ML Final Project

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Outline

- 1. Introduction
- 2. Training database
- 3. ANN model
- 4. Validation result
- 5. Solve
- 6. Result and discussion

Introduction

- 1. ML application on high entropy alloy lattice distortion effect
- 2. Ternary alloy system: FeCrNi
- 3. Compare delta and average atomic shear strain(AASS)

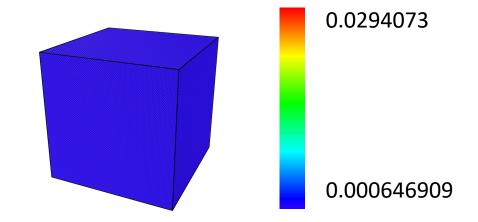
Delta
$$\delta = 100 \sqrt{\sum_{i=1}^{n} c_i (1 - r_i/\overline{r})^2}$$
AASS MD simulation

4. The prediction of AASS from machine learning can apply on dislocation behavior research

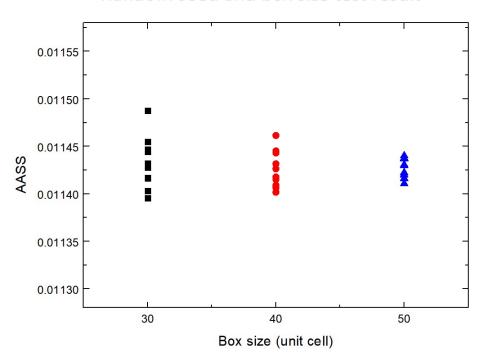
Introduction

- 1. Box size $50 \times 50 \times 50$ (unit cell)
- 2. 500000 atoms
- 3. $Fe_{33.3}Cr_{33.3}Ni_{33.3}$
- 4. Equiatomic alloy
- 5. Temperature = 0K
- 6. Cg minimization
- 7. Average atomic shear strain

$$(\eta_{\text{ave}}) = \frac{\sum_{i=1}^{500000} \eta_i}{500000}$$



Random seed and box size test result



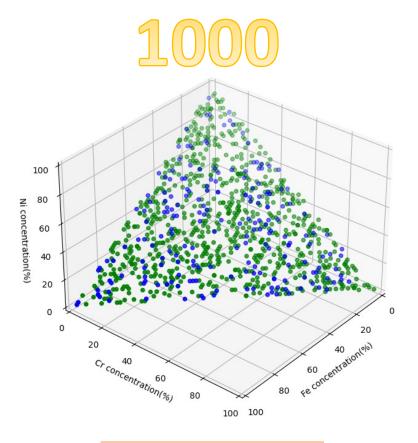
Introduction

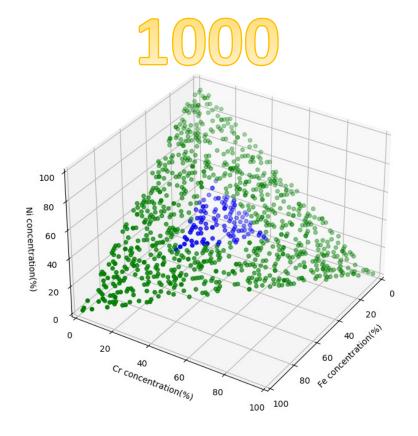
 $*Fe_xCr_yNi_z$ 此合金共有 4851 種不同的成分組成

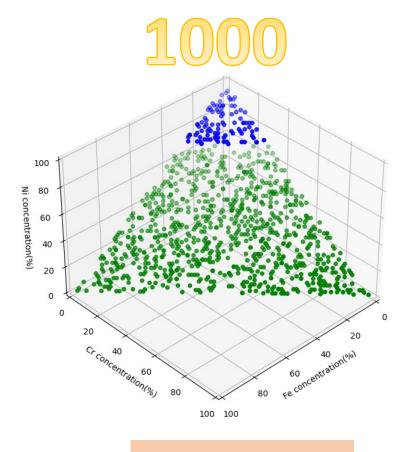
Fe (%)	Cr (%)	Ni (%)			
1	1	98		python	
1	2	97			
1	3	96			
1	4	95			
1	5	94		100 Z. 80	
1	6	93			
1	7	92		of 60	Dalta/fa\
1	8	91		ntration(%	Delta(formula) AASS(MD)
1	9	90		4851	
1	10	89		4051	AASS(MD)
1	11	88		20 40 to nico nico nico nico nico nico nico nic	· ·
				Cr concentration(%) 80 60 ke concentration	
				100 100	
					output
				X+Y+Z=100	
97	7 2	1		input	
98	3 1	1			

