Using computer vision-inspired techniques for event classification on low-level ATLAS-like data.

Høgskulen på Vestlandet

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Understanding the Early Universe: interplay of theory and collider experiments

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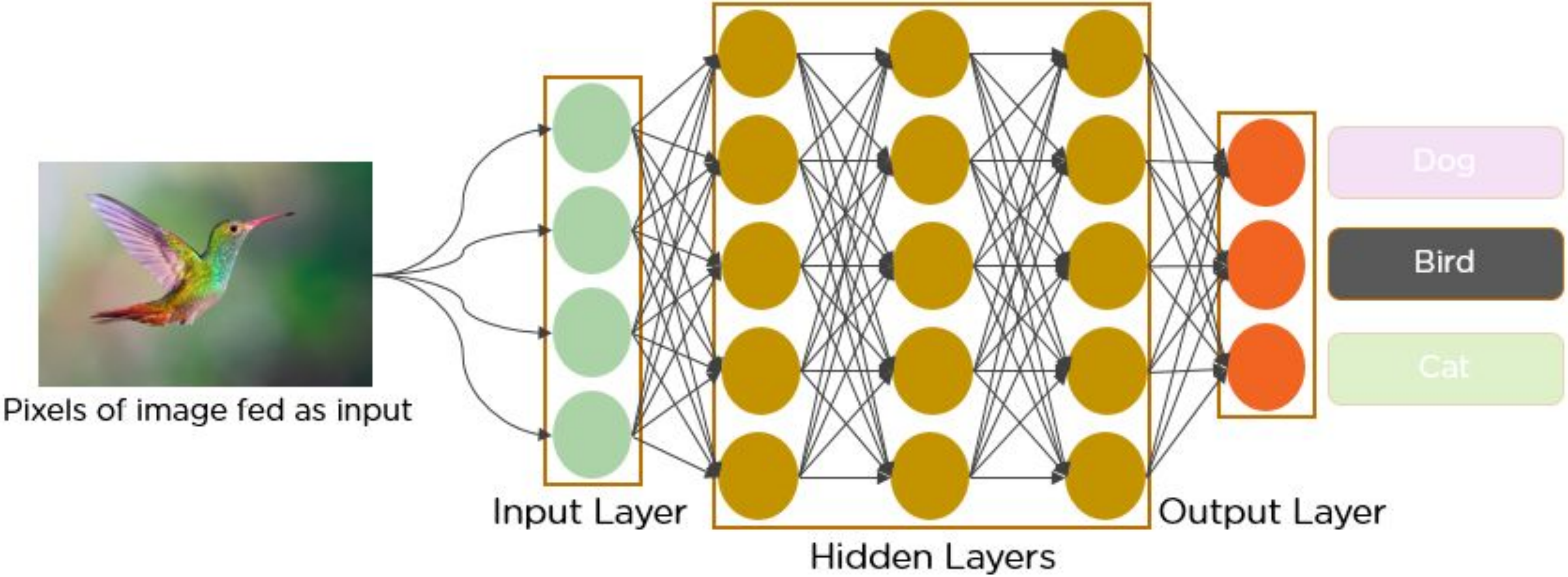
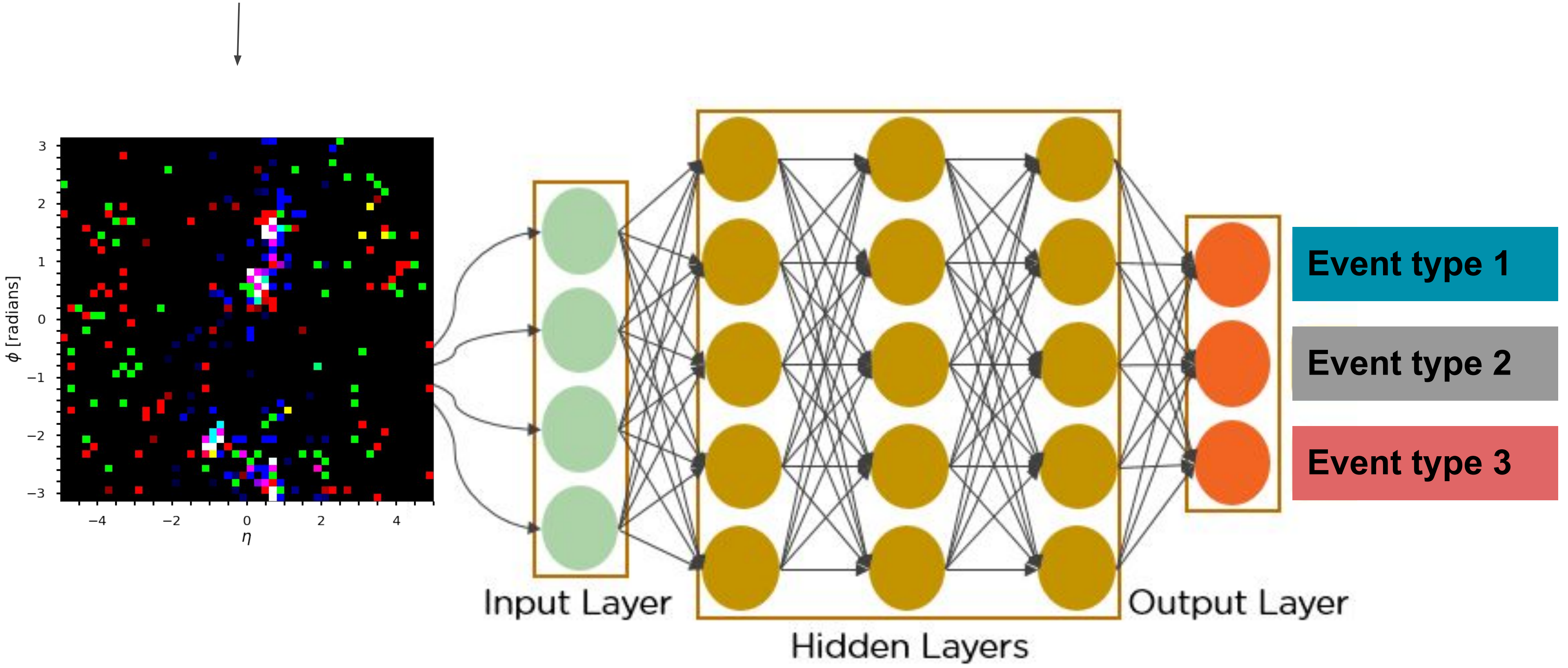
What is my goal?

