Using an Optical Processing Unit for tracking and calorimetry at the LHC

Laurent Basara (LRI-Orsay)
Biswajit Biswas, Aishik Ghosh, David Rousseau (IJCLab-Orsay)

Thanks to the LightOn team in particular Laurent Daudet, Iacopo Poli for access to LightOn OPU https://www.lighton.ai/

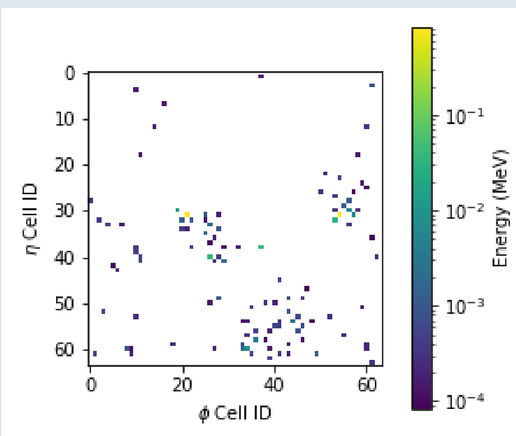
And to Steve Farrell, Wahid Bhimji ; Thong Nguyen Maurizio Pierini and Jean-Roch Vlimant for access to the dataset and useful discussions

Using an Optical Processing Unit for tracking and calorimetry at the LHC

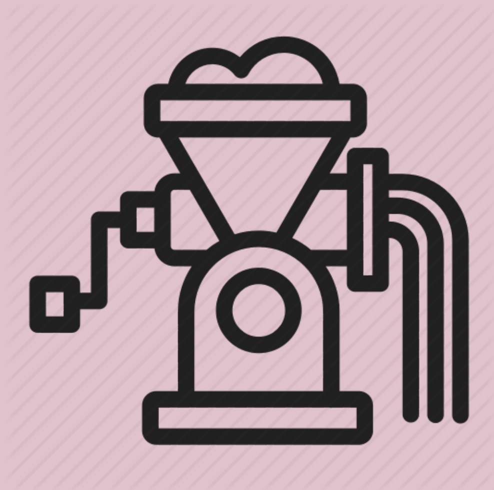
- Optical Processing Units
- OPU for Tracking
- OPU for Calorimetry

Supervised ML

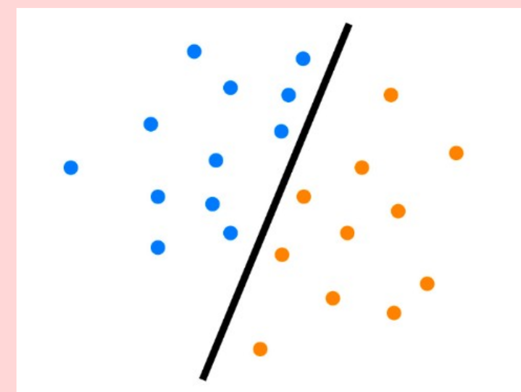
Data representation X
+ ground truth y



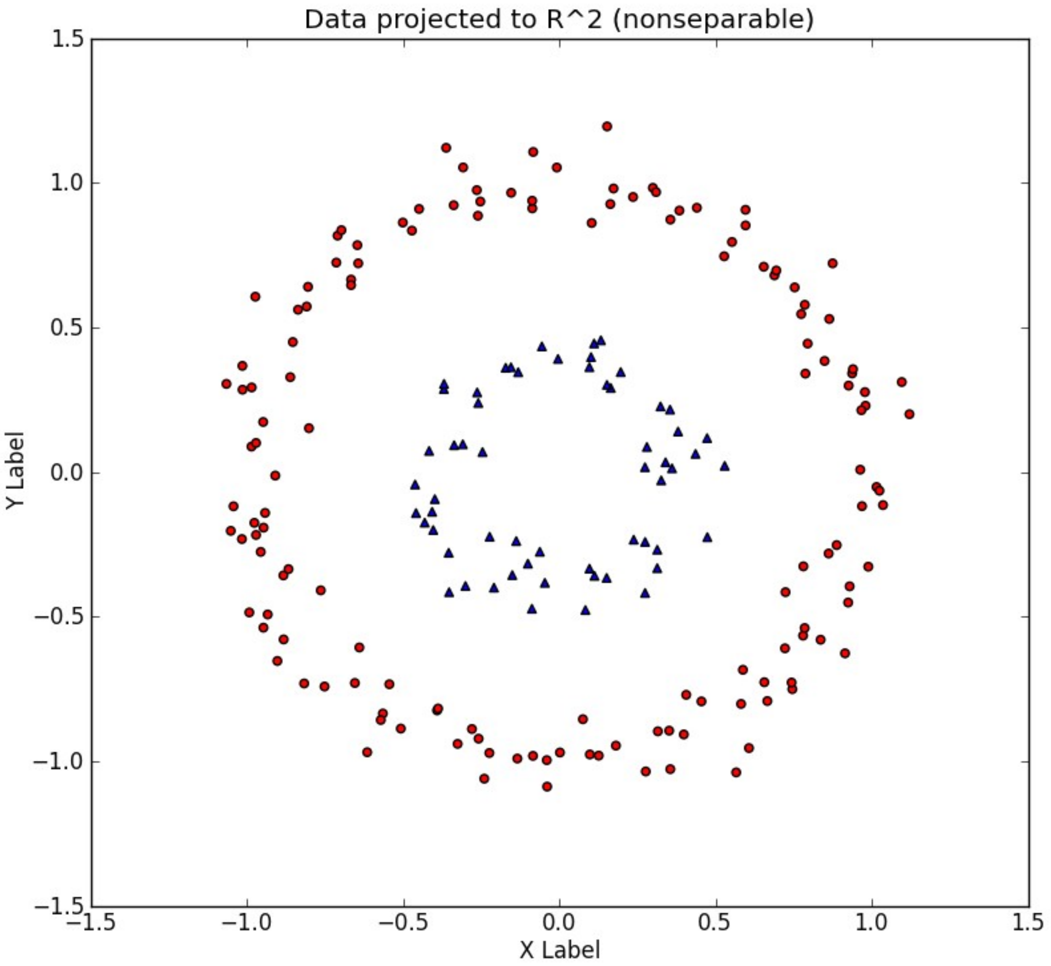
Supervised
ML algorithm

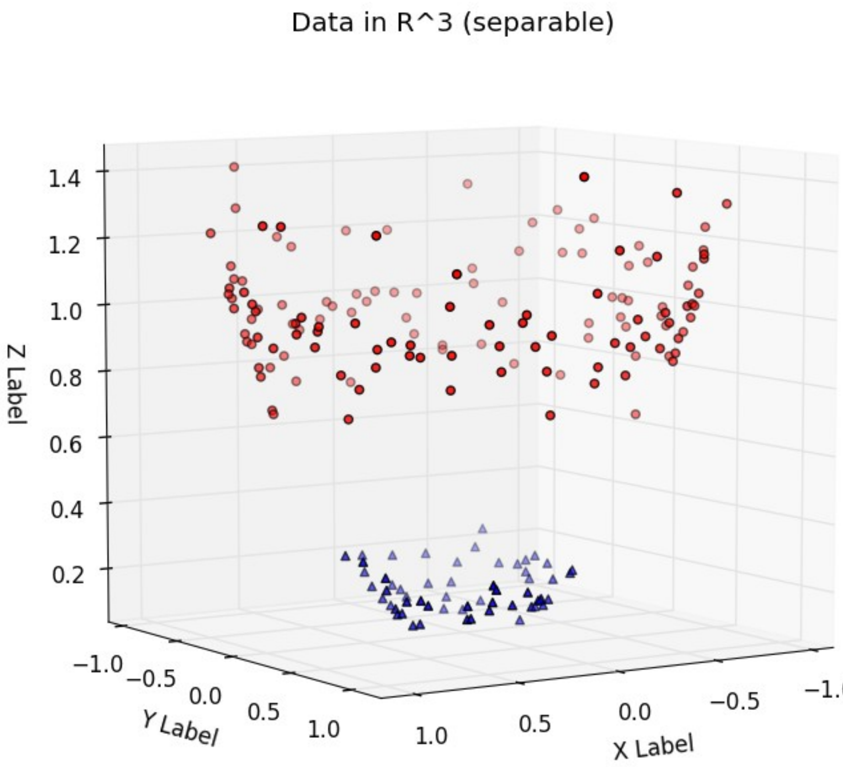


Signal / background
separation



Non-linear problems, SVM and the kernel trick





Kitchen sinks

Random Features for Large-Scale Kernel Machines

Ali Rahimi and Ben Recht

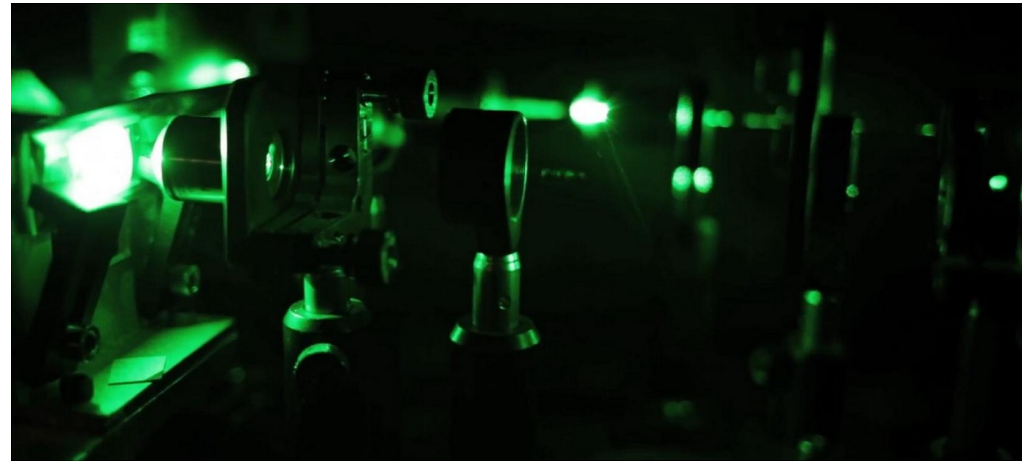
Abstract

To accelerate the training of kernel machines, we propose to map the input data to a randomized low-dimensional feature space and then apply existing fast linear methods. Our randomized features are designed so that the inner products of the transformed data are approximately equal to those in the feature space of a user specified shift-invariant kernel. We explore two sets of random features, provide convergence bounds on their ability to approximate various radial basis kernels, and show that in large-scale classification and regression tasks linear machine learning algorithms that use these features outperform state-of-the-art large-scale kernel machines.

