Exploring the flavor structure of quarks and leptons with reinforcement learning

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

JHEP12(2023)021 [arXiv : 2304.14176]

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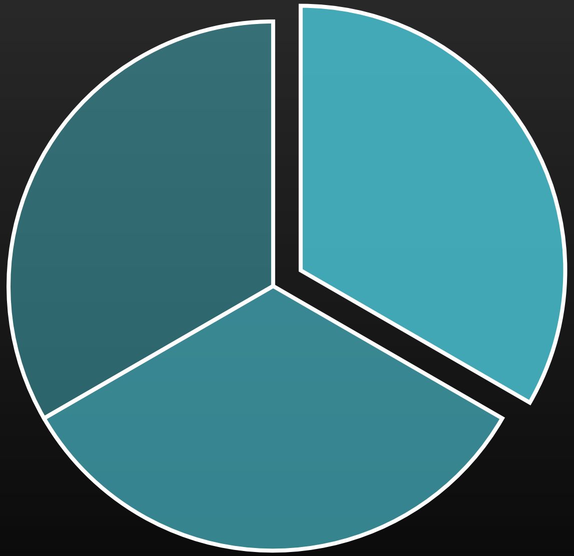
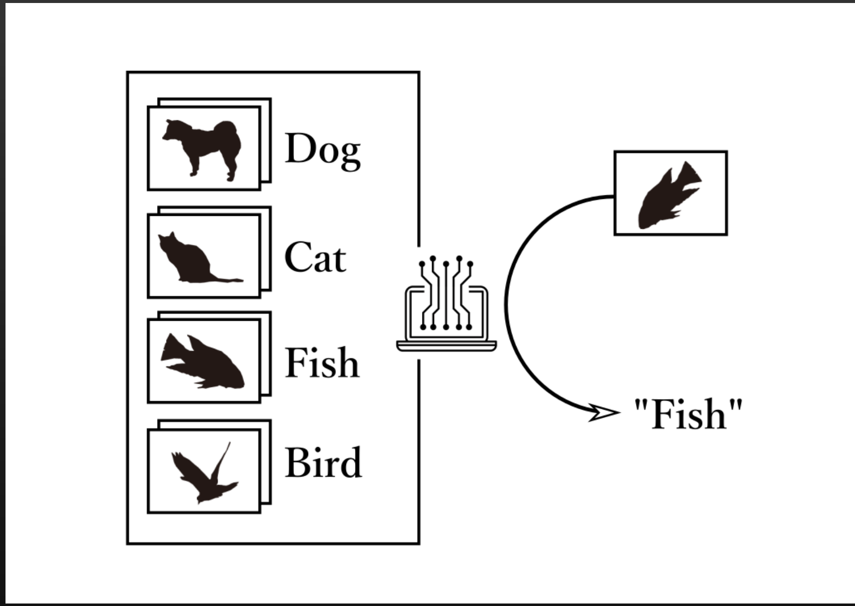
Machine Learning

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



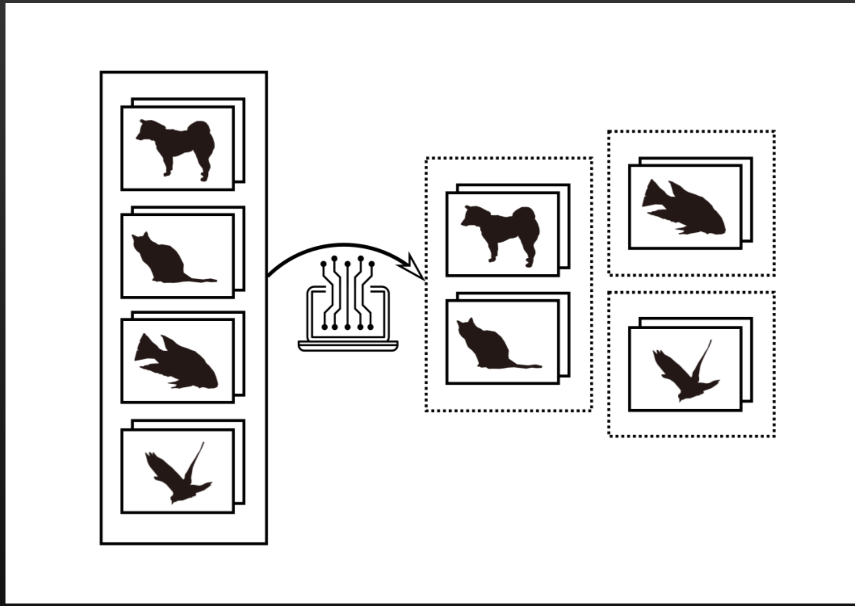
Supervised

estimates the correspondence between data and signals



Unsupervised

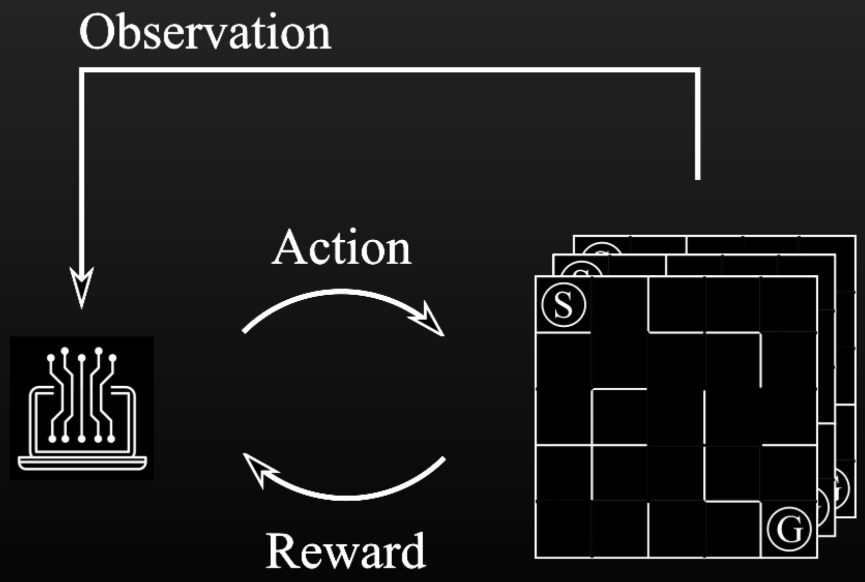
finds the similarity among data



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?

