Application of the Machine Learning to the Collider Experiments

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For RCNP/IDS DNN Project

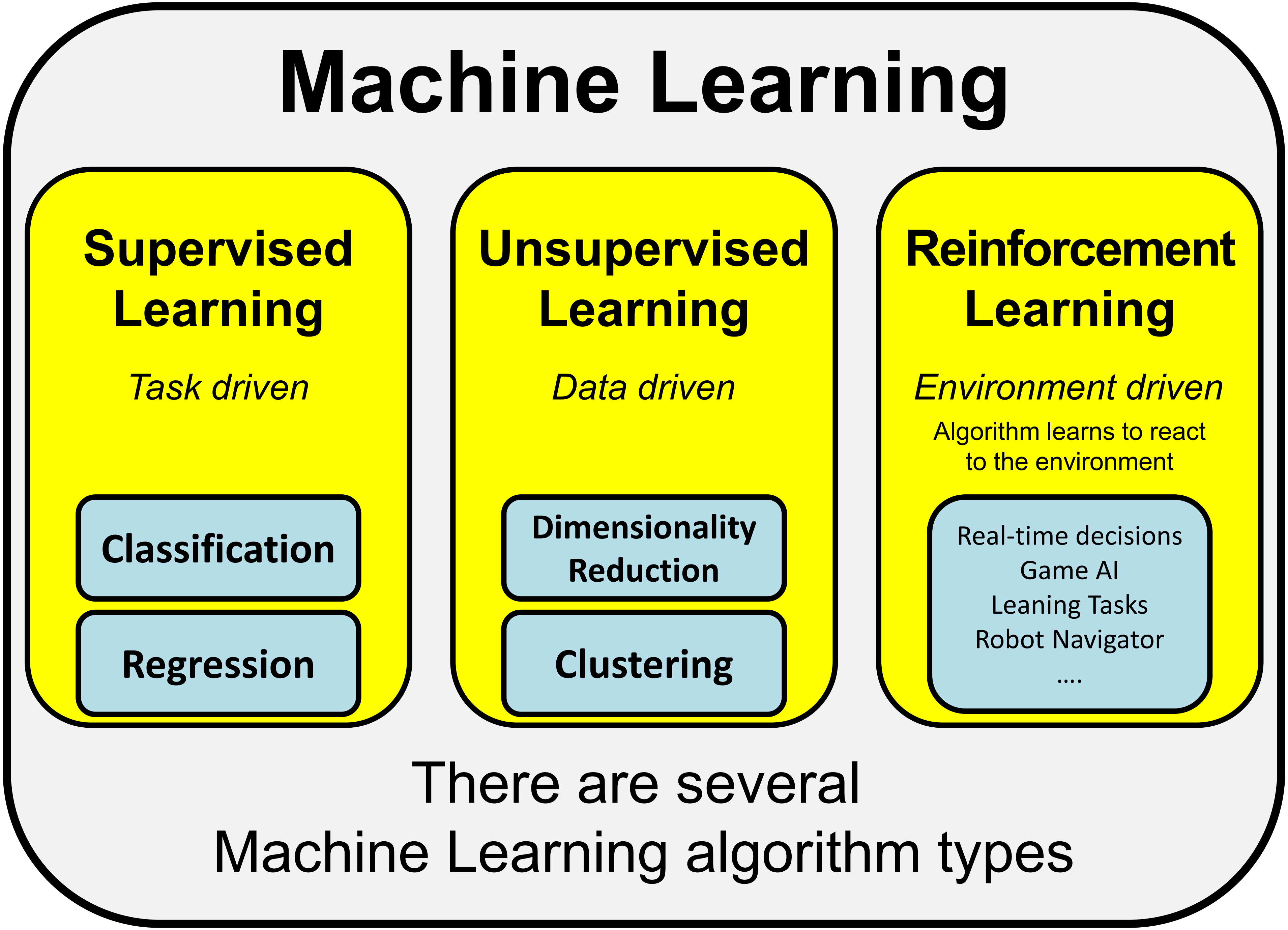
Machine Learning in Collider Experiments

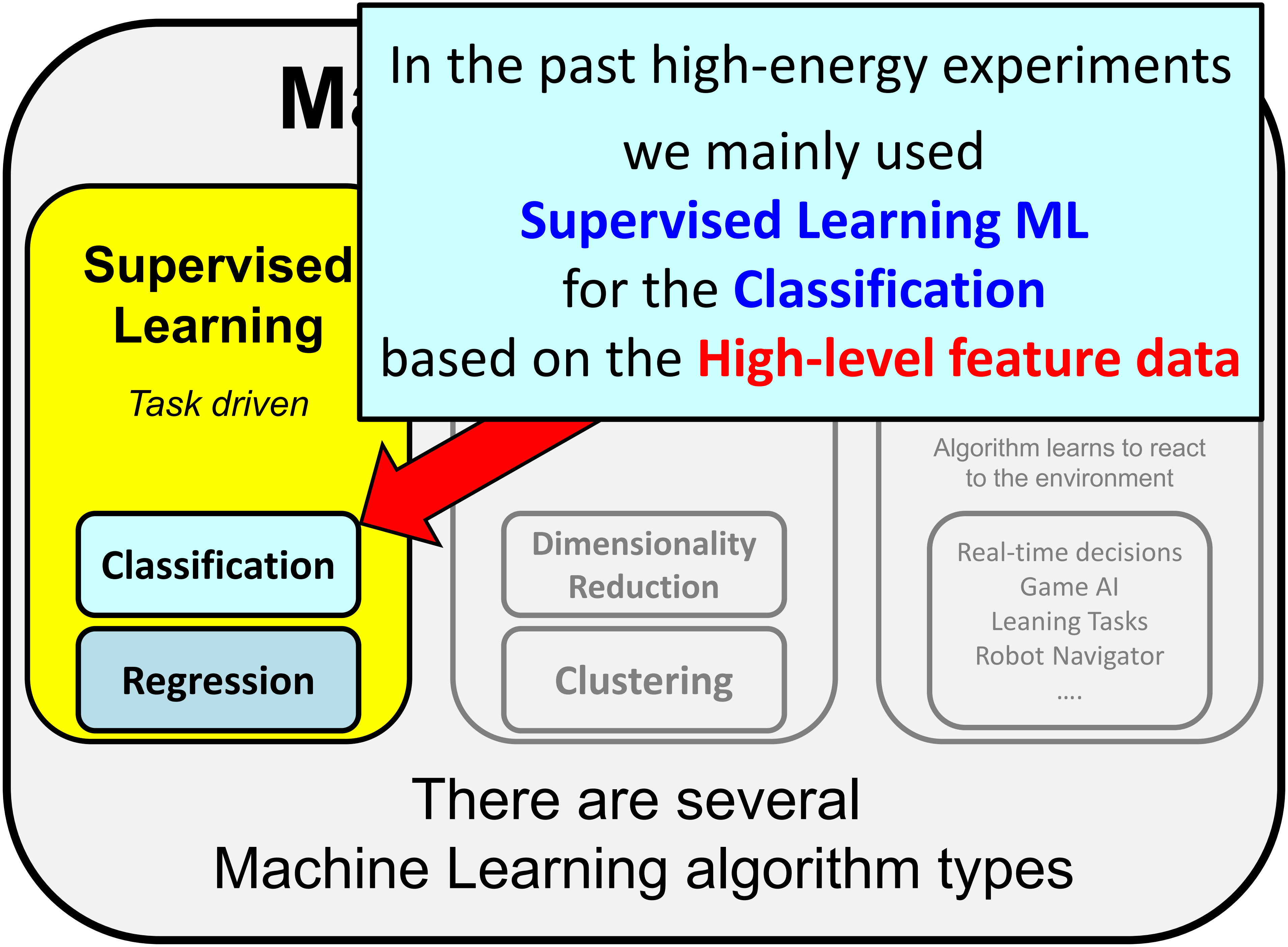
High Energy experiments are based on "Big Data"

