

# How machine learning changes particle physics

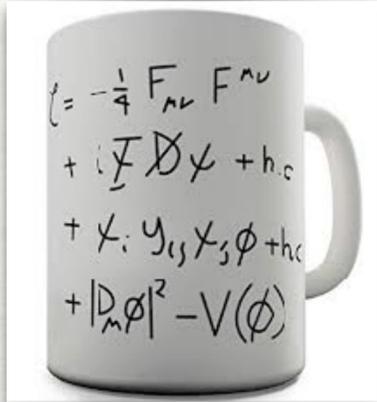
MIHOKO M. NOJIRI (KEK)  
ISCO2023 MARCH 1, 2023

# Particle physics

- Particle Physics has been answering big questions, and it keeps challenging remaining big questions
- Example
  - Higgs boson (explaining origin of mass)
  - Dark matter in the Universe
  - Origin of the matter
- Big Science connects people! ex CERN LHC ATLAS experiment: 3000 researcher 1200 PhD 42 countries, 182 Institutions

**and they are Science!**

# HOW PARTICLE PHYSICS RESEARCHWORKS ( DATA AND THEORY)



SM lagrangian

+

Prediction of yet unseen particles

" New Physics "

A few very precise data



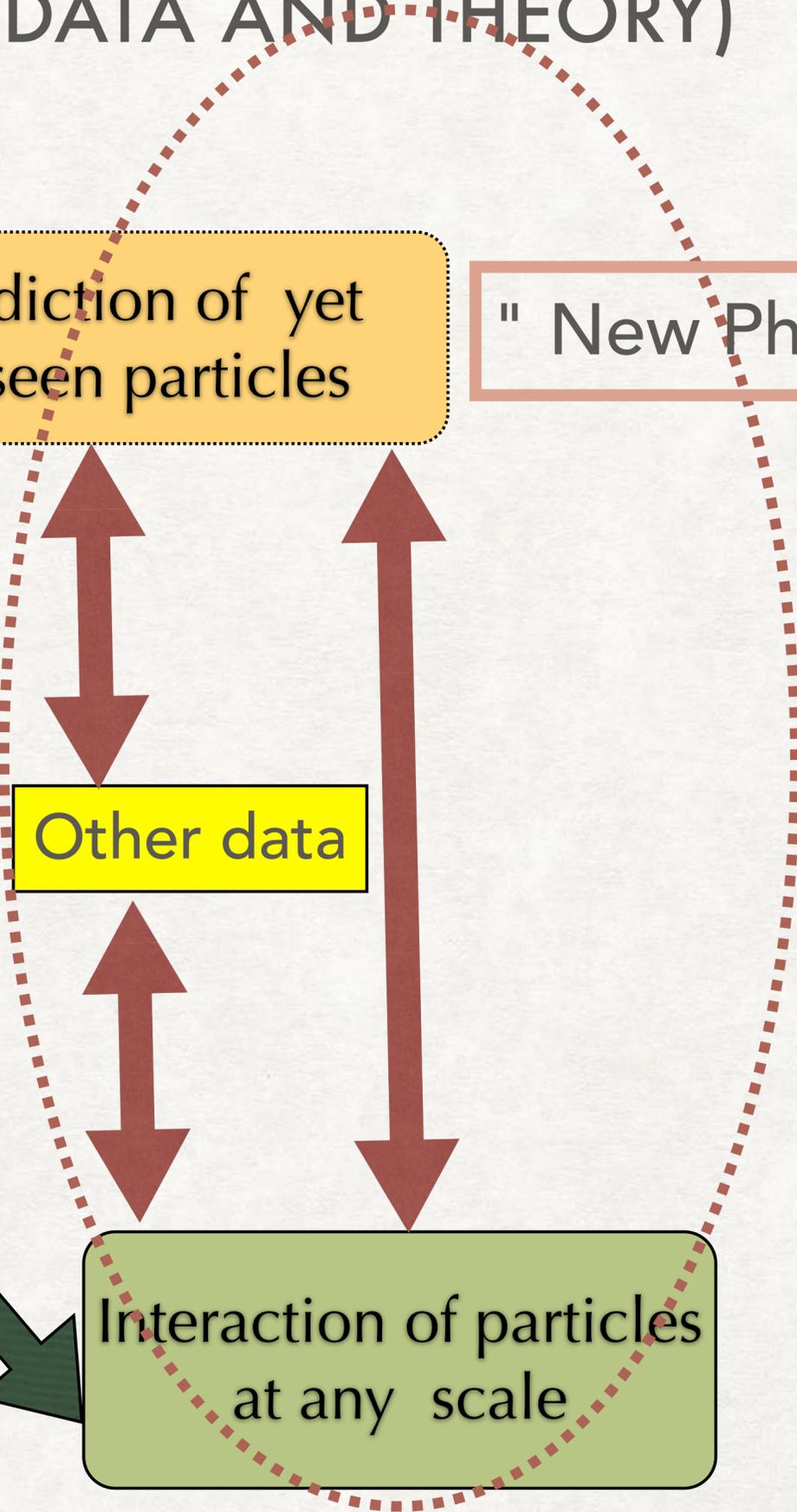
Field Theory  
Quantum Mechanics  
+ general relatively

Other data

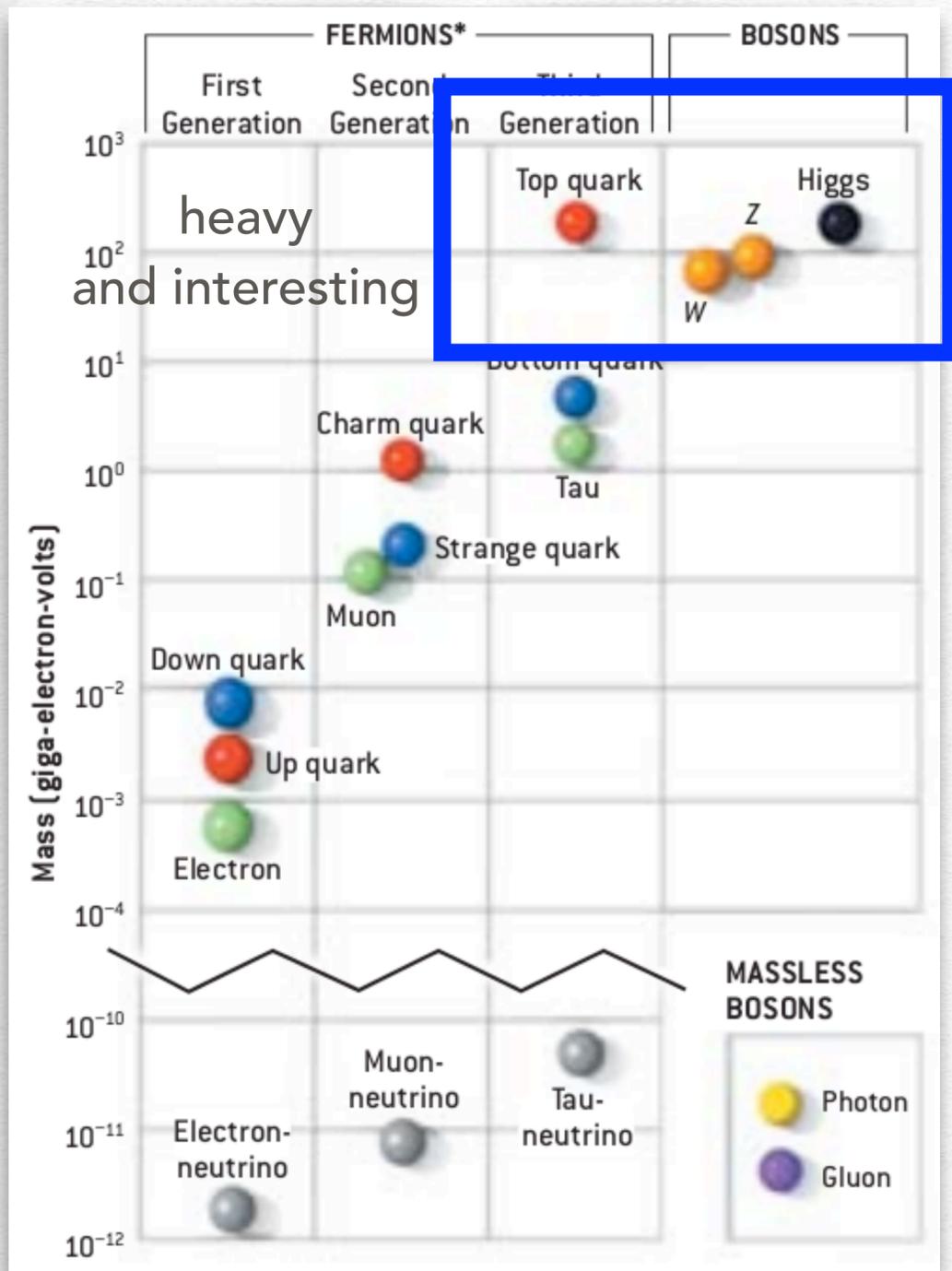
Phenomena at Early Universe  
.....

Predictions

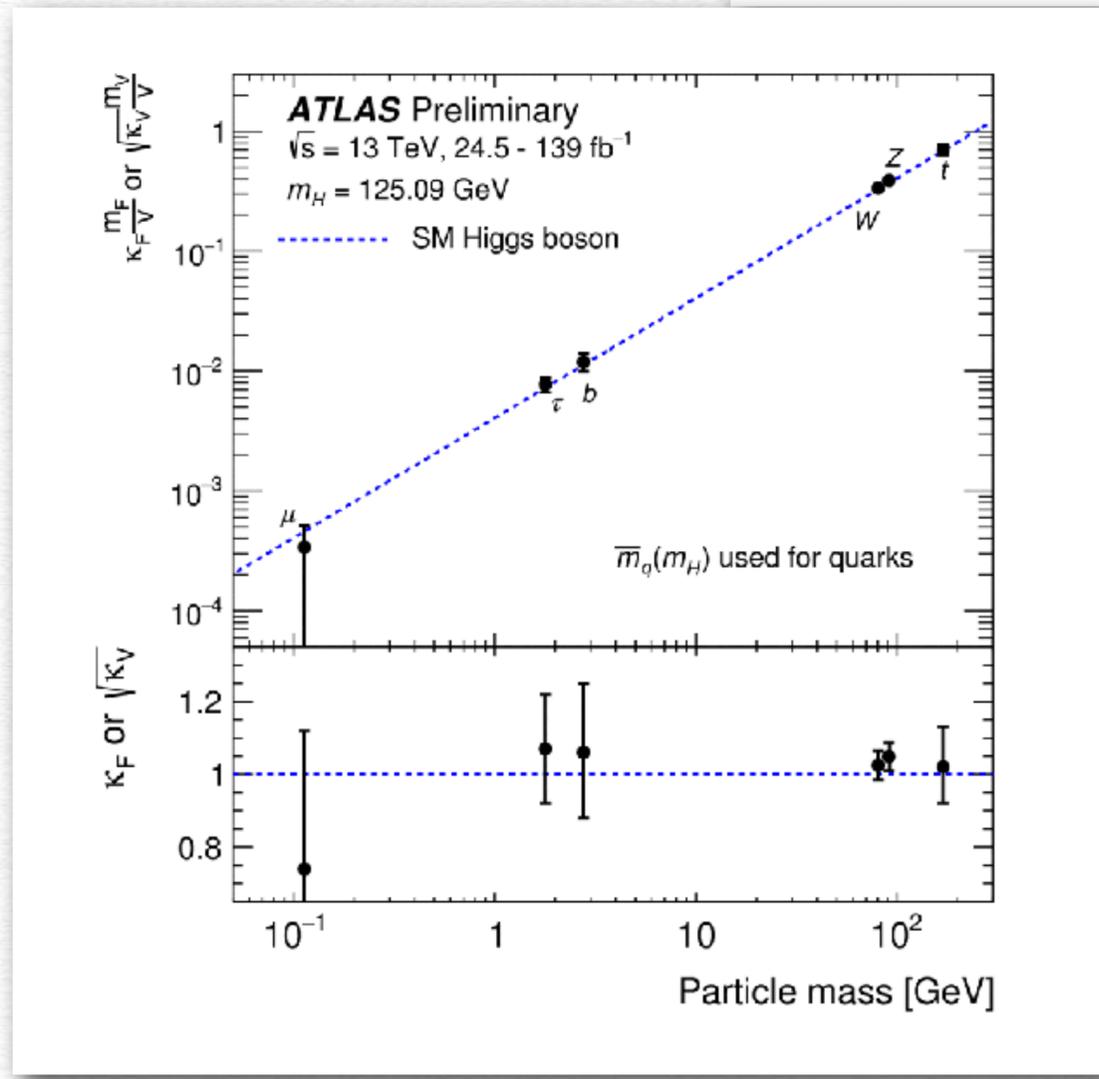
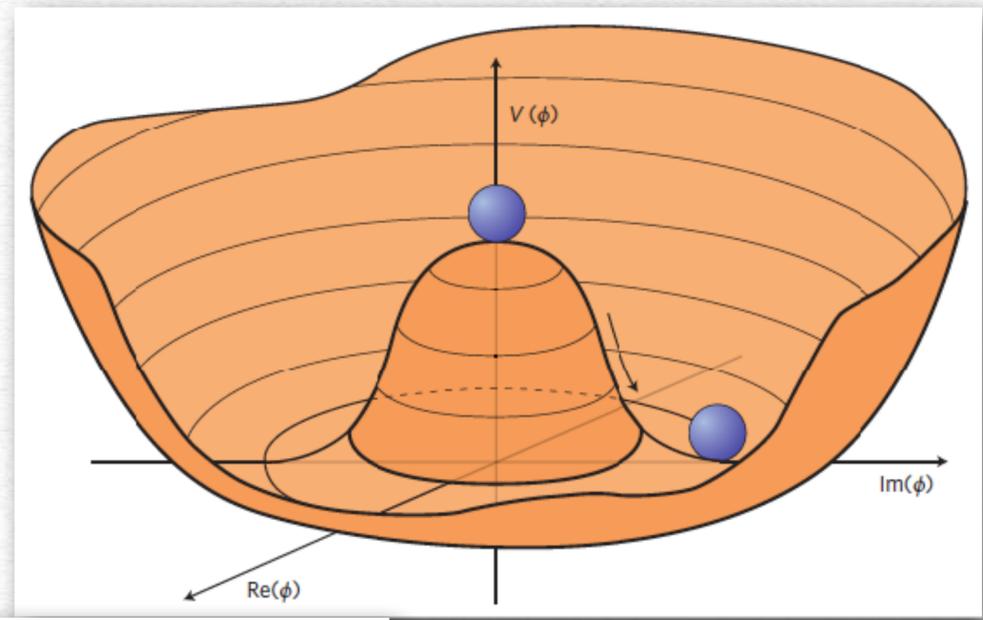
Interaction of particles at any scale