- The SM
  - Mass Hierarchy
  - Flavor Mixing

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

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

- 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.

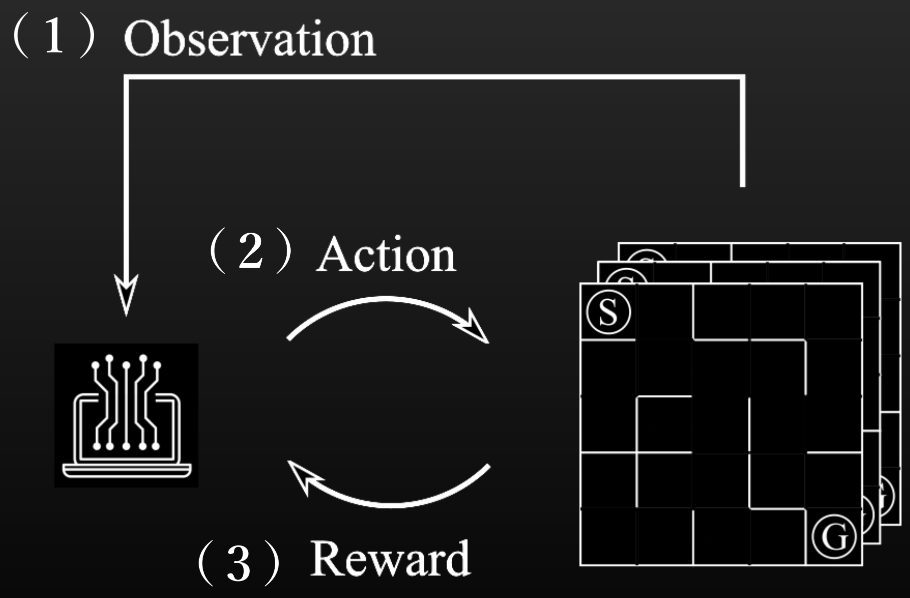
  parameter space：$-9 \leq q \leq 9 \;\rightarrow\; 19^{11} \sim 10^{14}$ patterns

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

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

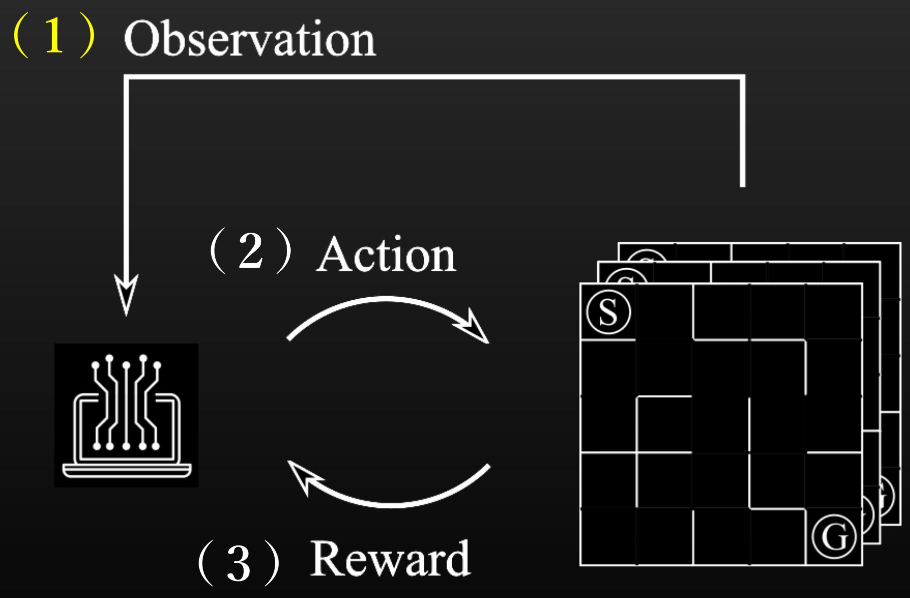
Reinforcement Learning

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



Reinforcement Learning

- Procedure：The agent observe the environment,

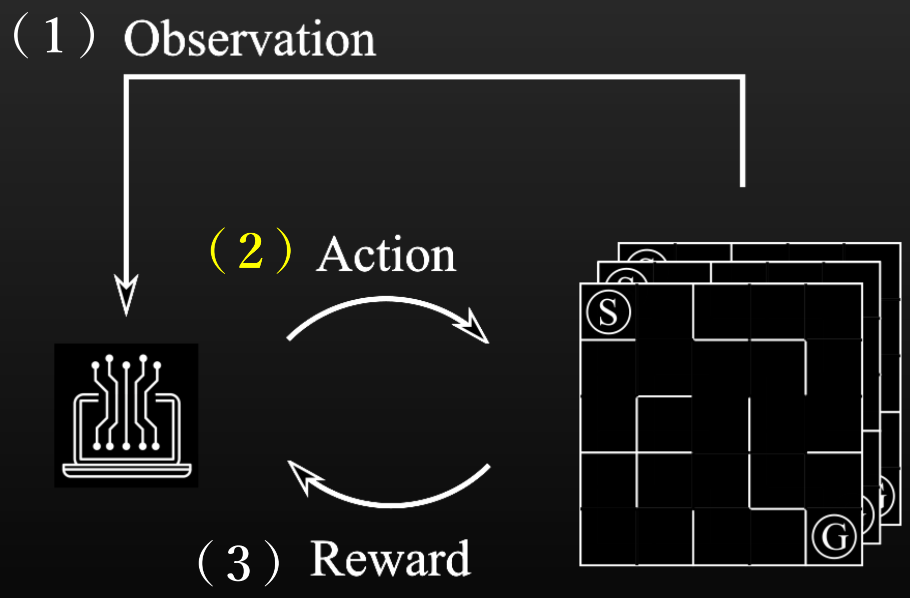


(Example of mazes)