There are many layers of big-data processing

Accelerator, detector operation, tuning, calibration,
Filtering, Data reconstruction, Physics analysis, ….

Modern Machine Learning techniques,
such as Deep Neural Network, developed in data science
are expected to be powerful tools
to provide more efficient / precise big-data processing
for the high energy collider experiments


Machine Learning
Supervised Learning
Task driven
Classification
Regression
Unsupervised Learning
Data driven
Dimensionality Reduction
Clustering
Reinforcement Learning
Environment driven
Algorithm learns to react to the environment
Real-time decisions
Game AI
Leaning Tasks
Robot Navigator
....
There are several Machine Learning algorithm types


Ma
In the past high-energy experiments
we mainly used
Supervised Learning ML
for the Classification
based on the High-level feature data
Supervised
Learning
Task driven
Classification
Regression
Algorithm learns to react
to the environment
Dimensionality
Reduction
Clustering
Real-time decisions
Game AI
Leaning Tasks
Robot Navigator
....
There are several
Machine Learning algorithm types

Recently, it is possible to apply

- Various **modern ML methods**
- ML based on the **Low-level feature data**

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react
to the environment

Classification

Regression

Dimensionality Reduction

Clustering

Real-time decisions
Game AI
Leaning Tasks
Robot Navigator
....

There are several
Machine Learning algorithm types

Since 2018, we form a group to proceed

"Application of Deep Learning for Accelerator Experiments"

→ *As RCNP project / IDS project*

The group is formed with particle physicists and data scientists

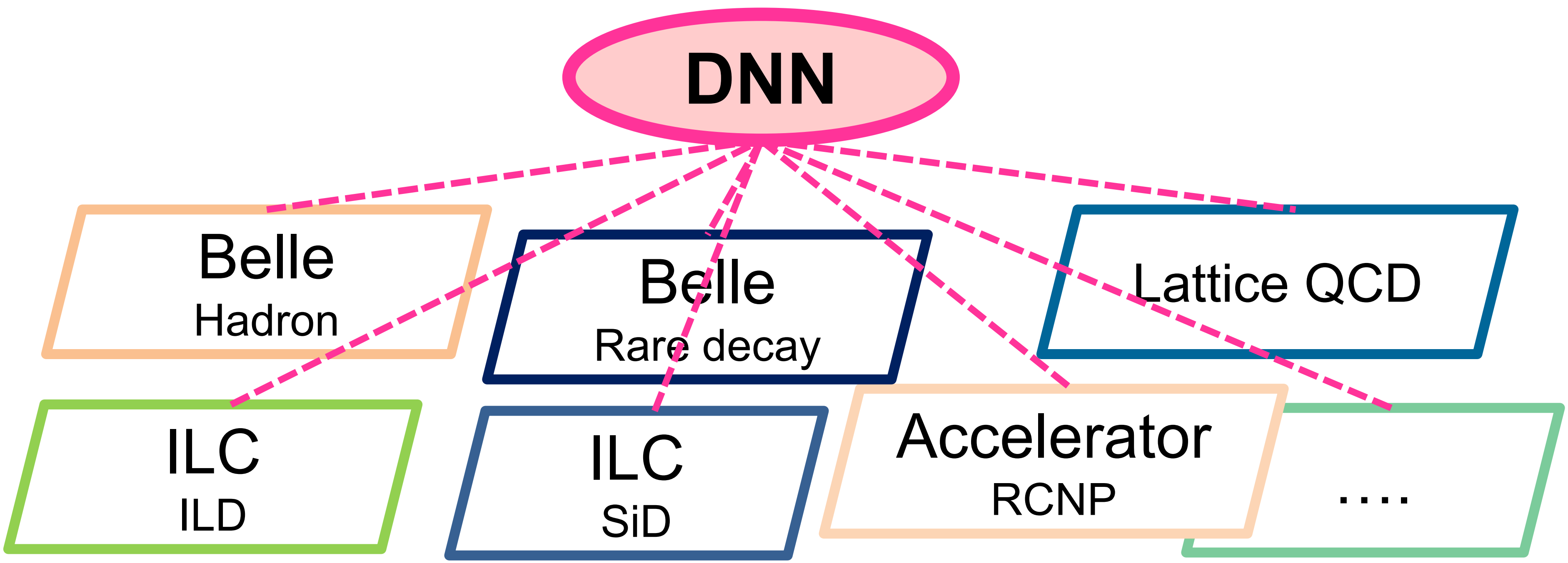
~10 institutes >20 scientists

Since 2018, we form a group to proceed

“Application of Deep Learning for Accelerator Experiments”

→ <u>*As RCNP project / IDS project*</u>

R&D is done within each group.
In our project, we discuss about the DNN applications



