Exploring neural networks to improve b-jet tagging with the ALICE detector

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for the ALICE collaboration

(21.03.2017)
1st IML Machine Learning Workshop, CERN

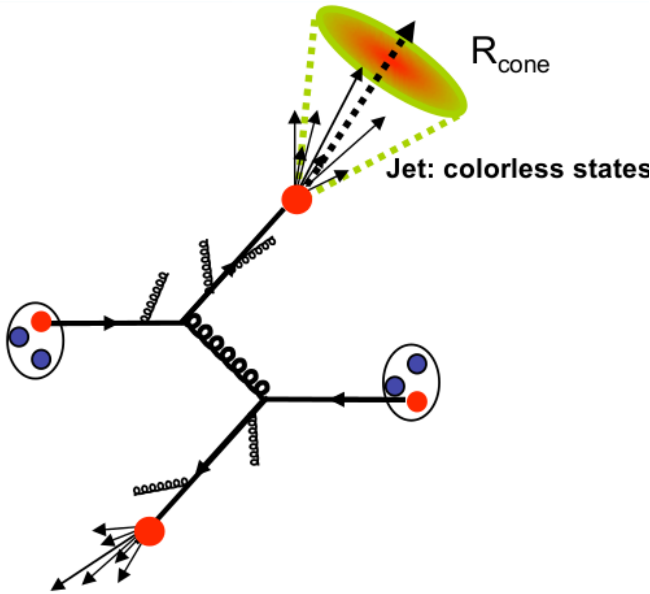
ALICE
A JOURNEY OF DISCOVERY

Talk outline

- Motivation: b-jets and their identification
- Model design
- Input features & data
- Results
- Summary & outlook

b-jets with the ALICE detector

- Conceptually, a jet is the final state of collimated hadrons that fragmented from a high-energy parton



- Jets can be used to shed light on the very early stage of a hadron collision

- The reconstructed *jet observable* is defined by the jet finding algorithm used to clusterize tracks into jets

  → "Charged jets", charged part of a jet

- b-jets: jets arising from beauty quarks

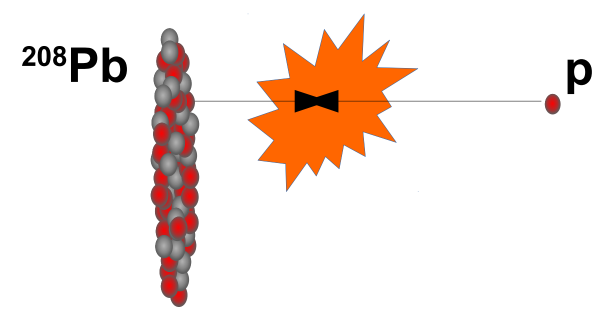
b-jets with the ALICE detector

- Main interest of heavy-ion physics: **Quark-Gluon Plasma (QGP)**
- Hot and dense medium, strongly interacting with high-energy partons
- 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: Understand better the influence of the medium on parton energy loss

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

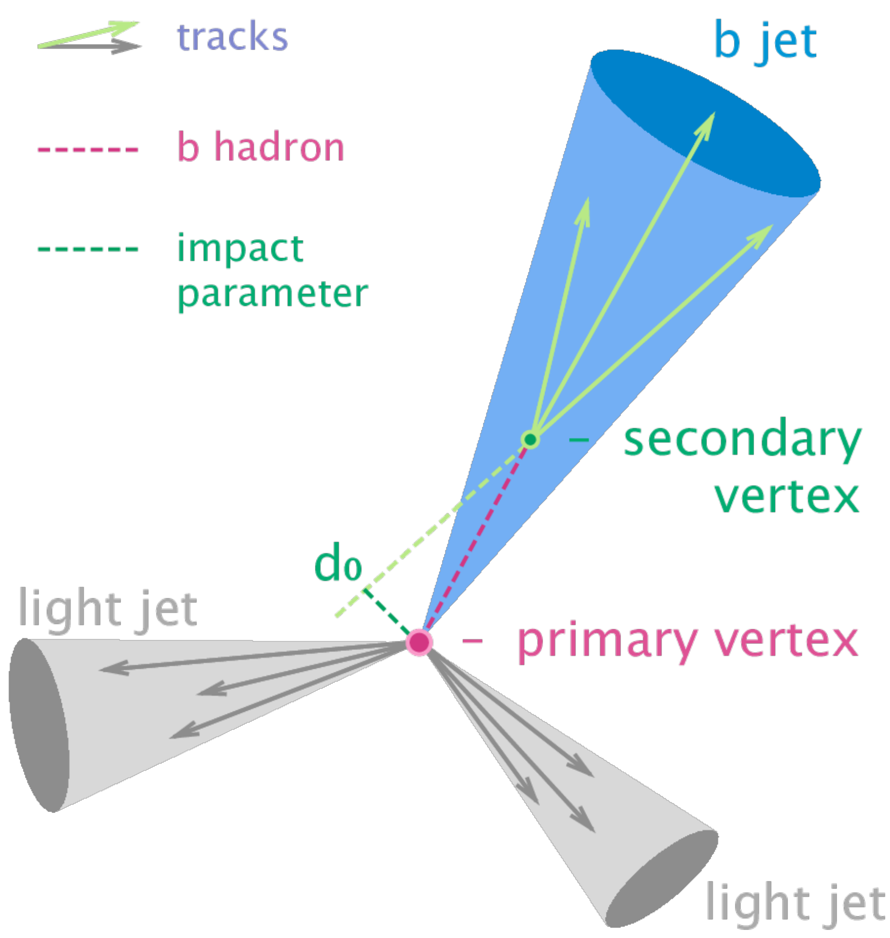


b-jet identification

- 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)
  - Dispersion as vertex quality measure



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

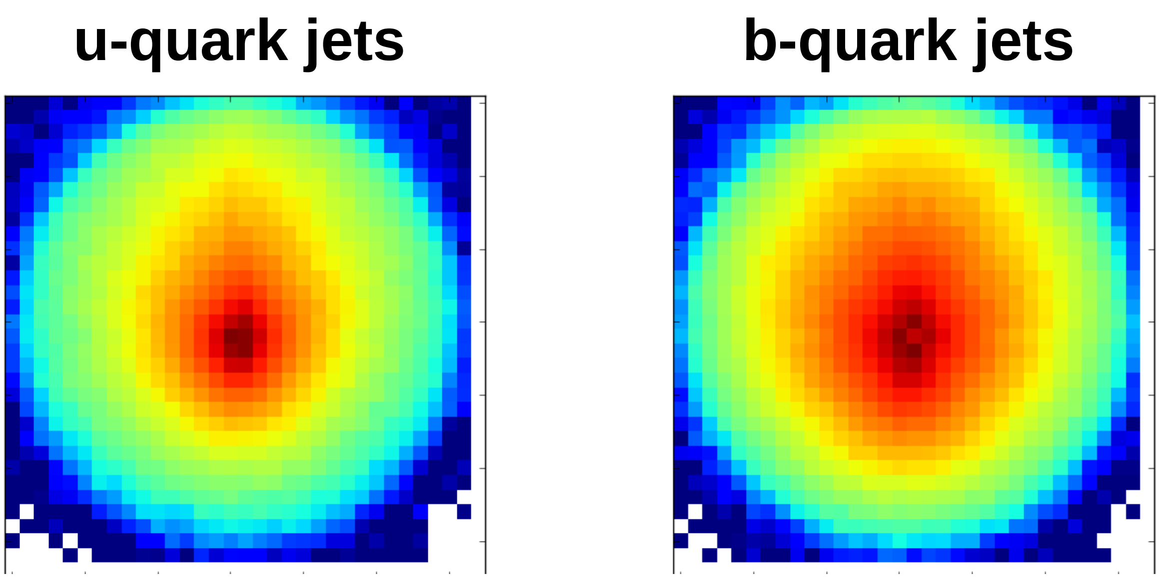
"Conventional" approach:

