Seoul National University

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Applications of AI-Based Analysis in Radiation Measurement and Fusion Reactor Diagnostics

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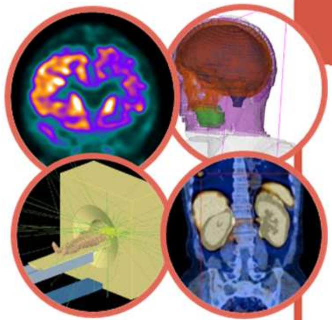
Contents

1. Why use AI to analyze radiation measurement data?

Diverse applications of radiation

Radiation analysis across diverse applications

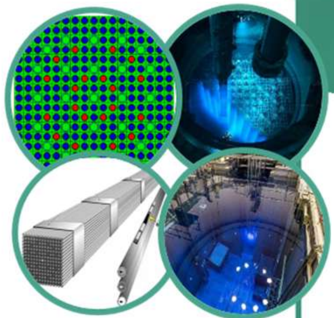


Medical radiation (imaging & therapy)

- Image reconstruction (PET, SPECT, CT)
- Radiation dose estimation & optimization

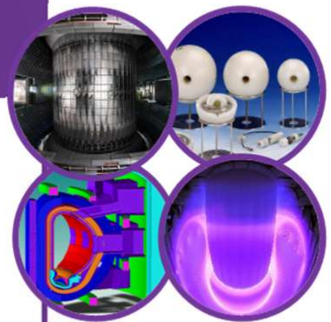
Nuclear security & safeguards

- Nonproliferation monitoring & verification
- Fissile material characterization



Reactor & Fuel Cycle Analysis

- Reactor monitoring & core diagnostics
- Non-destructive spent nuclear fuel assay



Fusion & accelerator diagnostics

- Plasma diagnostics & profile reconstruction
- Neutron spectrum unfolding

Challenges in Analyzing Radiation Measurement Data

Statistical Uncertainty [1]

- Stochastic nature of radiation
  - → Fluctuations in detected counts
  - → Uncertainty ↑ in analysis

Real-time Constraints [2]

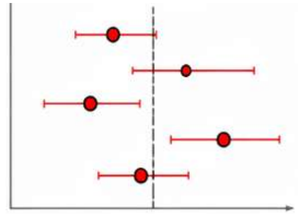
- Especially for iterative methods (ex. MLEM)
- Slow convergence & iterative burden
  - → Difficulty in real-time diagnostics

Limitations of Conventional Analysis [3]

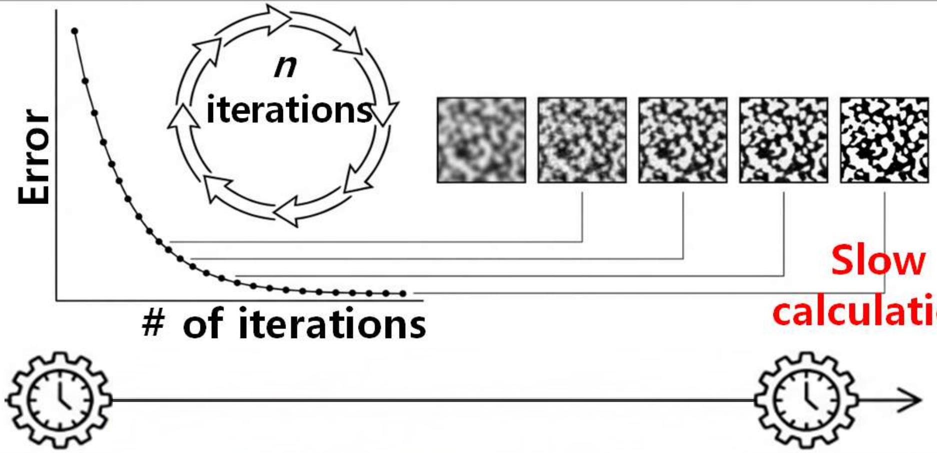
- Simplified physics-based models
  - → Neglecting other correlated variables

Detected counts

Trial 1 :	33
Trial 2 :	29
Trial 3 :	30
⋮	⋮
Trial 9 :	26



Uncertainty ↑ in analysis



Slow calculation

$$y = f(x_1, x_2)$$

Surely no x_3, x_4?

Why use AI to Analyze Radiation Measurement Data?

Statistical Uncertainty →

Robustness to Noise [4]

- Data-driven learning
  → Robust to noise and uncertainty

Real-time Constraints →

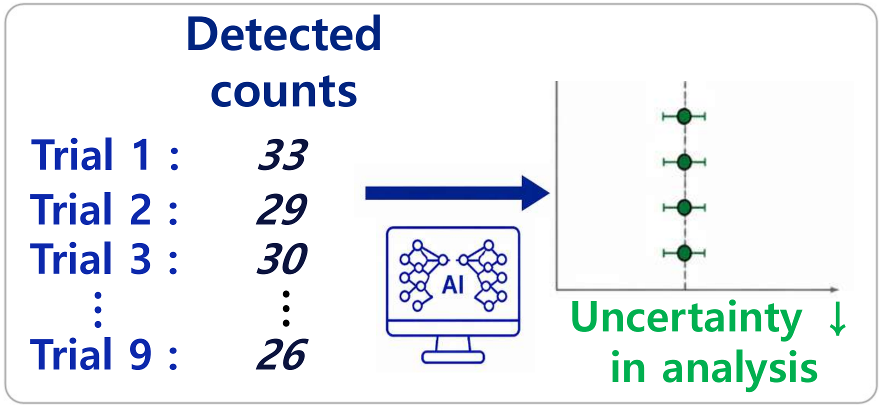
Real-time Computation [5]