ML applications in our project

- Continuum suppression in Belle & Jet flavor-tag in ILC (Osaka-City U., IDS, RCNP)
- ILC SiD ECL energy calibration
  (Osaka-City U., IDS, U. Oregon, SLAC)
- Jet Clustering (U. Tokyo, Kyushu U.)
- Vertex Finding using Recurrent Neural Network (Kyushu U.)
- Machine tuning for KEK Linac (KEK, Osaka-City U., IDS, RCNP)
- Machine tuning for RCNP Cyclotron (RCNP)
- RI Beam particle ID (Kyushu U., U. Tokyo)
- Beam size measurement in ILC (Tohoku U.)
- Lattice-QCD application (RCNP, IDS)

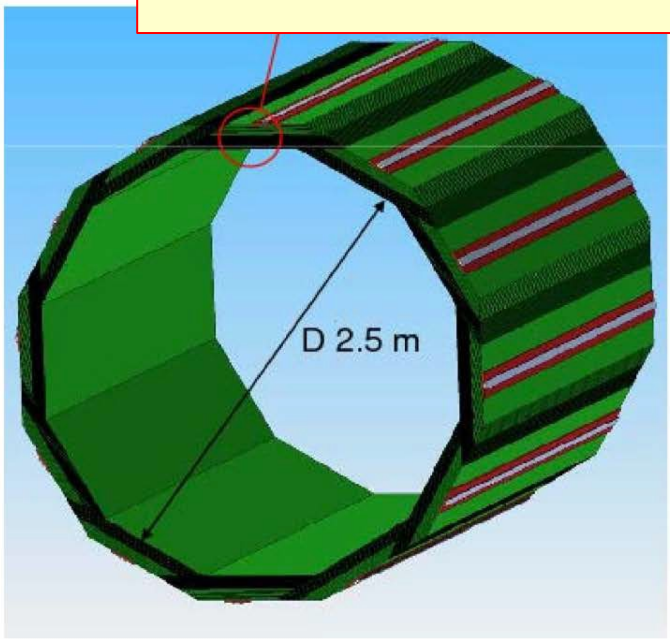
  …….

SiD EM Calorimeter (ECL) Energy Calibration using DNN

Osaka-City U. and Osaka U. IDS in collaborating with U. Oregon, SLAC

MC sample for this study is provided by J. Strube

- 30 Layer Si + W sampling calorimeter
- ~26X_0 in total
- Energy resolution(design value) $(17/\sqrt{E}\oplus 1)\%$



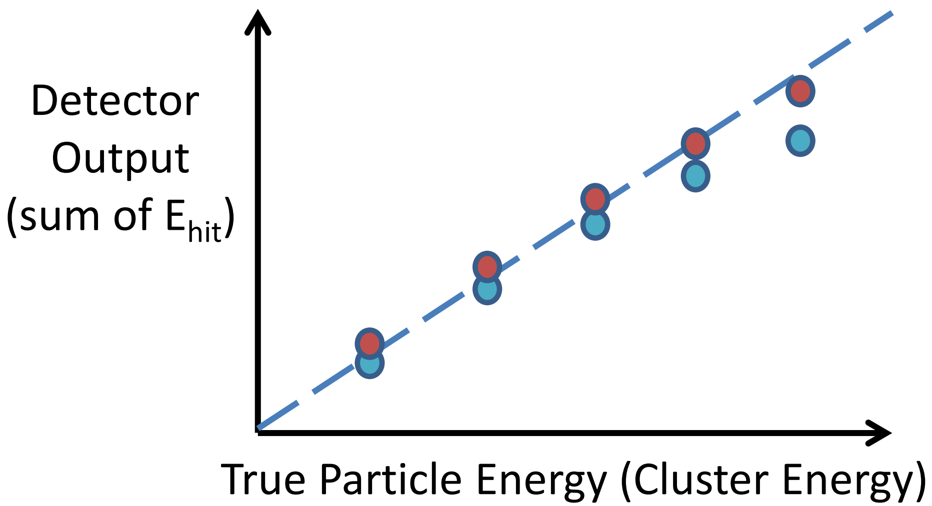
inner radius of ECL barrel	1.27 m
maximum z of barrel	1.76 m
longitudinal profie	20 layers × 0.64 X_0
	10 layers × 1.30 X_0
EM energy resolution	$(17/\sqrt{E}\oplus 1)\%$
readout gap	1.25 mm (or less)
effective Molire radius(R)	14 mm

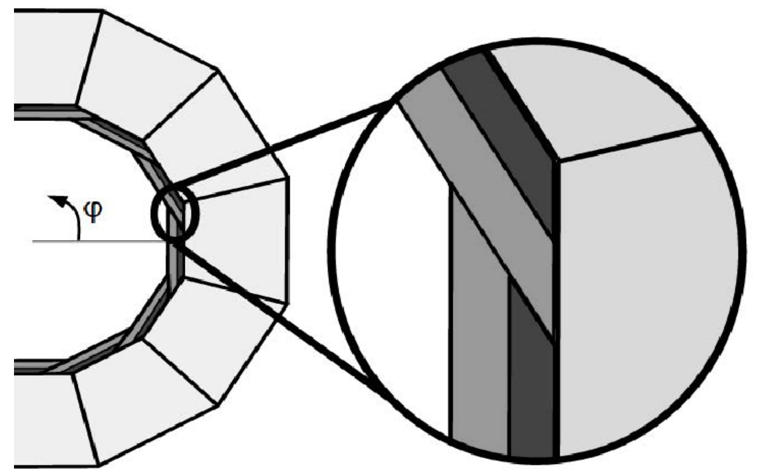
ILC TDR, vol.4,Page 89 **arXiv:1306.6329[physics.ins-det]**

SiD ECL Energy Calibration using DNN

Problems on the ECL energy calibration

1. Nonlinear detector response (due to shower leakage etc..)
2. Different detector response for e and γ (particle-species dependence)
3. Angular dependence due to the detector geometry

