Accelerating X-ray Burst Sensitivity Studies with Deep Learning

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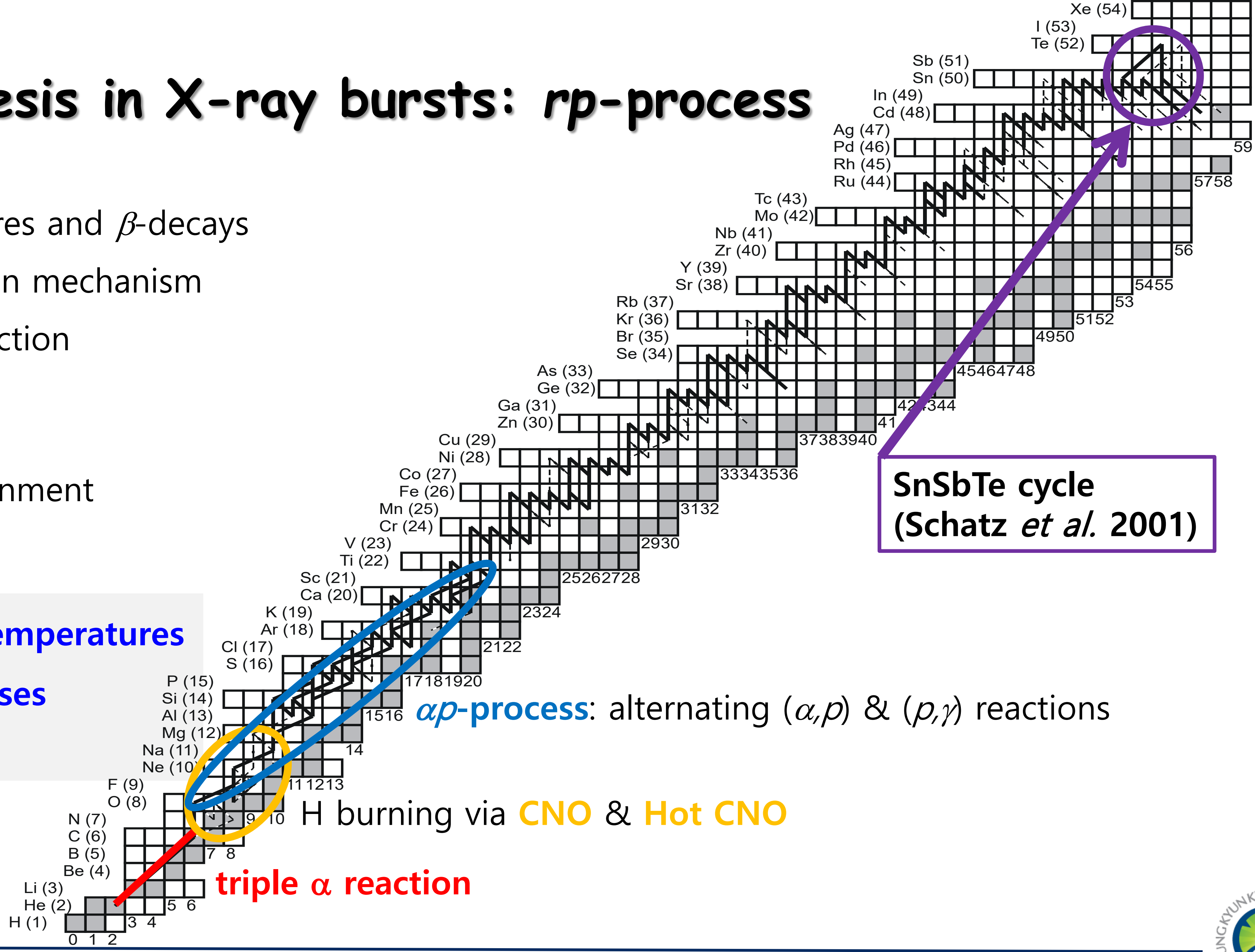
Nucleosynthesis in X-ray bursts: *rp*-process

- Series of proton captures and β-decays
- Main energy production mechanism
- Heavy elements production
- Conditions
  - High temperature
  - Hydrogen rich environment
  - Seed nuclei

Reaction rates at stellar temperatures are uncertain in MANY cases

→ Sensitivity study!



Nuclear Sensitivity Study: Identifying Key Reactions

Which nuclear reactions most strongly shape the X-ray burst light curve?

What is a Nuclear Sensitivity Study?

X-ray burst light curves result from a vast network of ~1000 nuclear reactions.

REACLIB

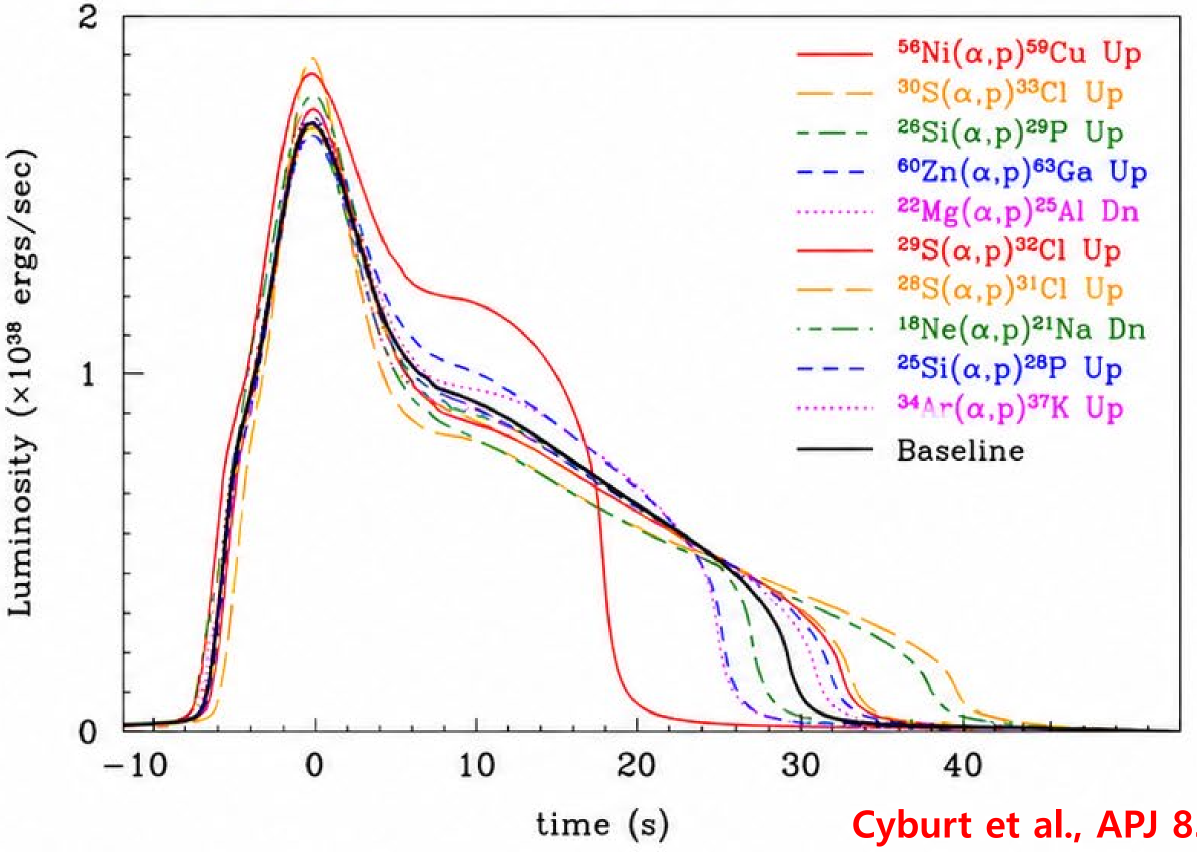
Vary one reaction rate at a time (typically ×0.01 – 0.1 – 10 – 100)

Quantify how the change alters the model light curve → evaluate sensitivity.

Why it matters

Focus experimental efforts on the few reactions that **most impact the light curve.**

Example: Light curves with single–reaction rate variations



Higher sensitivity (larger change in light curve)

Lower sensitivity (smaller change in light curve)

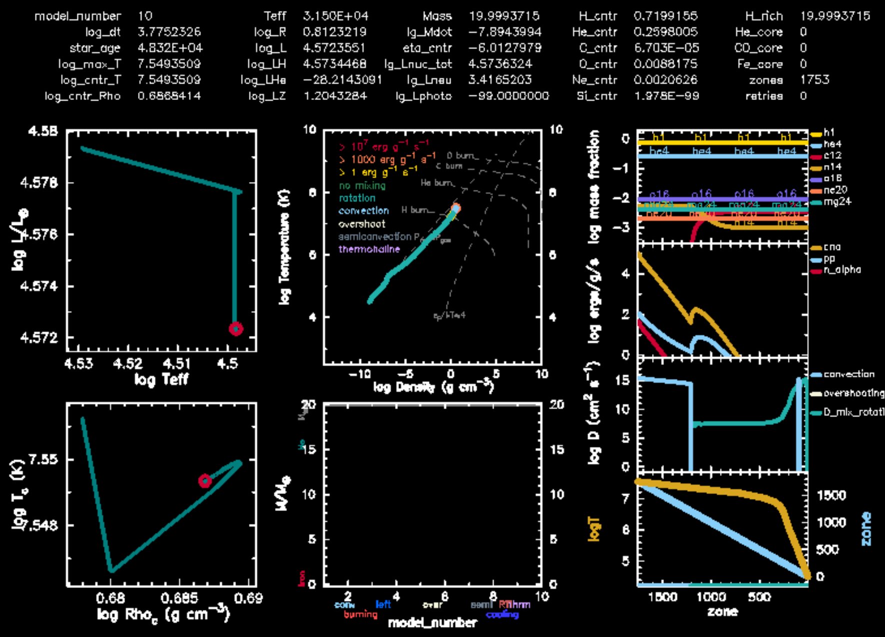
Cyburt et al., APJ 830, 55 (2016)

Sensitivity studies rank reactions by their impact.

They provide a quantitative roadmap for future nuclear experiments.