# LHC Higgs discovery and its nature

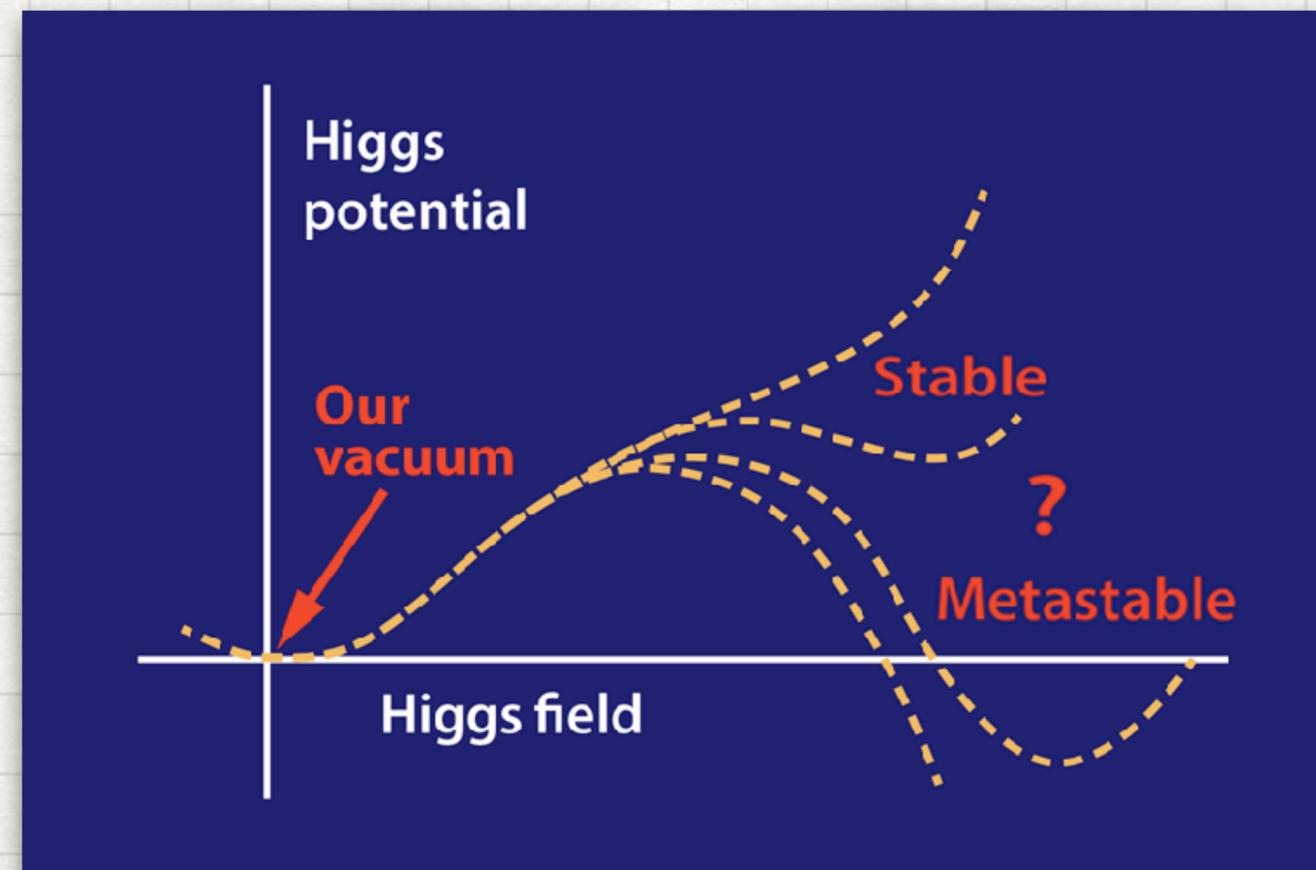
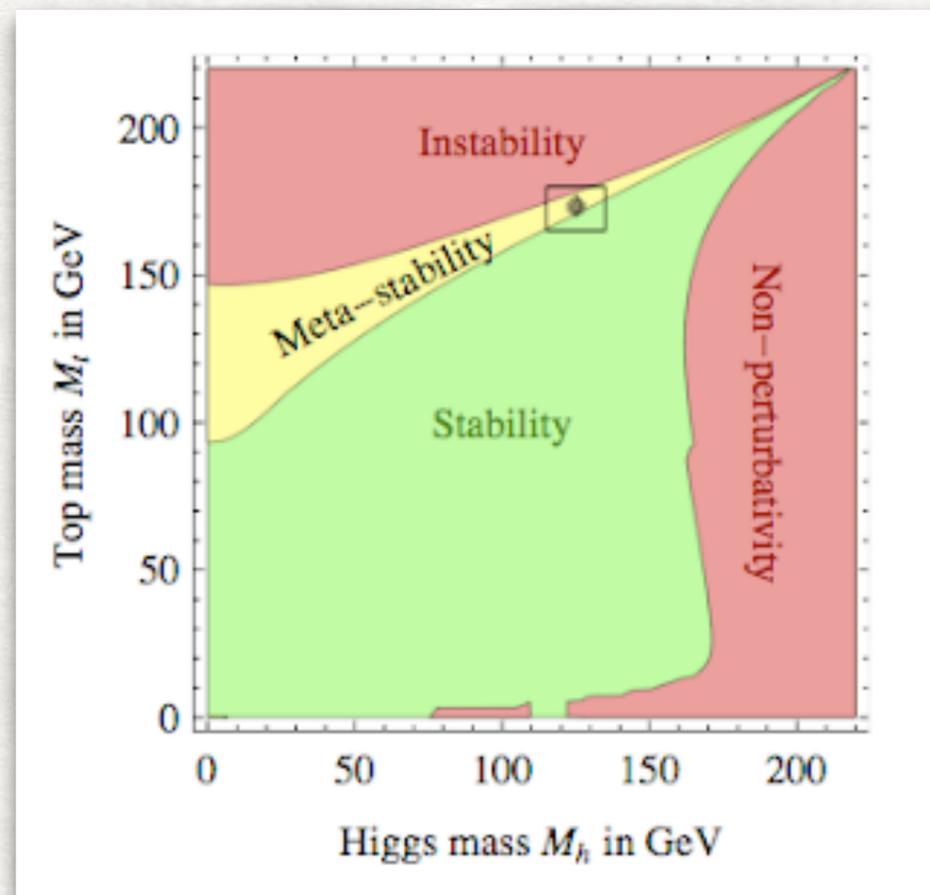


Higgs order param.  $v$   
 "yukawa coupling"  $y$   
 "particle mass"  $\sim yv$

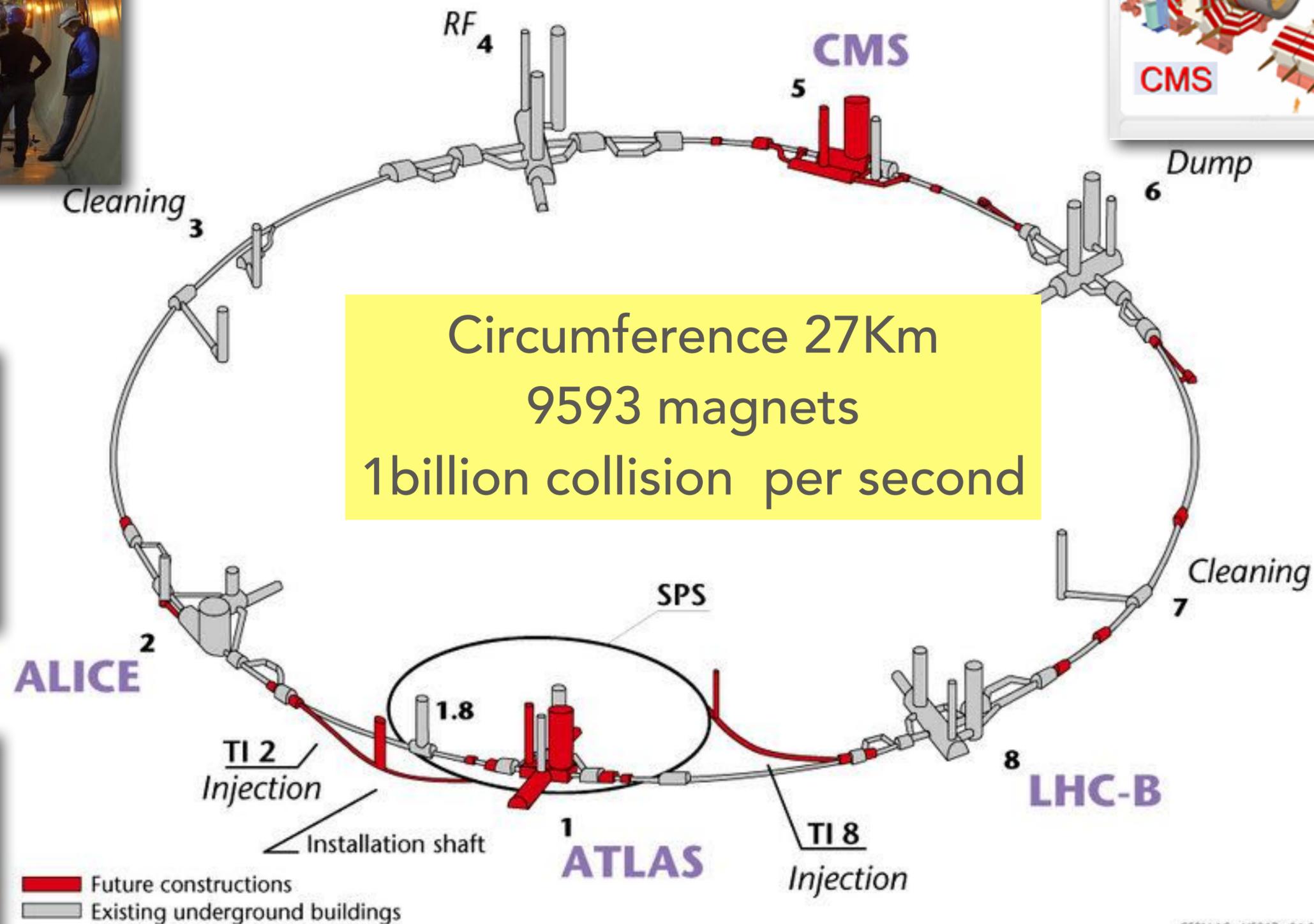
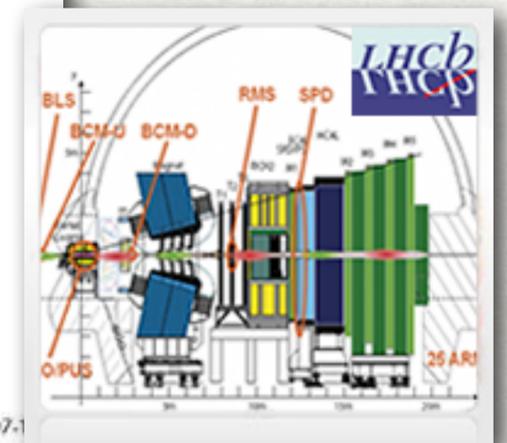
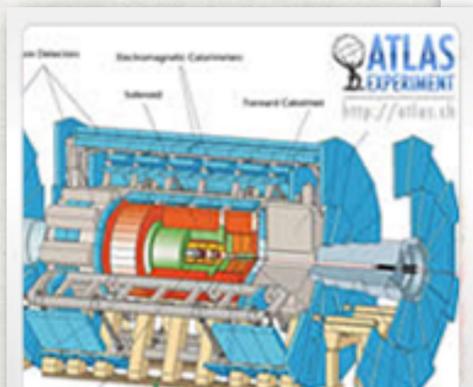
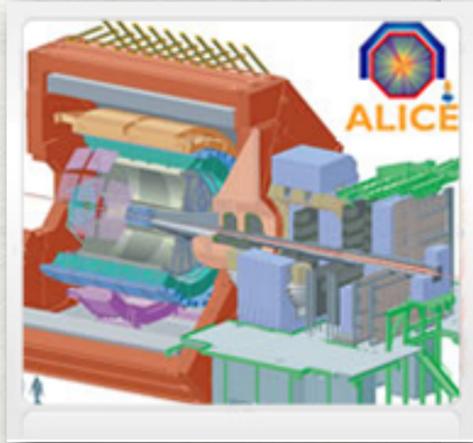
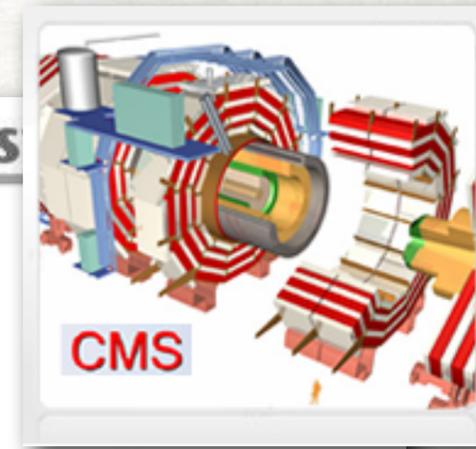


# HIGGS BOSON AND OUR UNIVERSE

- Our vacuum is not stable.
- This is problem! quantum mechanism says that the vacuum tunnel to the true vacuum sometime.
- We do not know how we settle in the current vacuum
- It is worth to study Higgs boson in detail!



