Studying hadronization with Machine Learning techniques and event variables

ELTE PARTICLE PHYSICS SEMINAR

GÁBOR BÍRÓ

16 11 2021

WIGNER RCP
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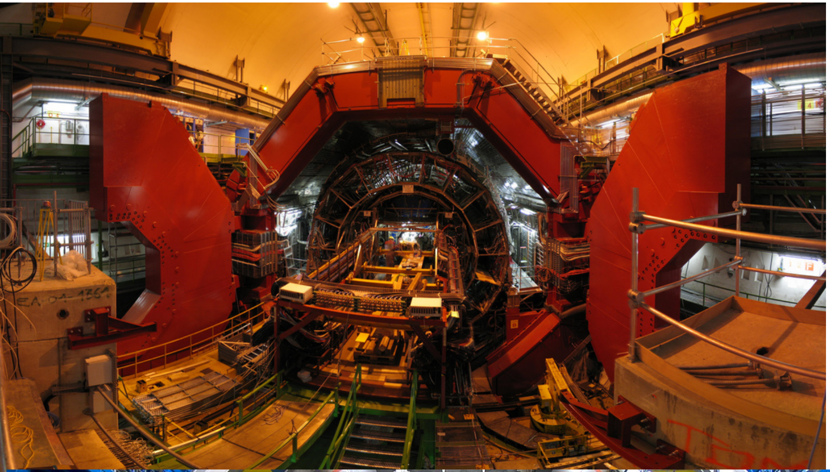
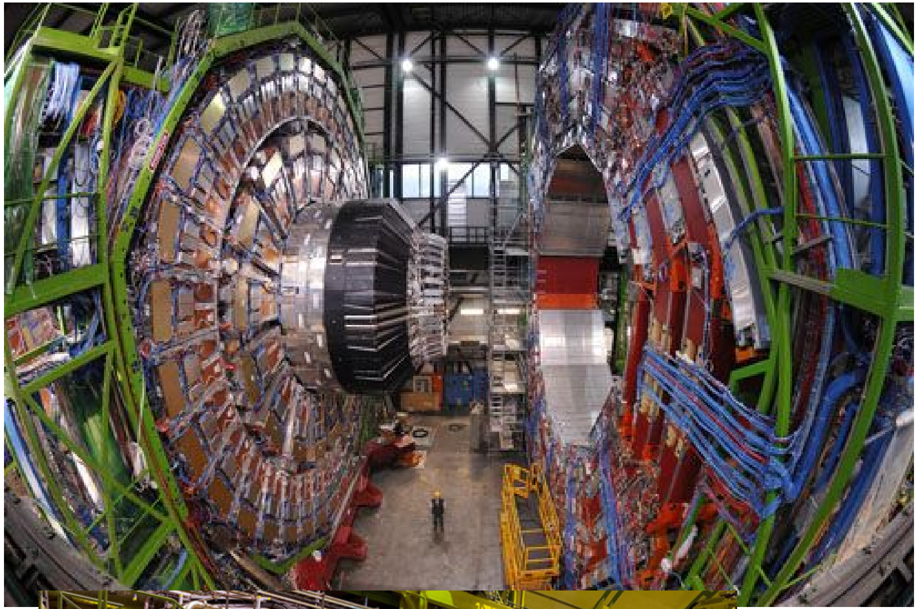
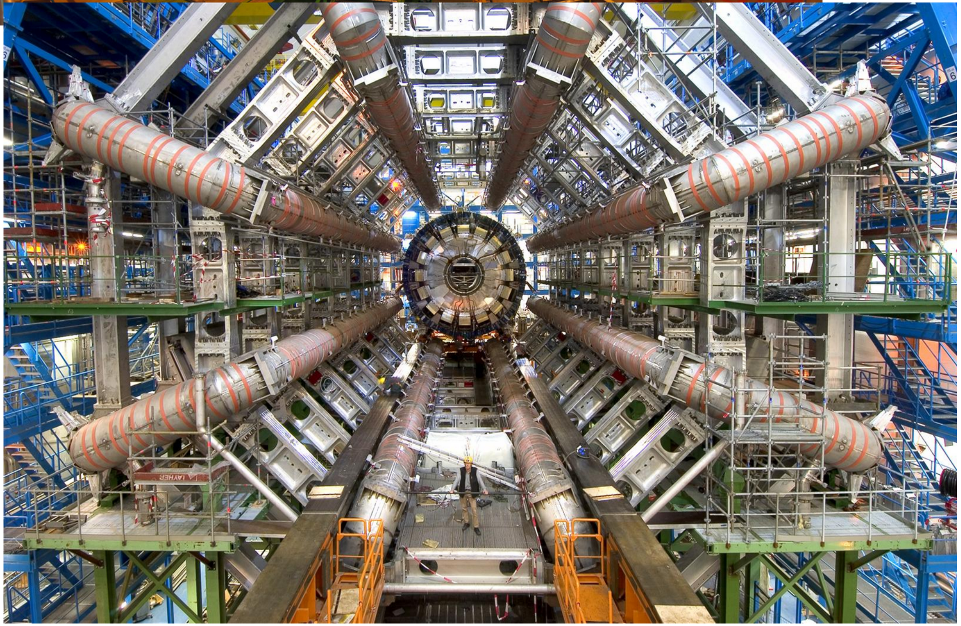
Outline

- Machine Learning: motivation
- Applications and examples
- Research goals
- Preliminary results
- Summary

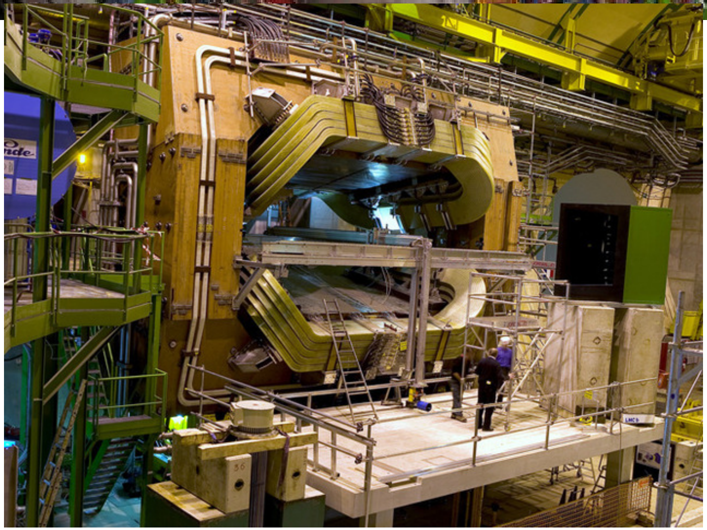




ALICE
CMS



ATLAS
LHCb



Data, data, and more data

Large Hadron Collider data:

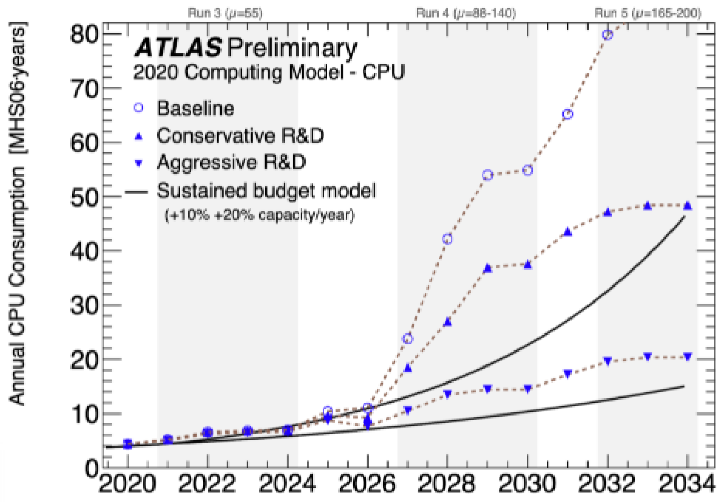
2021: 336 PB

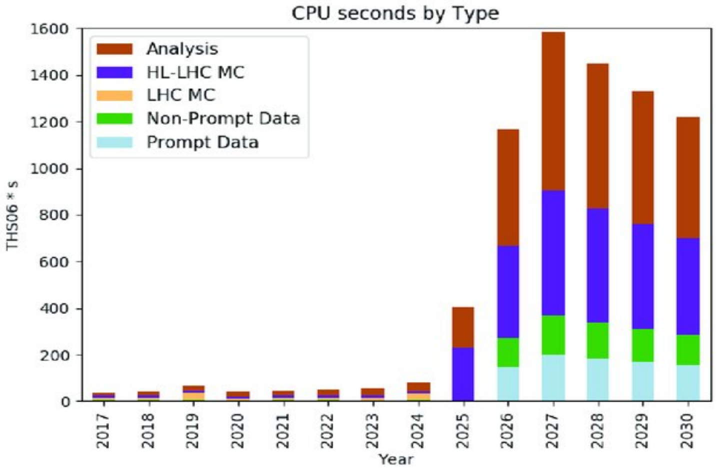
From 2022: 200+ PB/year

Simulations:

Computationally very expensive

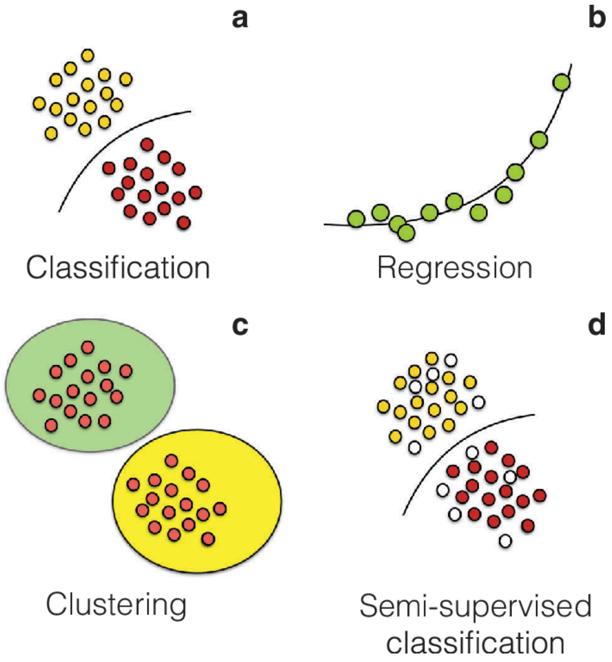
1s LHC data ~ days of CPU time





Machine learning

- Data driven decisions
- Automated analysis
- Perform tasks without being explicitly programmed to do so