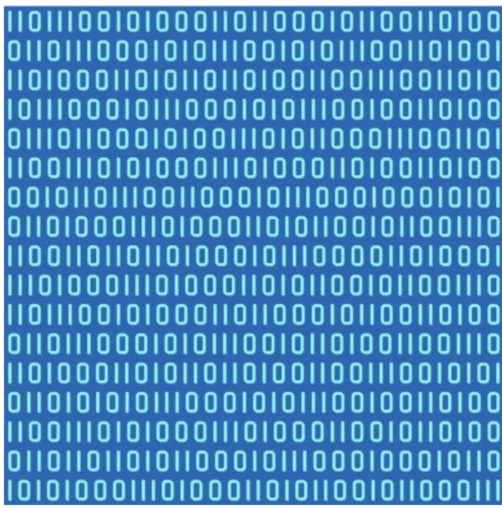
Original paper: https://people.eecs.berkeley.edu/~brecht/papers/07.rah.rec.nips.pdf

Popularization: http://www.argmin.net/2017/12/05/kitchen-sinks/

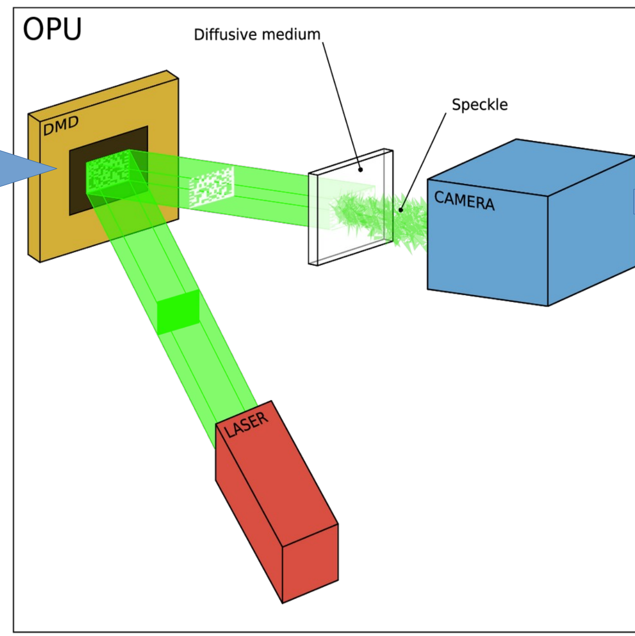
Optical Processing Unit



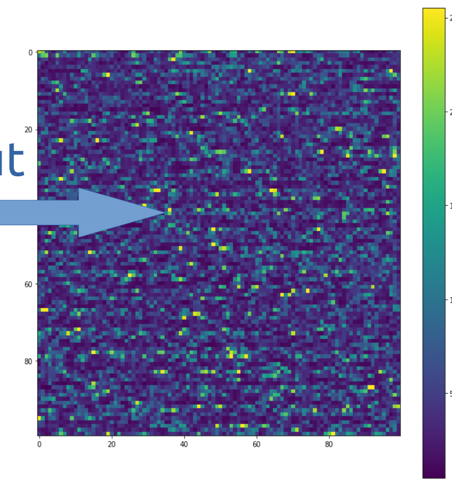
https://docs.lighton.ai/notes/opu.html



OPU in



OPU out



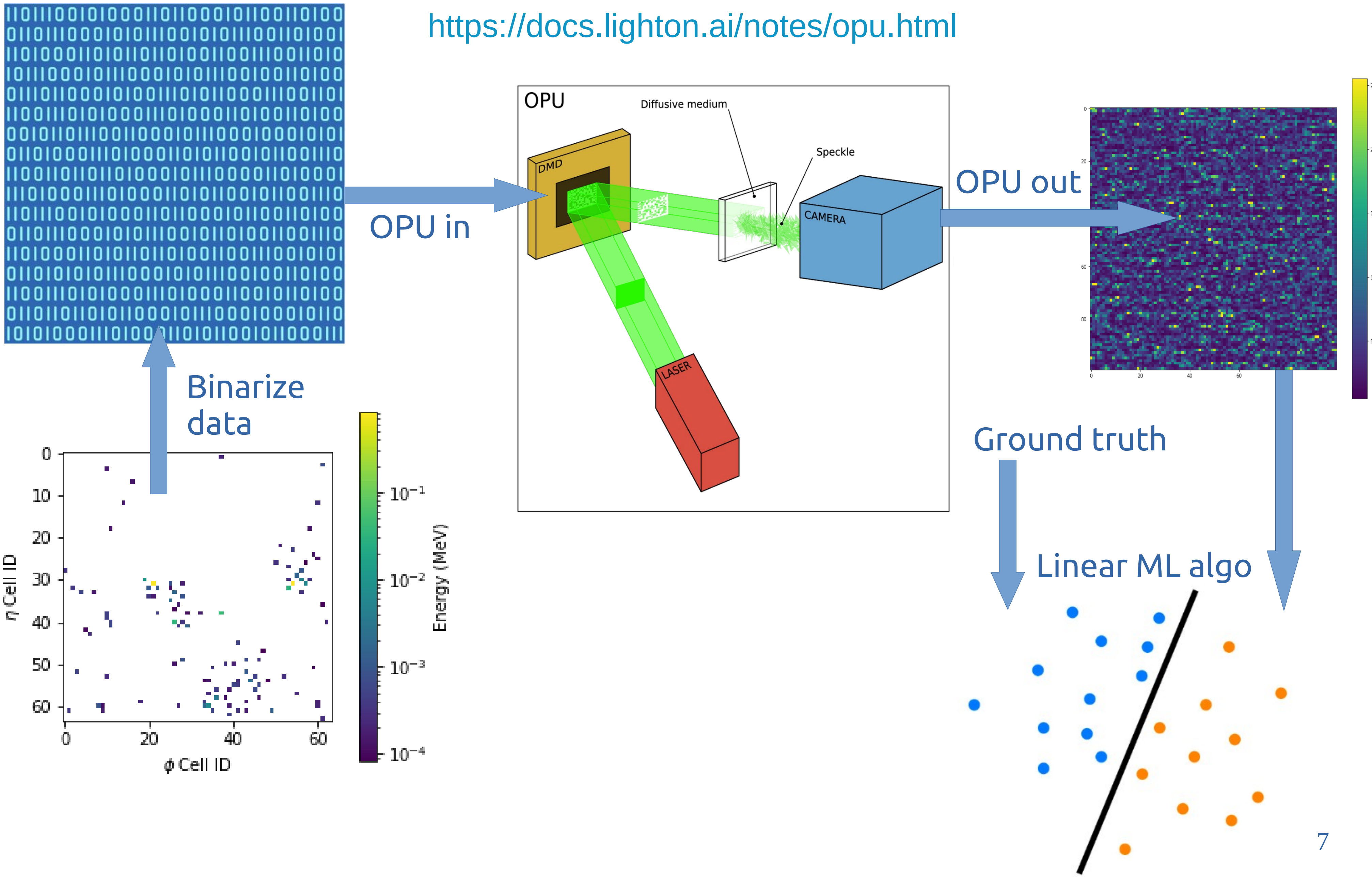
1 M bits vector X

In practice 10K to 100K bytes (random features)

Random matrix multiplication y = | Hx | ²
(H constant for given OPU)
Size 10^{12} pixels x Rate 2 kHz
~ 10^{15} operations / s for a few Watts

Optical Processing Unit ML workflow

https://docs.lighton.ai/notes/opu.html



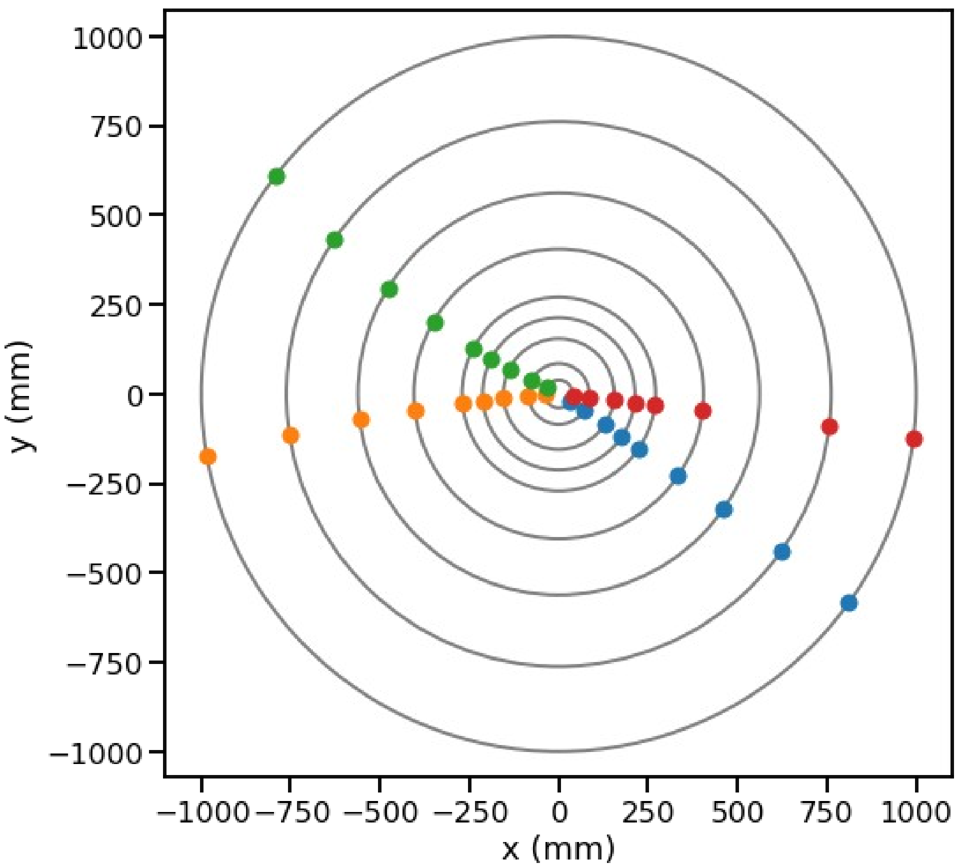
Using an Optical Processing Unit for tracking and calorimetry at the LHC

- Optical Processing Units
- OPU for Tracking
  - Single track parameter estimation
  - Multi-track parameter estimation
- OPU for Calorimetry