# Layout of the LEP tunnel including future LHC infras

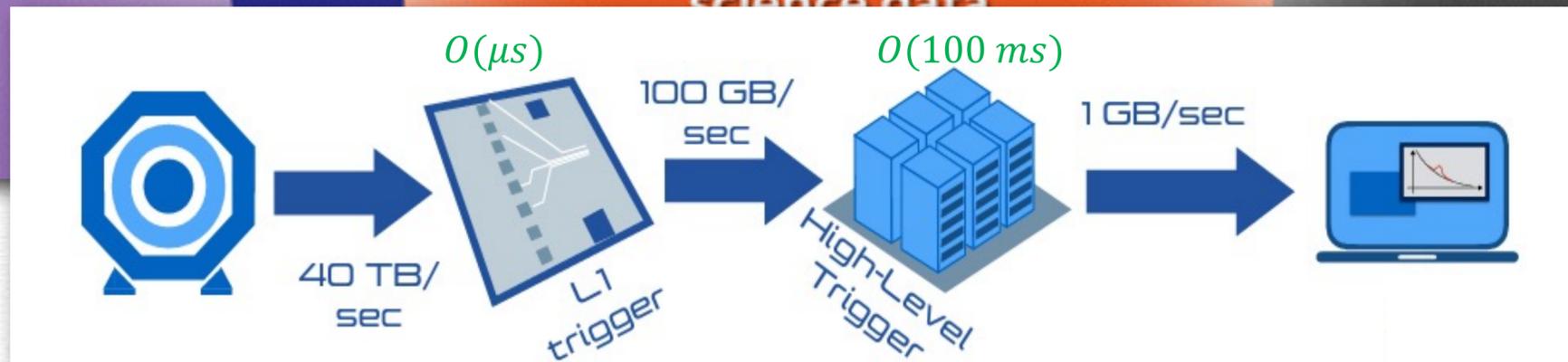


Circumference 27Km  
 9593 magnets  
 1 billion collision per second

# HL-LHC Challenge



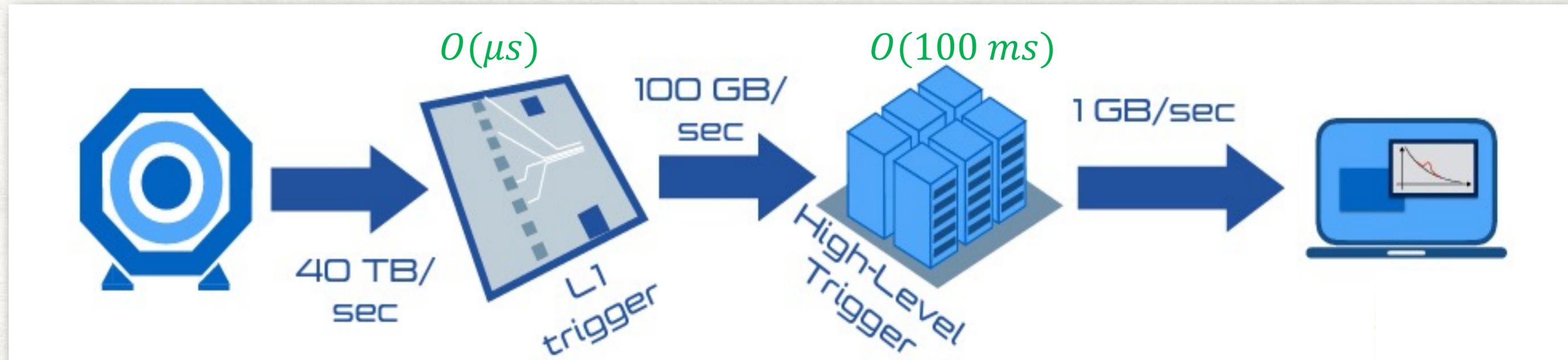
Highest Data rate in the Universe  
Can AI (Deep Learning) can help this?



# How ML can uncover "new physics" at LHC

- ❖ new particle production and its decay to known particles (such as top quark, Higgs boson) or unexpected distribution (deviation from SM)
- ❖ New gauge bosons, supersymmetric particles
- ❖ high energy top quark and Higgs boson can be signal
- ❖ Identify unexpected events (anomaly search)
  - ❖ Select "strange events" among huge event samples
  - ❖ dark matter, hidden sector particles (dark photons)

# HOW ML HELP EXPERIMENT ITSELF



- High rate + many data (factor 100 increase)
- We have to process event 10 times faster (reconstruct, recognize important events, record it)
- Whole system should not exceed computing budget, and naively it will exceed (because the roadmap takes into account improvements by "R&D")

# "ML at HEP workshop" in Japan

23-24 February 2023

KEK (High Energy Accelerator Research Organization)

Asia/Tokyo timezone



量子場計測システム国際拠点

International Center for Quantum-field Measurement Systems for Studies of the Universe and Particles

WPI research center at KEK

Overview

Timetable

Registration

Participant List

Poster session

Venue and access to KEK

Covid-19 measures at KEK

Accommodations

Information about entries to Japan

Restaurants

We are delighted to announce that the "ML at HEP workshop" will be held from February 23rd to 24th, 2023. After a successful workshop in 2022, this is our first time to organize such a workshop together with leading researchers on Machine-Learning together with researchers in high energy physics.

The scope of the workshop is to overview the current status of ML & AI in HEP and beyond, and to provide lively discussions about the directions of ML & AI technical developments in the field.

The topics of the workshop program include:

- Advanced ML techniques useful for HEP,
- Advanced architectures for ML,
- ML applications in HEP and beyond,
- Advanced applications at accelerators and systems, and
- Future directions in ML and AI x HEP and beyond.

The workshop format is hybrid (in-person at KEK and online via zoom). Presentations are given by

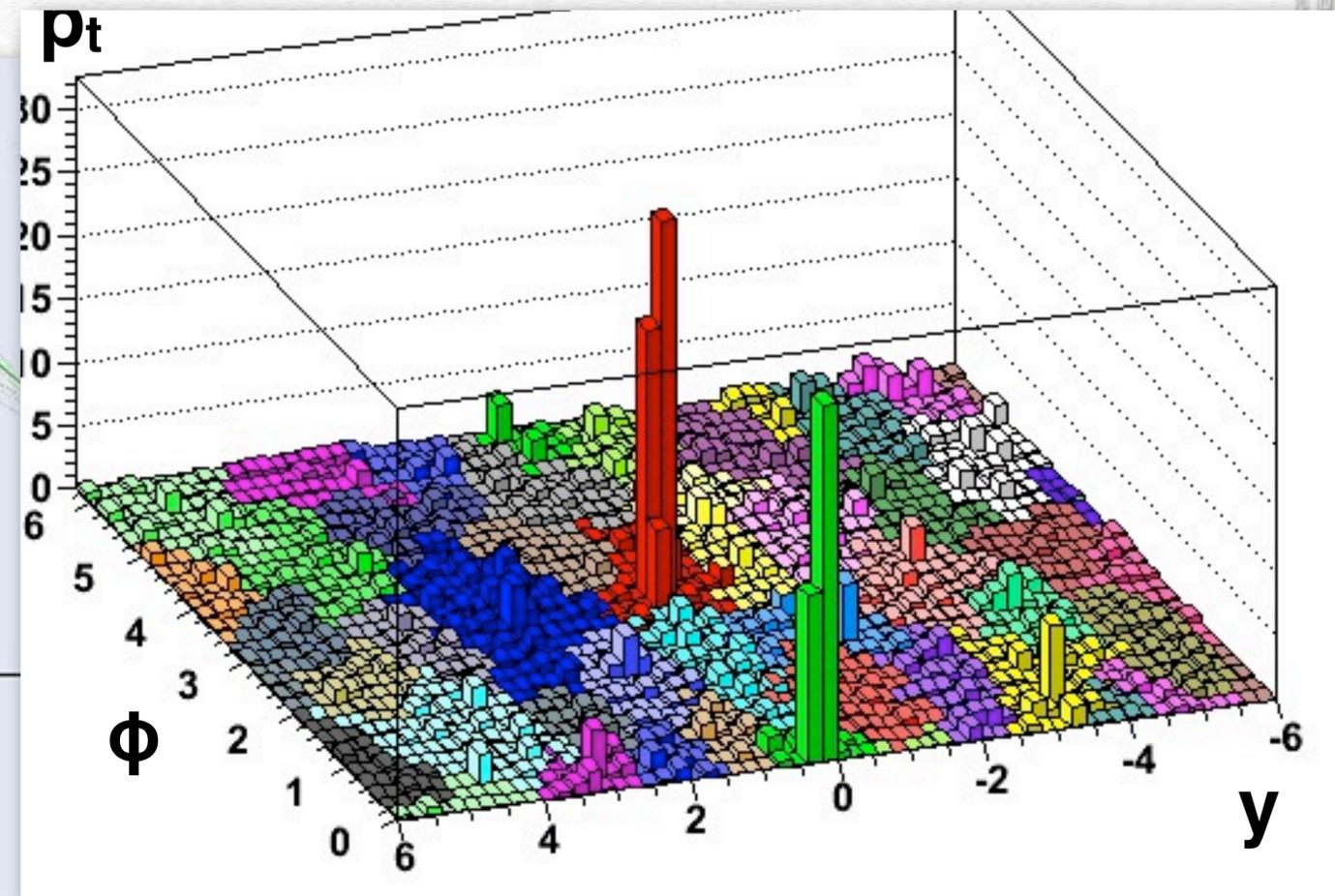
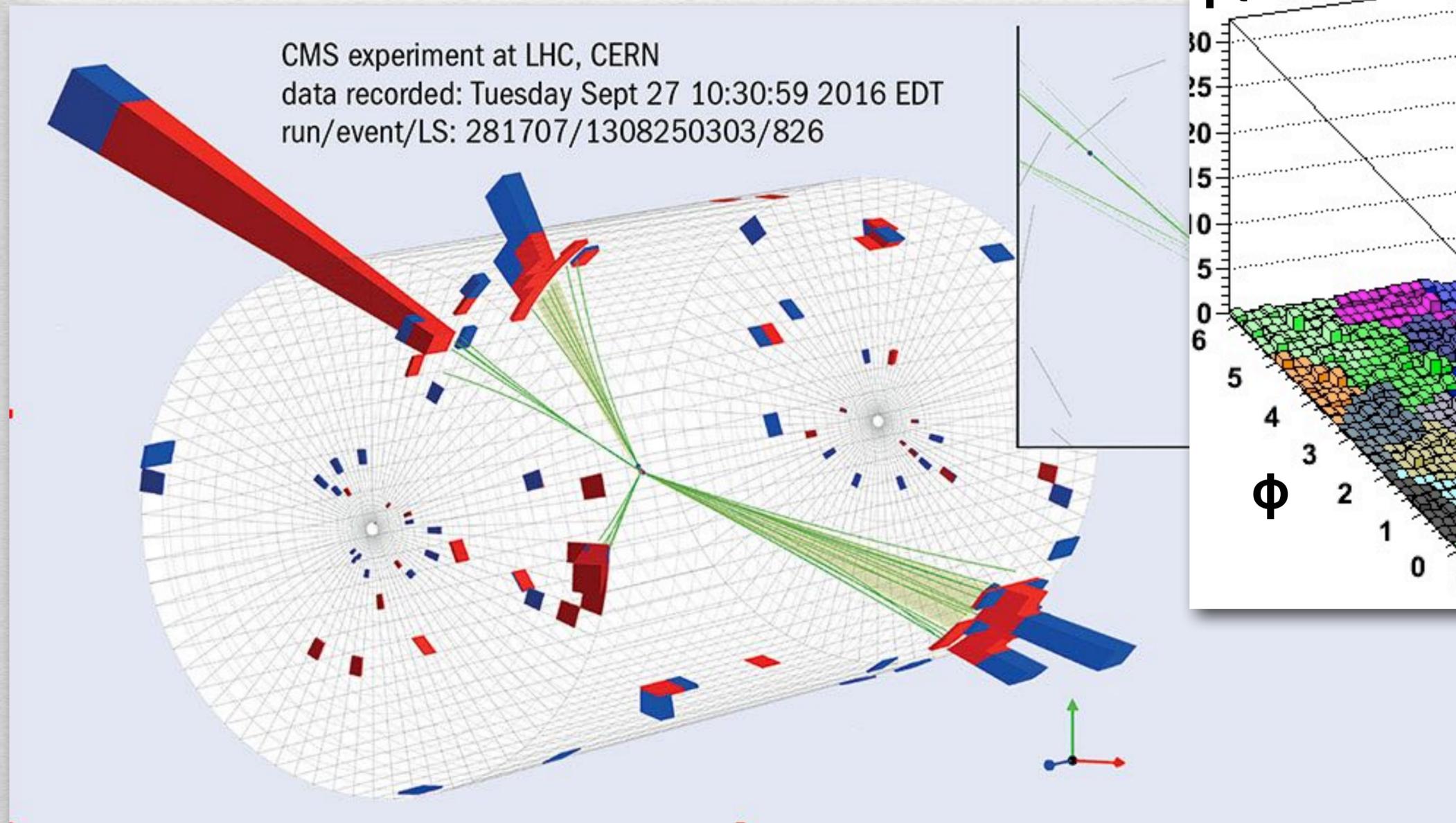
## MLPhYs Foundation of "Machine Learning Physics" Grant-in-Aid for Transformative Research Areas (A)