Training database

X+Y+Z=100







Train : 700

800 *Test : 100*

Validation: 200

Train : 700

Test : 186

Validation:114

886

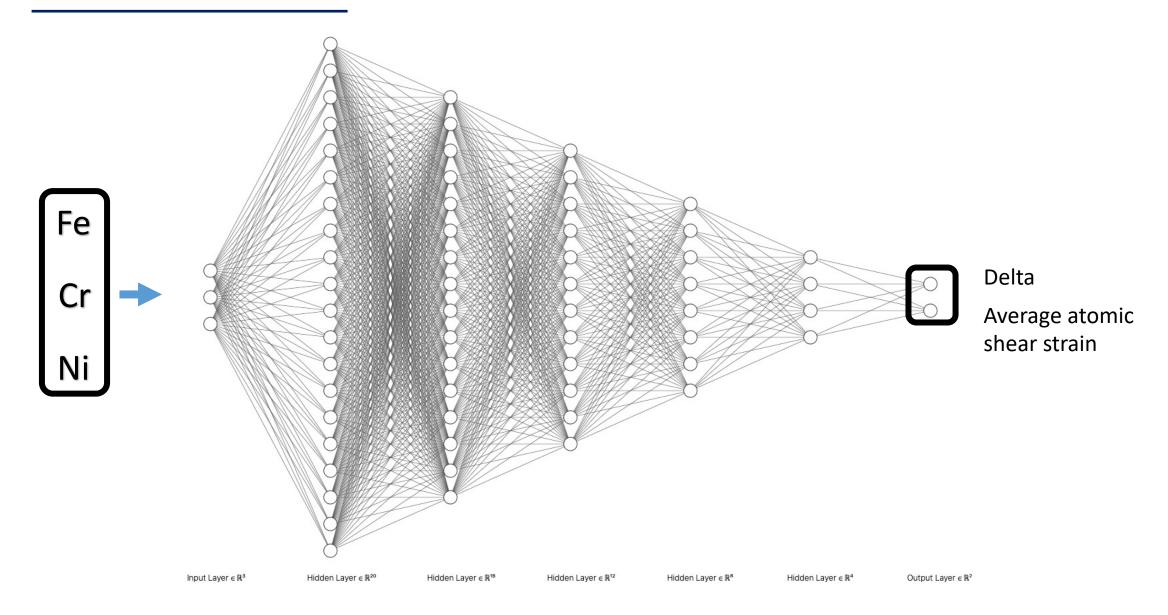
Train : 700

Test: 203

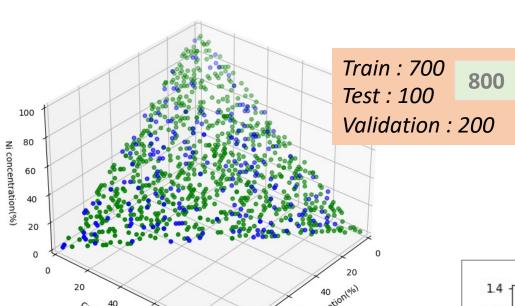
Validation: 97

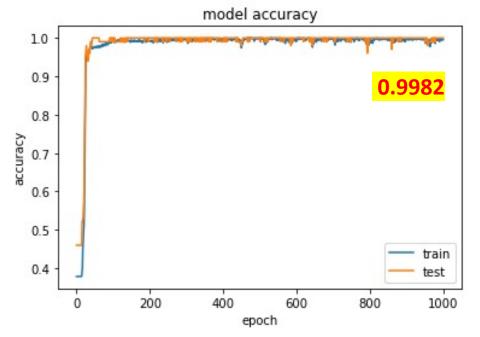
903

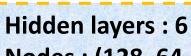
ANN model



Validation result1







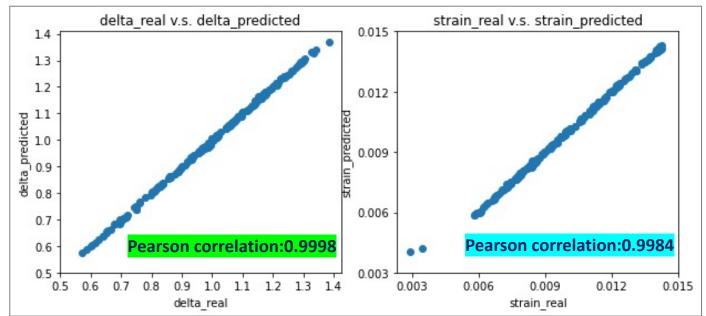
Nodes: (128, 64, 64, 32, 16, 8)