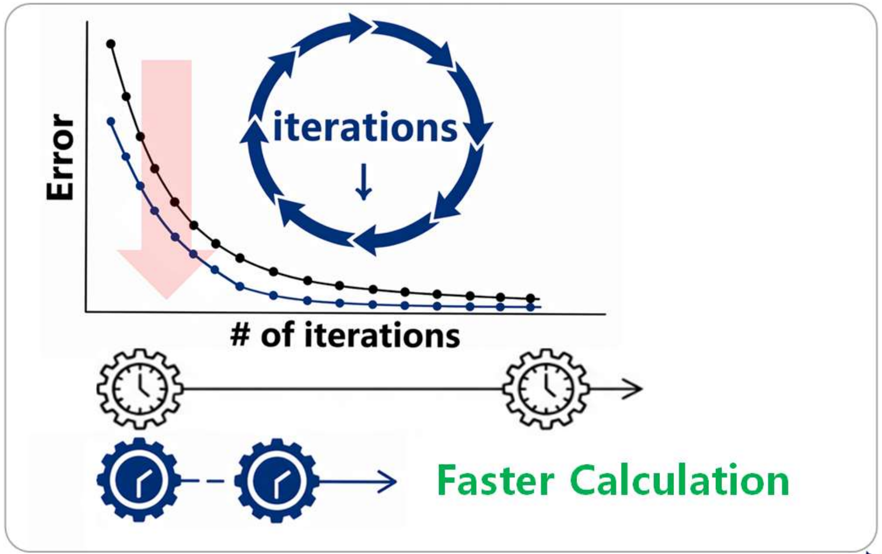
- Capability of faster calculation

Limits of Conventional Analysis →

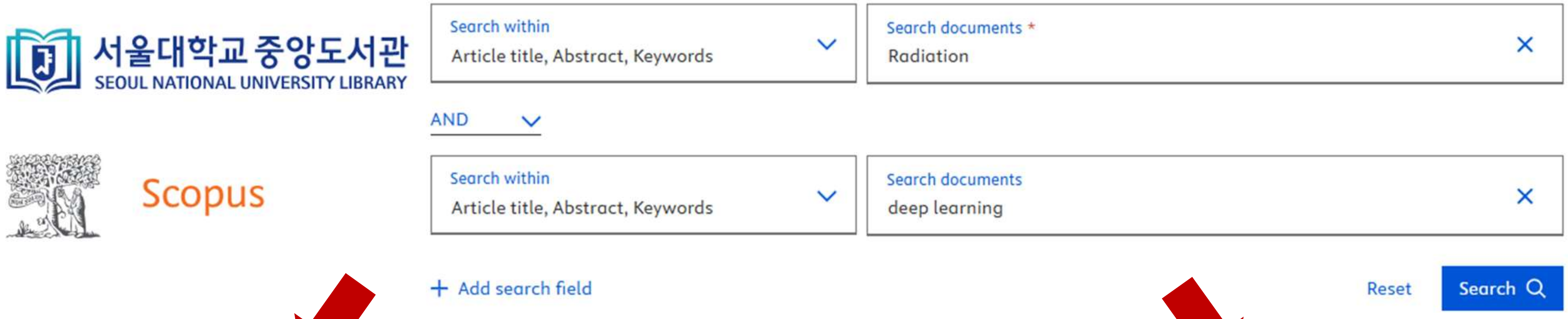
Direct Learning from Raw Data

- Capturing complex interactions without simplified assumptions

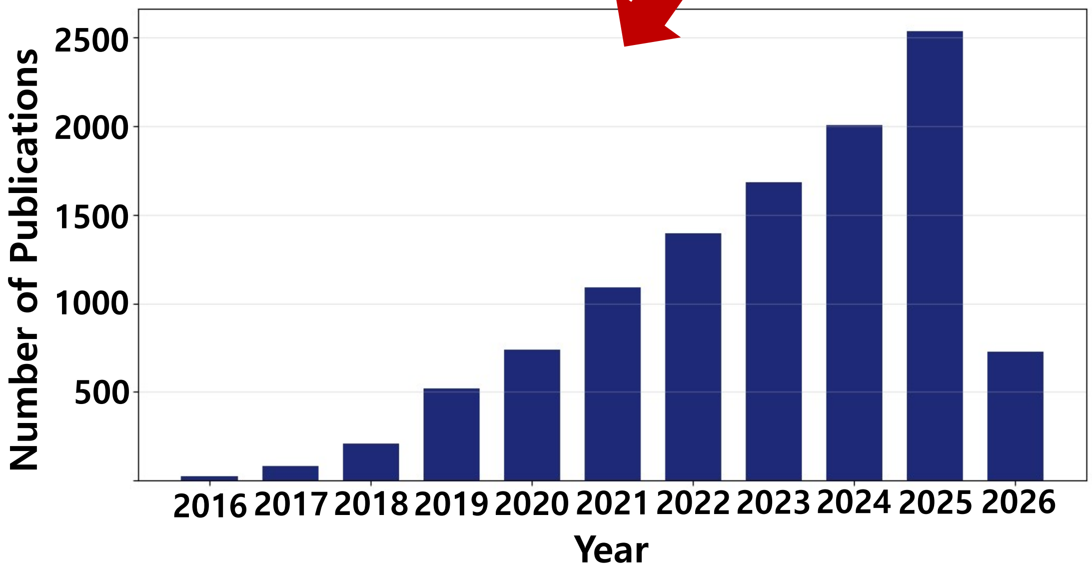




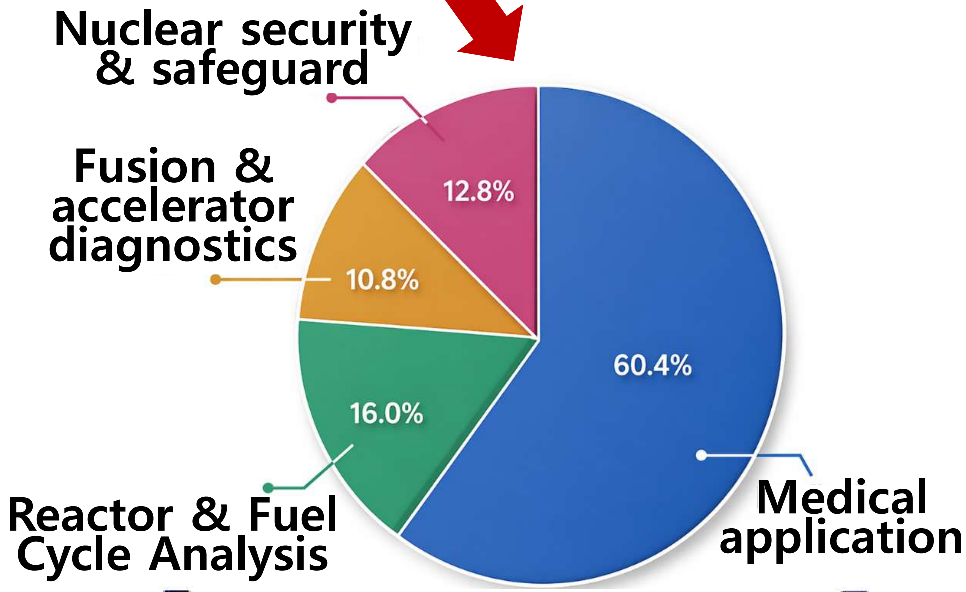
Trends in AI–Radiation Interdisciplinary Researches



[6]



「 Growth of AI applications in radiation fields 」



「 Proportion of AI Applications by Domain 」

2. Why does AI Outperform Conventional Methods?

Application 1 : Fissile Material Characterization

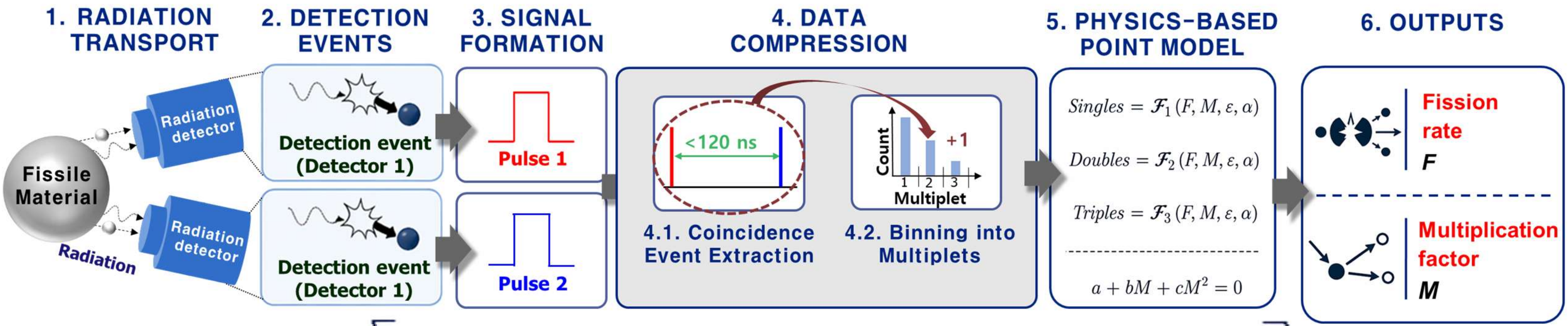
☐ Necessity of fissile material characterization

- **Accurate characterization of fissile materials critical for nuclear safeguards and security**
- **Key parameters: fission rate (*F*), neutron multiplication factor (*M*), …**

☐ Conventional physics-based point model approach [7]

- **Based on neutron multiplicity (= number of emitted neutrons per fission event)**
- **Estimating fission-related parameters (e.g., *F, M)* from multiplets and point model**

「Detection system simulated using Monte-Carlo code (MCNP)」

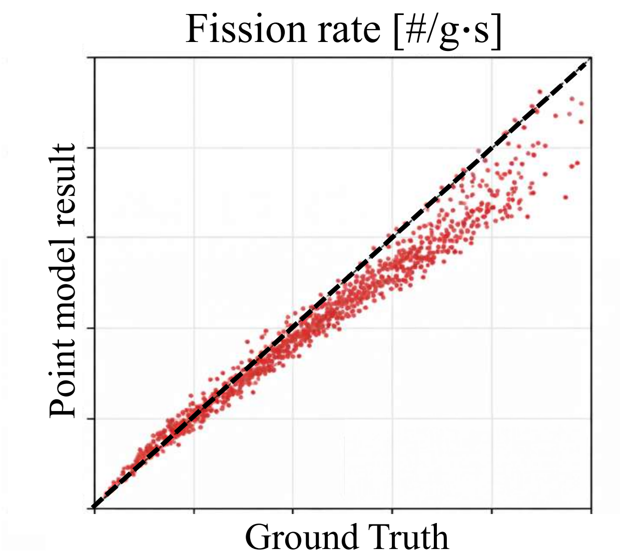


「Schematic of conventional point model-based fissile material characterization」

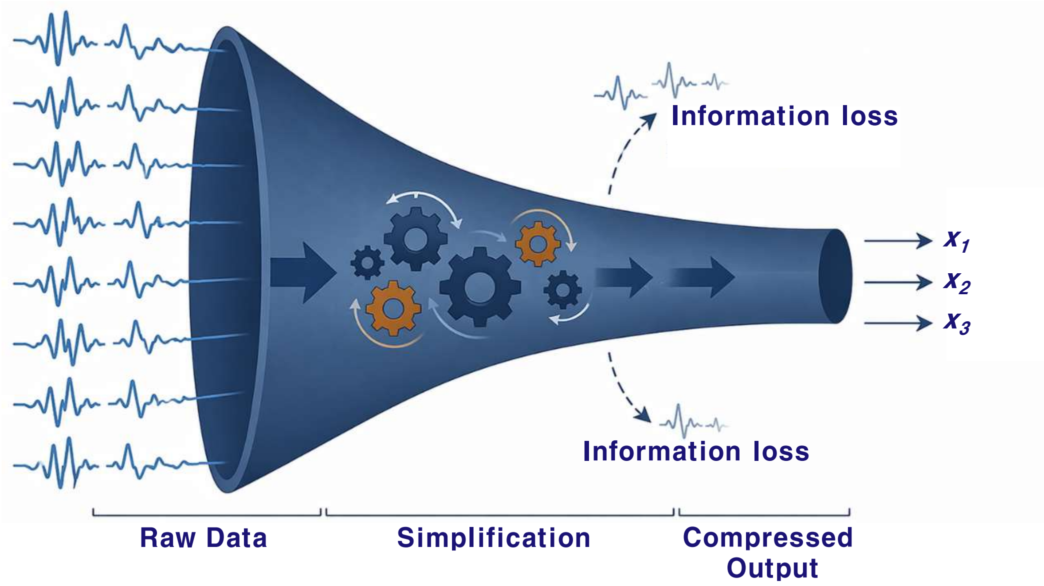
Why Does AI Outperform Conventional Methods?

☐ Why physics-based models show limitation?

- Simplified assumption → information loss & nonlinear bias ↑
  - Point model case : complex, geometry-dependent interactions assumed to be uncorrelated [8]
    → accuracy ↓ , uncertainty ↑
- But AI can direct learn from high-dimensional data → Captures complex interactions → accuracy ↑ , uncertainty ↓