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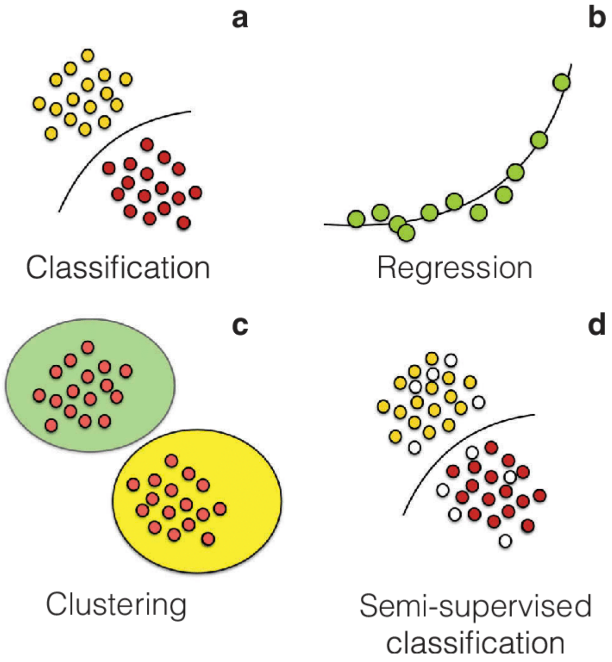
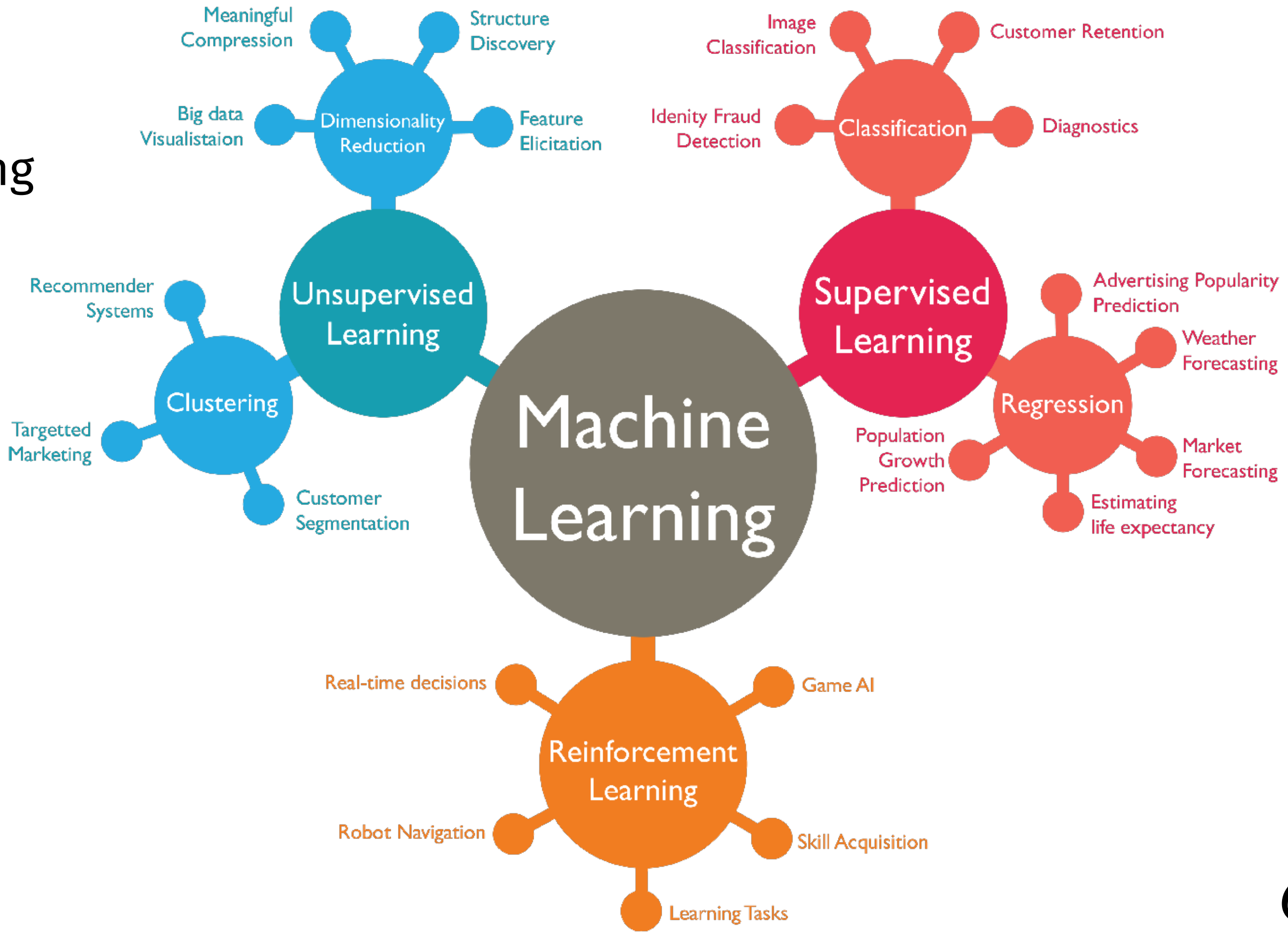
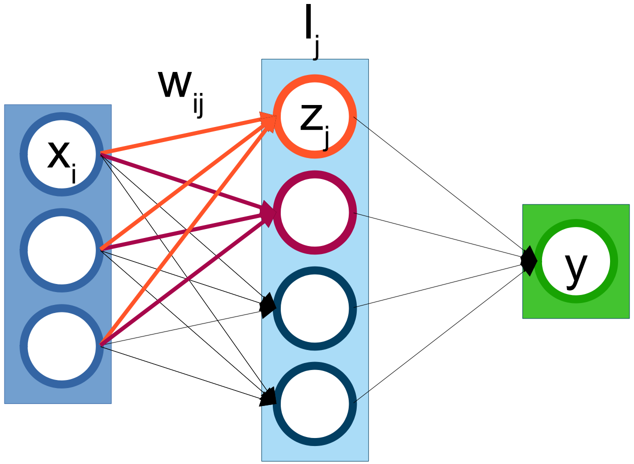


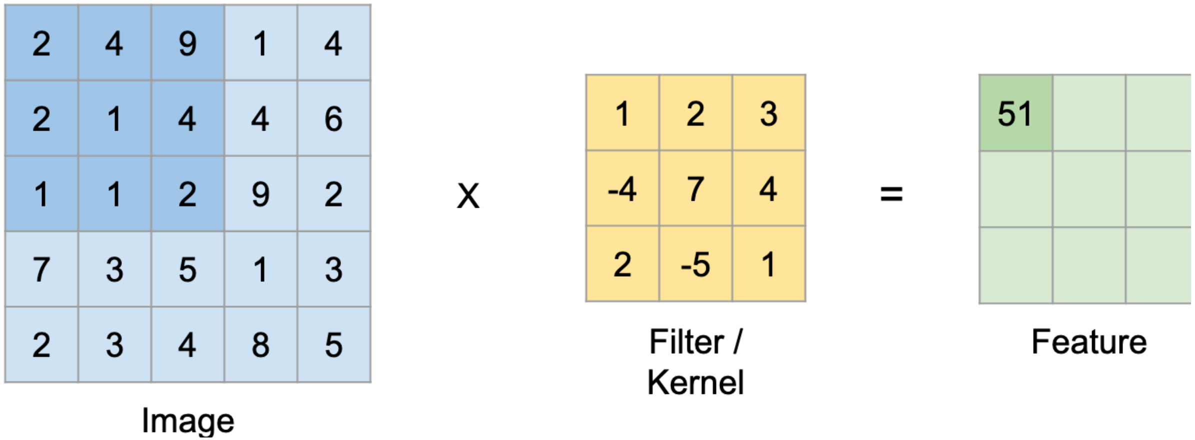


Basic building blocks of a neural network

Fully connected (dense):



