AI techniques for spatial calorimeters

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Outline

- MonteCarlo simulation
- AI techniques
- First preliminary results

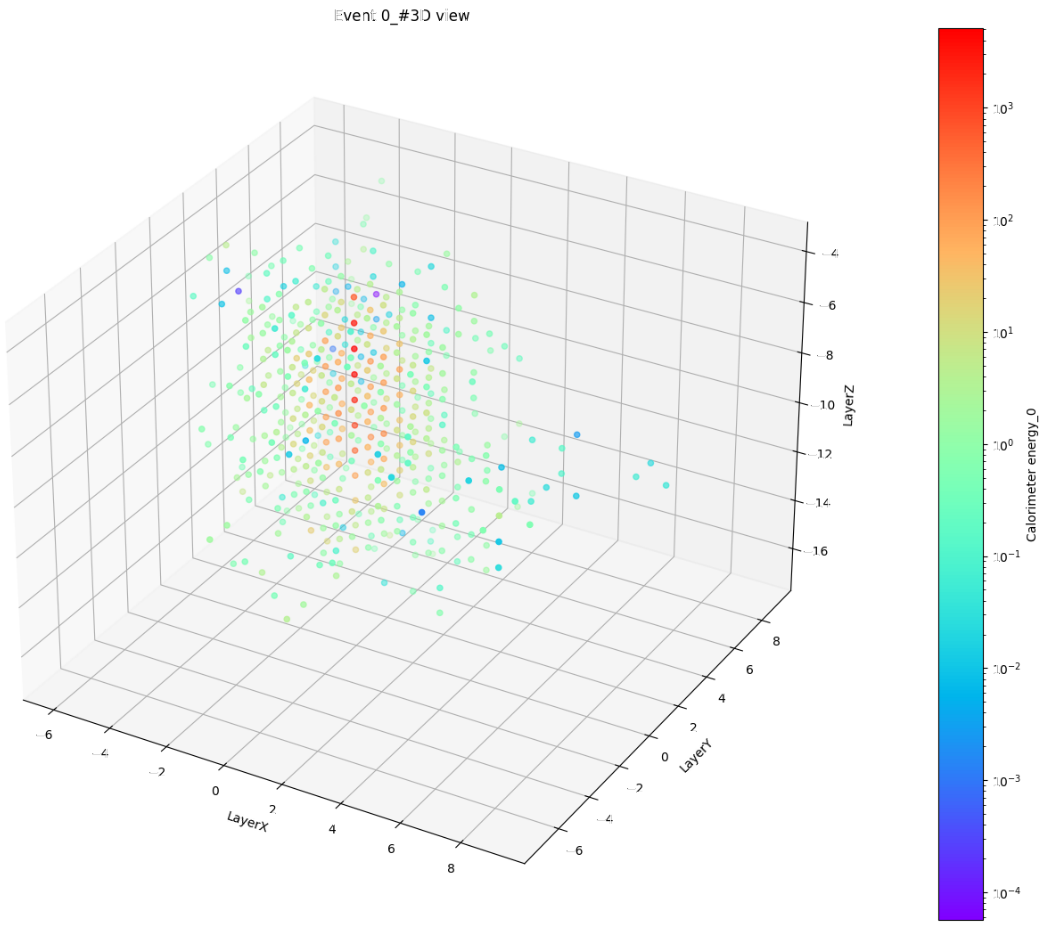
MonteCarlo simulation

The existing toy Monte Carlo model did not include a layered calorimeter. Therefore, it was necessary to modify both the simulation and the event reconstruction program.

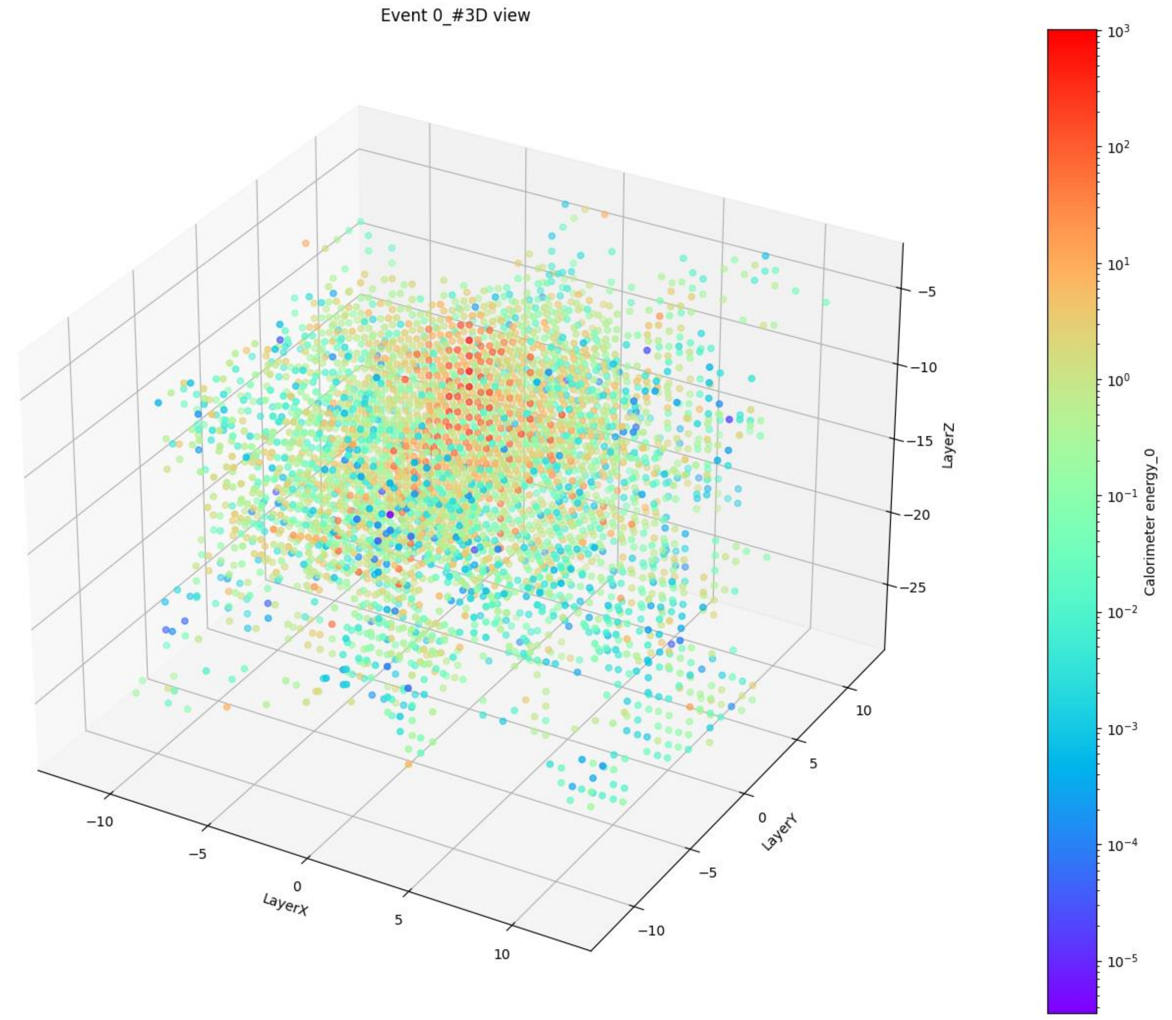
I simulated a cubic calorimeter composed of 25 layers, each measuring 3x3x3 cm, using LYSO, resulting in a total side length of 75 cm.