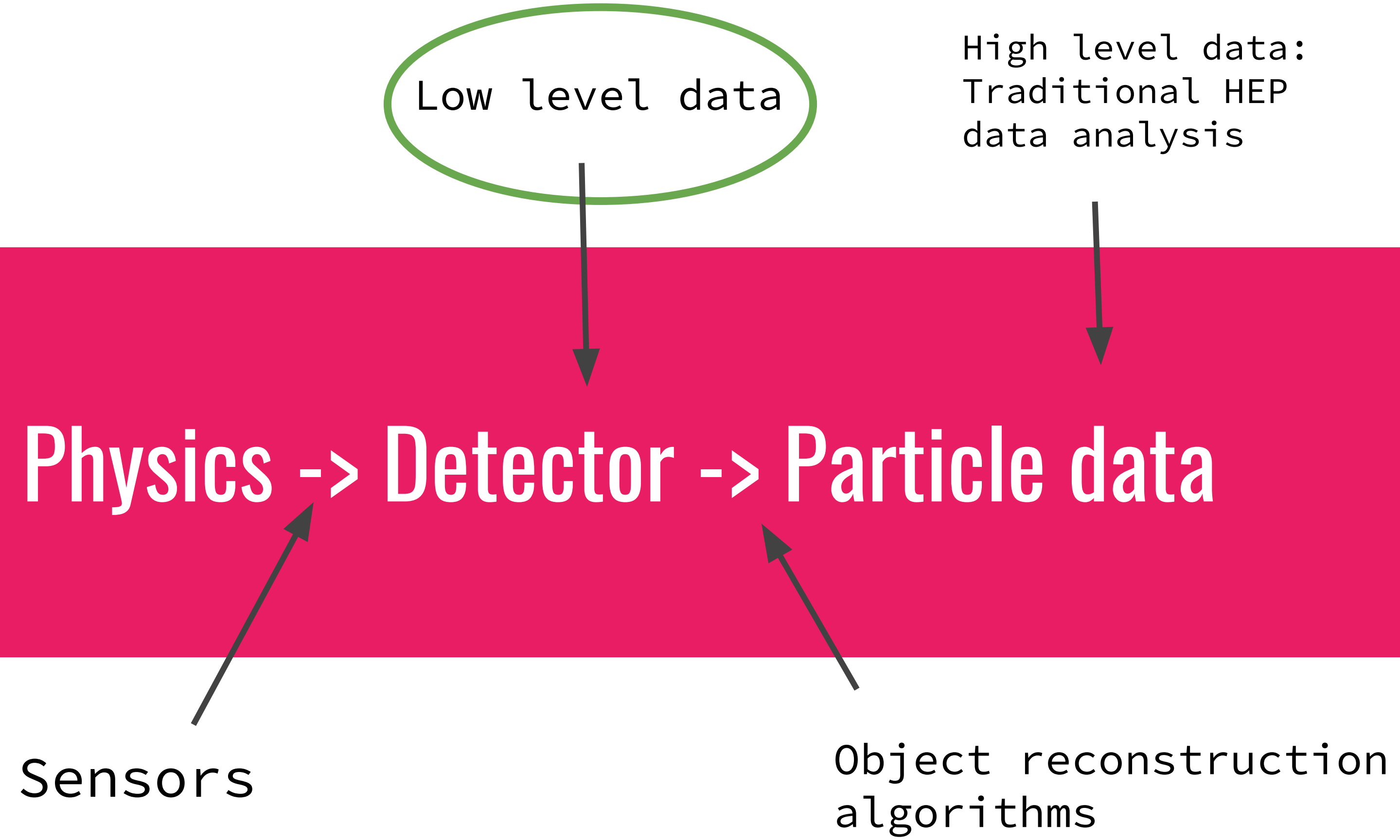
Apply ML computer vision techniques on LHC data.



