Neural Network Application to the Nuclear Binding Energies and Charge Radii

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XIV. International Conference on Nuclear Structure Properties,
2-4 June 2021

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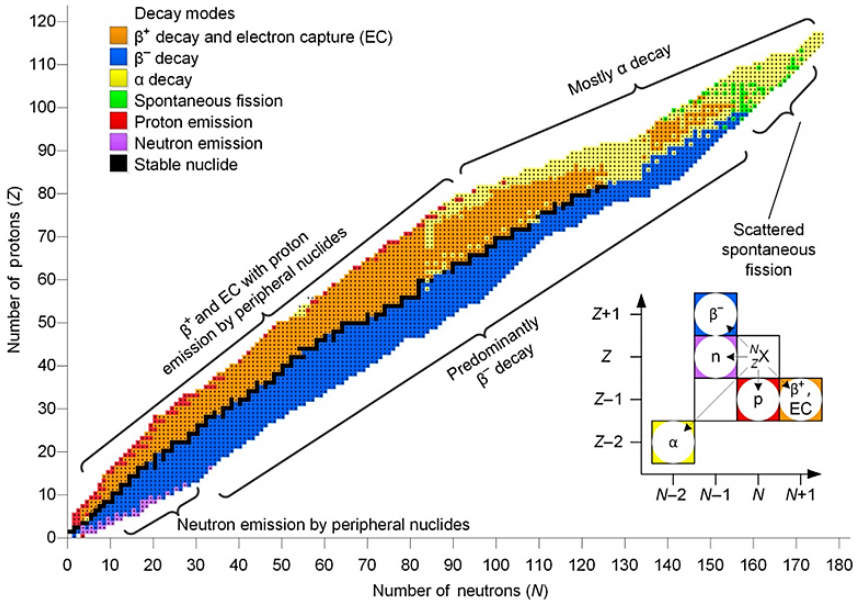
Introduction: Nuclear Physics

- AME2016 Total: 3435 (2497 experiment + 938 extrapolated).



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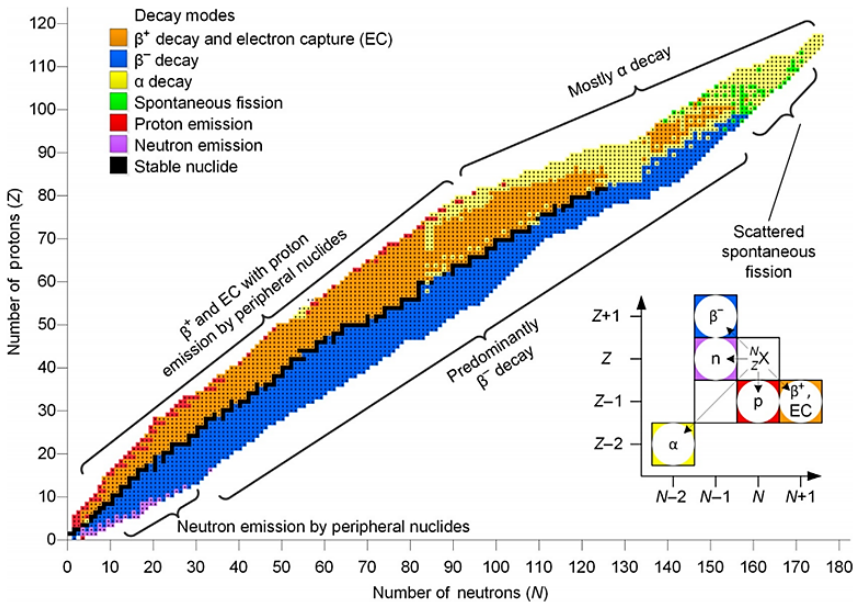

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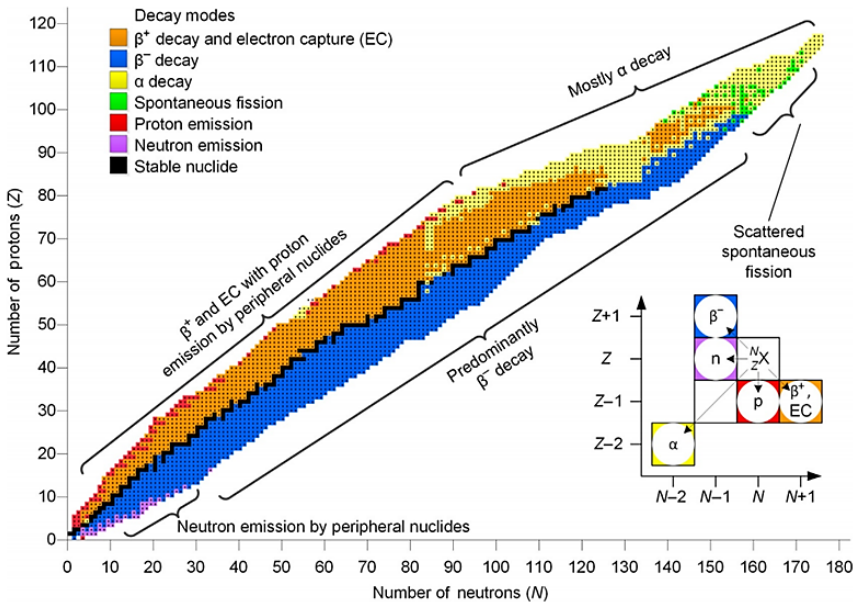

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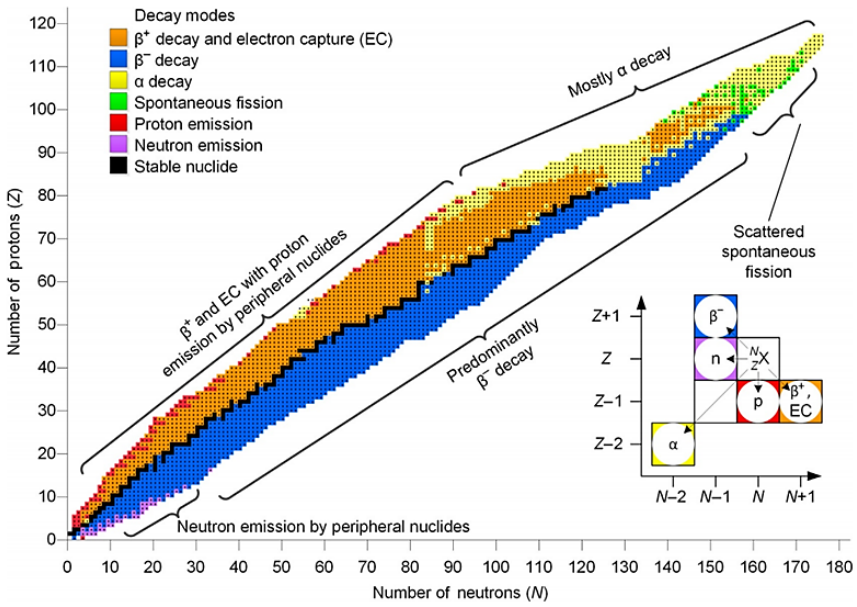
  - Mic-mac models errors have ~ 0.3 MeV.



