Application of the Machine Learning to the Collider Experiments

2019/10/31

M. Iwasaki

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

For RCNP/IDS DNN Project

Machine Learning in High Energy Experiments

High Energy experiments are based on "Big Data"

There are many layers of such big data processing

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

Modern Machine Learning techniques,
such as Deep Neural Network, for the big data processing
developed in data science are expected to be
powerful tools for High Energy experiments

Since 2018, we form a group working on

“Application of Deep Learning for Accelerator Experiments”

→ *Approved as RCNP project / IDS project*

The group is formed with particle physicists and data scientists

Particle Physics

Data Science

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Particle Physicists : Consisting with Experimentalists & Theorists

Particle Physicists

Experiment

Theory

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From various projects

Research Projects

Belle
Hadron, Rare decay, ..

Accelerator
KEK Linac, RCNP

ILC
ILD, SiD

Lattice QCD, …

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From various institutes

RCNP, Osaka U. Nuclear Physics Exp.Theory	IDS, Osaka U. Data Science	Osaka City U. High Energy Physics
Kyoto Sangyo U. Nuclear Physics	Nara Women's U. HEP, Nuclear Phys.	Tohoku U. High Energy Physics
Gifu U. Nuclear Physics	U.Tokyo / CNS HEP, Nuclear Phys.	Kyushu U. High Energy Physics
Showa P. U. Medical,Nuclear Phys.	Nagoya U. HEP, Nuclear Phys.	KEK High Energy Physics

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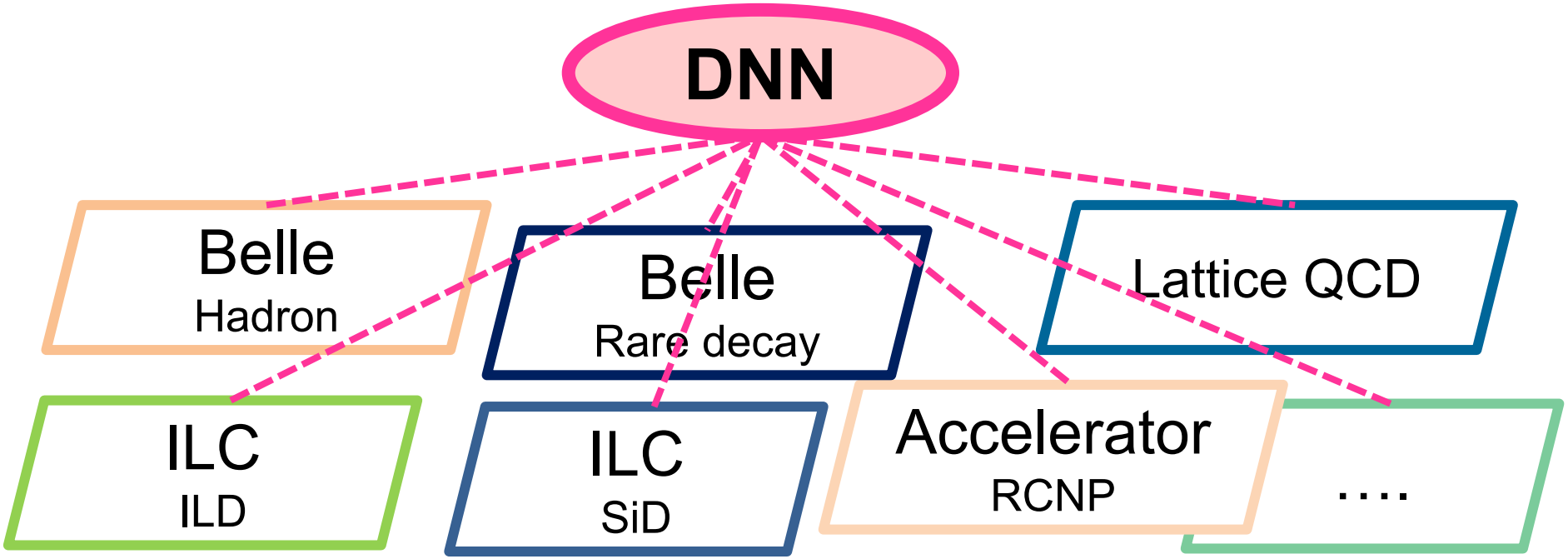
R&D is done within each group.
In our project, we discuss about the DNN applications



Machine Learning

Supervised Learning

Task driven

- Classification
- Regression

Unsupervised Learning

Data driven

- Clustering
- Association

Reinforcement Learning

Environment driven

Algorithm learns to react to the environment

- Classification
- Control

There are several Machine Learning algorithm types

Machine Learning

Supervised Learning

Task driven

- **Classification**
- **Regression**

Unsupervised Learning

Data driven

- Clustering
- Association

Reinforcement Learning

Environment driven

Algorithm learns to react to the environment

- Classification
- **Control**

Currently, in our applications, we use above types

Examples of ML applications in the particle physics

Supervised ML

1. Classification

Signal selection /BG rejection (Signal vs BG),
Flavor-tag (u/d/s, c, b), Particle ID (π,K,p..) (e, γ) ,
Pattern recognition (cluster finding, track finding,…)

2. Regression

Parameter measurements (analysis, monitoring, ..)
Detector calibration, Machine tuning, …

Reinforcement ML

Machine tuning / operation

ML applications in our project

Supervised ML

1. Classification

- Continuum suppression in Belle (u/d/s/c vs b) &
  Jet flavor-tag (u/d/s, c, b) in ILC (Osaka-City U., IDS, RCNP)
- Pattern recognition in Medical (Showa P. U.)