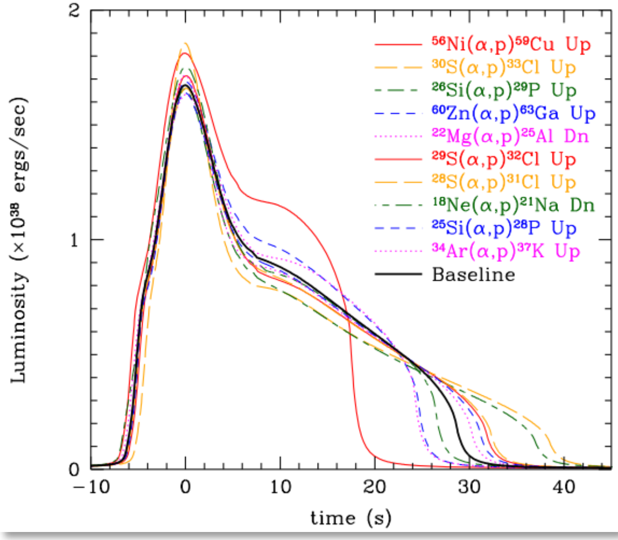
Modules for Experiments in Stellar Astrophysics (MESA)

- 1D multi-zone simulation code
- solves full set of 1D stellar structure and evolution equations, including:
  - nuclear energy generation
  - energy transport (radiative, convective)
  - gravitational contraction and expansion
  - surface boundary conditions
- stability and modular structure
  - adaptive time-stepping
  - automatic mesh refinement
  - implicit **hydrodynamics**
  - convection, diffusion, and rotational mixing models
  - replaceable modules for EOS, opacity, atmosphere, and more
- can model essentially the entire life cycle of a star: main-sequence, red-giant, nova, **x-ray burst**…



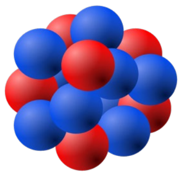
rather slow!

Weakness of conventional sensitivity studies



- Takes long time for the simulation
  (hydrodynamic calculations with large nuclear network)
- Only single reaction variations can be considered

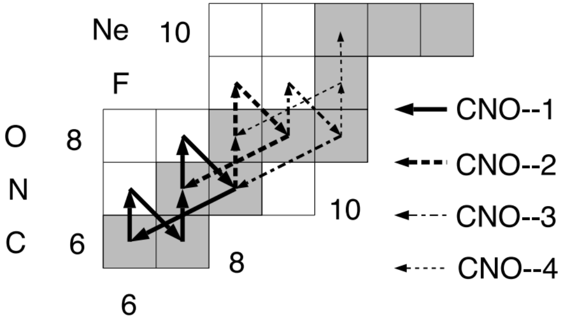
Collective effect of multiple reaction variation could not be investigated

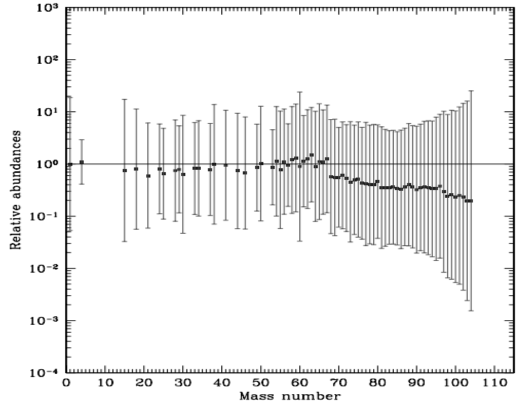


Γ_p
Γ_α
Γ_γ
B_λ
…

^{14}O(α,p)^{17}F

^{14}O(α,γ)^{18}Ne





Effect of a nuclear property uncertainty on nucler network

Collective impact of a cycle

Uncertainty propagation

M. Wiescher, J. Gorres and H.Schatz, J.Phys. G: Nucl. Part. Phys 25, R133 (1999)
A. Parikh *et al.*, APJS 178, 110 (2008)

Building a Deep Learning Emulator for Nuclear Astrophysics

Traditional (Physics-based Simulation)

nuclear input (reaction rates)

- $rate_1$
- $rate_2$
- …
- $rate_n$

MESA

- stellar evolution
- hydrodynamics
- nucleosynthesis
- …

astrophysical output

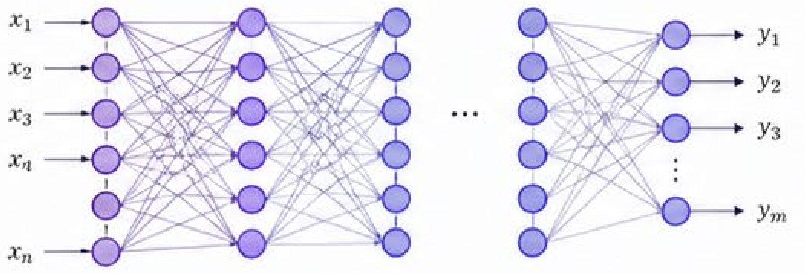
- light curve
- ash abundance
- recurrence time
- …

Our Approach (Deep Learning Emulator)

nuclear input (reaction rates)

- $rate_1$
- $rate_2$
- …
- $rate_n$

Deep Learning Emulator



Fast · Accurate · Differentiable

astrophysical output

- light curve
- ash abundance
- recurrence time
- …

Goal: making x-ray burst emulator using deep learning!

Data production

- Default reaction rates from JINA REACLIB Cyburt, *et al.*, APJS 189 (2010) 240
- Physical parameters were taken to best reproduce the light curve features of GS 1826-24 Z.Meisel, *et al.*, APJ 860, 147 (2018)
- Random factors for 726 reaction rates: (α,p), (p,γ) and (α,γ)

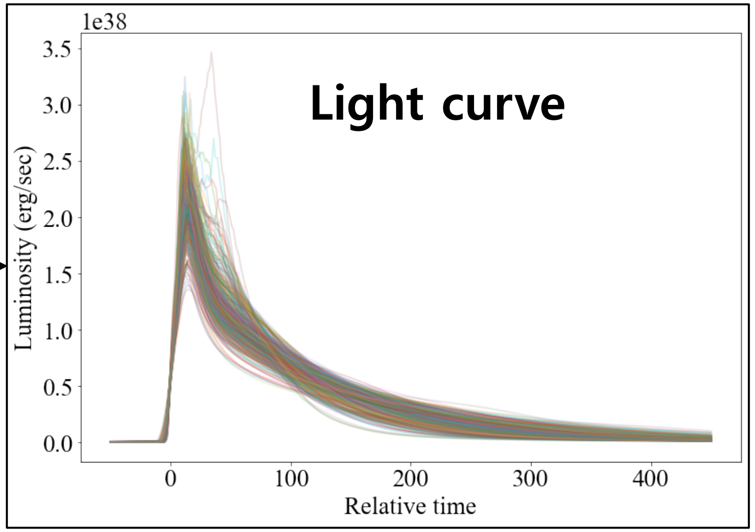
reaction	factor	factor	factor
$^{15}O(\alpha,\gamma)^{19}Ne$	x 0.1	x 1.5	x 9.3
$^{14}O(\alpha,p)^{17}F$	x 0.3	x 0.8	x 5.6
⋮	⋮	⋮	⋮
$^{56}Ni(\alpha,p)^{59}Cu$	x 1.9	x 2.3	x 0.5
$^{60}Zn(\alpha,p)^{63}Ga$	x 7.8	x 4.1	x 0.9
$^{63}Ga(p,\gamma)^{64}Ge$	x 2.5	x 0.2	x 3.2