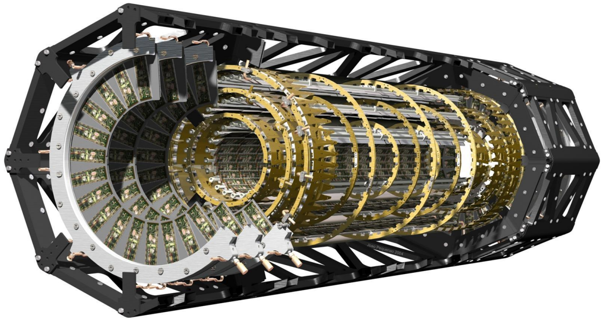
Event image



ϕ [radians]
η
Input Layer
Hidden Layers
Output Layer
Event type 1
Event type 2
Event type 3


Low level data
High level data:
Traditional HEP
data analysis
Physics -> Detector -> Particle data
Sensors
Object reconstruction
algorithms

End-to-end classification using computer vision inspired techniques



Images

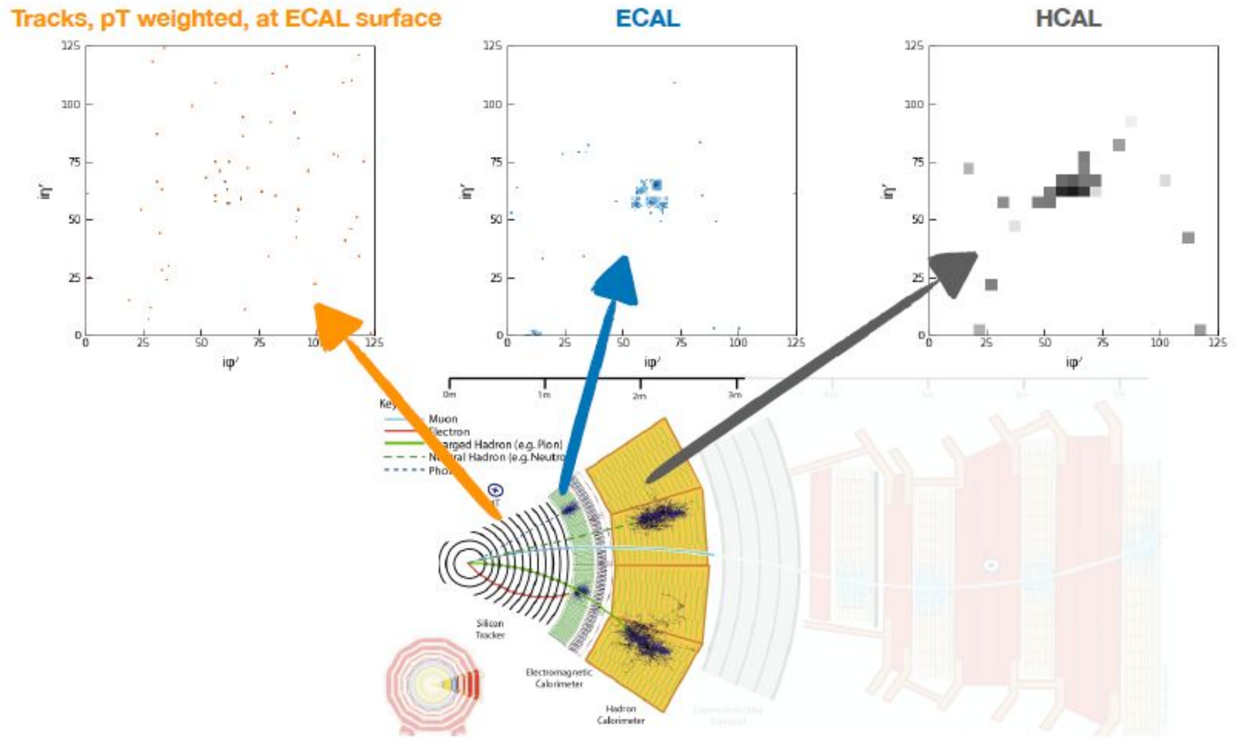
Resolution: 50x50

(R, G, B) = (EMCal, HCal, tracks)

Intensity ∝ Energy deposit

Process based on this paper:

