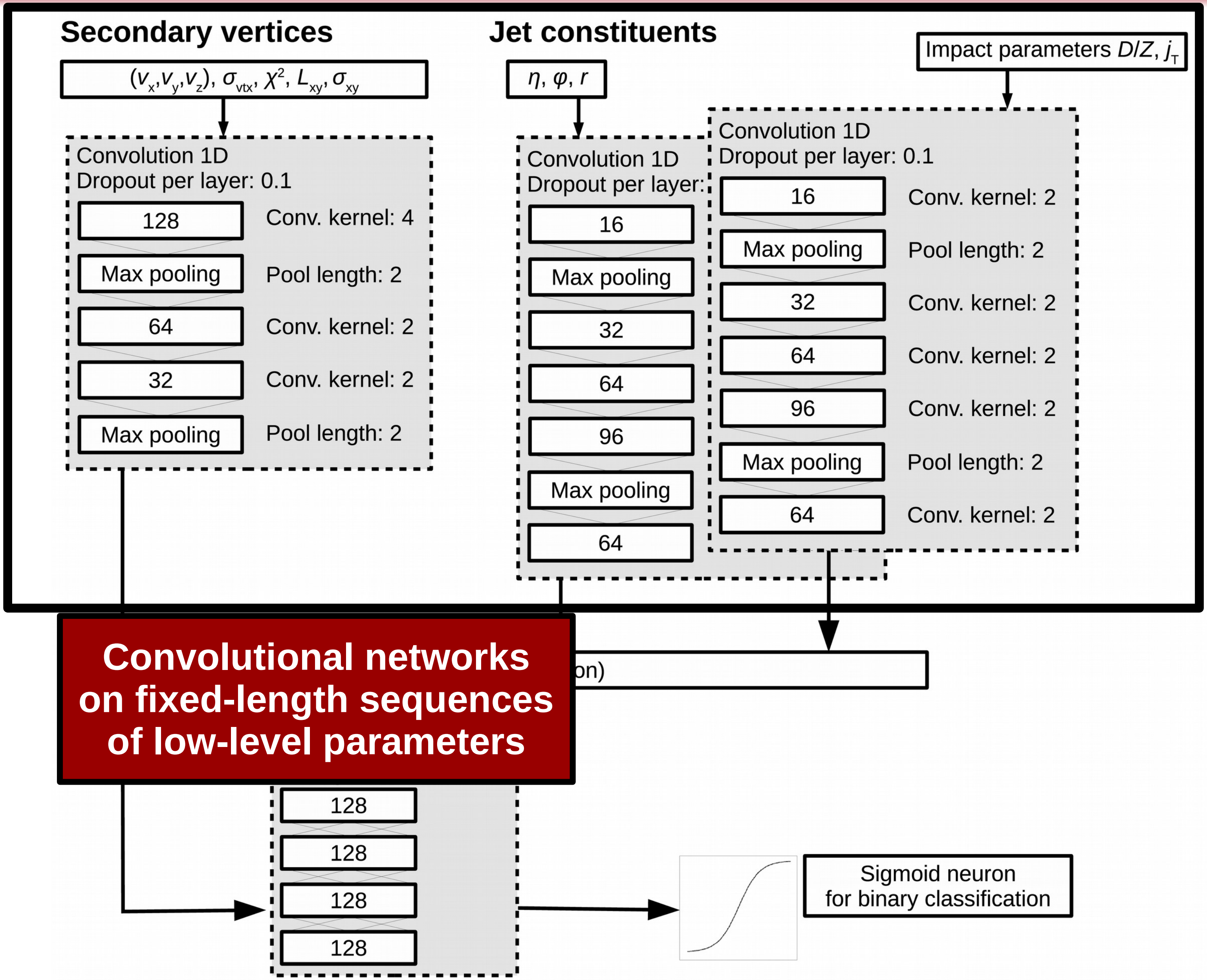
- Method strongly relies on accuracy of MC
- Ansatz: Change MC such that it better reproduces data in our feature space
  - Find differences: Use GBDT classifier to separate MC & data
  - Cure differences: Reweight regions in feature-space to have same effective population in MC & data
- Using MC-data adaption leads to significantly better results