Application of rectangular cuts on properties of most displaced vertices

b-jet identification

- In addition: fragmentation pattern should be different for b-jets
  - Jet shapes as discriminators?
  - Constituents as discriminators in deep learning?

Qualitative representation of the constituent distribution around the jet axis:



PYTHIA6, 7 TeV, particle level jets, p_T =30-40 GeV/c
For illustration purposes

Not yet directly exploited in the conventional method in ALICE

Model design I

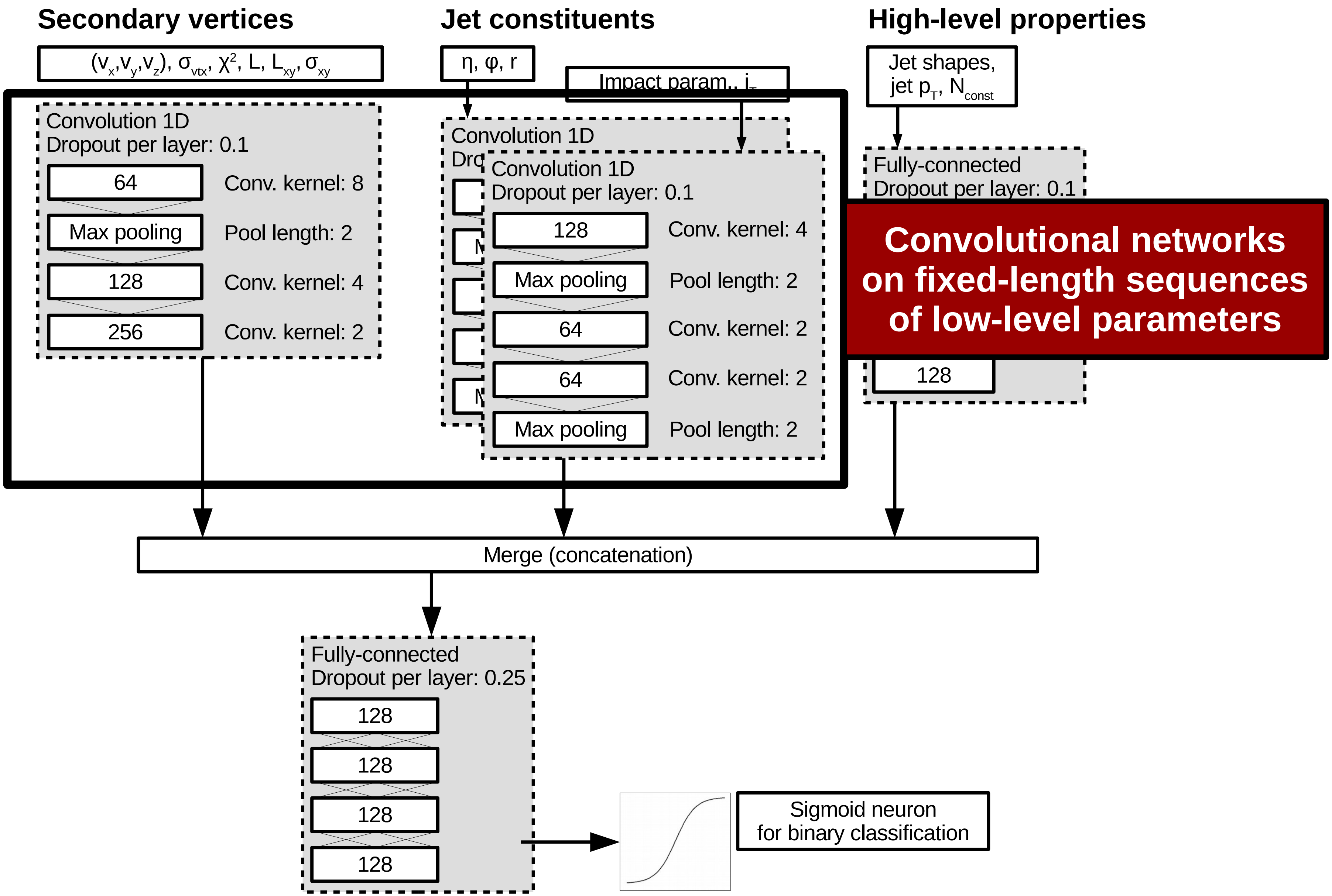
- Binary classification problem: b-jet *tagging*
- General design: Multibranched, multilayered neural network
  - Multiple subnetworks on several features
  - Output is merged and fed to multilayered fully-connected network
  - Training done for whole network
  - Keras[1] has been used for model creation & training
- Several different networks on different features has been tested:
  - LSTMs, 2D convolutional networks on jet images …