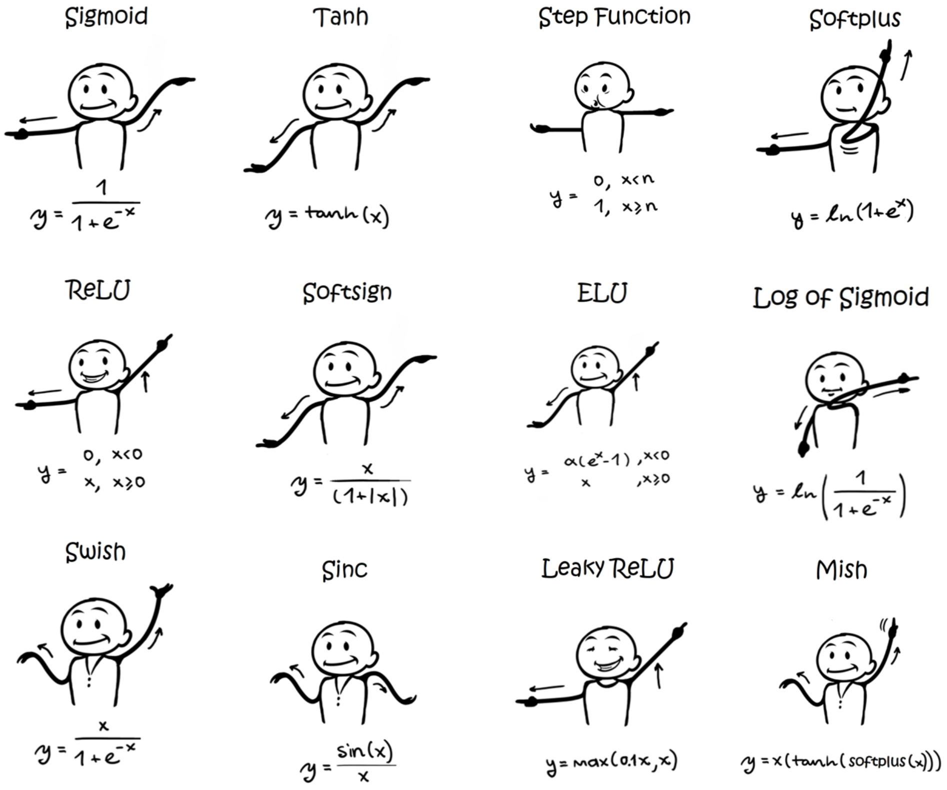
Convolutional:



$$z_j = \sum_{i=1}^{N} x_i w_{ij} + b_j$$

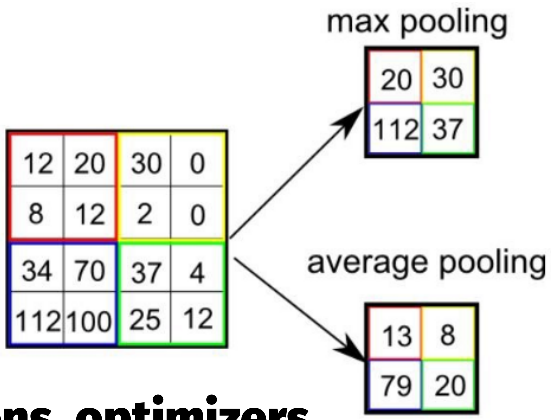
Basic building blocks of a neural network

Activation functions:



https://sefiks.com/2020/02/02/dance-moves-of-deep-learning-activation-functions/

Pooling:



https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Loss functions, optimizers...

Regression losses

- MeanSquaredError class
- MeanAbsoluteError class
- MeanAbsolutePercentageError class
- MeanSquaredLogarithmicError class
- CosineSimilarity class
- mean_squared_error function
- mean_absolute_error function
- mean_absolute_percentage_error function
- mean_squared_logarithmic_error function
- cosine_similarity function
- Huber class
- huber function
- LogCosh class
- log_cosh function

Probabilistic losses

- BinaryCrossentropy class
- CategoricalCrossentropy class
- SparseCategoricalCrossentropy class
- Poisson class

Available optimizers

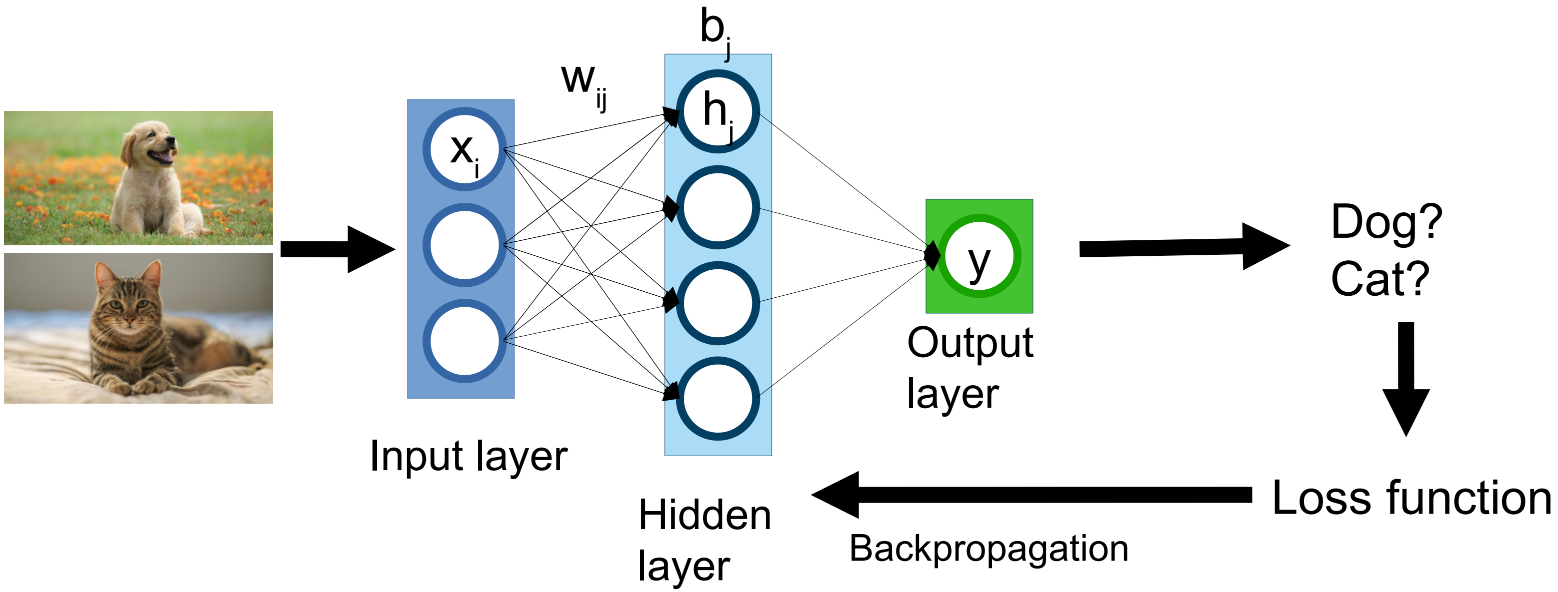
- SGD
- RMSprop
- Adam
- Adadelta
- Adagrad
- Adamax
- Nadam
- Ftrl

Hinge losses for "maximum-margin" classification

- Hinge class
- SquaredHinge class
- CategoricalHinge class

Example: FCNN

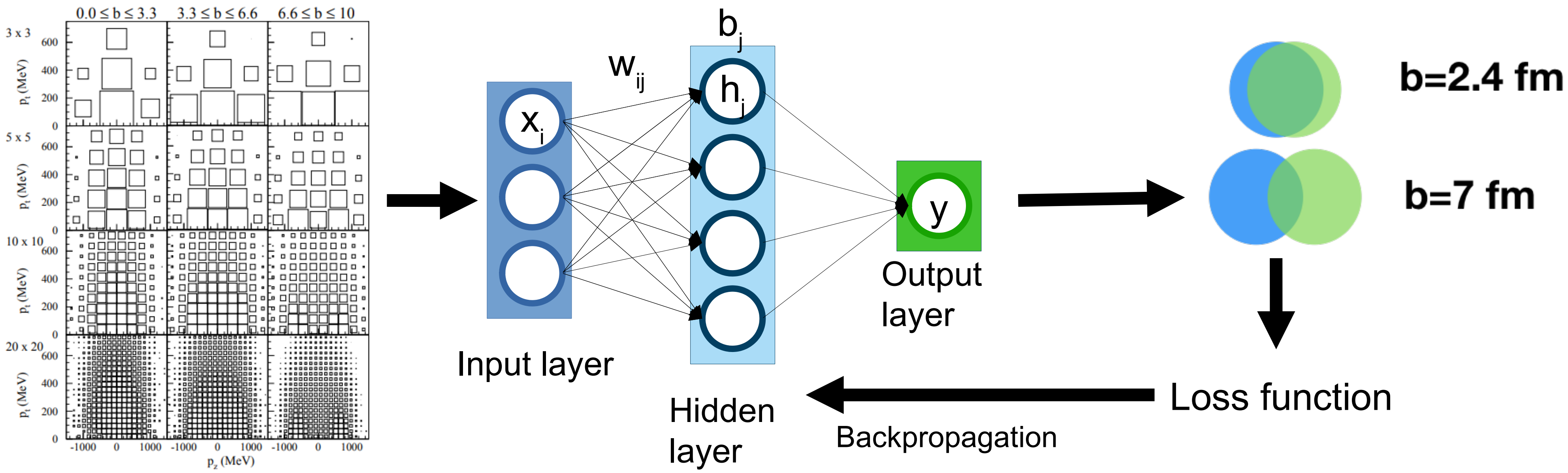
Simple classification



$$L_\delta(y, f(x)) = \begin{cases} \frac{1}{2}(y - f(x))^2, & |y - f(x)| \leq \delta \\ \delta(|y - f(x)| - \frac{1}{2}\delta) \end{cases}$$

Example: FCNN

Centrality determination



PRC.53.2358 (1996), Bass, S. A.; Bischoff, A.; Maruhn, J. A.; Stöcker, H.; Greiner, W.