2. Regression

- Beam size measurement in ILC (Tohoku U.)
- EM calorimeter calibration in ILC SiD
  (Osaka-City U., IDS, U. Oregon, PNNL, SLAC)
- Lattice-QCD application (RCNP, IDS)

Reinforcement ML

- Machine tuning for KEK Linac (KEK, Osaka-City U., IDS)
- Machine tuning for RCNP Cyclotron (RCNP)

ML applications in our project

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The next talk by N.Kishida

2. Regression

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- Machine tuning for KEK Linac (KEK, Osaka-City U., IDS)
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ML applications in our project

Supervised ML

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2. Regression

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- Lattice-QCD application (RCNP, IDS)

In this talk, we'll show these 2 topics

Reinforcement ML

- Machine tuning for KEK Linac (KEK, Osaka-City U., IDS)
- Machine tuning for RCNP Cyclotron (RCNP)

SiD EM calorimeter calibration using DNN

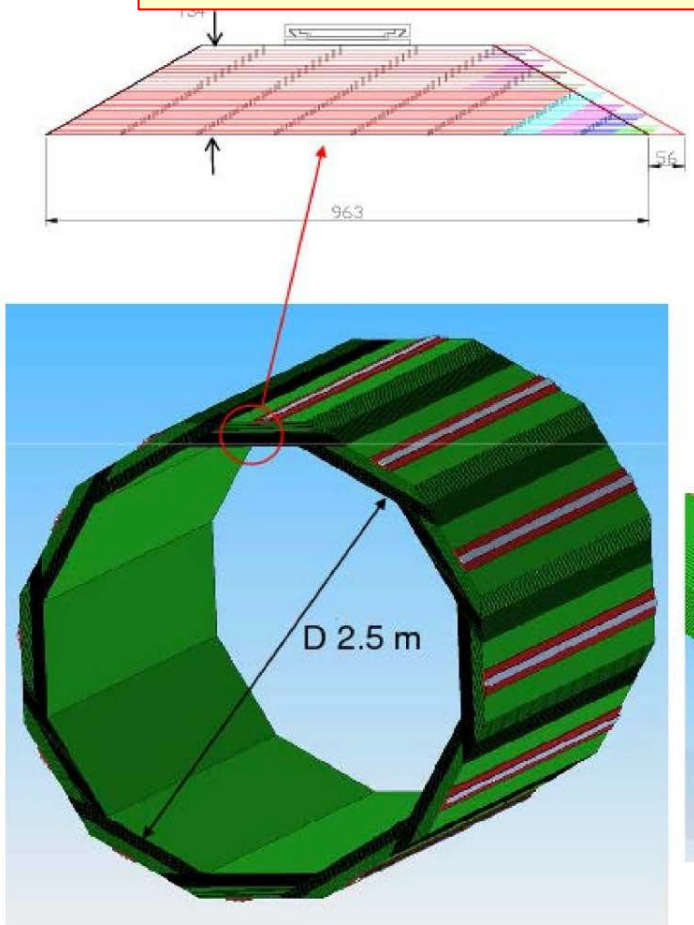
Osaka-City U. and Osaka U. IDS
in collaborating with U. Oregon, PNNL, SLAC

- **Please also refer SiD ECL talks by C. Potter (U. Oregon)**
  "Correcting for leakage energy in the SiD silicon-tungsten ECal " in Tuesday afternoon track3 session, and
  "pySiDR: Python Event Reconstruction for SiD" in this session

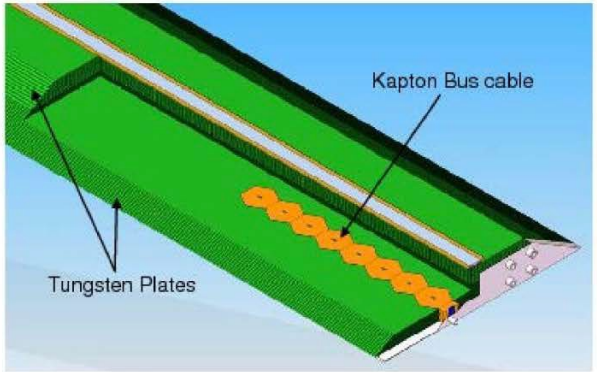
- **MC sample for this study is provided by J. Strube (PNNL)**