726

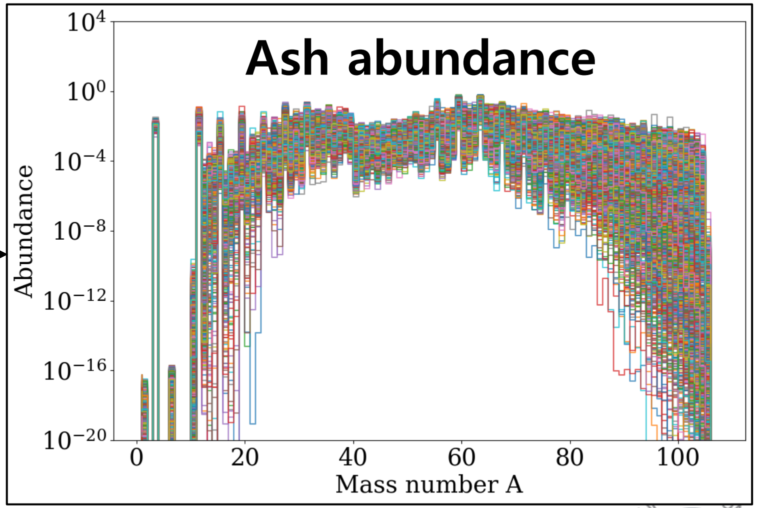
3000

• • •

From 1/120 to 120, Randomly sampled factors



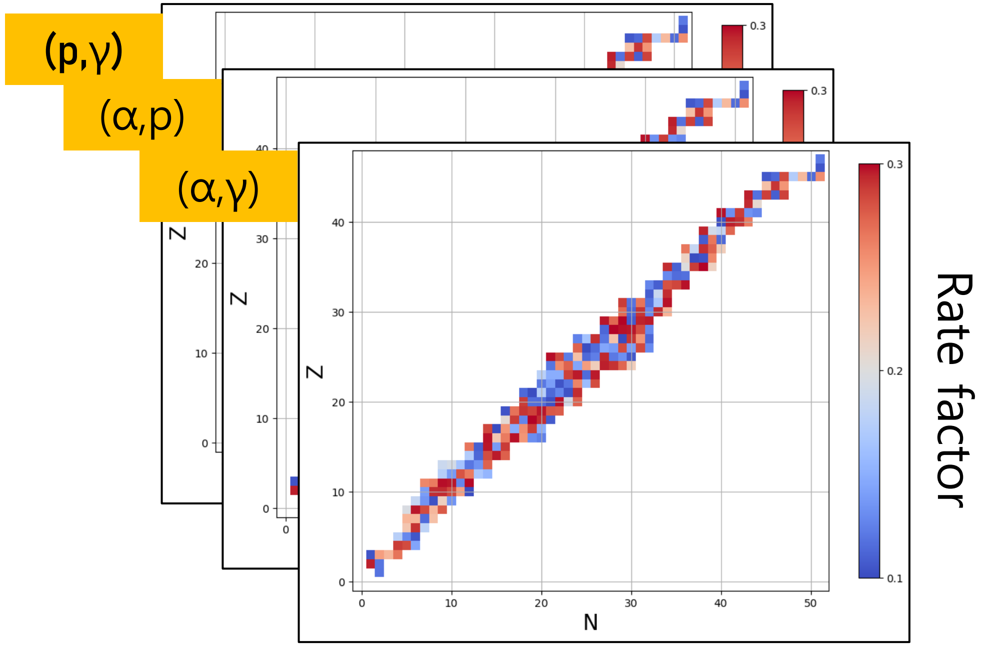
Recurrence time



Data preprocessing: input data

Nuclear chart format is similar to **RGB image data**

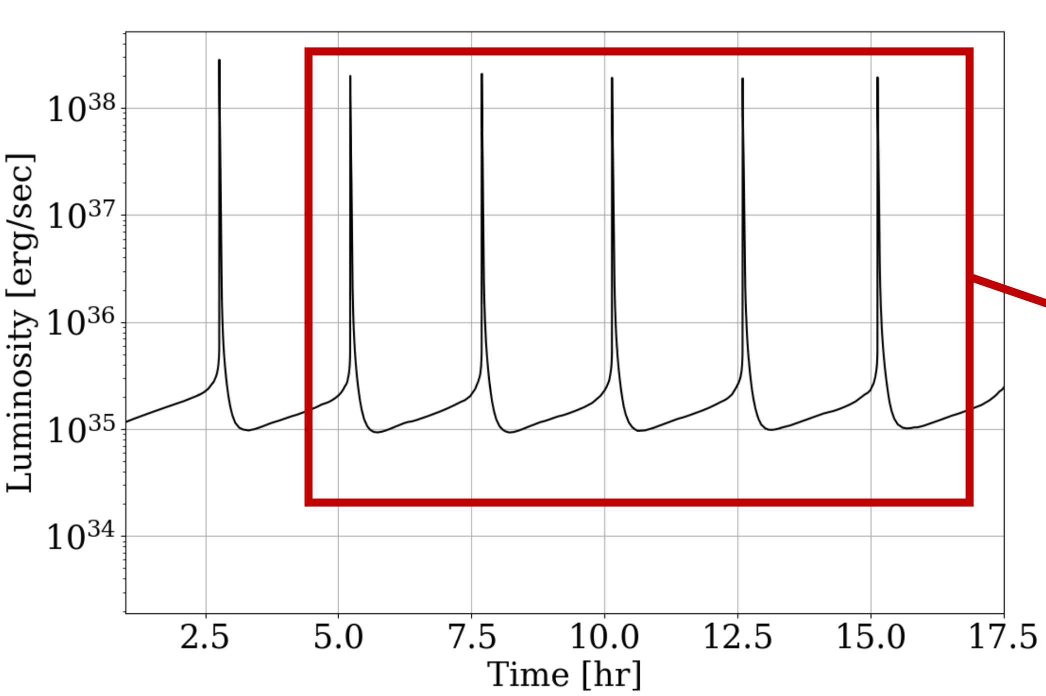
RGB 3 channel picture

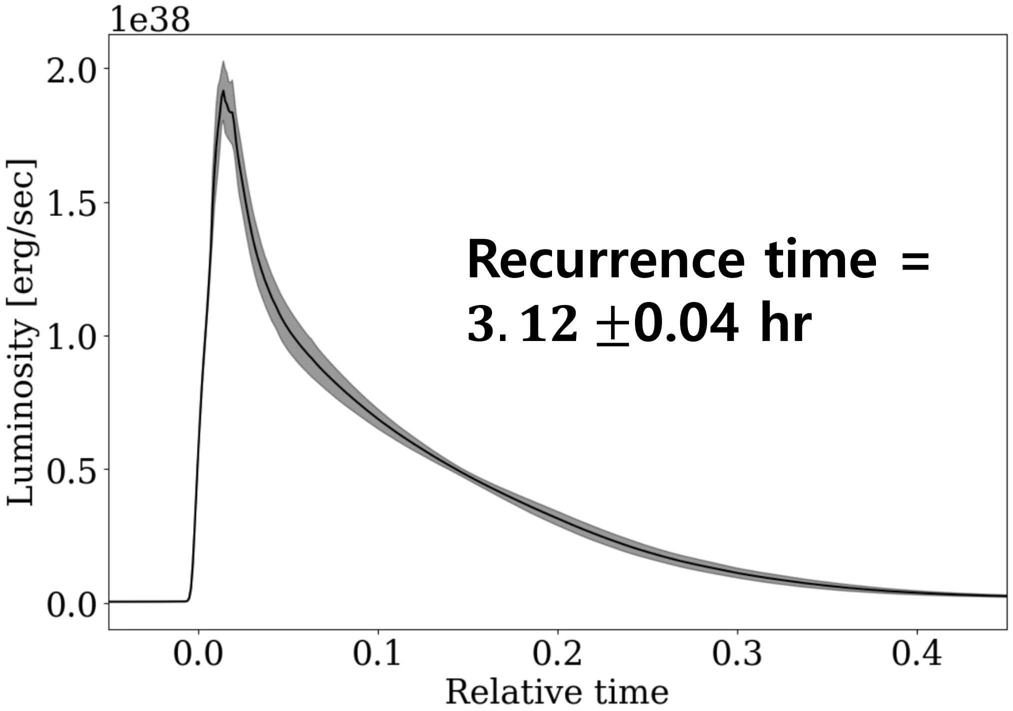


(α,p), (p,γ) and (α,γ)
3 channel nuclear chart

Data production: light curve

- GS 1826-24, regular burst
- took the average of 5 bursts (from the 2nd to the 6th)





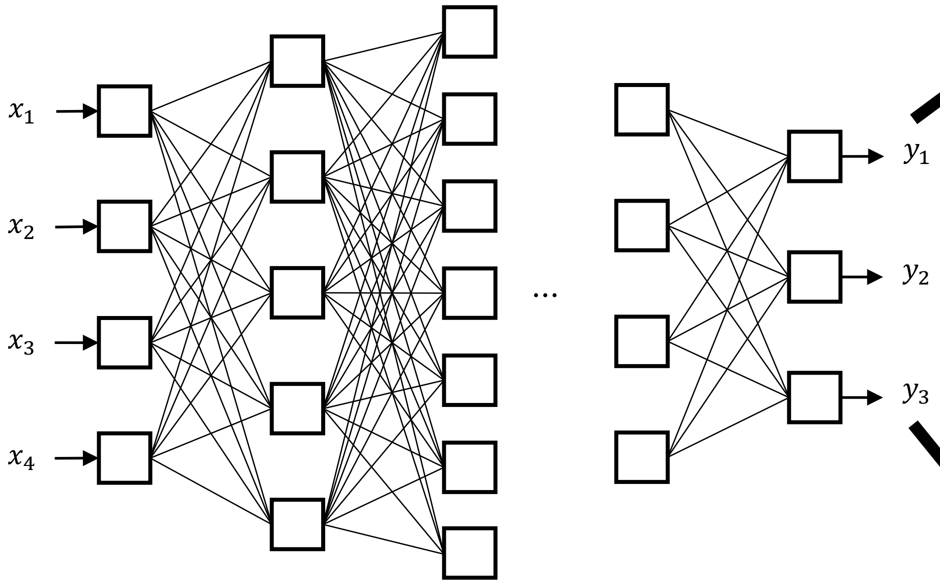
Novel technique using deep neural network

Input Data:
Reaction rate factors

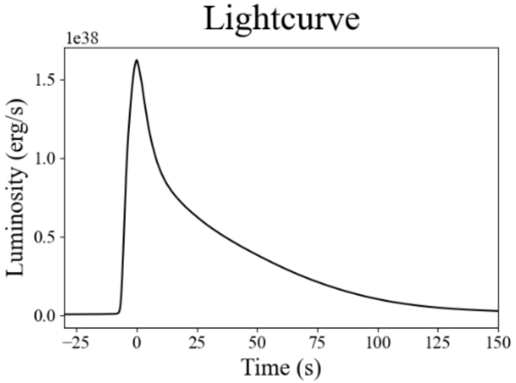
reaction	factor
$^{15}O(\alpha, \gamma)^{19}Ne$	x 1.051
$^{14}O(\alpha, p)^{17}F$	x 0.802
⋮	⋮
$^{56}Ni(\alpha, p)^{59}Cu$	x 23.08
$^{60}Zn(\alpha, p)^{63}Ga$	x 41.76
$^{63}Ga(p, \gamma)^{64}Ge$	x 0.002