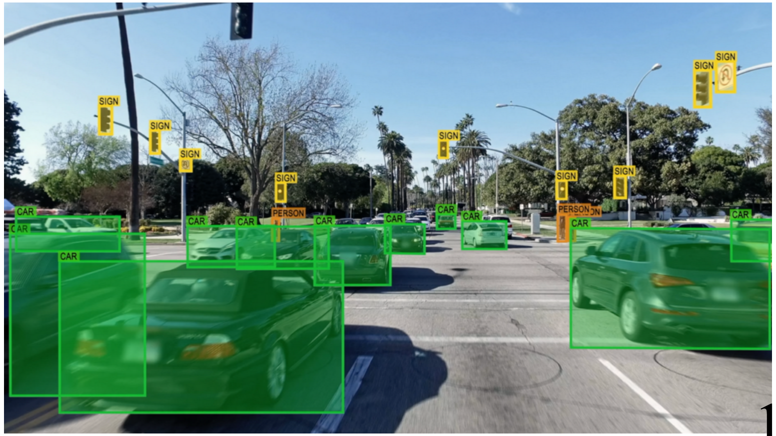
Popular architectures

Classifiers

- AlexNet (Comm. ACM. 60 (6): 84–90, 2012)
- VGG16 (138M parameters, 23 layers, arXiv:1409.1556)
- ResNet (25M+ parameters, arXiv:1512.03385)
- DenseNet (8M parameters, 121 layers, arXiv:1608.06993)

Object detection

- (Fast(er)) R-CNN (arXiv:1311.2524, arXiv:1504.08083, arXiv:1506.01497)
- YOLO (arXiv:1506.02640)
- Detectron (github.com/facebookresearch/detectron2)



Autonomous vehicles
Decision trees
Transformers
Generative adversarial networks (https://bit.ly/2YMCFdy)
(Variational) autoencoders
…

Machine Learning in HEP

A Living Review of Machine Learning for Particle Physics

https://iml-wg.github.io/HEPML-LivingReview/

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Machine Learning in HEP

Track reconstruction

Particle Track Reconstruction with Deep Learning

Steven Farrell, Paolo Calafiura, Mayur Mudigonda, Prabhat
Lawrence Berkeley National Laboratory
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Dustin Anderson, Josh Bendavid, Maria Spiropoulou, Jean-Roch Vlimant, Stephan Zheng
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Giuseppe Cerati, Lindsey Gray, Keshav Kapoor, Jim Kowalkowski, Panagiotis Spentzouris, Aristeidis Tsaris, Daniel Zurawski
Fermi National Accelerator Laboratory
{cerati,lagray,kkapoor,jbk,spentz, atsaris,zurawski}@fnal.gov

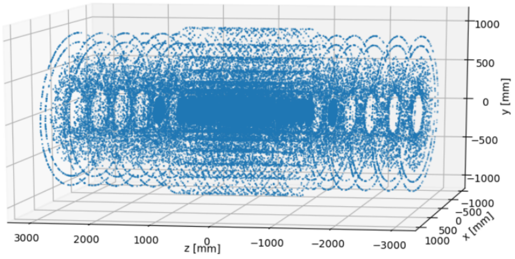
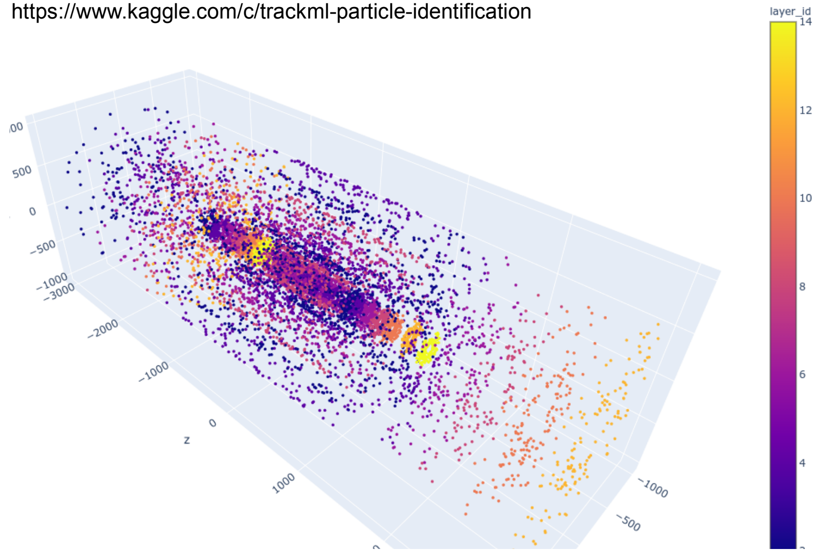


Figure 1: Distribution of particle spacepoints in a particle collision event in a generic simulated HL-LHC tracking detector.

https://www.kaggle.com/c/trackml-particle-identification



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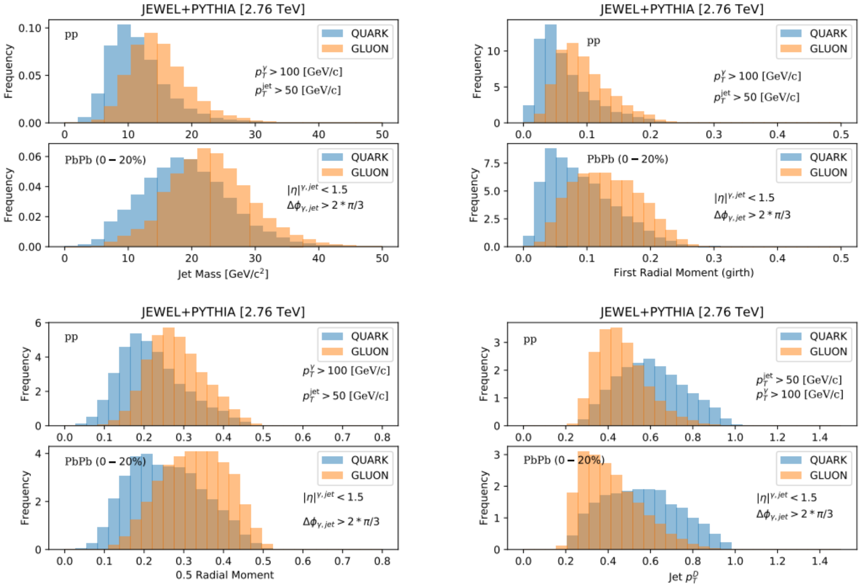
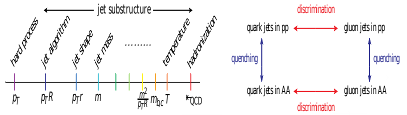


Probing heavy ion collisions using quark and gluon jet substructure

Yang-Ting Chien [a] and Raghav Kunnawalkam Elayavalli [b,c]

[a] *Center for Theoretical Physics*
Massachusetts Institute of Technology, Cambridge, MA 02139
[b] *Department of Physics and Astronomy*
Wayne State University, Detroit, MI 48201
[c] *Department of Physics and Astronomy*
Rutgers, the State University of New Jersey, New Brunswick, NJ 08901



arXiv:1803.03589

Quark/gluon jet separation

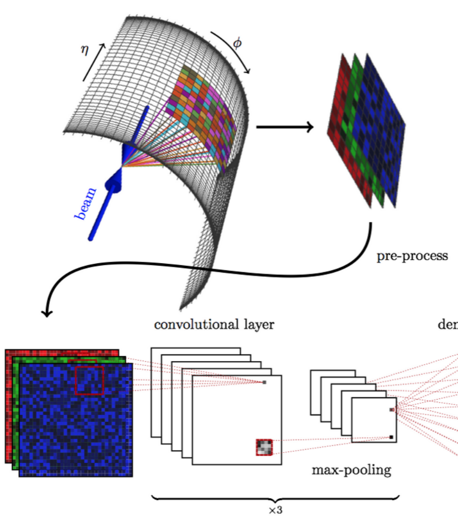


Figure 2: An illustration of the deep convolutional neural network architecture. The first layer is the input jet image, followed by three convolutional layers, a dense layer and an output layer.

P. Baldi, K. Bauer, C. Eng, P. Sadowski, and D. Whiteson, *Jet Substructure Classification in High-Energy Physics with Deep Neural Networks*, *Phys. Rev.* **D93** (2016), no. 9 094034, [arXiv:1603.09349].

D. Guest, J. Collado, P. Baldi, S.-C. Hsu, G. Urban, and D. Whiteson, *Jet Flavor Classification in High-Energy Physics with Deep Neural Networks*, arXiv:1607.08633.

J. S. Conway, R. Bhaskar, R. D. Erbacher, and J. Pilot, *Identification of High-Momentum Top Quarks, Higgs Bosons, and W and Z Bosons Using Boosted Event Shapes*, arXiv:1606.06859.

J. Barnard, E. N. Dawe, M. J. Dolan, and N. Rajcic, *Parton Shower Uncertainties in Jet Substructure Analyses with Deep Neural Networks*, arXiv:1609.00607.

Deep learning in color: towards automated quark/gluon jet discrimination

Patrick T. Komiske,[a] Eric M. Metodiev,[a] and Matthew D. Schwartz[b]

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https://doi.org/10.1007/JHEP01(2017)110

Deep CNN match or outperform traditional jet observables.

Machine Learning in HEP

Machine Learning based jet momentum reconstruction in heavy-ion collisions

Rüdiger Haake[1] and Constantin Loizides[2]
[1]Yale University, Wright Laboratory, New Haven, CT, USA
[2]ORNL, Physics Division, Oak Ridge, TN, USA
(Dated: June 24, 2019)

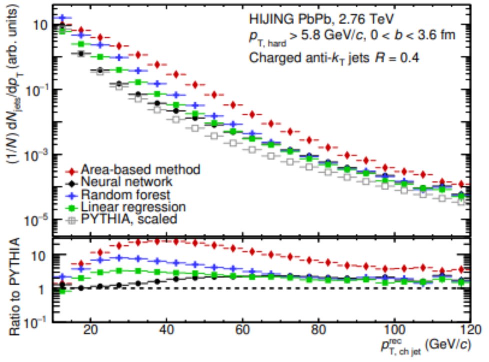


FIG. 9. Reconstructed charged jet spectra in HIJING events and the ratio to (N_{coll}-scaled) PYTHIA jet spectra.