100 100

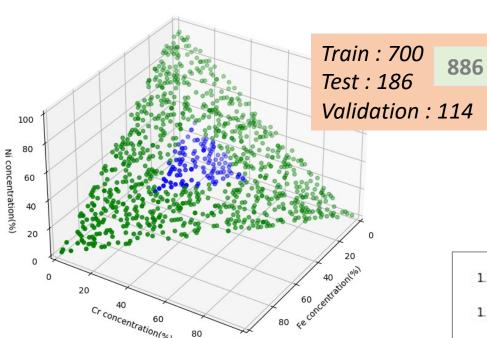
Epochs: 800

Learning rate: 0.001

Activation function: Relu



Validation result2



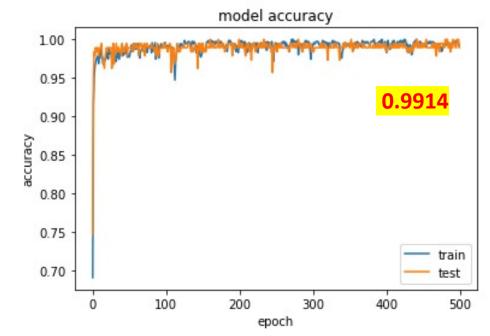
Hidden layers: 7

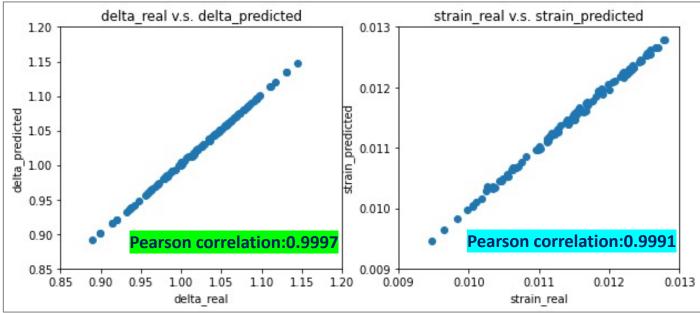
Nodes: (512, 256, 128, 64, 32, 16, 8)

Epochs: 500

Learning rate: 0.001

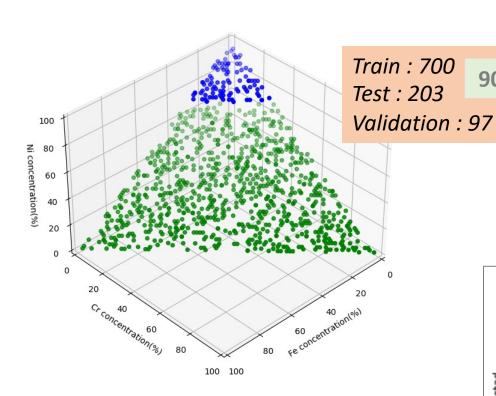
Activation function: Relu

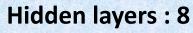




Validation result3

903



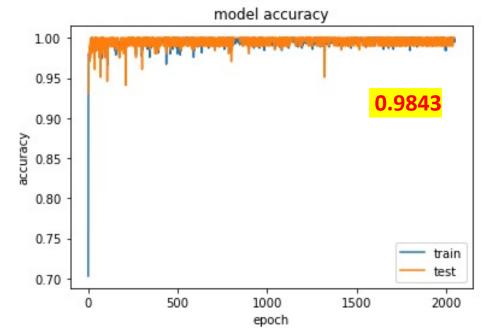


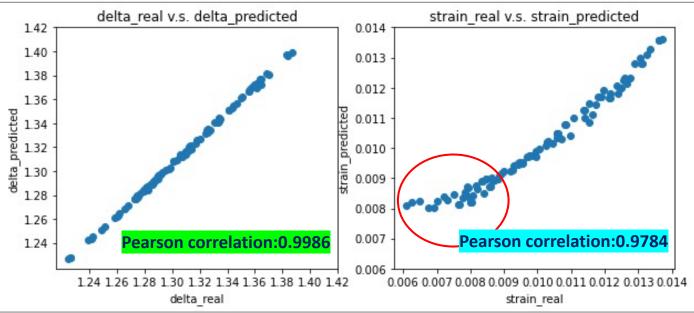
Nodes: (512, 256, 128, 64, 32, 16, 8, 4)