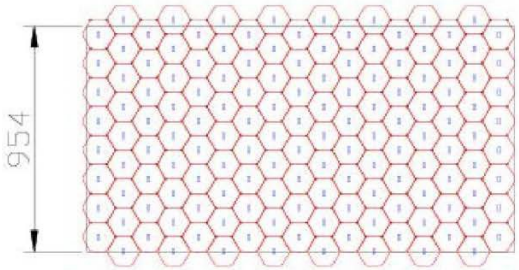
SiD EM Calorimeter (ECL)

- 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





Hexagon sensors arrangement

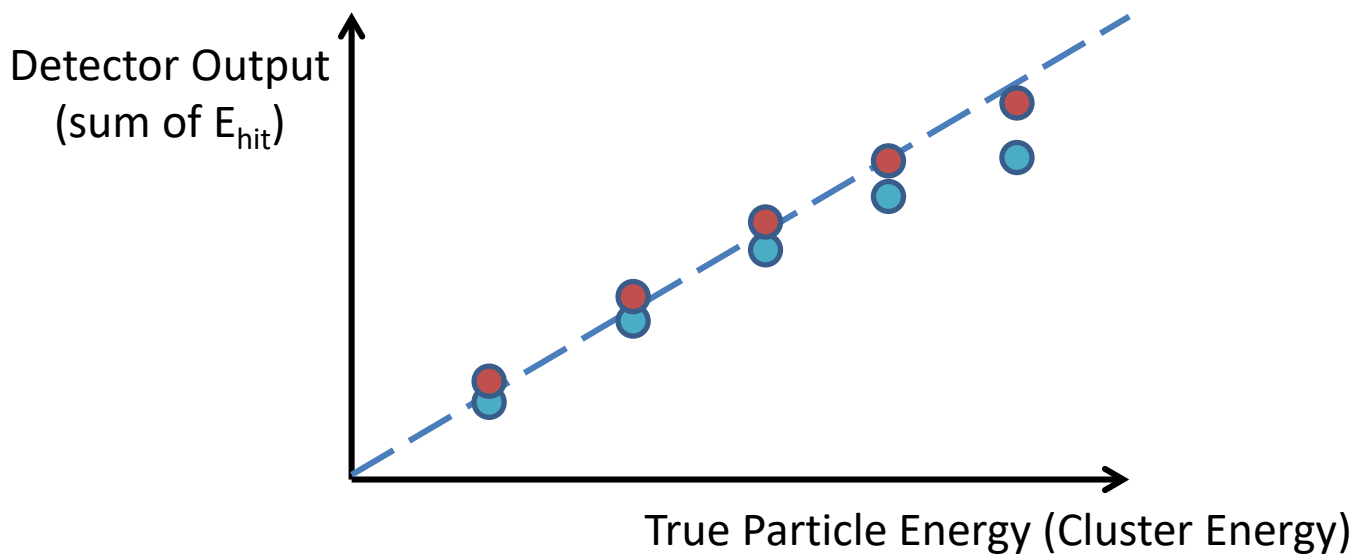
ILC TDR, vol.4,Page 89 arXiv:1306.6329[physics.ins-det]

Energy Calibration of the Calorimeter

In this study, we try the SiD ECL energy calibration using Deep Neural Network

Several problems on the EM calorimeter(ECL) energy calibration

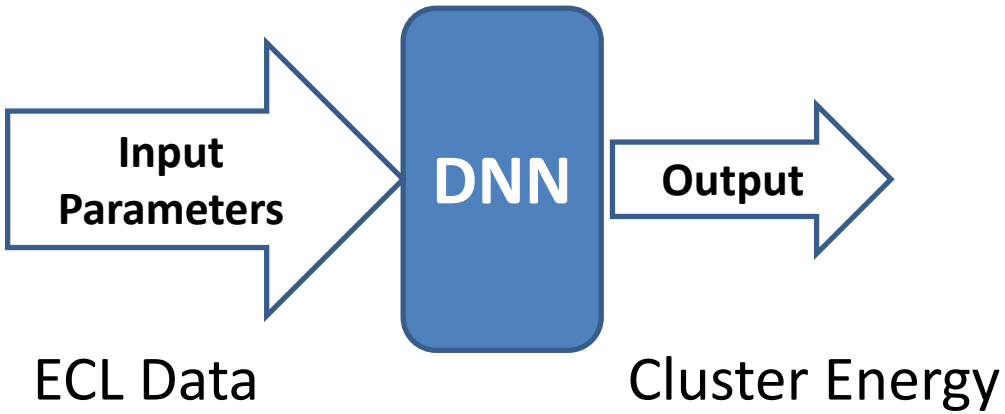
1. **Nonlinear detector response** (due to the detector geometry etc..)
2. **Different detector response for e and γ** (particle-species dependence)