Feature	Score	Feature	Score
Jet p_{T} (no corr.)	**0.1355**	$p^{1}_{\mathrm{T,\,const}}$	0.0012
Jet mass	0.0007	$p^{2}_{\mathrm{T,\,const}}$	**0.0039**
Jet area	0.0005	$p^{3}_{\mathrm{T,\,const}}$	0.0015
Jet p_{T} (area-based corr.)	**0.7876**	$p^{4}_{\mathrm{T,\,const}}$	0.0011
LeSub	0.0004	$p^{5}_{\mathrm{T,\,const}}$	0.0009
Radial moment	0.0005	$p^{6}_{\mathrm{T,\,const}}$	0.0009
Momentum dispersion	0.0007	$p^{7}_{\mathrm{T,\,const}}$	0.0008
Number of constituents	0.0008	$p^{8}_{\mathrm{T,\,const}}$	0.0007
Mean of const. p_{T}	**0.0585**	$p^{9}_{\mathrm{T,\,const}}$	0.0006
Median of const. p_{T}	0.0023	$p^{10}_{\mathrm{T,\,const}}$	0.0007

https://doi.org/10.1103/PhysRevC.99.064904

Jet reconstruction

Machine Learning based jet momentum reconstruction in Pb–Pb collisions measured with the ALICE detector

Rüdiger Haake* for the ALICE Collaboration
Yale University, Wright Laboratory, New Haven, CT, USA
E-mail: ruediger.haake@cern.ch

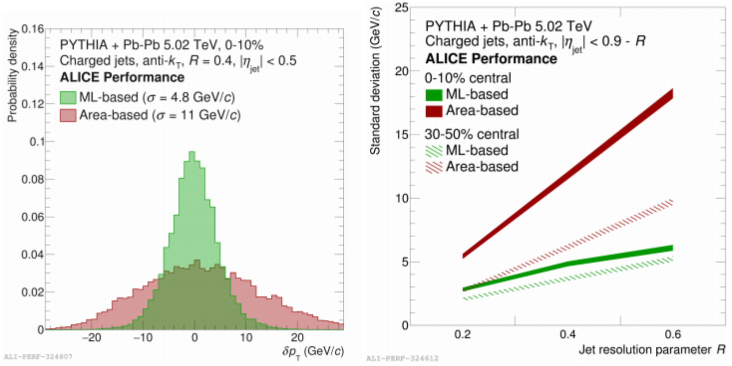
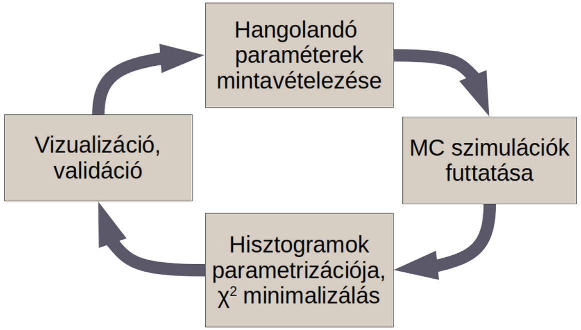


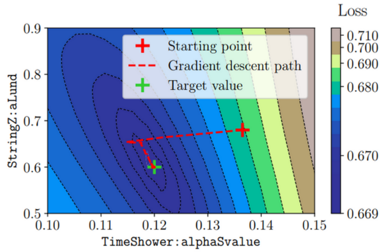
Figure 1: Residual p_{T}-distributions of embedded jet probes of known transverse momentum.

https://doi.org/10.22323/1.364.0312

Machine Learning in HEP

Tuning Monte Carlo event generators





Neural Networks for Full Phase-space Reweighting and Parameter Tuning

Anders Andreassen[1,2,*] and Benjamin Nachman[2,†]

[1]*Department of Physics, University of California, Berkeley, CA 94720, USA*
[2]*Physics Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA*

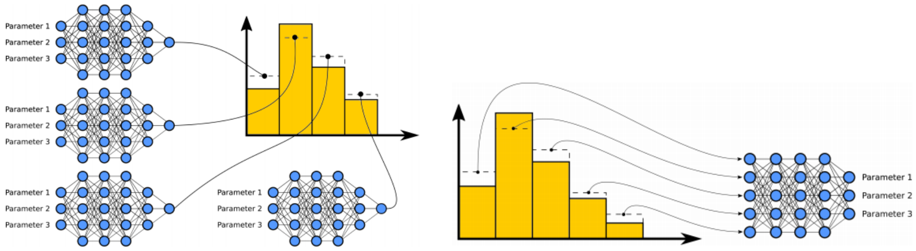


Figure 1: An illustration of the parametrisation of the generator response as implemented in the Per Bin Model.

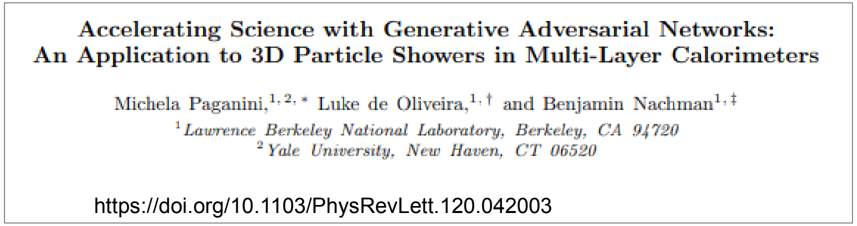
Figure 2: An illustration of the Inverse Model strategy.

MCNNTUNES: tuning Shower Monte Carlo generators with machine learning

Marco Lazzarin[a], Simone Alioli[b], Stefano Carrazza[a]

[a]*TIF Lab, Dipartimento di Fisica, Università degli Studi di Milano and INFN Sezione di Milano, Milan, Italy.*
[b]*Dipartimento di Fisica, Università degli Studi di Milano Bicocca and INFN Sezione di Milano Bicocca, Milan, Italy.*

https://doi.org/10.1016/j.cpc.2021.107908



Accelerating Science with Generative Adversarial Networks: An Application to 3D Particle Showers in Multi-Layer Calorimeters

Michela Paganini,[1,2,*] Luke de Oliveira,[1,†] and Benjamin Nachman[1,‡]

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[2]*Yale University, New Haven, CT 06520*

https://doi.org/10.1103/PhysRevLett.120.042003

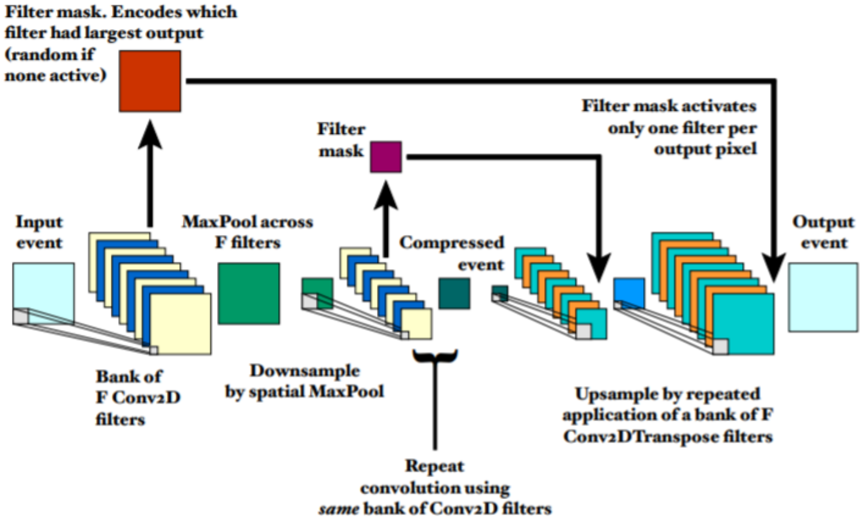
Parton shower and hadronization

Parton shower

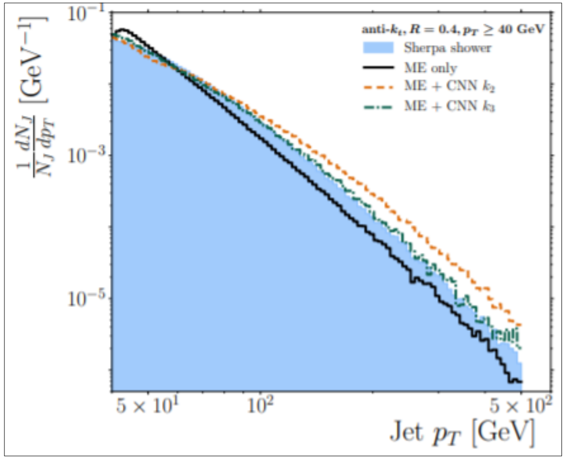
J.W. Monk: Deep Learning as a Parton Shower (arXiv:1807.03685)

Dataset:

- 500 000 QCD pp event @ 7 TeV, generated by Sherpa



parameter	model k_2	model k_3
Kernel size, k	2	3
Input image size, N	64	81
Size of filter bank, F	9	7
Levels of decomposition	5	3
Regularisation, λ	500	300
Learning rate	5×10^{-5}	1×10^{-5}
Loss weight w_1	5	4
Loss weight w_2	2	2
Loss weight w_3	1	1
Total number of trained weights	72	126