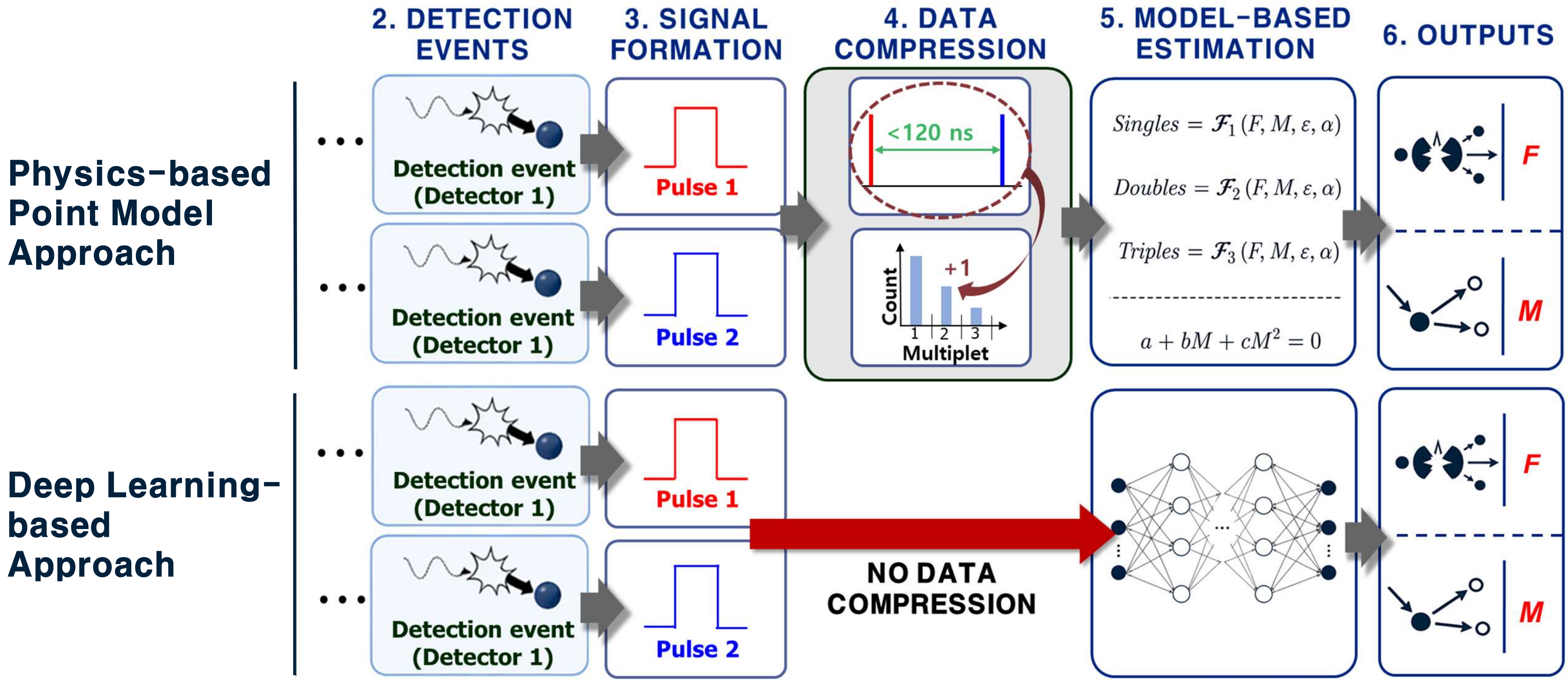


「 Point model result showing nonlinear bias [9] 」



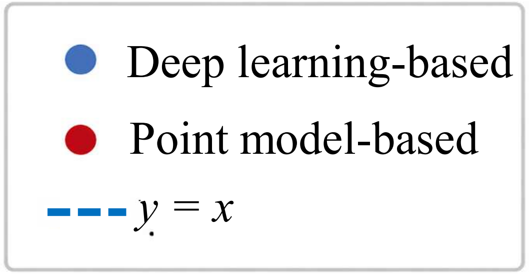
「 Loss of information while data simplification and compression 」

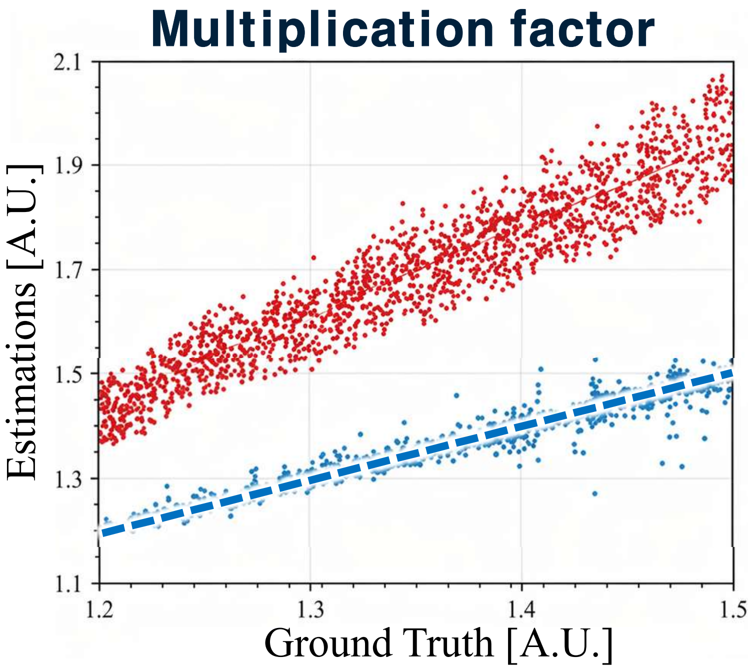
Physics-based Model vs Deep Learning-based Model

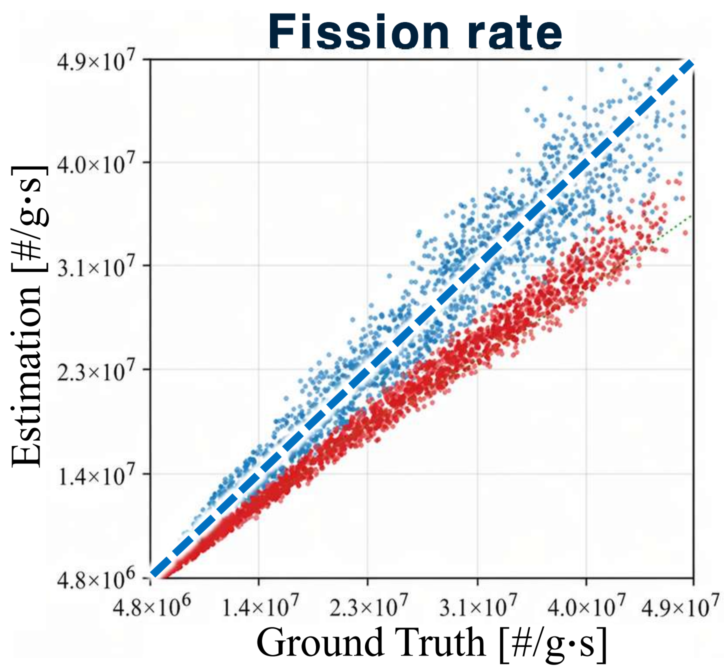


[Schematic of different approaches for fissile material characterization]

Result 1 : Deep Learning Outperforming Point Model





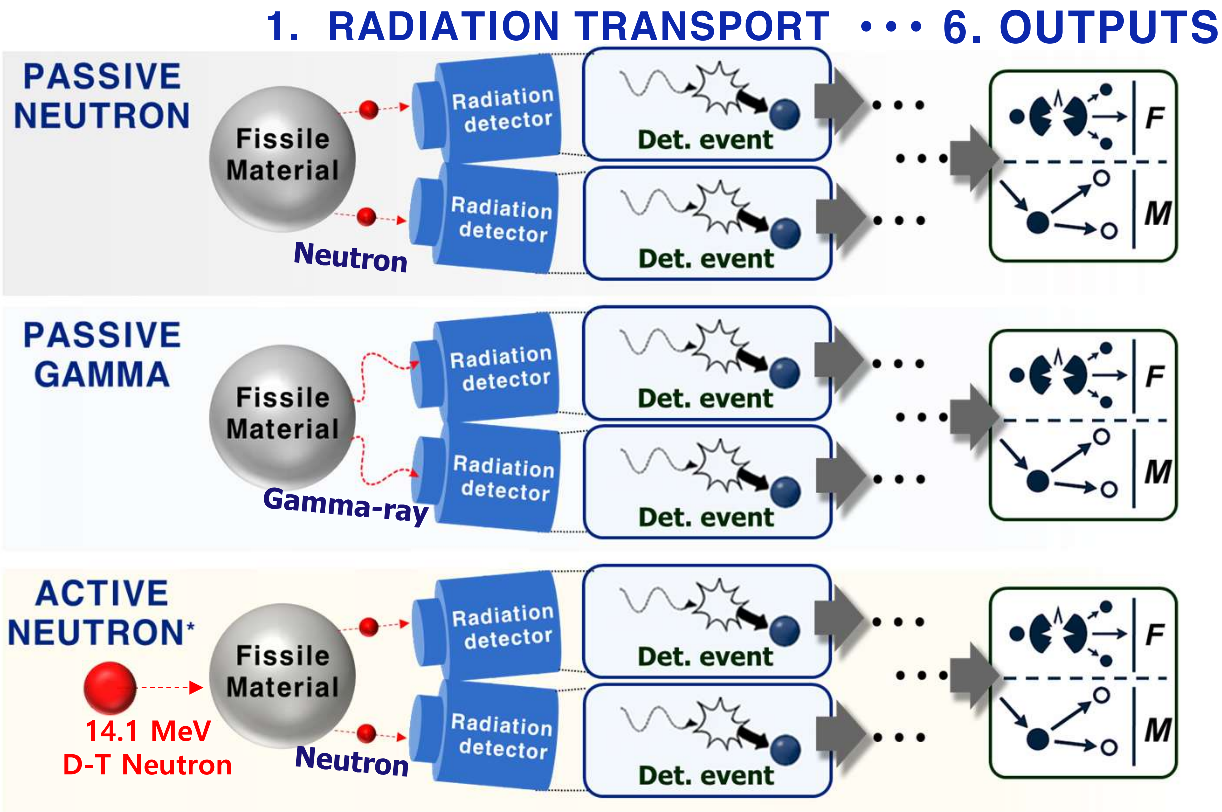


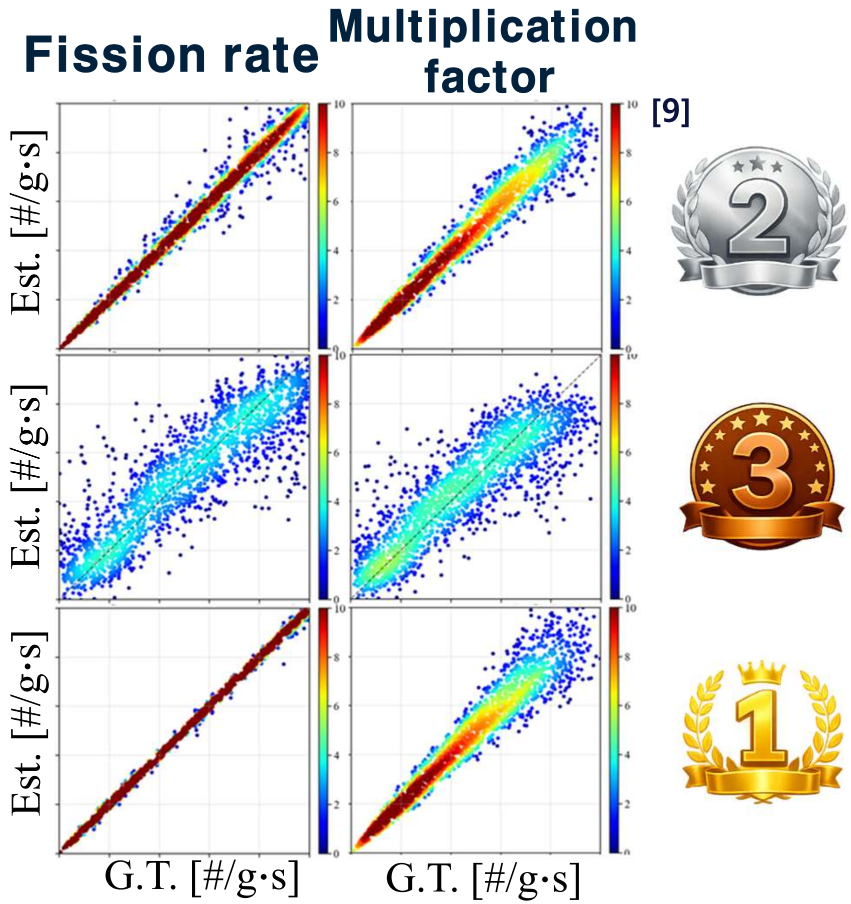
「 C2C-GRU estimation vs ground truth for fission rate (left) and multiplication factor (right) [9] 」

