Exploring the flavor structure of quarks and leptons with reinforcement learning

Satsuki Nishimura (Kyushu U.), Coh Miyao, Hajime Otsuka

[arXiv : 2304.14176]

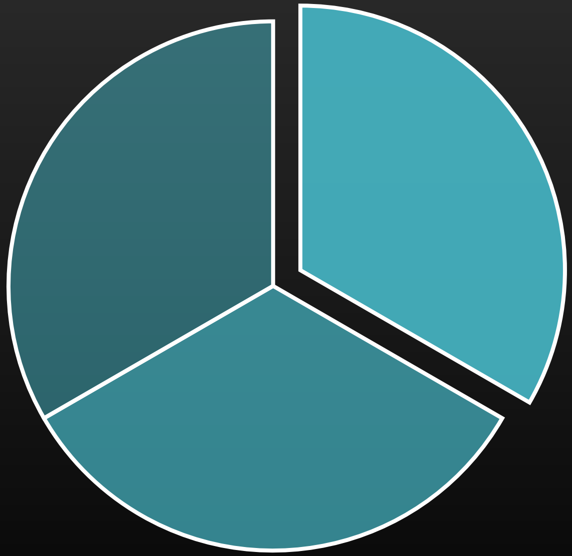
Exploring the flavor structure of quarks and leptons with reinforcement learning

Satsuki Nishimura (Kyushu U.), Coh Miyao, Hajime Otsuka

[arXiv : 2304.14176]

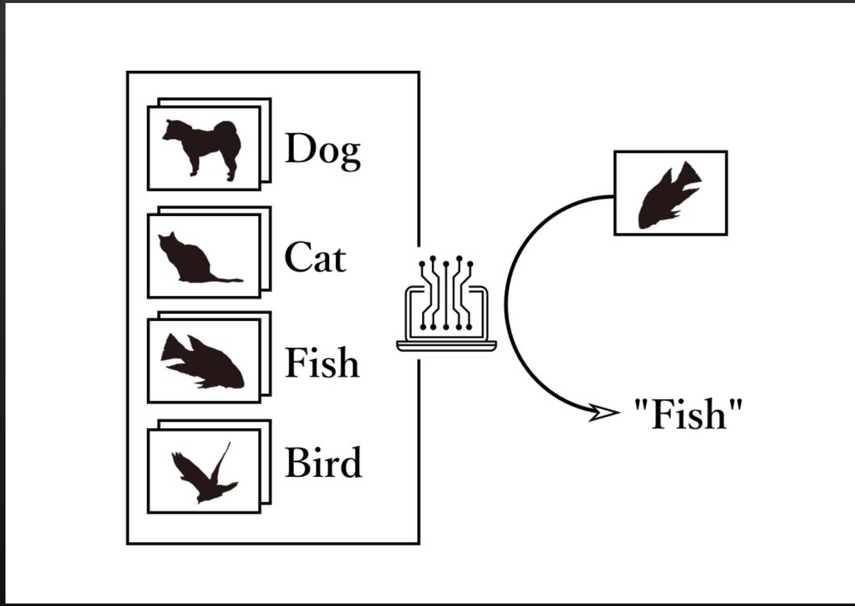
Machine Learning

- A technique in which a computer extracts hidden rules or patterns as it iteratively learns data.



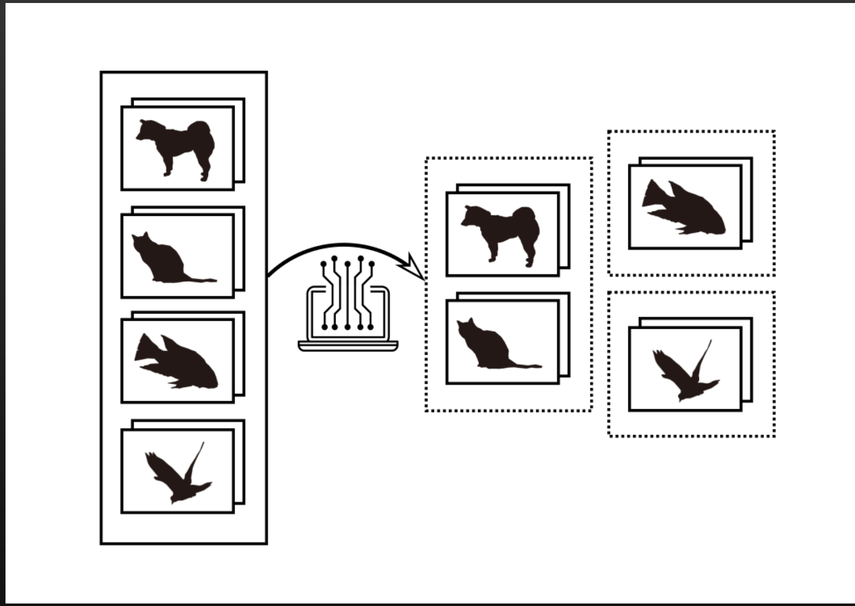
Supervised

estimates the correspondence
between data and signals



Unsupervised

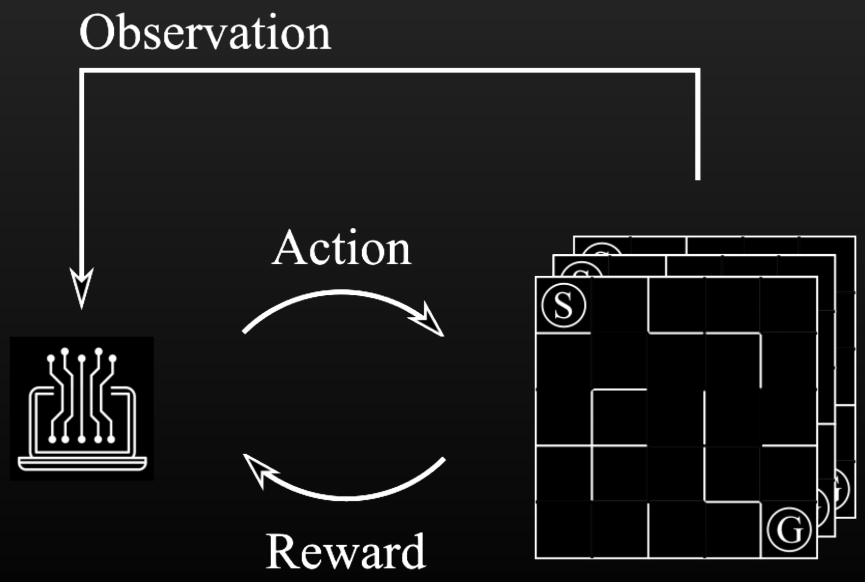
finds the similarity among data



It is needed to prepare a large amount of data.

Reinforcement Learning (RL)

- Reinforcement learning can find optimal solutions even from a small amount of reference data by repeatedly trying to solve problems to be solved.



Can we utilize and apply the unique feature of RL to searching for flavor models?

- Introduction
  - The Standard Model
  - Froggatt-Nielsen Model
  - Procedures in Reinforcement Learning
- Designs and Results
- Predictions
- Summary

- Introduction
  - The Standard Model
  - Froggatt-Nielsen Model
  - Procedures in Reinforcement Learning
- Designs and Results
- Predictions
- Summary

The Srandard Model (SM)

- SM describes the behavior of elementary particles with a high degree of accurately. It is valid for $\sim 10^{-18}$ m. However, there are many problems. (neutrino masses, generation, ……)

- The search for new physics beyond the Standard Model (BSM) is the challenge in particle physics.