RAMP 2D dataset

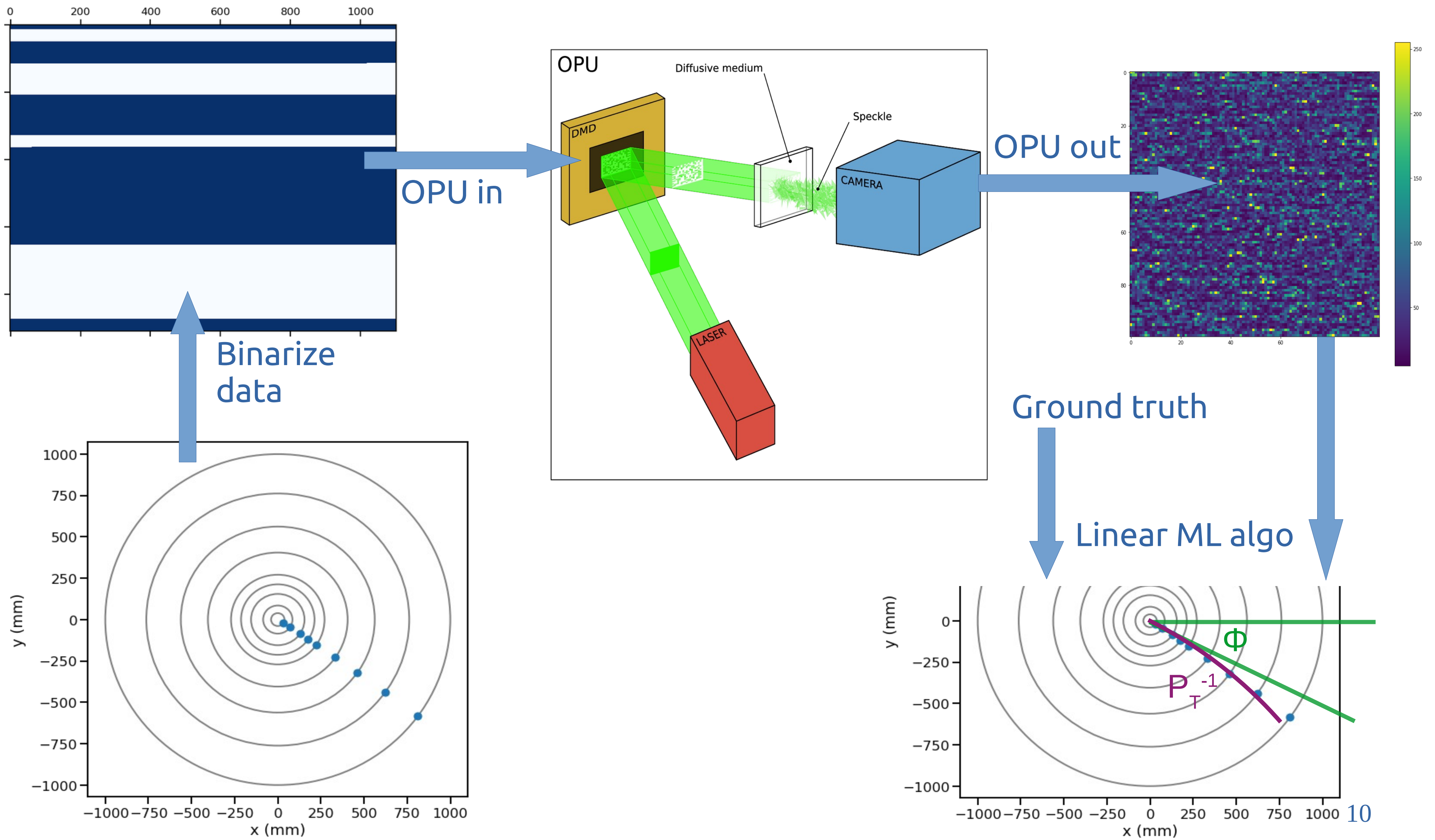
Track reconstruction at LHC as a collaborative data challenge use case with RAMP

Sabrina Amrouche , Nils Braun , Paolo Calafiura , Steven Farrell , Jochen Gemmler , Cécile Germain [1, 2] , Vladimir Vava Gligorov [3] , Tobias Golling , Heather Gray , Isabelle Guyon [2] , Mikhail Hushchyn , Vincenzo Innocente , Balázs Kégl [1, 4] , Sara Neuhaus , David Rousseau [1] , Andreas Salzburger , Andrei Ustyuzhanin , Jean-Roch Vlimant , Christian Wessel , Yetkin Yilmaz [1, 4] Détails



- Original paper : http://inspirehep.net/record/1616034
- Original library : https://github.com/yetkinyilmaz/tracking
- Python3 port : https://github.com/LAL/tracking2Dsim
- 60 K events
- 9 layers, 530 K pixels total