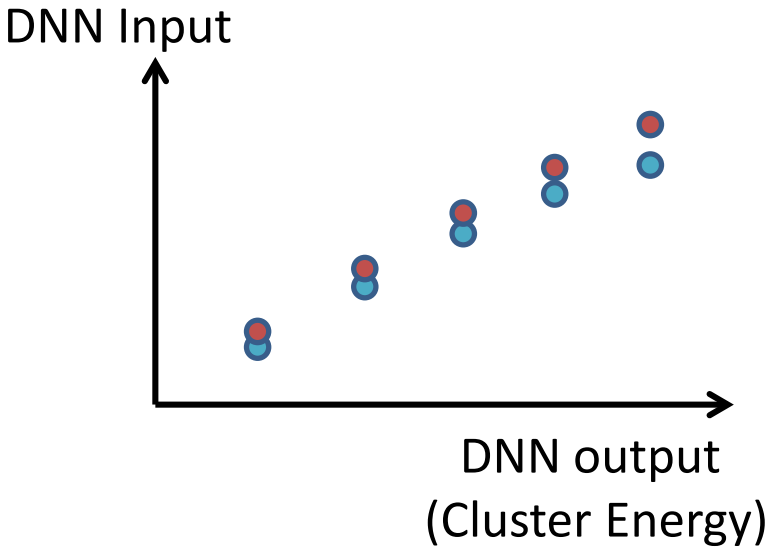


Energy Calibration using DNN

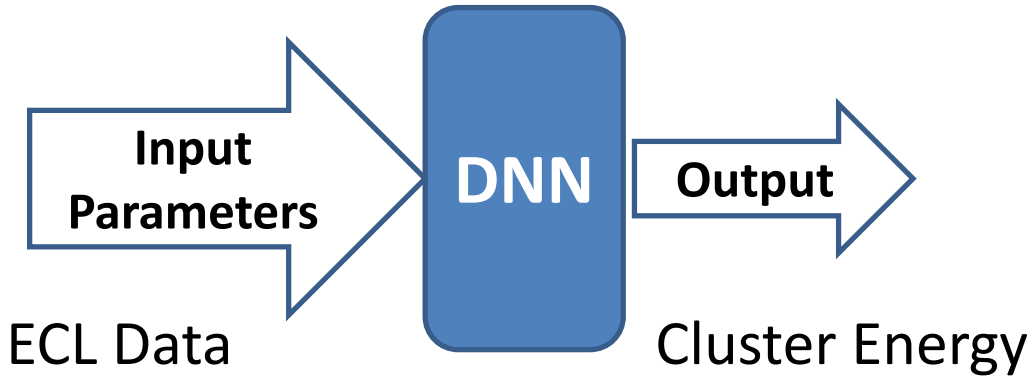
Neural Network can express the non-linear response

We use DNN regression <u>to obtain the cluster energy</u>





What kind of data do we input?



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

Low-level data	**Hit data** (position, Energy)
Middle-level data	**Layer data** (CM position, Sum of E hit in layer)
High-level data	**Cluster data** (CM position, Sum of E hit, …)

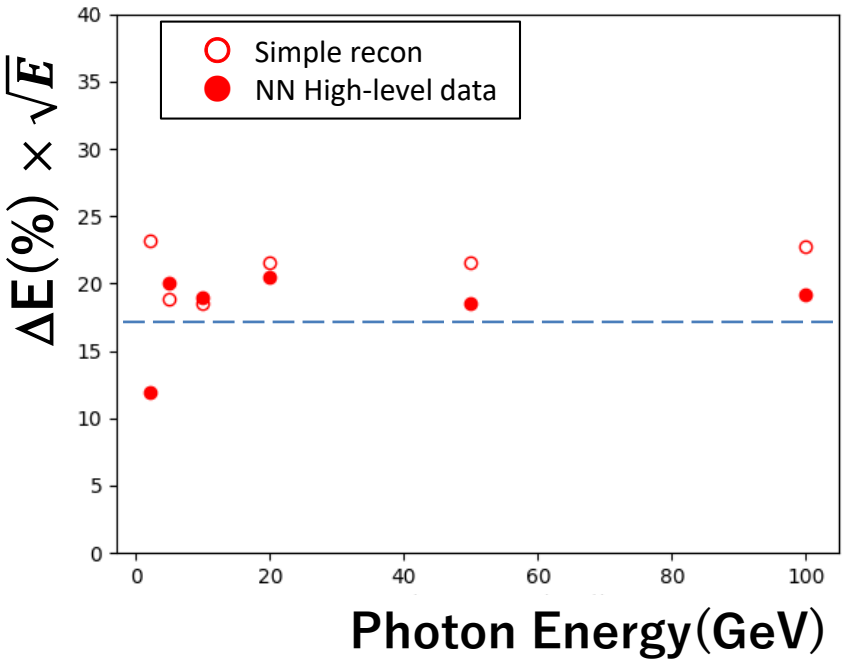
In our study, we use High- and Middle-level data for the DNN input

Results : Energy calibration with DNN

Preliminary

Y.Naka (Osaka-City U.)