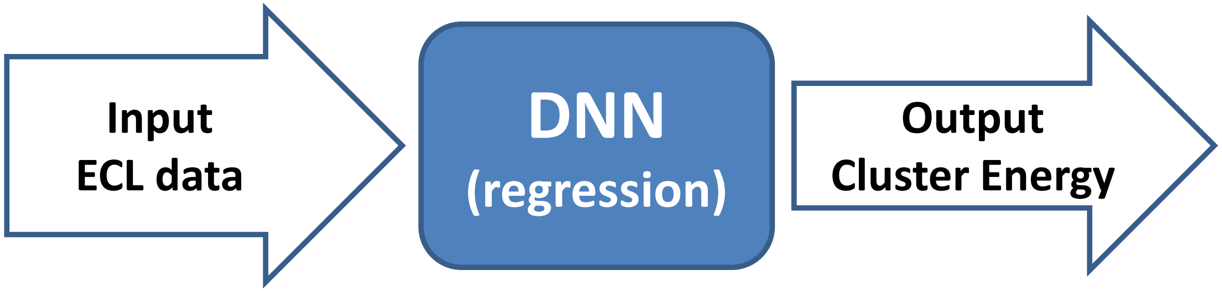


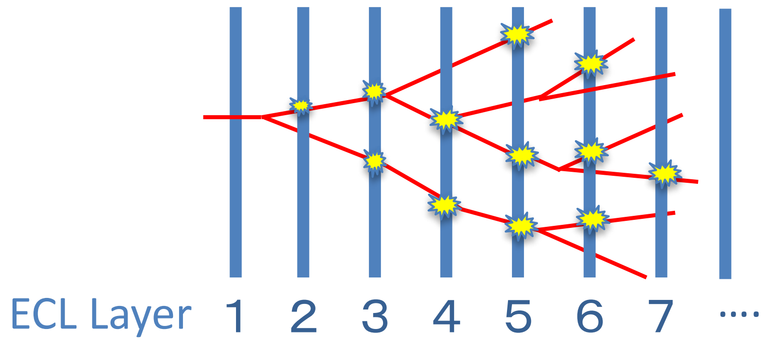


We use **DNN regression** to obtain the cluster energy

Input ECL data → **DNN (regression)** → **Output Cluster Energy**

What kind of ECL data do we input?





Low-level data **Hit data** (Position, Energy)

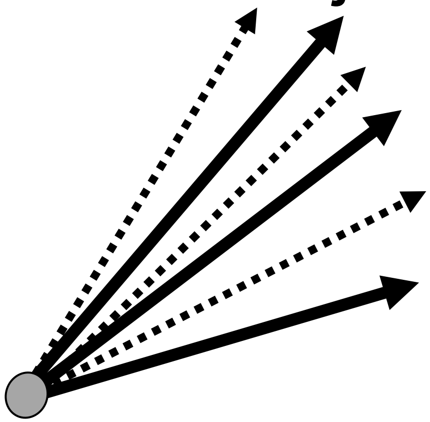
High-level data **Cluster data** (CM position, Sum of E hit, …)

There are several reports that **Low-level feature data** (pre-processing data) provides better DNN performance than **High-level feature data**

ML based on the HEP low-level data

In our previous study of Jet-flavor tagging,
we have developed the new method to directly input
the HEP low-level data (particle 4-momentum, position) to DNN

Particle jet



low-level data of jet

Part1 (E, Px, Py, Pz, x, y, z)
Part2 (E, Px, Py, Pz, x, y, z)
Part3 (E, Px, Py, Pz, x, y, z)
……

N. Kishida et. al., LCWS2019

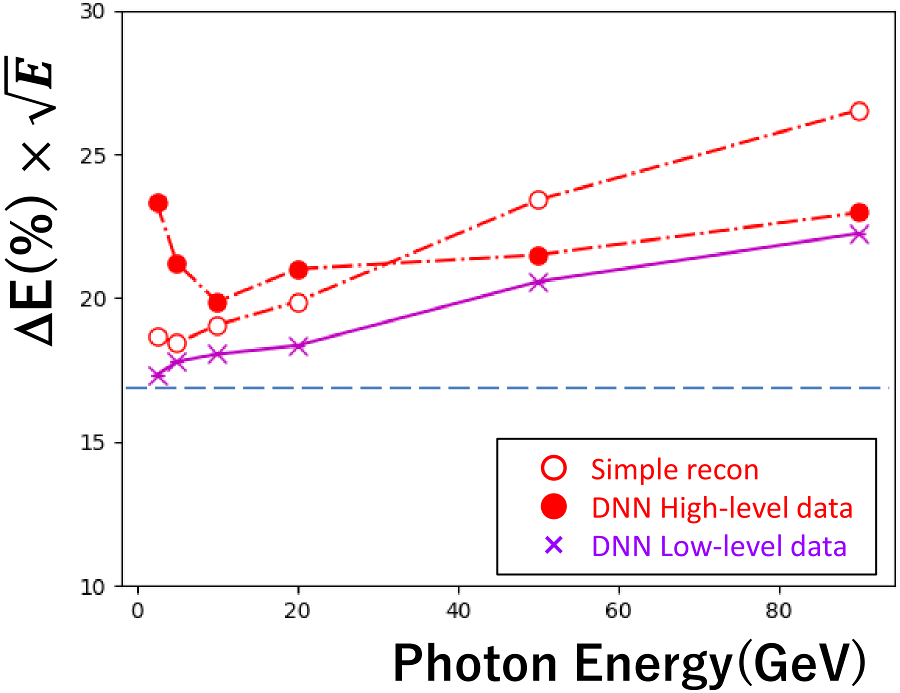
We apply the similar method
to input the ECL low-level data (hit position, E) to DNN