ROC curve of classifier: After reweighting, data and MC are hardly to separate in feature space

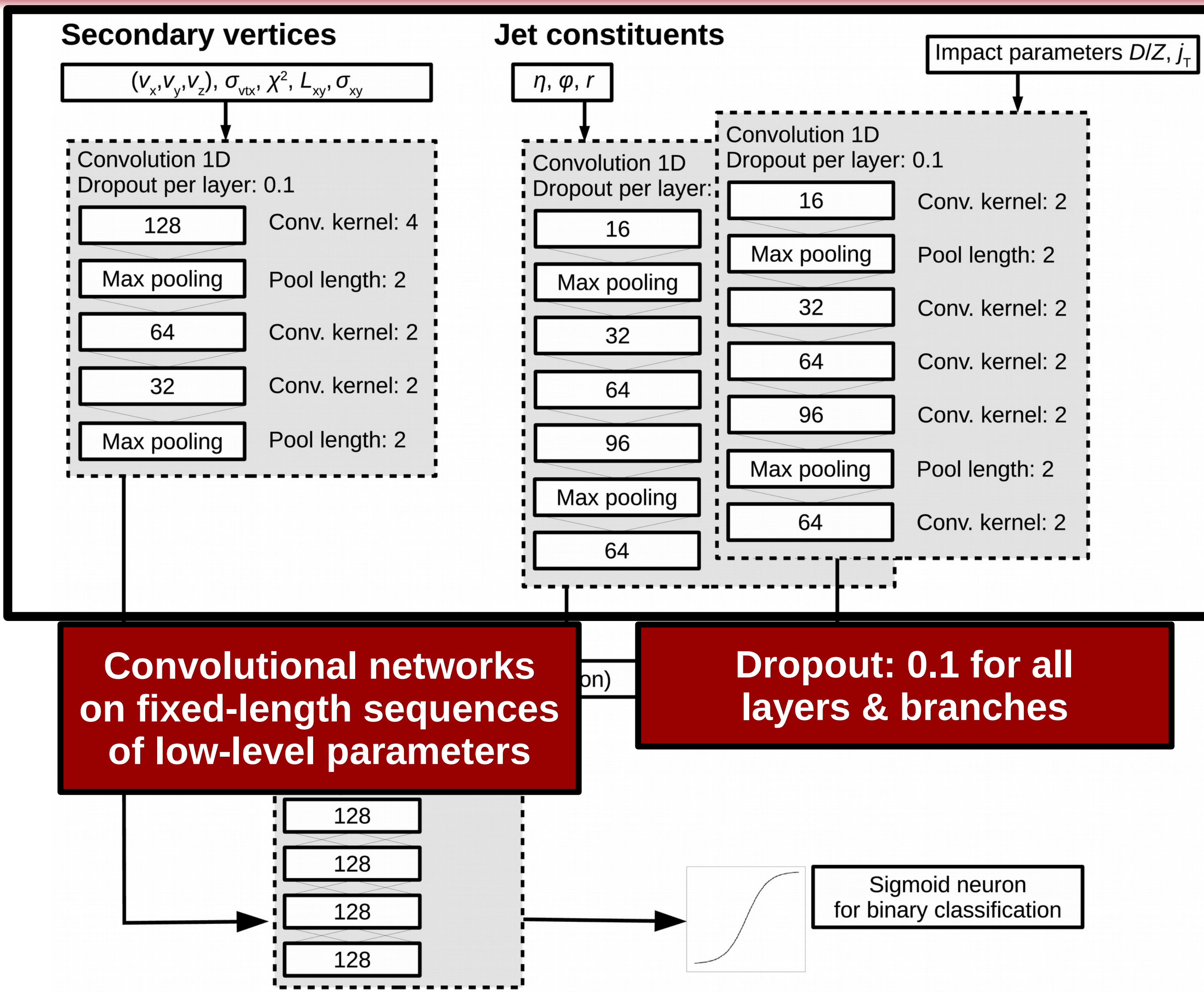
(A. Rogozhnikov, 1608.05806)