Deep learning model outperforming point model

- No information loss → Bias(M)↓ , Bias(F) ↓
- Var(M) ↓, but Var(F) not improved

Result 2 : Comparison between Radiation Type

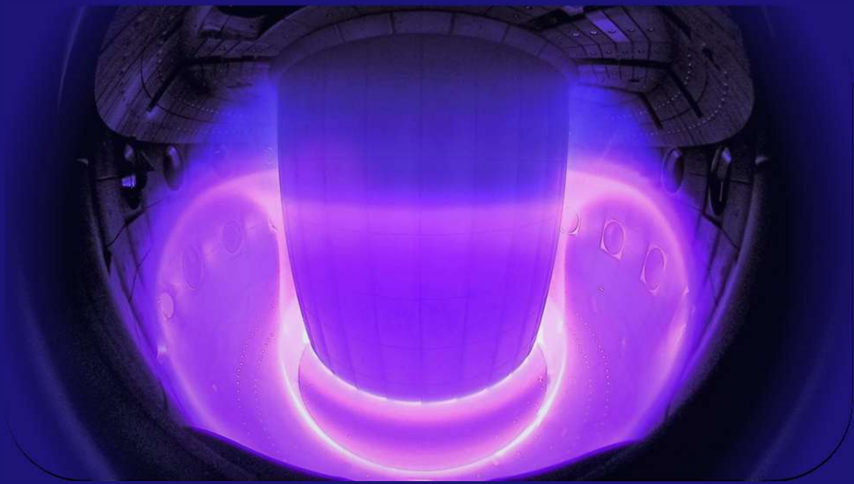




*Active Neutron = Neutrons induced by active interrogation

✔ **Consistent with conventional understanding**

2. AI for Fusion Reactor Diagnostics



Application 2 : Real-time Light Output Spectrum Unfolding

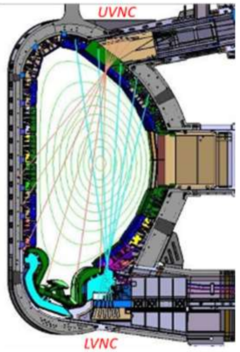
- ☐ **KSTAR (Korea Superconducting Tokamak Advanced Research)** [10]
  - ■ **Korean fusion reactor which uses D-D fusion reaction mainly**
    - ▪ D-D fusion : D + D → ^{3}He + n (2.45 MeV)

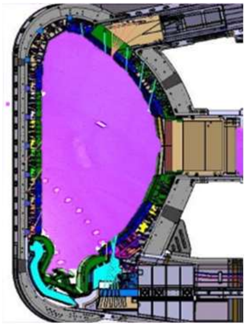
┌ Picture of KSTAR ┐

- ☐ **Procedure for diagnosing plasma instability in KSTAR** [11]

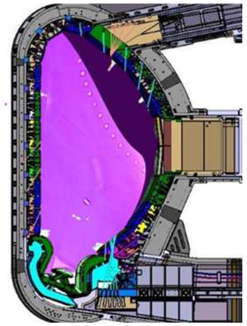
Neutron Imaging

[Within 100 milliseconds]

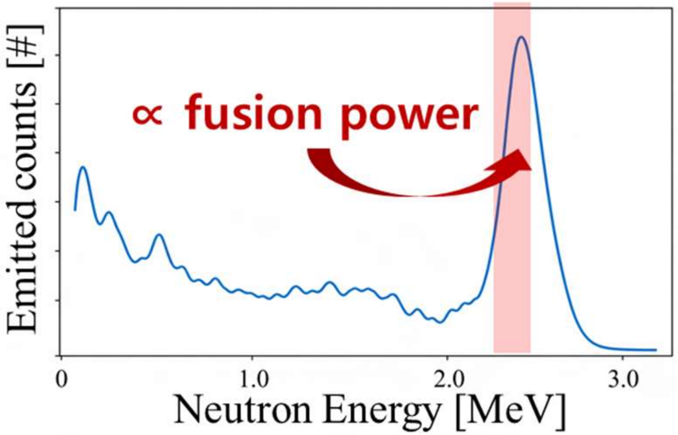




Stable Plasma



Unstable Plasma



┌ Energy distribution of neutrons from KSTAR ┘

- ☐ **Pros and cons of organic scintillator for real-time diagnostic**
  - ■ **Pros : Fast response & Decent neutron discrimination** [12,13]
    - ▪ Applicable for real-time diagnostics
  - ■ **Cons : No correlation btw. acquired light output spectrum & initial radiation source energy distribution** [14]

Application 2 : Real-time Light Output Spectrum Unfolding

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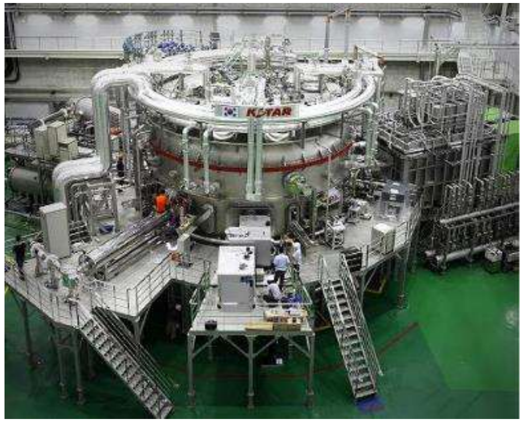
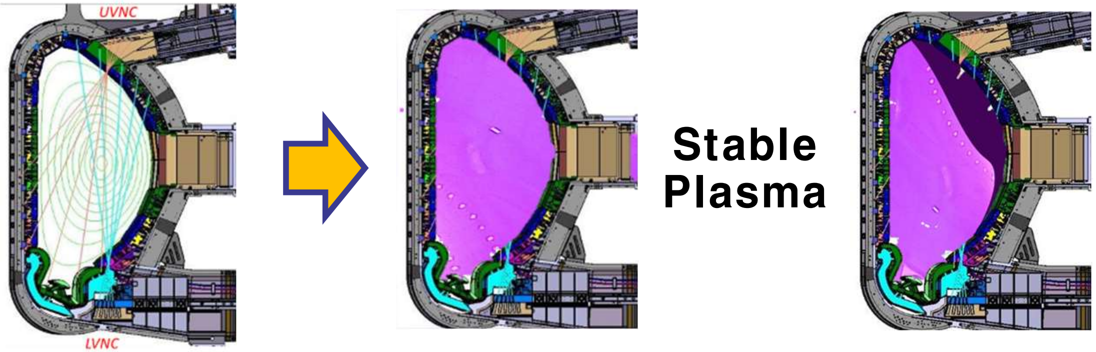


「 Picture of KSTAR 」

☐ Procedure for diagnosing plasma instability in KSTAR [11]

Neutron Imaging

[Within 100 milliseconds]



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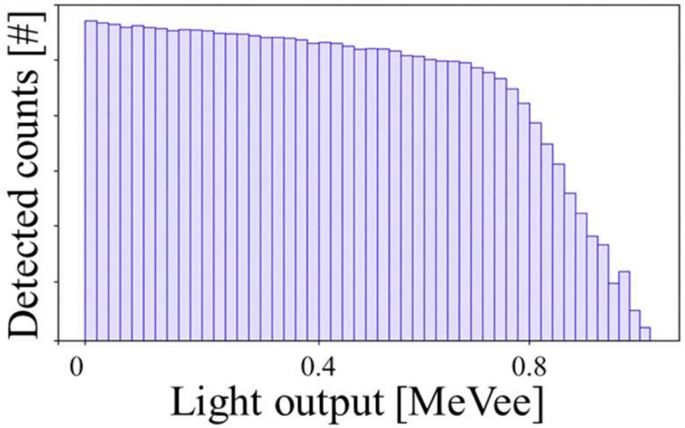


「 Corresponding light output spectrum 」

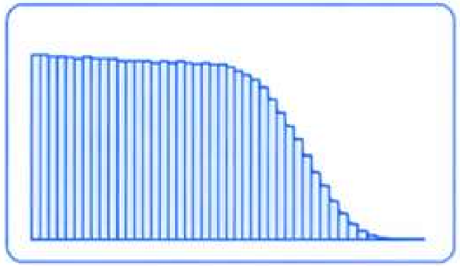
Application 2 : Real-time Light Output Spectrum Unfolding

Objective ▷▷ Real-time light output spectrum unfolding
(= Estimating initial neutron energy distribution)

Our materials

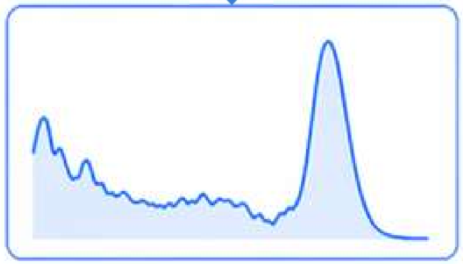
- Stilbene organic scintillator
  - Enables to get more neutron counts per unit time
- Deep learning
  - Simple matrix multiplication → Faster calculation
  - Regularization →Solves ill-conditioned problem

Approach ▷▷ Deep-learning based unfolding with dataset from plasma + neutron transport simulation



Light output spectrum (Our detection)