Mass Hierarchy of SM

- Quarks and leptons have the large hierarchical masses.

$$\frac{m_d}{m_u} \sim 1,\ \frac{m_t}{m_u} \sim 10^5$$

- The reason for this is that Yukawa couplings Y^u, Y^d

  have very different components in each generation.

$$L_{\mathrm{Yuk}} = Y^u_{ij}\bar{Q}^i H^c u^j + Y^d_{ij} Q^i H d^j + \mathrm{h.c.}$$

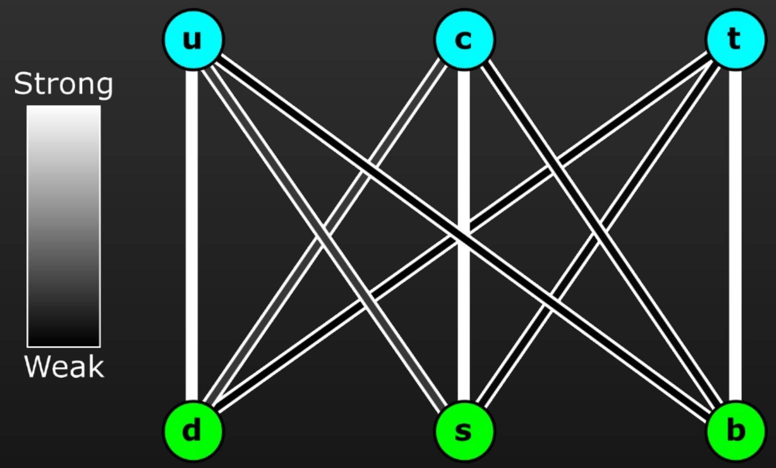
  What is the background cause of such hierarchy?

Flavor Mixing of SM

- Flavor mixing is characterized differently in each sector.

  CKM matrix for quarks : weak

  PMNS matrix for leptons : strong



https://upload.wikimedia.org/wikipedia/commons/6/66/Quark_weak_interactions.svg

- Various models have been proposed that focus on the flavor physics.

  Among them, we deal with Froggatt-Nielsen model in this work.

Froggatt-Nielsen Model（1）

- It is a flavor model that try to explain mass hierarchy and mixing by breaking $U(1)$ flavor symmetry.

- A complex scalar field ϕ is introduced to Yukawa lagrangian.

$$L_{\mathrm{Yuk}} = y_{ij}^{u}\phi^{n_{ij}^{u}}\bar{Q}^{i}H^{c}u^{j} + y_{ij}^{d}\phi^{n_{ij}^{d}}Q^{i}Hd^{j} + \mathrm{h.c.}$$

- $U(1)$ charges $q(Q), q(u), q(d), \ldots$ are assigned for each fields.

Froggatt-Nielsen Model（2）

- having $U(1)$ sym. $\quad\leftrightarrow\quad$ in each term, sum of $U(1)$ charges = 0

$$q(\phi)n_{ij}^{u} - q(Q^{i}) - q(H) + q(u^{j}) = 0$$

- When complex scalar field ϕ develop an expectation value $\langle\phi\rangle$:

$$Y_{ij}^{u} = y_{ij}^{u}\langle\phi\rangle^{n_{ij}^{u}},$$

- Froggatt-Nielsen (FN) charges will lead to a hierarchical structure of physical Yukawa couplings from indices n^{u}, n^{d}.

Froggatt-Nielsen Model（3）

- There is a problem. To find the appropriate parameters q & $\langle\phi\rangle$, a vast number of combinations must be searched.

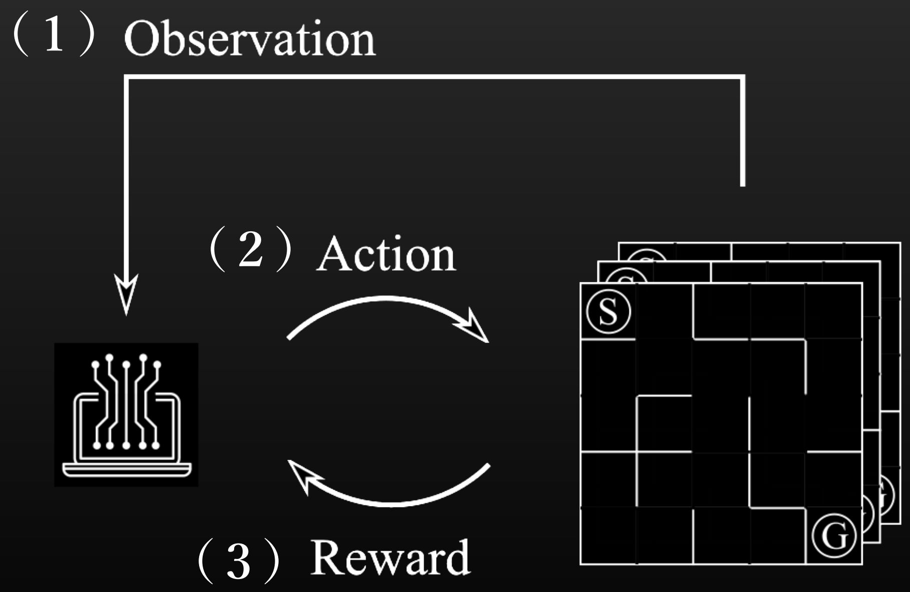
  parameter space：$-9 \le q \le 9 \;\rightarrow\; 19^{11} \sim 10^{14}$ patterns

  For each pattern, $\langle\phi\rangle$ should be determined properly.

- To efficiently explore charges which reproduce experimental results, we focus on application of RL.