Most of the subject of my talks  
can be found here

<https://kds.kek.jp/event/44830/>



# How machine Learning help Analysis

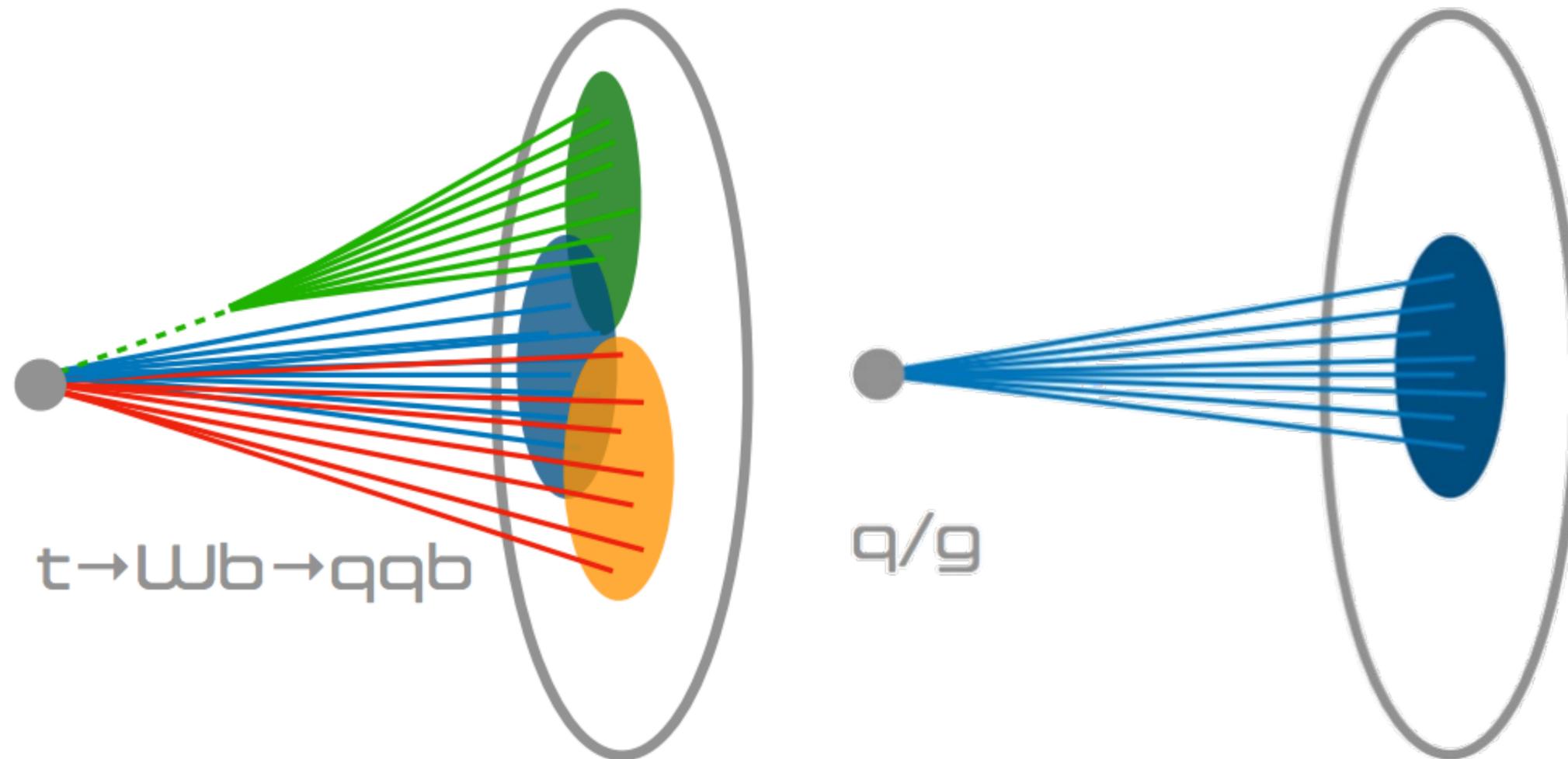


Jet clustering

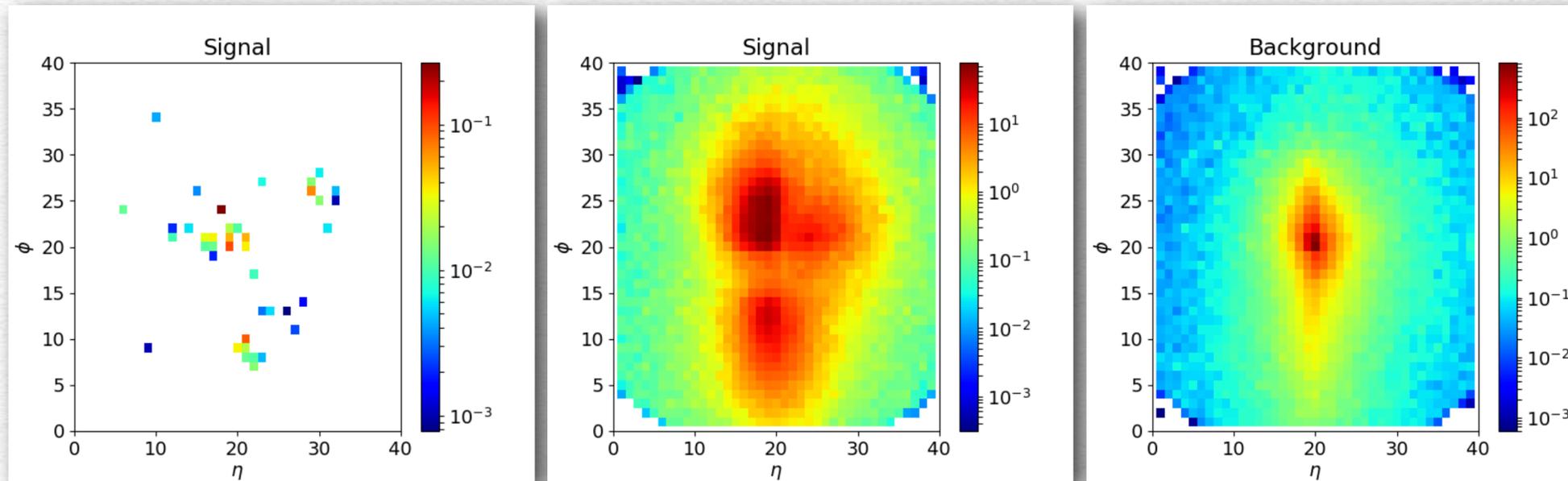
top quark at CMS

# Example boosted top identification

**Task:** Top-quark jets vs single quarks/gluons

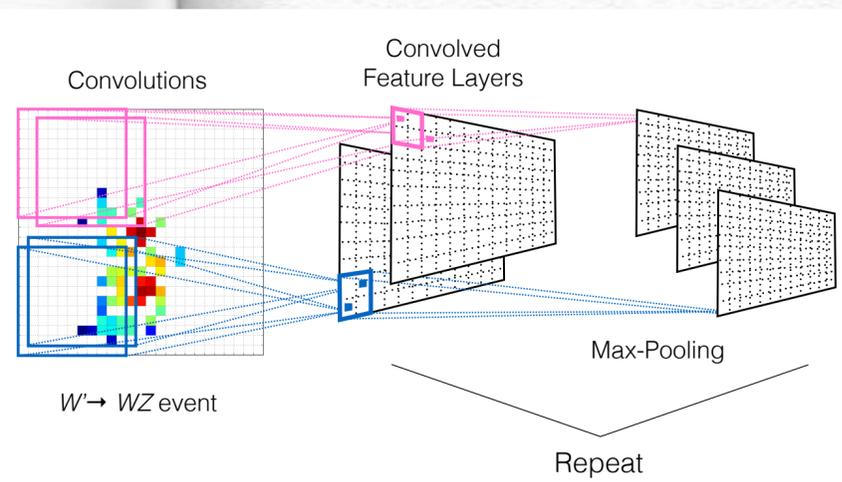


# New Physics search with ML



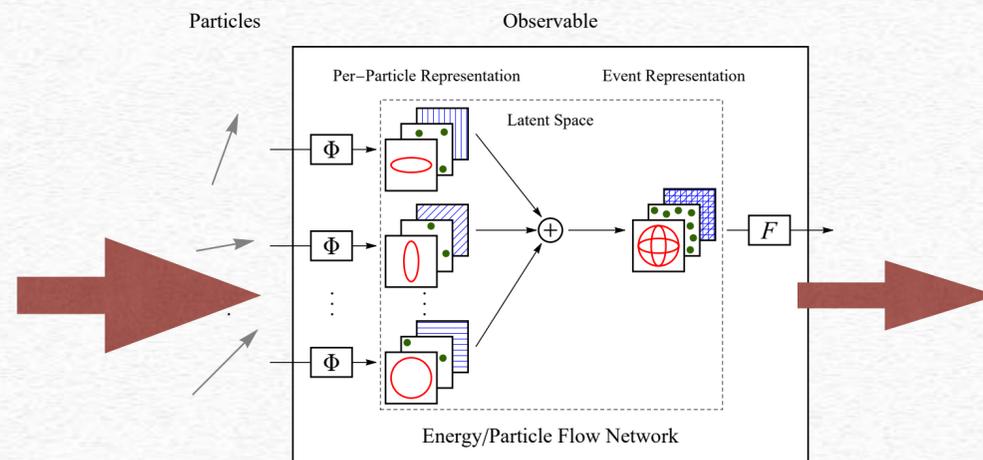
high energy top quark  
is similar to light quark and gluons  
but there is some difference

Jet as Image



CNN(2014)

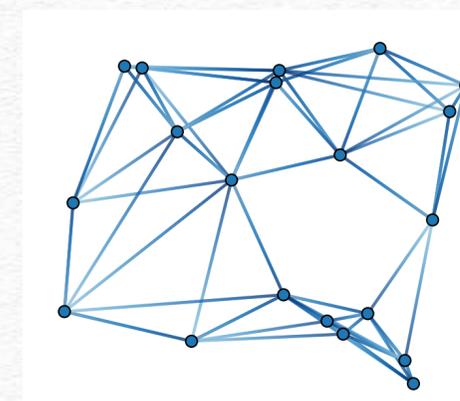
as sets



permutation invariance  
(stable)

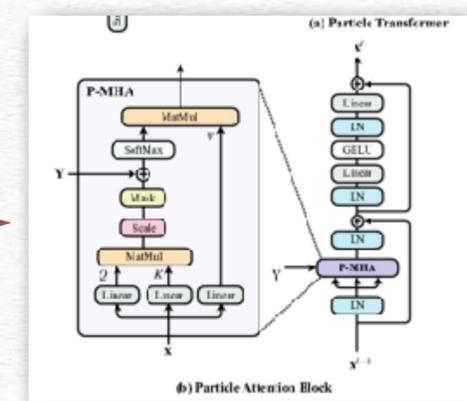
Easy to implement  
QCD "values"

as graphs



sparse data  
1902.08570  
Particle Net  
Lorentz net  
( Graph respect special relativity)