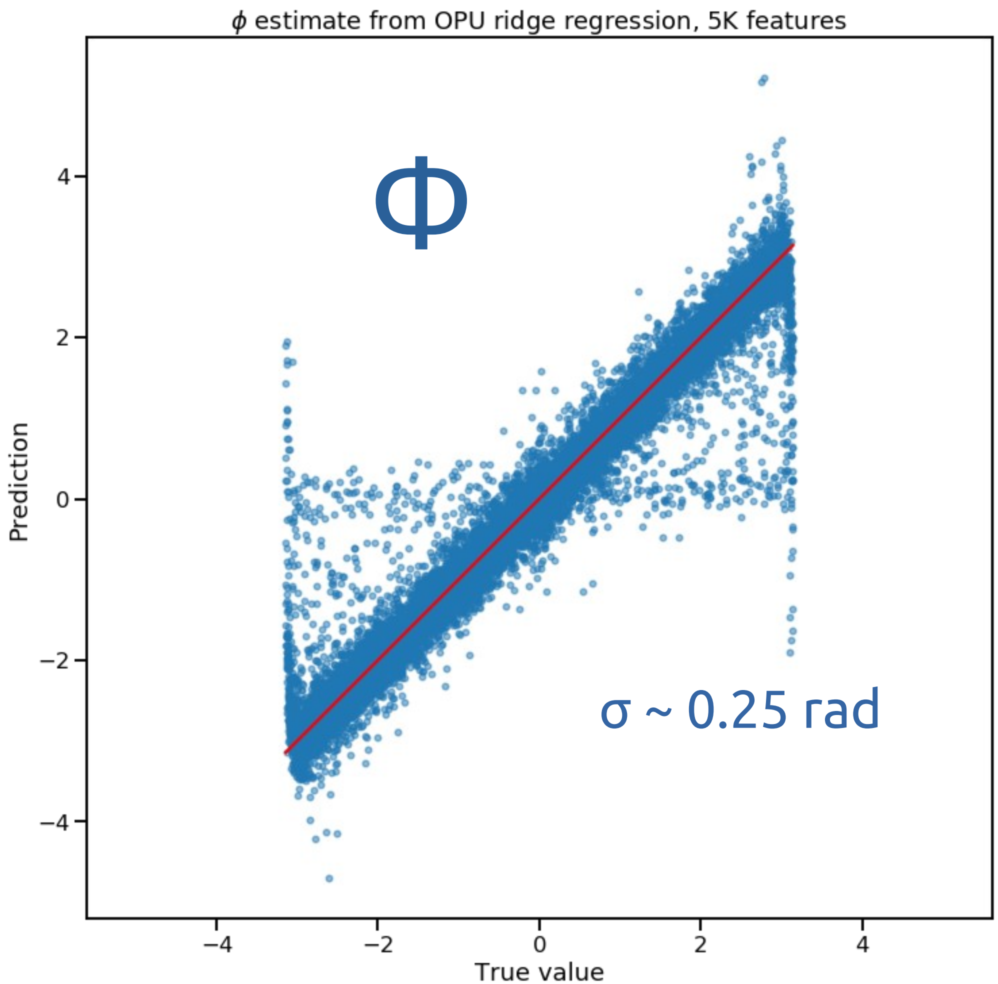
Single track parameter estimation

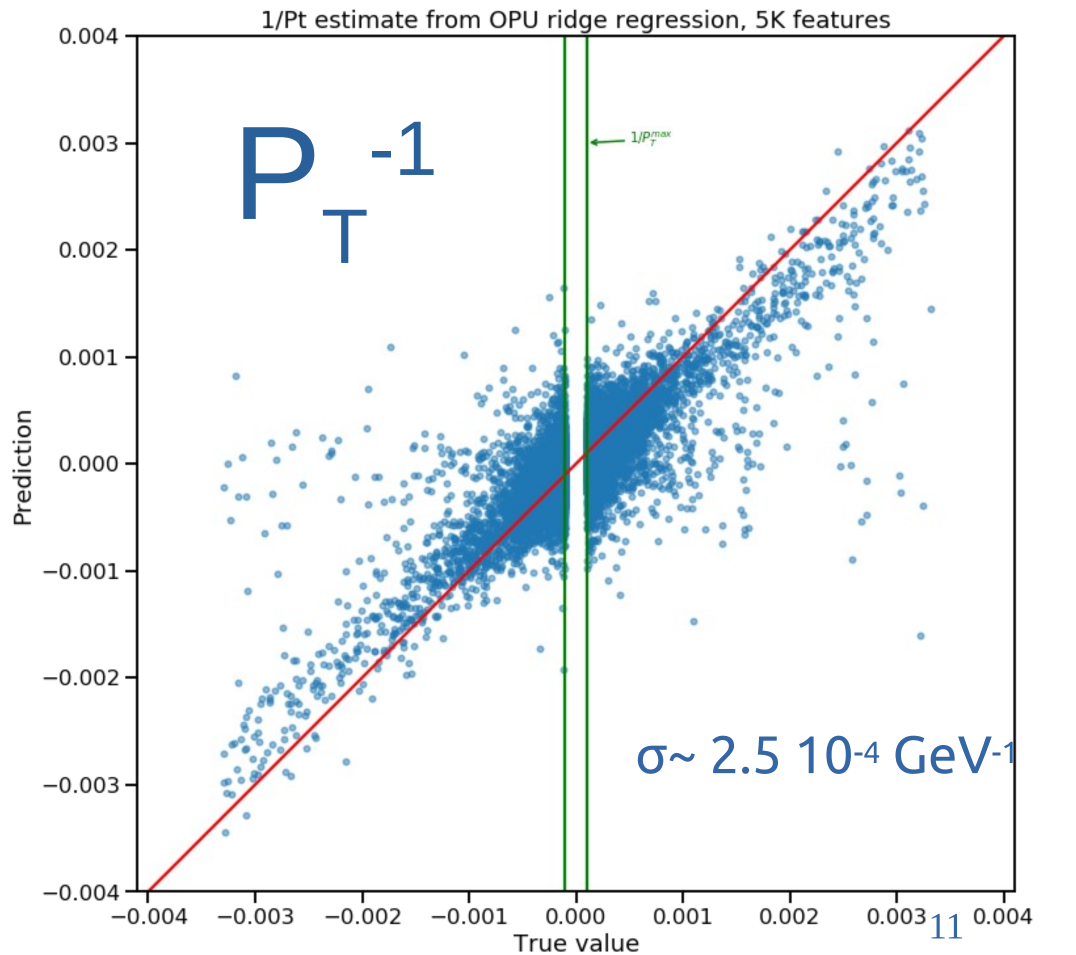


Parameter estimation

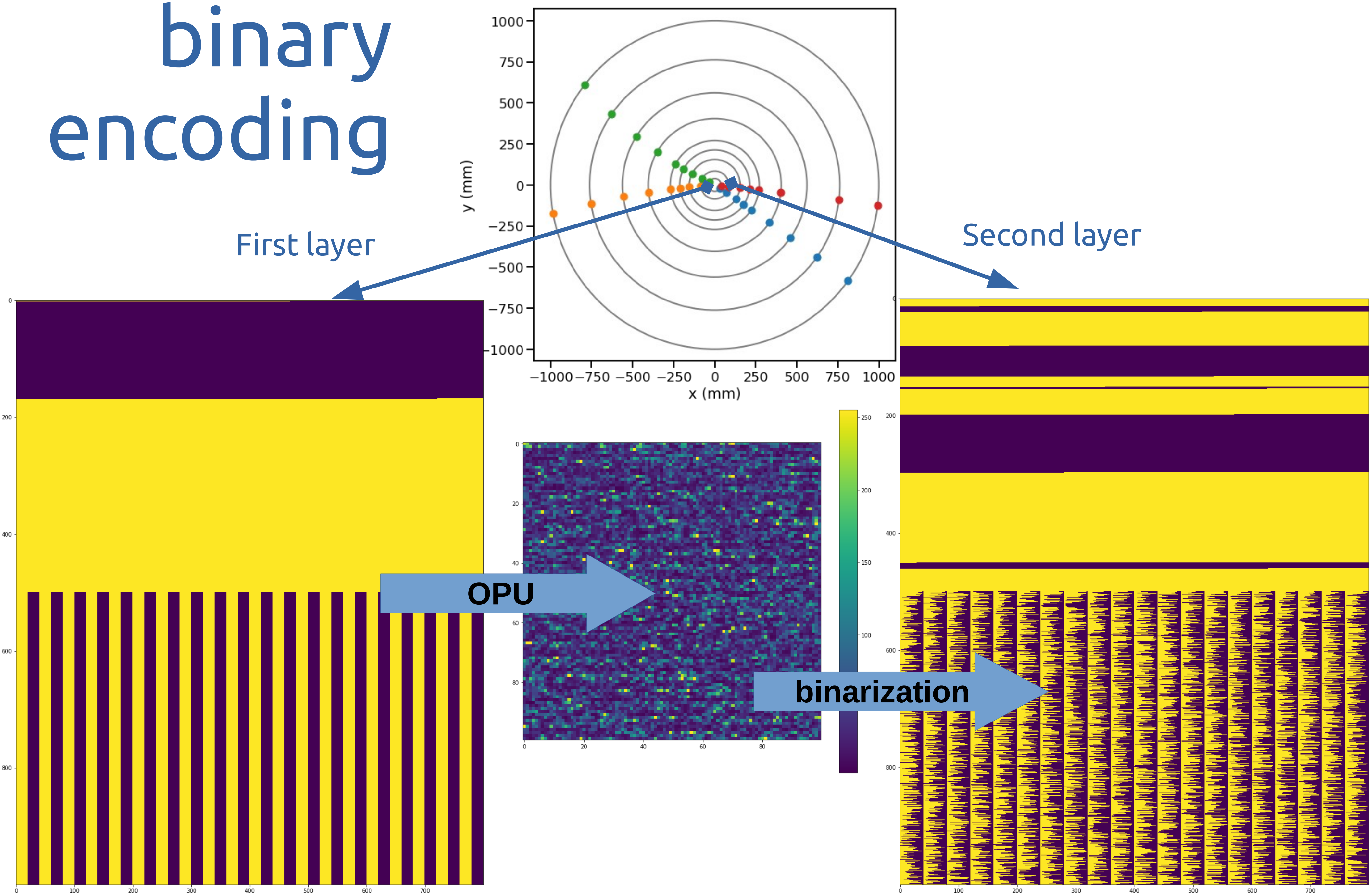
$$\boxed{\min_{\beta \in R^{m \times n}} ||X\beta - y|| + ||\gamma\beta||}$$

(5K) random features   Ground truth angle

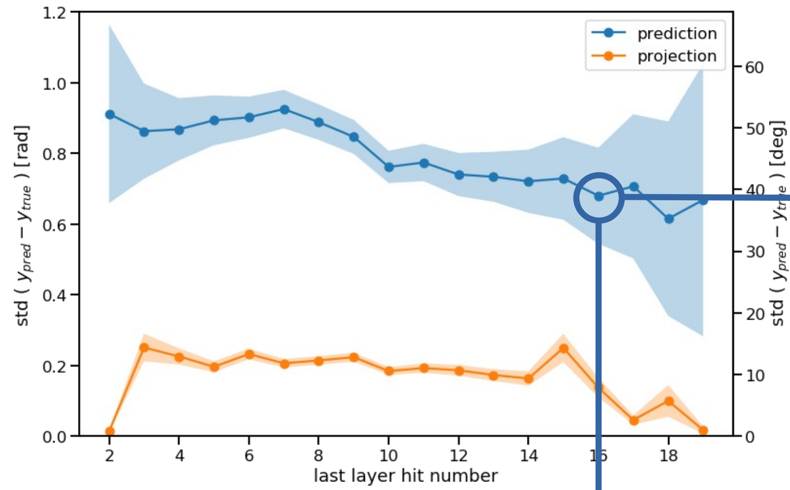


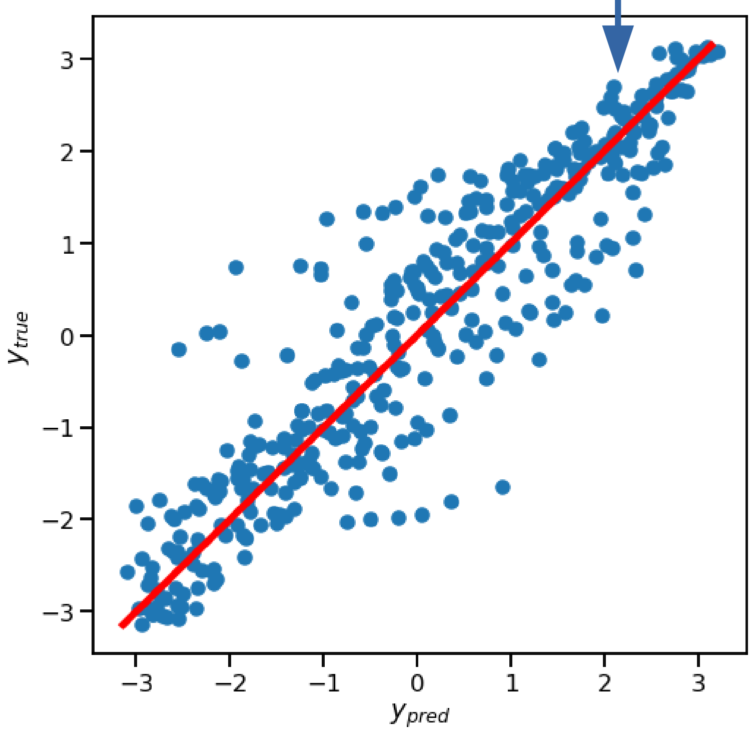


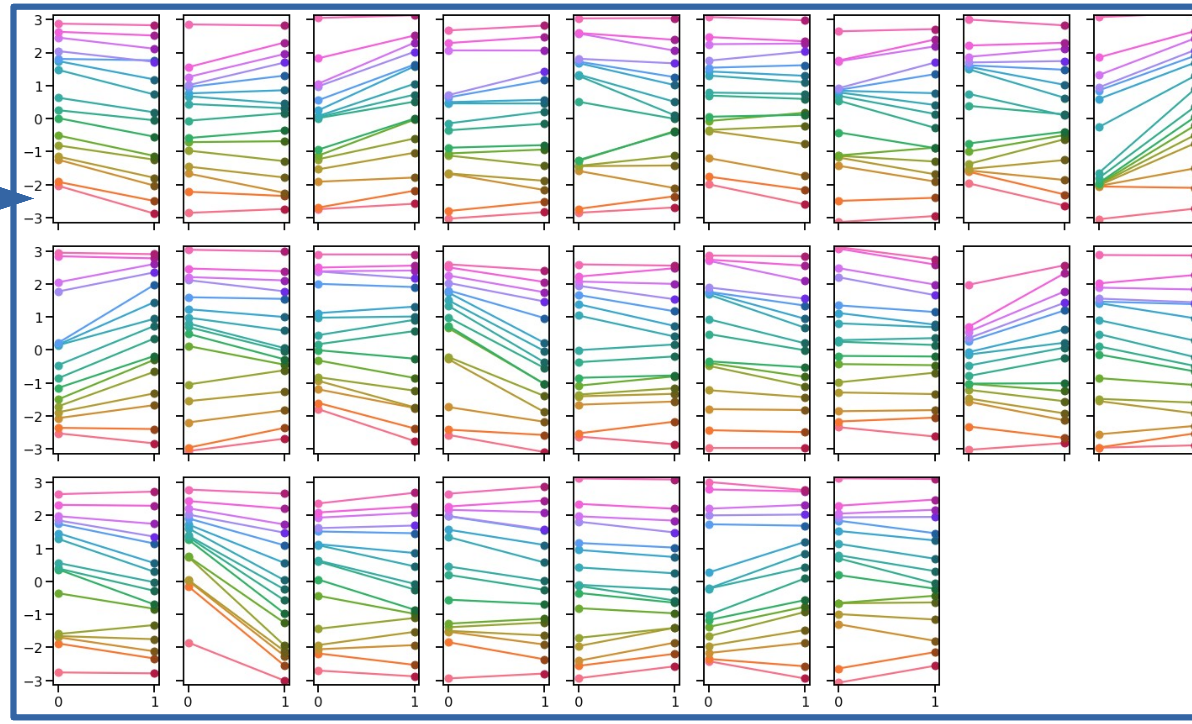
Multilayer binary encoding



Standard deviation wrt hit number







Conclusions on tracking:

- Estimations make sense
- Casting a problem for OPU hard
- More suited to calorimetry?

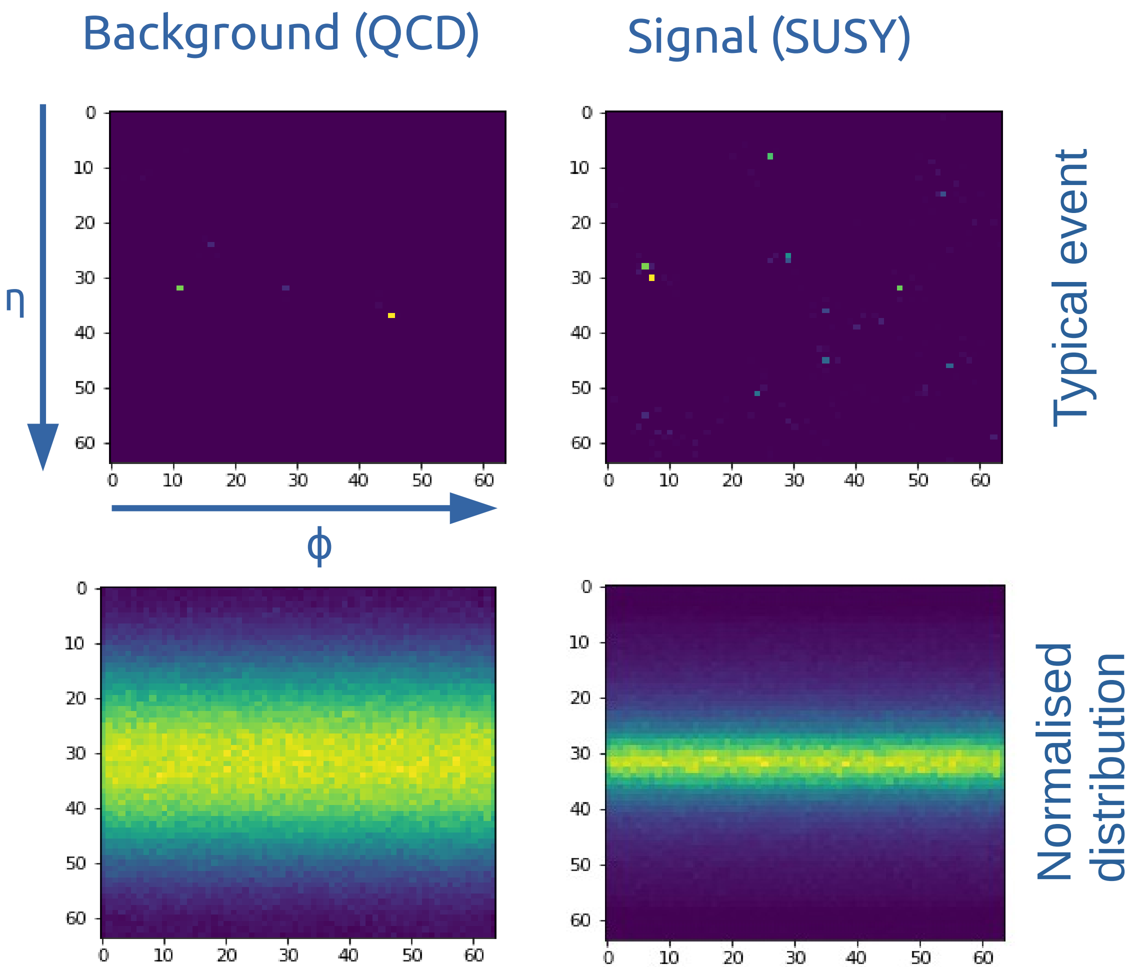
Using an Optical Processing Unit for tracking and calorimetry at the LHC