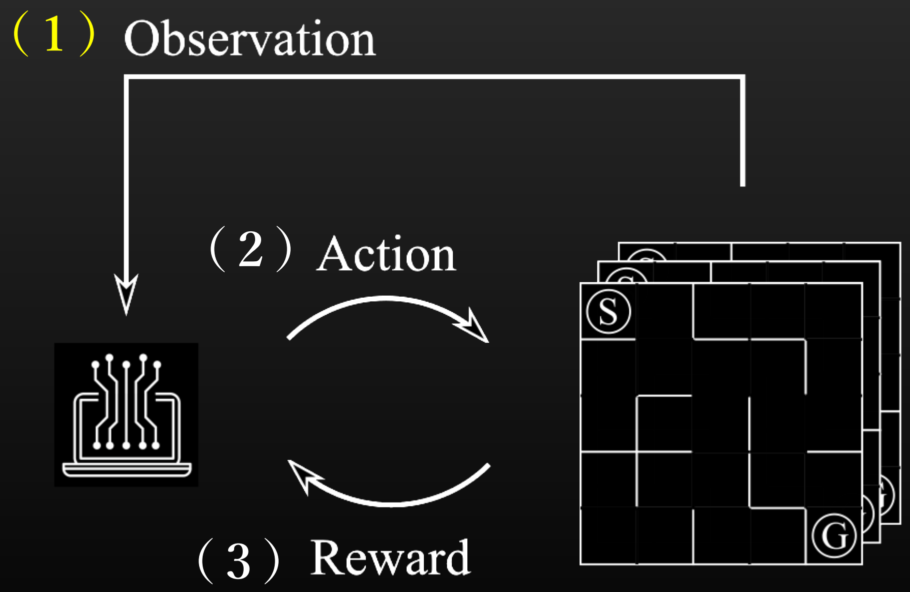
Reinforcement Learning

- Subject of learning　：Agent
- Problem to be solved：Environment



Reinforcement Learning

- Procedure：The agent observe the environment,

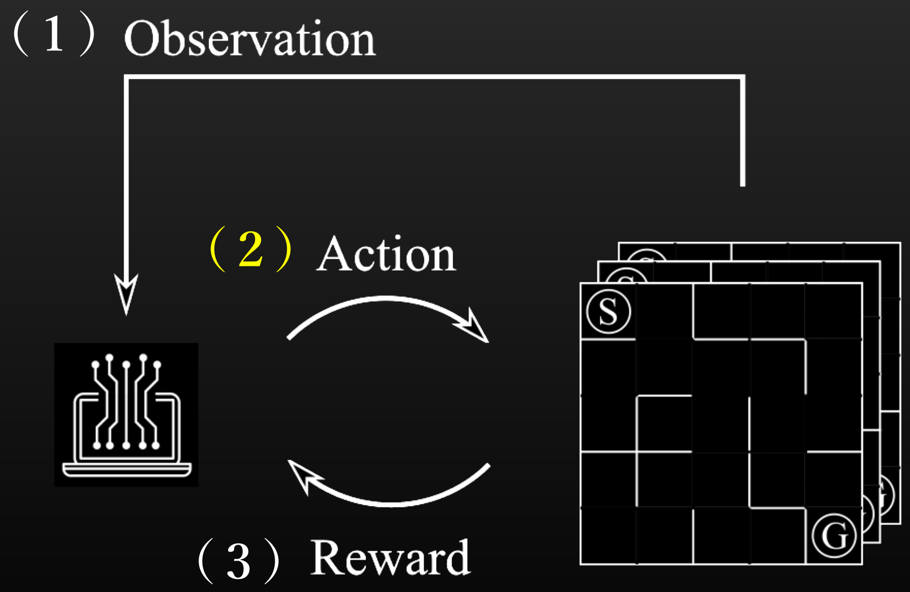


(Example of mazes)

（1） observe walls

Reinforcement Learning

- Procedure：The agent observe the environment, choose an action,



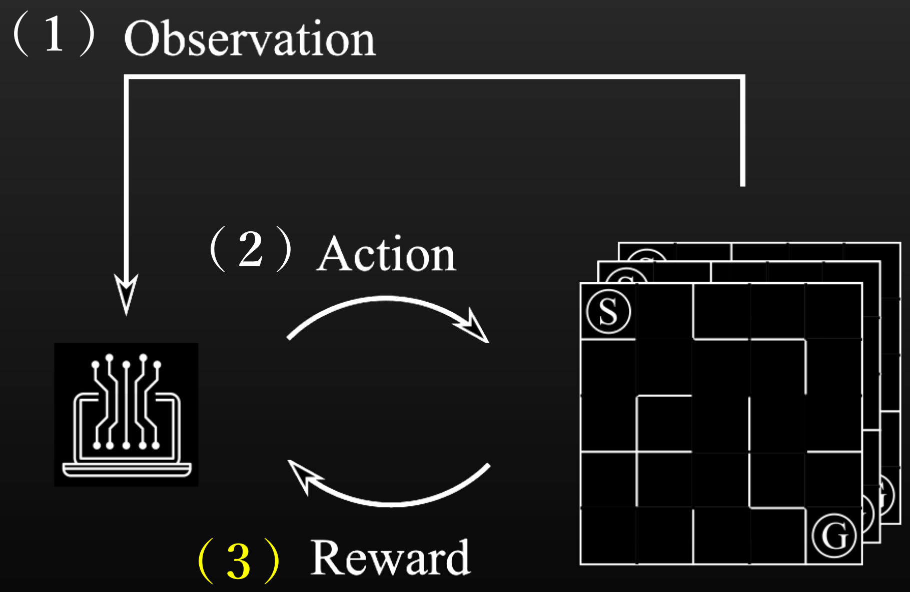
(Example of mazes)

（1） observe walls

（2） take one step

Reinforcement Learning

- Procedure：The agent observe the environment, choose an action, and get rewards depending on the action.



(Example of mazes)

（1） observe walls

（2） take one step

（3） get points as closing the goal

Reinforcement Learning

- Procedure：The agent observe the environment, choose an action,
  and get rewards depending on the action.

- The agent autonomously acquires a principle of action
  that maximizes the sum of rewards.

（Examples of mazes）By turning back upon reaching a dead-end,
the agent can solve mazes correctly.

Previous Work & This Work

- RL was constructed using the FN model as the environment, and it have explored FN charges that reproduce masses and mixings for quarks. T.R.Harvey, A.Lukas [JHEP08(2021)161]

- Extending this, we constructed the RL, and it have found FN charges that reproduce masses and mixings for quarks and leptons simultaneously.

- Introduction
  - The Standard Model
  - Froggatt-Nielsen Model
  - Procedures in Reinforcement Learning
- Designs and Results
- Predictions
- Summary

Design of RL (Environment)

- Yukawa lagrangian has FN mechanism for quarks and leptons, and the agent explore sets of charges $(-9 \leq q \leq 9)$

$$L_{\mathrm{Yuk}} = y_{ij}^{u} \left(\frac{\phi}{M}\right)^{n_{ij}^{u}} \bar{Q}^{i} H^{c} u^{j} + y_{ij}^{d} \left(\frac{\phi}{M}\right)^{n_{ij}^{d}} Q^{i} H d^{j}$$
$$+ y_{ij}^{\nu} \left(\frac{\phi}{M}\right)^{n_{ij}^{\nu}} \bar{L}^{i} H^{c} N^{j} + y_{ij}^{l} \left(\frac{\phi}{M}\right)^{n_{ij}^{l}} L^{i} H l^{j}$$
$$+ \frac{1}{2} y_{ij}^{N} \left(\frac{\phi}{M}\right)^{n_{ij}^{N}} M \bar{N}^{ci} N^{j} + \mathrm{h.c.}$$

Q	: Left-handed quark
u, d	: Right-handed quark
L	: Left-handed lepton
l	: Right-handed charged lepton
N	: Right-handed Neutrino
H	: Higgs
ϕ	: Complex Scalar
M	: Right-handed Neutrino Mass $= 10^{15}$ GeV

※ In trainings, we fixed yukawa couplings y as random $O(1)$ constants.

Difference of Parameter Space

- Previous work "analyzing for quark sector"

  $-9 \le q \le 9 \ \rightarrow\ 19^{11} \sim 10^{14}$ patterns. $\langle \phi \rangle$ is real.

- This work "analyzing for quark & lepton sector"

  $-9 \le q \le 9 \ \rightarrow\ 19^{20} \sim 10^{25}$ patterns. $\langle \phi \rangle$ is complex.

Design of RL (Reward)

- The agent gets points when the masses of particles and the mixing matrix, which are calculated from the FN charges, are close to the experimental values.

How to determine the reward

- Intrinsic Value $V(Q)$ is defined as follow.

$$V(Q) = -\min_{\langle\phi\rangle}(M_1 + M_2 + C + P)$$

For example, M_1 evaluates masses of charged leptons.

$$M_1 = \sum_{\alpha=u,d,l} E_\alpha = \sum_{\alpha=u,d,l} \left| \log_{10} \frac{|m_\alpha|}{|m_{\alpha,\exp}|} \right|$$

- closing to experimental values $\leftrightarrow$ increasing the intrinsic value

Design of RL (Reward)

- The agent gets points when the masses of particles and the mixing matrix, which are calculated from the FN charges, are close to the experimental values.