Epochs: 2048

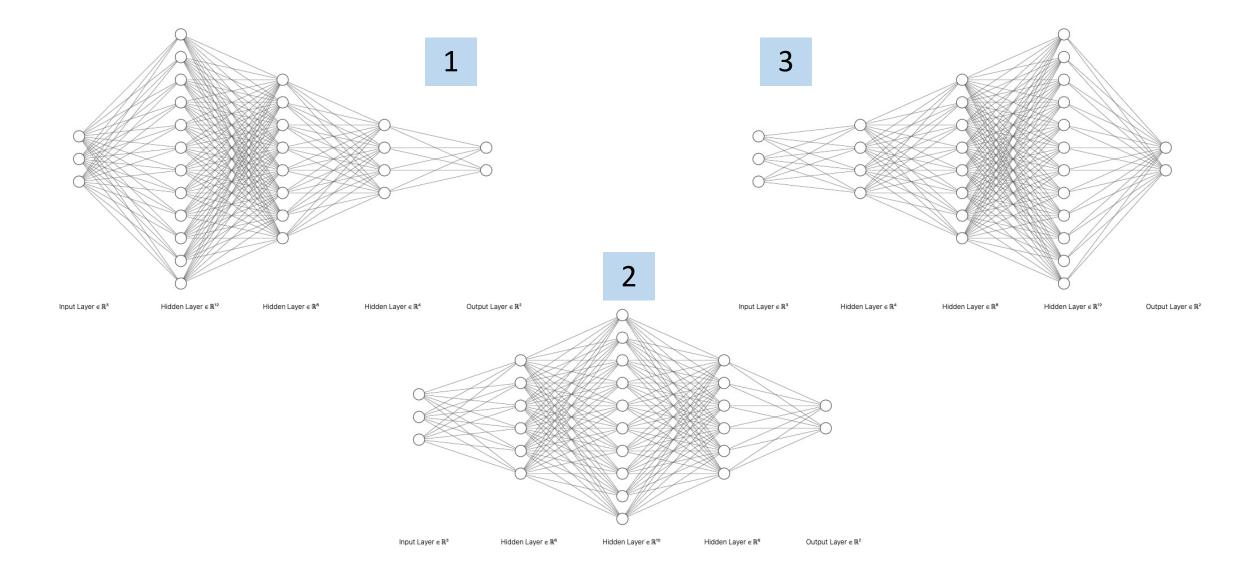
Learning rate: 0.001

Activation function: Relu

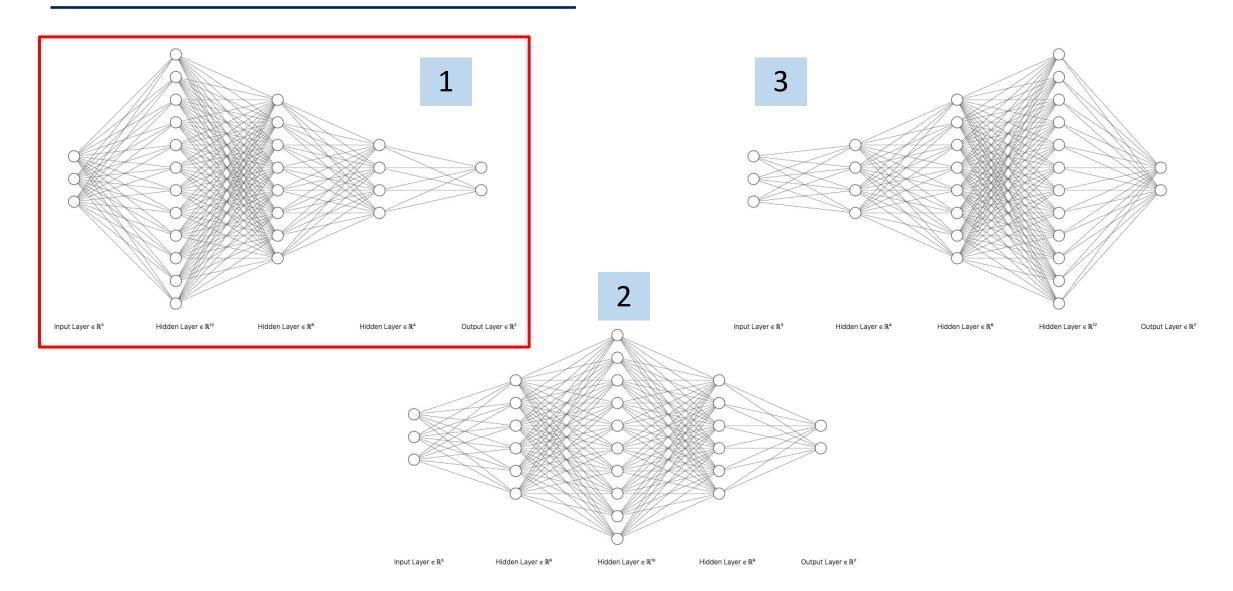