- Optical Processing Units
- OPU for Tracking
- OPU for Calorimetry
  - SUSY vs QCD
  - W / ttbar vs QCD

Study 1: following arXiv:1711.03573

Deep Neural Networks for Physics Analysis on low-level whole-detector data at the LHC

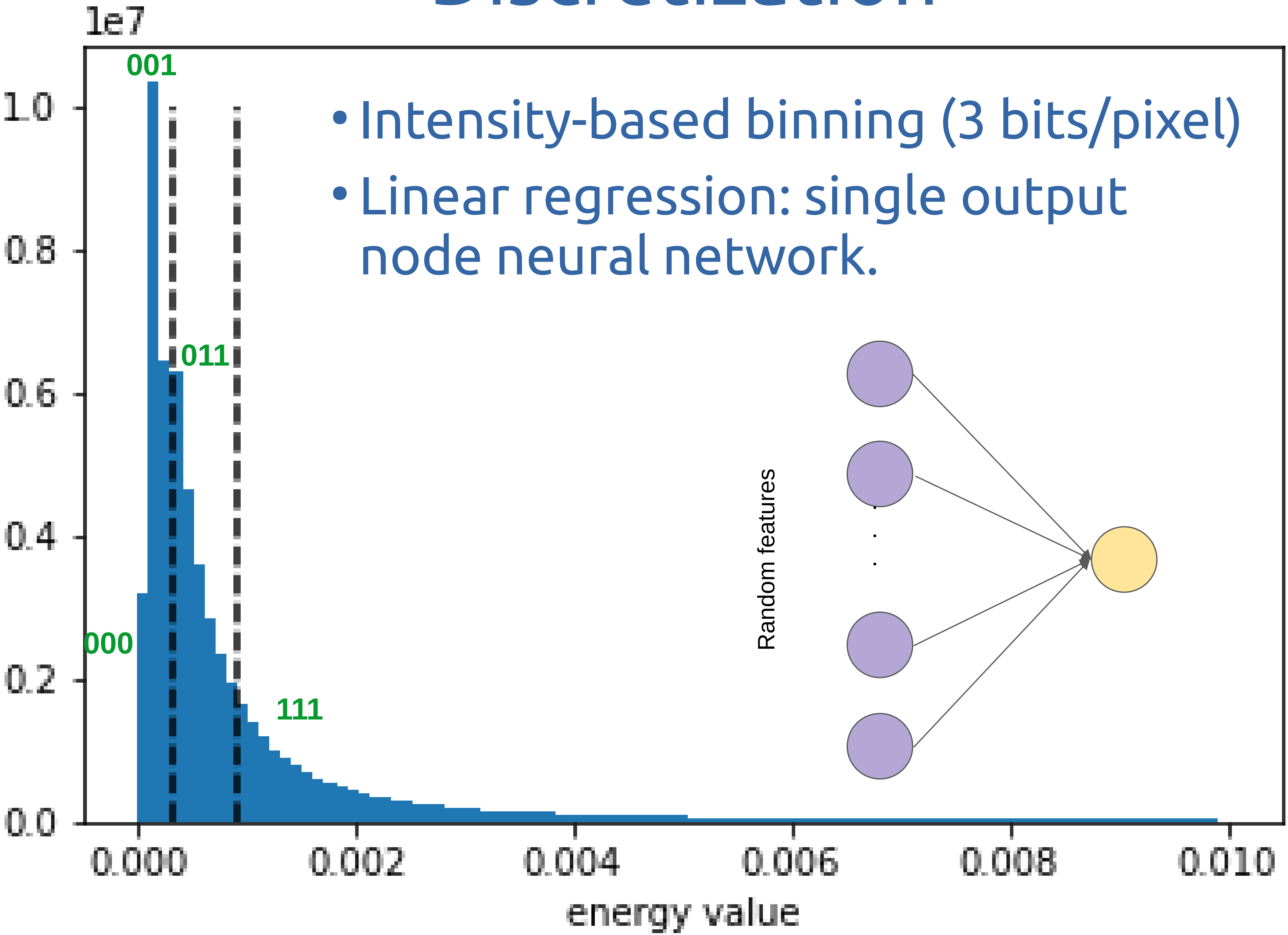
Wahid Bhimji[1], Steven Andrew Farrell[1], Thorsten Kurth[1], Michela Paganini[1,2], Prabhat[1], Evan Racah[1]



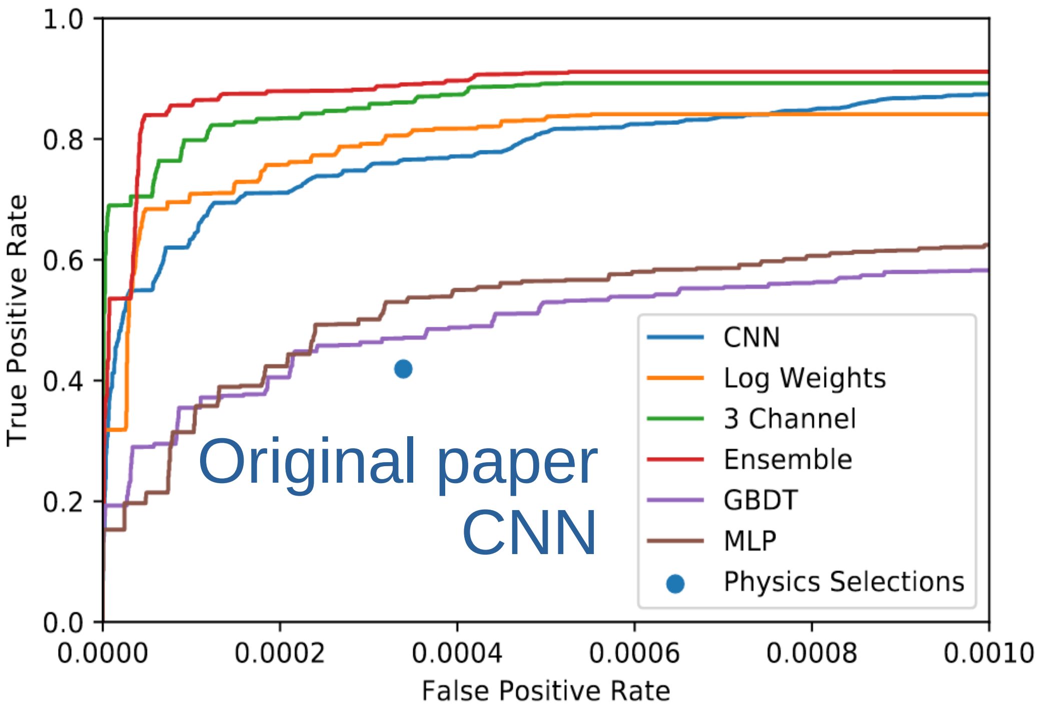
- Signal : RPV-Susy, gluino-cascade decays, gluino and neutralino masses of 1400 GeV and 850 GeV
- Background : QCD
- Training sample: 400k events
- Uniform 64x64 bins correspond 0.1x0.1(η×φ) ATLAS HCAL resolution ; intensity = energy deposited
- Images cover entire detector, whole events classification

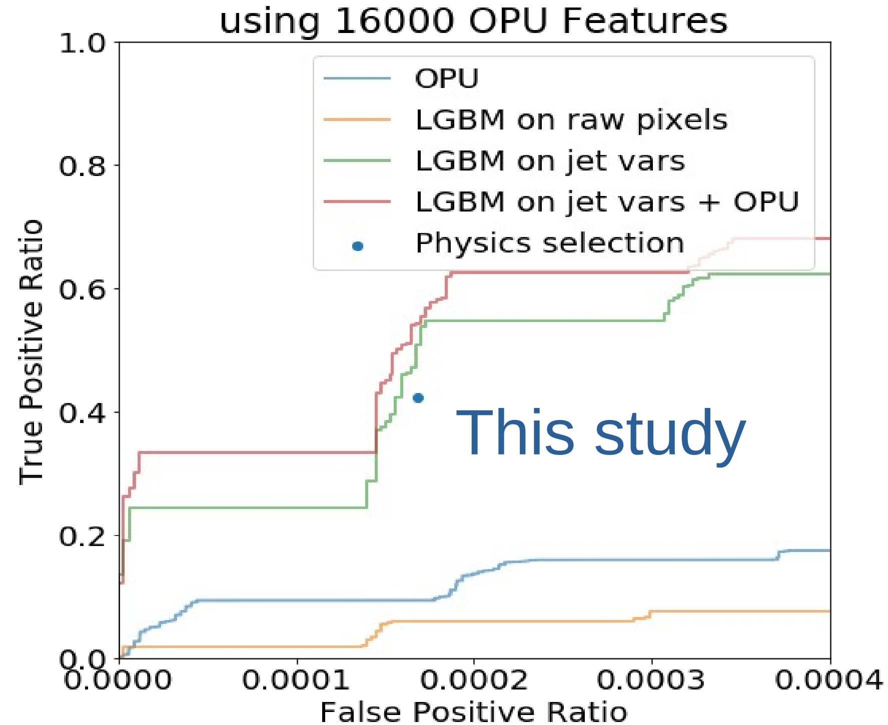
Discretization

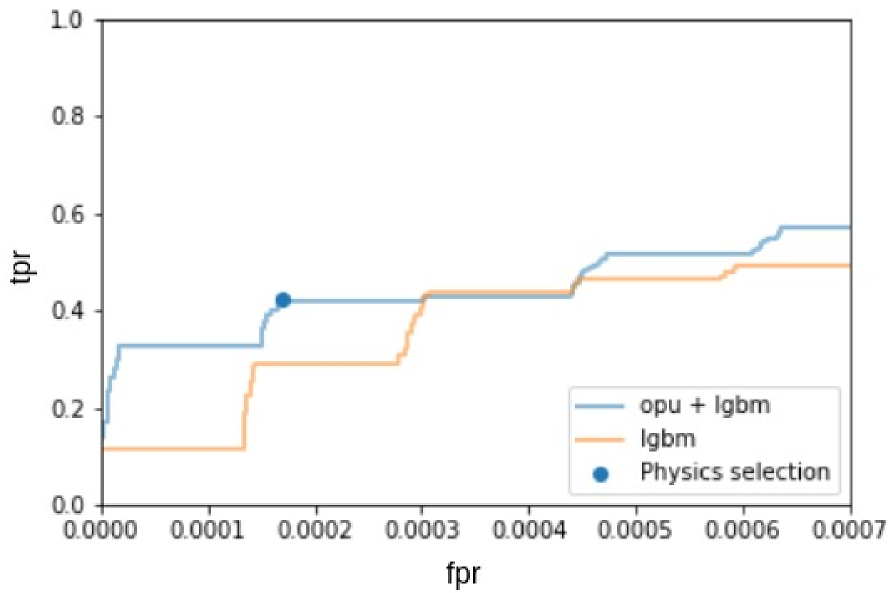
- Intensity-based binning (3 bits/pixel)
- Linear regression: single output node neural network.