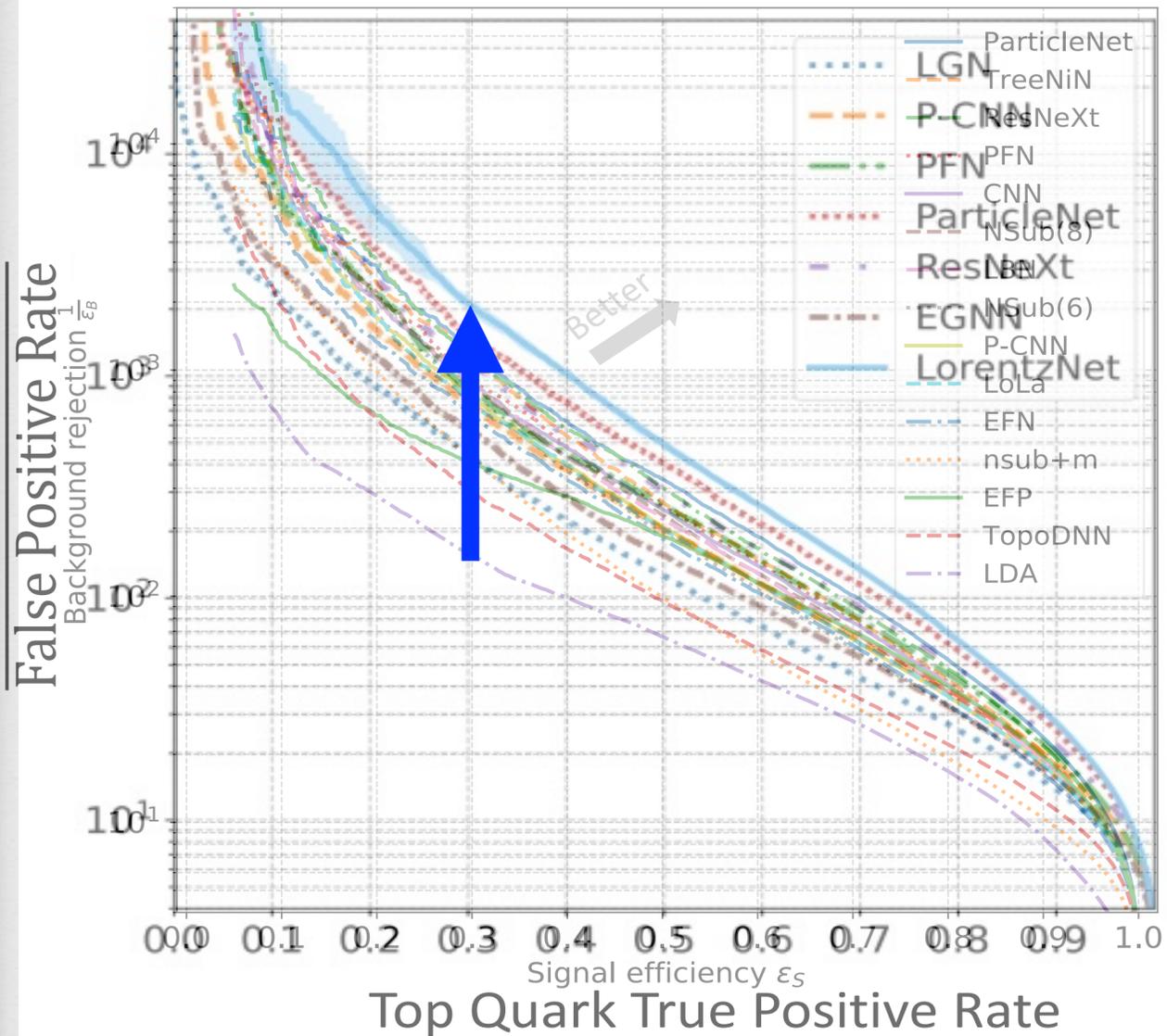
transformer



building key  
and query  
2202.03772

2018 to 2021

## Improved Performance



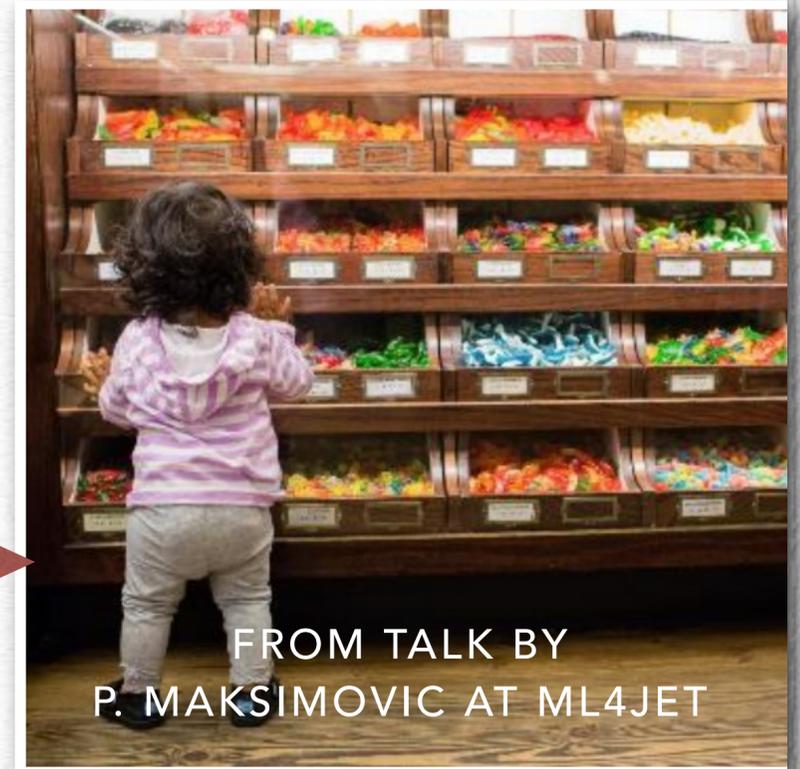
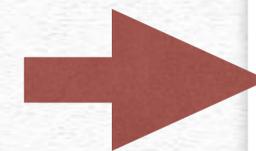
[2201.08187](#)

More than factor 10 reduction of background  
→ current cross section limit improve by factor 10

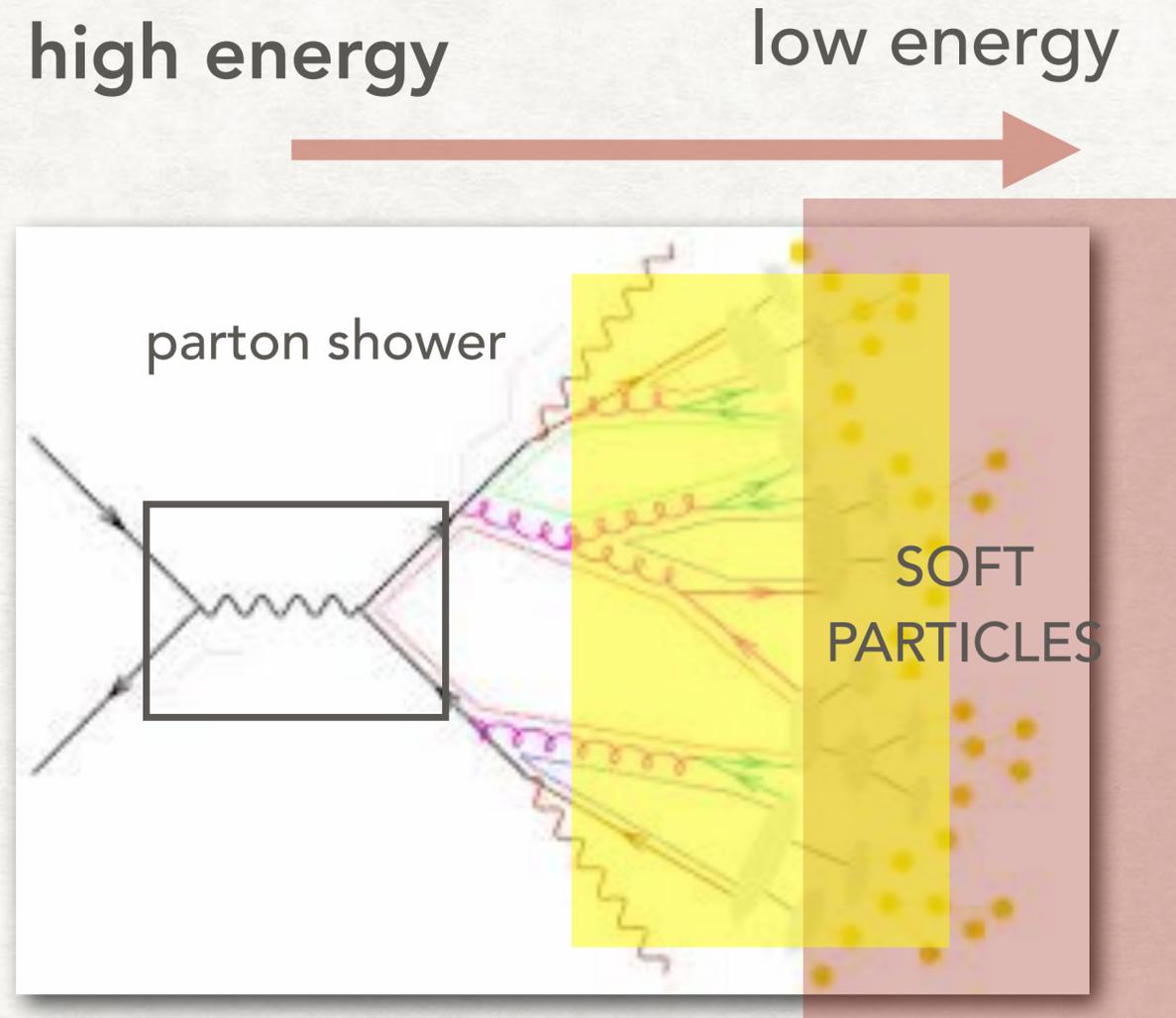
## Two questions

- ★ if it improve drastically, "why theory cannot explain it?"
- ★ Theorists start to get complaint from experimentalists that performance isn't that impressive.

"an experimentalist wondering why they cannot touch the top of the shelf "



# MACHINE DOESN'T CARE PHYSICS VALUES



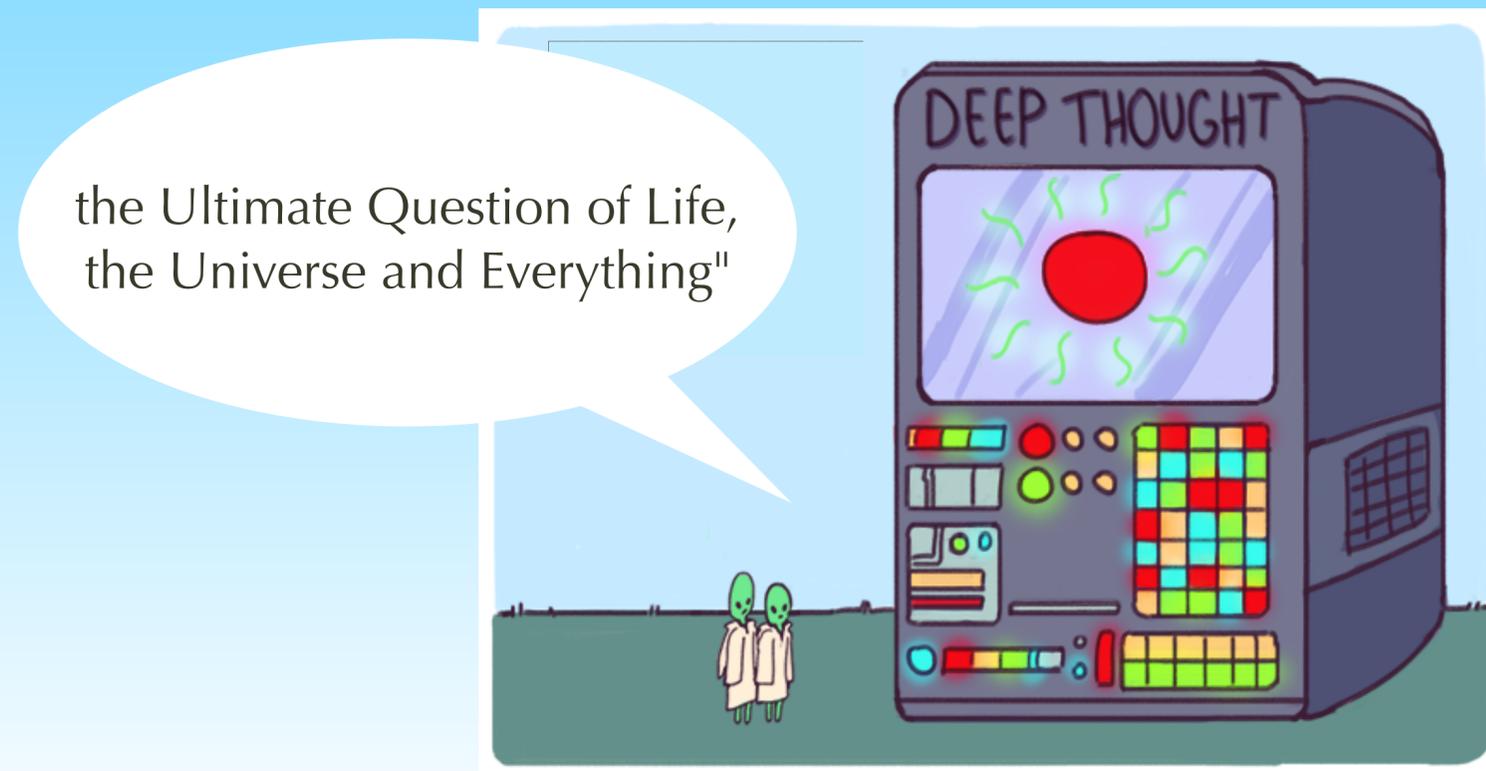
MESSAGE

Modern Deep learning models take into account ALL correlation.

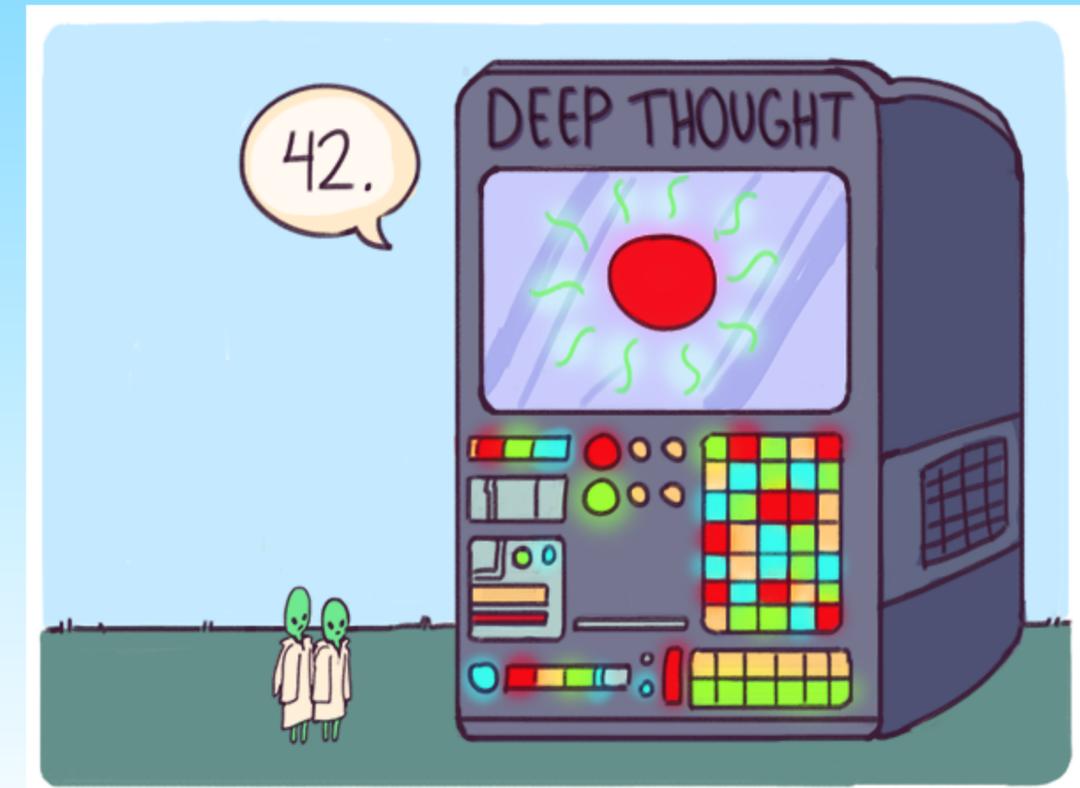
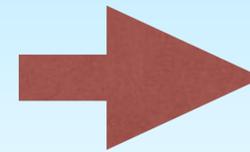
HEP analysis need simulation and we need updated our simulation to be consistent at all energy.