https://arxiv.org/abs/1807.11916

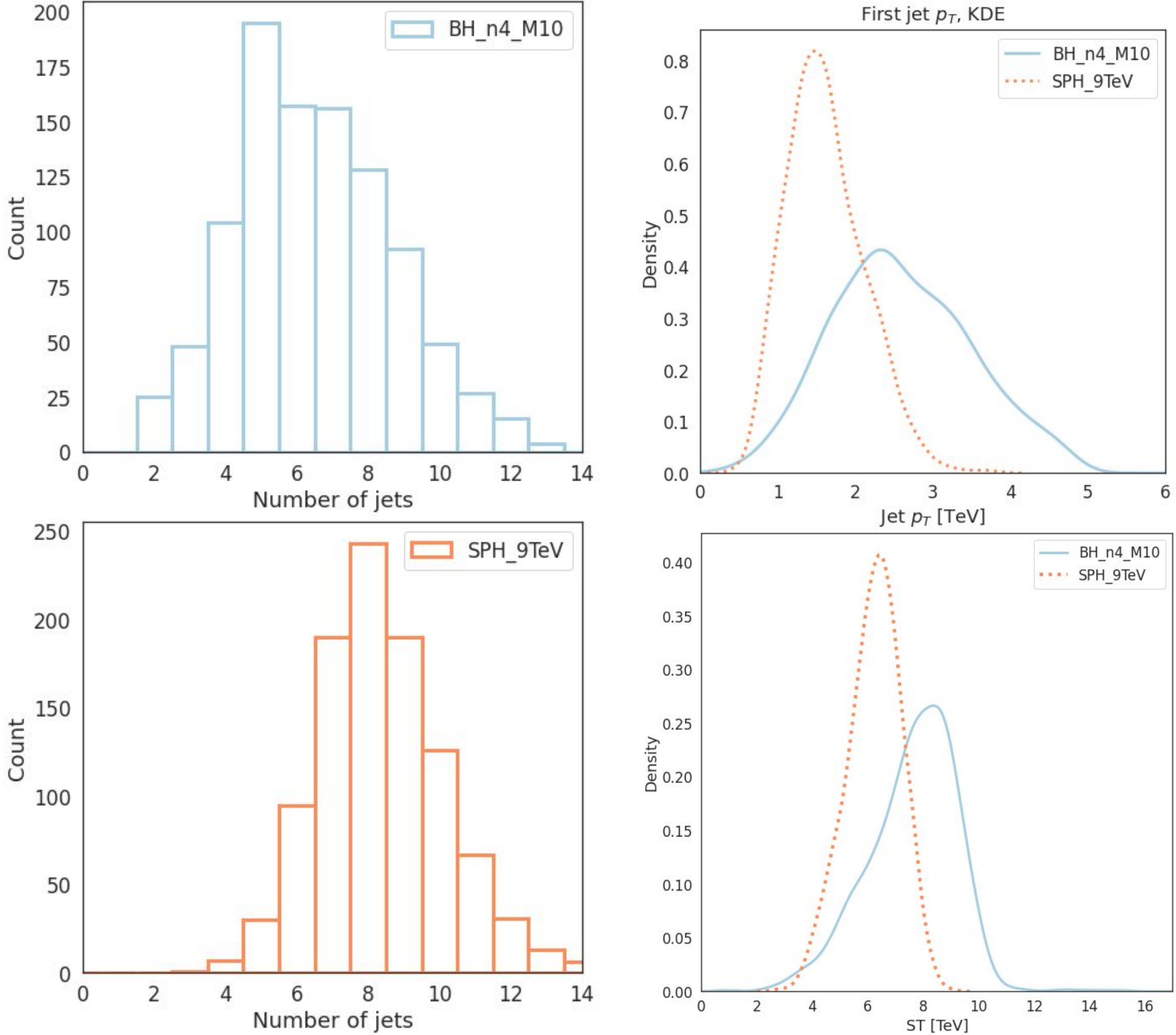


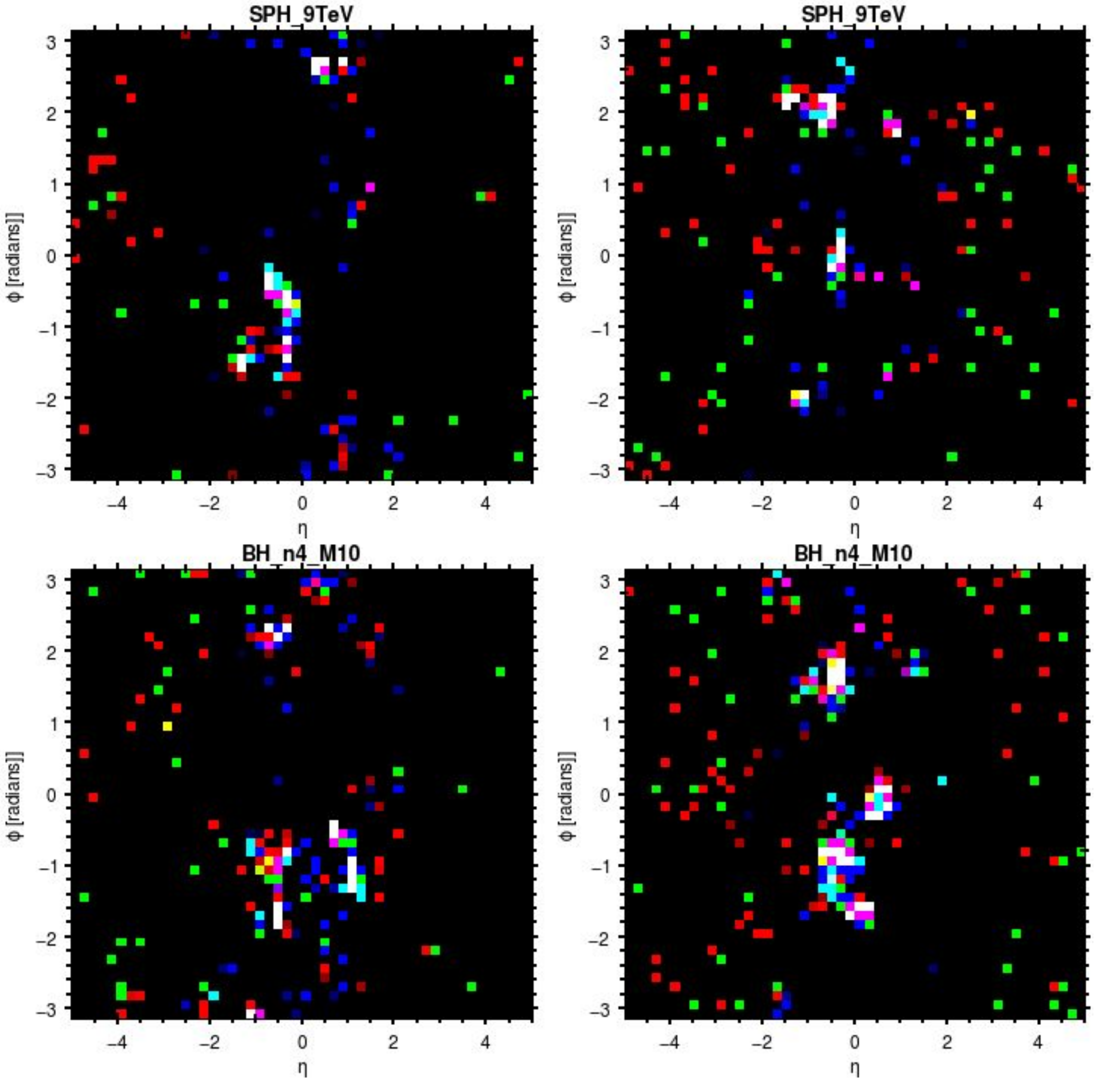
Example: Binary classification

SPH_9TeV: **Sphalerons**

BH_n4_M10: **microscopic black holes**

Special (theoretical) events that result in many jets. Could be hard to separate.





SPH_9TeV
SPH_9TeV
BH_n4_M10
BH_n4_M10
ϕ [radians]]
η
3
2
1
0
−1
−2
−3
−4
−2
0
2
4