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



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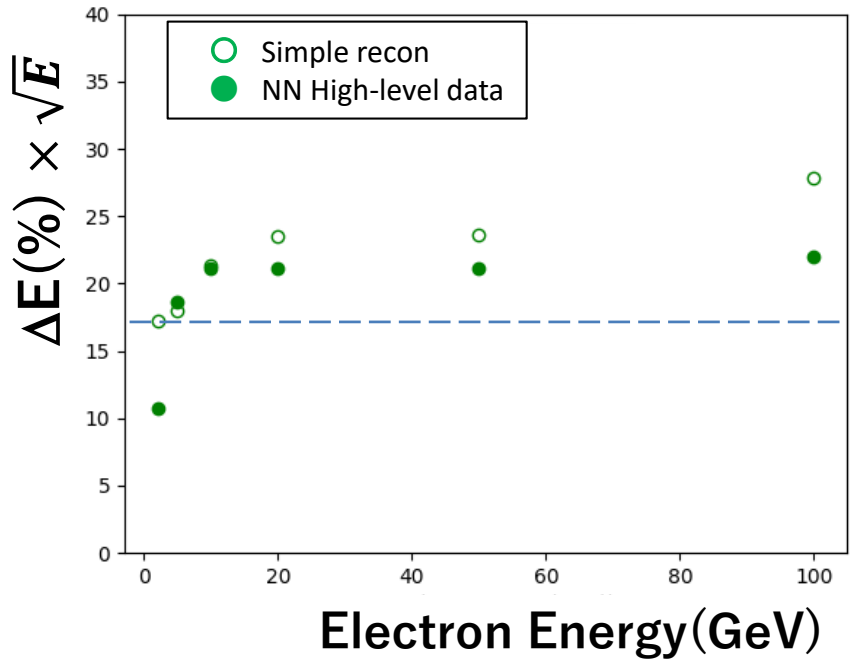

Using DNN, we get better resolution for both photon and electron in wide energy region

Results : Energy calibration with DNN

Preliminary

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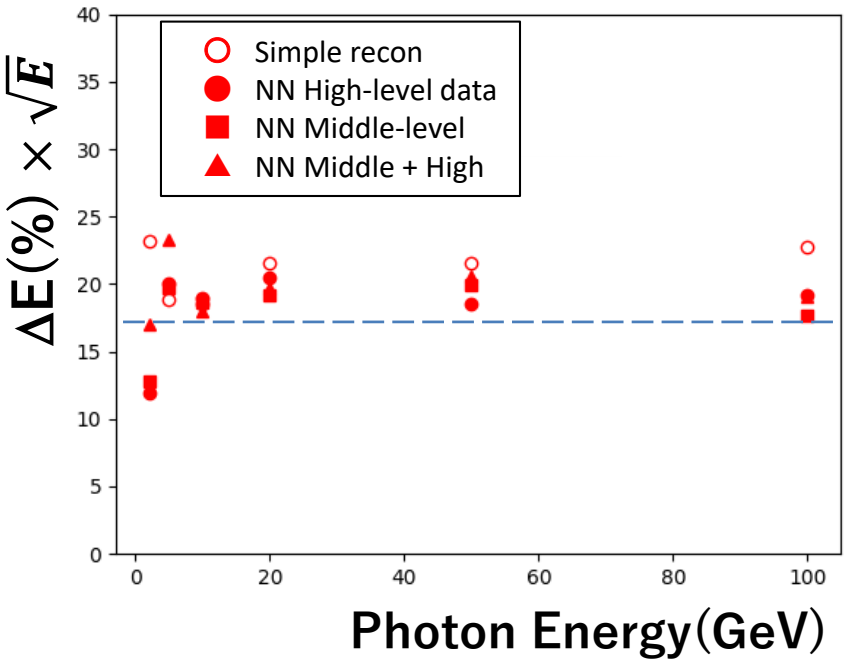

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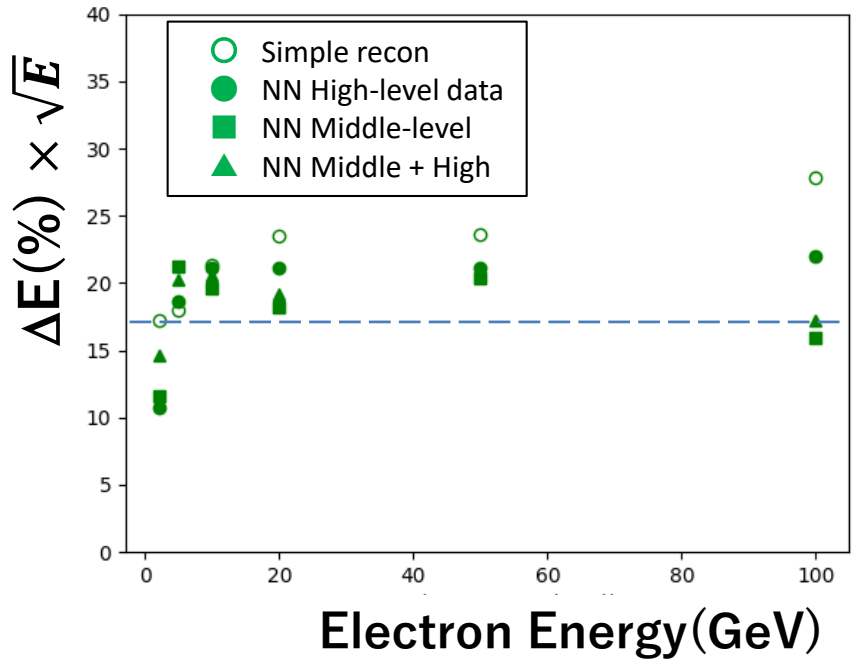