- IRC (infrared collinear) safe quantities : theoretically predictable
- IRC "sensitive" quantity: (soft physics) (ex low energy particles, number of particles)  
Difficult to predict theoretically because of the divergence of the theory. We need modelings but they often do not agree with data.
- **Soft physics might be useful** because low energy particle distribution has information of branching history strong interaction. just we need careful calibration

# About asking "something" to computer



750M years



*" I think the problem, to be quite honest with you, is that you've never actually know what the question is"*

*"So once you do know what the question actually is, you will know what the answer means"*

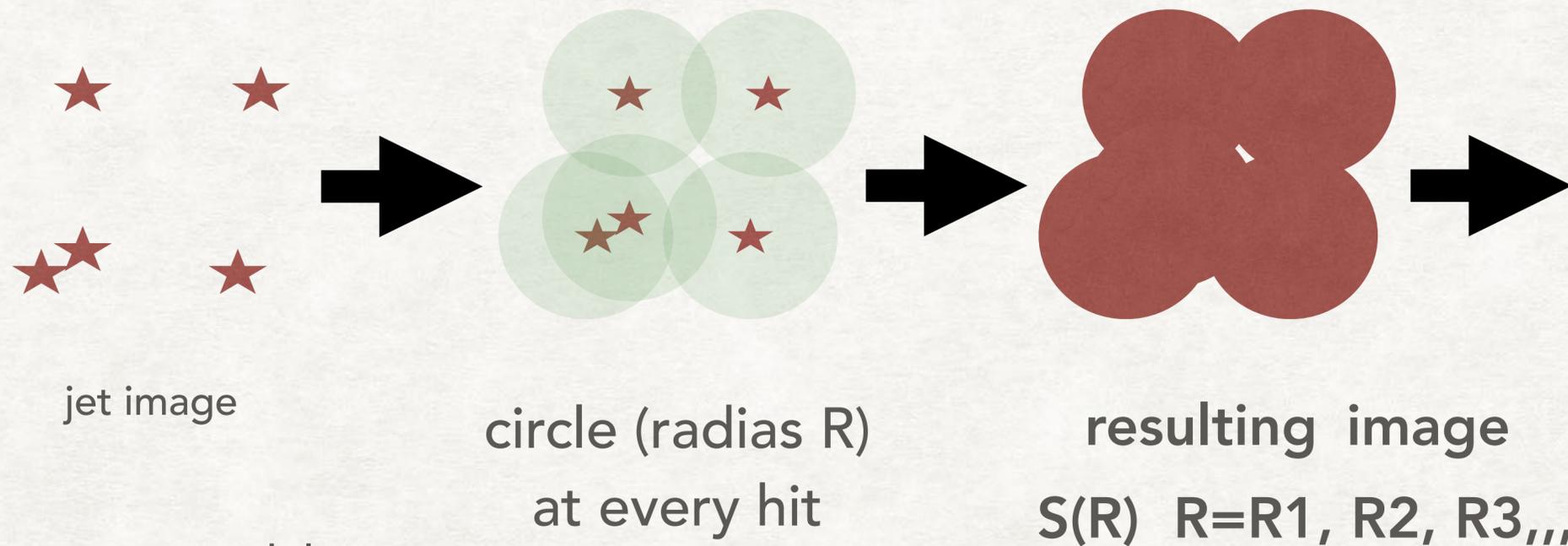
from "The Hitchhiker's Guide to the Galaxy"

by Douglas Adams



**Physics ≠ Getting good results by using ML and satisfy**

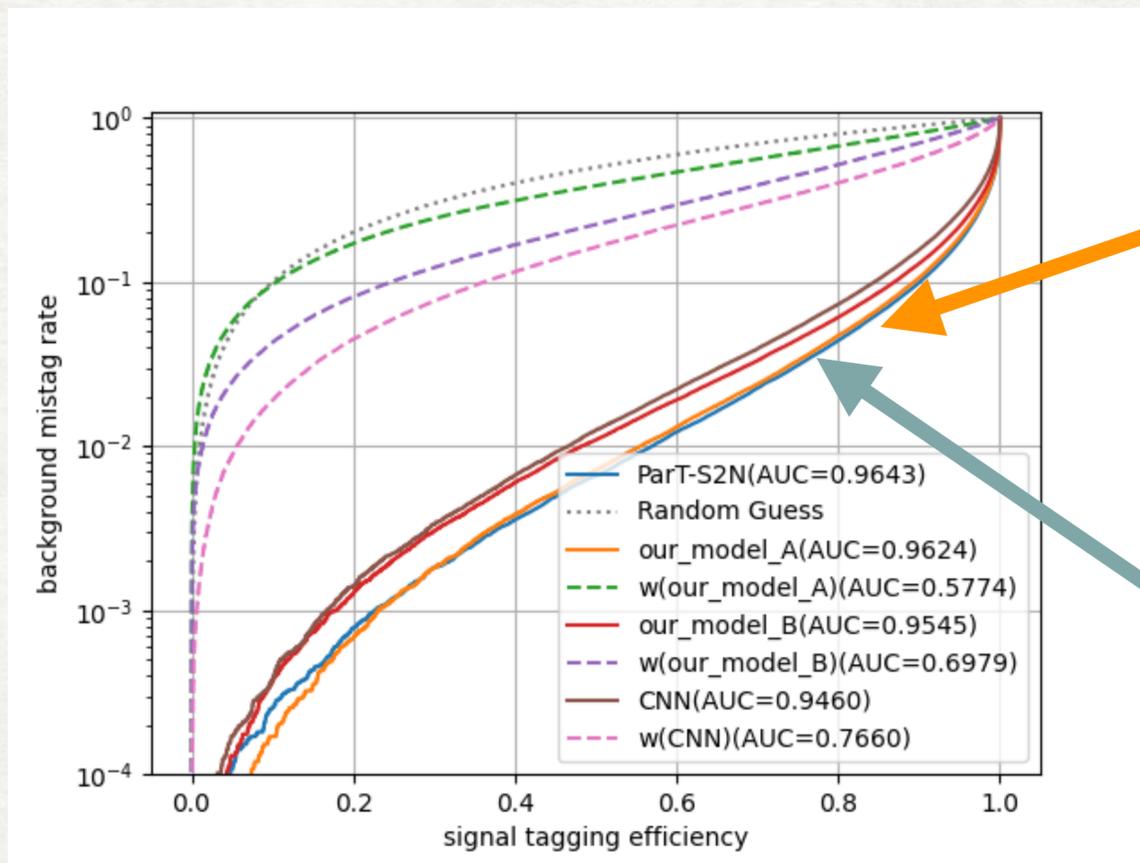
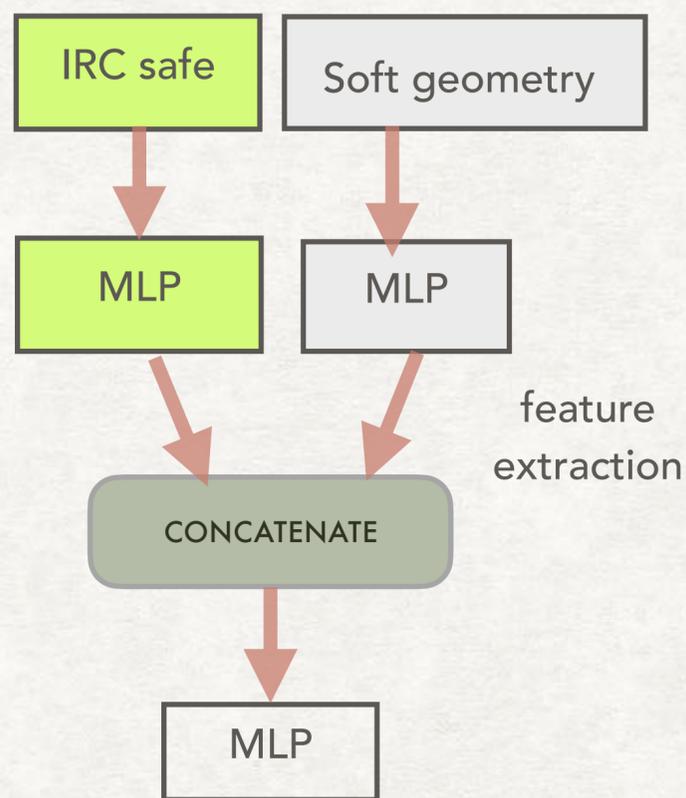
# SOFT PARTICLE GEOMETRY



Area ( $A$ ), boundary length ( $L$ )  
Euler character ( $E$ ) of  $S$  ( $R$ )

1. compress sparse data into real numbers
2. resilient to fluctuation of the inputs
3. permutation invariant

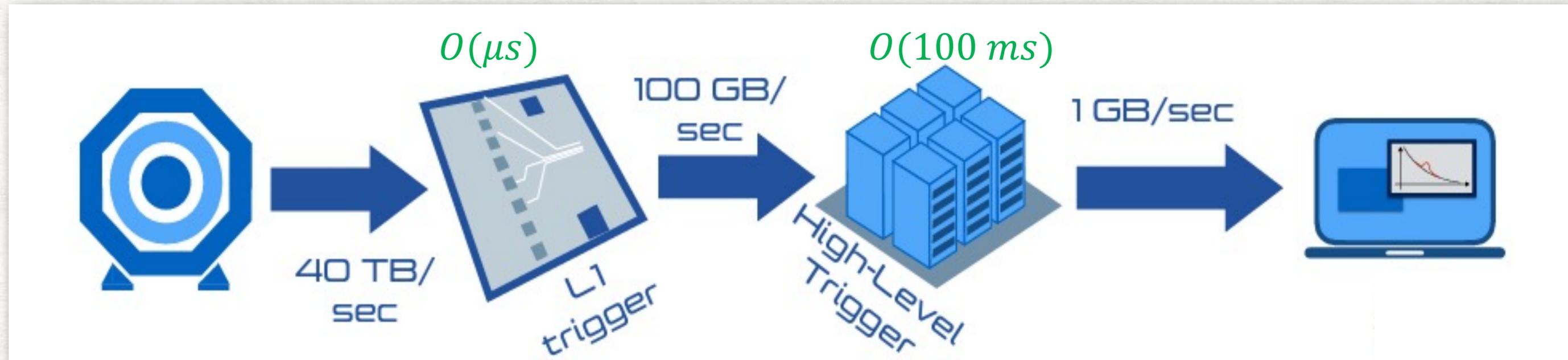
soft geometry model



**soft geometry model**  
inputs has clear interpretation  
on distance scale  
→ easy to infer the reasoning  
**Maybe we can create  
better simulation by DL**

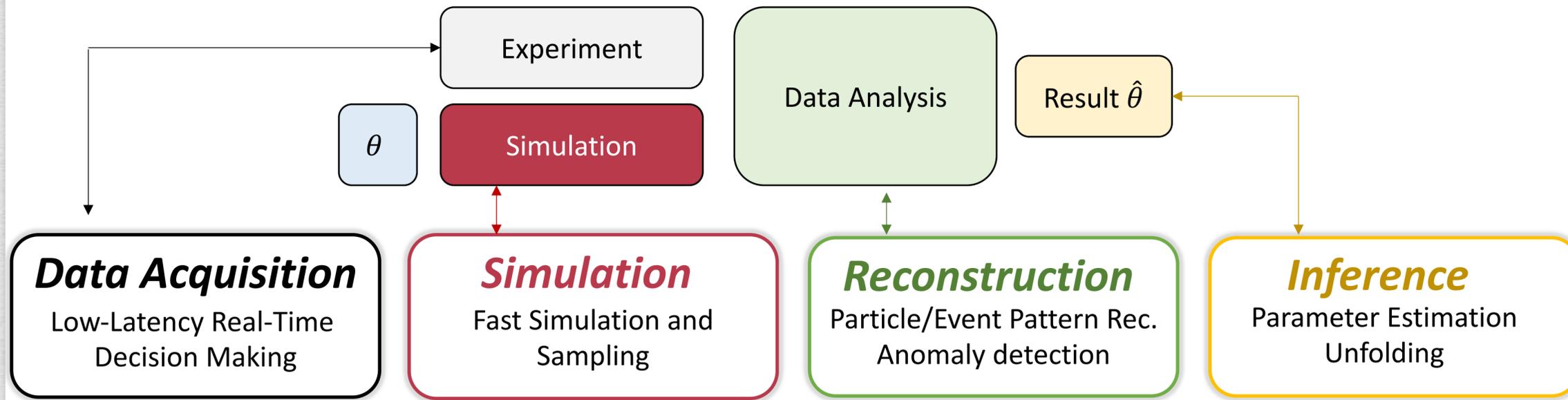
Particle Transformer  
(current world best set up )

# HOW ML HELP EXPERIMENT ITSELF

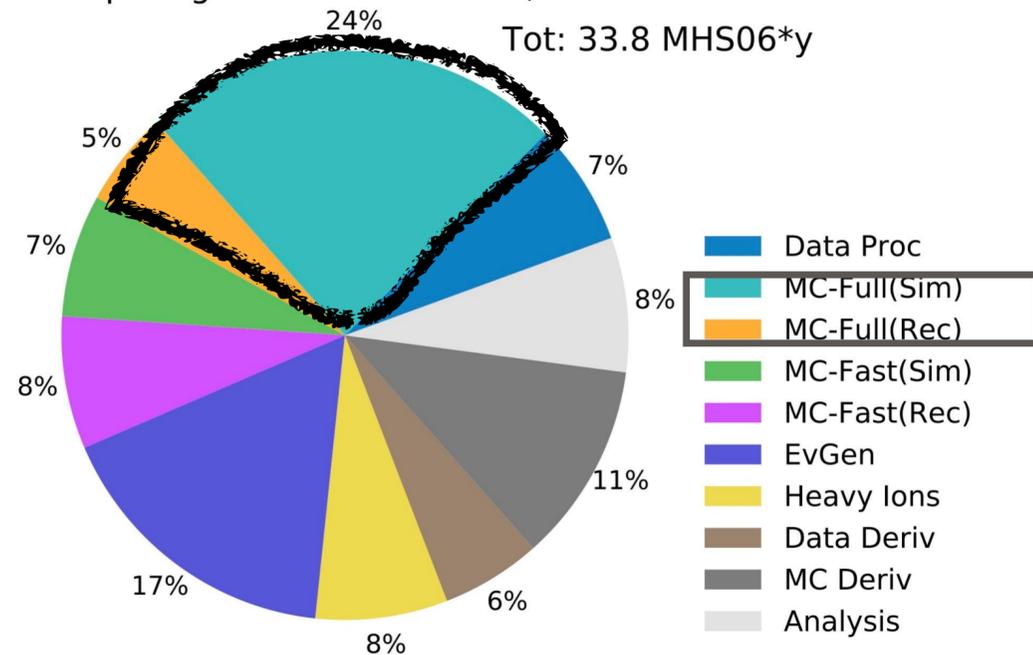


- High rate + many data (factor 100 increase)
- Experiment should process events 10 times faster (reconstruct, recognize important events, record it)
- Whole analysis chain should not exceed computing budget, and naively it exceeds (because the roadmap takes into account improvement by "R&D")