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

Model design II

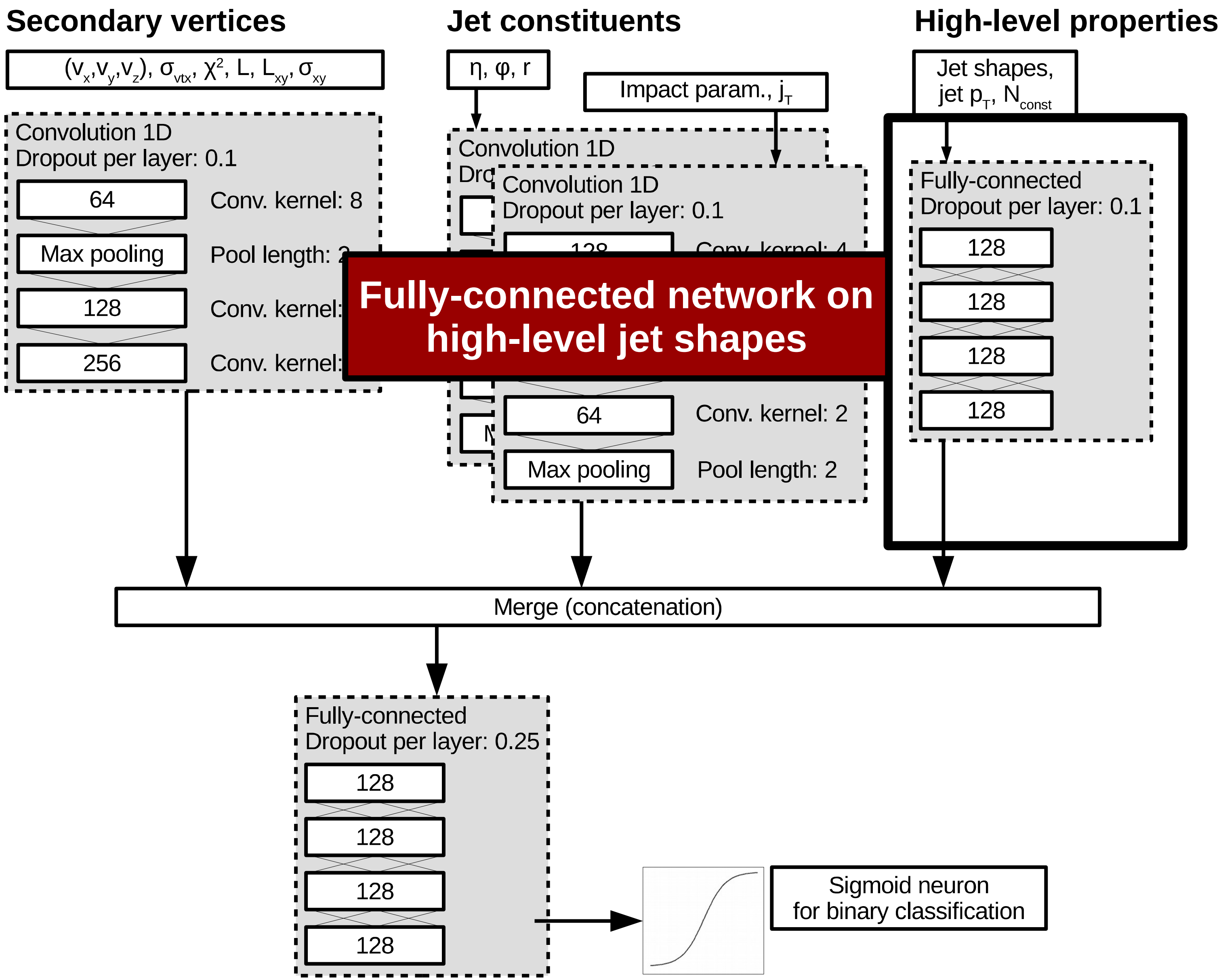
- Promising designs have been further refined with a parameter grid search
- Note: Due to limited time and computing performance, only a small fraction of all possible configurations has been tested
- A parameter correlation analysis has been done to check the relevance of potential input features