- Neutrino masses are only known to differ in mass squared between flavors, so different mass orders are possible.

  Normal : $m_1 < m_2 < m_3$　　Inverted : $m_3 < m_1 < m_2$

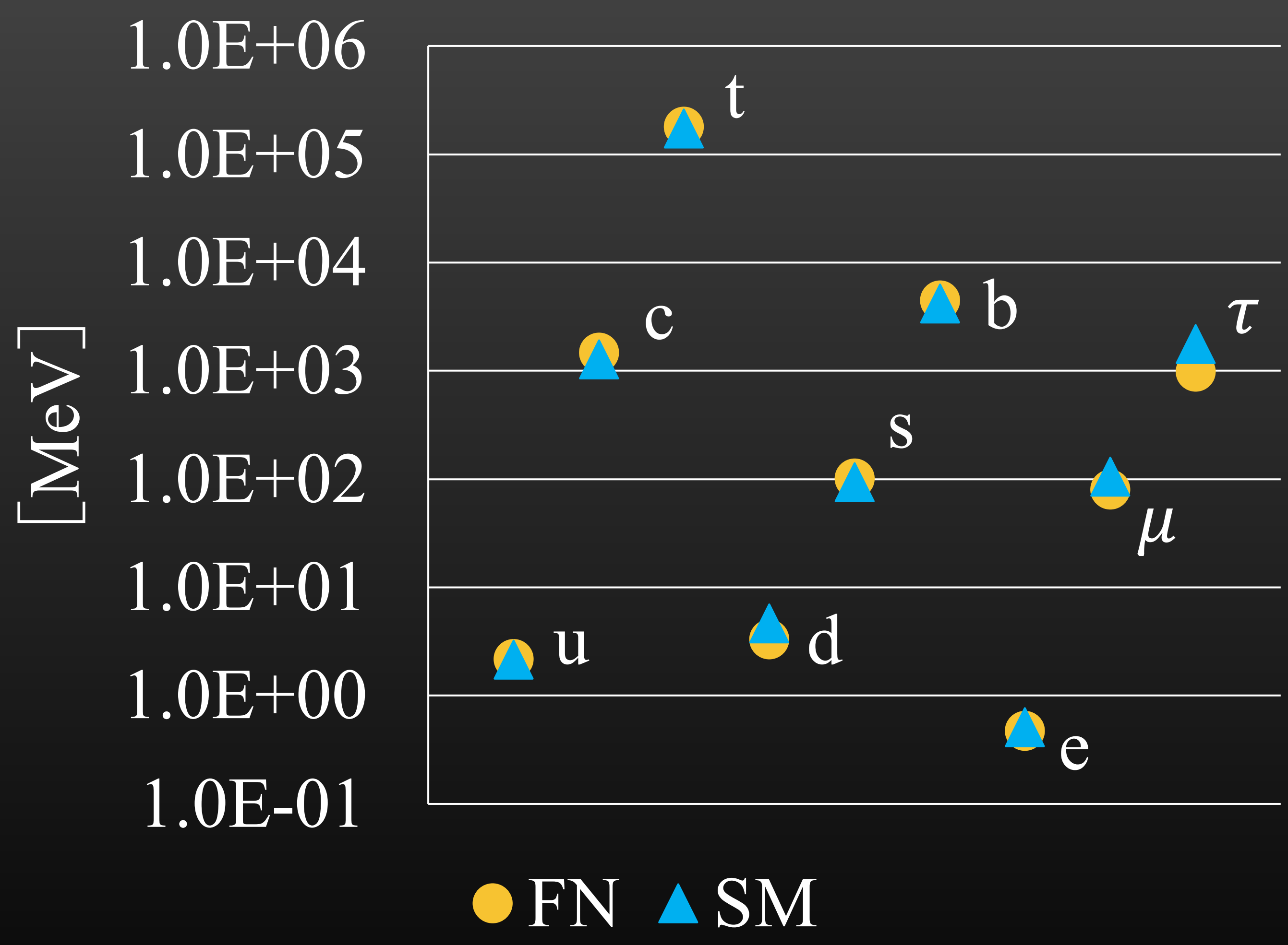
  In this talk, we designate one of the orders.

Physical Values for Reward

- 9 masses of quarks and charged leptons
- 2 values of differs in neutrino masses
- 9 absolute values of CKM matrix
- 9 absolute values of PMNS matrix

- Total: 29 values (with designated ordering)