Convolutional neural network

ResNet18.

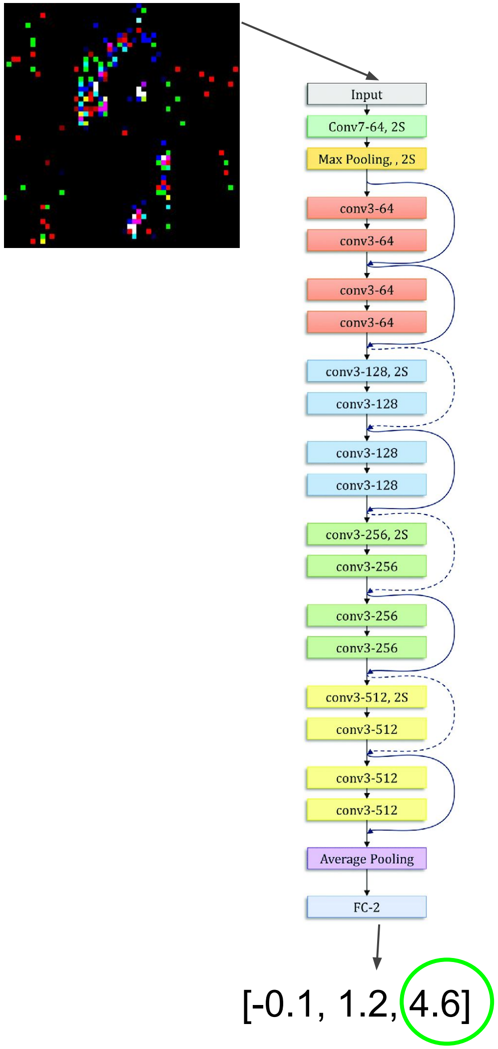
Added **circular convolution** for panoramic images.

Takes in 50x50 = **2500 features** (the image).

Outputs a tensor of values representing the classes, and the maximum value gives the **predicted class**.

Metric: In the end we can calculate the % correctly classified in each class, the **accuracy**.