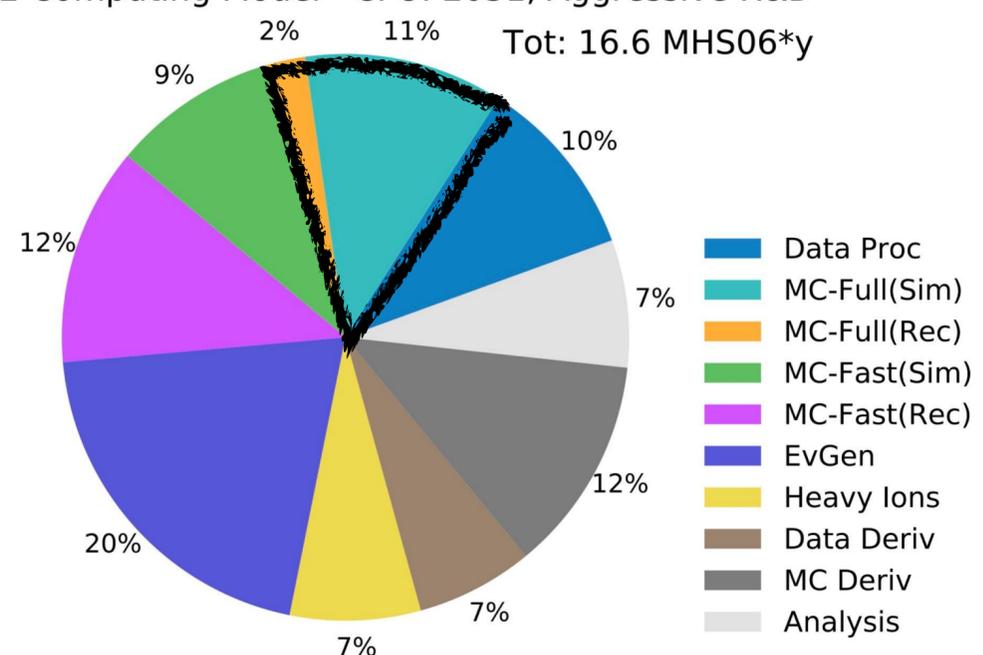
# Machine Learning Across Data Analysis



**ATLAS Preliminary**  
2022 Computing Model - CPU: 2031, Conservative R&D



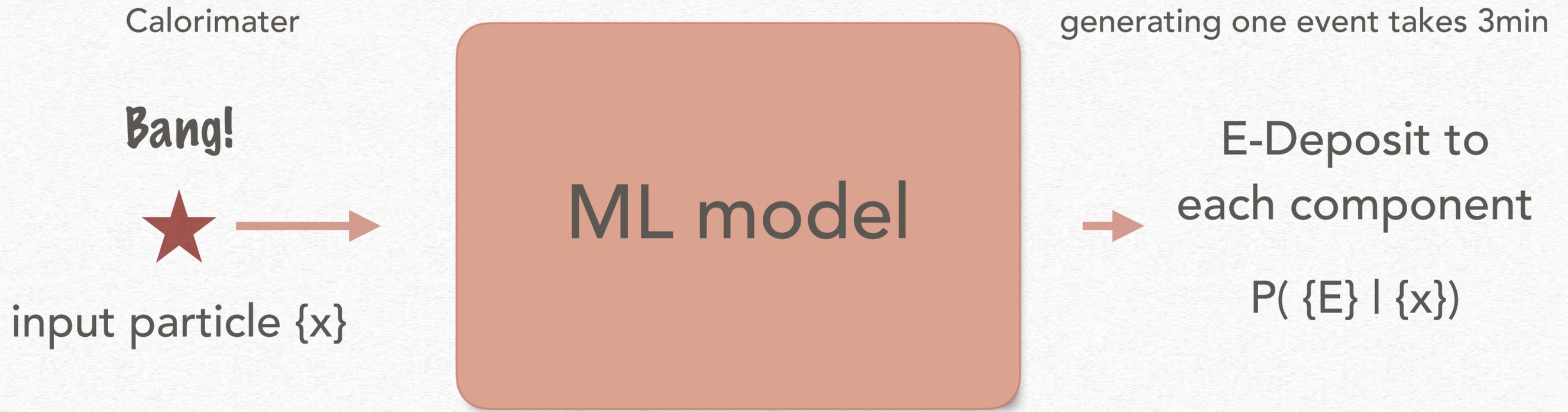
**ATLAS Preliminary**  
2022 Computing Model - CPU: 2031, Aggressive R&D



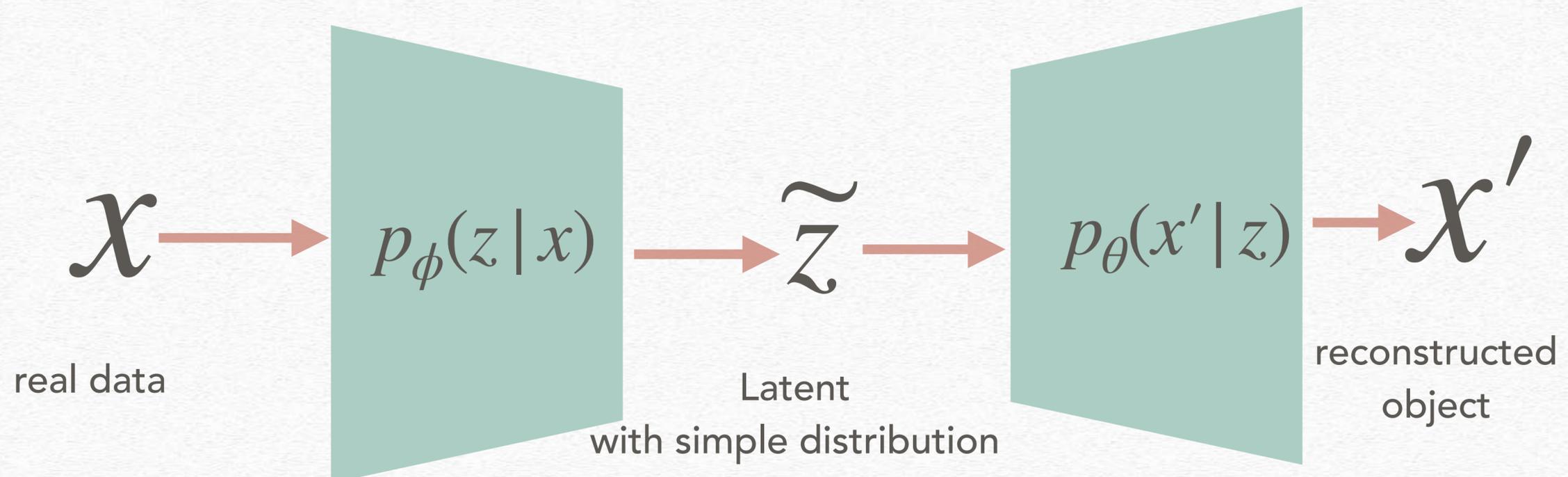
Aggressive R&D assume improvement by ML

Kagan "ML at HEP"

# event generation by ML



Variational AutoEncoder(VAE): bottle neck structure  $x \rightarrow z \rightarrow x'$



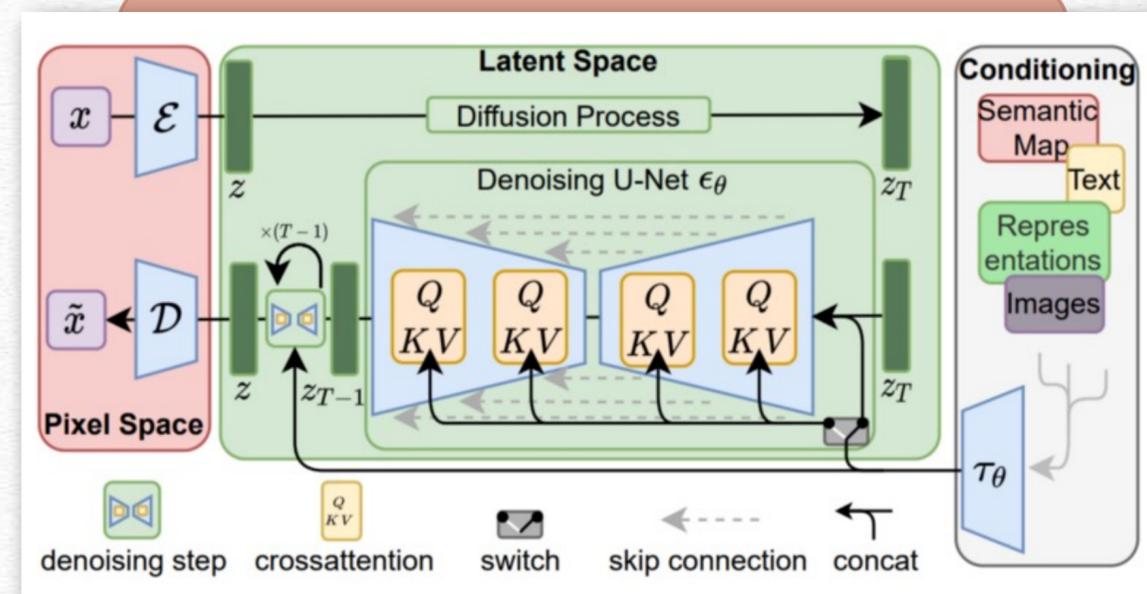
# event generation

Calorimeter

**Bang!**



input particle  $\{x\}$



E-Deposit to  
each component

$$P(\{E\} | \{x\})$$

## ML toolbox

GAN:  
competition between  
generator and discriminator

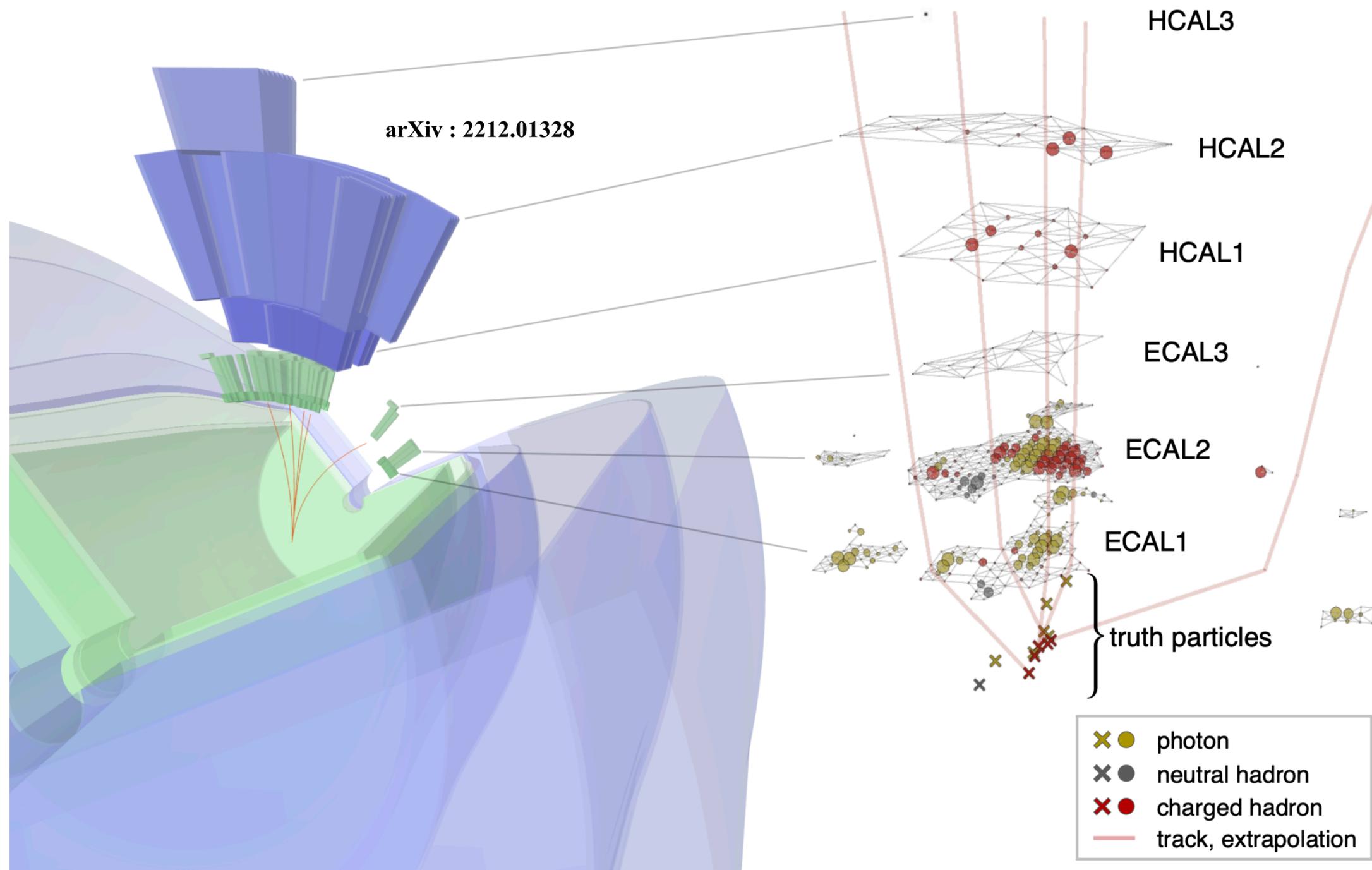
Normalizing Flows:  
map simple distribution to  
nontrivial function

Diffusion : Add noise step by step

Once we complete this map, we have fast and more precise model for everybody (even theorists). DL model is differentiable so that you can do parameter search using ML