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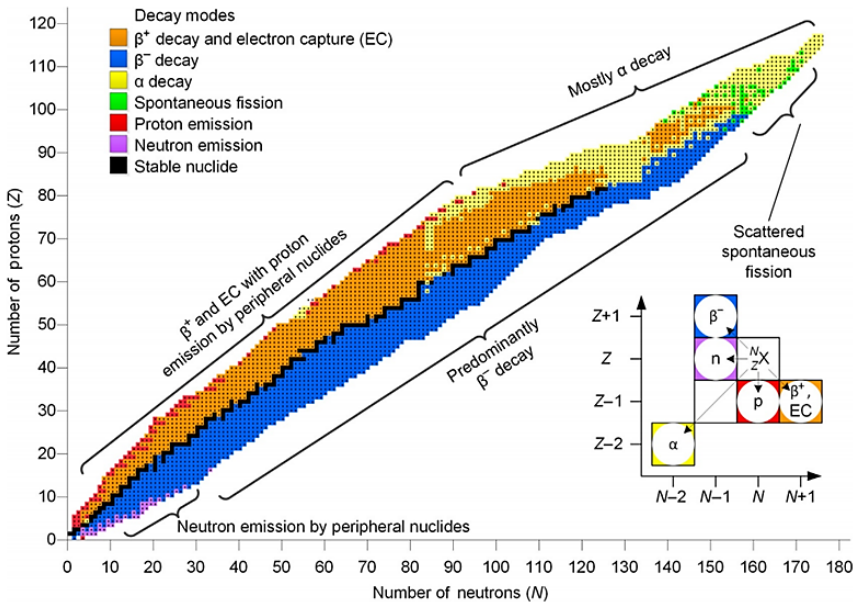

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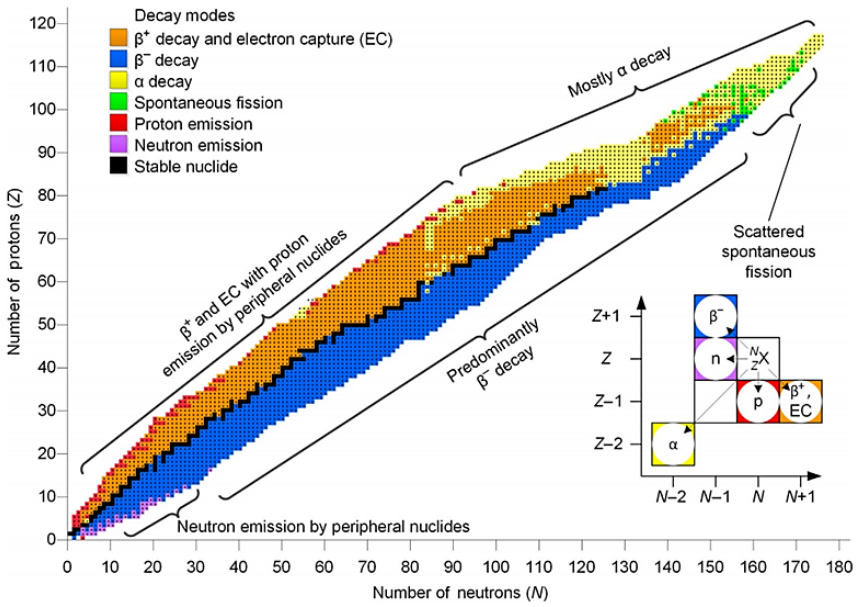
- "Alternate" model to understand these questions.



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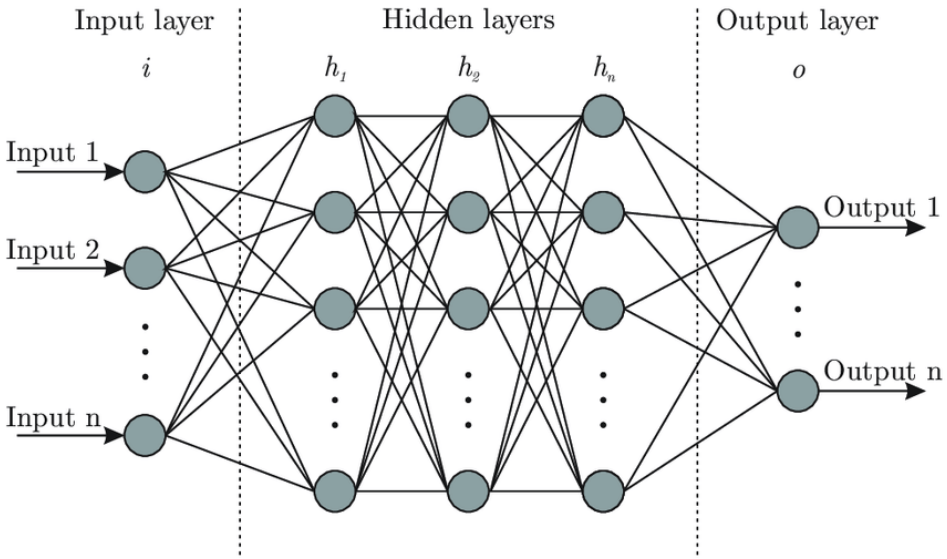

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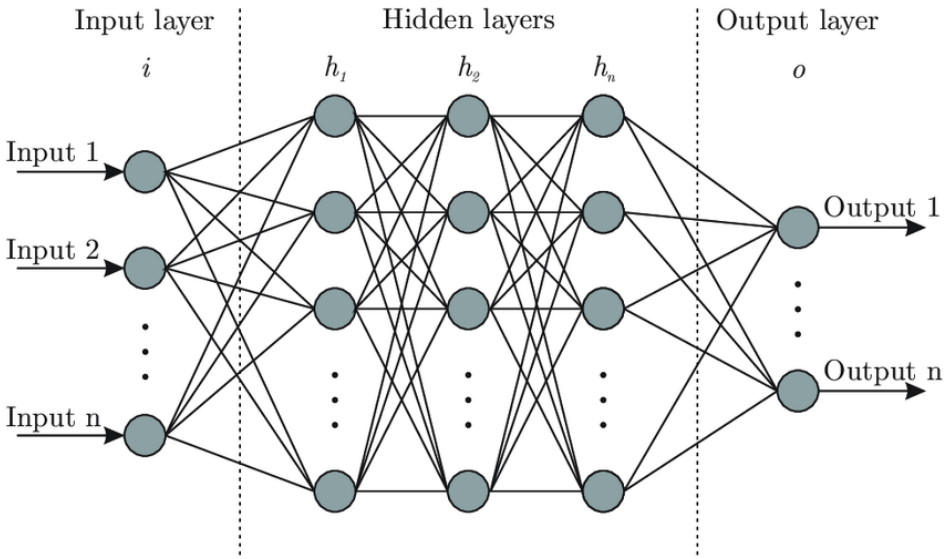

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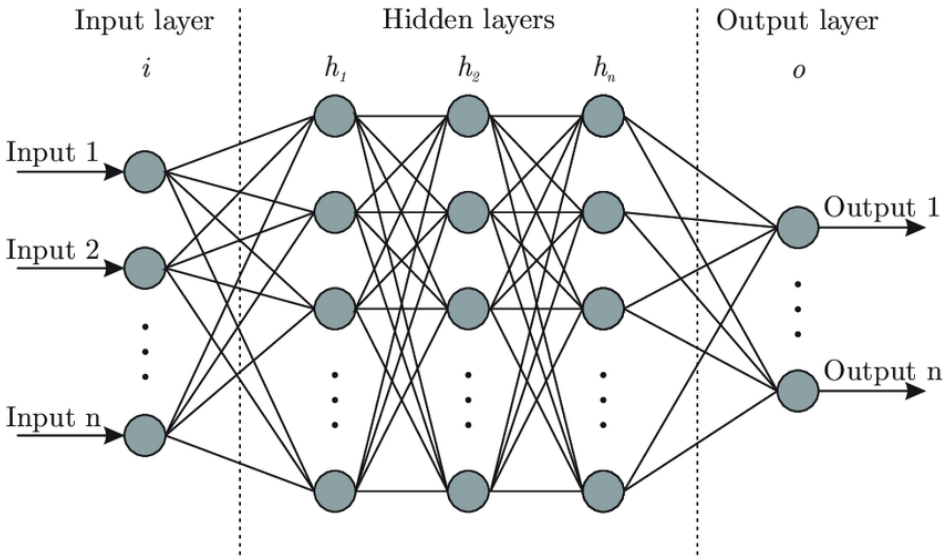