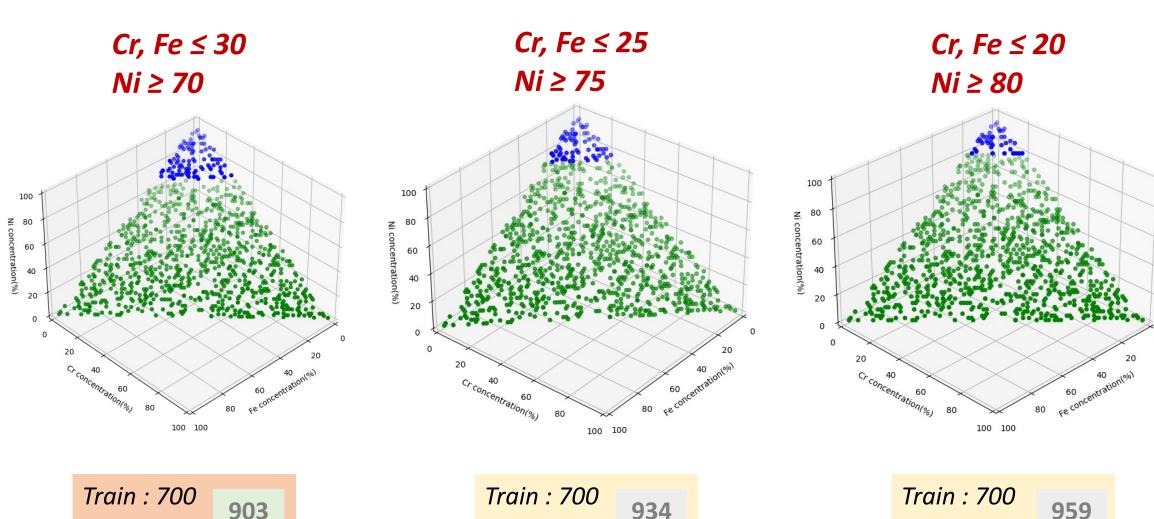
Solve – ANN model



Solve – ANN model



Solve - training database (add)