Model design

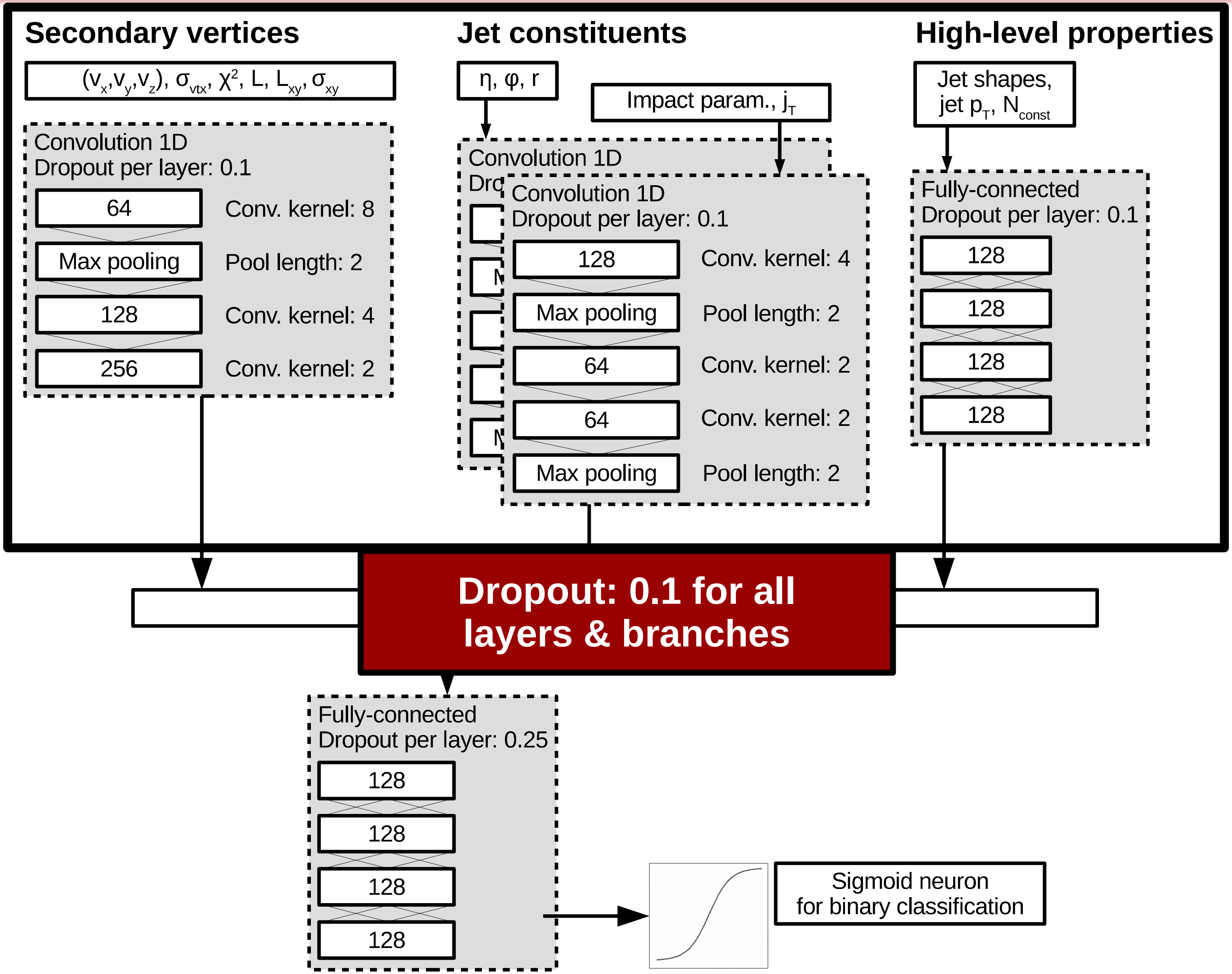


Convolutional networks on fixed-length sequences of low-level parameters

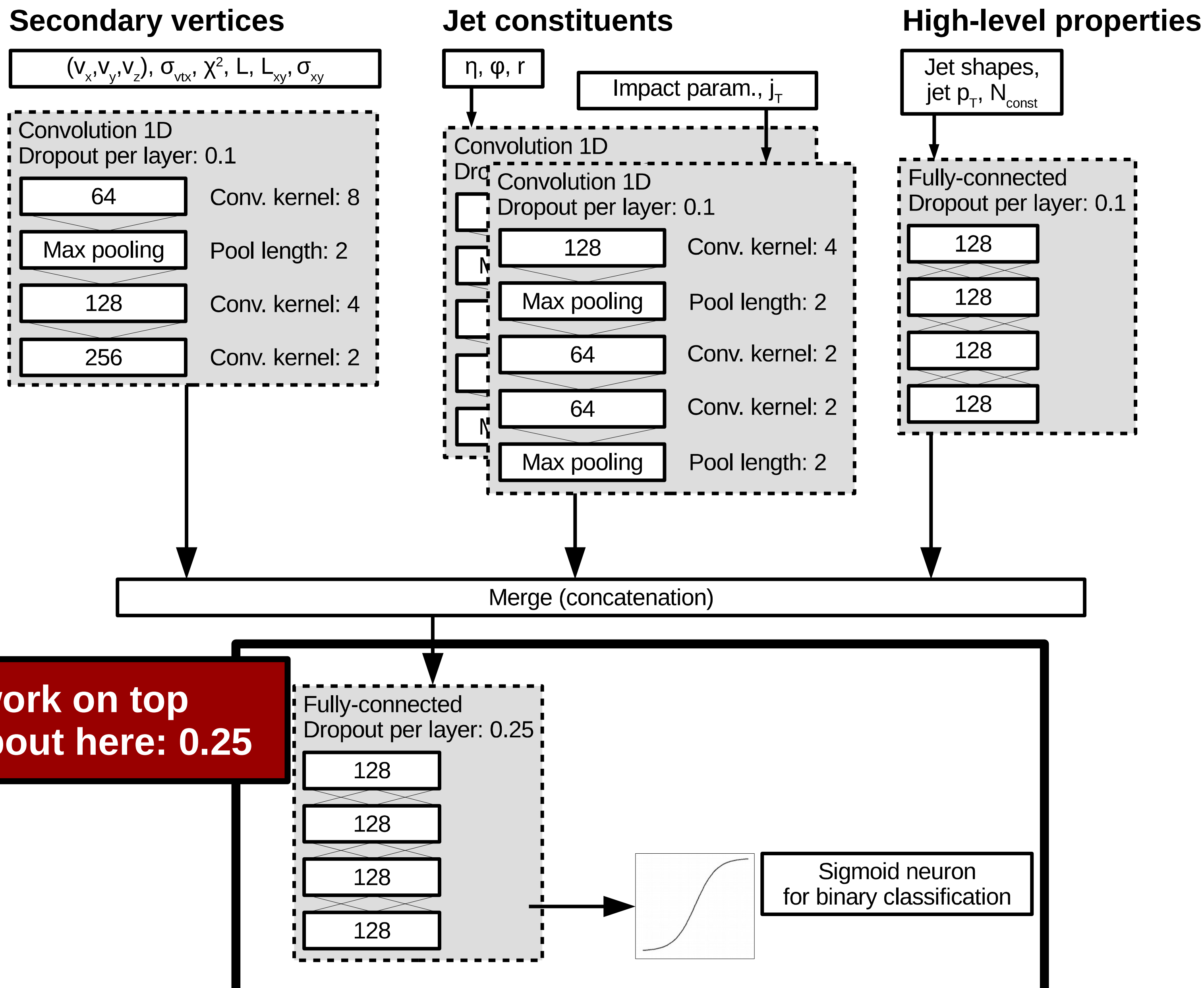
Model design



Model design

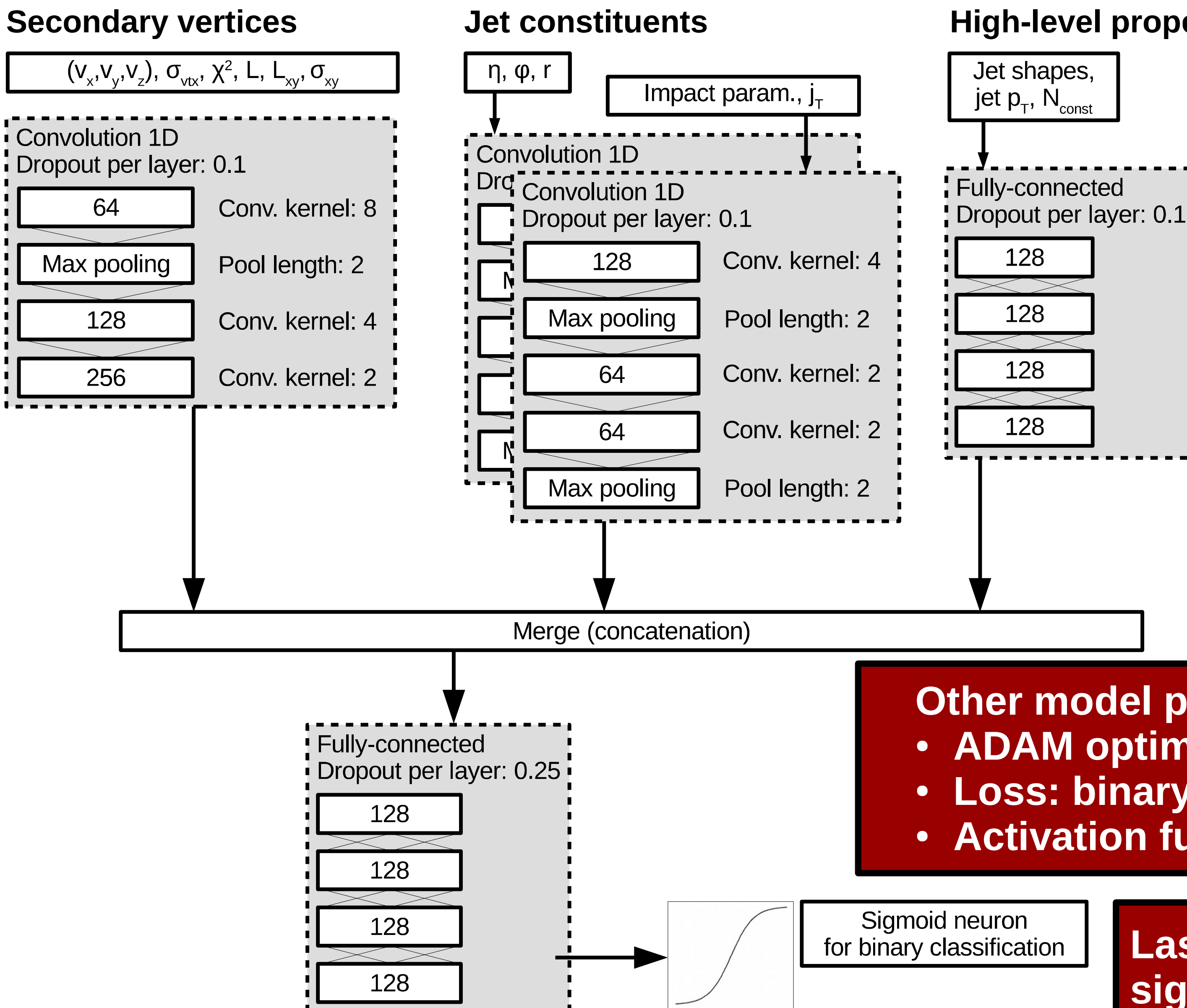


Model design



FC-network on top
Higher dropout here: 0.25

Model design



Other model properties

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

Last neuron is sigmoid-activated

Input features

Basis

- FastJet anti-k_T jets, resolution parameter R = 0.4, tracks only
- Underlying event corrected
- Jets fully contained within detector acceptance

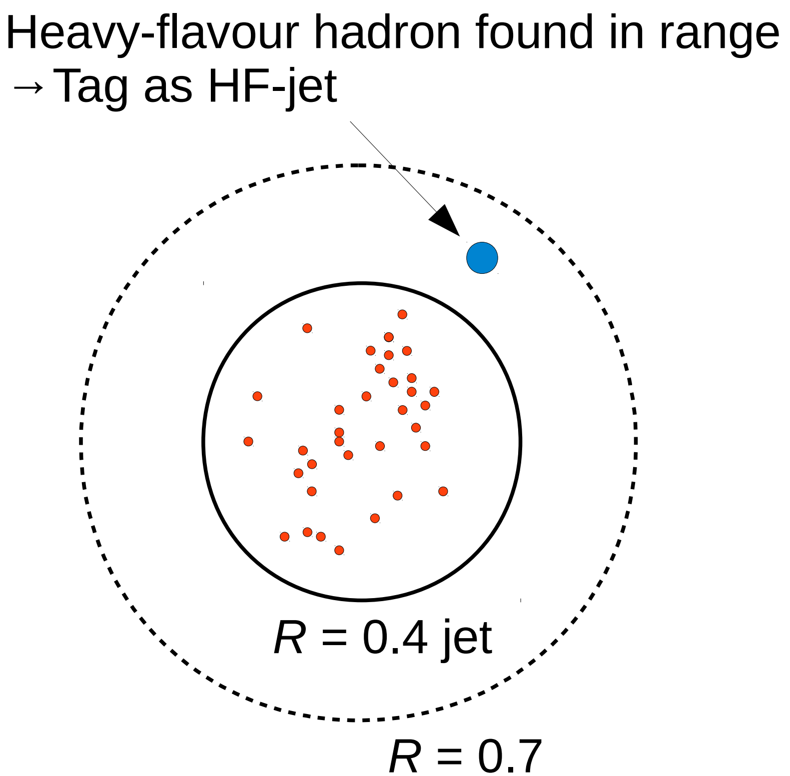
Features

- High level parameters: Jet mass, radial moment, momentum dispersion, LeSub, track count, jet p_T (see backup for definitions)
- Array of constituents: η, φ, r (relative to jet axis), impact parameter j_T
- Array of secondary vertices (3-prong, dispersion < 0.05)

  Each vertex:
  - (x, y, z) rel. to primary vertex
  - Transverse plane distance & uncertainty: L_{xy}, σ_{xy}
  - Vertex track dispersion σ_{vtx}, fit quality χ^2