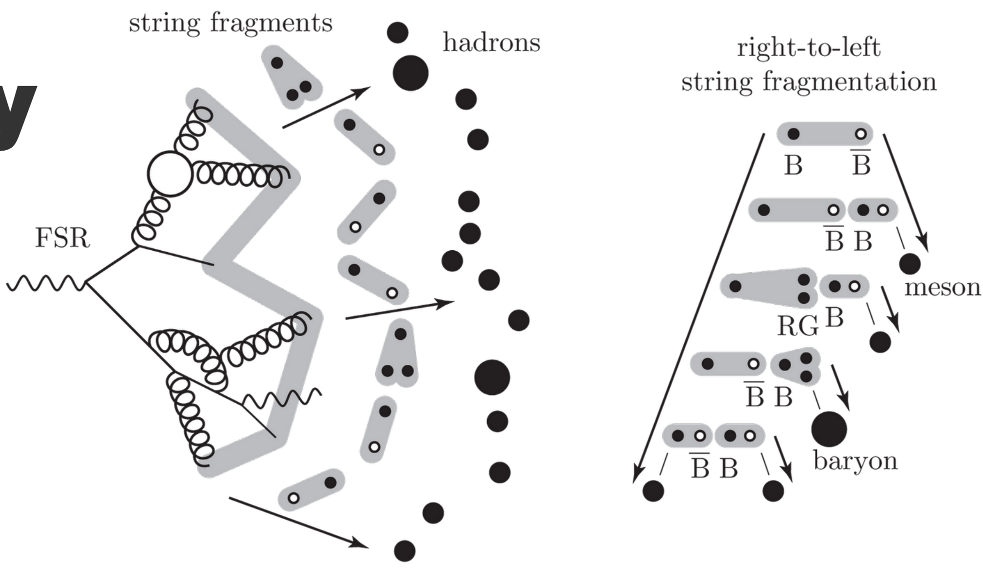
The goal of this study

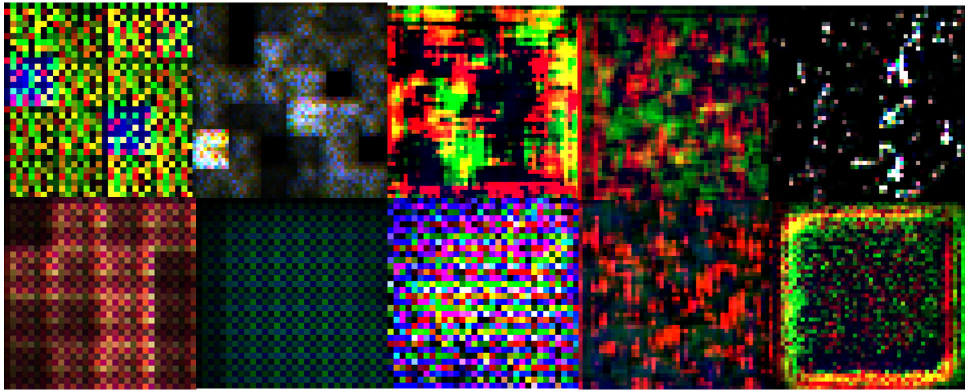
Hadronization

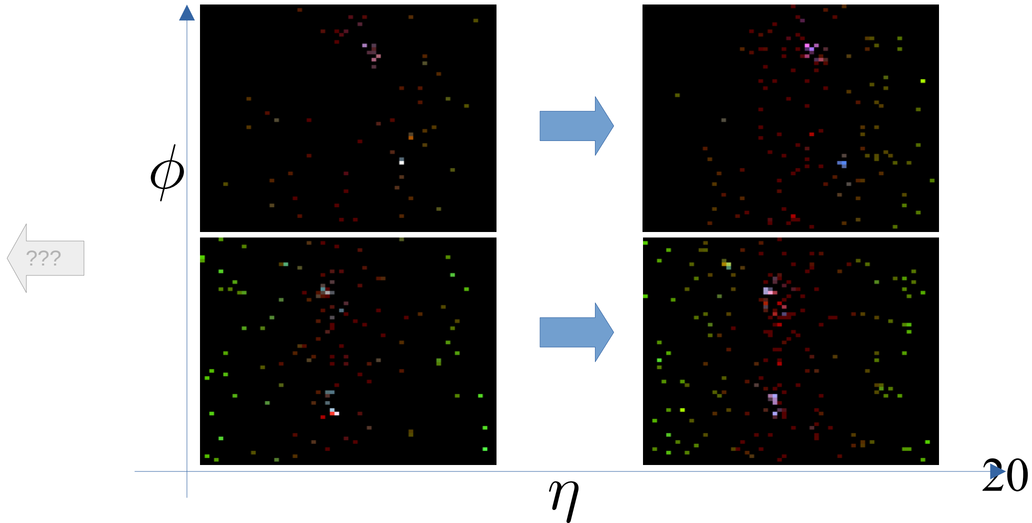
Partons → hadrons

Non-perturbative process

Lund-fragmentation (Comput.Phys.Commun. 27 (1982) 243)







“The nice thing about artificial intelligence is that at least it’s better than artificial stupidity.”

Terry Pratchett, Stephen Baxter: The Long War

Train and validation sets

Monte Carlo data: Pythia 8.303

Monash tune

Selection:

- All final particles with $|y| < \pi$
- At least 2 jets
  - Anti-k_T
  - R=0.6
  - p_T>40 GeV

Event number:

- Train: 100 000
- Validation: 30 000
- ~17 GB raw data

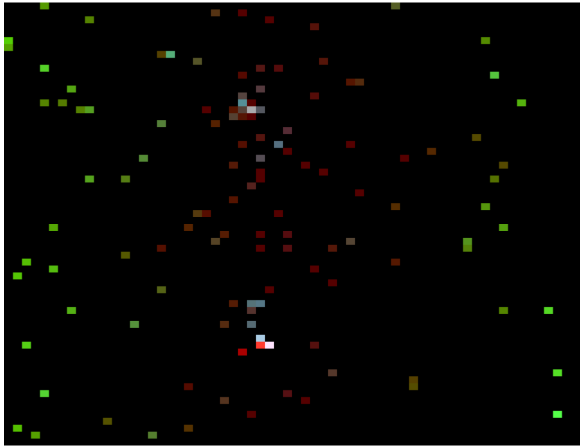
Input:

Parton level

Discretized in the (y, ϕ) plane: p_x, p_y, p_z, E, m, multiplicity

$y \in [\pi, \pi]$, 81 bins

$\phi \in [0, 2\pi]$, 54 bins



Train and validation sets

Output:

Hadron level

Event multiplicity, #Jets, aplanarity, sphericity, tr-sphericity

$$M_{xyz} = \sum_i \begin{pmatrix} p_{xi}^2 & p_{xi}p_{yi} & p_{xi}p_{zi} \\ p_{yi}p_{xi} & p_{yi}^2 & p_{yi}p_{zi} \\ p_{zi}p_{xi} & p_{zi}p_{yi} & p_{zi}^2 \end{pmatrix}$$

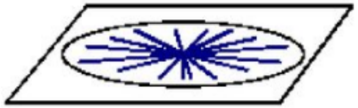
S=A=0

Eigenvalues: $\lambda_1 > \lambda_2 > \lambda_3$ $\quad \sum_i \lambda_i = 1$

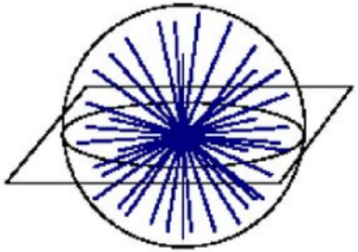
Sphericity: $S = \frac{3}{2}(\lambda_2 + \lambda_3)$

Transverse sphericity: $S_\perp = \frac{2\lambda_2}{\lambda_1+\lambda_2}$

Aplanarity: $A = \frac{3}{2}\lambda_3$



S=3/4 A=0



S=1 A=1/2

Models

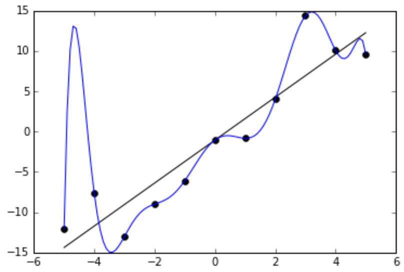
	Model 1	Model 2	Model 3	Model 4
Base	ResNet-32	ResNet-32	DenseNet-4x4	DenseNet-5x5
Last activation	Sigmoid	Sigmoid	Sigmoid	Sigmoid
Loss	Huber	Binary crossentropy	Binary crossentropy	Binary crossentropy
Trainable parameters	468 373	468 373	422 984	1 137 295

Used hardwares: Nvidia Tesla T4, GeForce GTX 1080, GeForce GTX 980

Framework: Tensorflow 2.4.1, Keras 2.4.0

ResNet and DenseNet variants

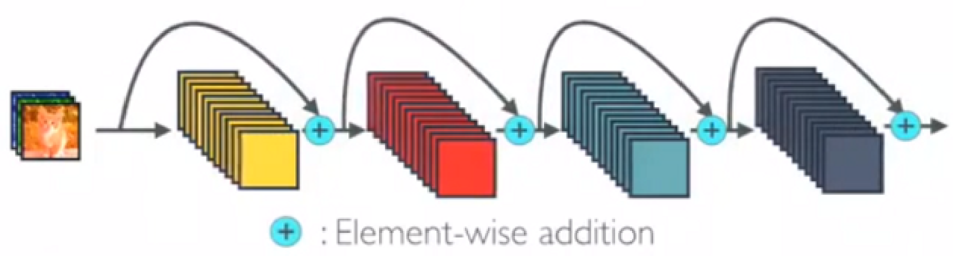
Stacking more layers: solve complex problems more efficiently, get highly accurate results



BUT:
Vanishing/exploding gradients (not to confuse with overfitting)

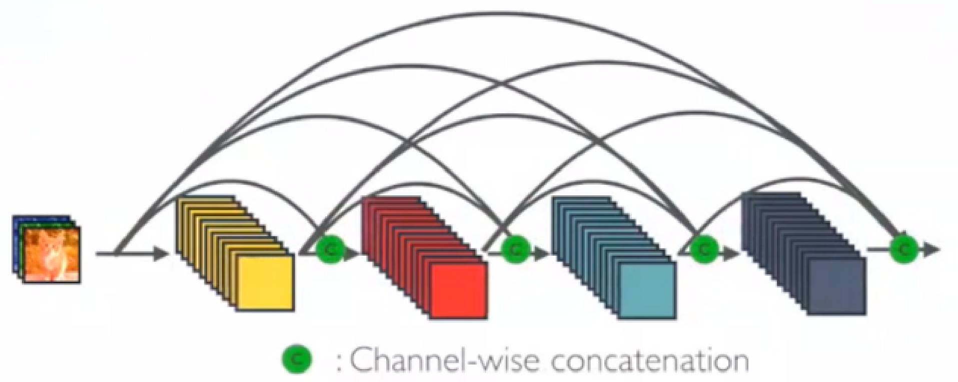
ResNet

Residual blocks with "skip connections"



