Machine learning approaches for giant dipole resonance parameters

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Introduction

One of the basic types of nuclear collective excitations is giant dipole resonance (GDR), which has energy greater than the binding energy per nucleon [1]. The study of GDR can contribute to the understanding of nuclear structure. The experimental GDR observables have been measured in various types of experiments, namely, photonuclear experiments [2] with photons from bremsstrahlung radiation, and more recently, laser Compton scattering (LCS), as well as (p, p') reaction, and so on. Experimental data of most nuclei near the β-stability line are available in major photonuclear data libraries (RIPL, IAEA, CENDL, etc.).

The increase in GDR experimental data puts a challenge on relevant theoretical models. With the advancement of computer techniques, machine learning (ML) has started to demonstrate its remarkable ability in learning huge complex data and making predictions. The basic characteristics of atomic nuclei have been studied extensively utilizing machine learning techniques. Recently, it was used to describe the parameters of the GDR using multitask neural networks [3]. This inspires us to apply different machine learning approaches to evaluate the GDR parameters.

Details of calculation

Using Lorentzian functions, it is possible to get a set of GDR parameters for each nucleus from the experimental photo absorption cross-section of GDR. The shape of a fundamental resonance in the absorption cross-section is that of the Lorentz curve

$$\sigma(E_\gamma) = \sum_i \frac{\sigma_{mi}}{1 + \left(E_\gamma^2 - E_{mi}^2\right)^2 / E_\gamma^2 \Gamma_i^2} \quad (1)$$

where Lorentz parameters E_γ, E_m, σ_m, and Γ are the photon energy, resonance energy, peak cross-section, and full width at half maximum, respectively. Here i represents the number of components of the GDR and is determined from the shape of the nucleus.

Considering the effect of deformation parameter β_2 on the shape of the Lorentzian curve, we will take β_2 as one of the inputs in the input layer, together with proton number Z and mass number A of the nucleus, i.e., (Z, A, β_2). The experimental GDR parameters to be trained are taken from the results fitted by the SLO model in International Atomic Energy Agency Photonuclear Data Library 2019 (IAEA) [2]. The deformation parameter β_2 in the input are a combination of experimental data [4], when available and finite-range liquid-drop model (FRDM) results [5]. We separate the entire data set into the training set and the validation set with a ratio of about 75% : 25%.

Results and discussion

In Fig. 1 and Fig. 2, we show GDR energies (E) and resonance widths (Γ) calculated by different ML algorithms, Goldhaber-Teller (GT) [6] and Steinwedel-Jensen (SJ) models [7] as the function of nuclear mass number (A), compared to the experimental data from RIPL-3 library. It is clear that generally, GDR peak energies have good systematics with nuclear mass number. However, there is no discernible trend in the growth of resonance widths with the mass number because resonance widths have more complex physical origins and poorer systematics than peak energies. In comparison to the theoretical GDR

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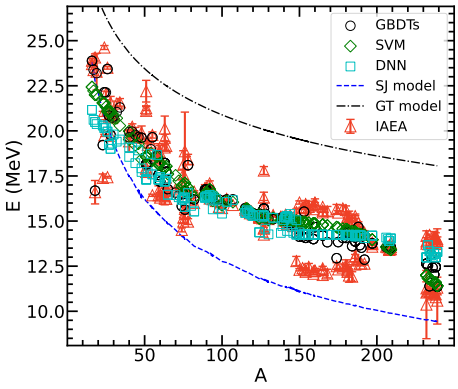

FIG. 1: GDR peak energy (E) as the function of nuclear mass number (A), calculated by gradient boosting decision trees (GBDTs), support vector machine (SVM), dense neural network (DNN), GT model [6] (dash-dot line) and SJ model [7] (dash line), in comparison with experimental data from RIPL-3 library [4].

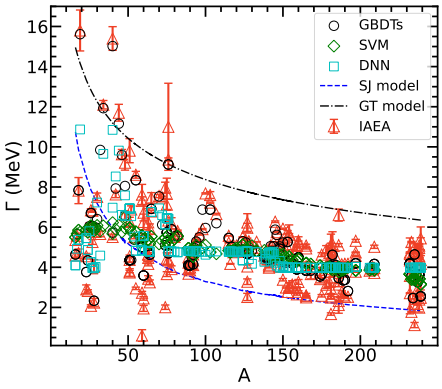

FIG. 2: Same as fig. 1, for GDR width (Γ) as the function of nuclear mass number (A).

TABLE I: The root-mean-square (RMS) deviations of GDR peak energies (E_{rms}) and resonance widths (Γ_{rms}) of different models from experimental data.

S. No.	ML Techniques	E_{rms} (MeV)	Γ_{rms} (MeV)
1.	GT Model	27.11	17.10
2.	SJ Model	11.21	6.41
3.	Gradient Boosting Trees (GBDTs)	1.94	1.83
4.	Support Vector Machine (SVM)	1.96	3.09
5.	Dense Neural Network (DNN)	1.88	1.76

parameters computed using the GT model and SJ model, the accuracy of the ML-based parameters has significantly increased, as shown in Table I. We have tested the sensitivity of the trained model with respect to hyperparameters, including the learning rate and sizes of training and validation data sets. We have verified that our neural networks are not overfitted by comparing the RMS deviations between the training set and the validation set which produce comparable values for both data sets.

Conclusion

Our ML models learned and predicted critical GDR parameters, such as peak energies and resonance widths more accurately than the phenomenological GT and SJ models. As an improvement to the present work, the determination of a complete and global set of GDR parameters using ML technique is under progress.

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