same as the MESA input

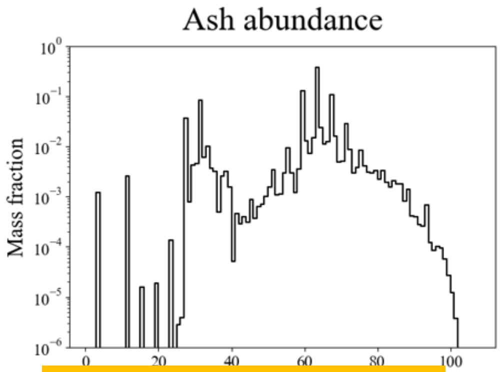
Deep Neural Network



Output Data:
XRBs properties

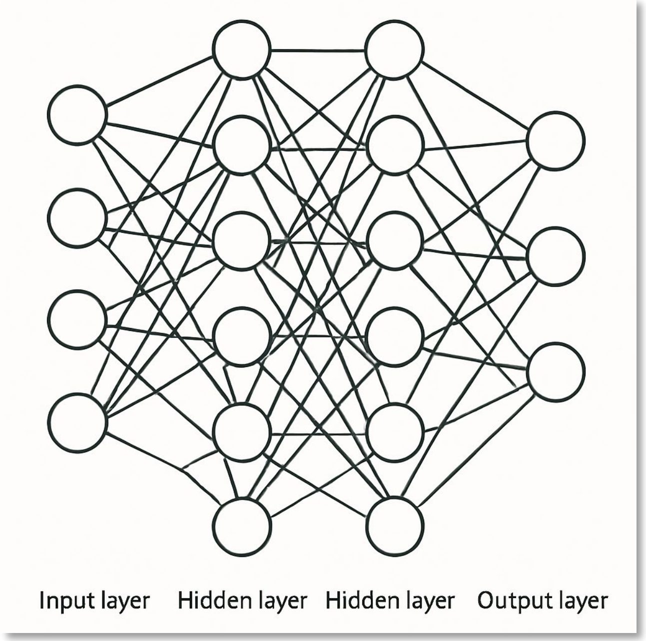


Recurrence time

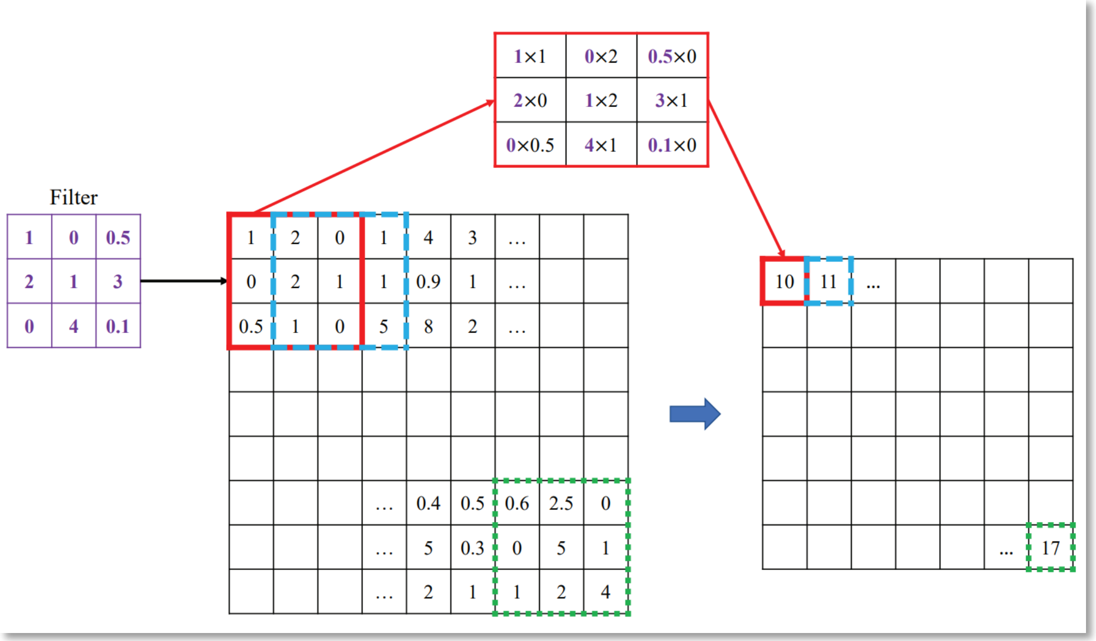


compare with the MESA output

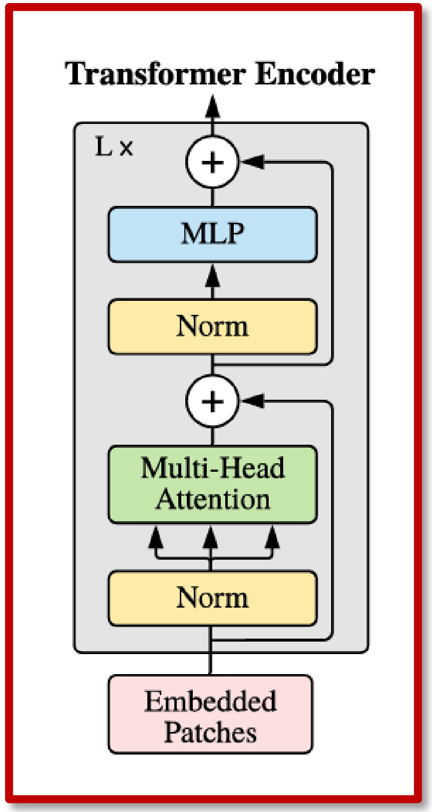
various types of Deep Neural Network



Linear net



ConvNet

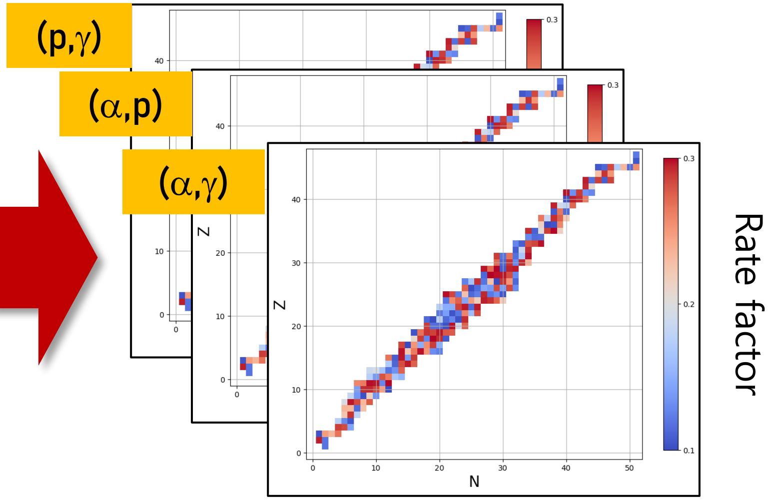


Vision Transformer

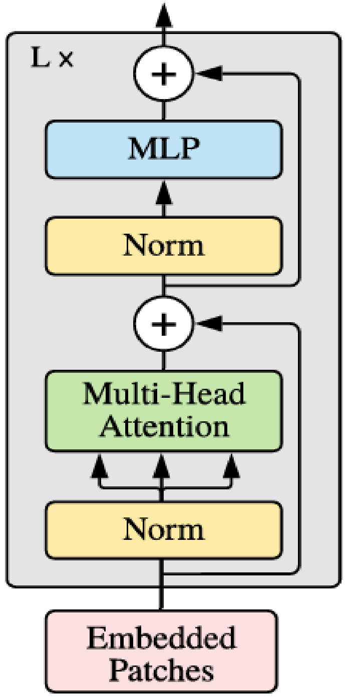
Model training

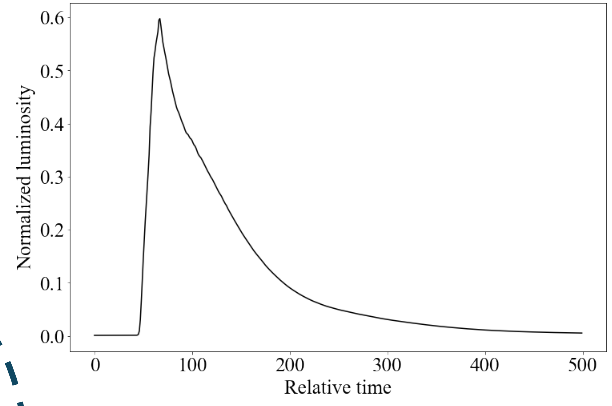
- Input(=Features) and Output(=Labels) are pre-processed.
- By modifying the hyper-parameters, appropriate DNN can be built up.

reaction	factor
$^{15}O(\alpha,\gamma)^{19}Ne$	x 0.1
$^{14}O(\alpha,p)^{17}F$	x 0.3
. . .	. . .
$^{56}Ni(\alpha,p)^{59}Cu$	x 1.9
$^{60}Zn(\alpha,p)^{63}Ga$	x 7.8
$^{63}Ga(p,\gamma)^{64}Ge$	x 2.5



(p,γ) (α,p) (α,γ)
3-channel nuclear chart

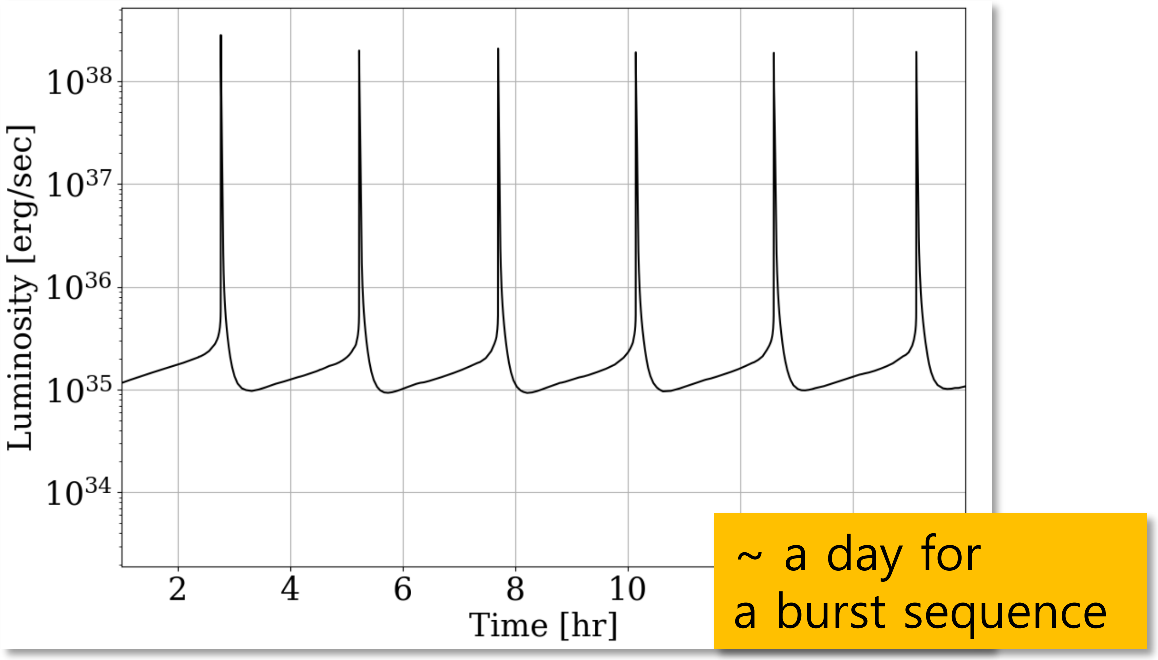




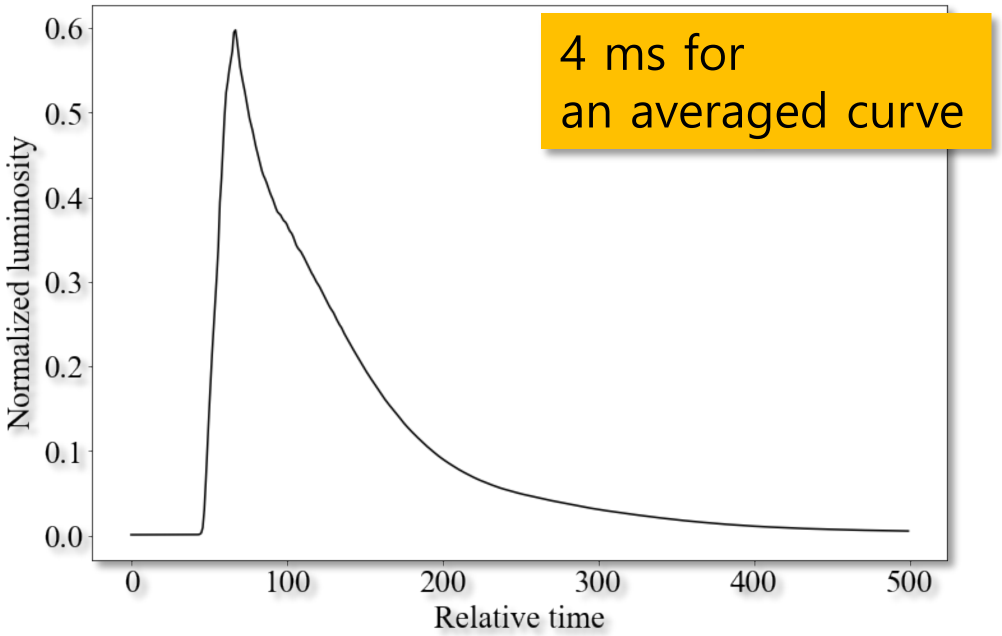
Light curve

- # encoder blocks
- embedding length
- structure of MLP
- learning rate…

Performance test



Intel Xeon Platinum 8360Y
(2.6 GHz, 36 Cores)