  - In addition: L_{xy} /σ_{xy}, total decay length L → information is in there, but it makes it easier for the network to learn

Simulation dataset I

- p-Pb dataset PYTHIA6 Perugia 2011 + HIJING
- Enhanced b-/c-quark production, $\sqrt{s_{NN}}$ = 5.02 TeV
- Sample truth (i.e. jet type) is set with geometrical matching and particle level information:
  - If a B-hadron is found within *R* = 0.7 of the jet, it is considered a b-jet.
  - If instead of a B-hadron, a C-hadron is found, the jet is considered a c-jet.
  - All other jets are tagged as light-flavor jets.



Simulation dataset II

- Strictly separated samples for training, validation, and testing
- 200’000 (training), 40’000 (validation) for each class
  - Signal class: 100% b-jets
  - Background class: 20% c-jets & 80% 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:
  ~1.2M udsg-jets, ~150k c-jets

Results

Observables

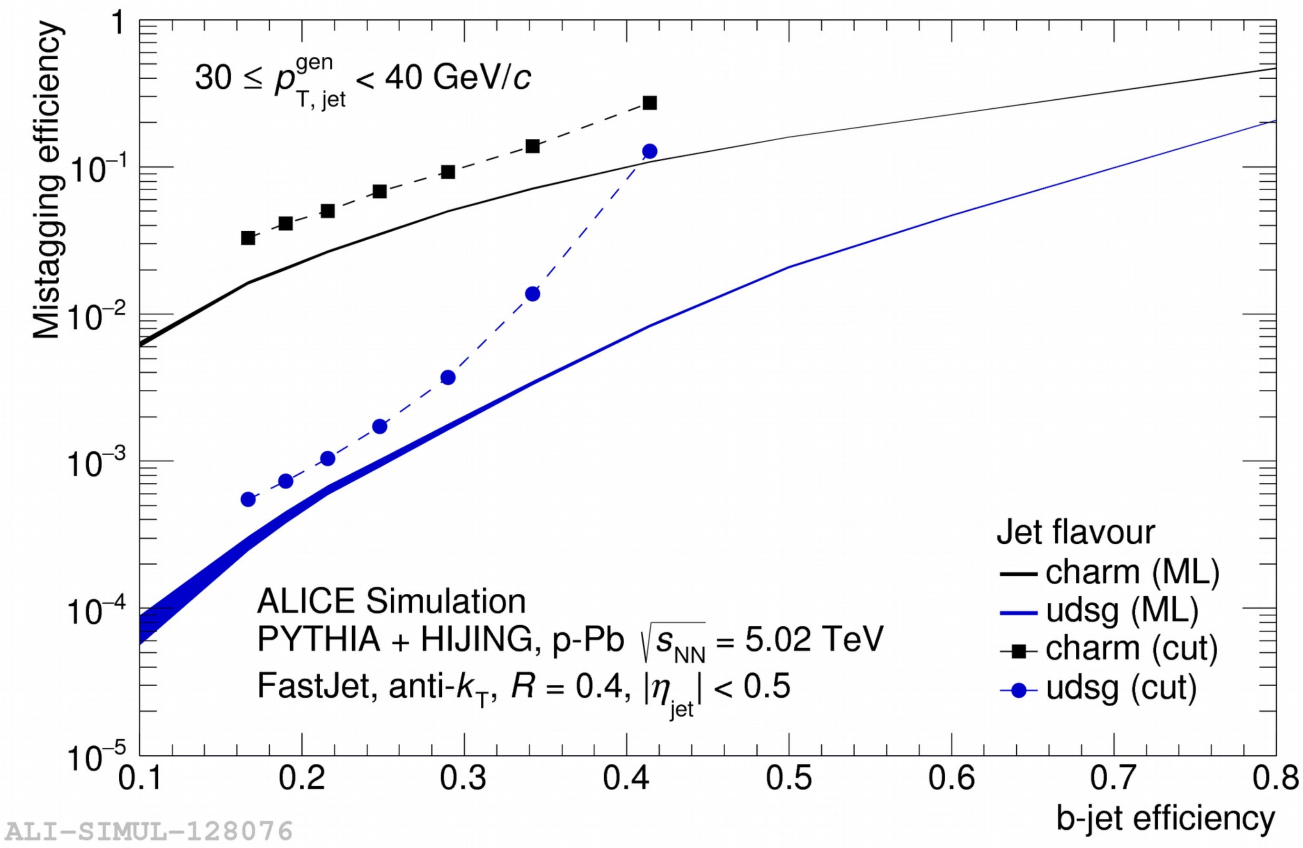
- Goal at this stage:
  Performance evaluation & comparison to conventional, cut-based method