Unfolding



Energy distribution of emitted fusion neutrons (Our goal)

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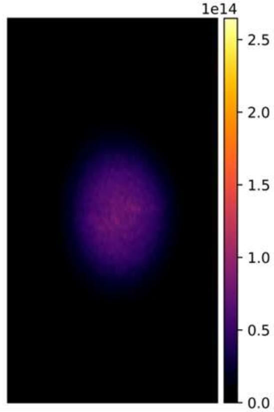
Neutron Source Acquisition & Detector System Setup

Dataset Generation

01 Neutron source : TRIASSIC plasma simulation output

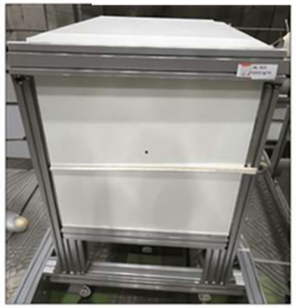
- TRIASSIC : Tokamak reactor Integrated automated suite for simulation and computation [15]
- Various initial plasma scenarios implemented
- Output : Spatio-temporal D-D fusion reaction rate
  = Spatial neutron emission probability within unit time



「Spatio-temporal DD fusion reaction rate for shot #22663」

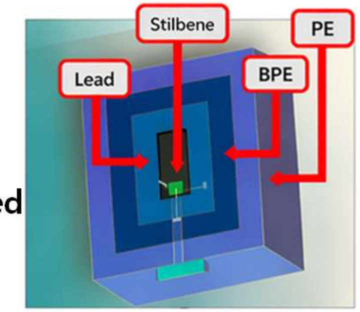
02 Detector system : stilbene with collimation [16]

- For shielding too much incoming radiations
- Stilbene shielded with polyethylene(PE), borated polyethylene(BPE), lead
- Stilbene displacement adjusted to avoid pile-up



「Neutron detection system in KSTAR」

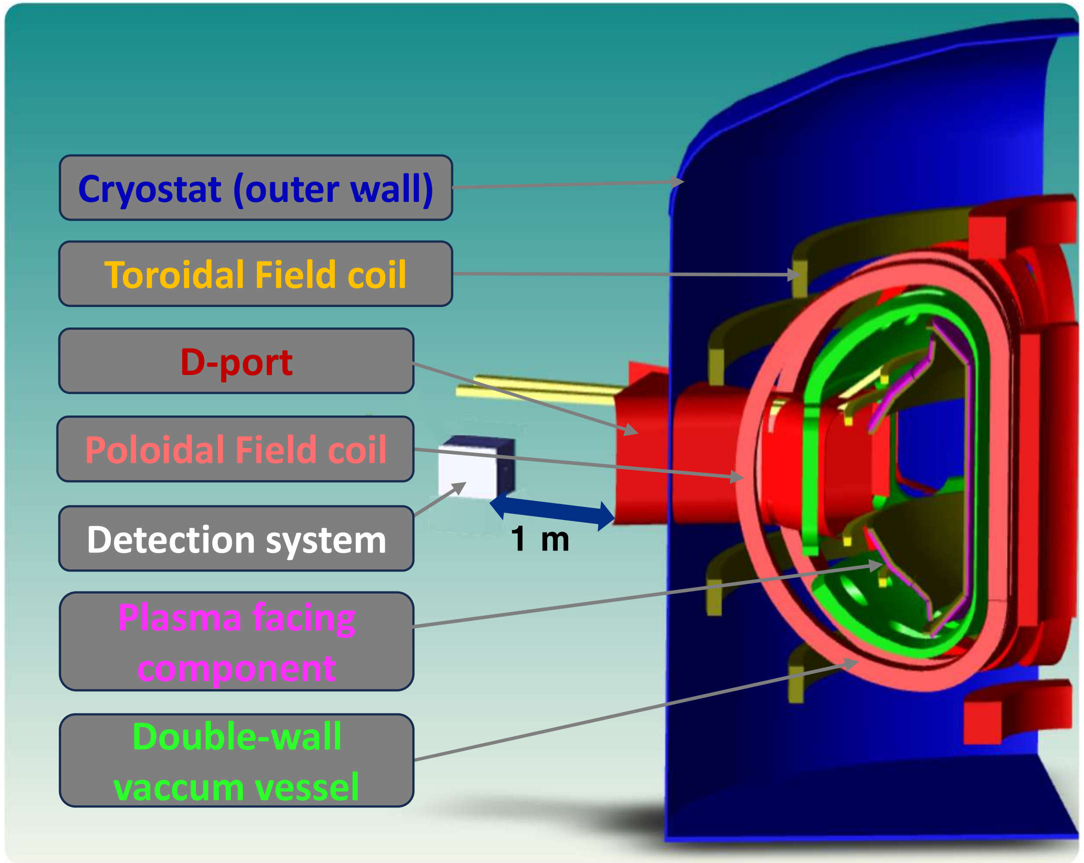
Simulated



「Simulated detection system」

KSTAR Geometry Implementation & Data Processing

Dataset Generation



01 Geometry of simulated KSTAR [17]

- Simulated in MCNP
- Including KSTAR major components & neutron detection system

02 Post-processing simulated output

- Artificially adding poisson noise to simulated spectrum

  → Ill-conditioned unfolding problem

03 Validation of Simulation output against experiment

- Experiment with D-D fusion neutron generator

Features Needed for Our Deep Learning Model

Designing DL Model

What properties do we need?

Fast computation

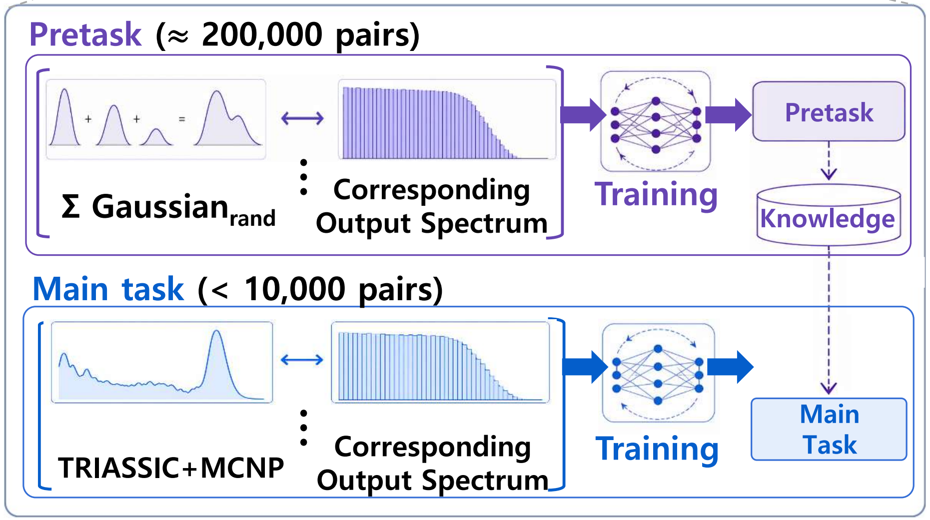
- Problem : unfolding in ms order
- How? : Minimized model size & complexity

Regularization

- Problem: Overfitting & ill-conditioned problem
- How? : Promoting sparsity and stability via L_1/L_2 regularization

Generalization

- Problem : Insufficient dataset
  - \# of data < 10,000
- How? : Transfer learning



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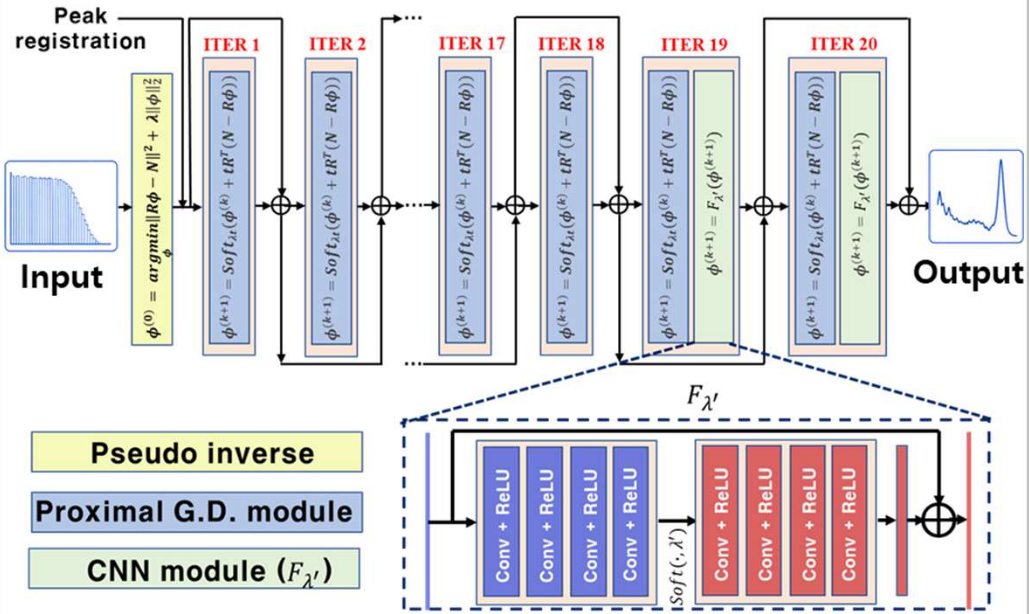
FISTA-Net for Unfolding Algorithm

Designing DL Model



「 Architecture of FISTA-Net 」

01 Principle of FISTA-Net [17,18]

Solving inverse problem $N = R\Phi$

N : Input, Φ : Output, R: response matrix

FISTA (Gradient step)

- Proximal gradient step
- L1 Soft-thresholding → Regularization
- Momentum acceleration → faster calculation

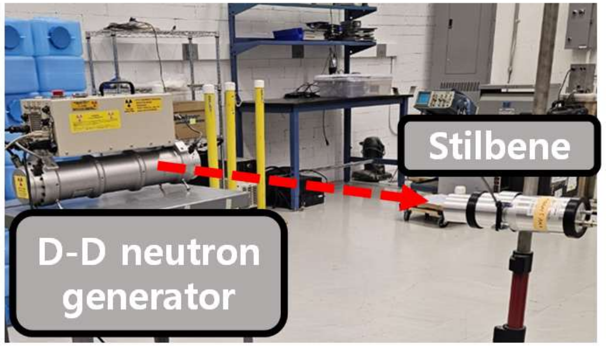
$$\phi^{(k+1)} = Soft_{\lambda}(\phi^{(k)} + tR^{T}(N - R\phi^{(k)}))$$