MonteCarlo simulation - results

At present, we have simulated only electrons and protons, each with varying energies: 10 GeV, 20 GeV, 30 GeV, and 50 GeV. (Additional energies and particle types will be included later).



e-



proton

AI techniques

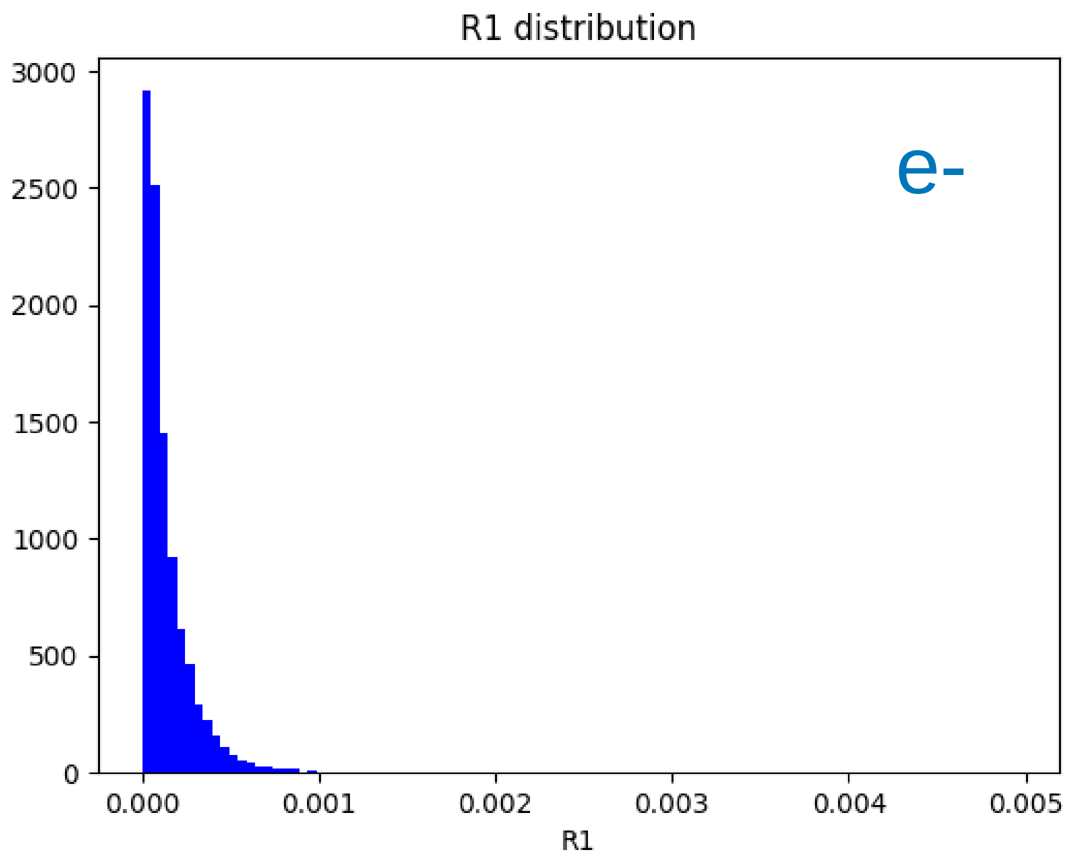
Choice of parameters

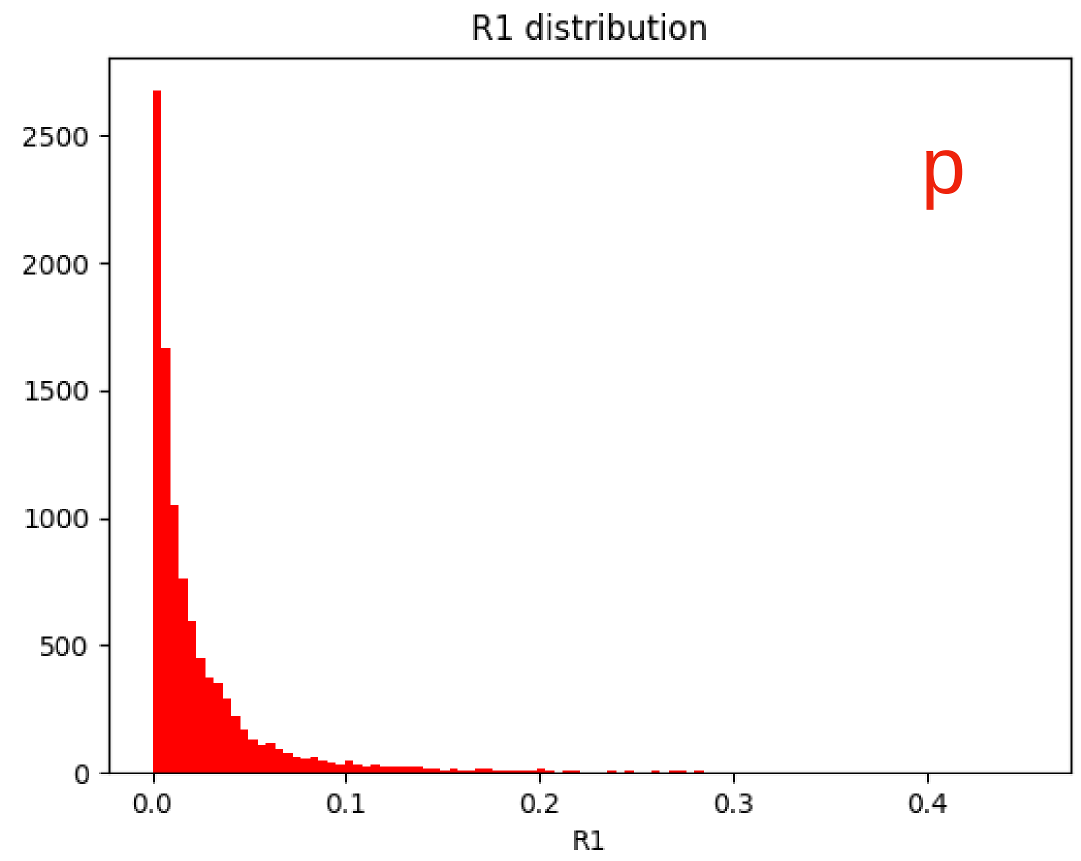
For the machine learning model, I identified the following parameters:

- R1: Ratio of energy deposited in the last layer to the total energy deposited in the calorimeter.
- R2: Ratio of the maximum energy deposited to the total energy deposited in the calorimeter.
- R3: Ratio of energy released in each layer to the total energy deposited in the calorimeter (25 parameters in total).
- R4: Moliere radius
- R5: Z-coordinate of the last hit layer.
- R6: Z-coordinate of the maximum energy deposited.