Results







(a)4096 Training images

Better results on calorimetry

- Not on par with CNN
- But OPU + BDTs scalable even when $N_{events} \simeq N_{pixels}$

Study 2: following arXiv:1807.00083

Topology classification with deep learning to improve real-time event selection at the LHC

Thong Q. Nguyen, Daniel Weitekamp III, Dustin Anderson, Roberto Castello, Olmo Cerri, Maurizio Pierini, Maria Spiropulu, Jean-Roch Vlimant

- Synthetic data corresponding to W, ttbar and QCD (100 K events each), loosely inspired by the LHC running configuration in 2015-2016
- List of reconstructed particle flow candidates associated to charged particles, photons and neutral hadrons
- Binned in 2D arrays consisting of :
  - two barrel region ($|\eta|<1.5$; bin size 0.0187×0.0187)
  - two end-cap regions ($1.5\leq |\eta| <3.0$; bin size 0.0187×0.0187)
  - two forward regions ($3.0\leq |\eta| <5.0$; bin size : 0.175 in η, 0.175 to 0.35 in φ)
  - value : scalar sum of the pT of the particles in that cell.

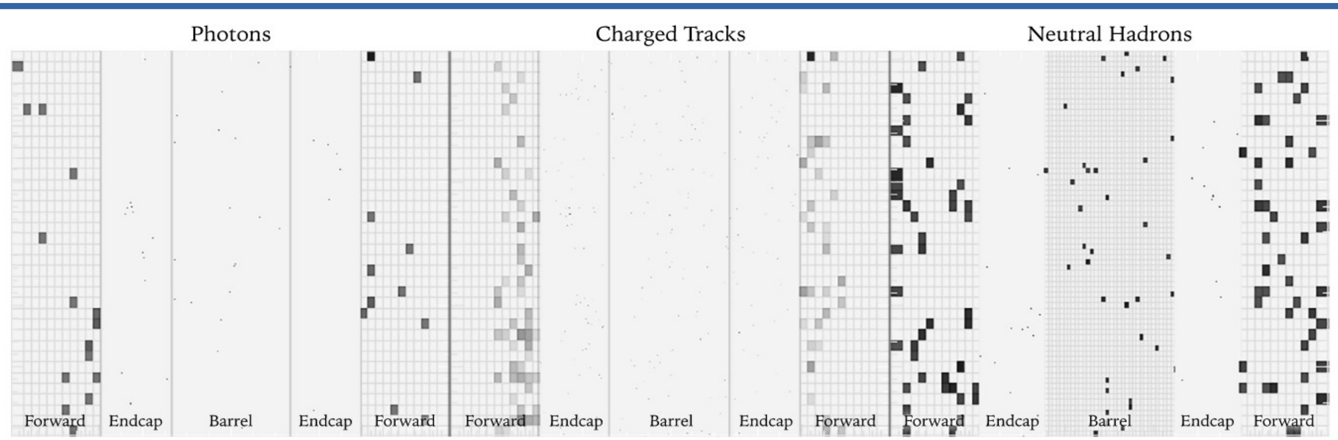
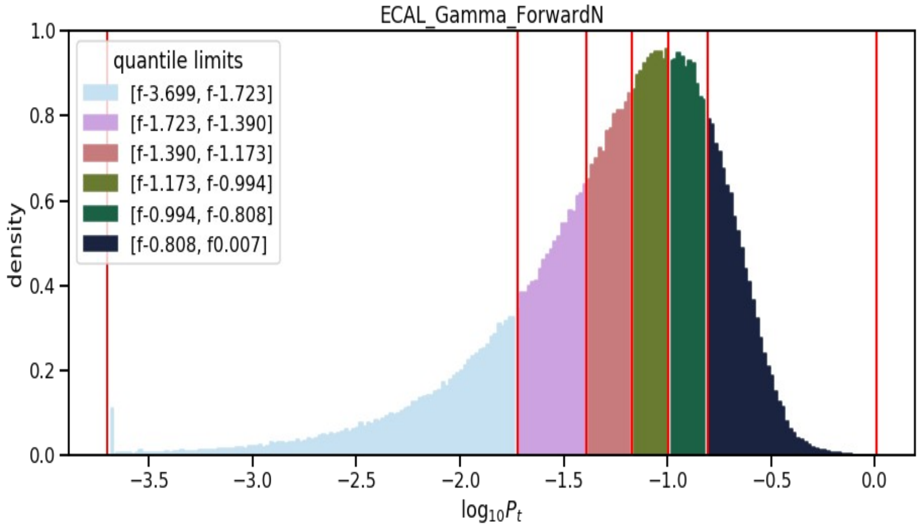
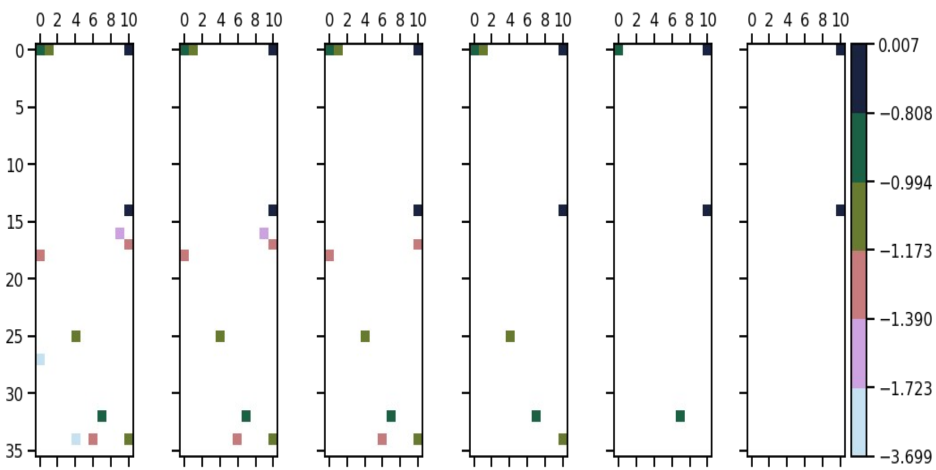
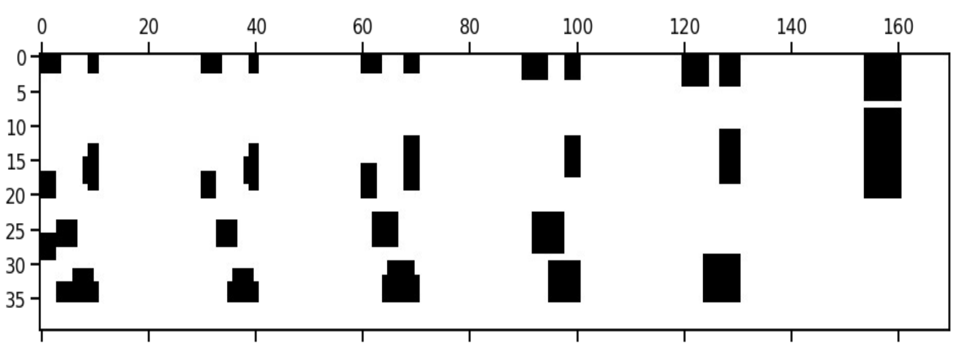


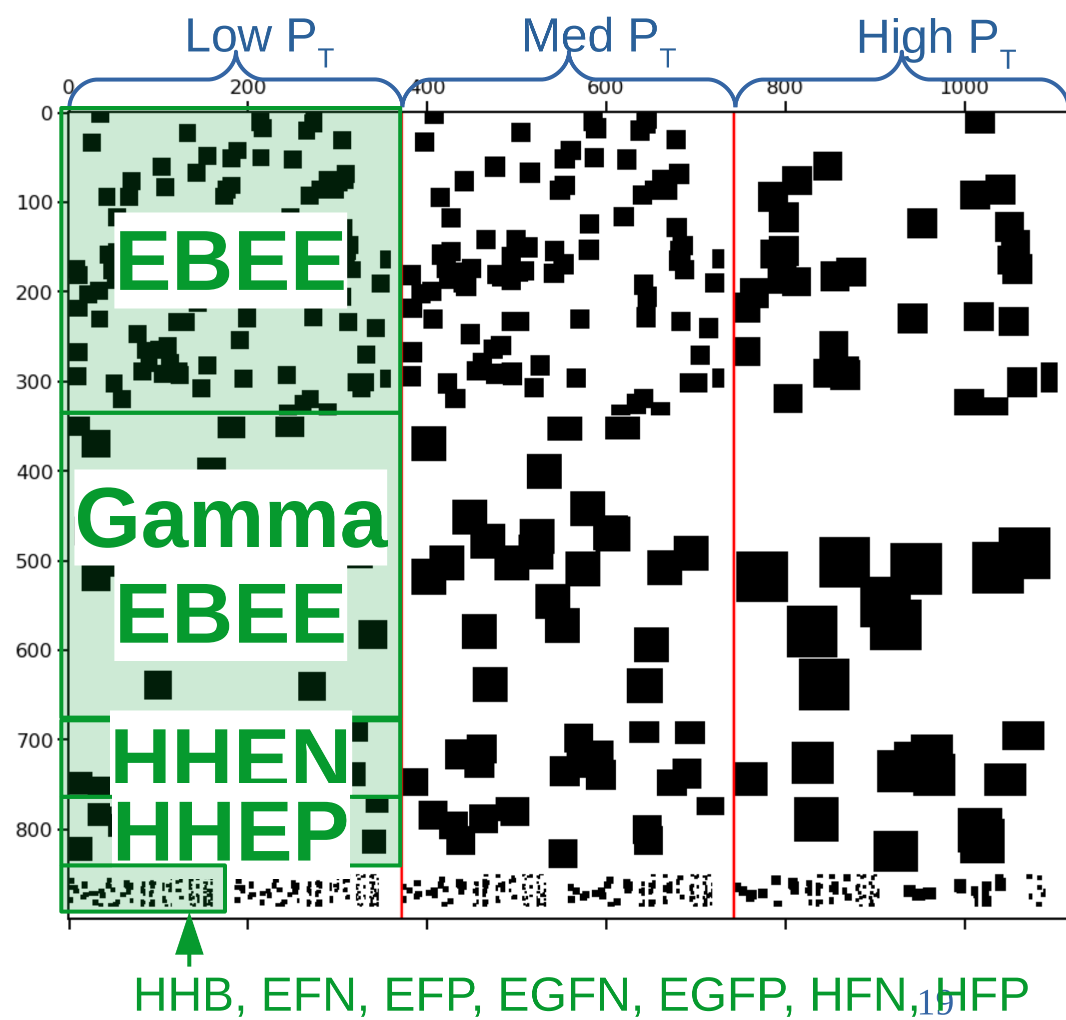
Figure 2: An example of a $t\bar{t}$ event as the input of the raw-image classifier. Vertical and horizontal axess are the ϕ and η coordinates, respectively, of the sub-detectors.