- Indicator: b-jet tagging & c-/udsg-mistagging efficiencies
- The higher the b-jet efficiency, the higher the mistagging efficiencies
  → Need to find optimum working point

- Here: b-jet tagging efficiency directly set by cutting on score
  score/efficiency relation known in MC simulations
- In the following, the mistagging efficiencies will be shown for several working points

- Note: jet p_T from geometrical matching with particle-level jets

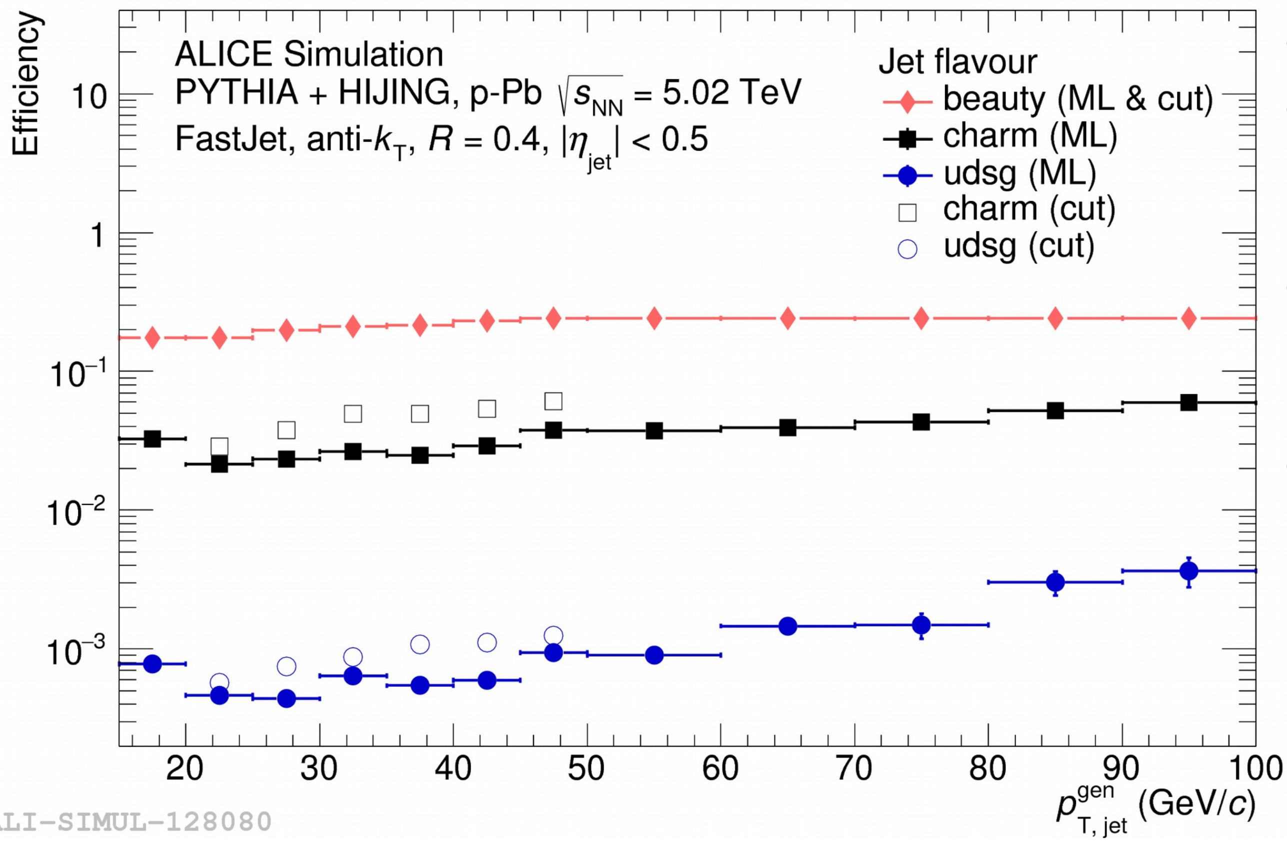
Mistagging efficiencies vs. b-jet efficiency



- Mistagging efficiency vs. b-jet efficiency
- Solid lines represent efficiencies with present ML-based method
  Statistical uncertainties shown as width of line
- Dashed lines show conventional, cut-based performance
  (cf. arXiv:1605.00143)

The present ML-assisted tagging method is very promising, compared to conventional method
– mistagging efficiency lower for c- and udsg-jets
– mistagging efficiencies rise less steep when considering higher b-jet tagging efficiency