（1） observe walls

Reinforcement Learning

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



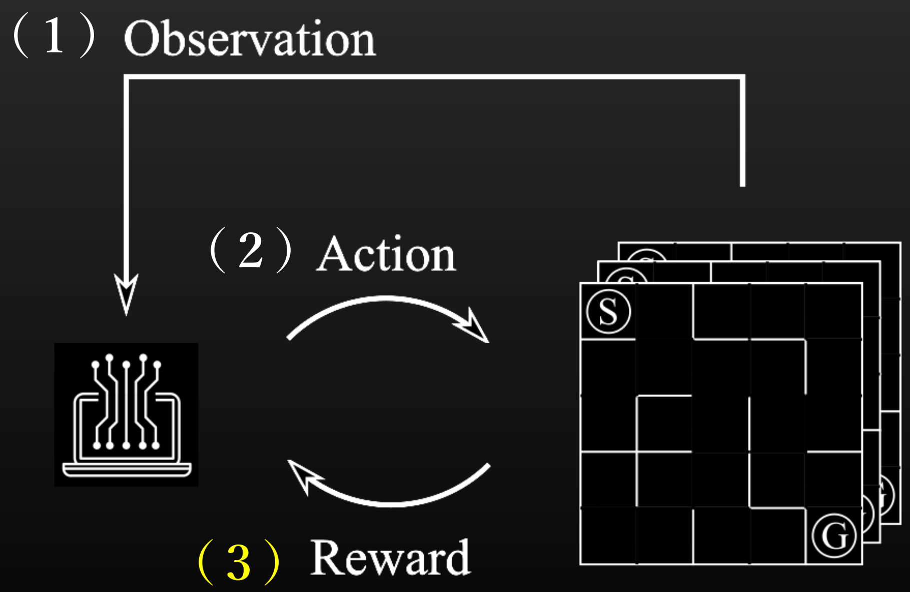
(Example of mazes)

（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 & leptons simultaneously.

Design of RL (Environment)

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

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

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 FN couplings y as random real $O(1)$ constants.

Design of RL (Reward: 1)

- 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 particle.

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

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

Design of RL (Reward: 2)

- 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 : $m_3 < m_1 < m_2$

  We can choose whether to designate the order or not.

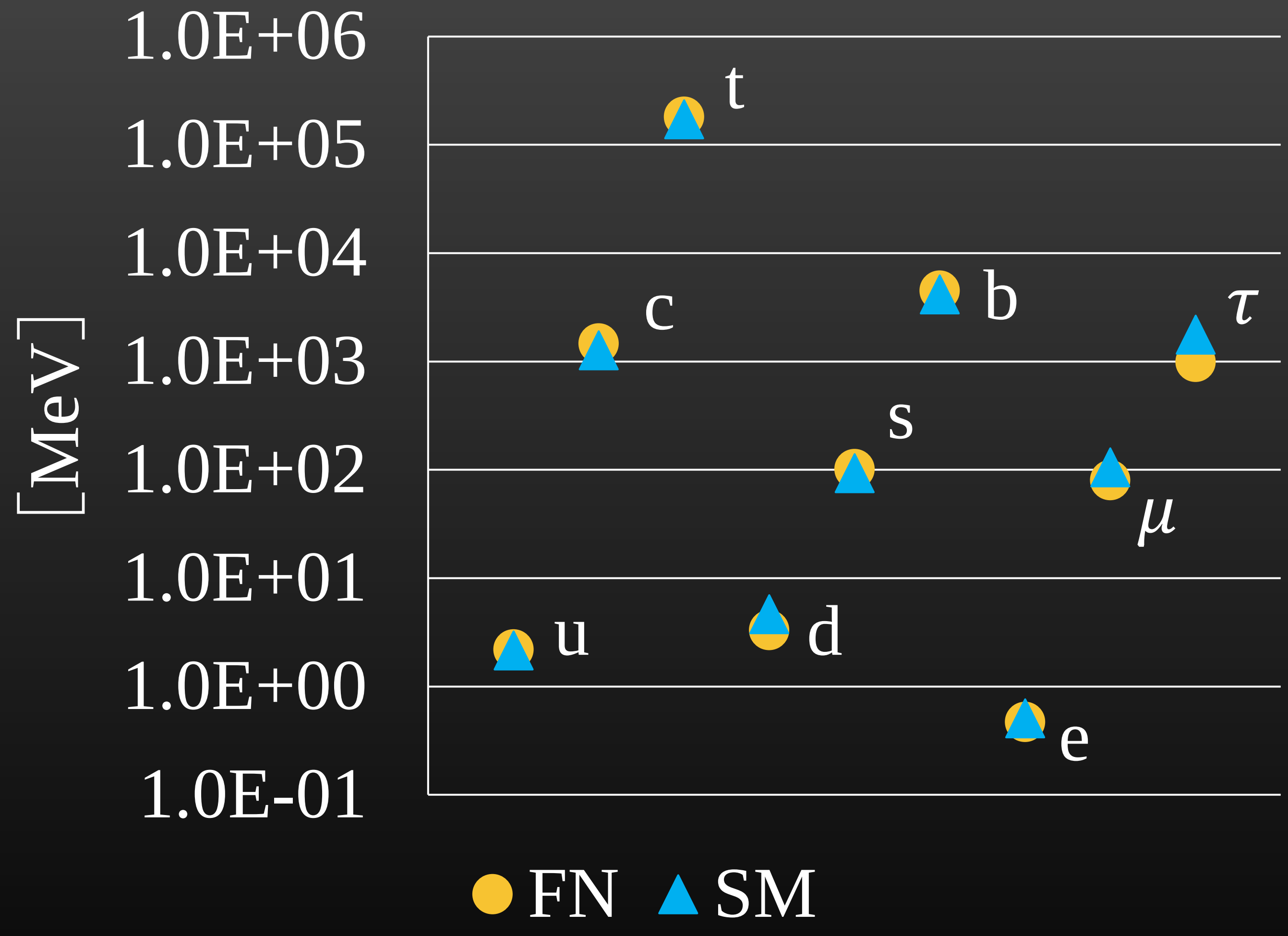
Physical Values for Reward

- 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)

  27 values (without designated ordering)

