Transfer learning (TL)

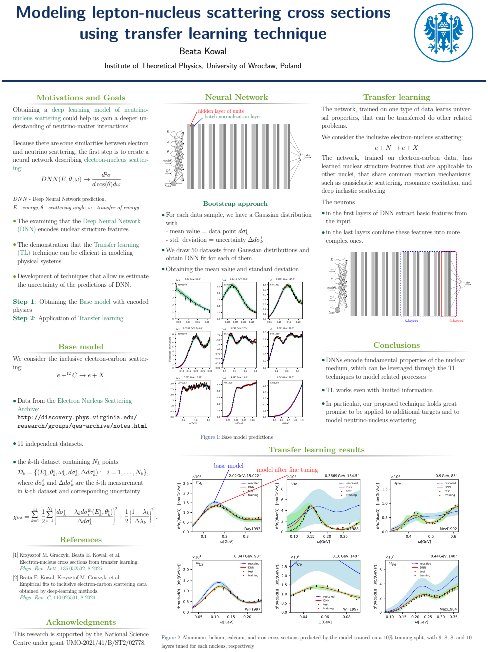
The ability of a person who has learned skills in one specific field to easily acquire skills needed in related areas of life.

TL can by applied in deep learning: The neural network learns the details of one kind of data, and after fine-tuning, it makes predictions for related problem.

We propose to use the TL technique in physics

Electron-nucleus cross sections from transfer learning
Phys. Rev. Lett. 135, 052502
K.Graczyk, B. Kowal, et al.

Empirical fits to inclusive electron-carbon scattering data obtained by deep-learning methods
Phys. Rev. C 110, 025501
B. Kowal, K.Graczyk, et al.



Modeling lepton-nucleus scattering cross sections using transfer learning technique

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Motivations and Goals

Obtaining a deep learning model of neutrino-nucleus scattering could help us gain a deeper understanding of neutrino-matter interactions.

Because there are some similarities between electron and neutrino scattering, the first step is to create a neural network describing electron-nucleus scattering:

$$DNN(E,\theta,\omega) \to \frac{d^2\sigma}{d\cos(\theta)d\omega}$$

DNN - Deep Neural Network prediction,
E - energy, θ - scattering angle, ω - transfer of energy

- The examining that the Deep Neural Network (DNN) encodes nuclear structure features
- The demonstration that the Transfer learning (TL) technique can be efficient in modeling physical systems.
- Development of techniques that allow us estimate the uncertainty of the predictions of DNN.

Step 1: Obtaining the Base model with encoded physics
Step 2: Application of Transfer learning

Base model

We consider the inclusive electron-carbon scattering:

$$e + {}^{12}C \to e + X$$

- Data from the Electron Nucleus Scattering Archive: `http://discovery.phys.virginia.edu/research/groups/qes-archive/notes.html`
- 11 independent datasets.
- the k-th dataset containing N_k points $\mathcal{D}_k = \{(E_k^i, \theta_k^i, \omega_k^i, d\sigma_k^i, \Delta d\sigma_k^i): \ i = 1,\dots,N_k\}$, where $d\sigma_k^i$ and $\Delta d\sigma_k^i$ are the i-th measurement in k-th dataset and corresponding uncertainty.

$$\chi_{\rm tot} = \sum_{k=1}^{11}\left[\frac{1}{2}\sum_{i=1}^{N_k}\left(\frac{d\sigma_k^i - \lambda_k d\sigma_i^{\rm fit}(E_k^i,\theta_k^i)}{\Delta d\sigma_k^i}\right)^2 + \frac{1}{2}\left(\frac{1-\lambda_k}{\Delta\lambda_k}\right)^2\right],$$

References

[1] Krzysztof M. Graczyk, Beata E. Kowal, et al. Electron-nucleus cross sections from transfer learning. *Phys. Rev. Lett.*, 135:052502, 8 2025.

[2] Beata E. Kowal, Krzysztof M. Graczyk, et al. Empirical fits to inclusive electron-carbon scattering data obtained by deep-learning methods. *Phys. Rev. C*, 110:025501, 8 2024.

Acknowledgments

This research is supported by the National Science Centre under grant UMO-2021/41/B/ST2/02778.

Neural Network

Bootstrap approach

- For each data sample, we have a Gaussian distribution with
  - mean value = data point $d\sigma_k^i$
  - std. deviation = uncertainty $\Delta d\sigma_k^i$
- We draw 50 datasets from Gaussian distributions and obtain DNN fit for each of them.
- Obtaining the mean value and standard deviation

Figure 1: Base model predictions

Transfer learning

The network, trained on one type of data learns universal properties, that can be transferred do other related problems.

We consider the inclusive electron-nucleus scattering:

$$e + N \to e + X$$

The network, trained on electron-carbon data, has learned nuclear structure features that are applicable to other nuclei, that share common reaction mechanisms: such as quasielastic scattering, resonance excitation, and deep inelastic scattering

The neurons

- in the first layers of DNN extract basic features from the input.
- in the last layers combine these features into more complex ones.

Conclusions

- DNNs encode fundamental properties of the nuclear medium, which can be leveraged through the TL techniques to model related processes
- TL works even with limited information.
- In particular, our proposed technique holds great promise to be applied to additional targets and to model neutrino-nucleus scattering.

Transfer learning results

Figure 2: Aluminum, helium, calcium, and iron cross sections predicted by the model trained on a 10% training split, with 9, 8, 8, and 10 layers tuned for each nucleus, respectively

Goals

- The examining that the Deep Neural Network (DNN) encodes nuclear structure features

- The demonstration that the Transfer learning technique can be efficient in modeling physical systems.

- Obtaining a electron-nucleus scattering model using deep learning techniques

$$DNN(E,\theta,\omega) \rightarrow \frac{d^2\sigma}{d\cos(\theta)d\omega}$$

  DNN - Deep Neural Network prediction,
  E = Energy, θ = scattering angle, ω = transfer of energy

  - Step 1: Obtaining the Base model with encoded physics
    We consider the inclusive electron-carbon scattering:

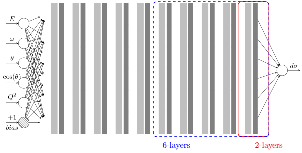
$$e +^{12} C \rightarrow e + X$$

  - Step 2: Application of Transfer learning
    Transfering physics from carbon to other targets
    We consider the inclusive electron-nucleus scattering:

$$e + N \rightarrow e + X$$

- Development of techniques that allow us estimate the uncertainty of the predictions of DNN.

We consider the situations in which some number of last layer is fine-tuned.



Bootstrap approach

i For each data sample, we have a Gaussian distribution with
- mean = data point $d\sigma_k^i$
- std. deviation = uncertainty $\Delta d\sigma_k^i$

ii we draw 50 bootstrap (clone) datasets from Gaussian distributions

iii For each bootstrap (clone) data set, obtain DNN fit.

iv Obtaining the mean and standard deviation