CNN (Deep learning)

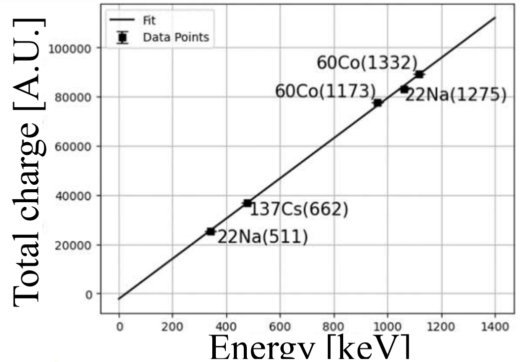
- Learning correction
  - Data-driven
- Feature extraction → Faster convergence accuracy, stability ↑

Result 1 : Validation of Simulation against Experiment

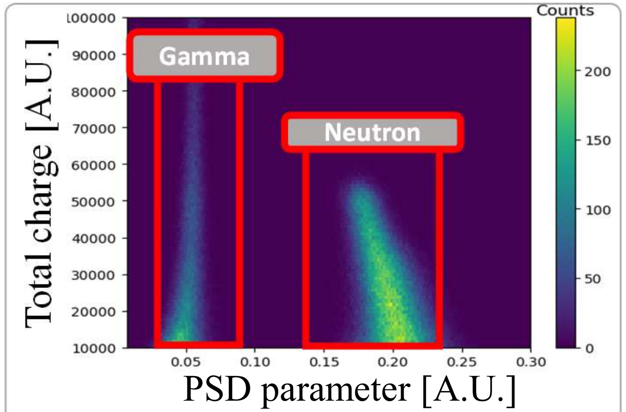
- **D-D fusion neutron measurement experiment with stilbene** [17]
  - Experiment at Univ. of Michigan (Upper left)
- **Energy-Channel calibration** (Upper right)
  - R^2 : 09997
  - Linearship btw. energy & light output
- **Pulse shape discrimination** (Lower left)
  - Figure-of-Merit : 2.15
  - Well-separated neutrons from gamma
- **Validating** $\textit{Stilbene}_{exp} \approx \textit{Stilbene}_{simul}$
  - Mean relative error < 5% for over 200 keVee (Lower right)



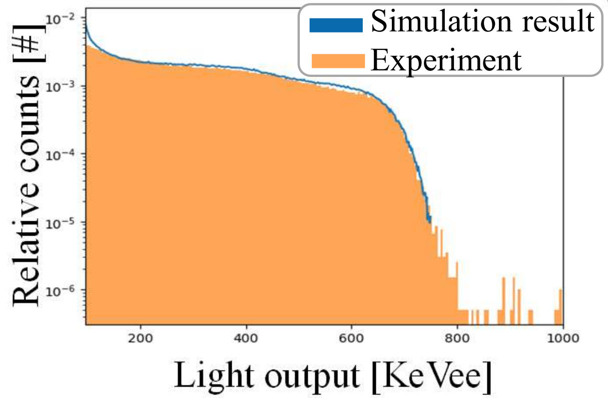
Experimental setup at U of M



Energy-Channel calibration

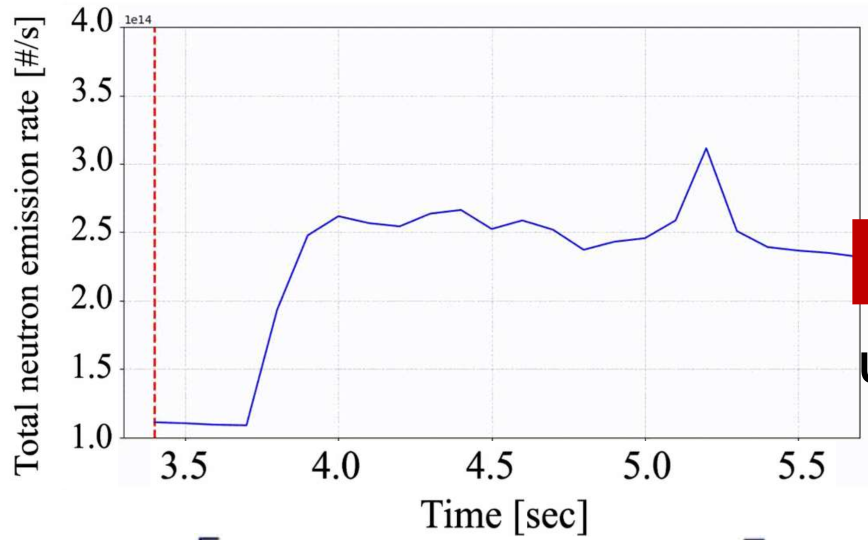


Pulse shape discrimination for D-D neutron



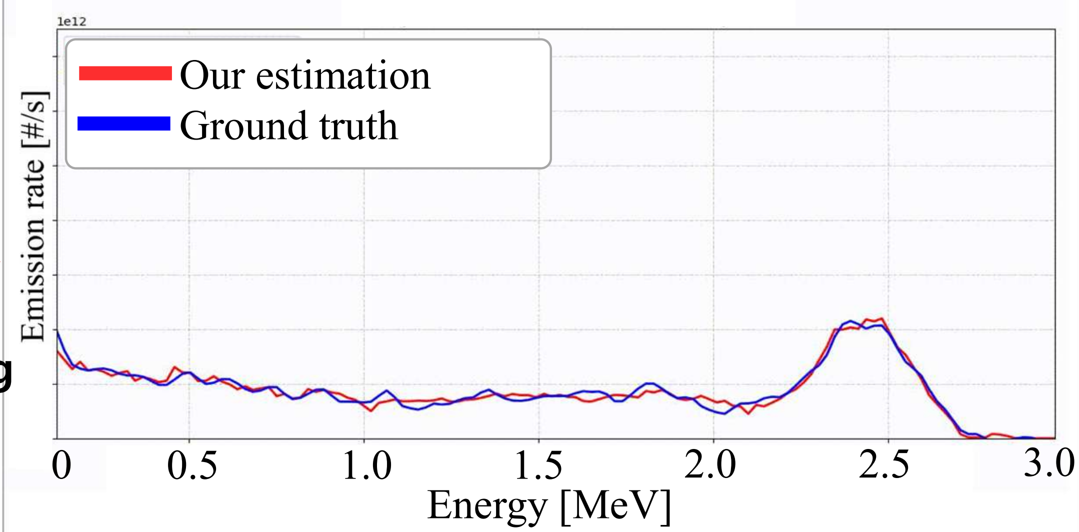
Neutron-only light output spectrum comparison

Result 2 : Reconstructed Energy Distribution over Time



「 Neutron emission rate over time 」

Unfolding



「 Unfolded result with ground truth 」

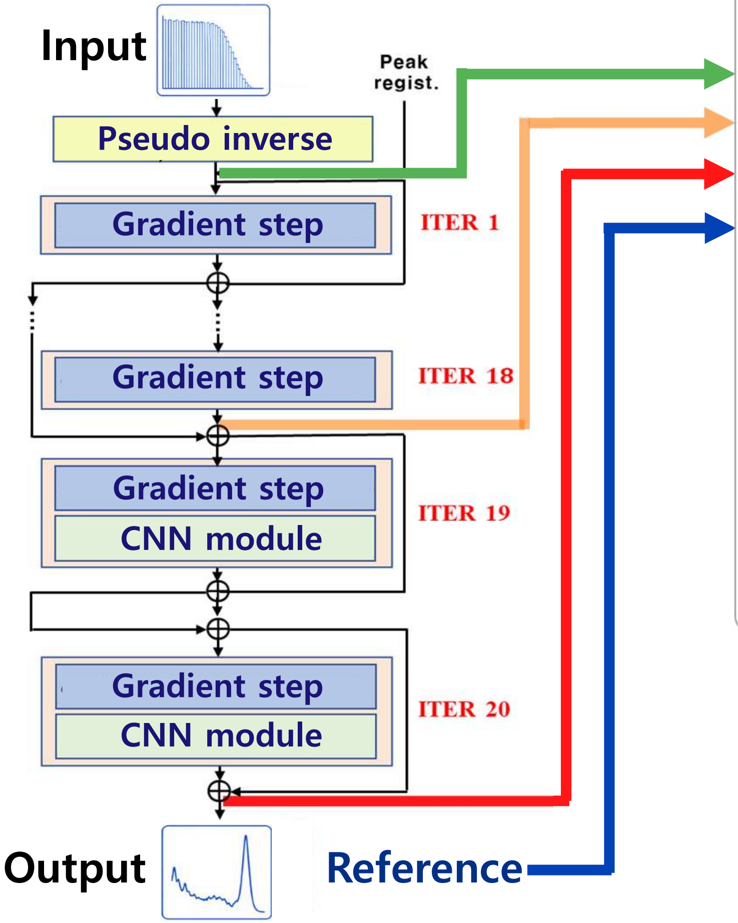
☐ **Calculation time spent for unfolding a single spectrum**