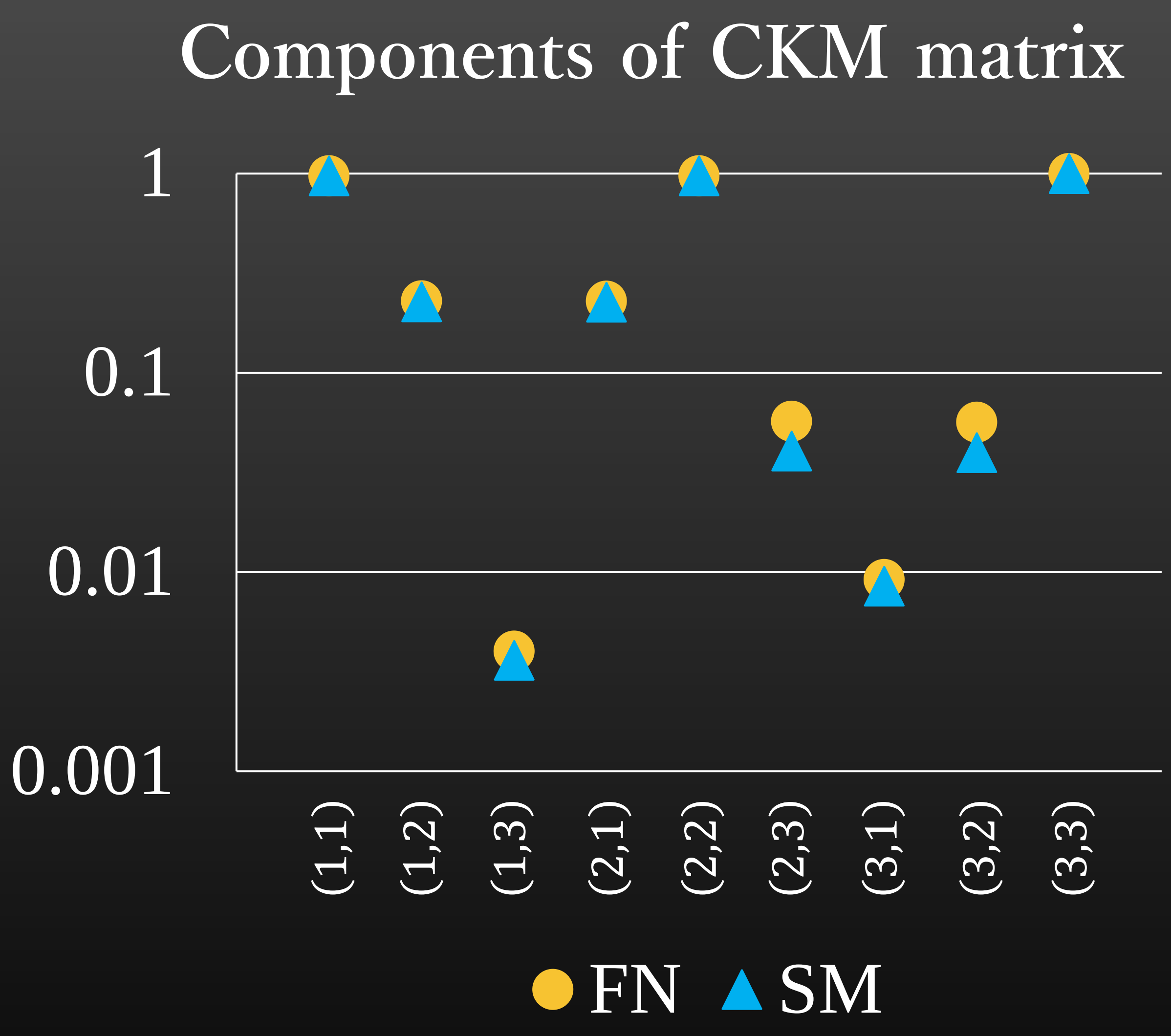
Masses of charged particles

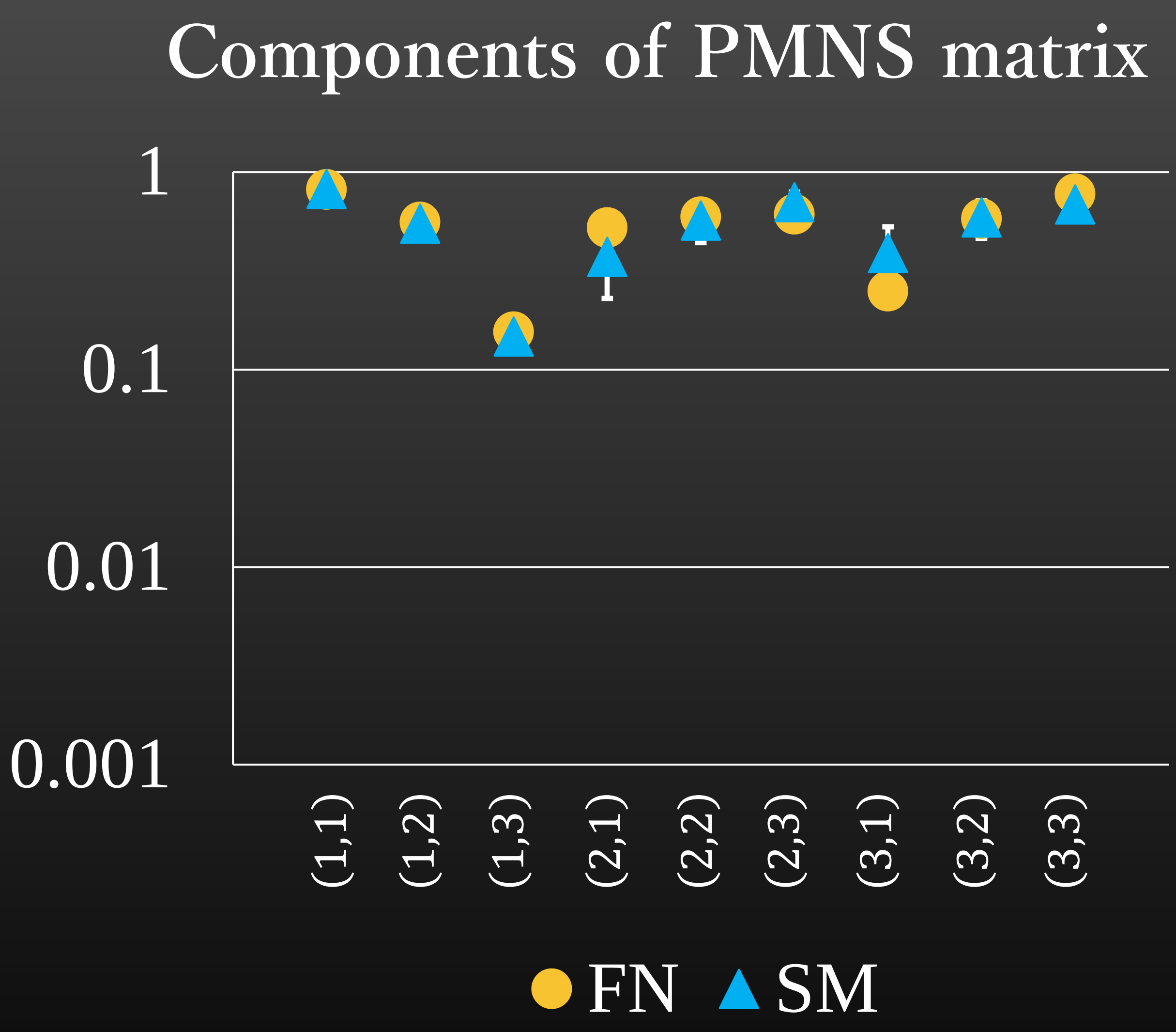


One example of charges

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

It reproduces hierarchical structure.





It also reproduces flavor mixing.

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:

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

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

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

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.

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

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

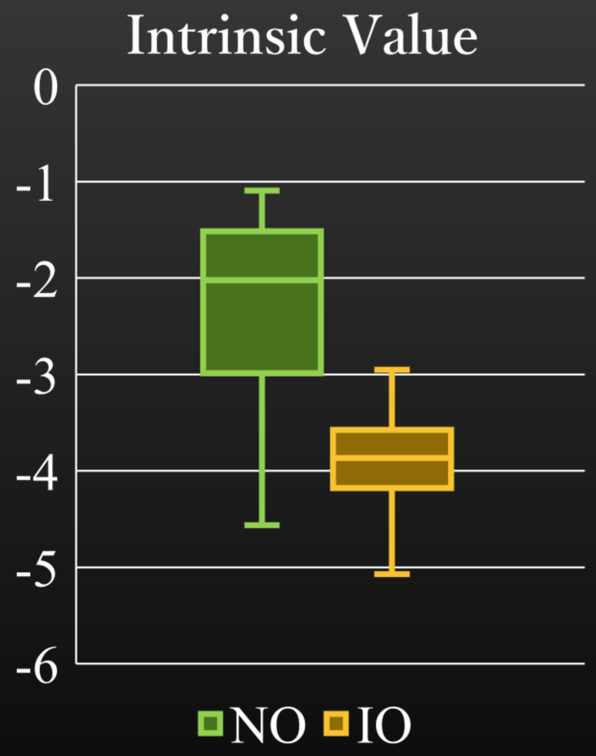