Results : Energy calibration with DNN

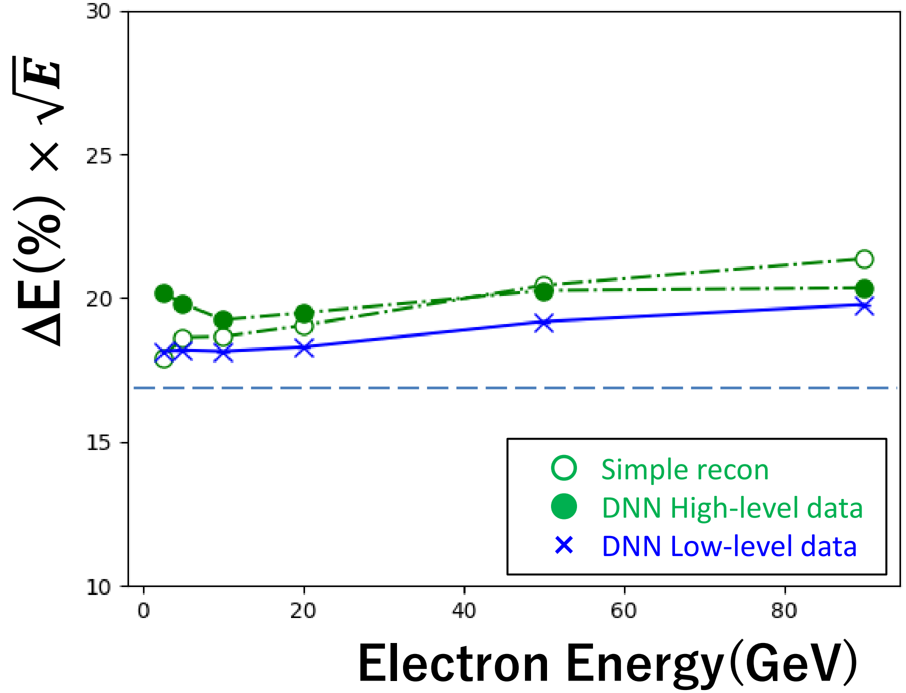
Preliminary

Y.Naka (Osaka-City U.)

Photon Energy Resolution $\Delta E(\%) \times \sqrt{E}$



Electron Energy Resolution $\Delta E(\%) \times \sqrt{E}$

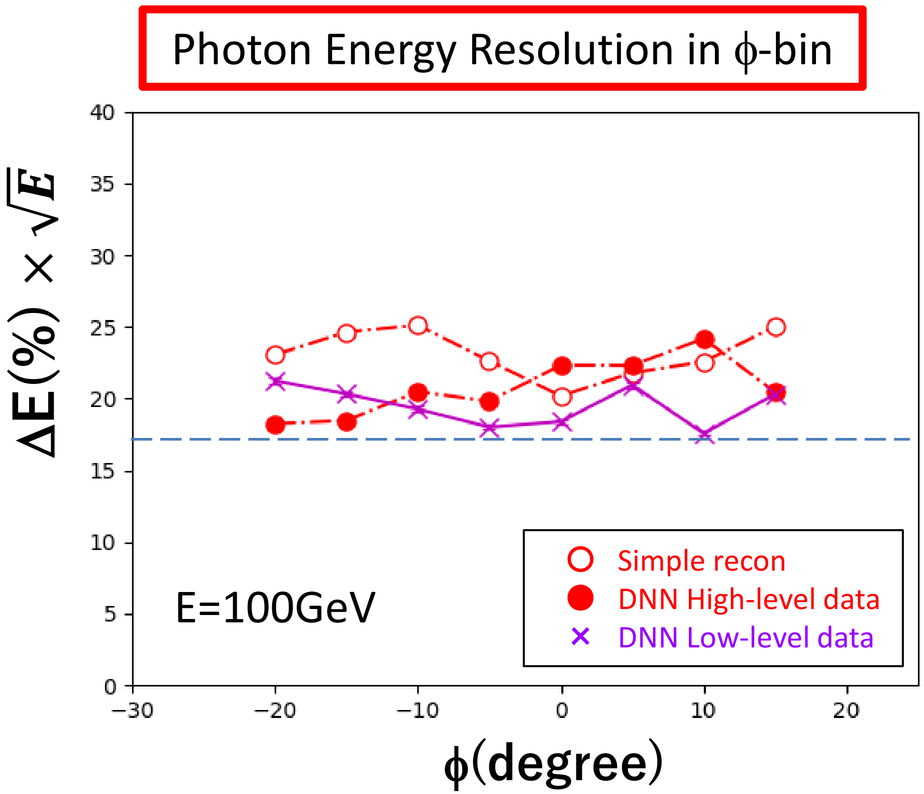


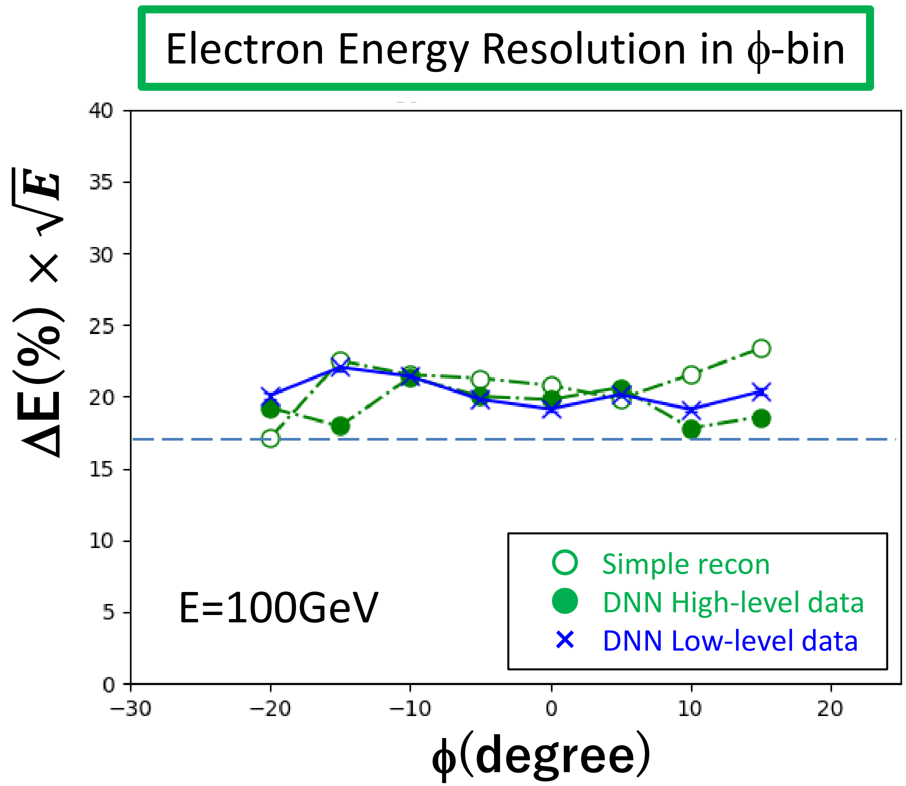
Using DNN with the low-level data input, we get the better resolution for both photon and electron in wide energy region

Results : Energy calibration with DNN

Preliminary

Y.Naka (Osaka-City U.)