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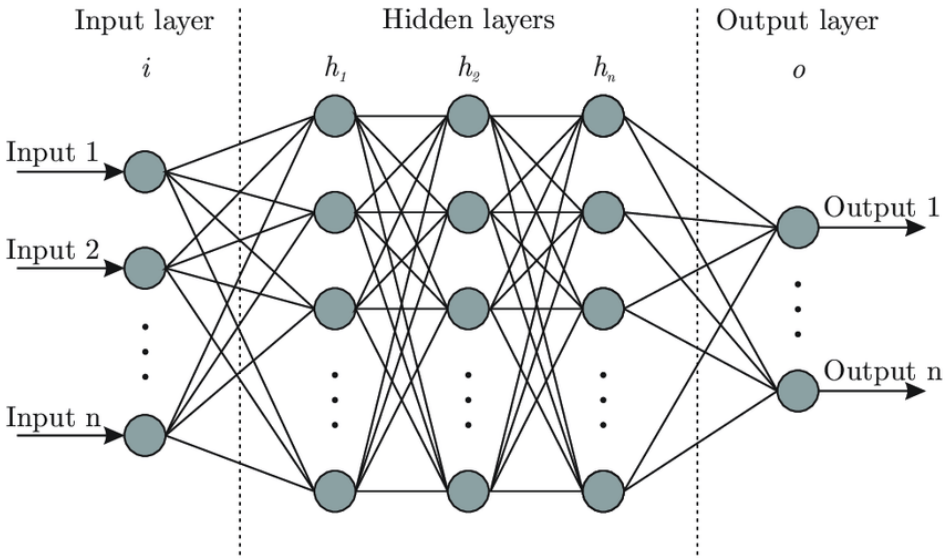

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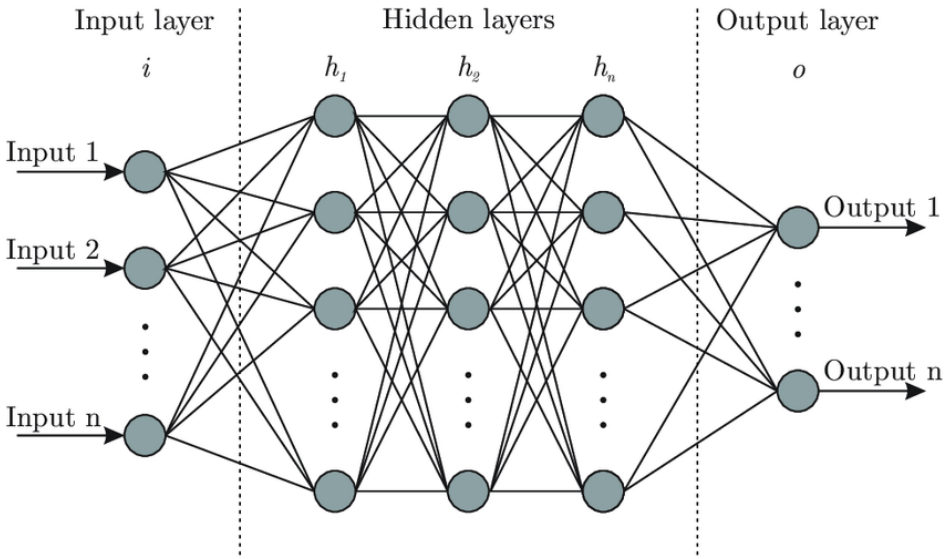
- **Batch size:** The size of data from training to estimate the error gradient before the model weights are updated.



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Binding Energy: Previous Works

From our previous study[3] E.Yuksel et al. Int.J.Mod.Phys.E 30 (2021) 03, 2150017
The latest AME2016 table is used (3413 nuclei):

- Z: Proton Number
- A: Mass Number (Z+N)
- δ: Pairing Term

Definition:

$$\delta(Z,N) = \frac{[(-1)^Z + (-1)^N]}{2}$$

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- Z: Proton Number
- A: Mass Number (Z+N)
- δ: Pairing Term
- P: Promiscuity Factor

Definition:

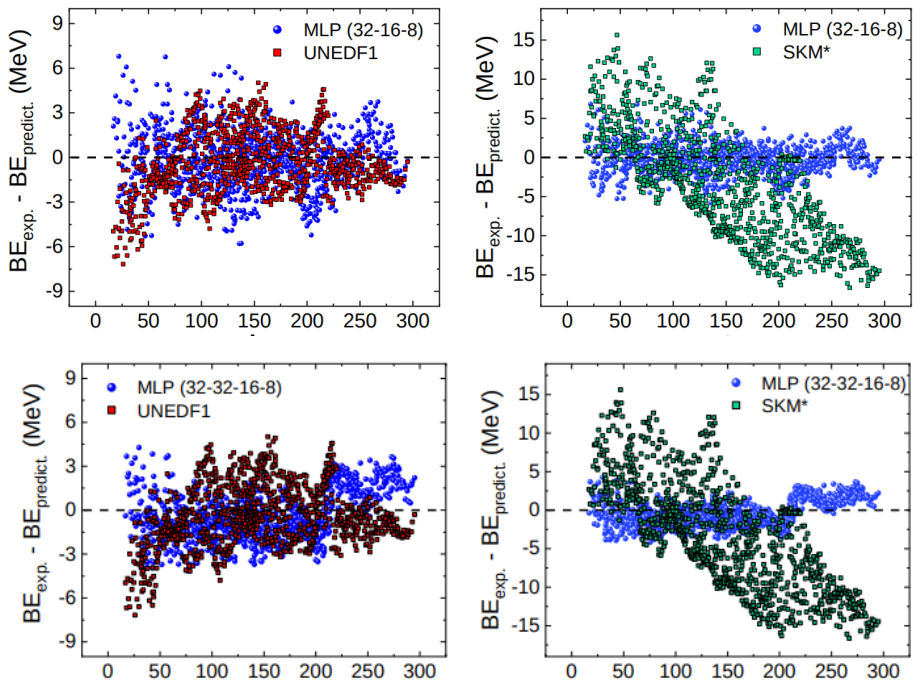
$$P = \frac{\nu_p \nu_n}{\nu_p + \nu_n}$$

ν: Difference between the actual proton (neutron) number and the nearest magic number.
Z=8, 20, 28, 50, 82, 126
N=8, 20, 28, 50, 82, 126, 184

Binding Energy: Previous Works

Keras, Python 3, 800 Epochs, 16 Batches, Adam optimization algorithm, Mean Absolute Error.