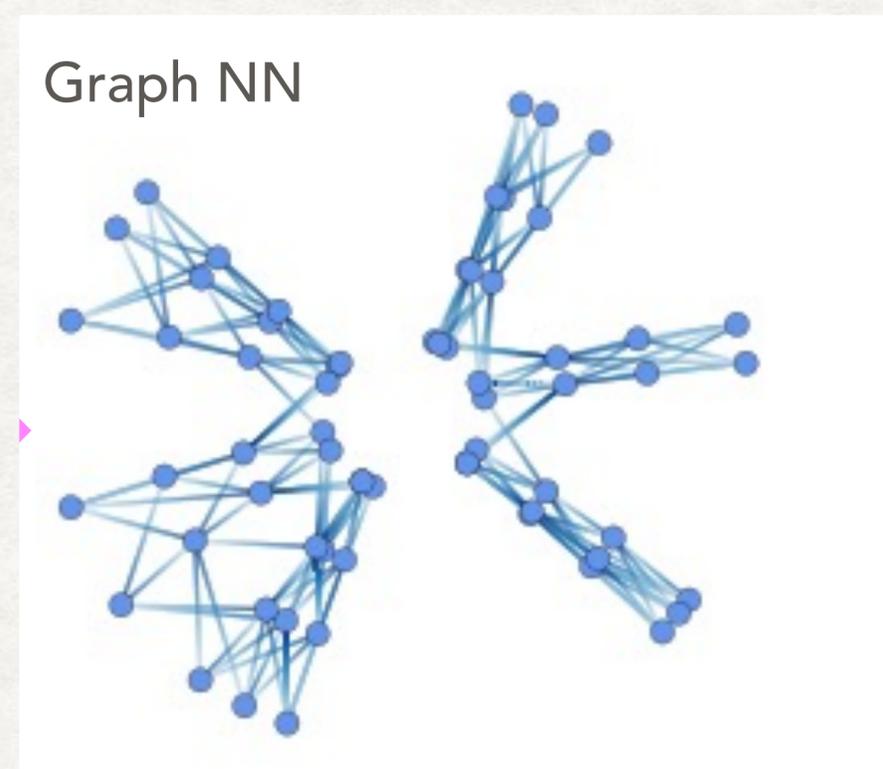
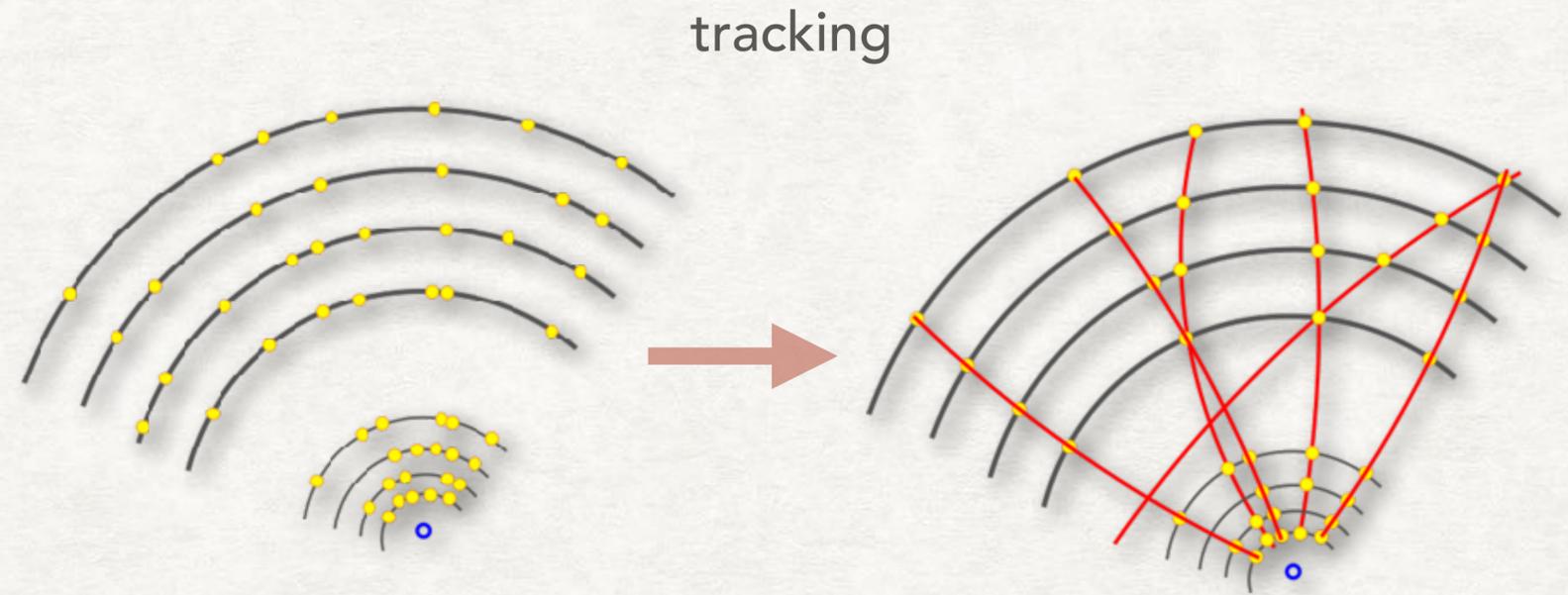
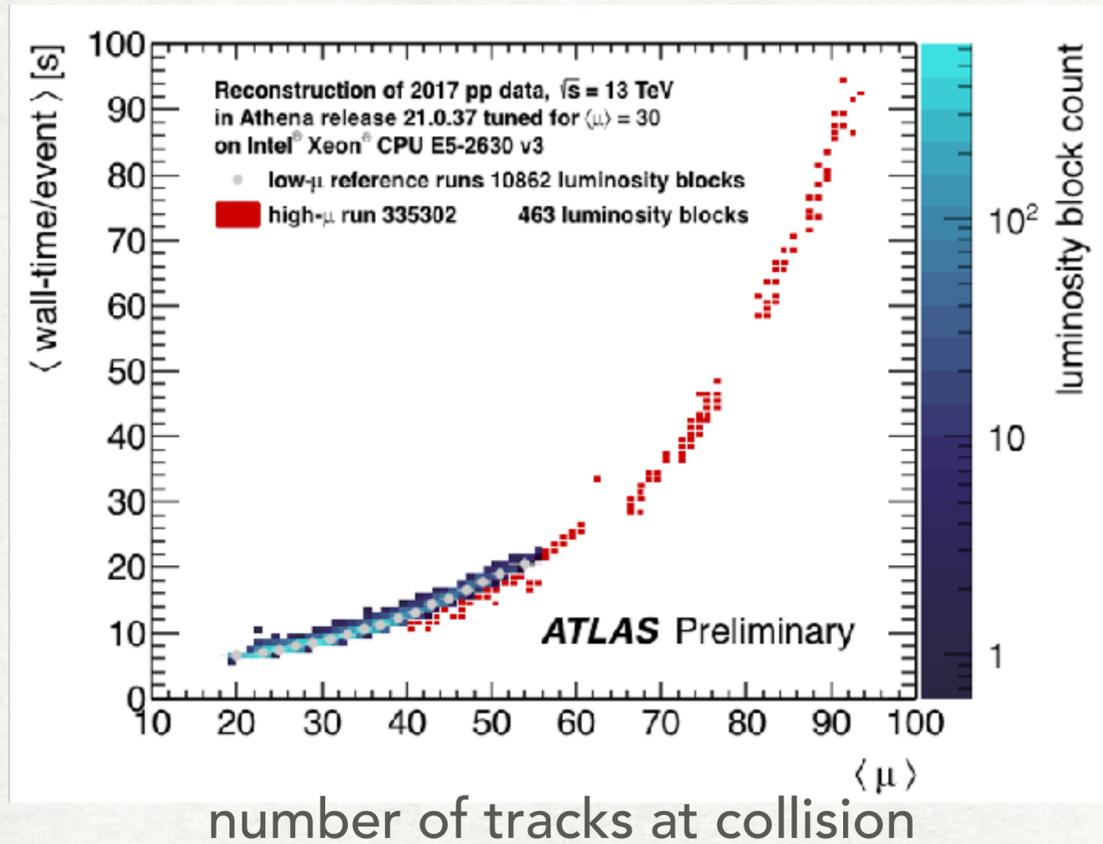
# The PF reconstruction algorithm



PF lepton, hadron, photon =  $F_{PF}$  (track hits + calo cells)

# BREAKING THE WALL

events in pipeline → **select interesting one** → save (physical constraints)



EXA.TrkX (Eur. Phys J. C(2021) 81:87)

determine near by node → GNN to handle edge classification

training time ~36 hour(by A100),

prediction 2.2 s/event (GPU), 220 s/event (CPU)

# ML on hardware

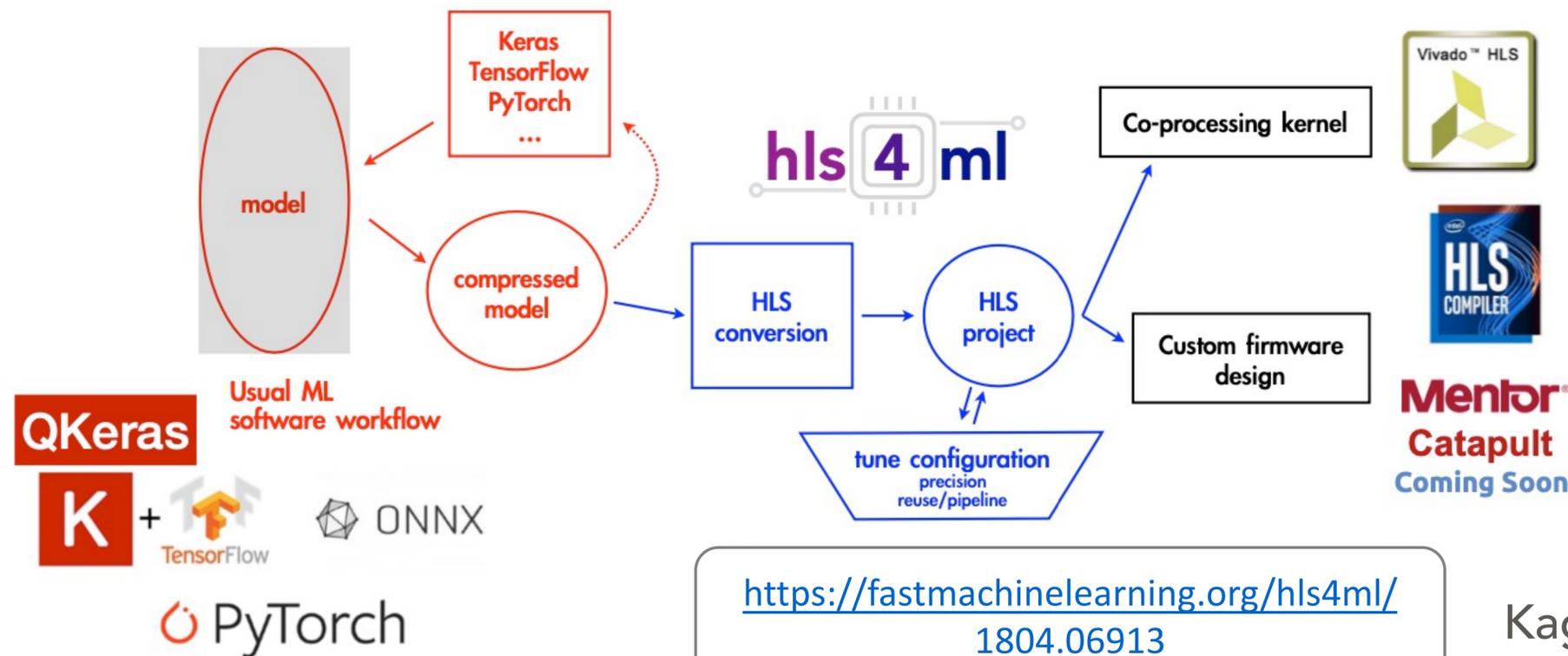
## Real-Time Low Latency ML

Goal: Move improvements from ML for reconstruction to on

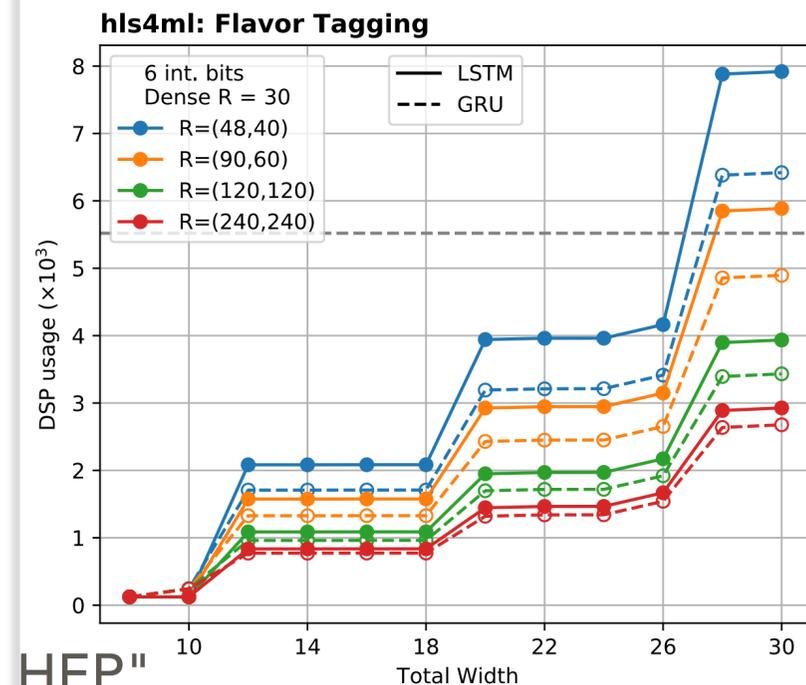
FPGA= Field Programmable Gate Array  
HLS =its compiler

hls4ml:

- HEP Community developed tool do deploy NN as electronic circuit on hardware
- FPGA-as-accelerator library → Whole model on chip
- Model Compression essential



### Example: Resource Usage in Jet Classification with RNNs



Kagan "ML at HEP"

Khoda, ..., MK, et. al, [2207.00559](https://arxiv.org/abs/2207.00559)

# summary

- ❖ HEP people are working to merge DL to most precise, large data science under extreme environment.
- ❖ The outcome will certainly shared to outside community, so stay tuned.