Discretization









Ridge regression results

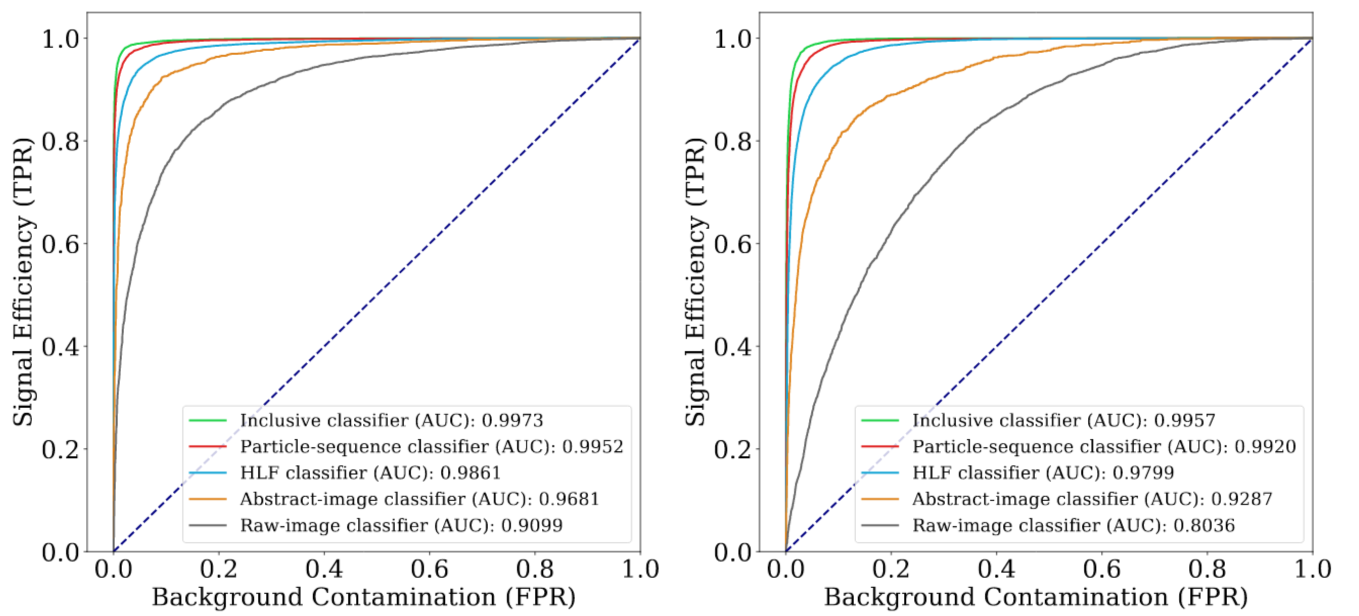
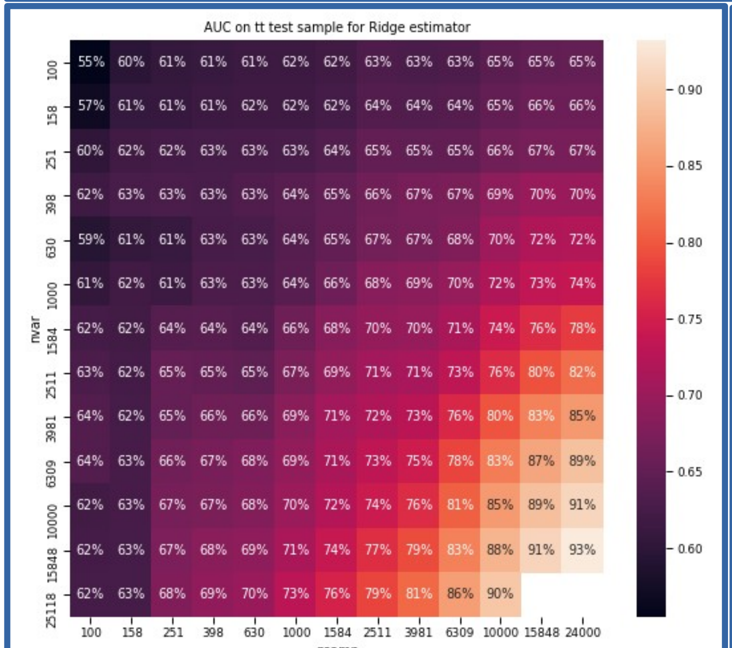
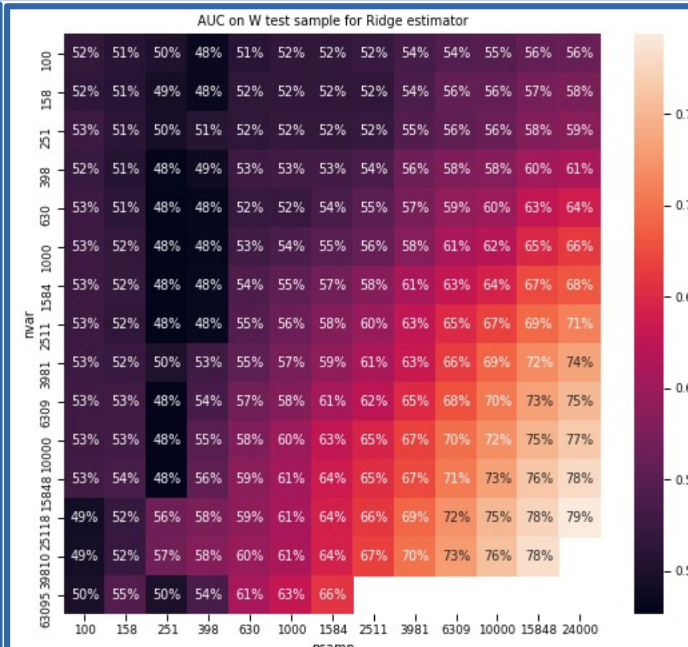


Figure 5: ROC curves for the $t\bar{t}$ (left) and W (right) selectors described in the paper.



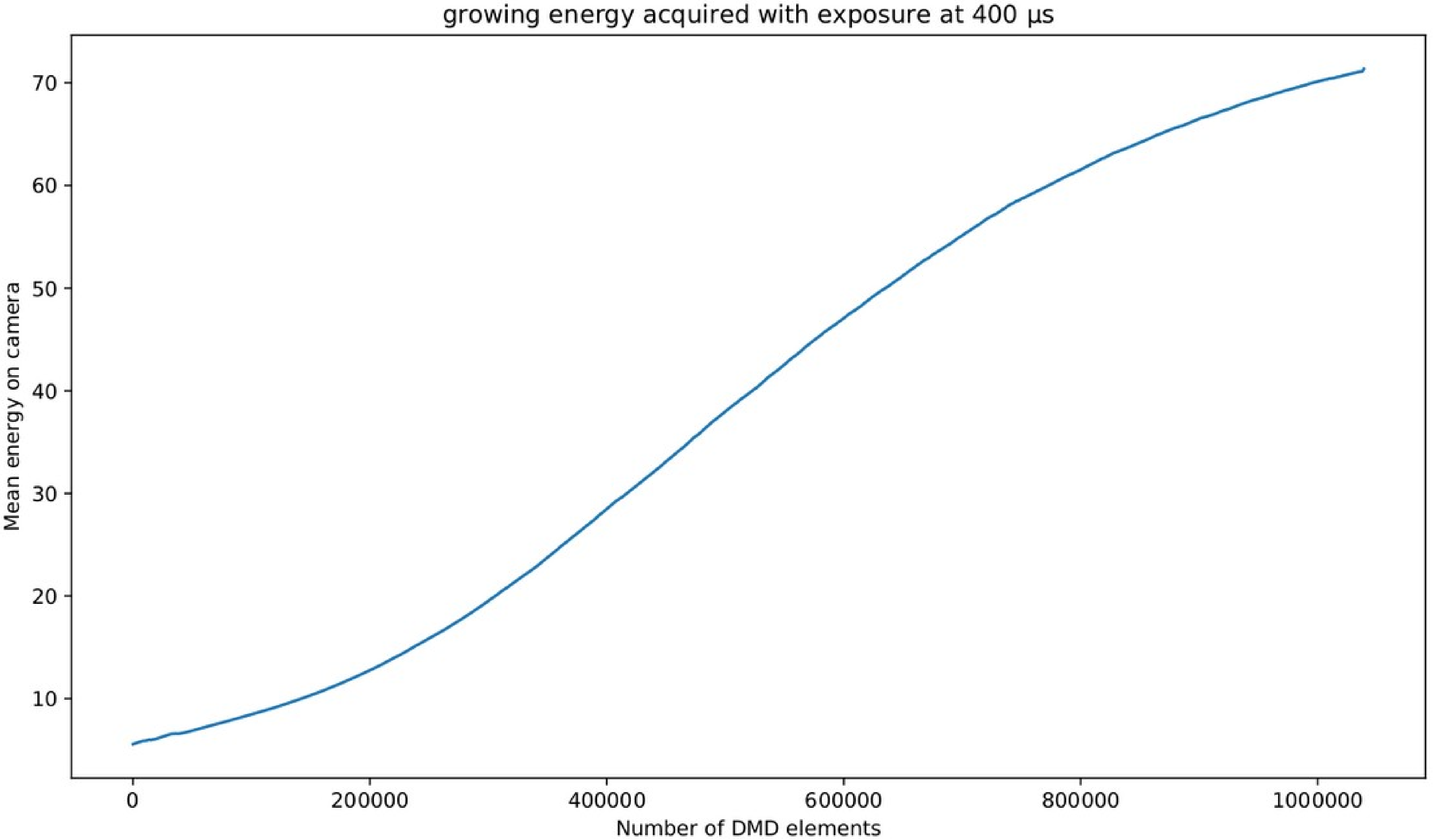


Summary

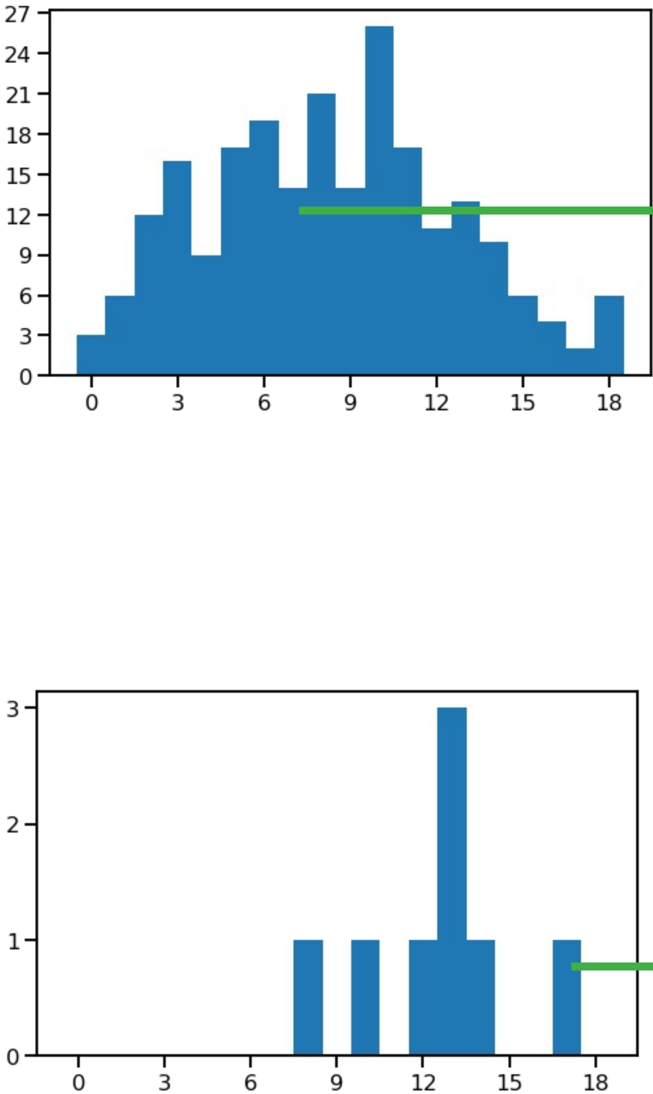
- OPU provides a device to reduce classification dimensionality / training time through physical random matrixes
- Casting a Tracking problem for OPU is hard
  - Estimations of various parameters
  - OPU « makes sense » without matching traditional methods
- Calorimetry
  - Faster training than CNNs, far less training data ($N_{features} \simeq N_{pixels}$), more robust
  - Study 2 : results on par with original paper classifier if feature and sample number reach ~ 20K
- OPU can have a niche application for frequent retrainings on few events, but casting it for HEP applications is non trivial