MLP	Input	RMS
32-16-8	Z,A	3.98
32-32-16-8	Z,A	2.60
32-16-8	Z,A,δ,P	2.16
32-32-16-8	Z,A,δ,P	1.84



E.Yuksel, D.Soydaner and H.B., Int.J.Mod.Phys.E 30 (2021) 03, 2150017,ArXiv:2101.12117

Binding Energy: Recent Results

Same dataset: AME2016
Different Models: 64-16-16, 64-16-16-8, 128-8
Epochs: 800-1000-2000
Batch: 16-32-64-128

- Z: Proton Number
- A: Mass Number (Z+N)
- δ: Pairing Term
- P: Promiscuity Factor
- C: Coulomb Term

Definition:

$$C = Z(Z-1)A^{-\frac{1}{3}}$$

Binding Energy: Recent Results

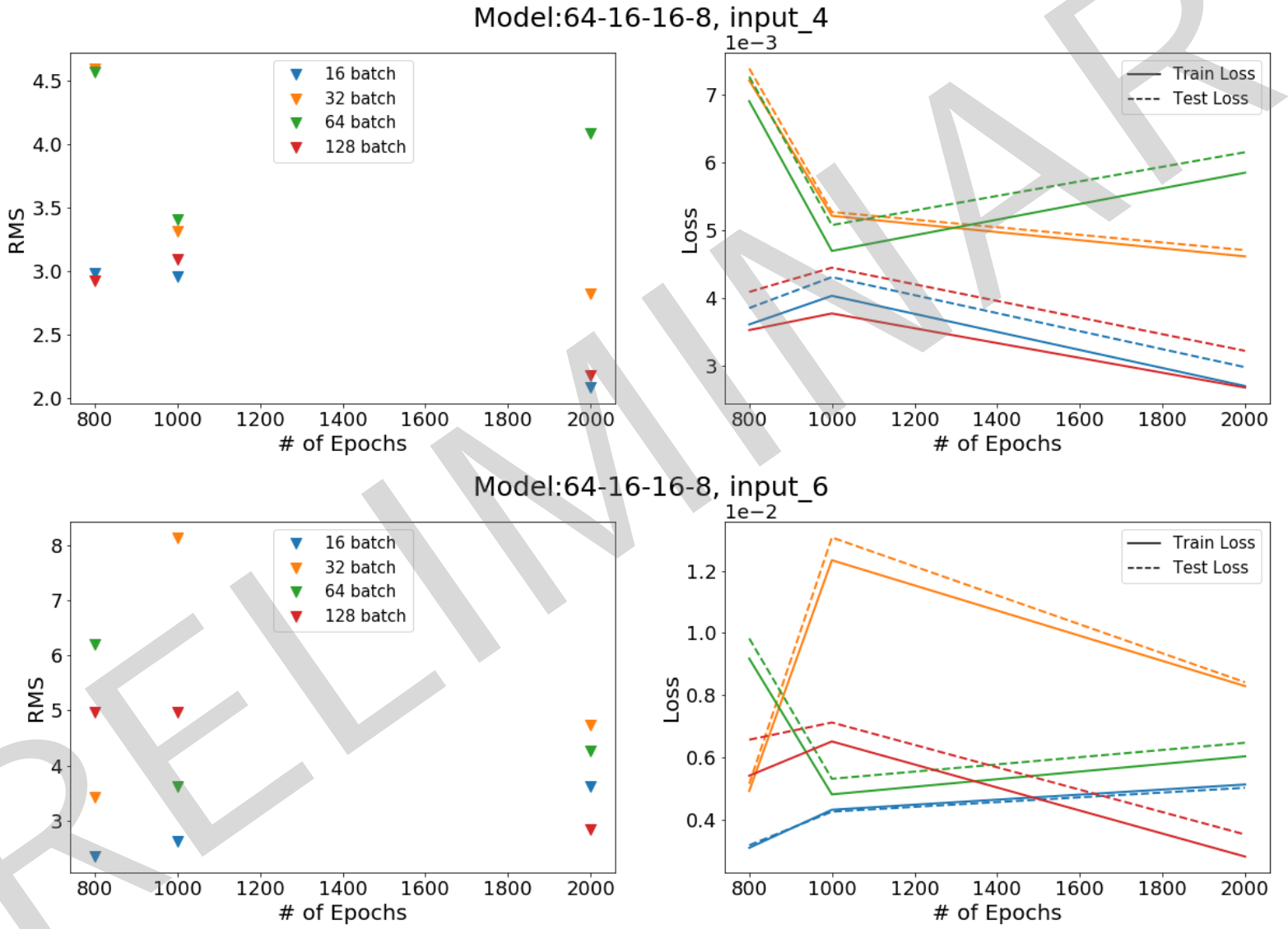
Same dataset: AME2016
Different Models: 64-16-16, 64-16-16-8, 128-8
Epochs: 800-1000-2000
Batch: 16-32-64-128

- Z: Proton Number
- A: Mass Number (Z+N)
- δ: Pairing Term
- P: Promiscuity Factor
- C: Coulomb Term
- S: Symmetry Term

Definition:

$$S = \frac{(A-2Z)^2}{A}$$

Binding Energy: Recent Results



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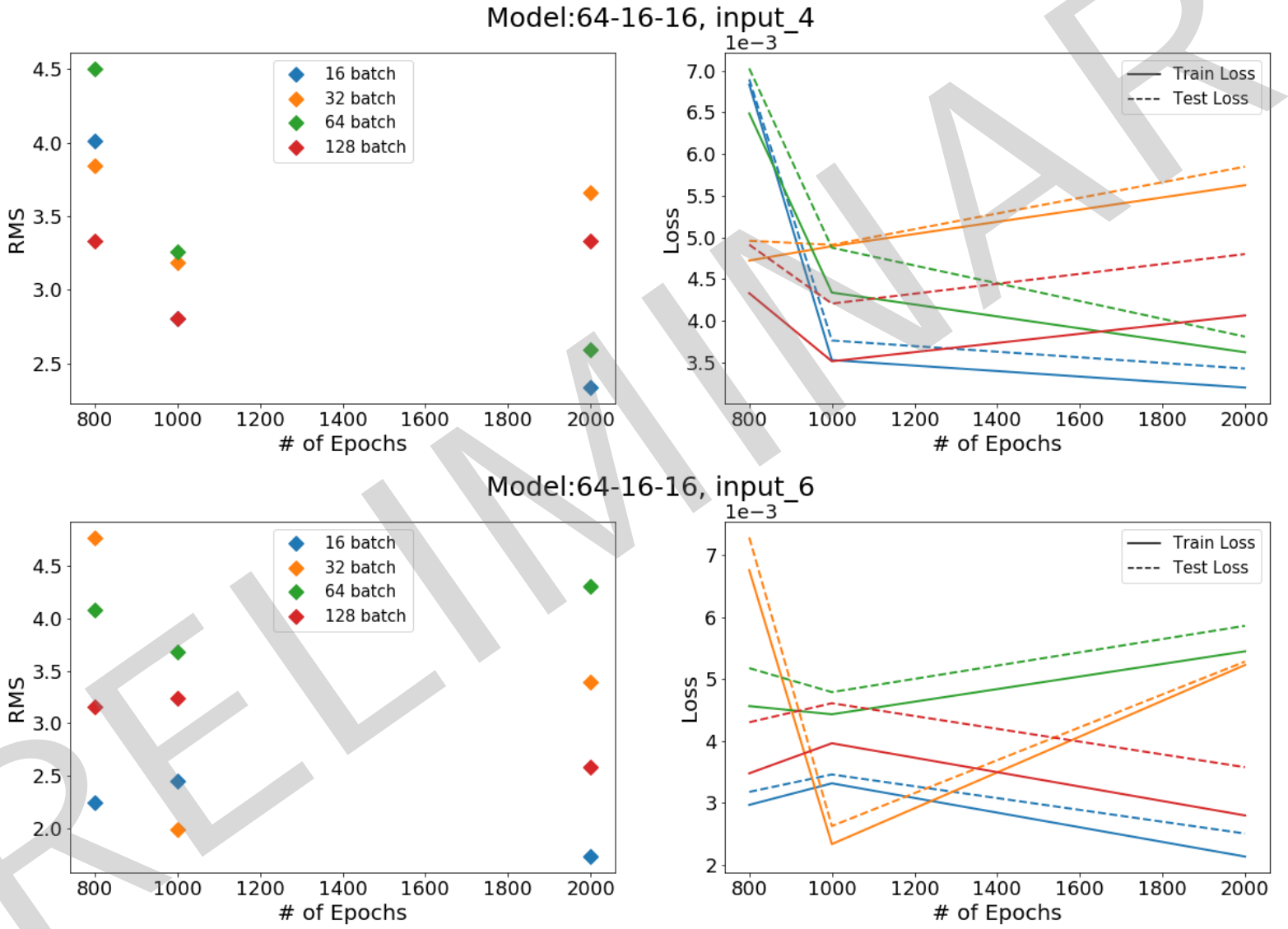