$$\sum m_\nu = 66.66 \text{ meV} < 87 \text{ meV}$$

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.



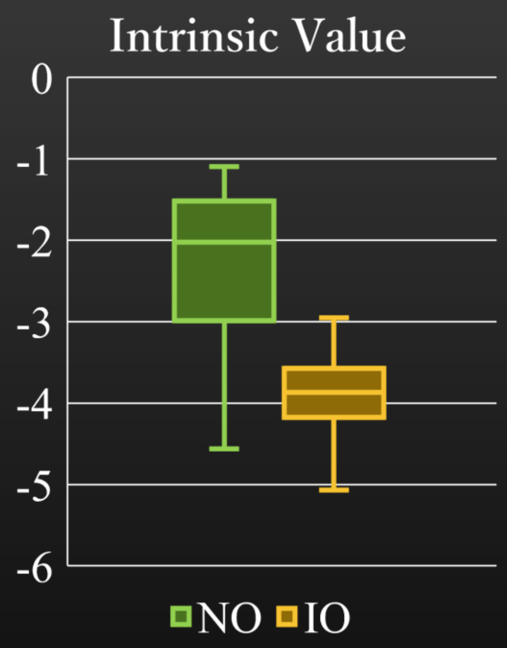
Summary（1）

- 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.

→ 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.



→ RL can be a new method for understanding the flavor structure.

What is new

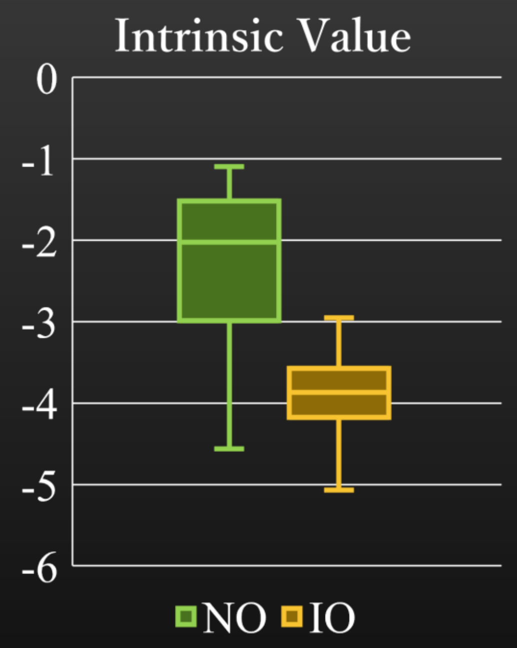
- Previous work

  “RL can reproduce experimental values”

- This work

  “RL can also give some predictions”

  (not only reproducing)



Potential of reinforcement learning in flavor physics

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 $M = 10^{15}\ \mathtt{GeV}$ 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.)