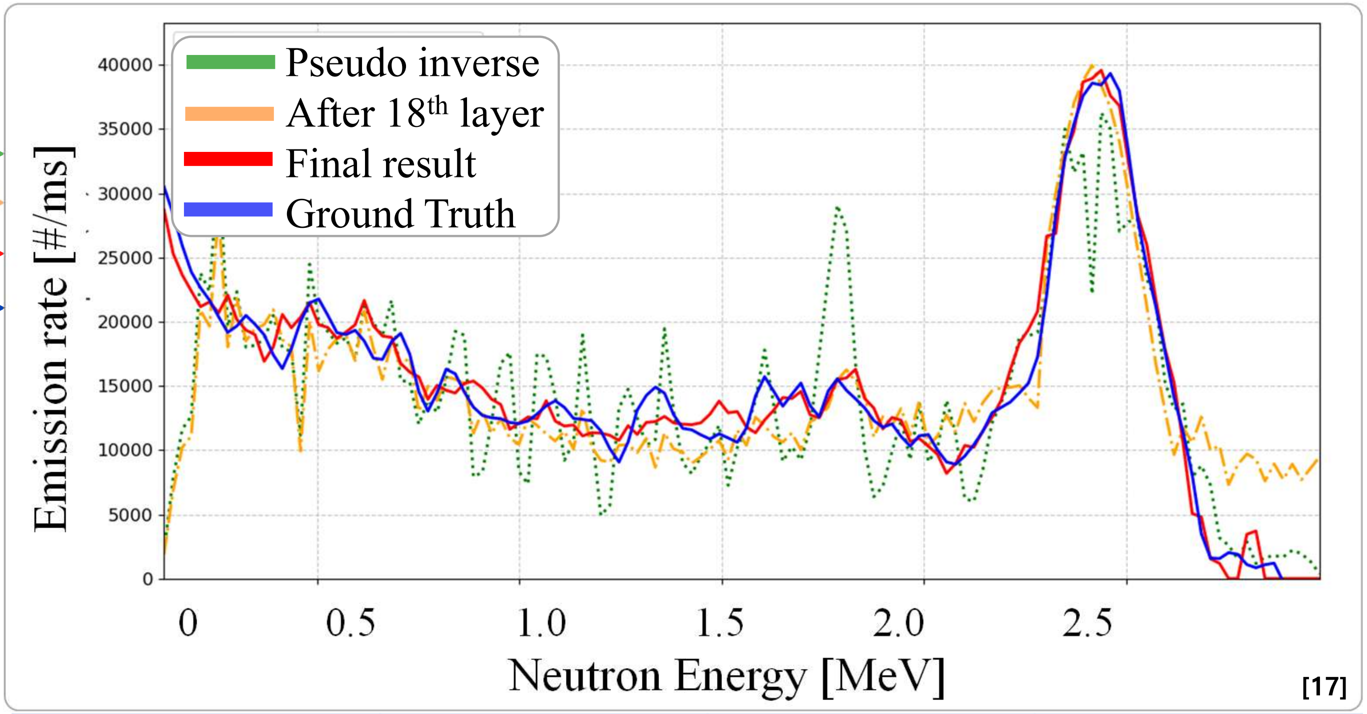
4.79 ms
on average

< 100 ms
Neutron Imaging

GOAL ACHIEVED!

Result 3 : FISTA-Net Result at Each Step



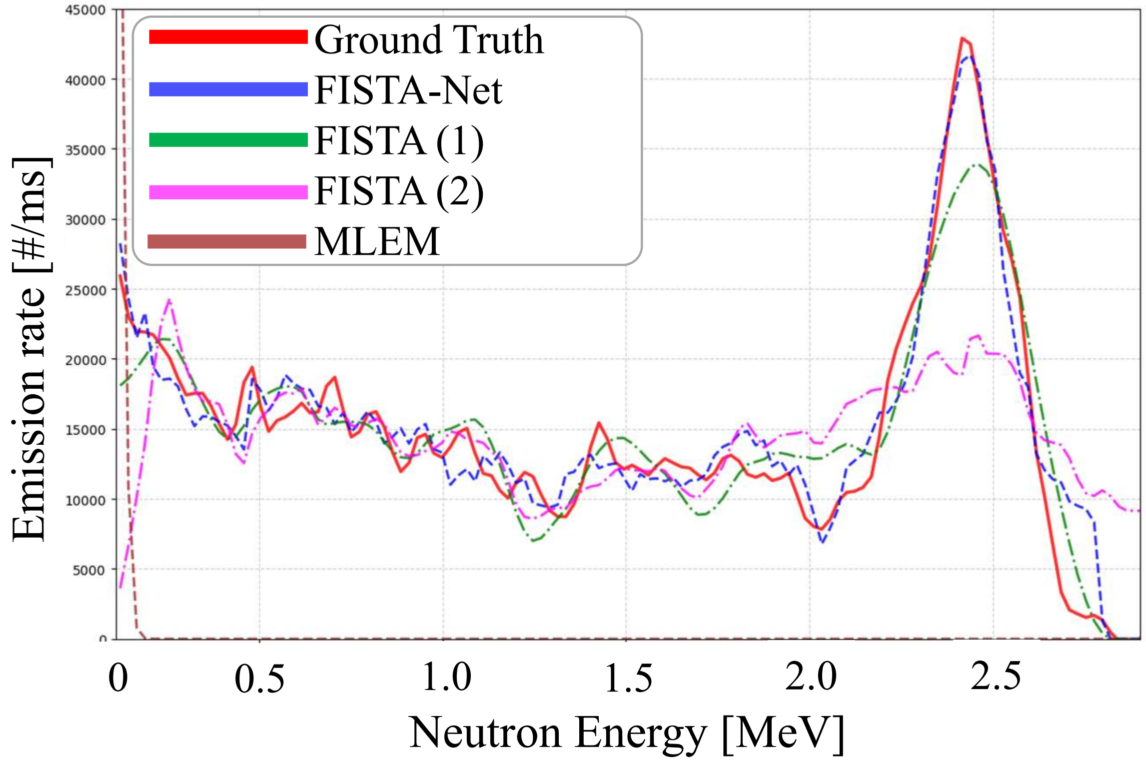


	Total area RMSE* [#]	Peak area RMSE [#]	Max. peak rel. error [%]
Pseudo inverse	5.14E+3	5.29E+3	17.2
After 18th layer	5.01E+3	3.63E+3	8.05
Final result	1.93E+3	2.45E+3	7.69

*RMSE = Root Mean Square Error

Result 4: Comparison with Other Algorithms

- Comparison with maximum likelihood estimation(MLEM), FISTA



「Unfolded results for each unfolding algorithm」 [17]

	# of layer	Tot. area RMSE [#]	Peak area RMSE [#]	Peak max. rel. error [%]	Calc. time [ms]
FISTA-Net	20	1.45E+3	1.63E+3	1.84E+0	6.18
FISTA (1)	5000	2.19E+3	3.13E+3	1.91E+1	198
FISTA (2)	100	5.01E+3	7.85E+3	4.90E+1	4.83
MLEM	N/A	>1E+4	>1E+4	>9.99E+1	N/A

*RMSE = Root Mean Square Error

Deep learning model outperforming other conventional methods

- In terms of accuracy, robustness, and calculation time

- Ill-condition problem → estimation accuracy ↓
  - Especially matters for conventional methods
- CNN-module : prediction acceleration

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Summary

01 Why use AI to analyze radiation measurement data?

→ Robust to noise · Real-time capability · Limits of conventional methods

02 Why does AI outperform conventional methods?

→ Direct learning from high-dimensional (minimal information loss)

03 AI for fusion reactor diagnostics

→ Real-time spectrum unfolding (Fast, accurate and robust)

Thank you

Reference

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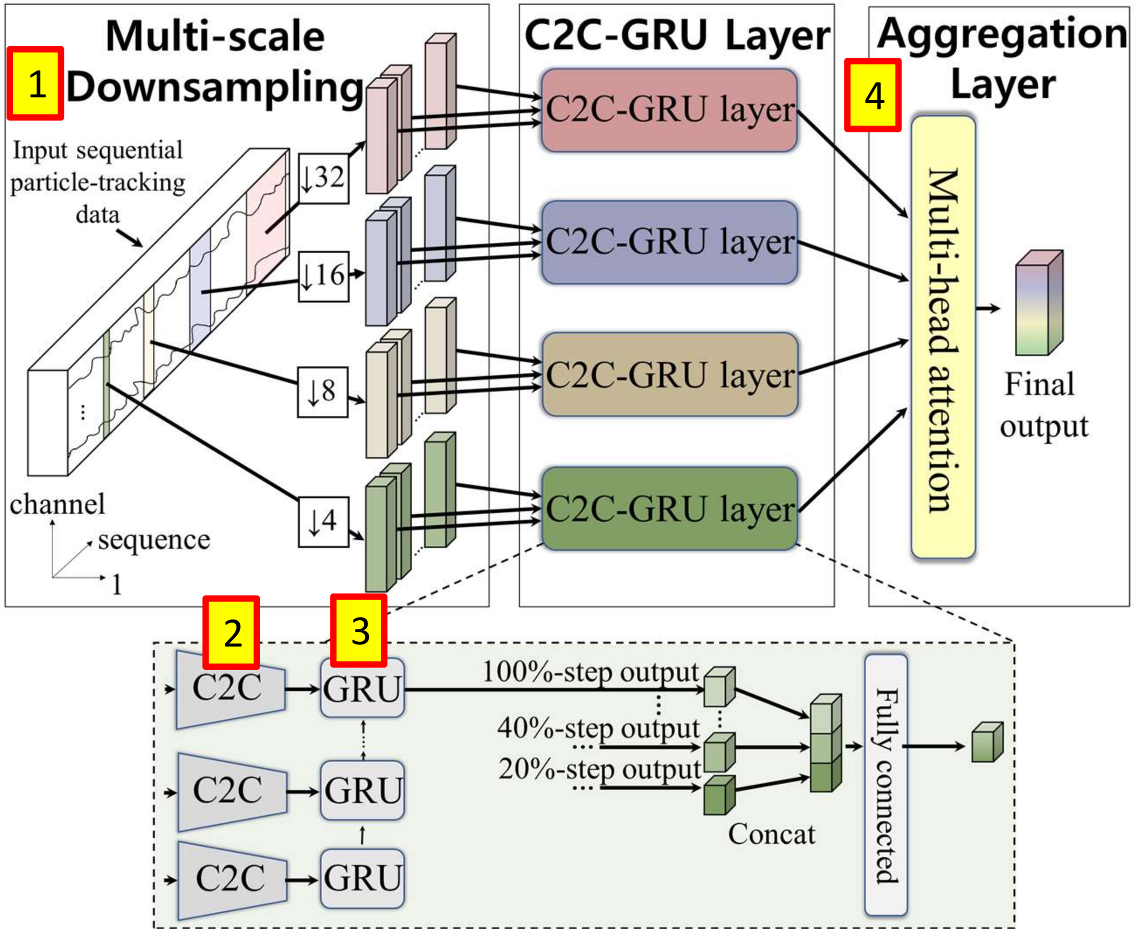
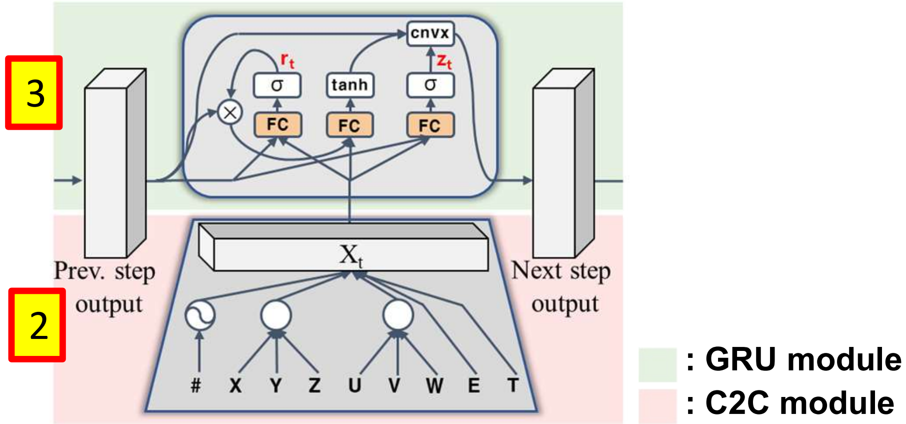
Backup