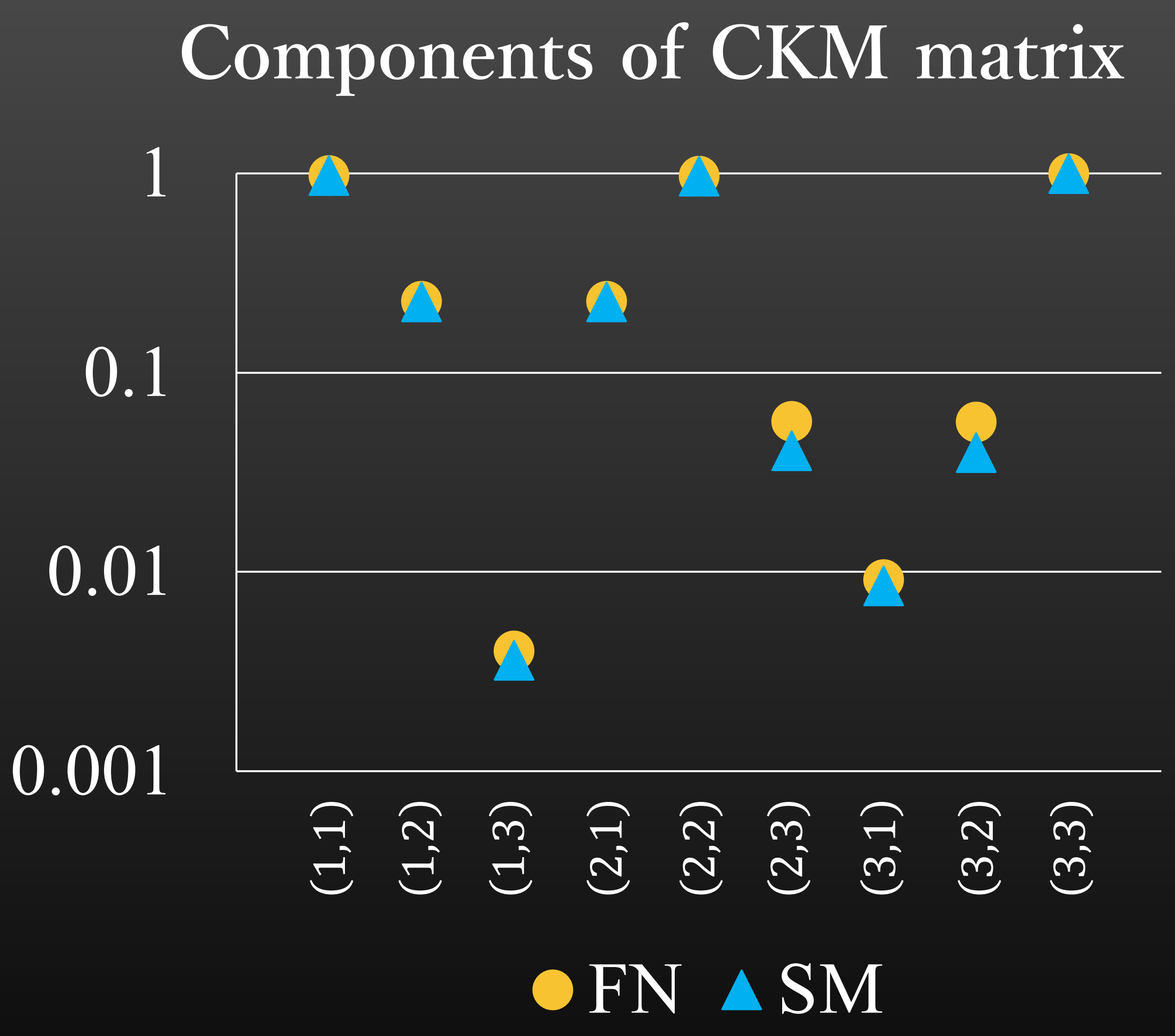
Masses of charged particles

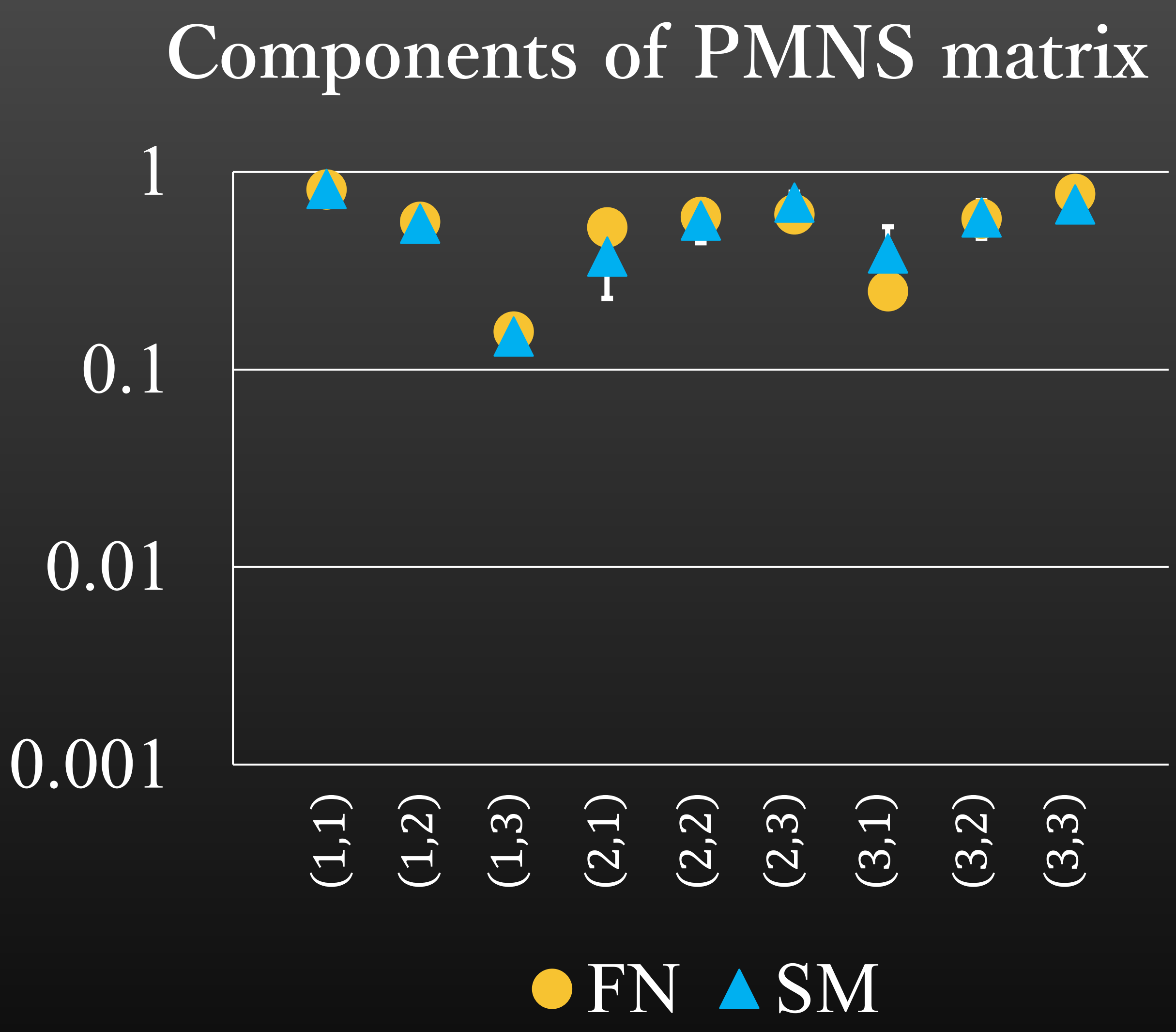


One example of charges

$$Q = \left(\begin{array}{ccc|ccc|ccc|c} Q_1 & Q_2 & Q_3 & u_1 & u_2 & u_3 & d_1 & d_2 & d_3 & H \\ 9 & 8 & 6 & 1 & 3 & 4 & 6 & 5 & 5 & -2 \\ \hline L_1 & L_2 & L_3 & N_1 & N_2 & N_3 & l_1 & l_2 & l_3 & \phi \\ 3 & 3 & 2 & -3 & -7 & -6 & 1 & -2 & 0 & 1 \end{array}\right)$$

It reproduces hierarchical structure.





It also reproduces flavor mixing.

- Introduction
    - The Standard Model
    - Froggatt-Nielsen Model
    - Procedures in Reinforcement Learning
- Designs and Results
- Predictions
- Summary

Majorana Phases and $0\nu\beta\beta$ decay（1）

- $0\nu\beta\beta$ decay is important to search Majorana neutrinos.

  The decay width is affected by the effective Majorana mass:

$$m_{\beta\beta} = \left| m_{\nu 1} c_{12}^2 c_{13}^2 + m_{\nu 2} s_{12}^2 c_{13}^2 e^{i\alpha_{21}} + m_{\nu 3} s_{13}^2 e^{i(\alpha_{31} - 2\delta_{CP})} \right|$$

$$\begin{pmatrix} m_{\nu 1} \\ m_{\nu 2} \\ m_{\nu 3} \end{pmatrix} = \begin{pmatrix} 2.187\times 10^{-6} \\ 9.821 \\ 56.84 \end{pmatrix} \mathrm{meV} \qquad \begin{pmatrix} \delta_{CP} \\ \alpha_{21} \\ \alpha_{31} \end{pmatrix} = \begin{pmatrix} 0.000 \\ 0.000 \\ 0.5495\pi \end{pmatrix}$$

$$\sum m_\nu = 66.66\ \mathrm{meV} < 87\ \mathrm{meV}$$

PDG (PTEP 2022 083C01)

Majorana Phases and $0\nu\beta\beta$ decay（2）

- RL can be used to calculate neutrino masses & Majorana phases, and to expand the possibilities of model validation.

$$m_{\beta\beta} = 3.155\ \mathrm{meV}$$

$$\begin{pmatrix} m_{\nu 1} \\ m_{\nu 2} \\ m_{\nu 3} \end{pmatrix} = \begin{pmatrix} 2.187\times10^{-6} \\ 9.821 \\ 56.84 \end{pmatrix} \mathrm{meV} \qquad \begin{pmatrix} \delta_{CP} \\ \alpha_{21} \\ \alpha_{31} \end{pmatrix} = \begin{pmatrix} 0.000 \\ 0.000 \\ 0.5495\pi \end{pmatrix}$$