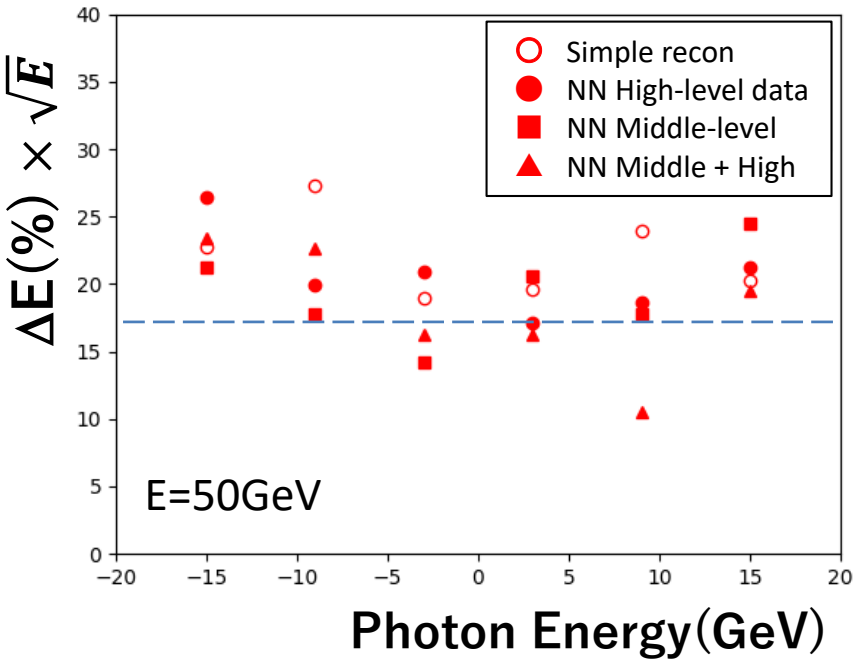
- **Using DNN, we get better resolution for both photon and electron in wide energy region**
- **Little difference btw High-level and Middle-level data**

Results : Energy calibration with DNN

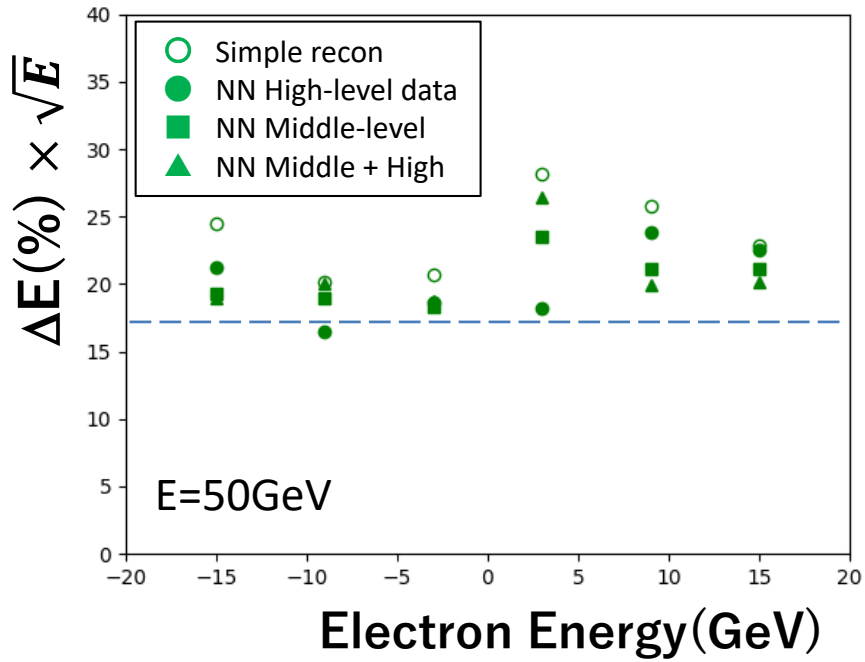
Preliminary

Y.Naka (Osaka-City U.)

Photon Energy Resolution in ϕ-bin



Electron Energy Resolution in ϕ-bin



- **Using DNN, we get better resolution for both γ and electron**
- **Little difference btw High-level and Middle-level data**
- **We still have ϕ-dependence**

→ DNN optimization? DNN with low-level data??