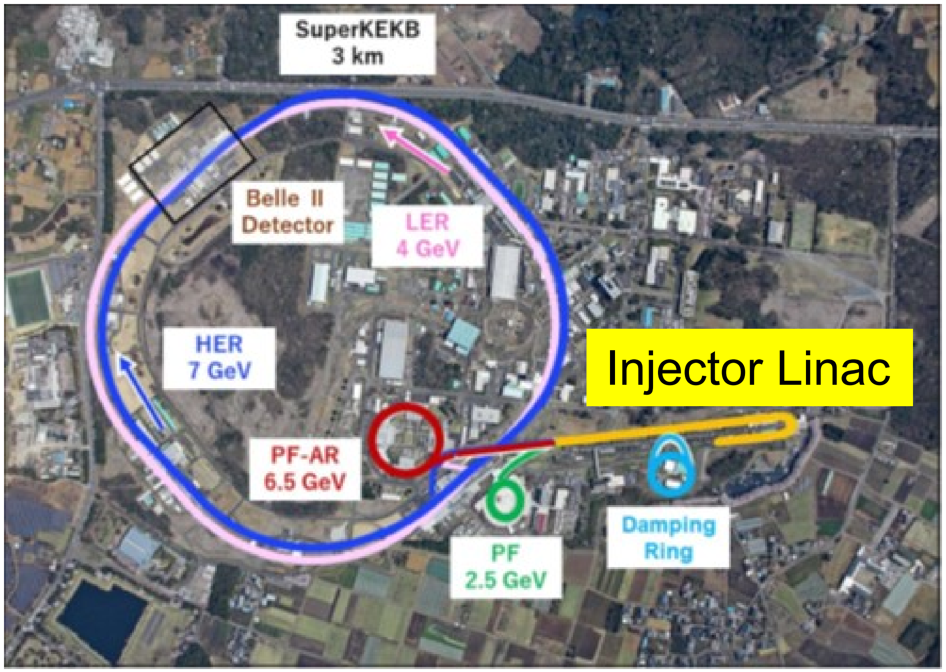




Using DNN with the low-level data input,
we get less ϕ-dependence in both photon and electron

KEK Injector Linac Operation Tuning using ML

KEK, Osaka-City U., Osaka U. IDS, RCNP

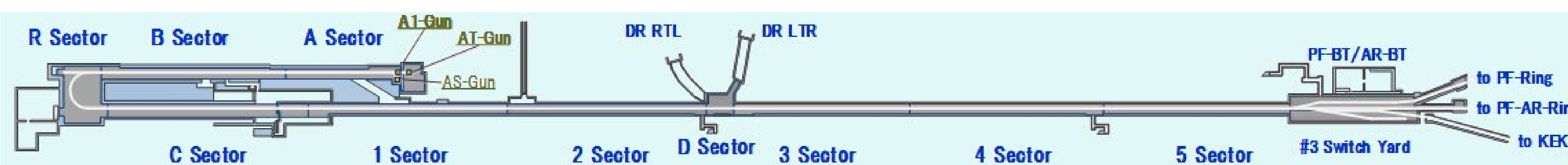


100 Beam Position Monitors (BPM)
200 Steering Magnets, 60 RF monitors

To achieve the high luminosity, operation tuning for the higher injection efficiency is important

R&D of operation tuning for the KEK injector Linac using ML is ongoing

We use the Linac operation data accumulated in 2018 Nov. - 2020 June



Linac Operation Tuning using ML

Problems on the operation tuning

1. Due to the large number of the control points (~1000), the operation system becomes much complicated.

→ We introduce **VAE(Variational AutoEncoder)** for **Dimensionality Reduction** to model and monitor the accelerator status (Visualization of the accelerator status)

2. Accelerator condition (environment) vary due to ground motion, tidal force, temperature, etc. Then the operation tuning is continuously done by operators.

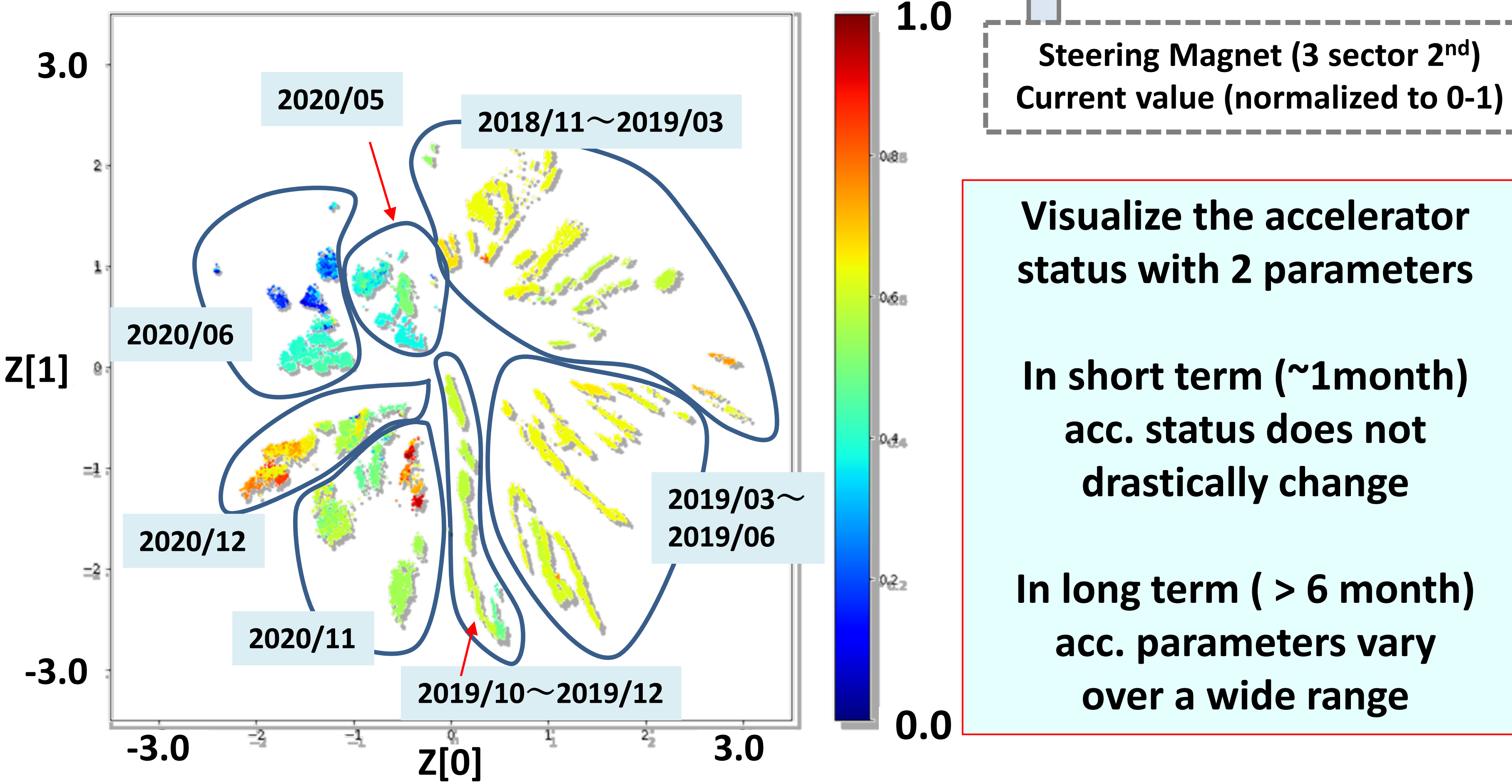
→ We have studied the operation tuning method based on **Reinforcement ML** to continuously optimize the parameters to maximize the injection efficiency