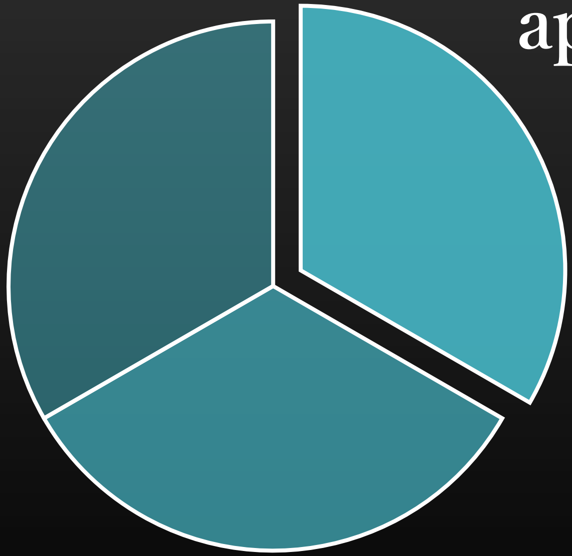
Backup

Machine Learning (Advertisement)

- ChatGPT = Supervised + Reinforcement

Keiya.I, Satsuki.N, Hajime.O, arXiv:2312.07181 [hep-th]

application for string theory



Unsupervised Learning

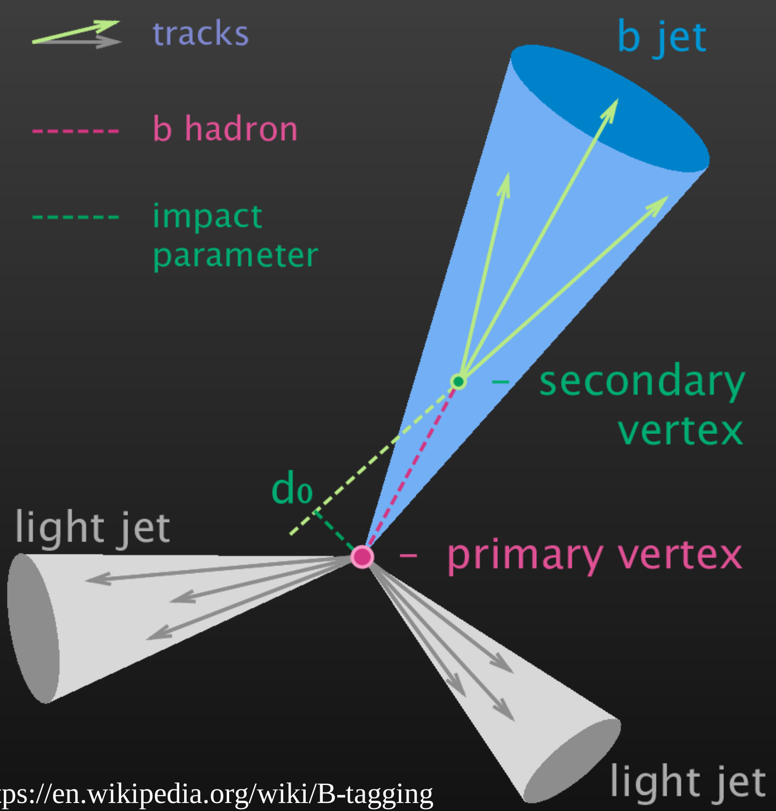
Supervised

Unsupervised

These are good methods

for particle experiments.

Ex) jet tagging



https://en.wikipedia.org/wiki/B-tagging

It is needed to prepare a large amount of data.

The Standard 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.

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

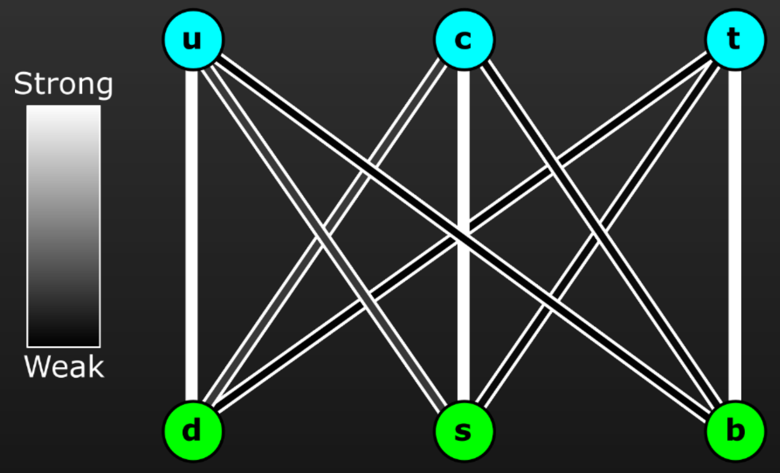
What is the background cause of such hierarchy?

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.

Difference of Parameter Space

- Previous work "analyzing for quark sector"

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

$$\left(0.01 \leq \langle\phi\rangle \leq 0.3\right)$$

- This work "analyzing for quark & lepton sector"

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

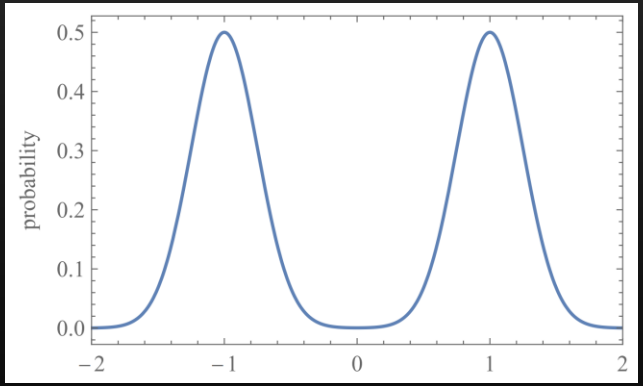
$$\left(0.01 \leq |\langle\phi\rangle/M| \leq 0.3, -\pi \leq \arg\langle\phi\rangle \leq \pi\right)$$

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.



Design of RL (Action)

- The agent make increasing or decreasing any FN charges by ± 1.

Ex)

$$Q = (1,1,3,3,5,\cdots)$$

1 step

$$Q' = (1,1,2,3,5,\cdots)$$

"3rd charge should be added -1."

The agent has a neural network (NN) as a brain.
The agent observes the current charges as an input, and take an action by an output of NN.

Terminal State（1）

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

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

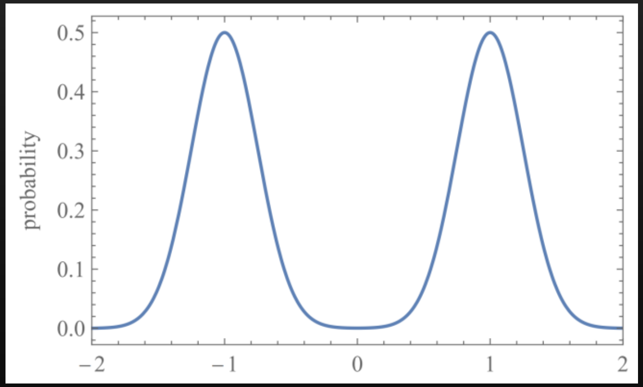
- We adopt $V_0 = 10.0, V_1 = 1.0, V_2 = 0.2$ based on previous work.