Parameters distributions

Electrons vs protons of 20 GeV

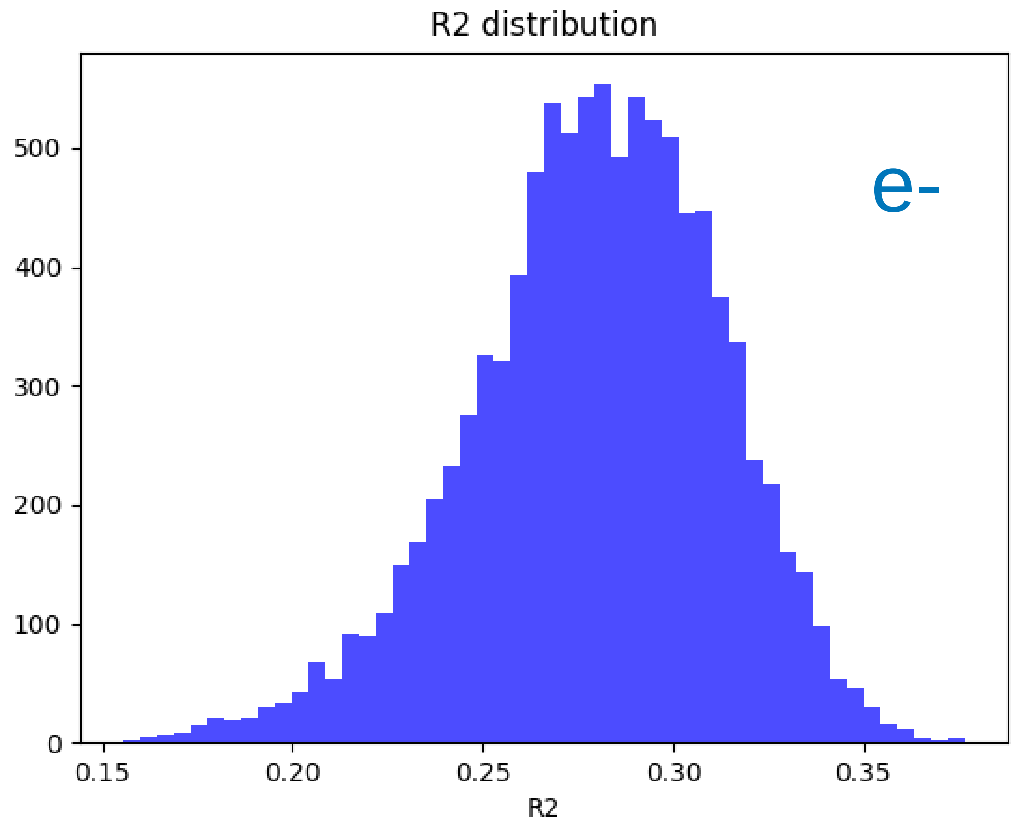


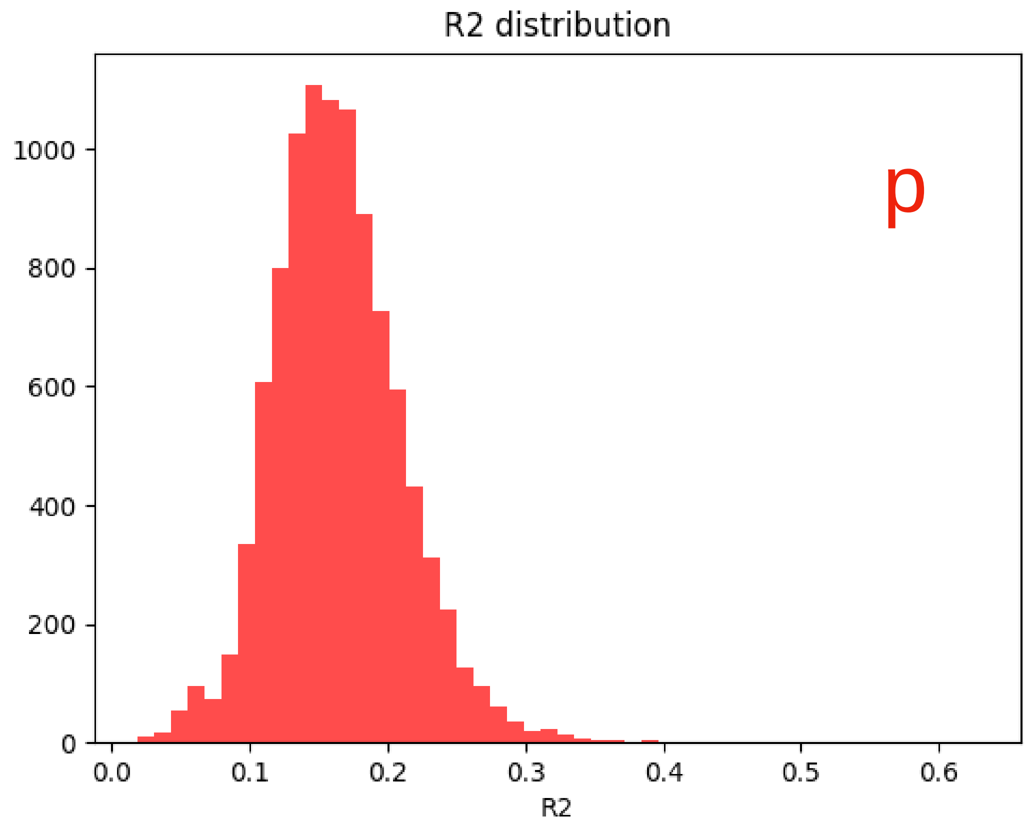


$$R1 = \frac{E_{LastLayer}}{E_{dep}^{tot}}$$

Parameters distributions