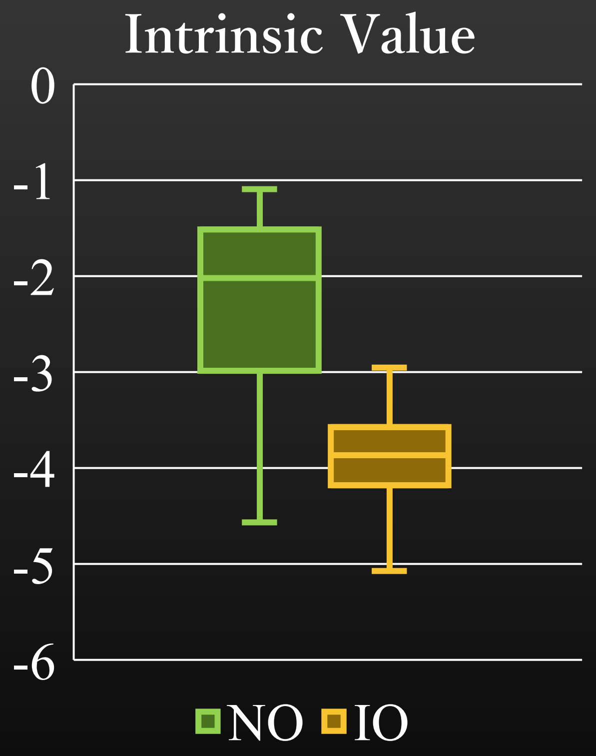
$$\sum m_\nu = 66.66\ \mathrm{meV} < 87\ \mathrm{meV}$$

PDG (PTEP 2022 083C01)

Mass Structure of Neutrinos

- This boxplot shows distribution of the intrinsic values V which is found by RL. The values of normal ordering tends to be larger than that of inverted ordering.

→ The normal ordering is well fitted with the current experimental data in contrast to the inverted ordering.



- Introduction
  - The Standard Model
  - Froggatt-Nielsen Model
  - Procedures in Reinforcement Learning
- Designs and Results
- Predictions
- Summary

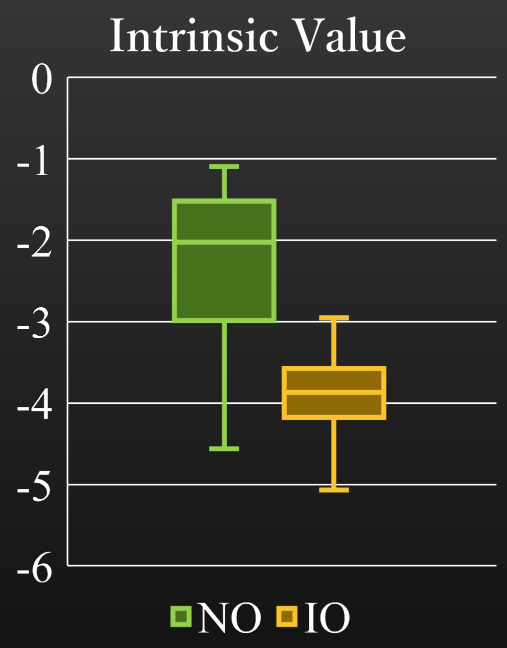
Summary (1)

- We applied reinforcement learning (RL) to the search for charge assignment in the Froggatt-Nielsen model.
  RL efficiently found FN charges that reproduce the masses and flavor mixing of quarks & leptons, simultaneously.

→ Our finding results indicate that the RL is useful to explore parameters of flavor models.

Summary（2）

- We calculated Majorana phases from the charges which is found by RL, and statistically derived that the normal order of neutrino masses is reasonable.



→ Our finding results indicate that the RL can be a new method for understanding the flavor structure.

Future Work

- This work do not derive CP violation in quark sector

  → Adding a complex scalar ($\phi \to \phi_1, \phi_2$) is promising.

- The scale of right-handed neutrino $M = 10^{15}\ \mathrm{GeV}$ can be changed.

  → More precise sets of parameters may be found.

- Exhaustive search for flavor models, Black-box problem of AI, ⋯

  (Modular flavor models, etc.)

Backup

Key Points (1)

- We applied reinforcement learning (RL) to the search for charge assignment in the Froggatt-Nielsen model.
  RL efficiently found FN charges that reproduce the masses and flavor mixing of quarks and leptons simultaneously.

→ Our finding results indicate that the RL is useful to explore parameters of flavor models.

Key Points（2）

- We calculated Majorana phases from the charges which is found by RL, and statistically derived that the normal order of neutrino masses is reasonable.

→　Our finding results indicate that the RL can be a new method for understanding the flavor structure.

The Standard Model（1）

- SM describes the behavior of elementary particles with a high degree of accurately. It is valid for ~ 10^{-18} m.

https://higgstan.com/category/phys-item/

Difference of Parameter Space (2)

- The search space is much larger, so the search itself is difficult. Furthermore, it is nontrivial that a solution may exist since both the quark and lepton sectors are considered.

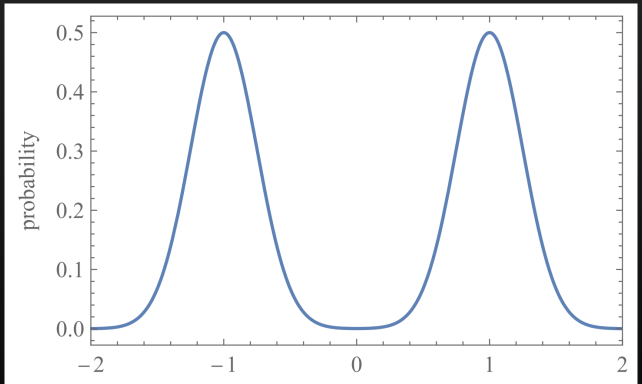
- This research shows that there is indeed a solution in the search space, and that RL still powerful as a means of efficiently searching for it.

Terminal State

- Terminal states are defined as FN charges that realize sufficiently high intrinsic value.

$$|V(Q)| < V_0, \qquad E_\alpha, E_\alpha^\nu < V_1, \qquad E_{C,P}^{i,j} < V_2, \qquad (\forall \alpha, i, j)$$

- For terminal states, $O(1)$ Yukawa couplings are optimized using Monte Carlo method.



Neutrino Mass

with designated ordering (NO)