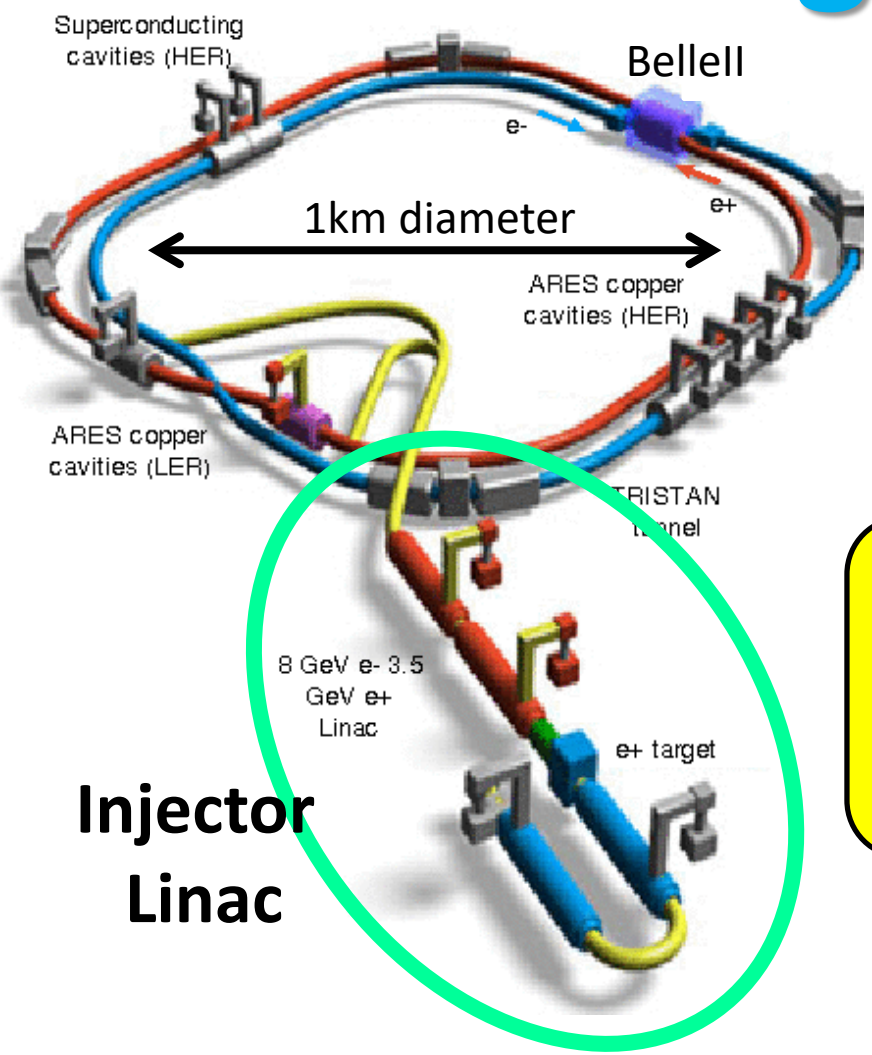
Further studies are on going

KEK Injector Linac Operation Tuning using ML

KEK Acc. group, Osaka-City U. and Osaka U. IDS, RCNP

H. Joan (Osaka-City U.), M. Iwasaki (Osaka-City U., NITEP, Osaka U. RCNP, Osaka U. IDS), M. Satoh (KEK, SOKENDAI), I. Satake (KEK), Y. Nakashima, N. Takemura, H. Nagahara (Osaka U. IDS), and T. Nakano (Osaka U. RCNP, Osaka U. IDS)

KEK Injector Linac Operation Tuning using ML

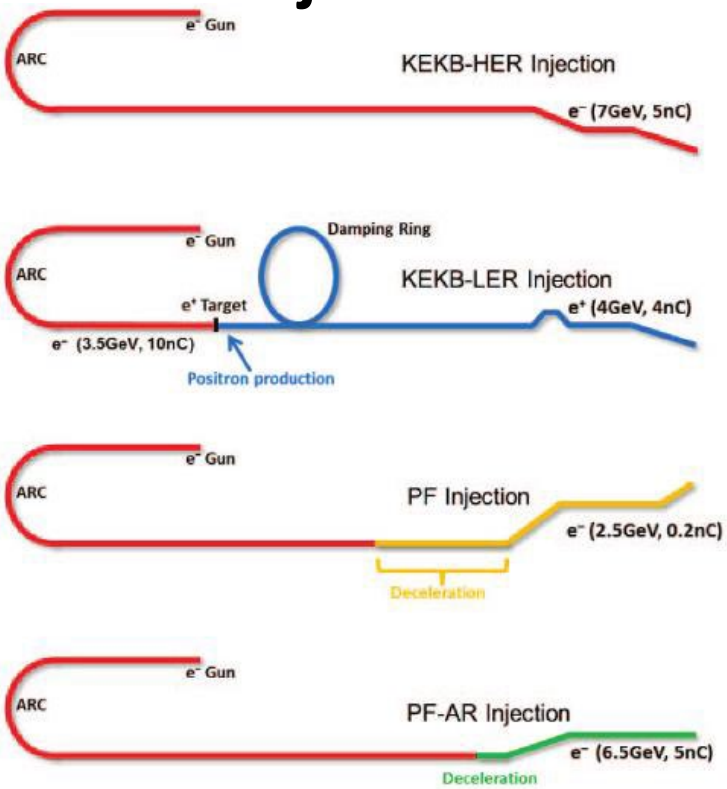


To achieve the high luminosity, precise operation tuning to get the higher injection efficiency is very important