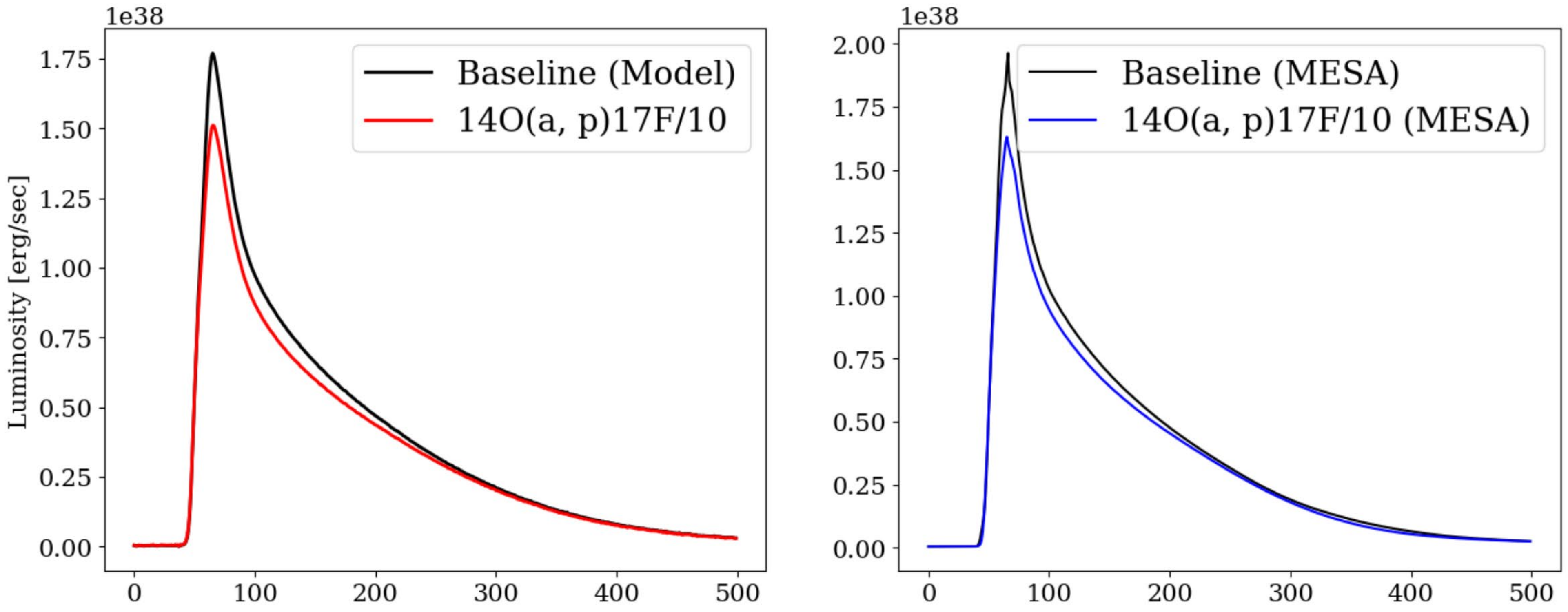


Tesla V100 32GB SXM2

7-8 orders of magnitude enhancement!

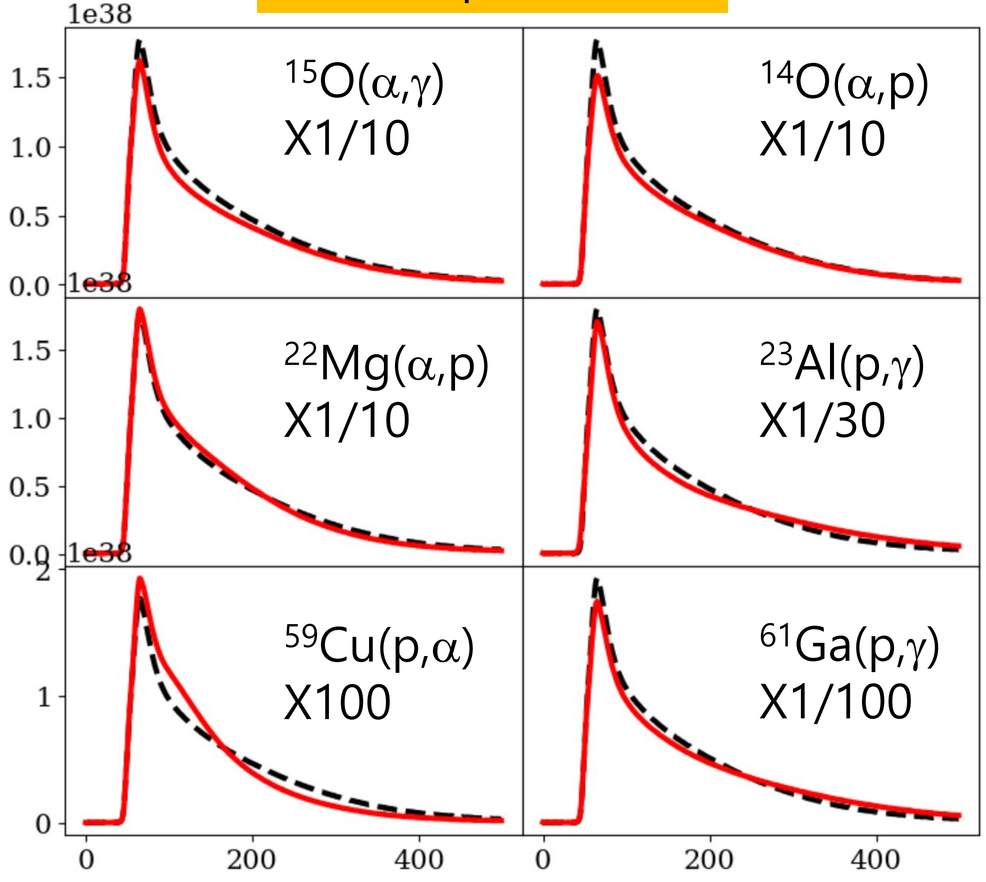
Single reaction variation

changed each of 726 reaction rates individually



Comparison with previous study

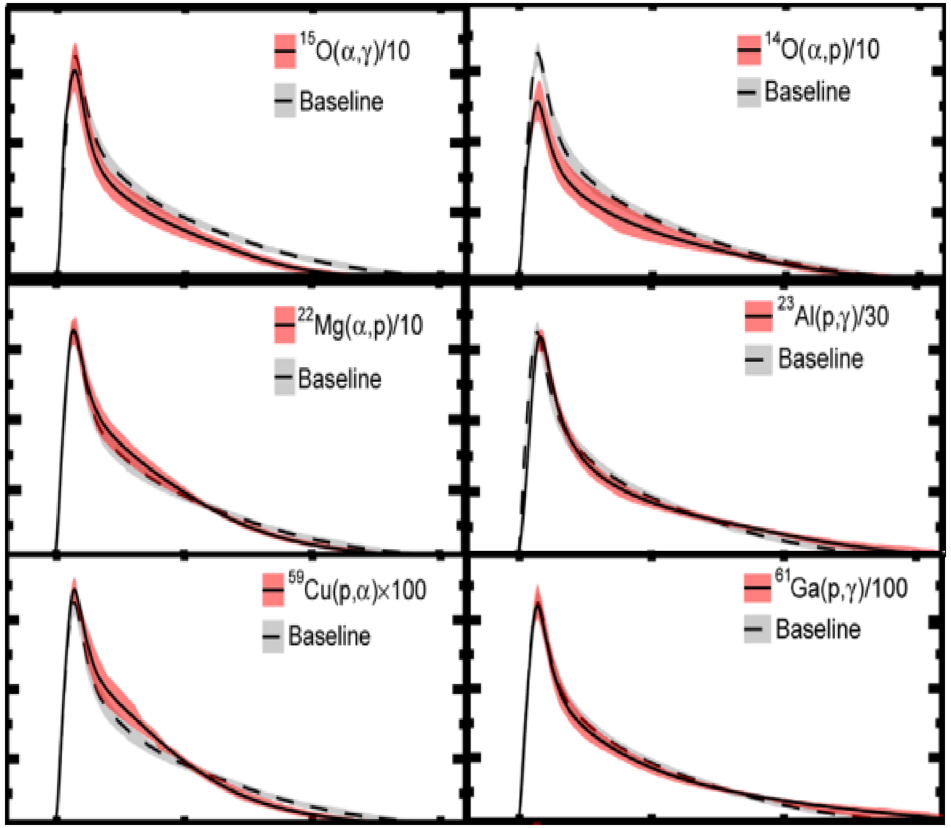
Model prediction



Baseline

Rate variation

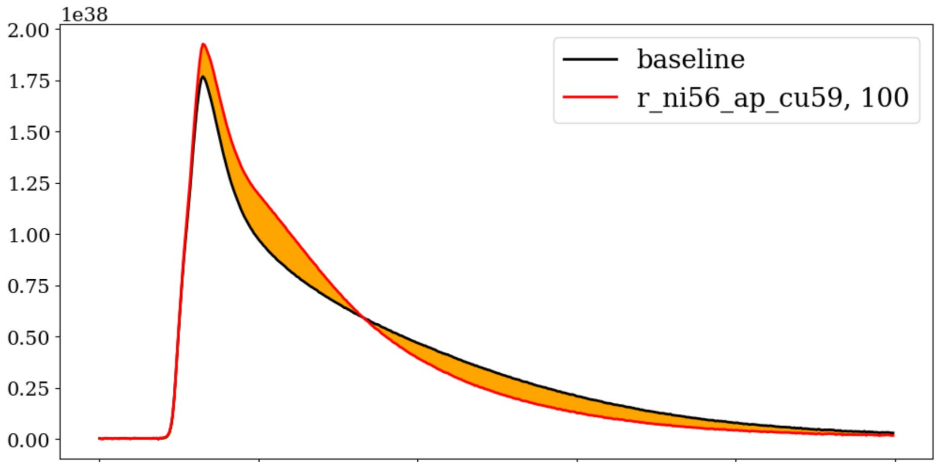
MESA (from previous study)