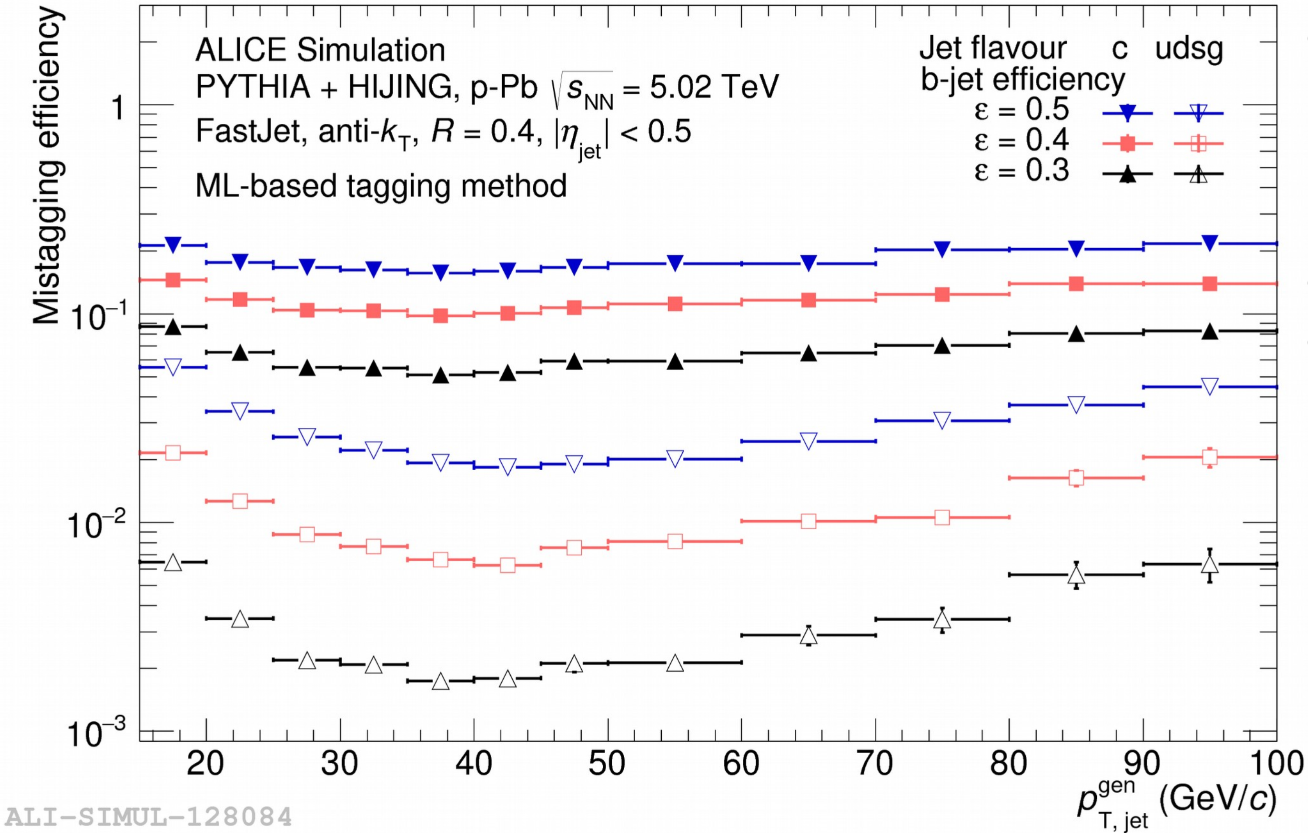
Mistagging efficiencies vs. jet p_T



- Mistagging efficiency vs. jet p_T
- Solid symbols represent efficiencies with present ML-based method
- Open symbols show conventional, cut-based performance
- For the sake of comparison: Between 20-50 GeV/c b-jet efficiency set to values used in cut-based method

The present ML-assisted tagging method is very promising, performance better over whole jet p_T-range

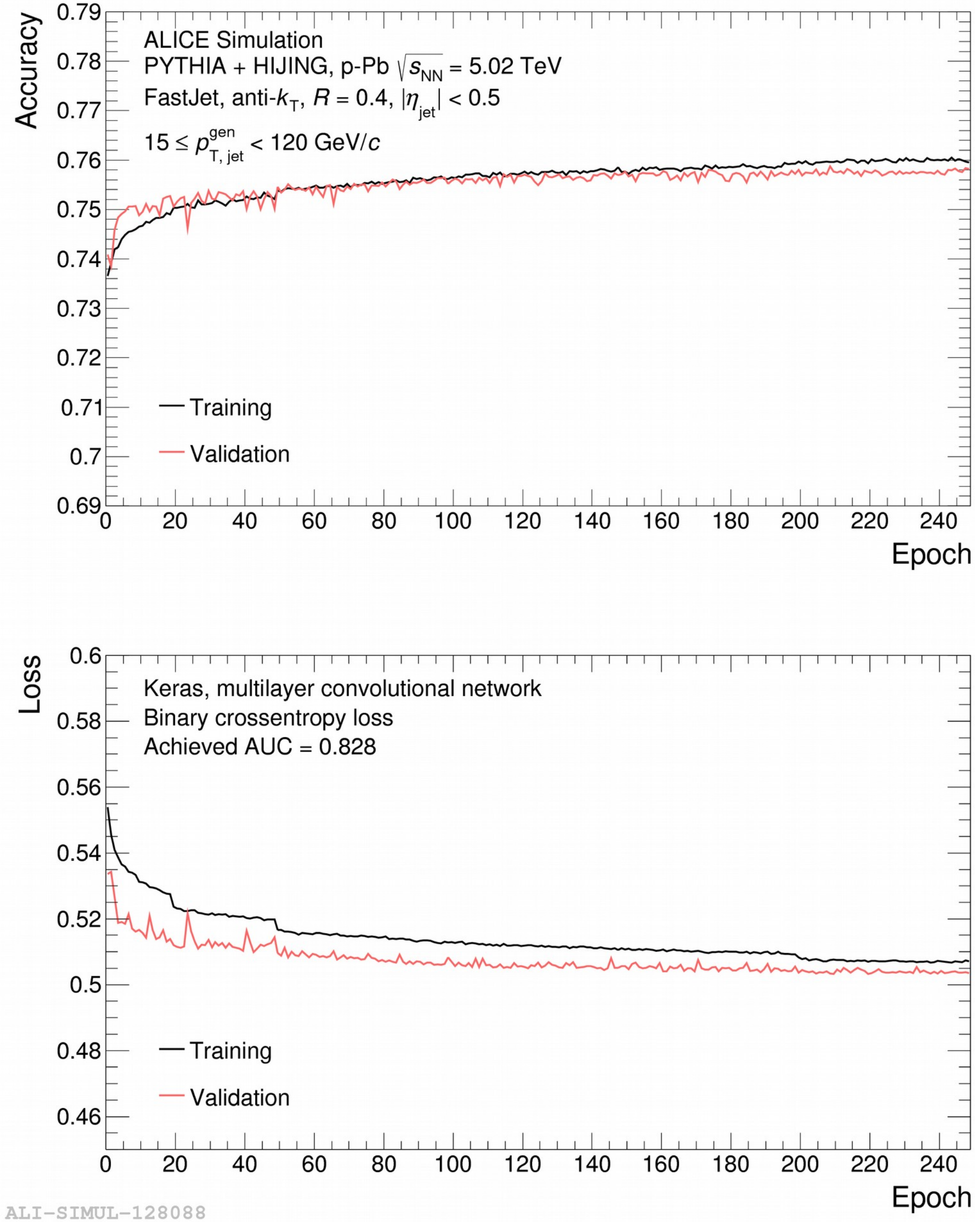
Mistagging efficiencies vs. jet p_T



- Mistagging efficiency vs. jet p_T for higher b-jet efficiencies (ML-based method only)
- Solid symbols: c-efficiency
- Open symbols: udsg-efficiency