Electrons vs protons of 20 GeV

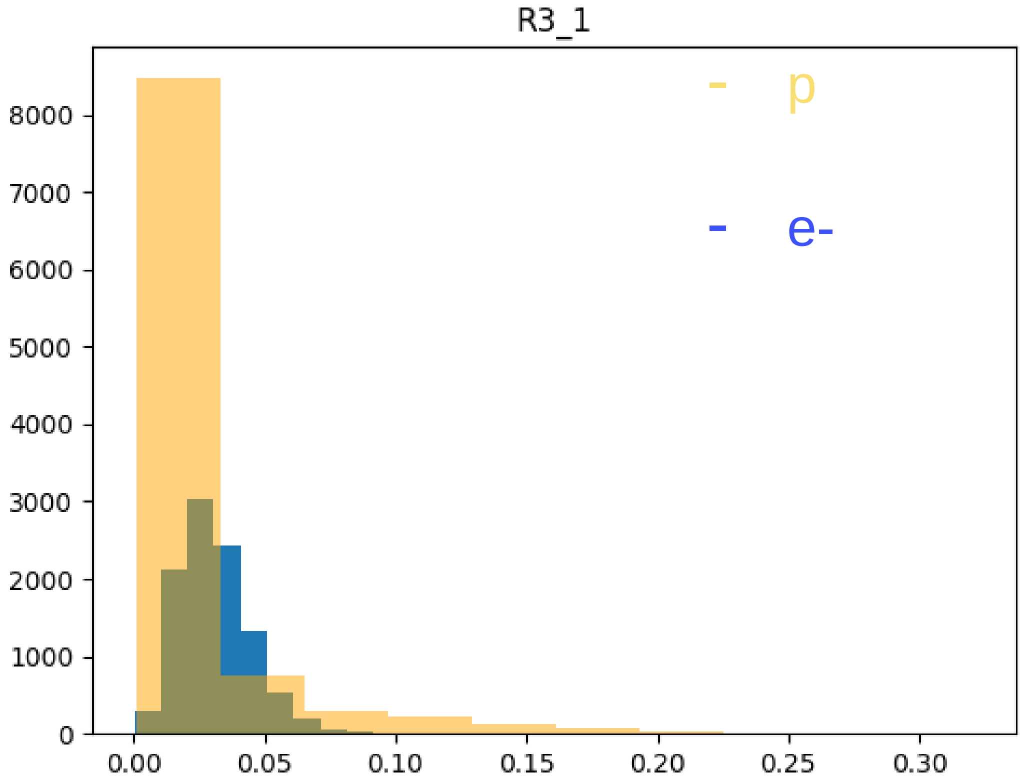


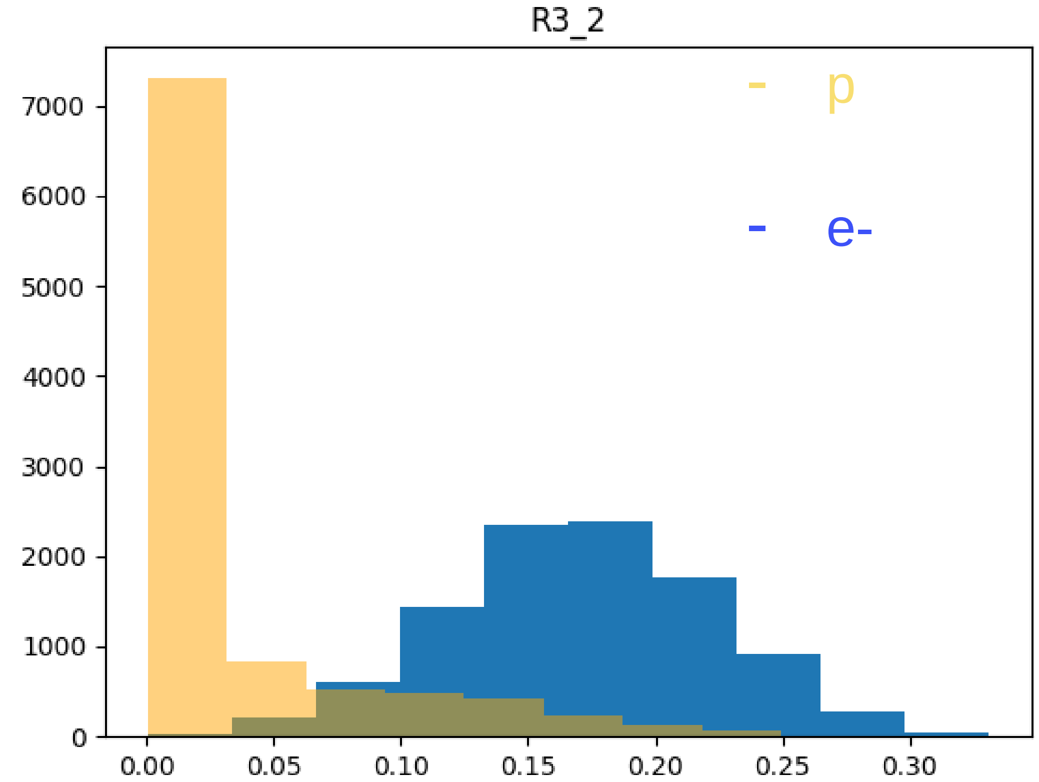


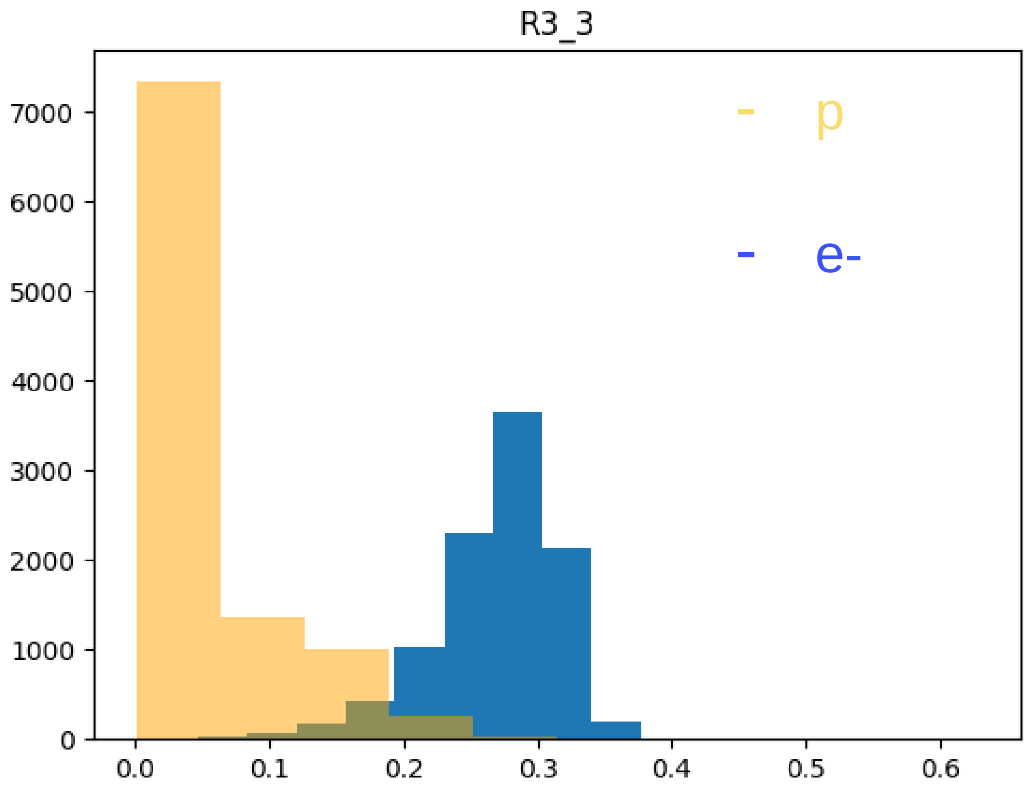
$$R2 = \frac{E_{dep}^{max}}{E_{dep}^{tot}}$$