Z. Meisel *et al.*, APJ (2019)

NEW sensitive reaction list

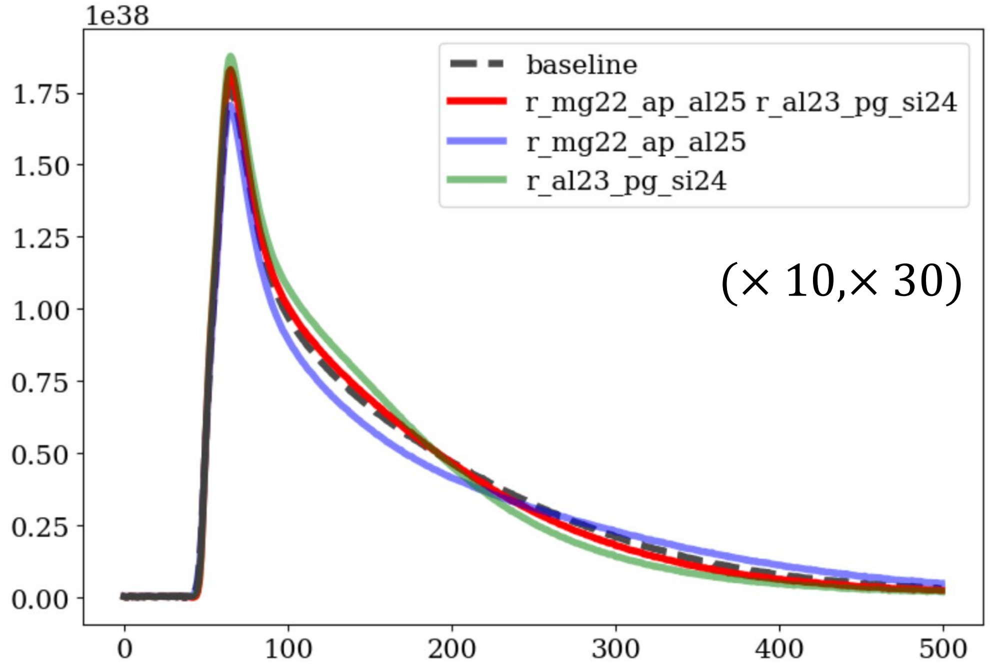
- Calculated "different factor" to quantify the impact of a reaction variation
- Different factor $\equiv \int |\langle L_{base}\rangle - \langle L_{varied}\rangle| dt$ Cyburt, et al., APJ 830, 55 (2016)

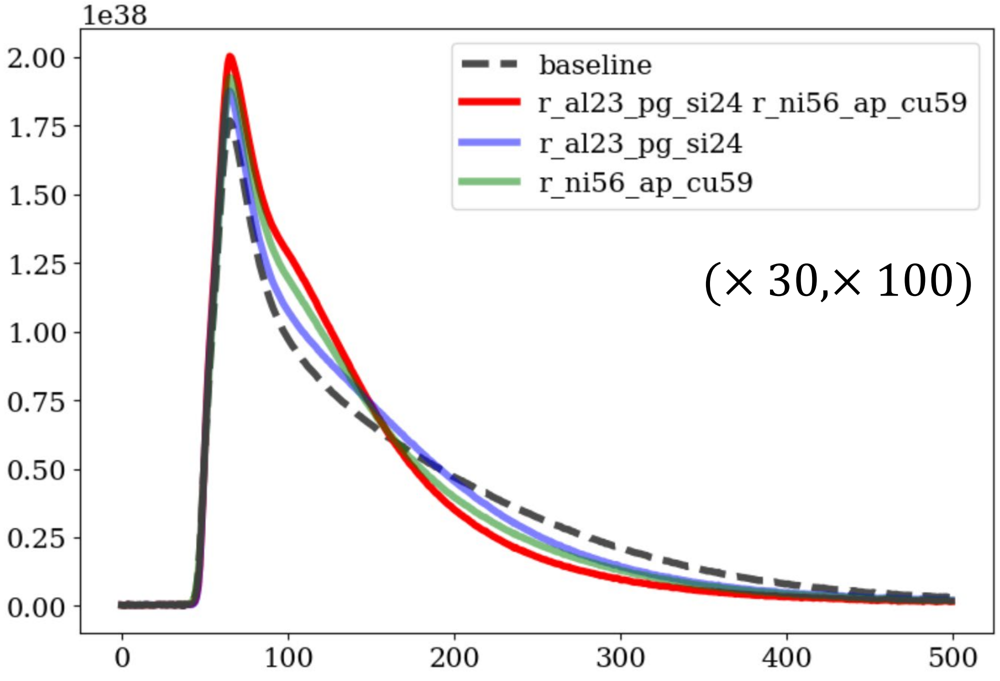


Reaction	Up/down	Diff_factor
$^{35}K(p,\gamma)^{36}Ca$	Up	1.75E+38
$^{31}P(p,\gamma)^{32}S$	Down	1.19E+38
$^{23}Na(p,\gamma)^{24}Mg$	Down	3.02E+38
$^{20}Ne(\alpha,p)^{23}Na$	Up	4.06E+38
$^{12}C(\alpha,p)^{15}N$	Down	1.49E+38

Simultaneous variation of two reaction rates

- Considered all possible combinations (~1,000,000 pairs) just in a few hours
- Linear combination for most cases

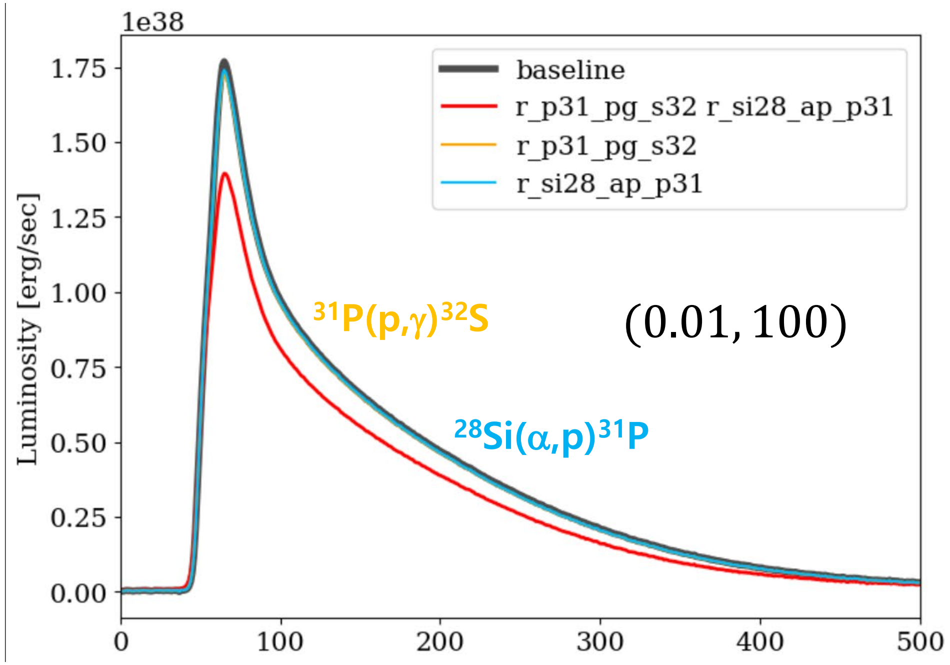


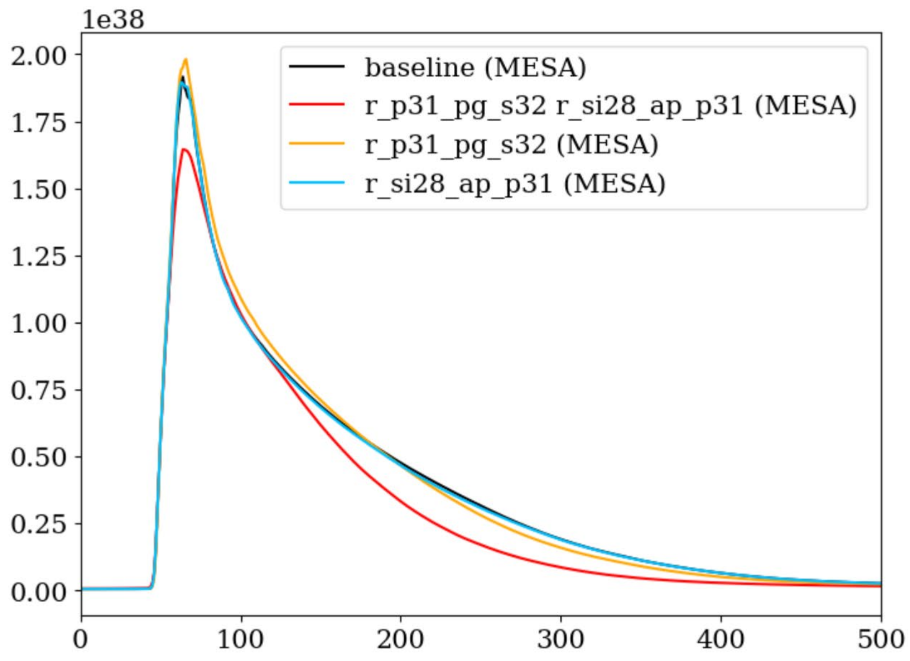


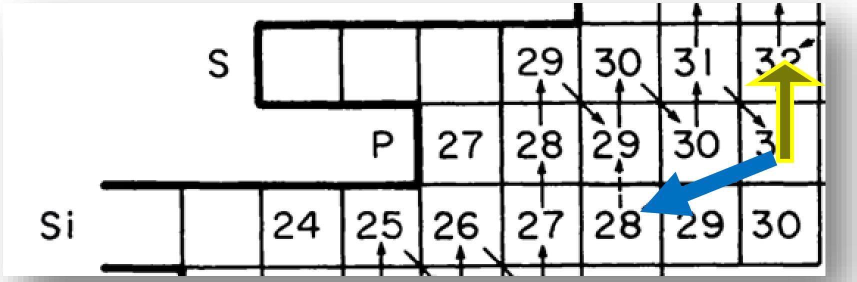
Effect of the SiP cycle strength


Sohyun Kim

Chanhee Kim
(Ben)