  It means $0.1 \leq \frac{|m_{\mathrm{mass}}|}{|m_{\mathrm{mass,exp}}|} \leq 10.0, 0.63 \leq \frac{|m_{\mathrm{mixing}}|}{|m_{\mathrm{mixing,exp}}|} \leq 1.58.$

Terminal State (2)

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

- We used the two Gaussian distribution. (average ± 1 & standard deviation 0.25) Then, FN Yukawa couplings are still $O(1)$.



Design of RL (Reward: 3)

- The reward R of 1 step is determined as $R = R_{\text{base}} + R_{\text{term}}$

- Q : the charge assignment observed by the agent

  Q' : the charge assignment after the action

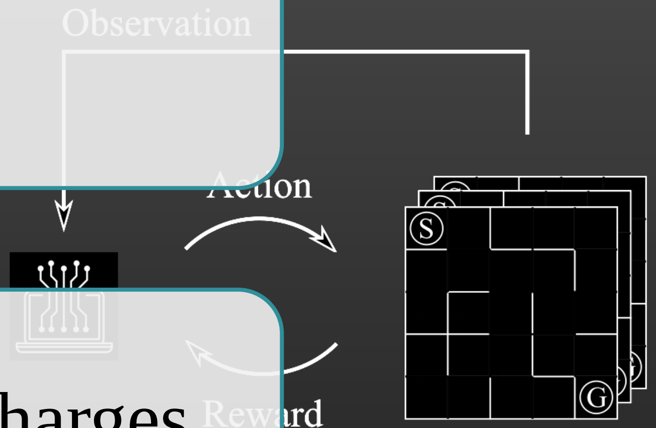
$$R_{\text{base}} = \begin{cases} V(Q') - V(Q) & \text{if } V(Q') > V(Q) \\ R_{\text{offset}} = -10 & \text{if } V(Q') \leq V(Q) \end{cases}$$

- When Q' is a terminal state, $R_{\text{term}} = +100$.

  When it is not so, $R_{\text{term}} = 0$.

random

- Random $U(1)$ charges
- Random $O(1)$ Yukawa couplings

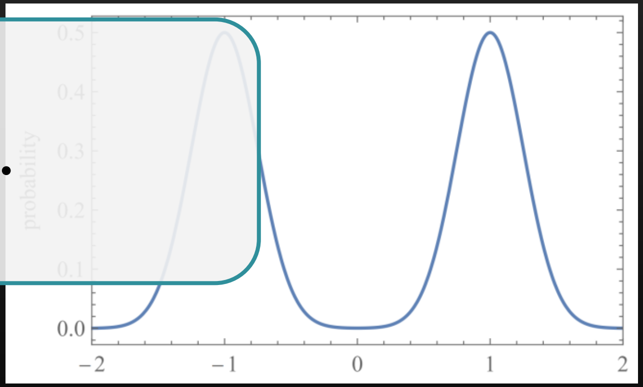


RL

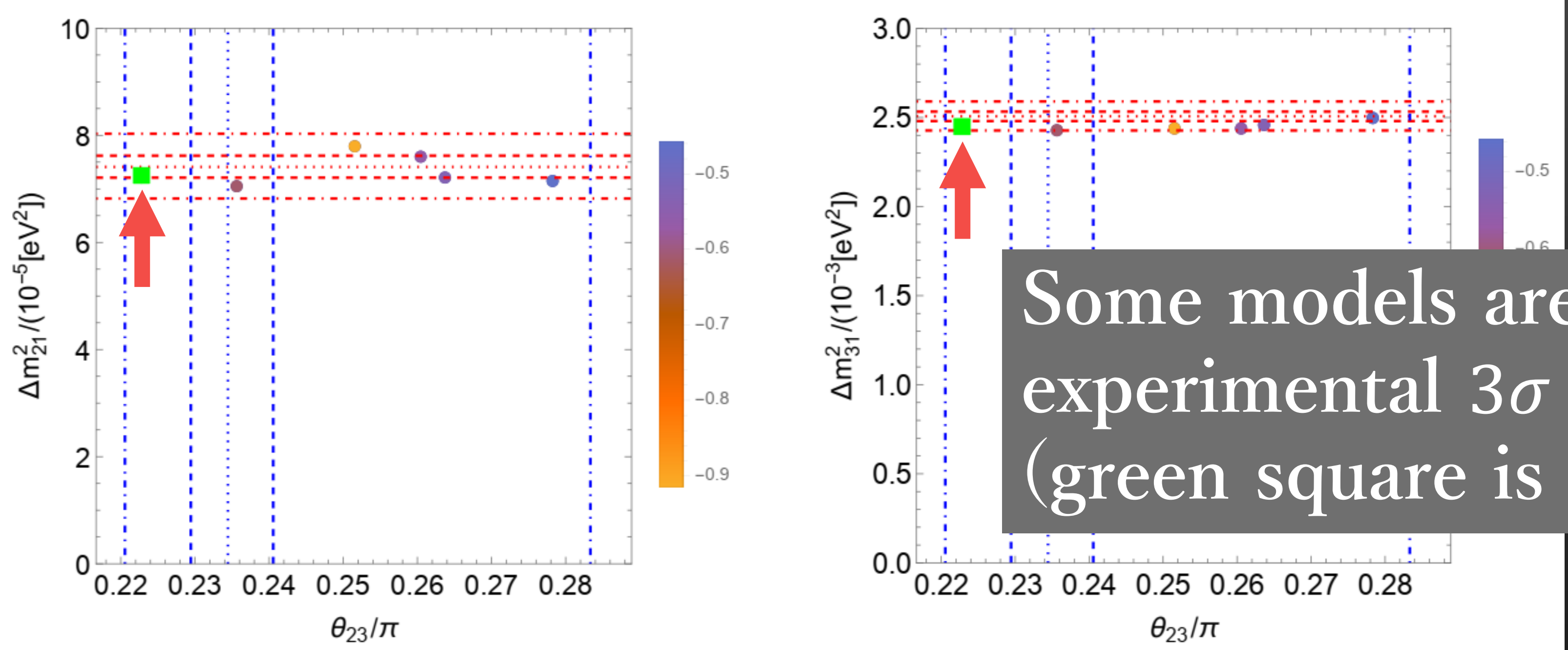
- RL gives candidates of appropriate charges.

human

- We optimize $O(1)$ Yukawa couplings.