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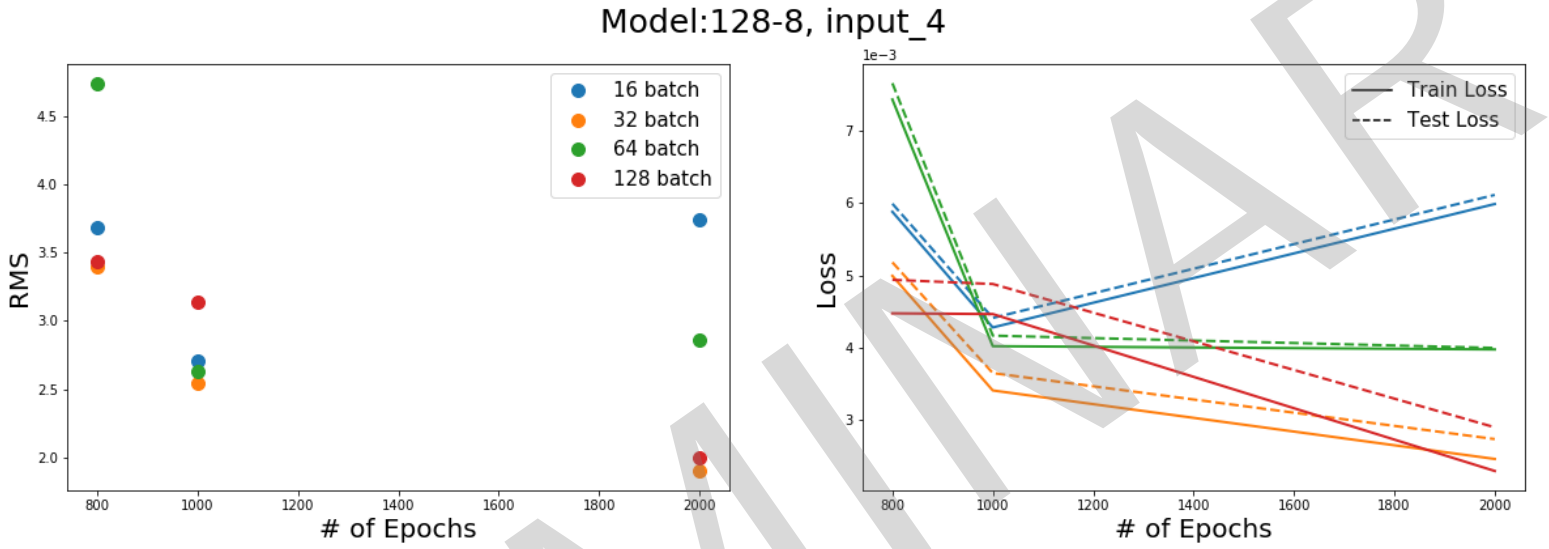
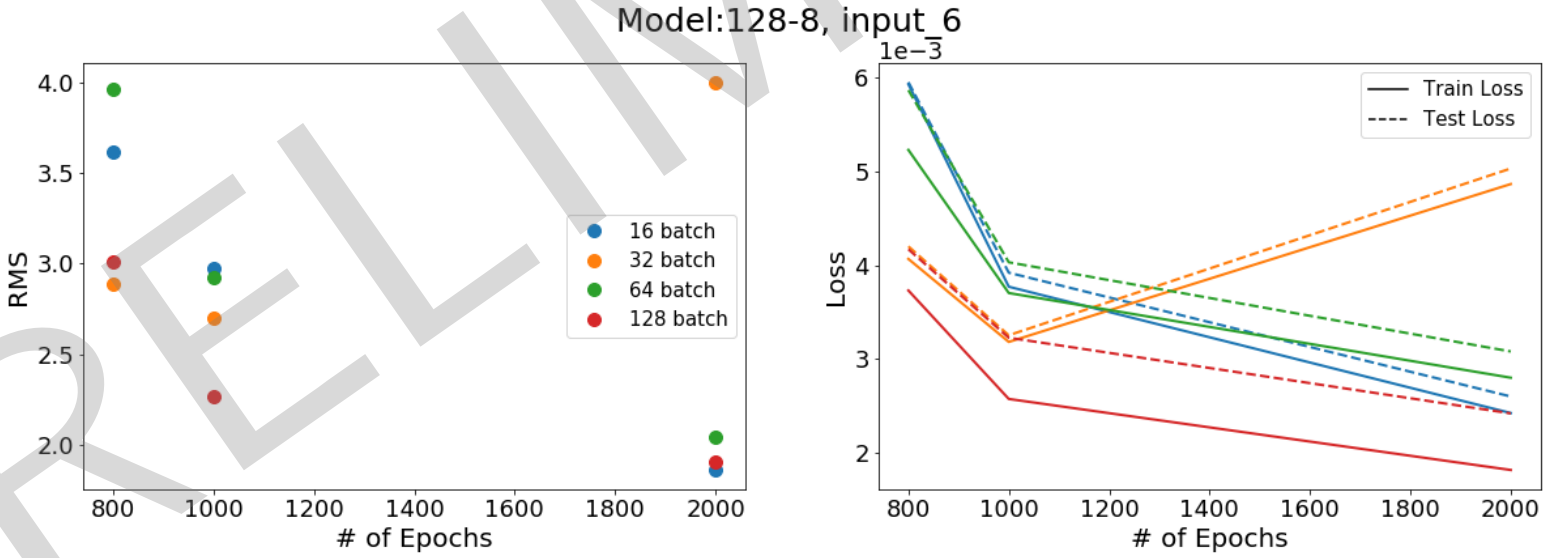
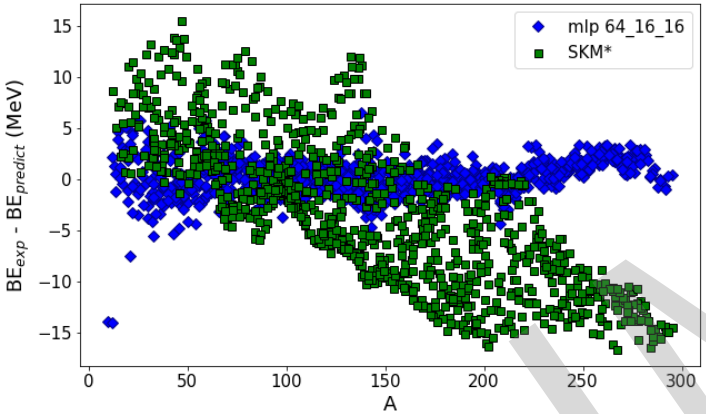
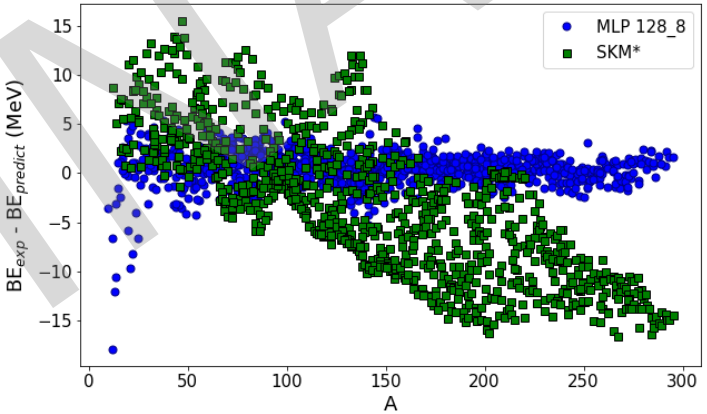