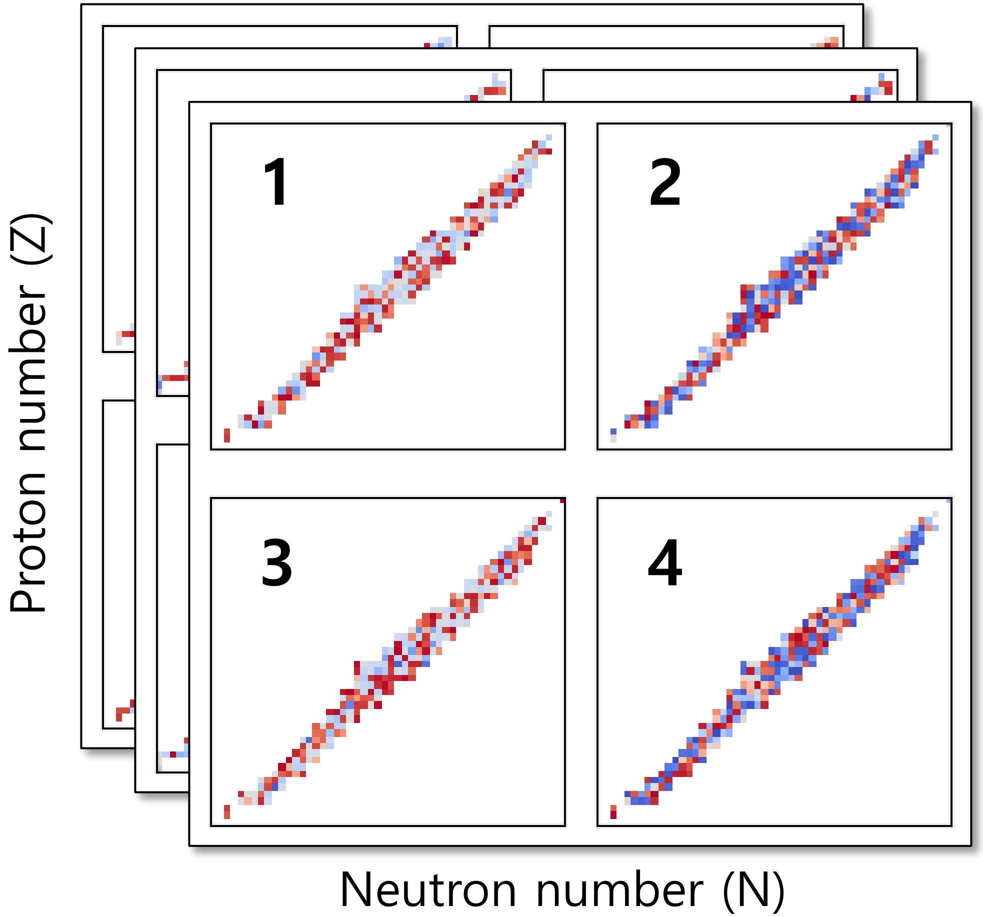
C.Iliadis, et al., Nucl.Phys.A 559, 83 (1993)

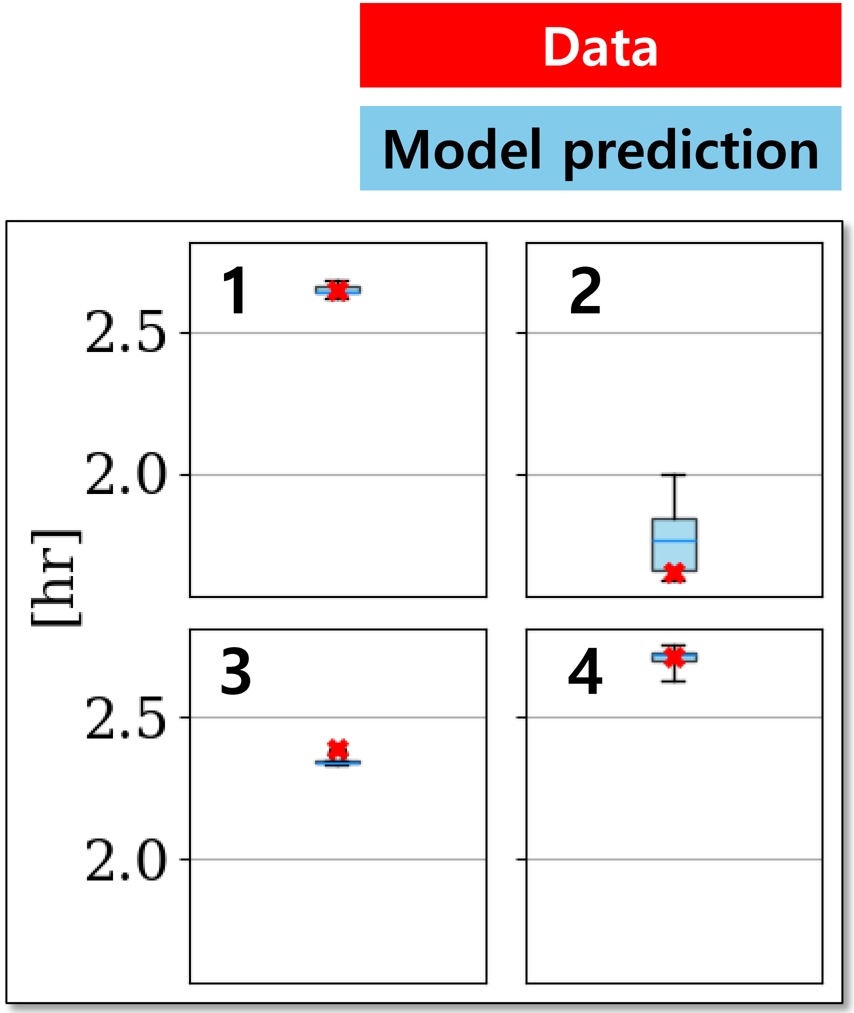
SiP cycle
→ reduced energy generation
→ decreased luminosity