Data augmentation: Random flips across η = 0 and random rotations in ϕ-direction, completely necessary for training



Igor Slazyk

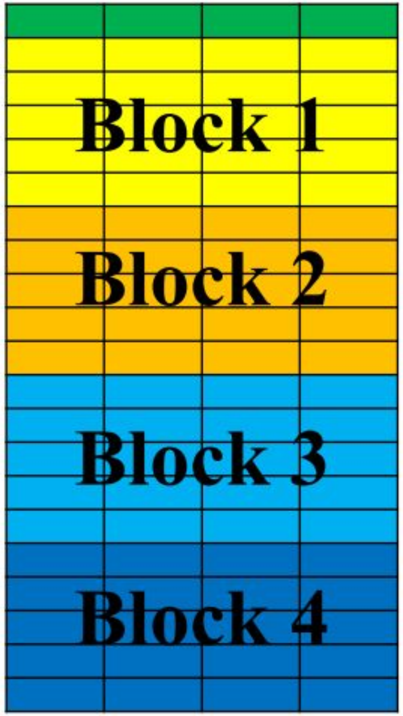
[Indico presentation]

XGBoost

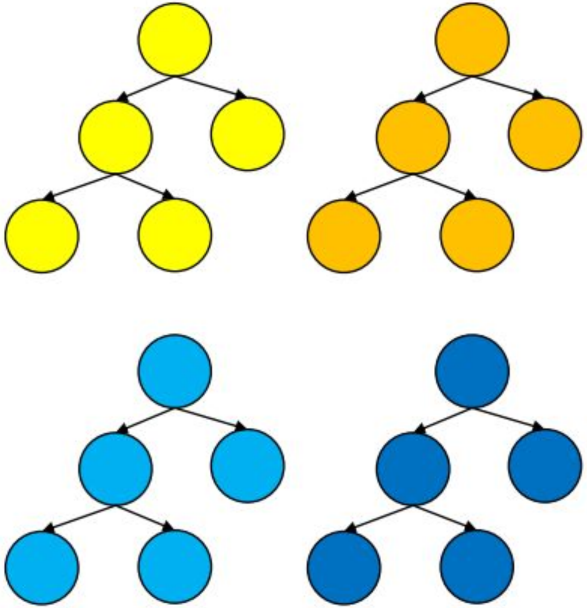
XGBoost – external open-source library (framework) based on the Gradient Boosting. In comparison to the regular Gradient Boosting algorithm, the XGBoost increases speed and performance significantly.

Major improvements:

- Parallelized tree building
- Tree pruning
- Efficient handling of missing data
- Regularization to prevent overfitting
- In-built cross-validation capability
- Hardware optimization



Parallelism



Xgboost data

Low level data (45 features):

- Five most energetic hits in
  - ECal
  - HCal
  - Tracks

Ehad_0	Ehad_1	Ehad_2	Ehad_3	Ehad_4	Ehad.Eta_
574.719055	469.435333	411.811890	299.050201	293.904053	-0.81859
1083.457520	488.901917	480.192688	333.622101	230.357330	-1.02049
611.114319	334.008911	247.336731	238.140228	217.595657	0.16008
584.671692	574.643494	408.249054	378.885986	341.893982	-0.07938
687.085571	464.160858	417.404846	382.948364	378.882172	-1.58845

High-level data (39 features):

- First eight jets
- First two leptons
- MET

Jet.Eta_0	Jet.Eta_1	Jet.Eta_2	Jet.Eta_3	Jet.Eta_4	Jet.Eta_5	Jet.Eta_6
-0.761235	-0.376034	-0.386358	-0.358008	0.557922	0.439379	0.289839
-0.355793	-1.065034	0.162526	0.601317	-0.023609	0.551750	0.072058
-0.501687	0.166702	0.749015	-0.579402	0.166687	-0.904145	0.471734
-0.009252	0.593912	-1.416952	-0.461862	1.373964	1.546215	-0.270171
-1.634426	0.558831	0.555065	0.615552	-0.639208	1.104151	-0.186942