Neutrino Masses with NO designated



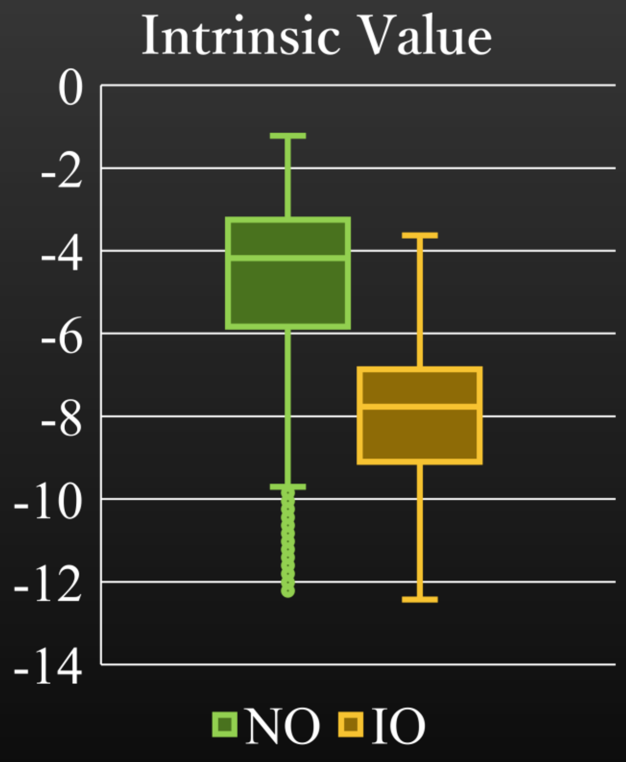
Some models are found which satisfy experimental 3σ constraints.
(green square is a best-fit model)

Figure 9. Neutrino masses vs mixing angle θ_{23}, where the dotted line represents the global best fit value in NuFIT v5.2 results with Super-Kamiokande atmospheric data [17], and the inside region of each line represents dashed line $\leq 1\sigma$, dotdashed line $\leq 3\sigma$ CL, respectively. The sum of neutrino masses is constrained by 0.15 eV (95% CL) corresponding to the black solid line in the case of ΛCDM model [20]. We denote a best-fit point within 3σ by a square, and the intrinsic value (3.14) is written in the legend. Note that the neutrino mass ordering is fixed as NO in the training of the neural network.

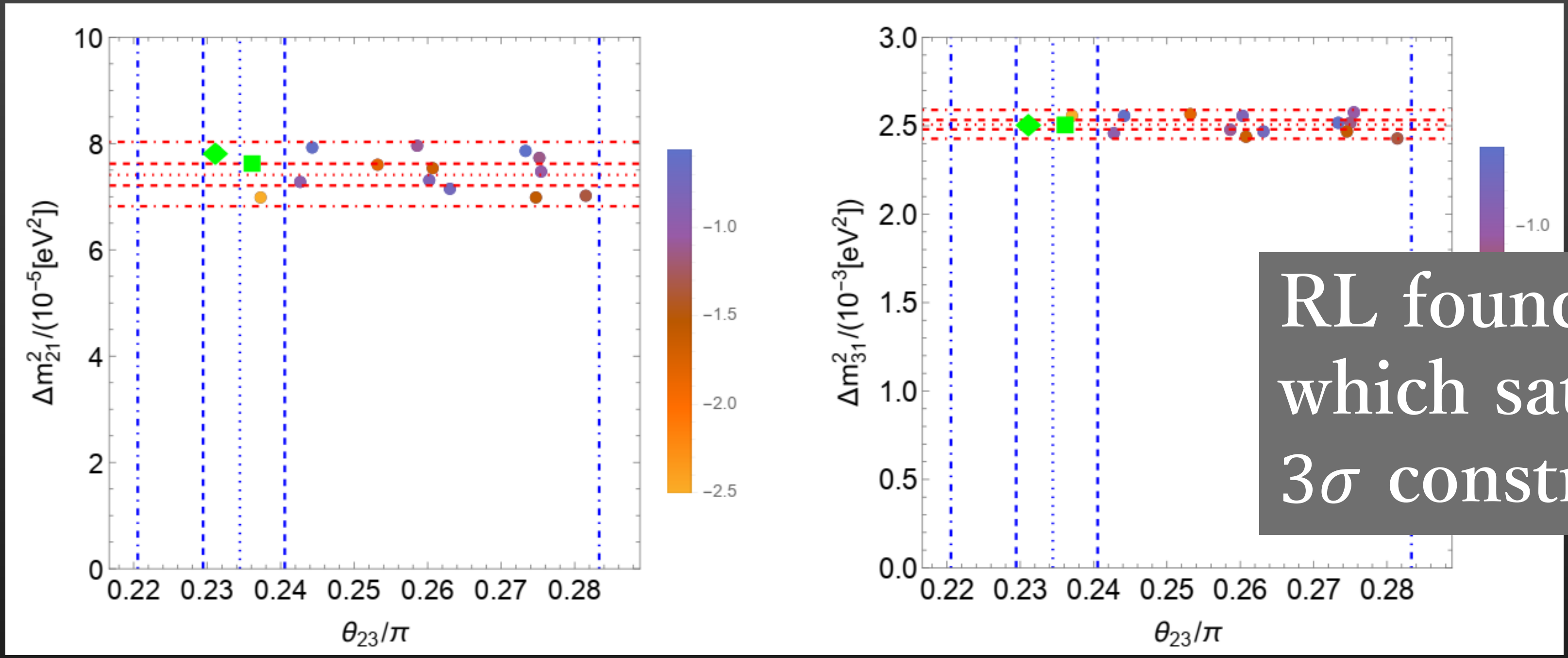
Mass Structure of Neutrinos (2)

- 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.



Neutrino Masses without designated ordering



RL found some models which satisfy experimental 3σ constraints **for only NO.**

- Without designated ordering, the agent does not know the structure of neutrino masses.

  → RL helps to investigate what flavor structure the theory leads to.