Visualization of Accelerator Parameters using VAE

Using VAE, we did dimensionality reduction
815 parameter accelerator parameters
→ 2 parameter Latent Variable

A.Hisano (Osaka-City U.)

2D Latent Variable Z(0, 1)



Visualize the accelerator status with 2 parameters

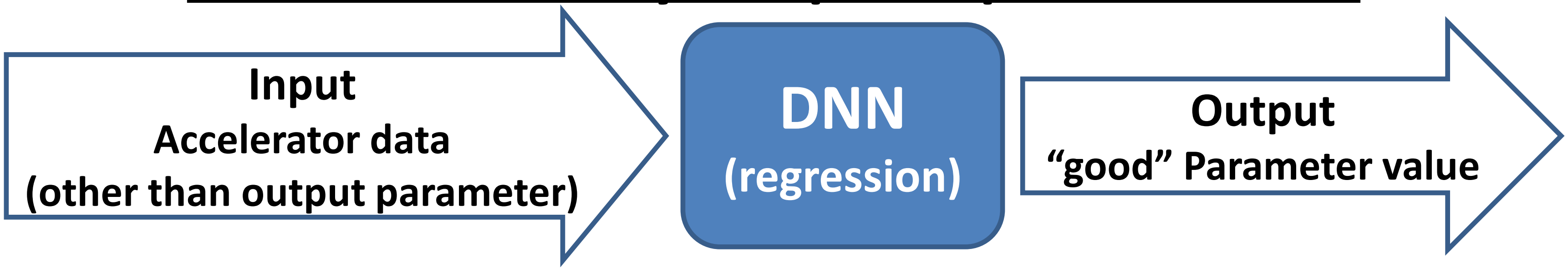
In short term (~1month) acc. status does not drastically change

In long term (> 6 month) acc. parameters vary over a wide range

Parameter Tuning using DNN

To get the "good" accelerator tuning value
to achieve the high injection efficiency, we use DNN

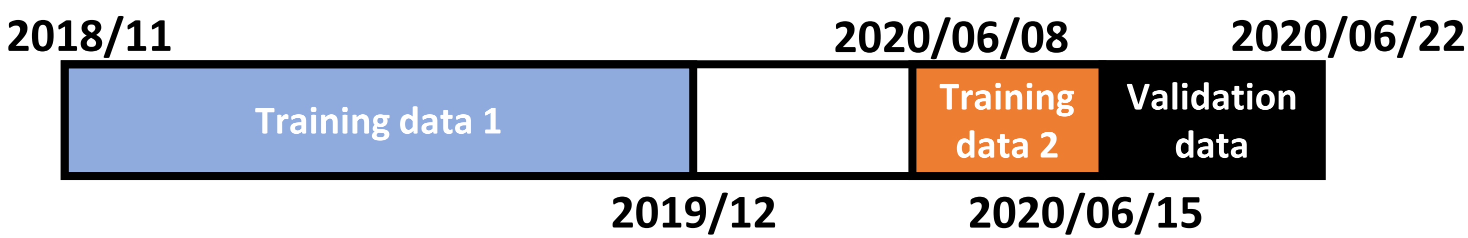
DNN is trained by the past operation data



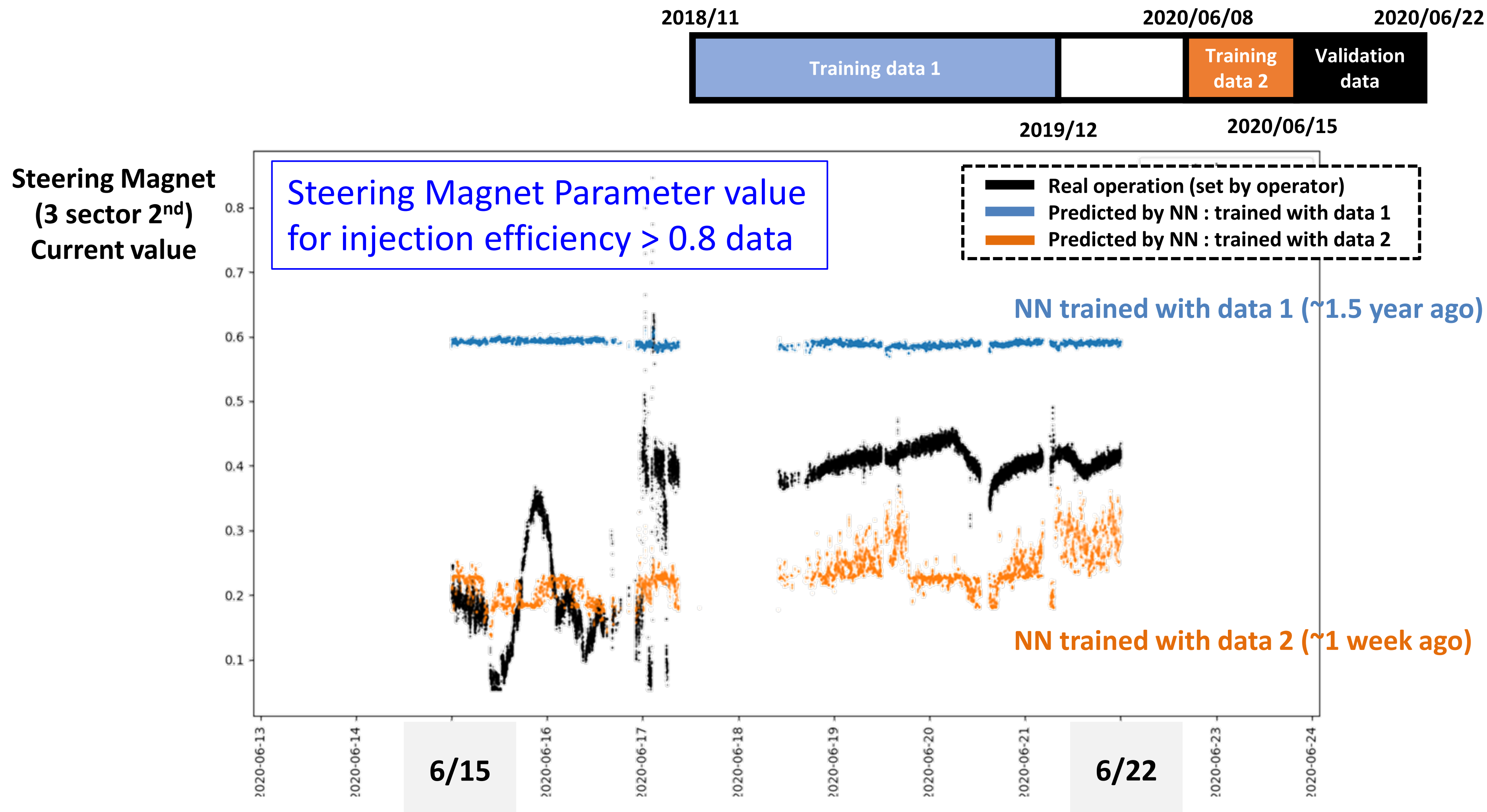
Env. Data, RF data,
Steering magnet data…