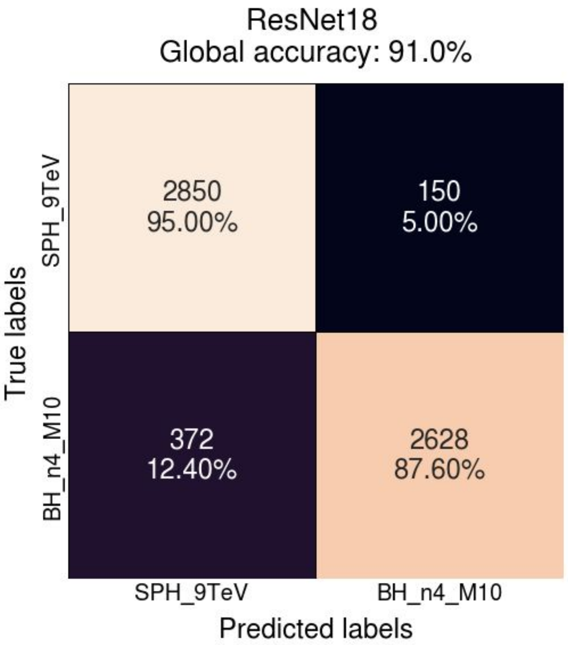
Preliminary results

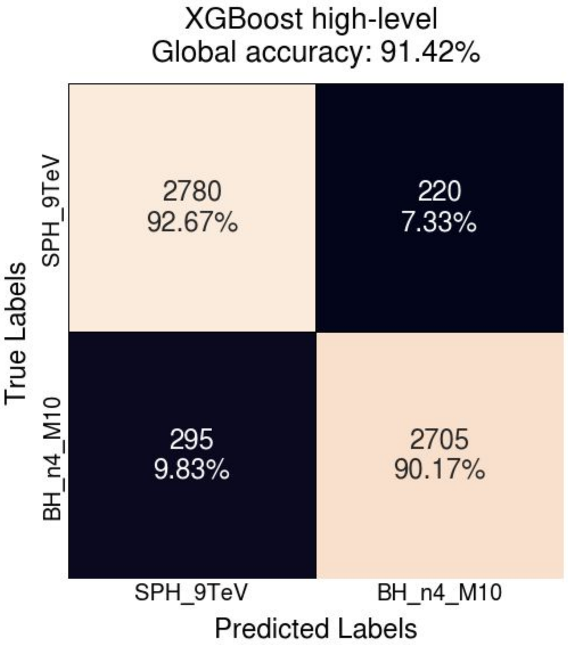
ResNet18 is performing comparable to XGBoost with high-level data, and better than XGBoost with low-level data.

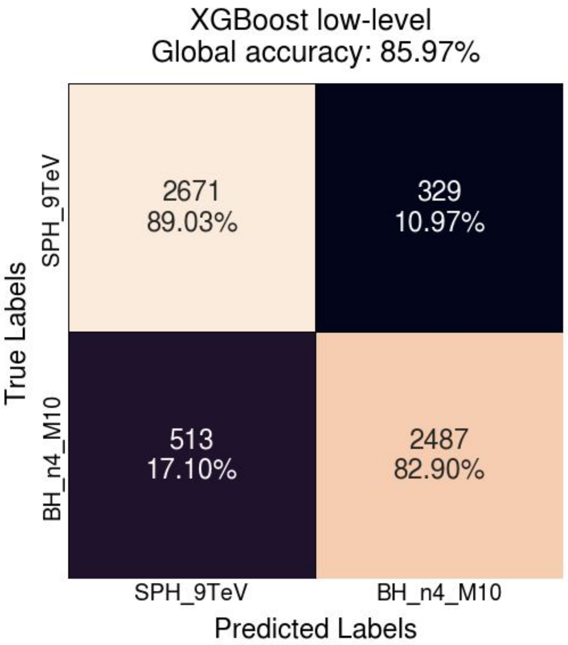
Using low-level data **with the CNN we can skip object reconstruction** and get similar precision.

	Resnet18 low level	XGBoost low level	XGBoost high level
Binary classification	0.907 +- 0.007	0.861 +- 0.001	0.914 +- 0.002

Confusion matrices







Thank you for your attention! :)

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