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

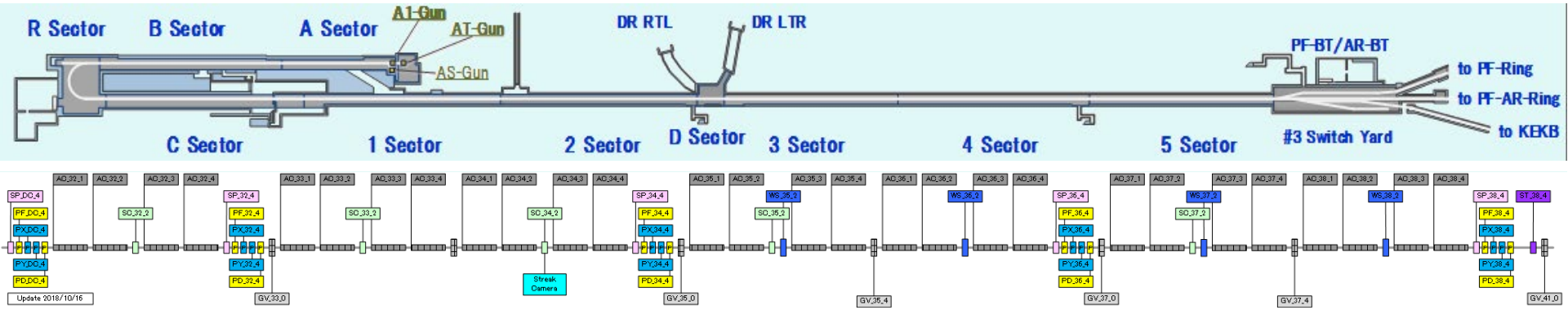
Online Data for the ML study

Injector Linac is for SuperKEKB, PF and PF-AR



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

In this study, we use the KEK Linac operation data accumulated in 2018 Nov. - 2019 June (81 days 1,180,500 shot)



Linac Operation Tuning using ML

To obtain the high injection efficiency,
injector linac is continuously tuned by operators.

The optimized parameter values for RF, Steering magnet, etc., to get the high injection efficiency **vary** depending on the accelerator condition (environment) etc.

To efficiently get the "good" (or "best") parameter values for RF and Steering magnets, which provide high injection ε, we try to introduce ML

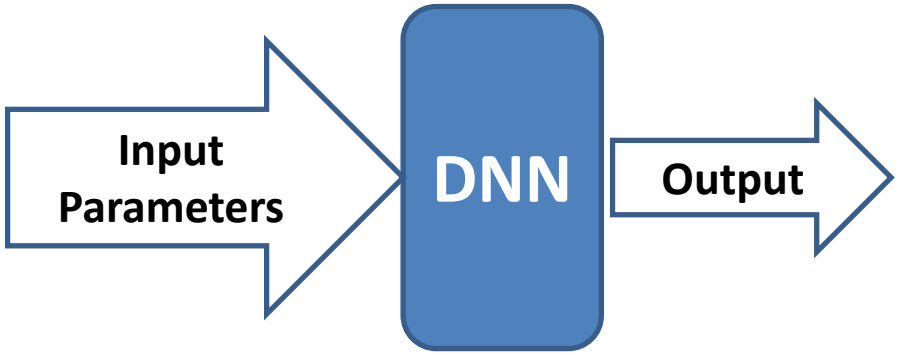
Our Strategy:

1. Obtain "good" initial parameter value by regression
   → **based on the past operation experience**
2. Obtain "best" parameter value by reinforcement
   → **based on the current environment**

Parameter Tuning using DNN

To get the "good" initial parameter value, we use DNN

<u>DNN is trained by the past operation data</u>



Acc. parameters

Env. Data, RF data,
Steering magnet data…

Parameter value

RF, Steering magnet,,

This time we use <u>classification</u> to get the "good" parameter value for RF and Steering Magnets to get high injection efficiency

Parameter Tuning using DNN

H. Joan (Osaka-City U.)

To get the "good" initial parameter value, we use DNN

DNN Validation check is done by the past operation data

Input : 1071 acc. parameters
Output : the "good" RF value
(For Sector B, 5th RF)

		DNN Output				
		0	*1*	*2*	*3*	*4*
True Value	*0*	1029	0	0	5	5
	1	10	137	14	12	19
	2	1	7	14	26	10
	3	20	30	0	457	270
	4	12	51	1	113	757

Accuracy ≅ 80%

Input : 1881 acc. parameters
Output : the "good" Steering magnet current value
(For Sector 1, 7th magnet)

		DNN Output			
		0	*1*	*2*	*3*
True Value	*0*	1584	271	0	2
	1	350	1642	0	1
	2	0	0	645	265
	3	0	0	166	1065

Accuracy ≅ 82%

Preliminary

The RF and Steering-manet current values are classified into 4 - 5 blocks

Summary

ML is expected to be a powerful tool for big data processing

To apply ML to High Energy Experiments we form a group

Several Studies to apply ML are on going