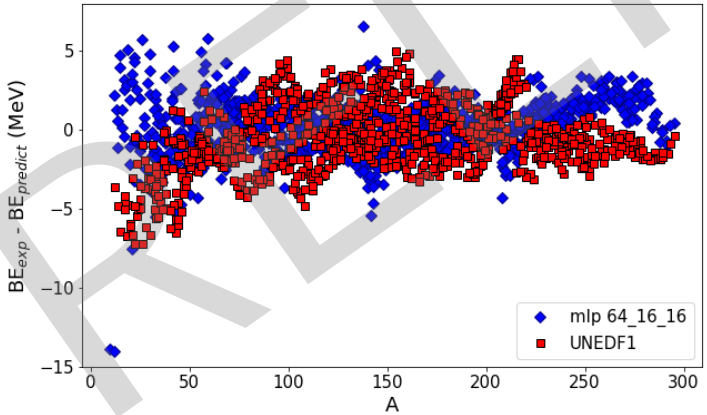


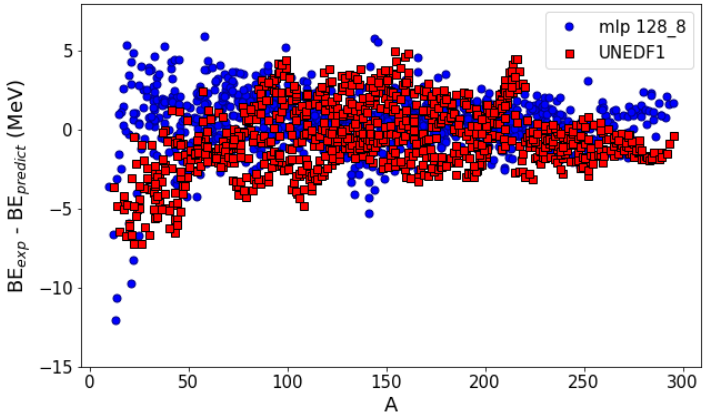
Binding Energy: Comparison

MLP	Input	RMS	Input	RMS
128-8	Z,A,δ,P	3.744	Z,A,δ,P,C,S	1.858
64-16-16	Z,A,δ,P	2.335	Z,A,δ,P,C,S	1.733









Charge Radii: Dataset

Dataset: Atomic Data and Nuclear Data Tables (ADNDT) 99 (2013) 69-95

10.1016/j.adt.2011.12.006.

Inputs [1] :

Angeli et. al., 10.1088/0954-3899/42/5/055108

- Z: Proton Number

Input:

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Inputs [1] :

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- Z: Proton Number
- A: Mass Number (Z+N)

Input:

Two inputs: 910 Nuclei

Charge Radii: Dataset

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Inputs [1] :

Angeli et. al., 10.1088/0954-3899/42/5/055108

- Z: Proton Number
- A: Mass Number (Z+N)
- S(2n) : Two-neutron separation energy.

Input:

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- Z: Proton Number
- A: Mass Number (Z+N)
- S(2n) : Two-neutron separation energy.
- S(2p) : Two-proton s.e.

Input:

Four inputs: 860 Nuclei

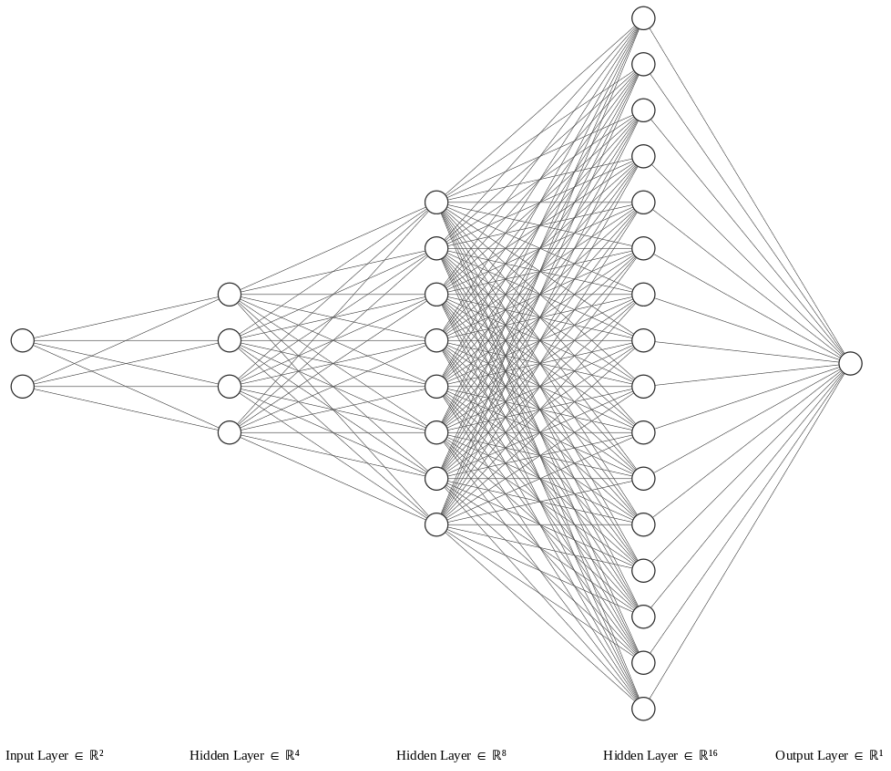
Input	**# of Nuclei**	70% **Training Set**
Two	910	636
Four	860	602

Charge Radii: Neural Network

Program: Keras with Tensorflow2 and Python 3.
N.N. Details: Adam optimization algorithm, Glorot Normal and Mean Absolute Error, %70 Train-Test split.

Overtrain!