DenseNet

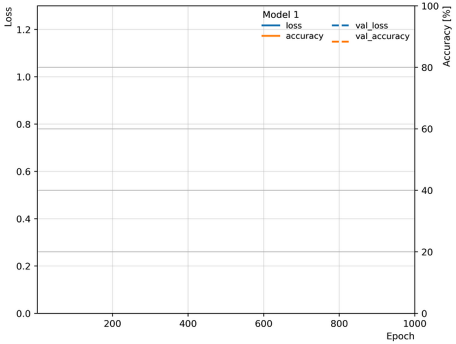
Each layer is receiving a "collective knowledge" from all preceding layers

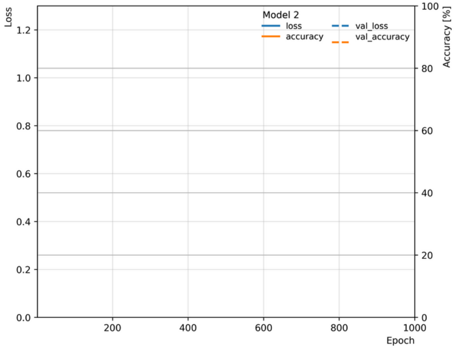


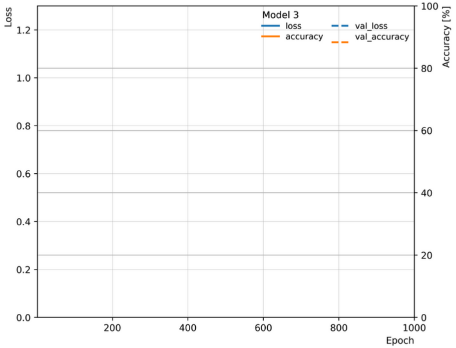
Preliminary results
(any feedback is very welcome!)

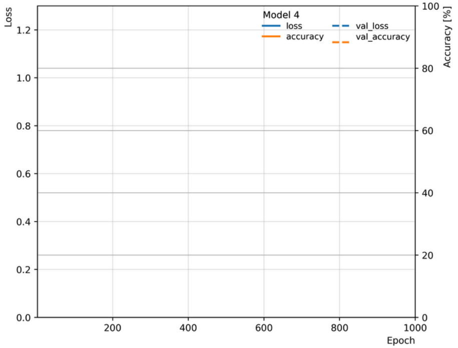
Proton-proton @ 7 TeV Training + Validation

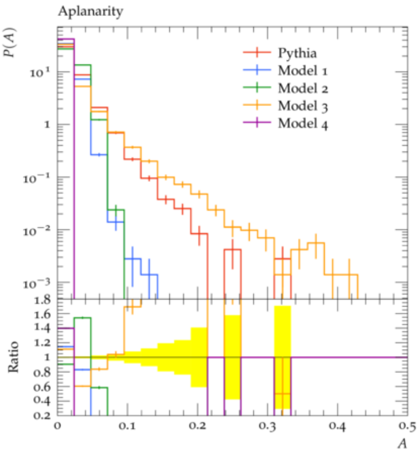
Model 1	Model 2	Model 3	Model 4
ResNet-Huber	ResNet-BinCrossE	DenseNet small	DenseNet large

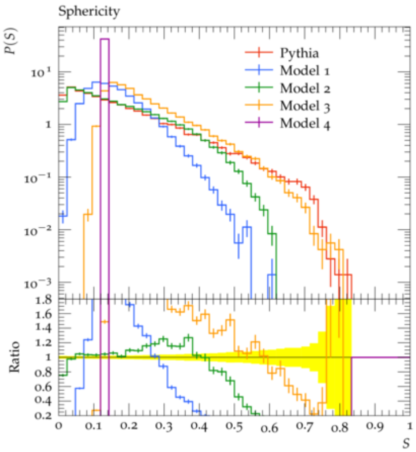


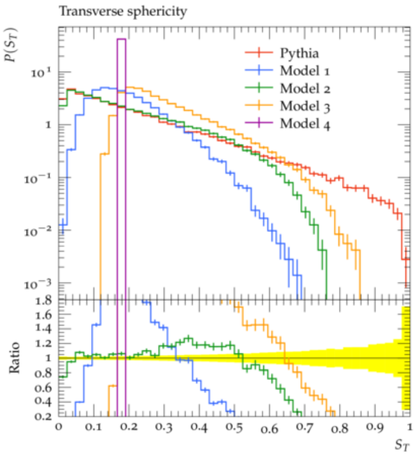


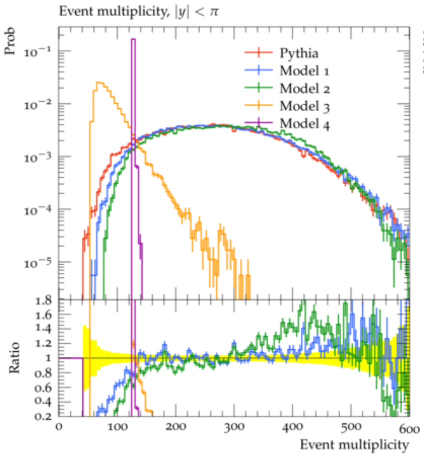


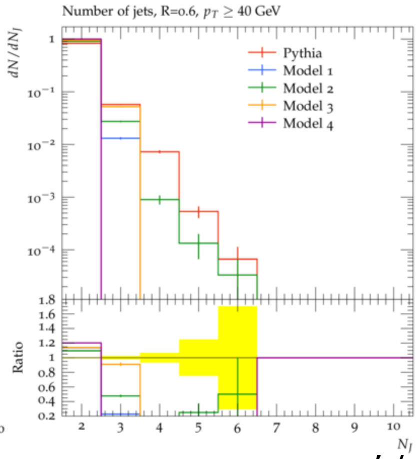






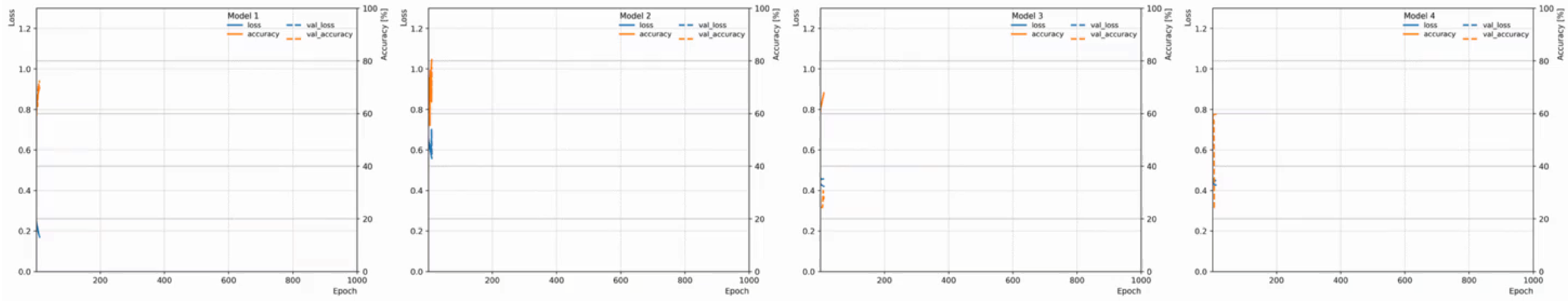


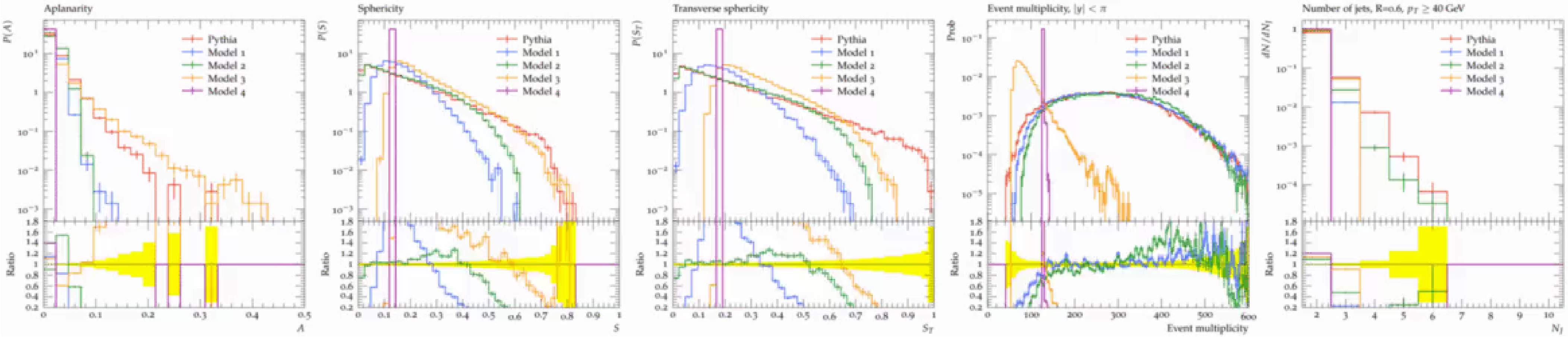




Proton-proton @ 7 TeV Training + Validation

Model 1	Model 2	Model 3	Model 4
ResNet-Huber	ResNet-BinCrossE	DenseNet small	DenseNet large