b-jets: Model design



Convolutional networks on fixed-length sequences of low-level parameters

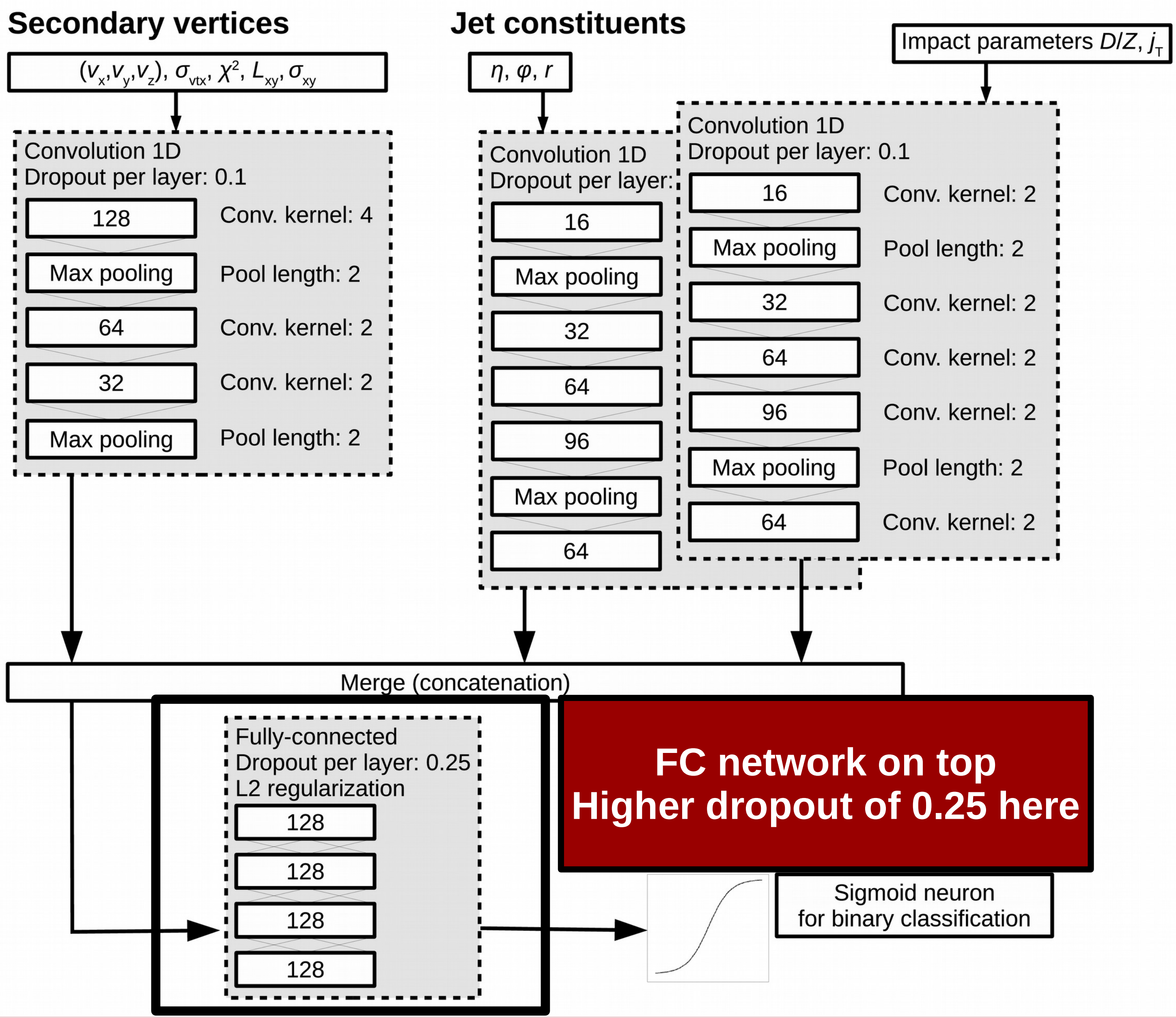
b-jets: Model design



Convolutional networks on fixed-length sequences of low-level parameters

Dropout: 0.1 for all layers & branches

b-jets: Model design



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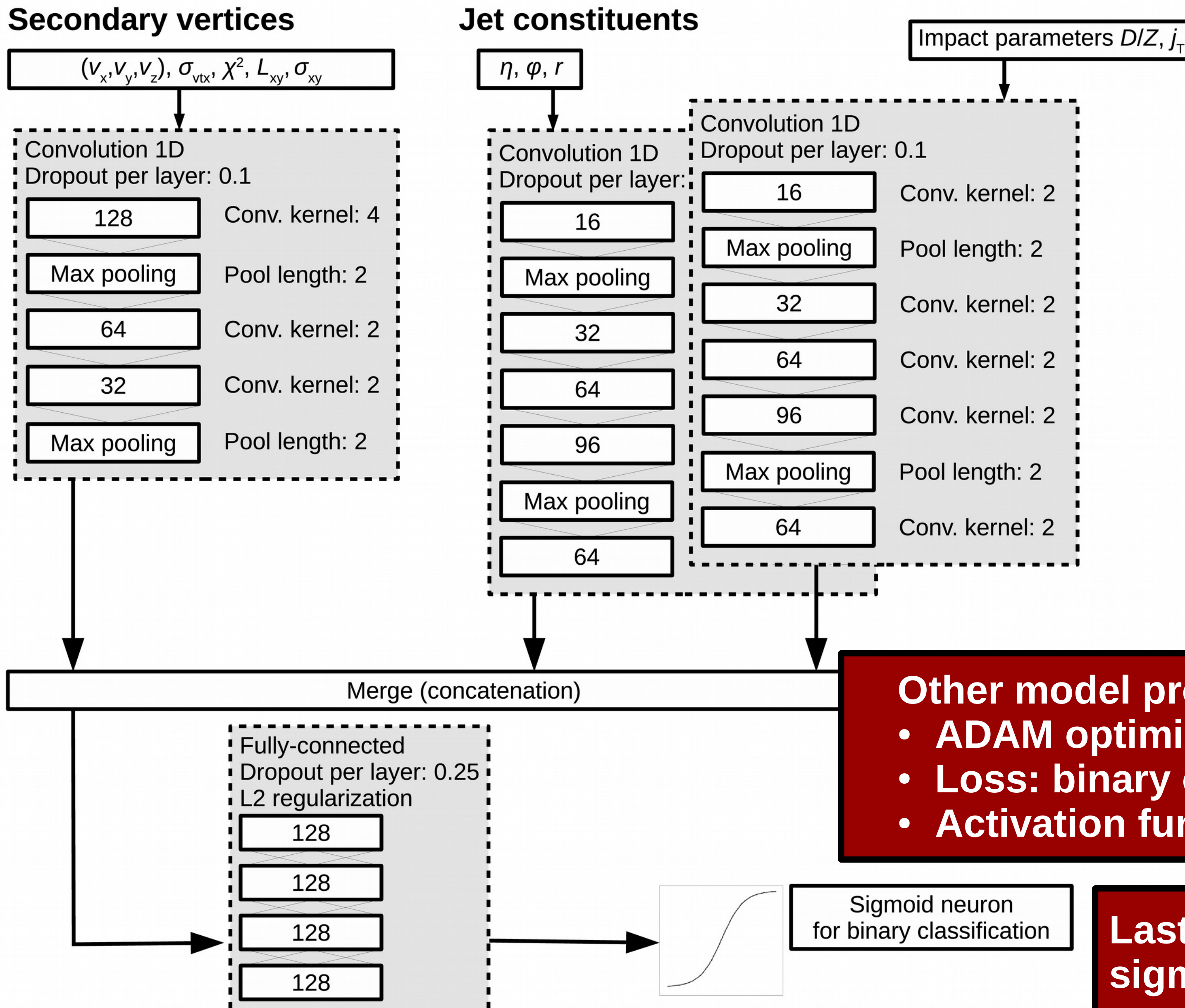

Other model properties

- **ADAM optimizer**
- **Loss: binary crossentropy**
- **Activation function: ReLU**

Last neuron is sigmoid-activated

b-jets: Simulation dataset II

- Strictly separated samples for training, validation, and testing
- 200’000 (training), 50’000 (validation) for each class
  - Signal class: 100% b-jets
  - Background class: 10% c-jets & 90% udsg-jets

  Note: This is for the network to adjust better to udsg-jets
  The impact of using different percentages is small
- Testing statistics is higher:
  ~1.8M udsg-jets, ~500k c-jets, 580k b-jets