Backup

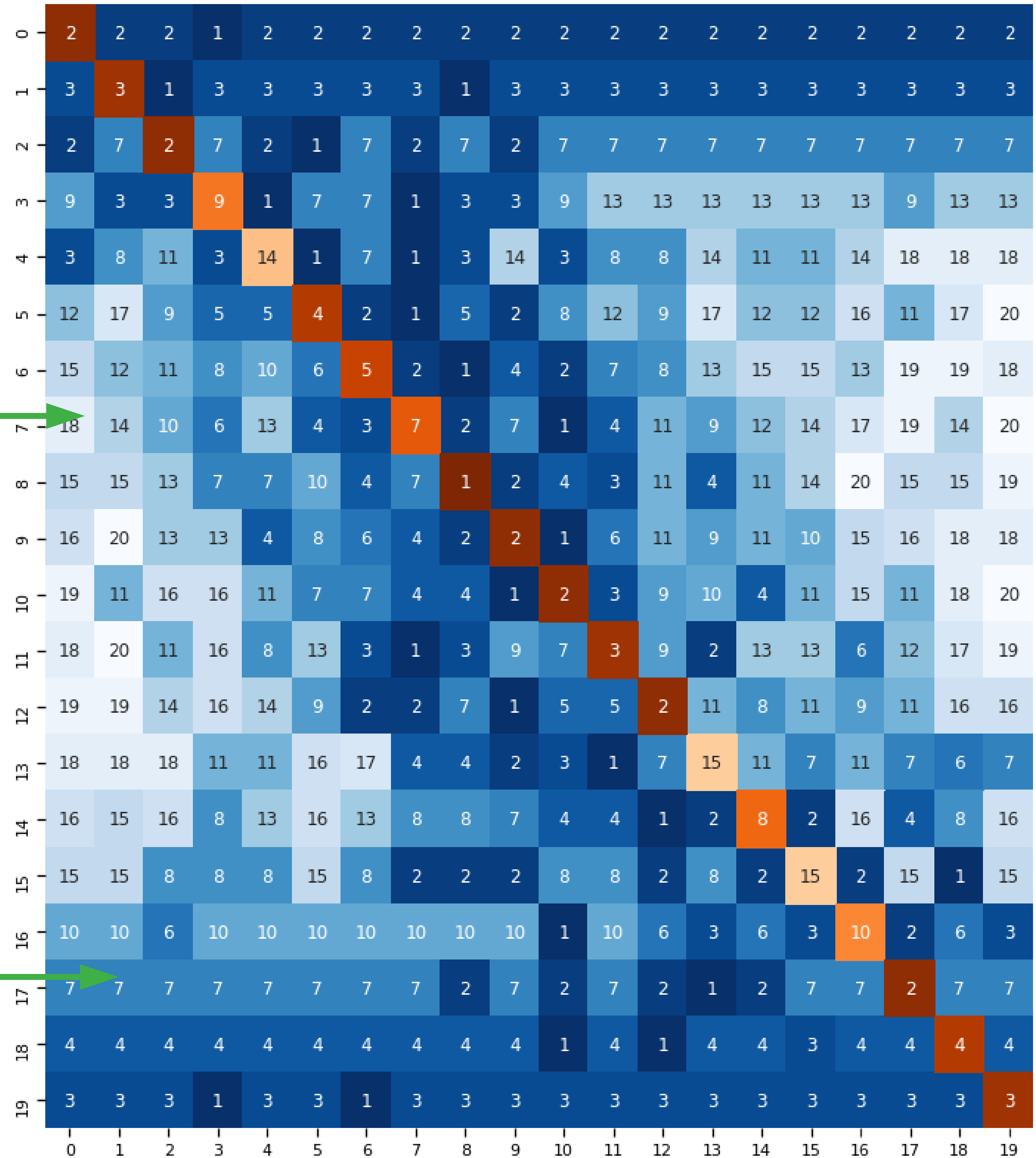
OPU response curve



How bad is it ?

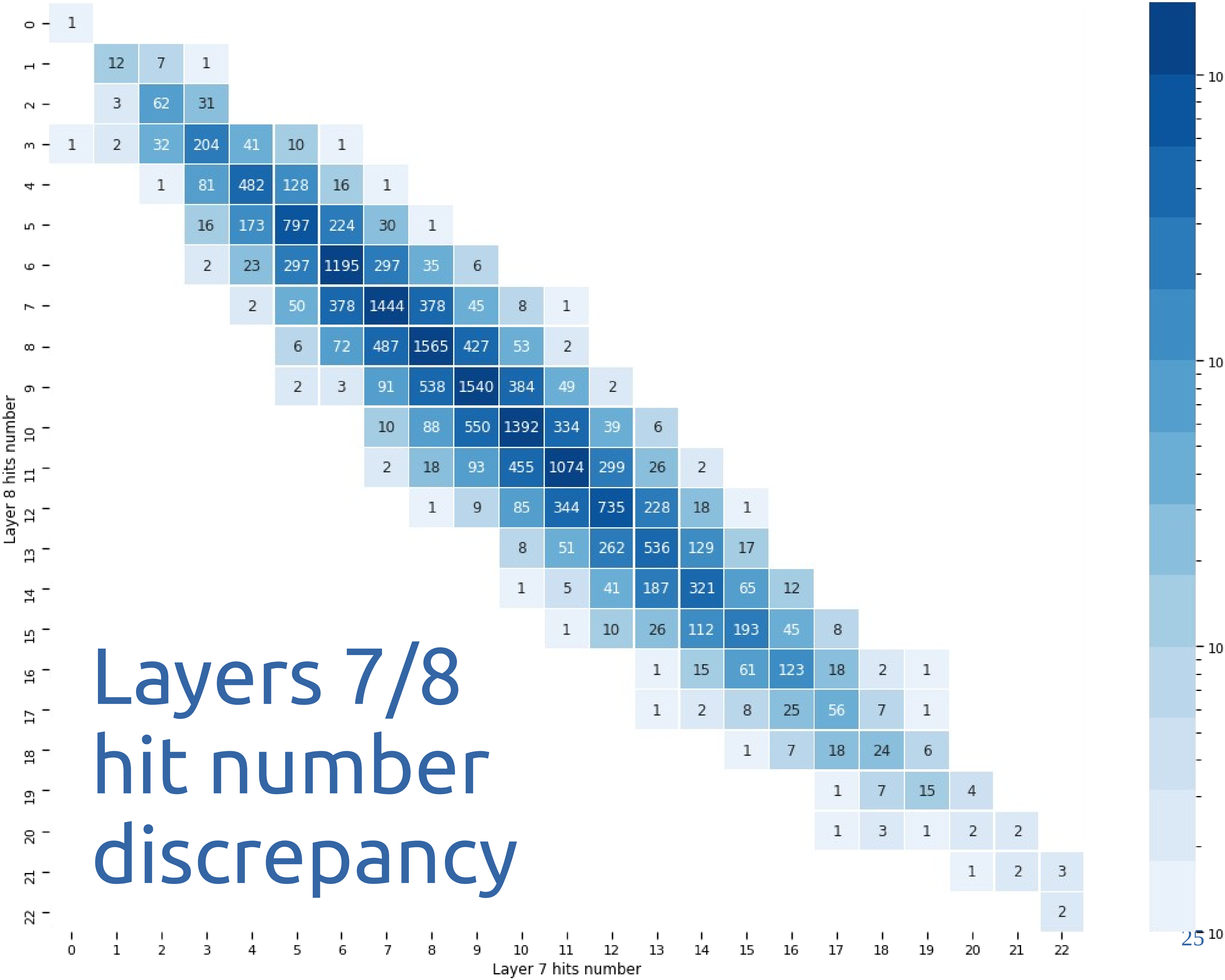


27
24
21
18
15
12
9
6
3
0
0 3 6 9 12 15 18
3
2
1
0
0 3 6 9 12 15 18



0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19
0: 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
1: 3 3 1 3 3 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3
2: 2 7 2 7 2 1 7 2 7 2 7 7 7 7 7 7 7 7 7 7
3: 9 3 3 9 1 7 7 1 3 3 9 13 13 13 13 13 13 9 13 13
4: 3 8 11 3 14 1 7 1 3 14 3 8 8 14 11 11 14 18 18 18
5: 12 17 9 5 5 4 2 1 5 2 8 12 9 17 12 12 16 11 17 20
6: 15 12 11 8 10 6 5 2 1 4 2 7 8 13 15 15 13 19 19 18
7: 18 14 10 6 13 4 3 7 2 7 1 4 11 9 12 14 17 19 14 20
8: 15 15 13 7 7 10 4 7 1 2 4 3 11 4 11 14 20 15 15 19
9: 16 20 13 13 4 8 6 4 2 2 1 6 11 9 11 10 15 16 18 18
10: 19 11 16 16 11 7 7 4 4 1 2 3 9 10 4 11 15 11 18 20
11: 18 20 11 16 8 13 3 1 3 9 7 3 9 2 13 13 6 12 17 19
12: 19 19 14 16 14 9 2 2 7 1 5 5 2 11 8 11 9 11 16 16
13: 18 18 18 11 11 16 17 4 4 2 3 1 7 15 11 7 11 7 6 7
14: 16 15 16 8 13 16 13 8 8 7 4 4 1 2 8 2 16 4 8 16
15: 15 15 8 8 8 15 8 2 2 2 8 8 2 8 2 15 2 15 1 15
16: 10 10 6 10 10 10 10 10 10 10 1 10 6 3 6 3 10 2 6 3
17: 7 7 7 7 7 7 7 7 2 7 2 7 2 1 2 7 7 2 7 7
18: 4 4 4 4 4 4 4 4 4 4 1 4 1 4 4 3 4 4 4 4
19: 3 3 3 1 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3

Layers 7/8 hit number discrepancy



Estimate next layer hits number

$$\min_{\beta \in R^{m\times n}} ||X\beta - y|| + ||\gamma\beta||$$

(10K) random features
X (10K) events

(1) last layer hit number
X (10K) events