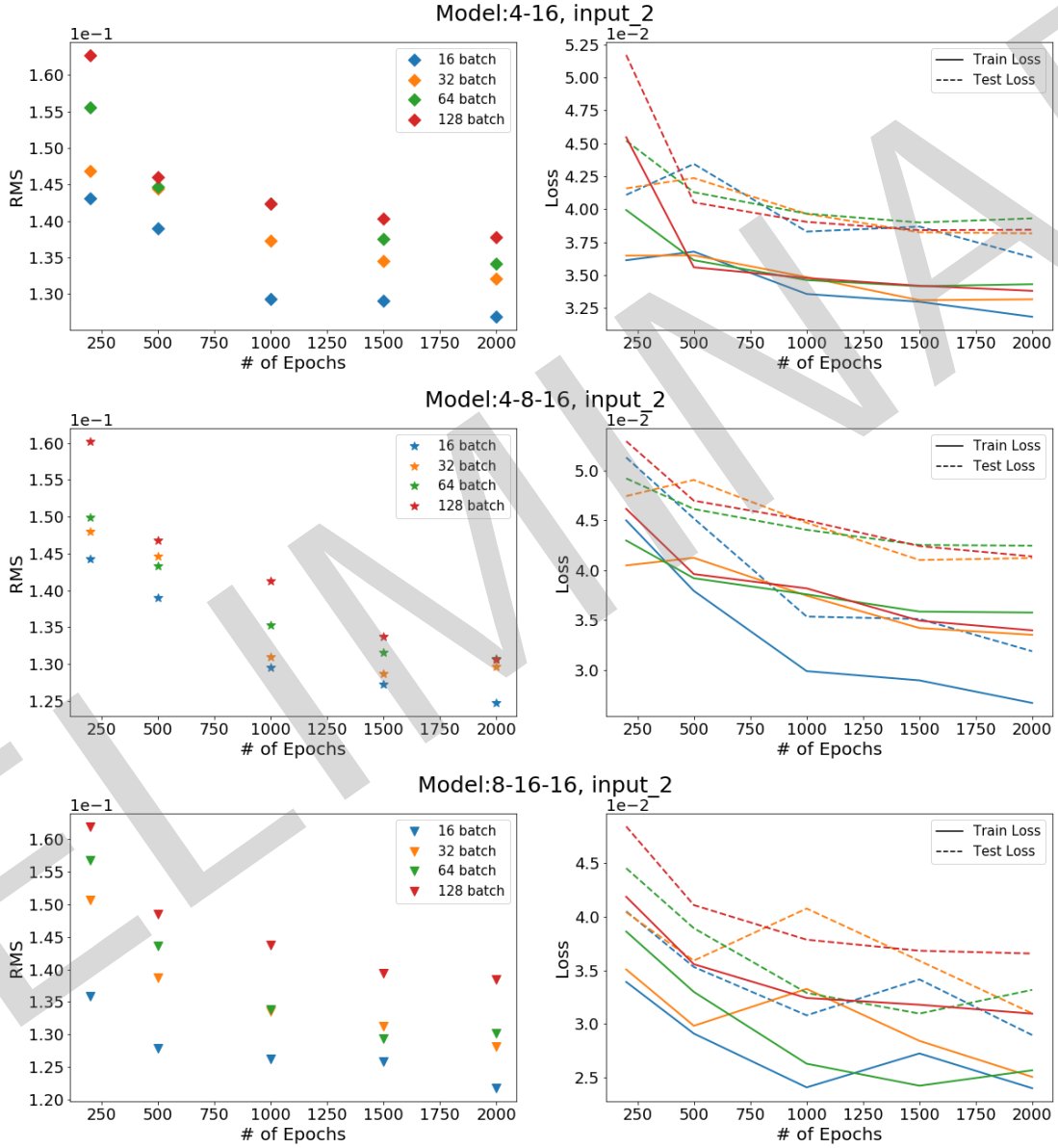
Careful!
# of parameters < # of Nuclei
Train Loss ∼ Test Loss



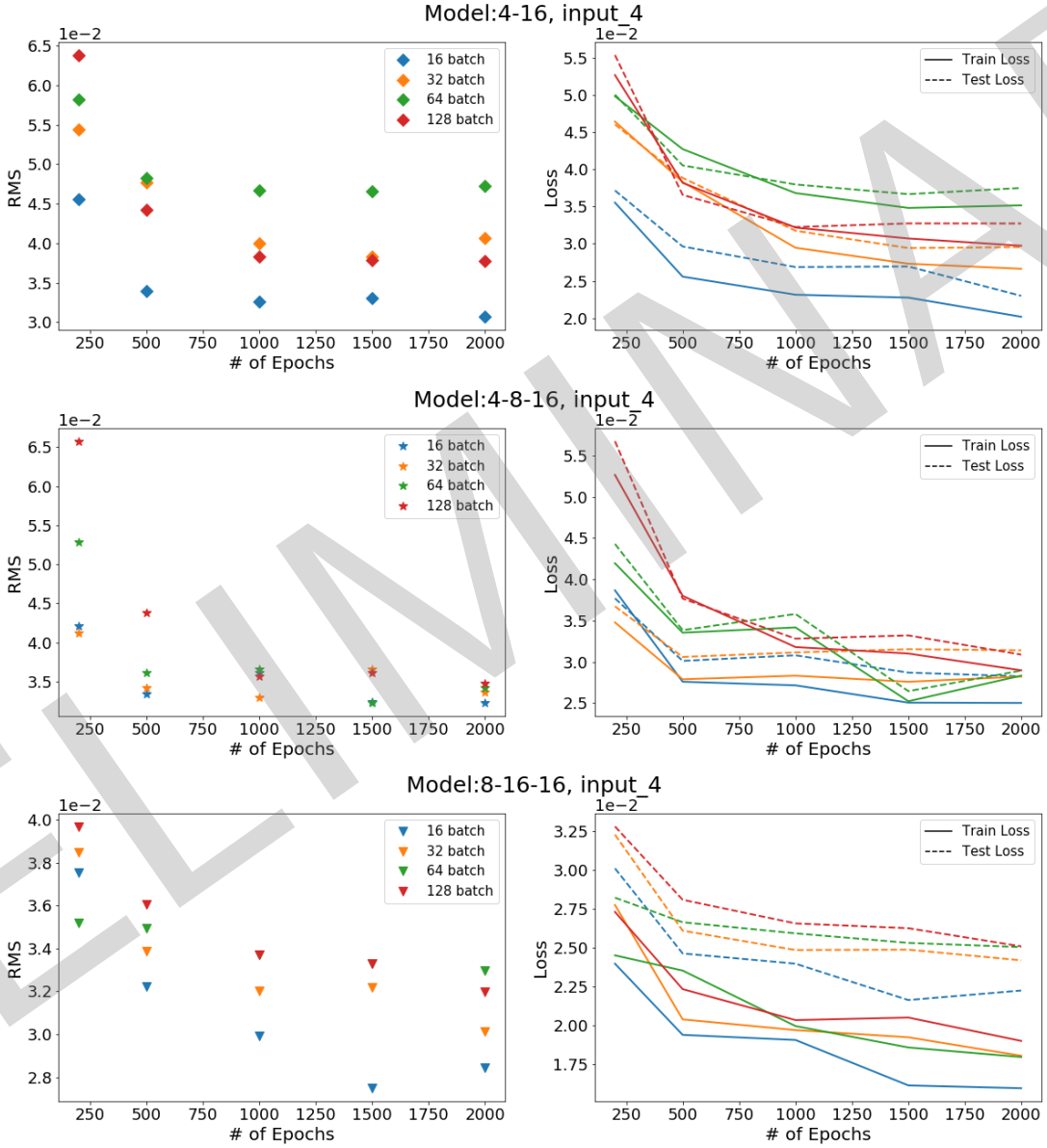
MLP	2 Inputs	4 Inputs
4-16	109	117
4-8-16	213	221
8-16-16	457	473

$$p = (i \times h_1 + h_1 \times h_2 + \cdots + h_n \times o) + (o + \sum_{n}^{i} h_i)$$