$$(m_1 \quad m_2 \quad m_3) = (0.01176 \quad 9.547 \quad 43.28)\ \mathrm{meV}$$

$$\sum m_\nu = 52.84\ \mathrm{meV} < 87\ \mathrm{meV}$$

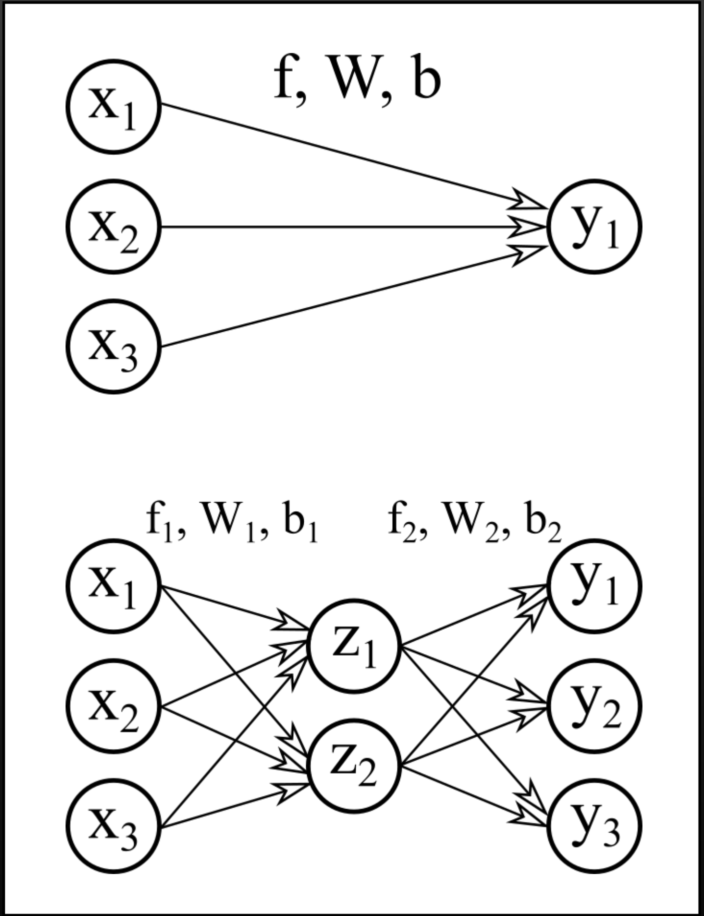
without designated ordering (NO)

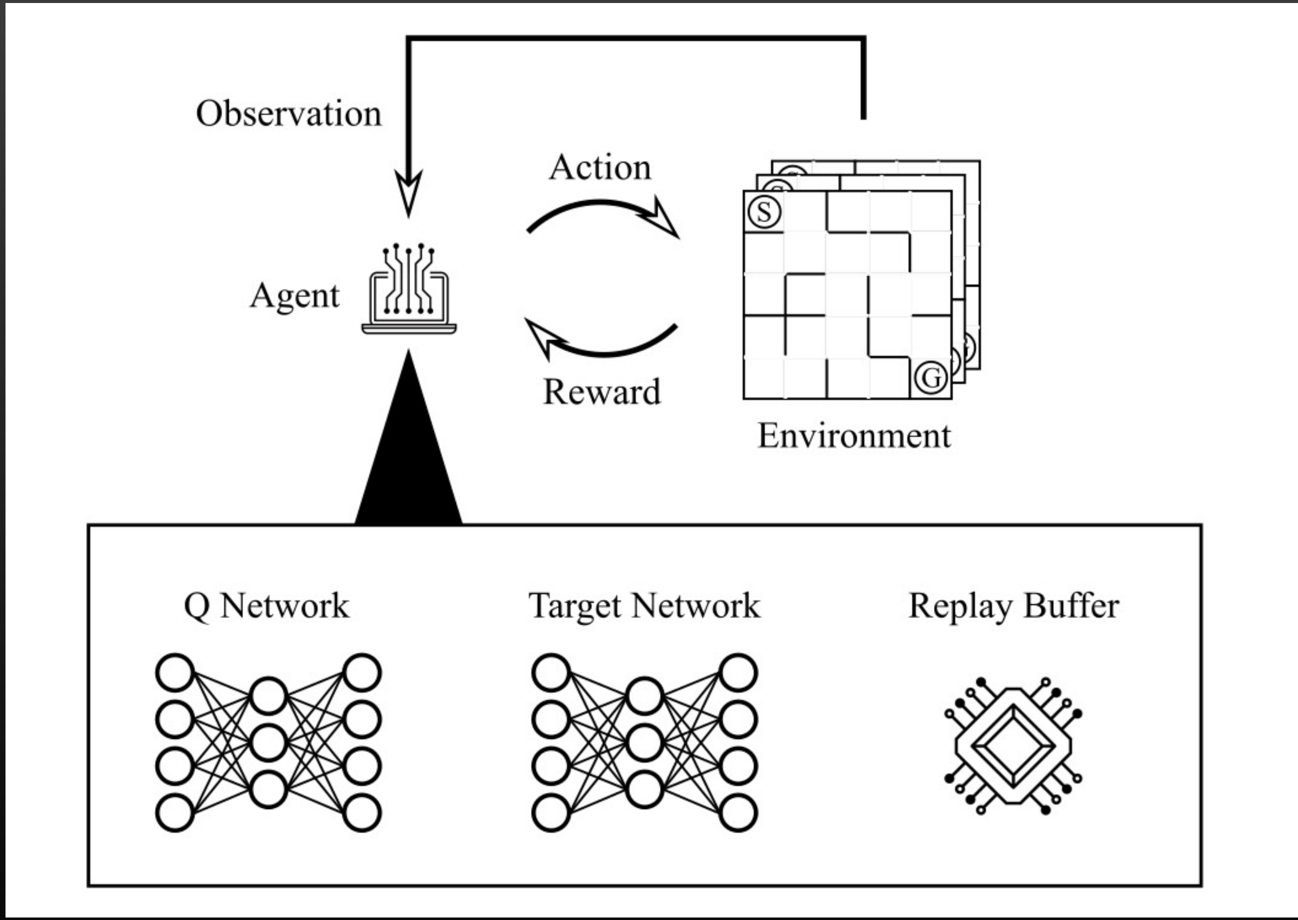
$$(m_1 \quad m_2 \quad m_3) = (2.401 \quad 5.607 \quad 41.26)\ \mathrm{meV}$$

$$\sum m_\nu = 49.26\ \mathrm{meV} < 87\ \mathrm{meV}$$

PDG (PTEP 2022 083C01)

Neural Network & DQN





Episode & Step

	Step 1	Step 2	$\cdots$	Step N_{step}
Episode 1	s_1^1	s_2^1	$\cdots$	$s_{N_{\text{step}}}^1$
Episode 2	s_1^2	s_2^2	$\cdots$	$s_{N_{\text{step}}}^2$
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$
Episode N_{ep}	$s_1^{N_{\text{ep}}}$	$s_2^{N_{\text{ep}}}$	$\cdots$	$s_{N_{\text{step}}}^{N_{\text{ep}}}$

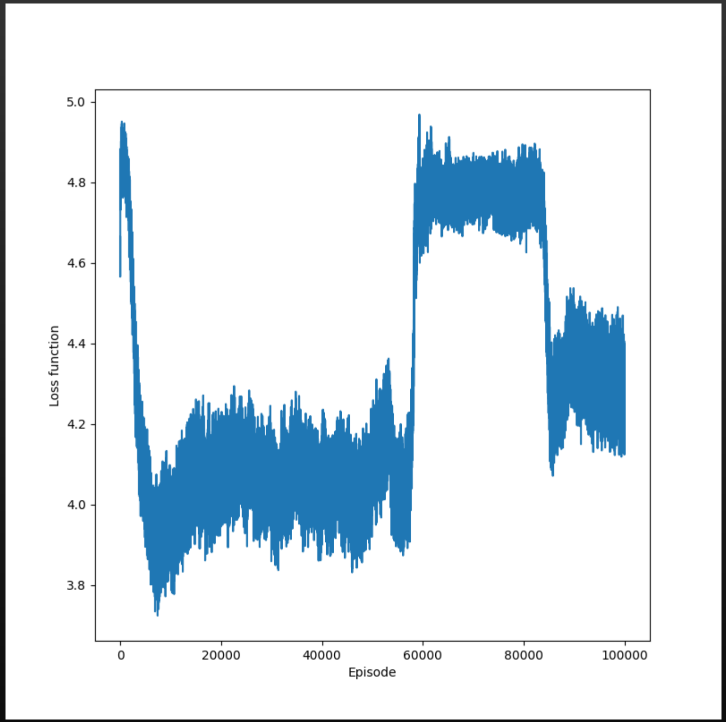
Table 1. The environment states s are changed by the actions. The agent performs at most N_{step} step for one episode.