Proton-proton @ 7 TeV Training + Validation

Model 1	Model 2	Model 3	Model 4
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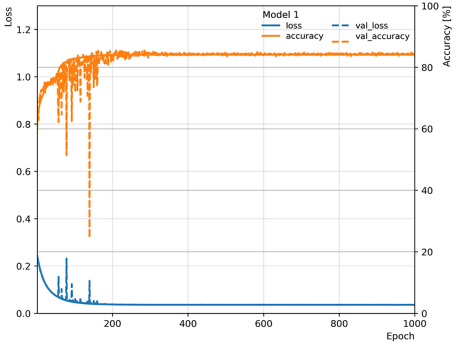
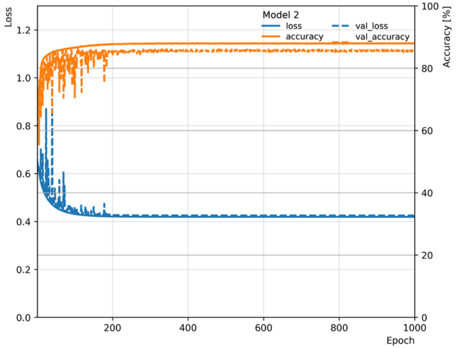
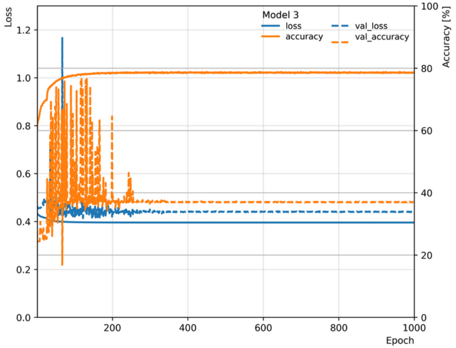
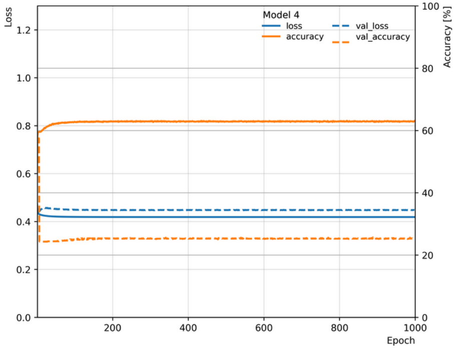
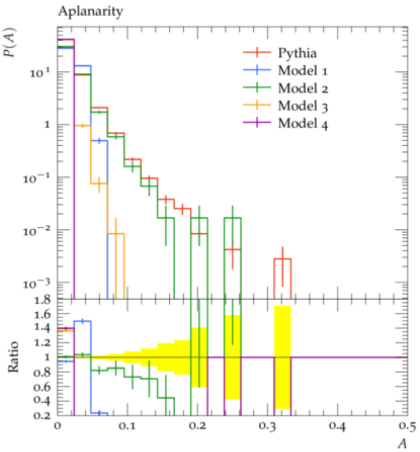
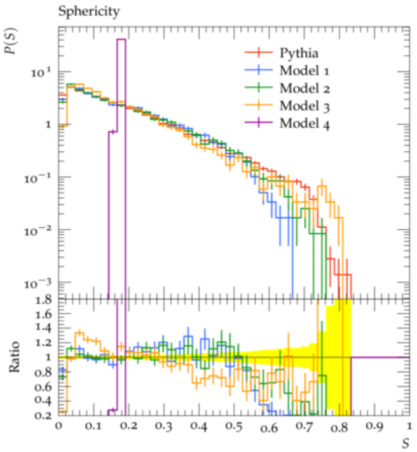


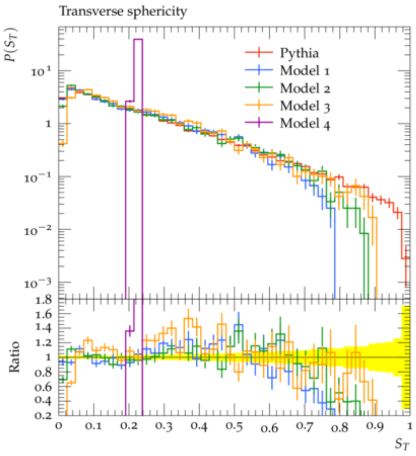


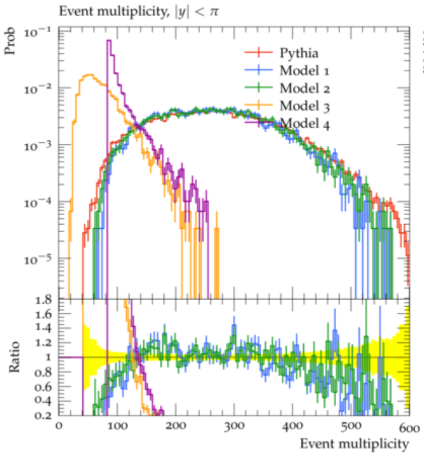


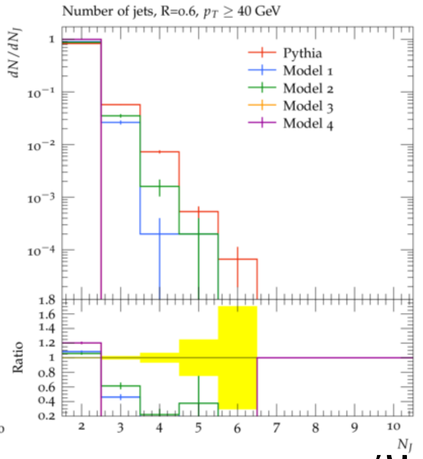






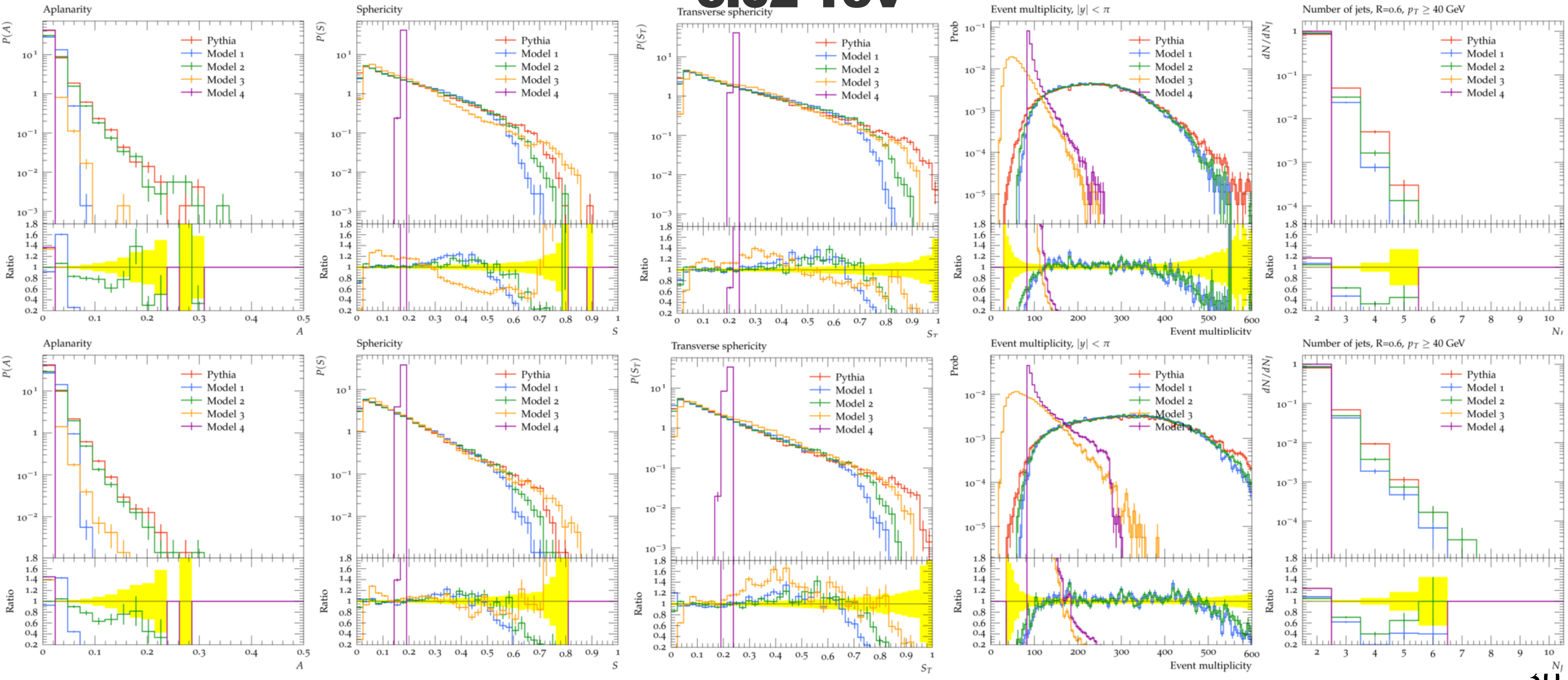






Proton-proton @ 5.02 TeV, 13 TeV Prediction

5.02 TeV



13 TeV

Summary

Traditional computer vision algorithms capture the main features of high-energy event variables successfully

Generalization to other CM energies: multiplicity scaling

Plans

Various architectures (hyperparameter fine-tuning)

Other observables (p_T, rapidity, particle species)

Heavy ion (centralities, collective effects)

The research was supported by OTKA grants K135515, K123815, NKFIH 2019-2.1.6-NEMZKI-2019-00011, NKFIH within the framework of the MILAB Artificial Intelligence National Laboratory Program and by the Wigner GPU Laboratory.

Thank you for your attention!