RF, Steering magnet,,

Training data 1 = ~ 1.5 year ago
Training data 2 = ~ 1 week ago, just before the validation data
Training data 3 = continuously update (~ 1 day)



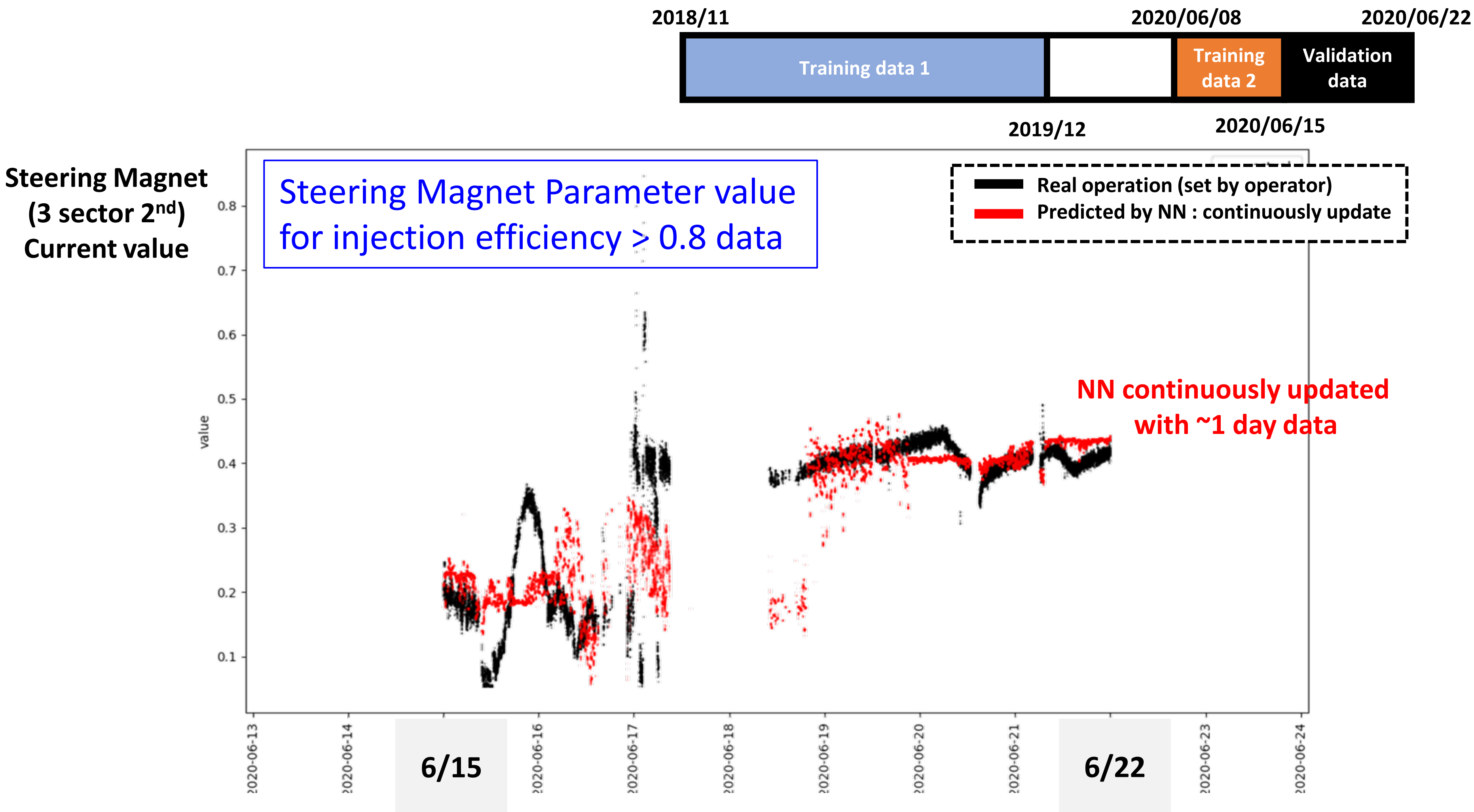
Parameter Tuning using DNN



A.Hisano (Osaka-City U.)

NN trained with data 1 (~1.5 year ago) cannot predict the "good" tuning value

Parameter Tuning using DNN



A.Hisano (Osaka-City U.)

NN continuously updated (with ~1 day data) can predict the “good” tuning value

Summary

Modern ML provides powerful tools for HEP big data processing

We have developed several ML application methods to High Energy Experiments

- **We obtain good data-processing performance by applying ML**
- **Several new studies to apply ML are on going**