Manuscript in preparation

S.H. Kim, C.H. Kim, K.Y. Chae, M.S. Smith, K. Kwak, G. Seong

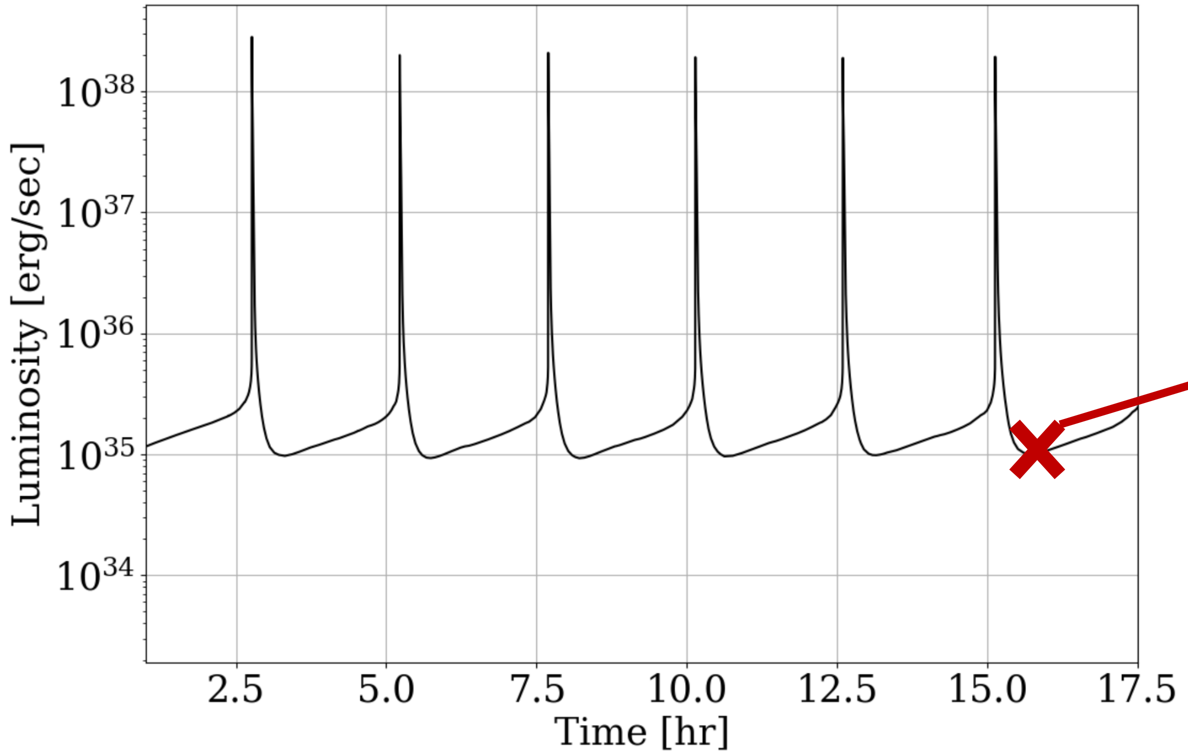
Model for recurrence time

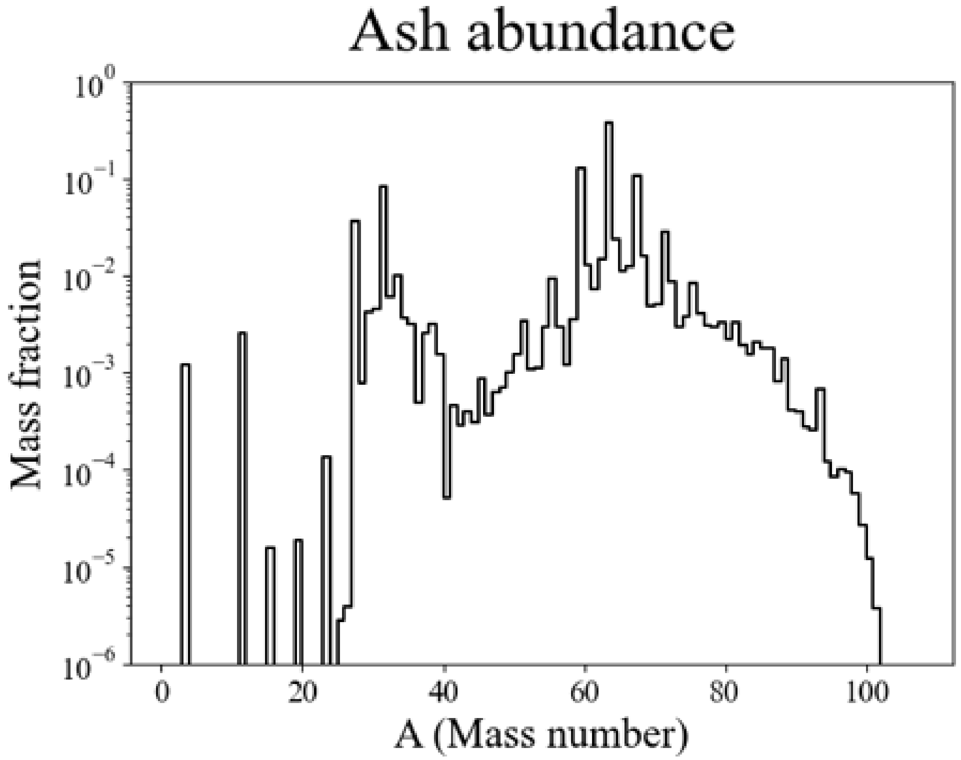




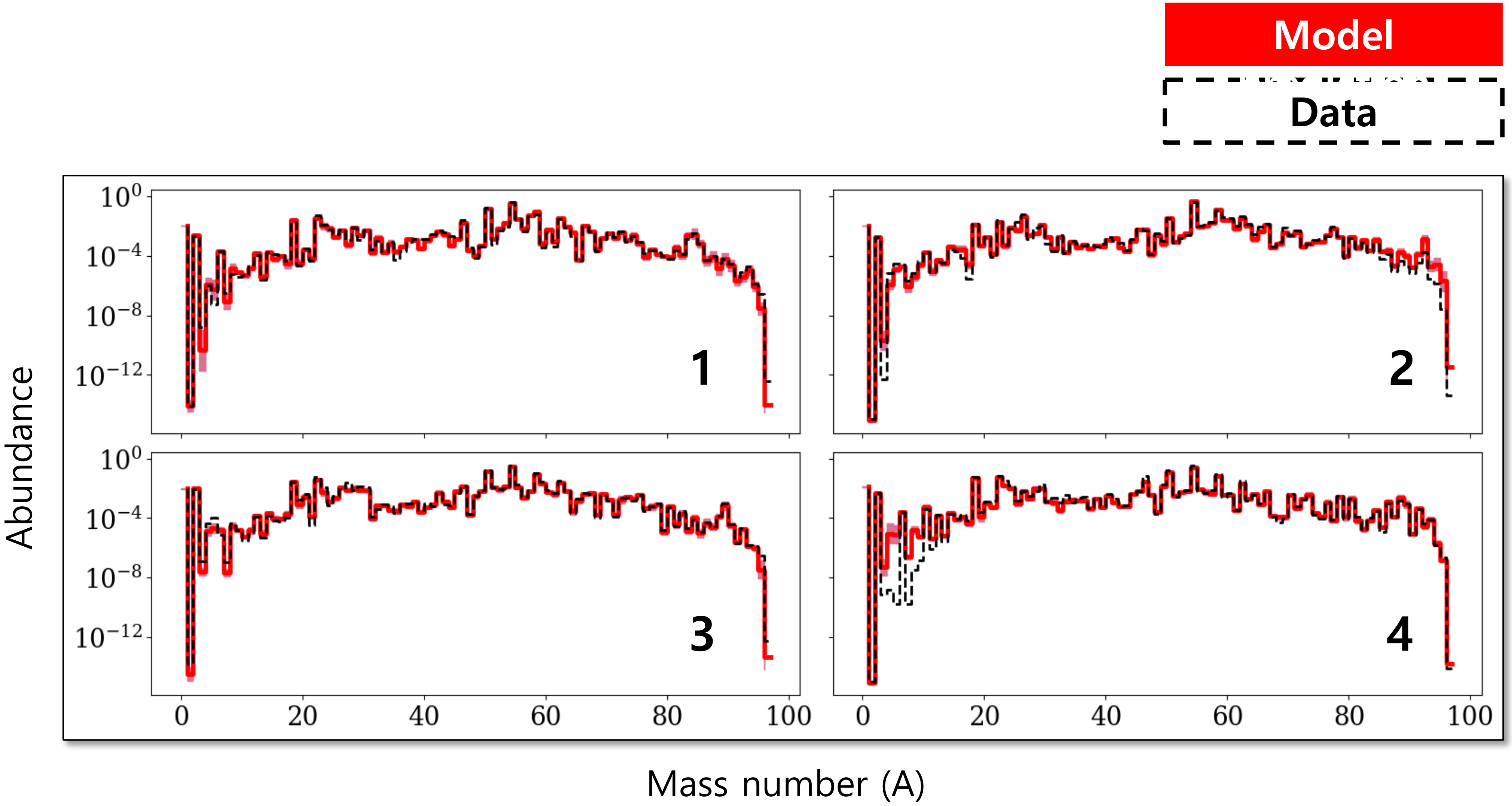
Ash abundance: training data

The ash abundance of the last burst is extracted

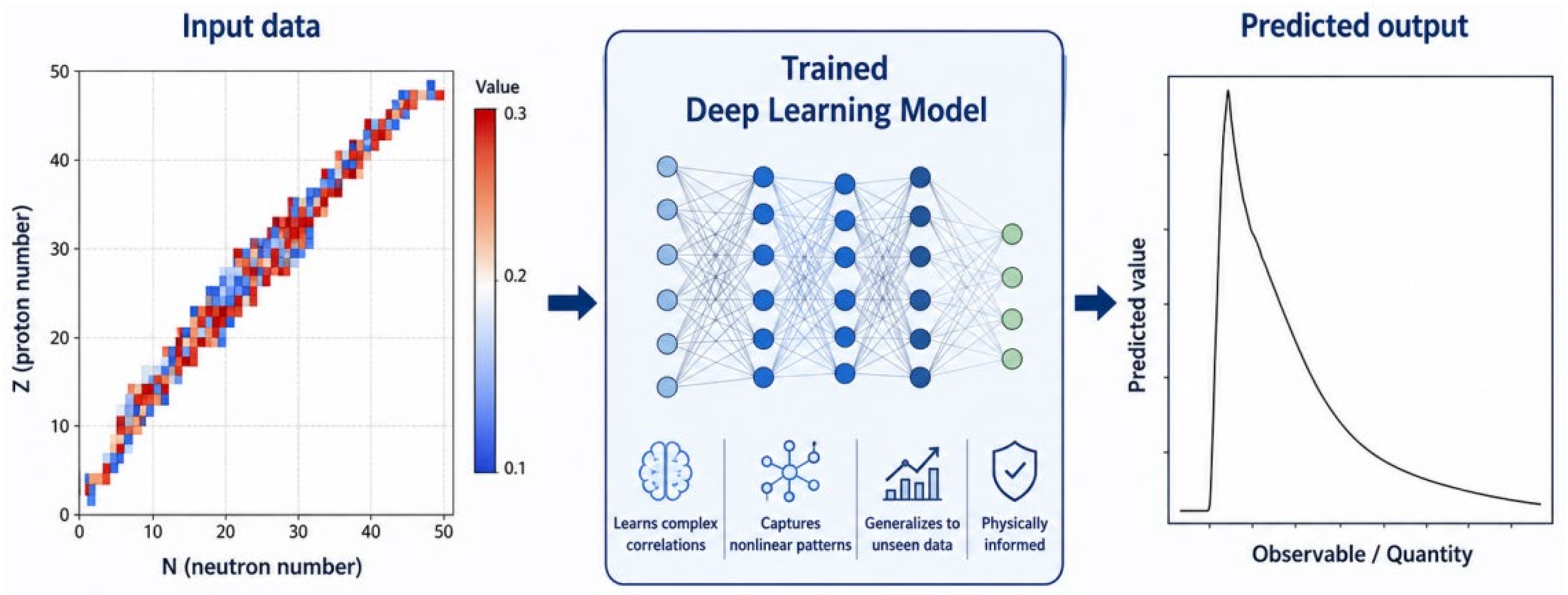




Model for ash abundance

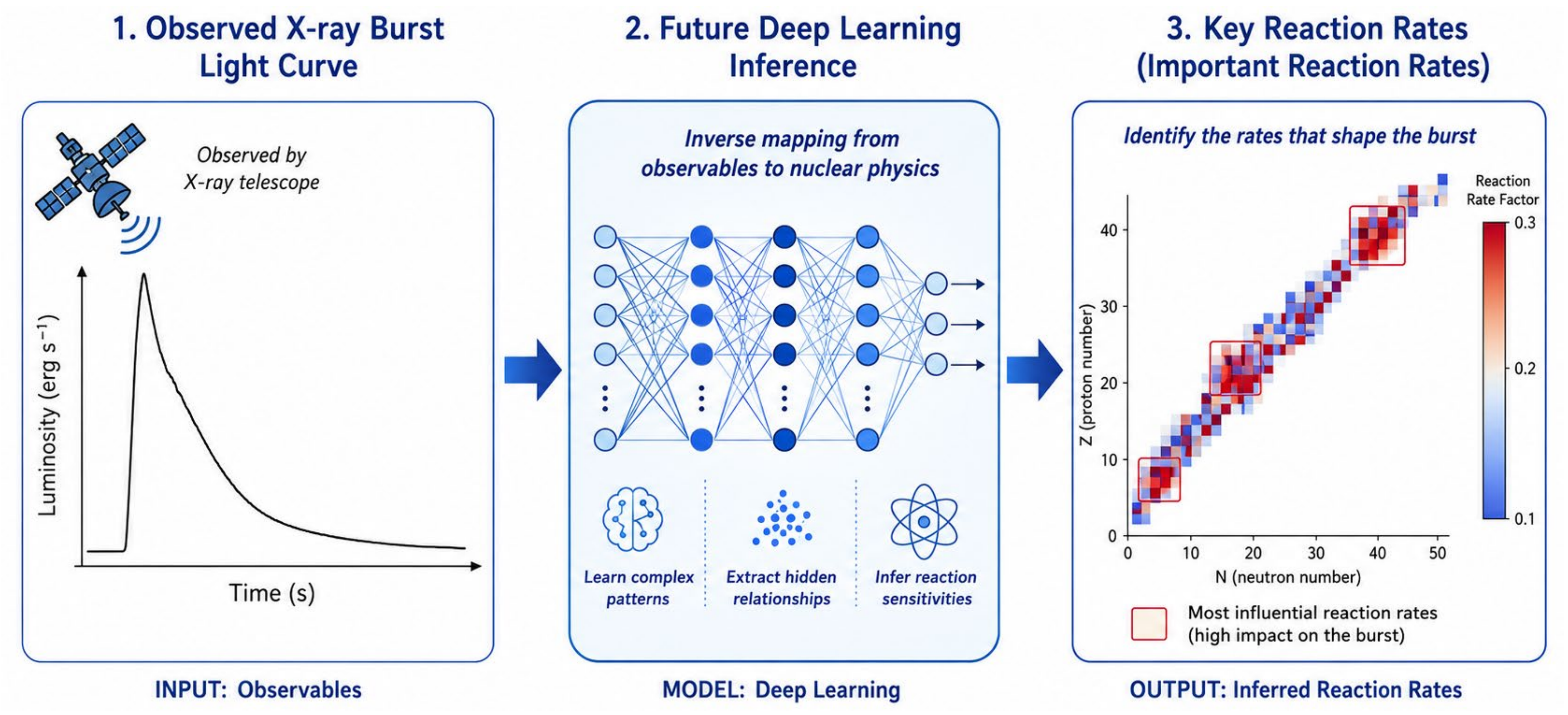


Not just faster…



Revealing complex correlations jumans often miss!

Idea


1. Observed X-ray Burst Light Curve
Observed by X-ray telescope
Luminosity (erg s^{-1})
Time (s)
INPUT: Observables
2. Future Deep Learning Inference
Inverse mapping from observables to nuclear physics
Learn complex patterns
Extract hidden relationships
Infer reaction sensitivities
MODEL: Deep Learning
3. Key Reaction Rates (Important Reaction Rates)
Identify the rates that shape the burst
Reaction Rate Factor
0.3
0.2
0.1
Z (proton number)
0
10
20
30
40
N (neutron number)
0
10
20
30
40
50
Most influential reaction rates (high impact on the burst)
OUTPUT: Inferred Reaction Rates