Architecture of C2C-GRU for High-dimensional Data





1 Multi-scale downsampling

- Reduced computation, preserved global features

2 Context-to-coordinate module

- Embedding into latent representations

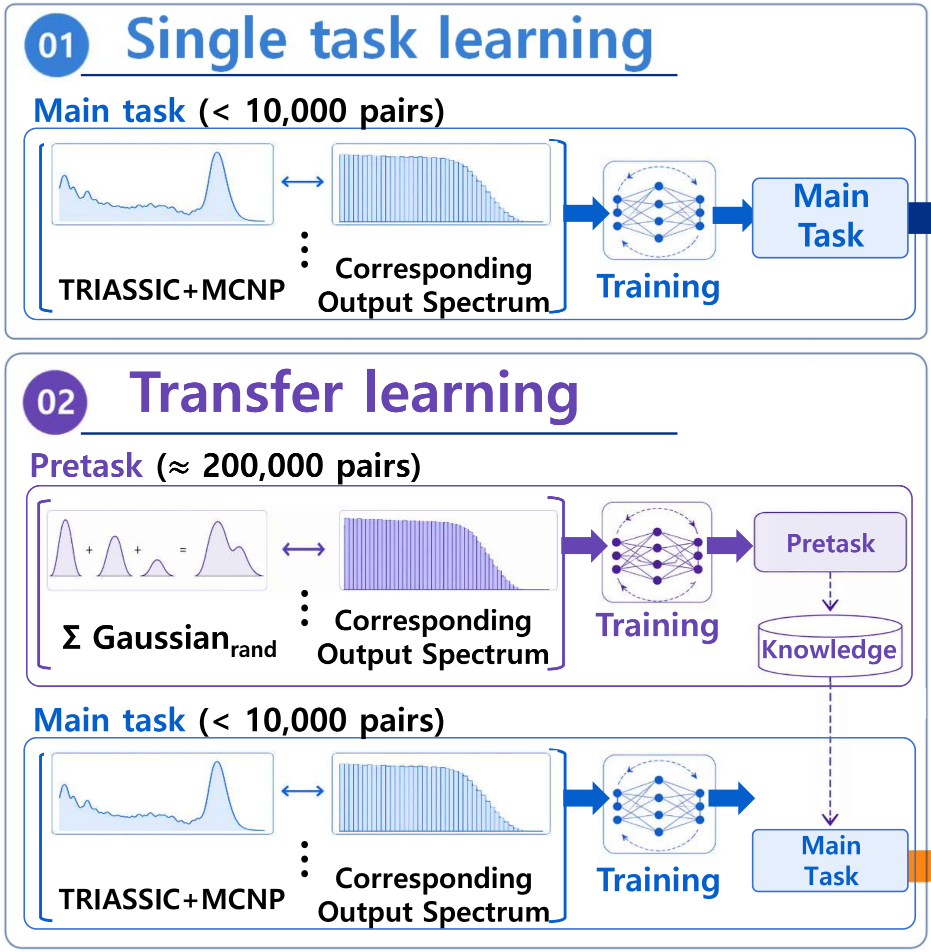
3 GRU module

- Extracting global features from time-series data

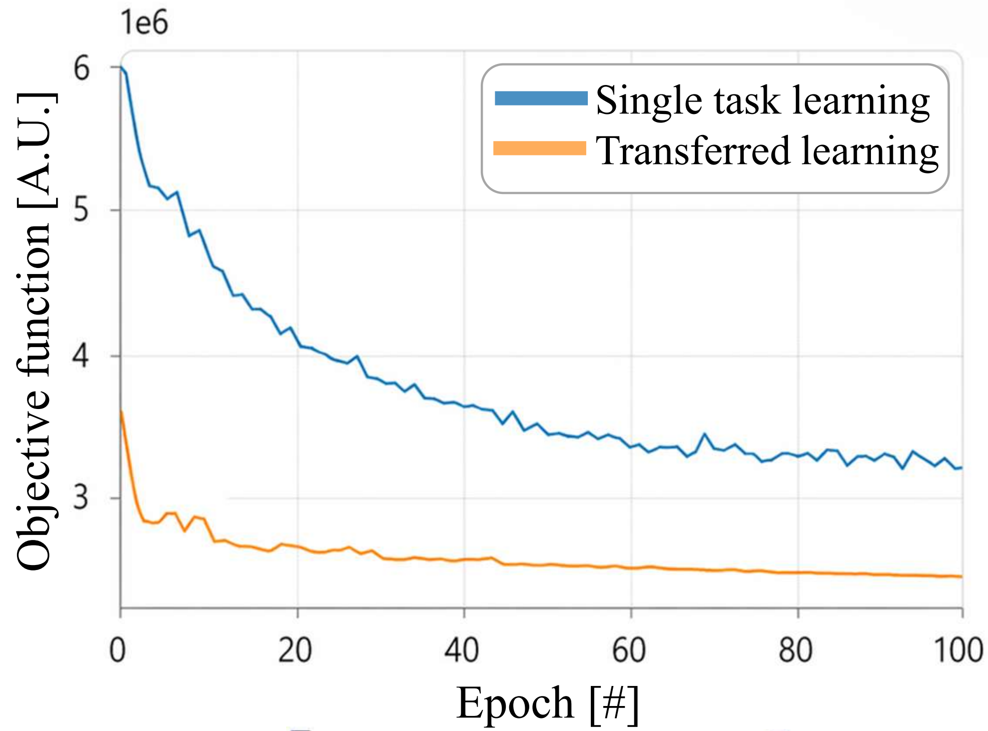
4 Aggregation Layer

- Integrating multiple downsampled representations

Result 5 : Effect of Transfer Learning on FISTA-Net

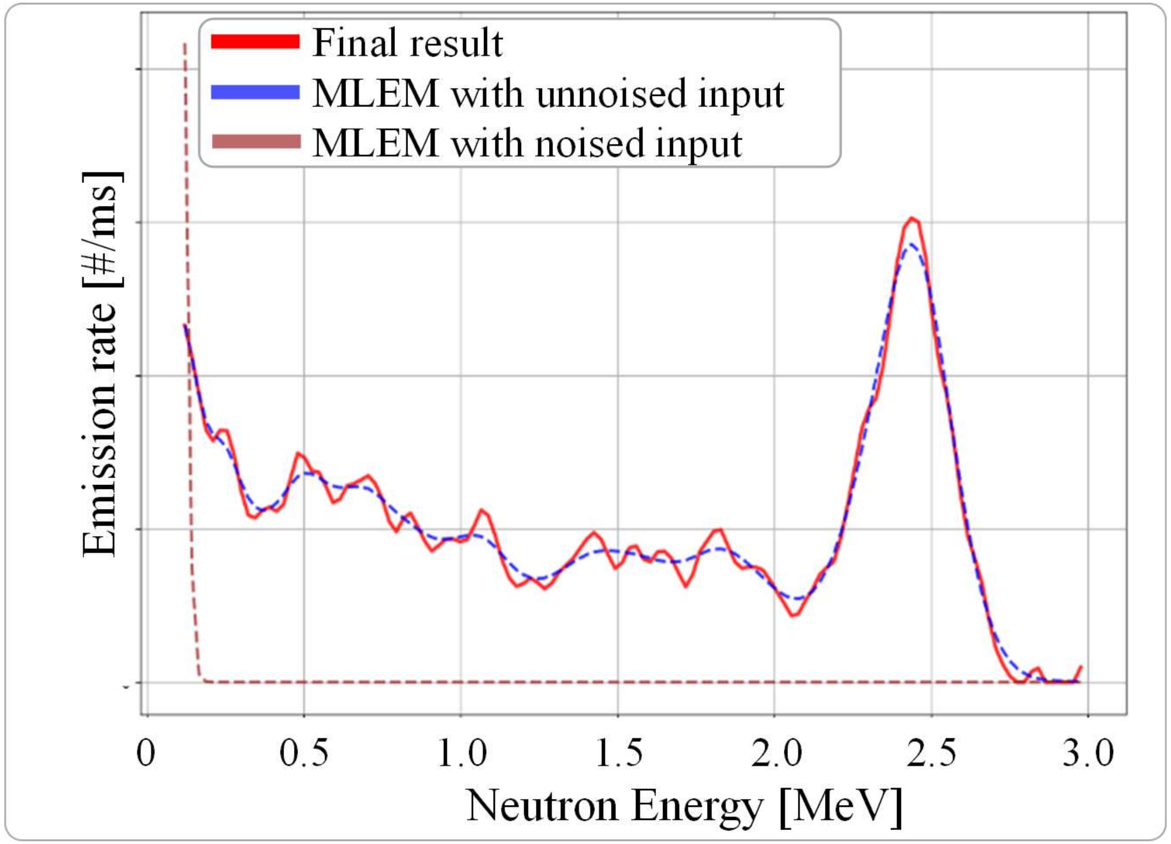


Objective function w & w/o transfer learning



「 Objective function vs epoch 」

Result 6 : MLEM unable to unfold for noised input



「Unfolded neutron energy distribution using MLEM for noised/unnoised input (left)」

- Decent performance of MLEM when given unnoised light output spectrum
- MLEM unable to unfold when given noised light output spectrum due to ill-conditioning