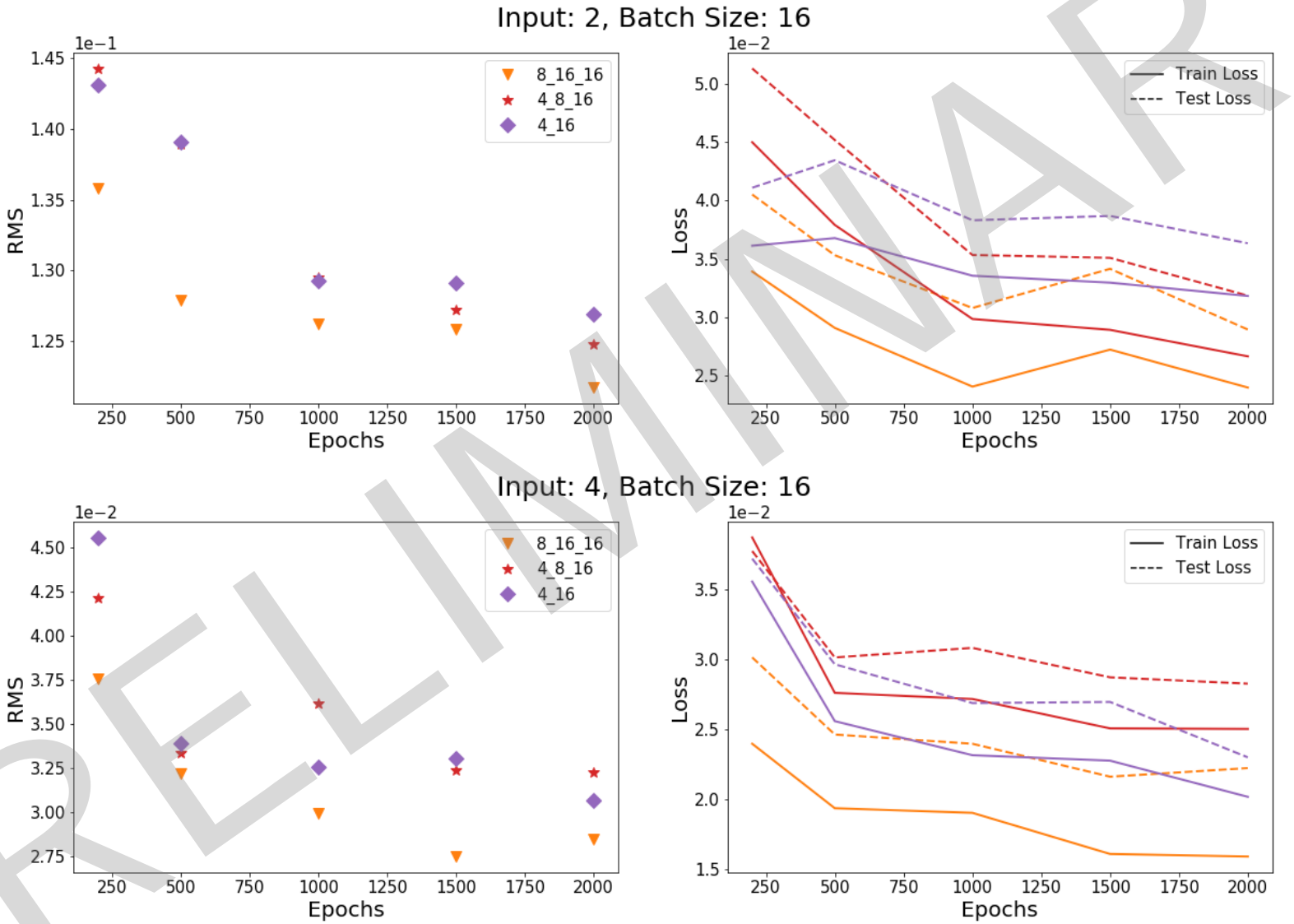
Charge Radii: Two inputs



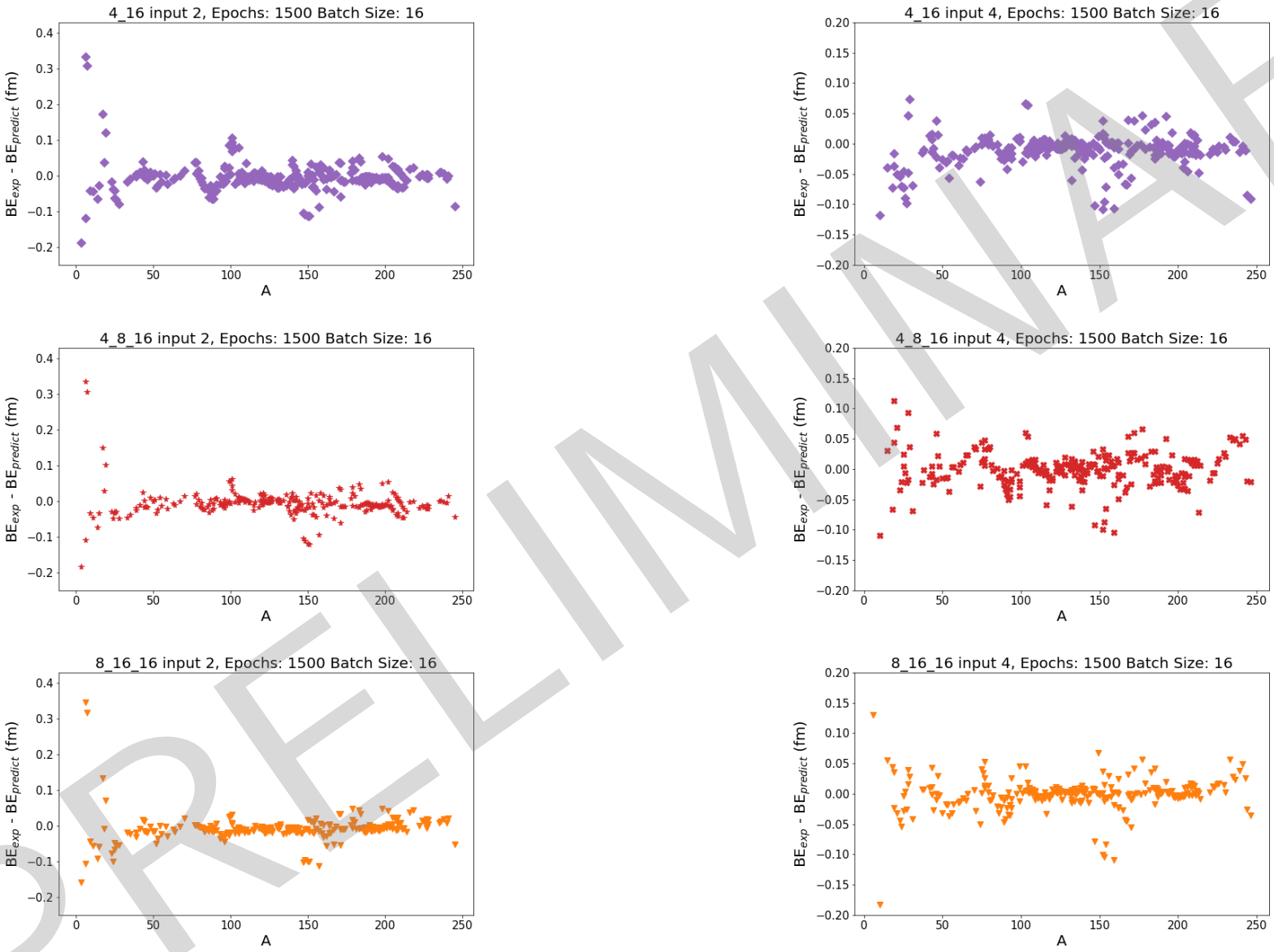
Charge Radii: Four inputs



Charge Radii: Models, Batch: 16



Charge Radii: Comparison



Charge Radii: Results

MLP	2 Inputs	4 Inputs
4-16	0.129	0.033
4-8-16	0.129	0.032
8-16-16	0.126	0.027

- The smallest RMS was found around 0.023 in recent Ref. [2].
- Our model needs to be improved.
- Overtraining problem needs a closer look (K-fold cross validation?)

Closing Remarks

- We investigate Nuclear Binding Energy and Charge Radii using Multi Layer Perceptron.
- We study different models and slightly improve our previous B.E. results.
- Apropriate or relevant input improves the predictions of the neural network.
  - The results become inconsistent in deeper neural networks.
- Neural network approaches seem to be promising tools to study the nuclear structure.

Acknowledgments: H.B. thanks to Dr. Esra Yüksel and Dr. Derya Soydaner for discussions and support.

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