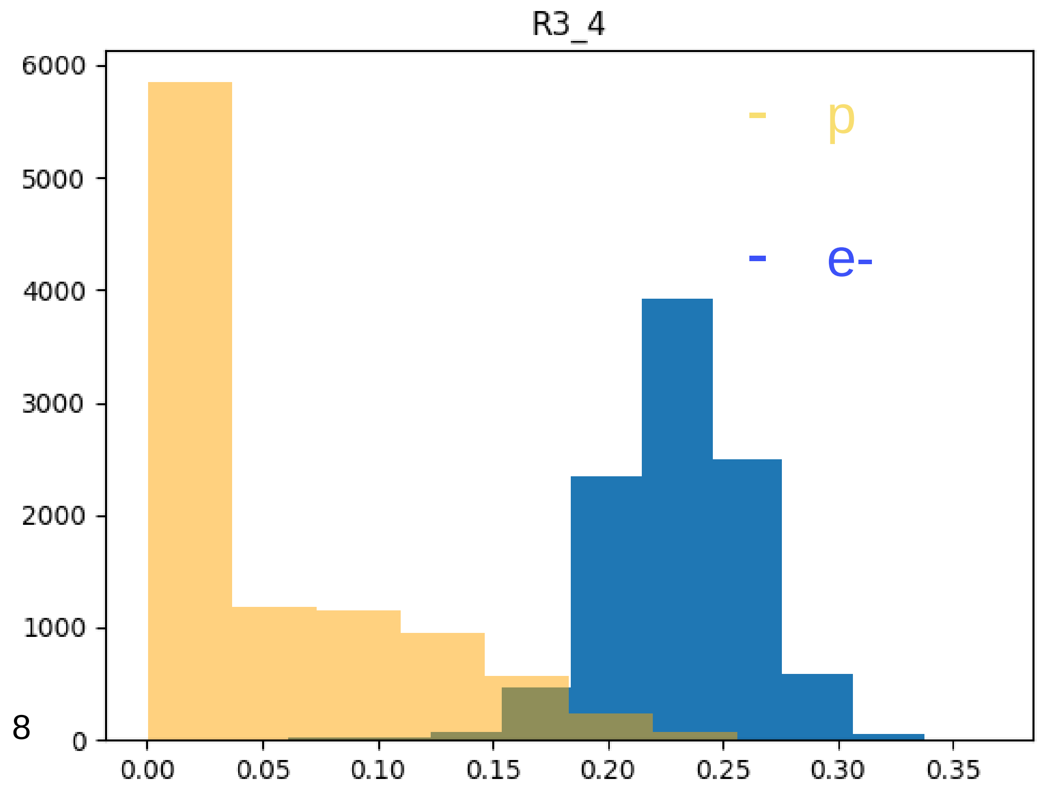
Parameters distributions

Electrons vs protons of 20 GeV



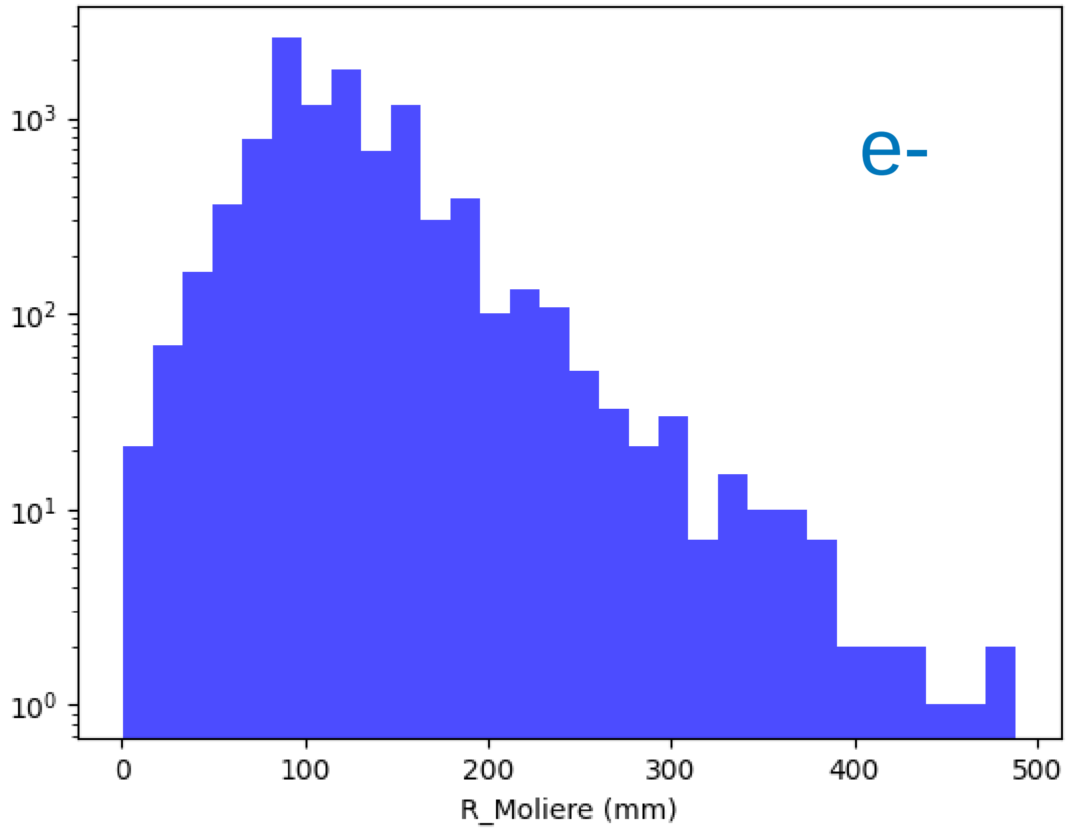


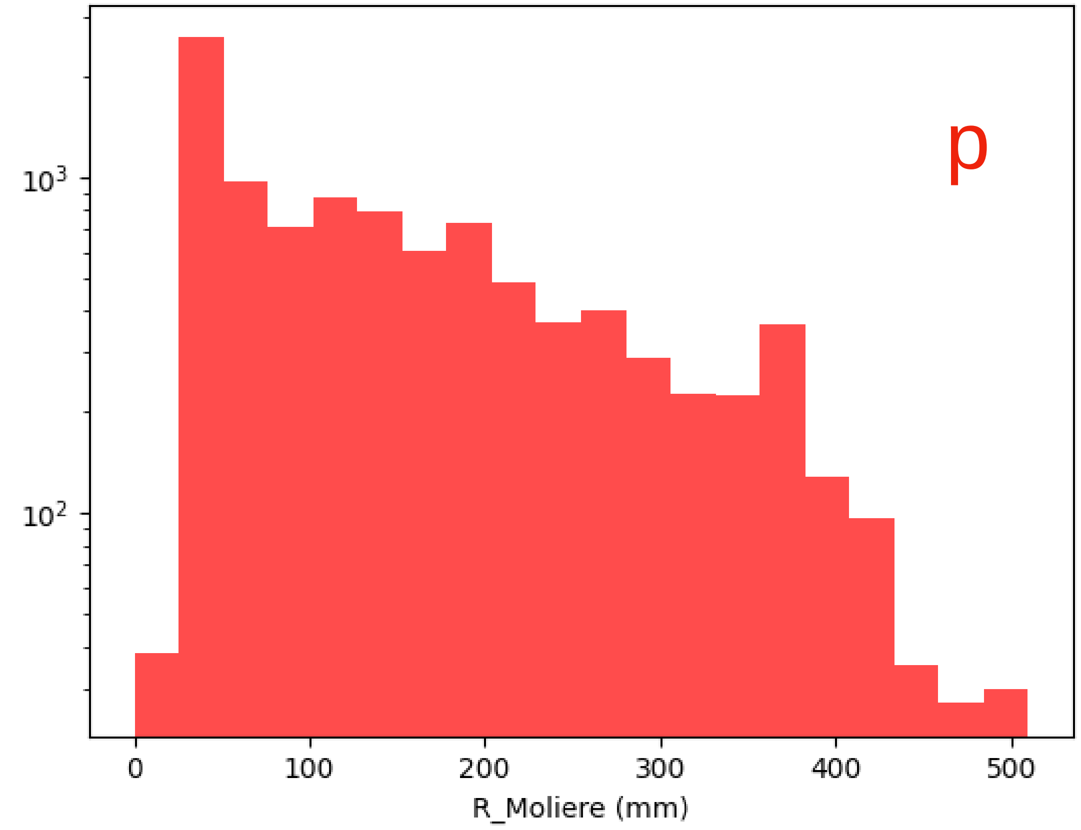




Parameters distributions

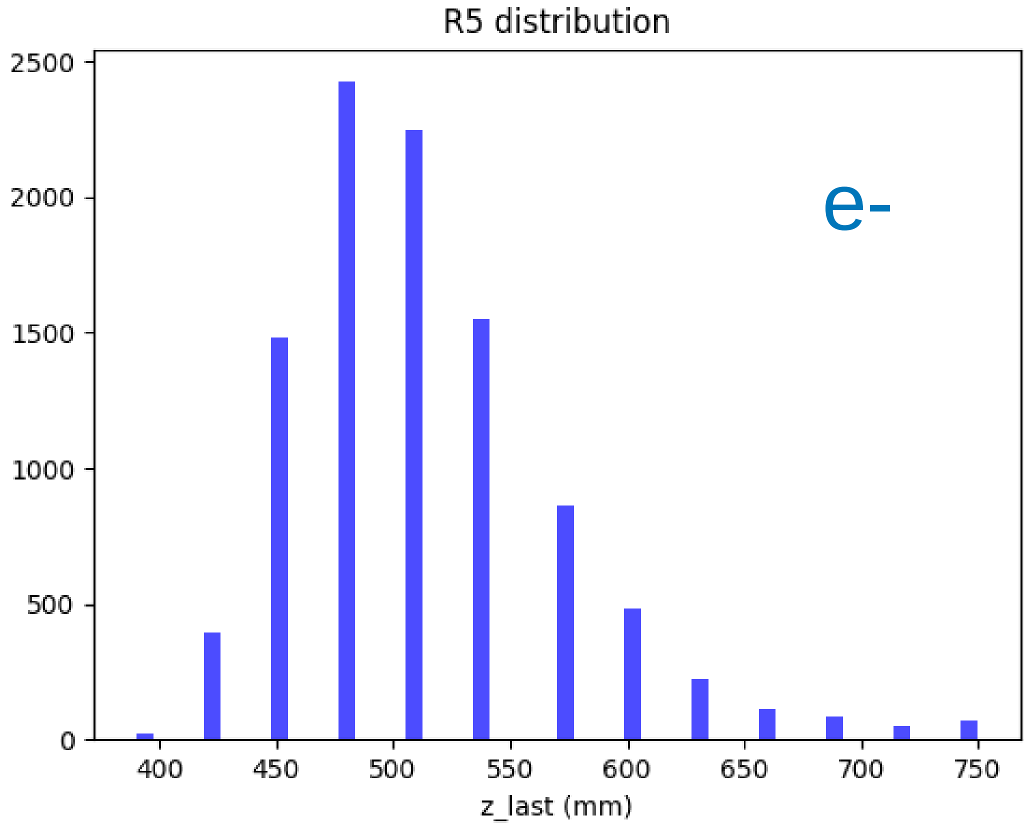
Electrons vs protons of 20 GeV

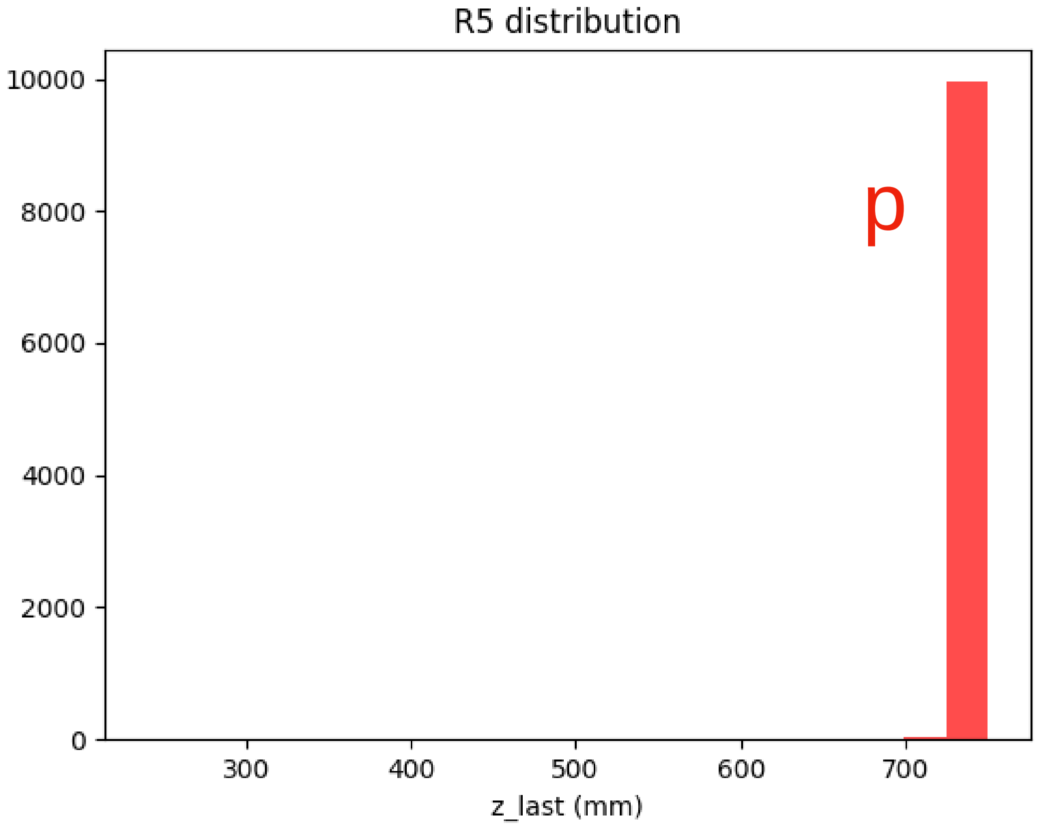




Parameters distributions

Electrons vs protons of 20 GeV





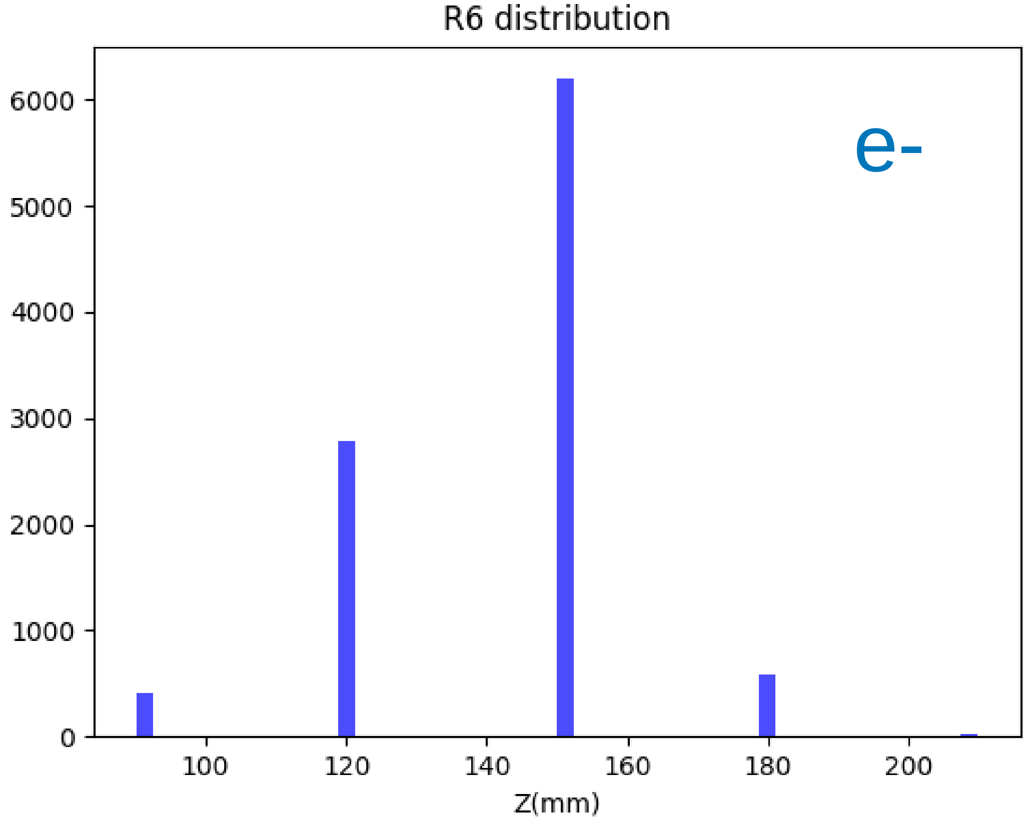
layer ~15-16

layer ~25th

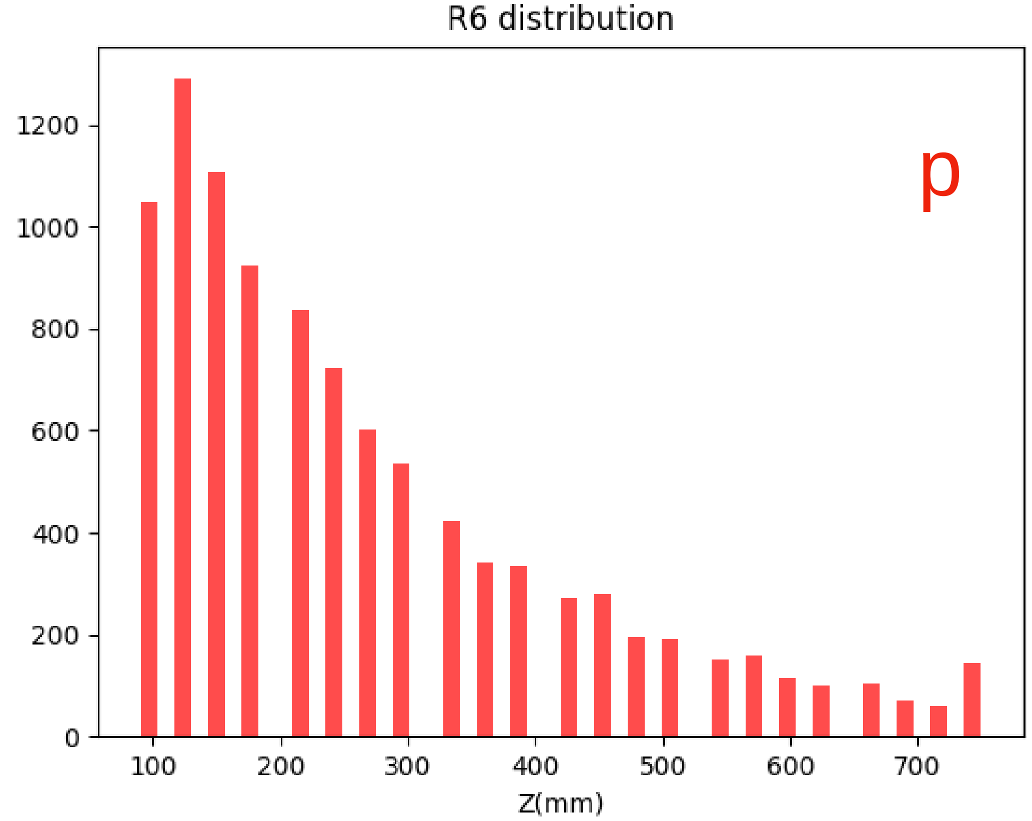
R5 = last hit layer

Parameters distributions

Electrons vs protons of 20 GeV



layer ~ 5th



layer ~ 4th

R6 = maximum energy deposited

XGBoost algorithm

XGBoost (Extreme Gradient Boosting)

- The main goal of XGBoost is to find the best balance between the complexity of the trees (how deep and complex they are) and the accuracy of the prediction

- XGBoost is based on decision trees, similar to random forest. The difference lies in the fact that XGB trains these trees one at a time. It starts with one tree and then adds more incrementally. Each new tree tries to correct the errors made by the previous ones.

- Weak trees have associated weights - these weights represent how skilled each tree is at solving the problem. XGBoost assigns a higher weight to trees that contribute more to the overall error reduction."

XGBoost algorithm

Results

Training an algorithm of machine leanring with XGBoost, on a sample of 20k events, the results are:

Accuracy XGB Classifier: 99.85%

Recall XGB Classifier: 99.90%

Precision XGB Classifier: 99.80%

EXplanable Artificial Intelligence (XAI)