Loss Function

Failure

5.0

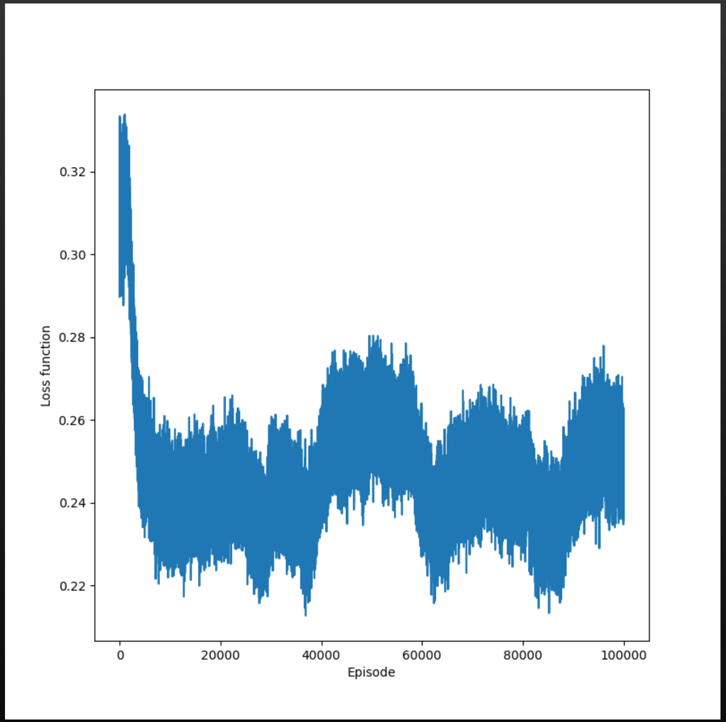
3.8



Success

0.32

0.22

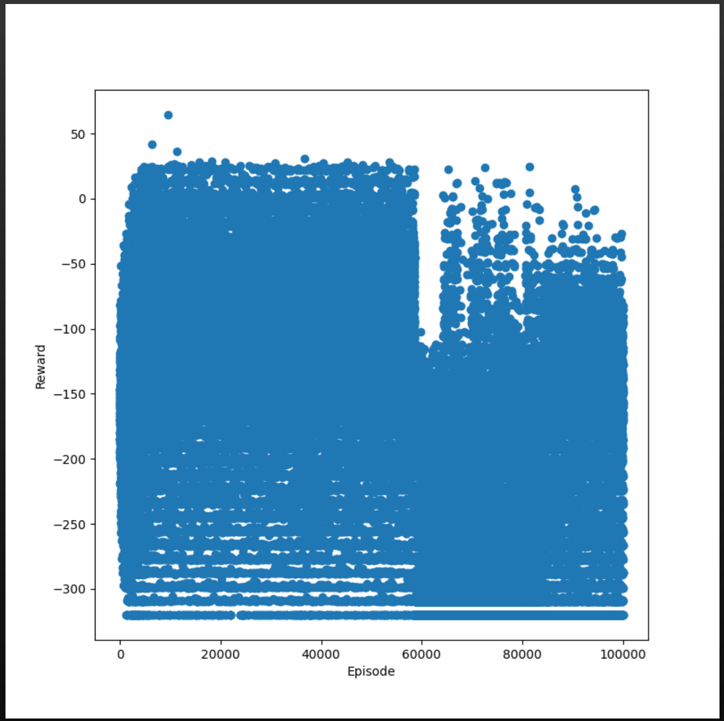


Reward

Failure

50

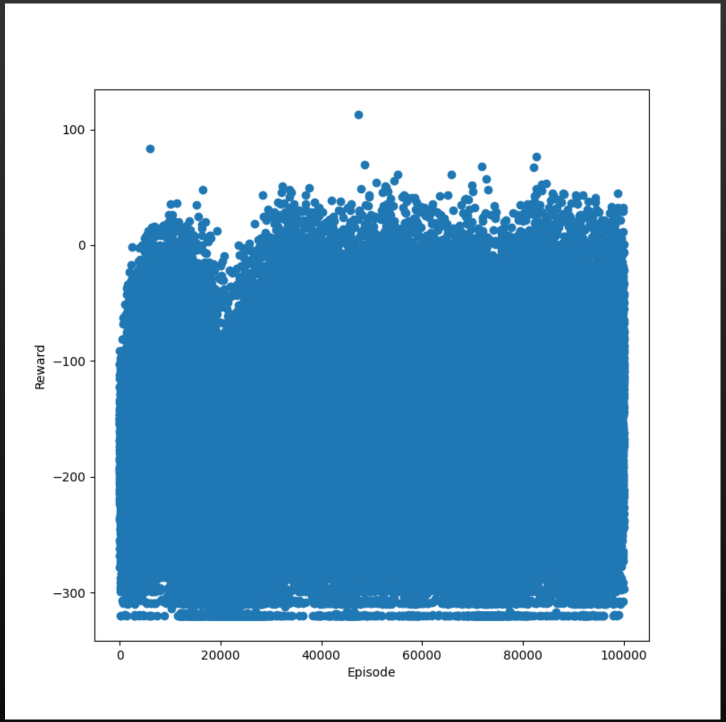
-300



Success

100

-300



Mass Structure of Neutrinos

- Training with designated ordering

  → The information of neutrino masses is an input.

- Training without designated ordering
- → It is possible to predict from RL

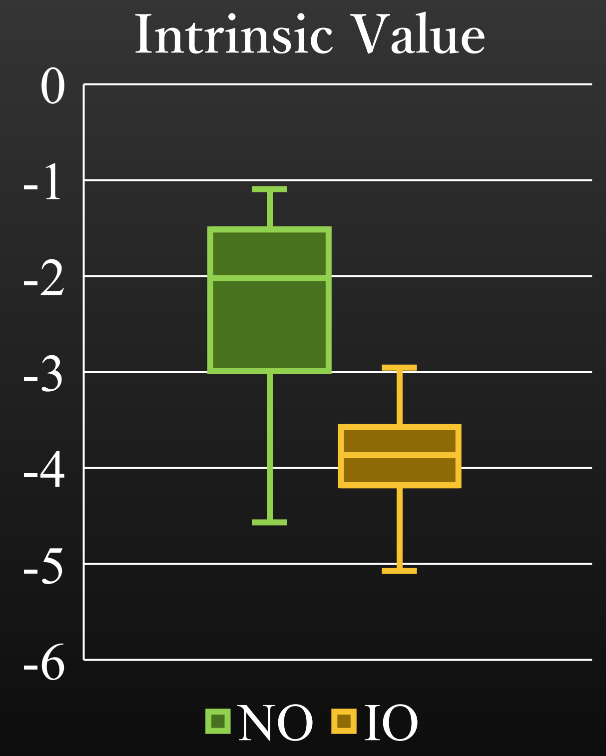
  which ordering is preferred, normal or inverted.

- Multiple 100,000 episodes were run and we obtained 111 charges.

Mass Structure of Neutrinos (1)

- This boxplot show distribution of the intrinsic values V which is found by RL.

- The values of normal ordering tends to be larger than that of inverted ordering.



Mass Structure of Neutrinos（2）

- About without designated ordering, the values of NO also tends to be larger than that of IO.

→ The normal ordering is well fitted with the current experimental data in contrast to the inverted ordering.