- As expected, higher b-jet efficiencies lead to much higher mistagging rates
- ML-based method expected to allow higher b-jet efficiencies than cut-based methods while showing same mistagging efficiencies
- A future analysis could compare several working points

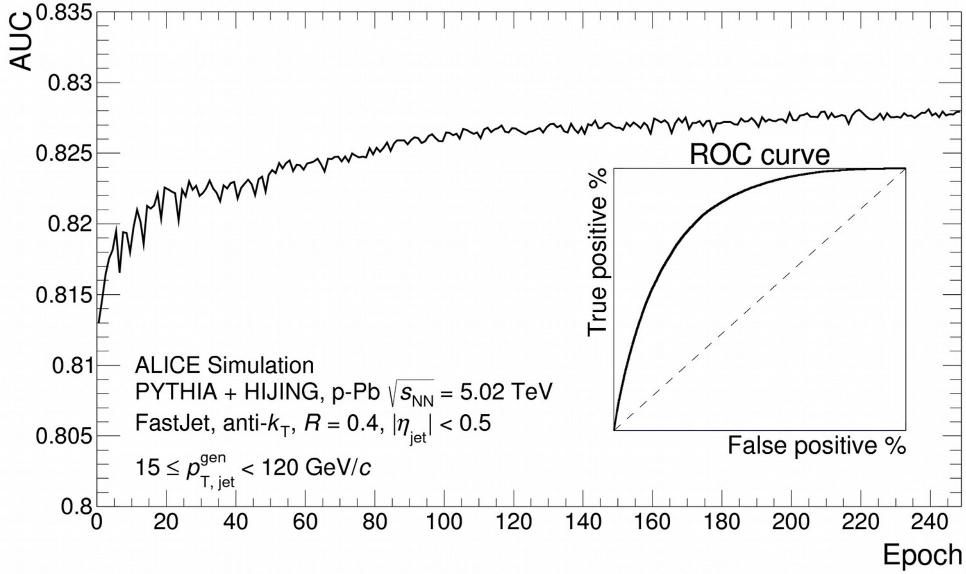
Training control plots

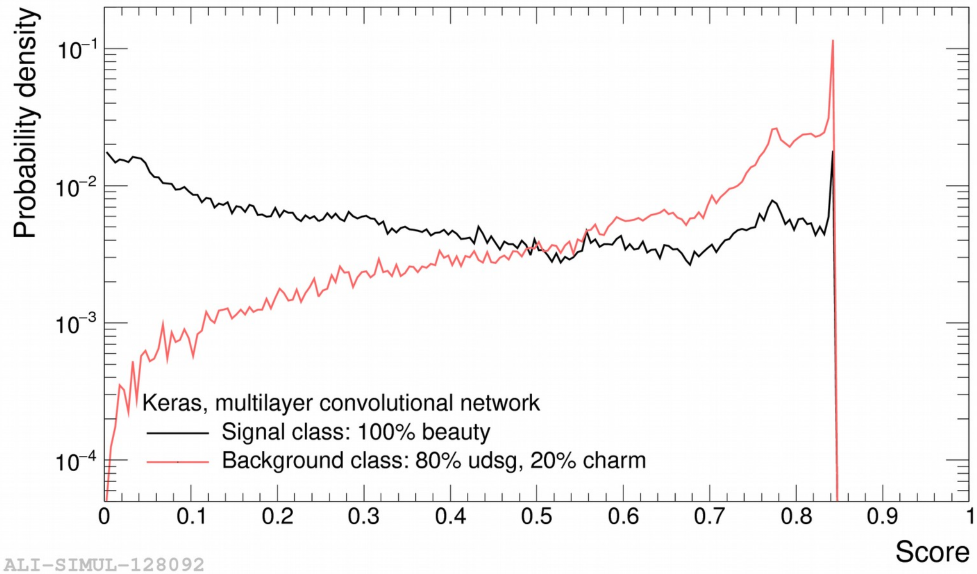


- Model shows slow learning up to roughly 250 epochs
- After 250 epochs, model remains stable
- Learning rate successively lowered:
  [0.001, 0.0005, 0.0002, 0.0001]
- Strong loss differences due to regularization

- Accuracy shows slight overfitting, but AUC (see next slide) and loss still fine

Training control plots





- AUC = **A**rea **U**nder ROC **C**urve
- AUC reveals slow, but constant learning up to 250 epochs
- Tests show that the performance cannot be improved by just learning more epochs
- Interesting: Learning onset between epochs 60-80

Summary

- ML-assisted tagging method has been developed
- Mixture of deep/shallow learning
  - Conventional FC networks on high-level parameters
  - Deep convolutional networks on low-level parameters

- Performance evaluated in p-Pb MC simulations and compared to cut-based method

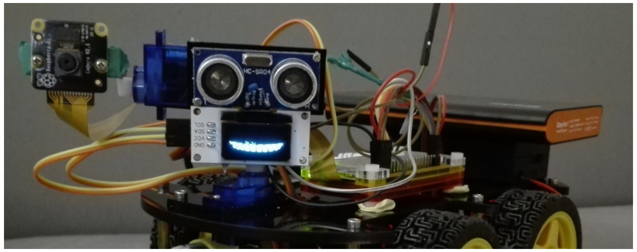
Results are very promising
  - Tagging method might allow higher b-jet efficiencies
  - Lower mistagging rates
  - Systematic uncertainties still to be assessed
  - Data applicability to be checked → Better generalization with data from different generator/decayer?

Outlook

- Next step: Apply tagging method in p-Pb collisions and test performance on data
- Idea: Use both conventional and ML-assisted method and compare performance in a paper
  Strength of ALICE: reach down to low p_T

- On agenda: Train model with higher statistics at high p_T

- Tagging bias: All tagging methods (ML or cut-based) potentially bias the sample in an unwanted way
  → Careful examination of tagged sample



Thank you for your attention!

Backup

Jet shape definitions

Radial moment

“p_T-weighted width of jet”

$$g = \sum \frac{p_{\mathrm{T,const}}}{p_{\mathrm{T,jet}}} |\Delta R_{\mathrm{const}}|$$

Momentum dispersion

Contains direct information about jet fragmentation

$$p_{\mathrm{T}} D = \sqrt{\sum p^2_{\mathrm{T,const}}} / \sum p_{\mathrm{T,const}}$$

LeSub

Difference between leading and subleading constituent

$$\mathrm{LeSub} = p_{\mathrm{T,lead.}} - p_{\mathrm{T,sub.}}$$

Jet mass

Connected to virtually of initial parton that showered into jet

$$M = \sqrt{E^2 - p^2_{\mathrm{T}} - p^2_{\mathrm{Z}}}$$