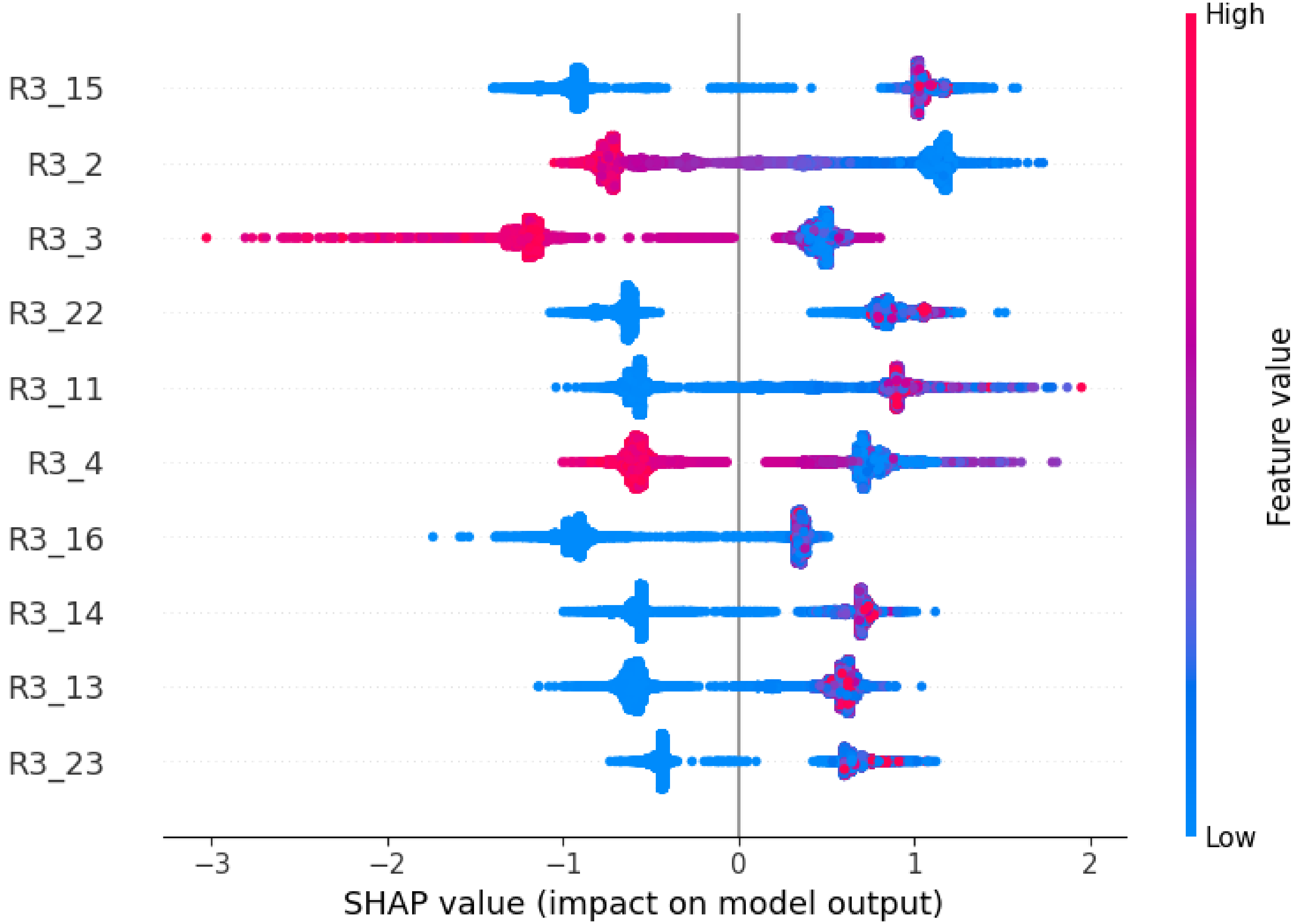
SHAP Analyses

SHAP stands for SHapley Additive exPlanations, is the most powerful method for explaining how machine learning models make predictions.

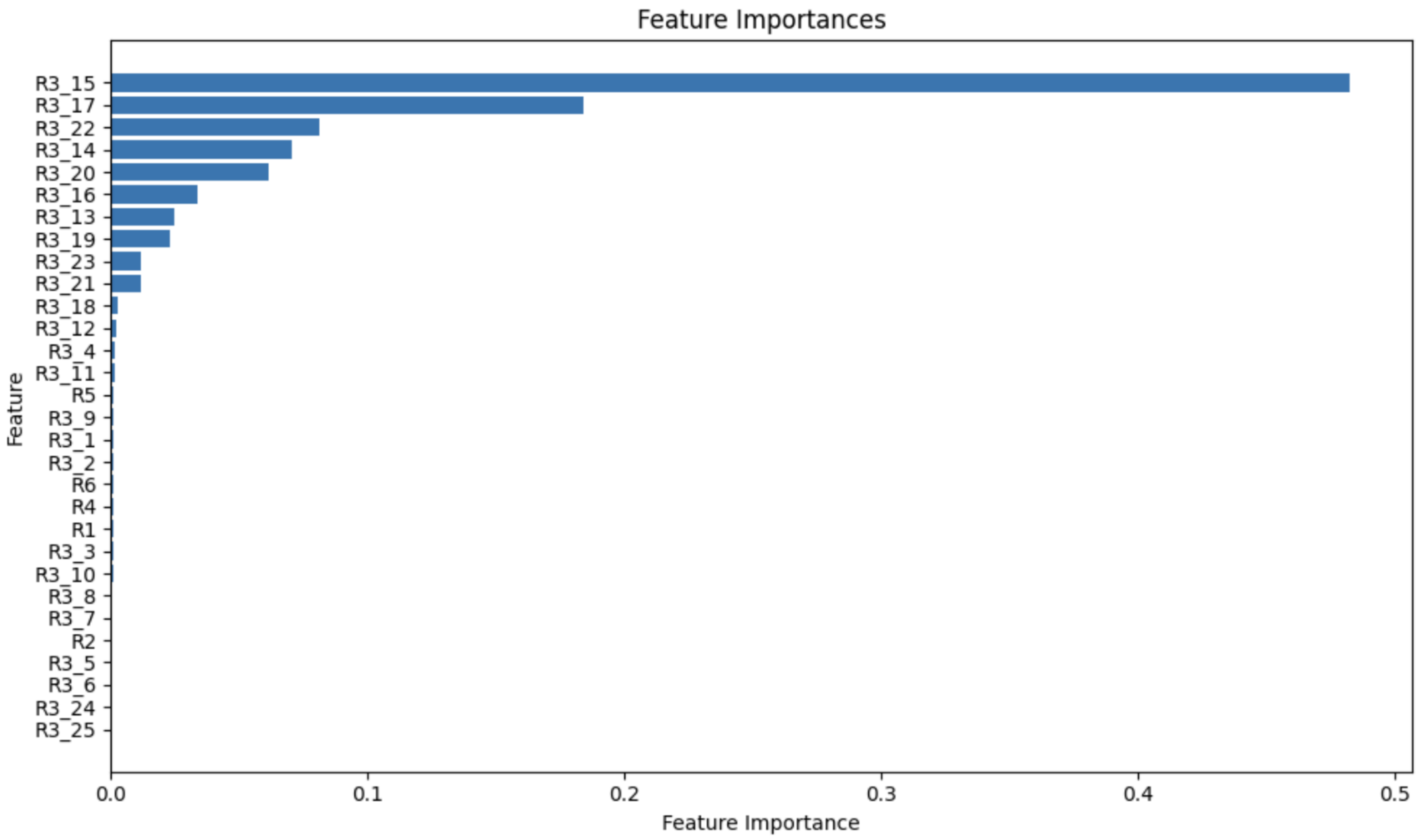
In particular Beeswarm plots are a more complex and information-rich display of SHAP values that reveal not just the relative importance of features, but their actual relationships with the predicted outcome.

SHAP Analysis

Beeswarm plot



Features Importance



Thank you