903 *Test : 203*

Validation: 97

934

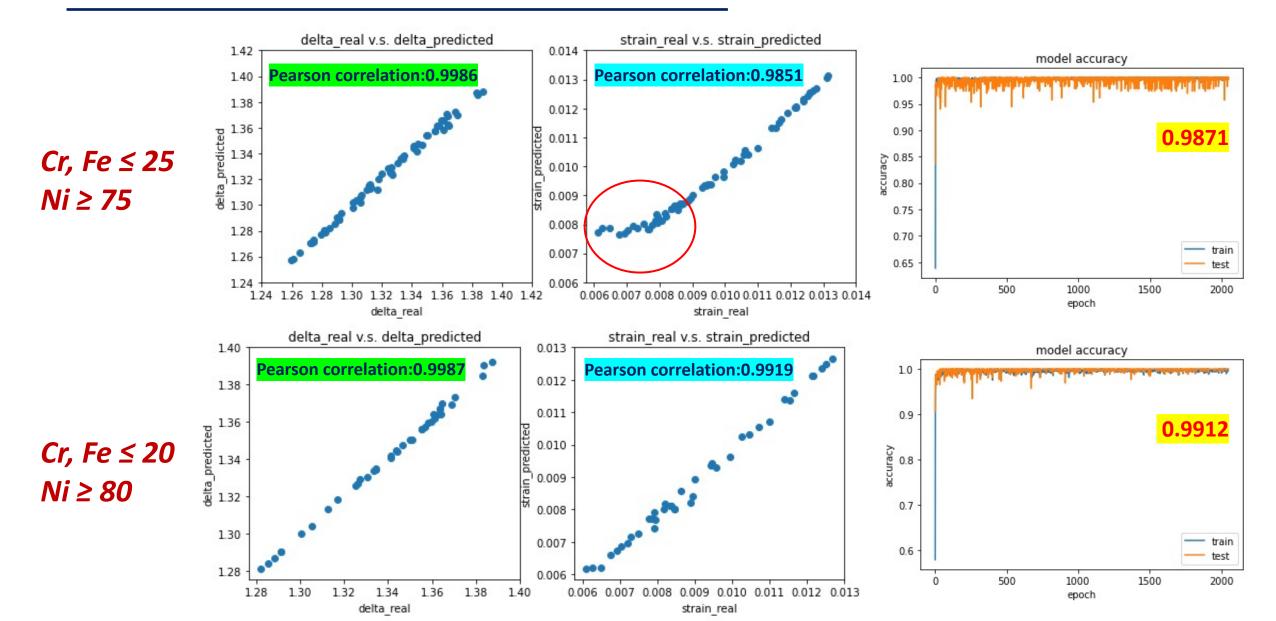
Test : 234

Validation: 66

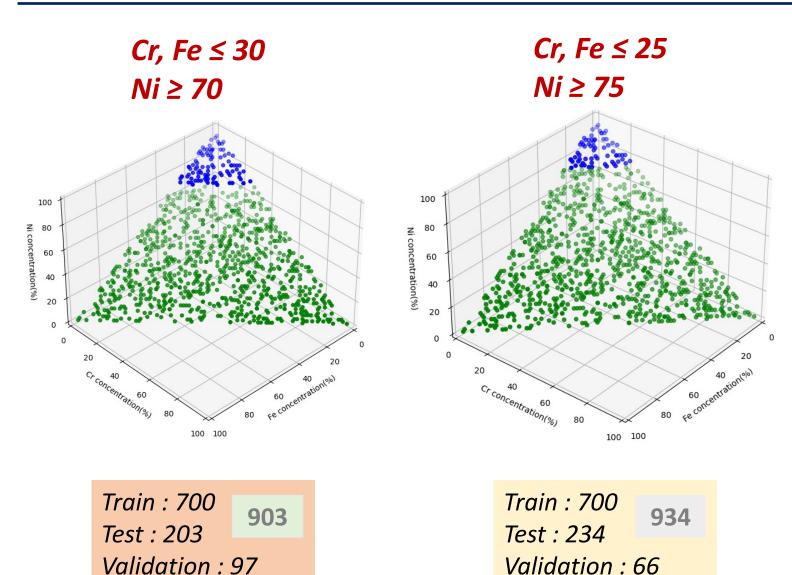
Test : 259

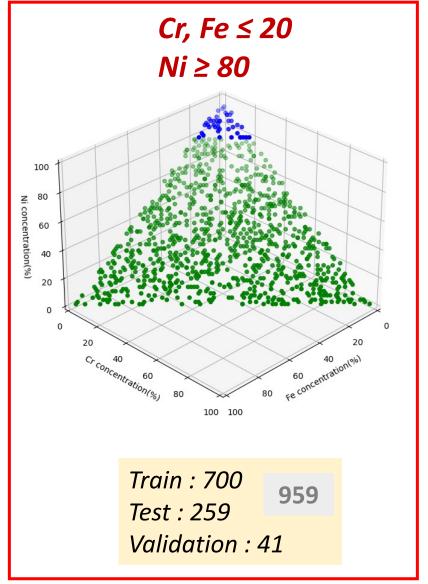
Validation: 41

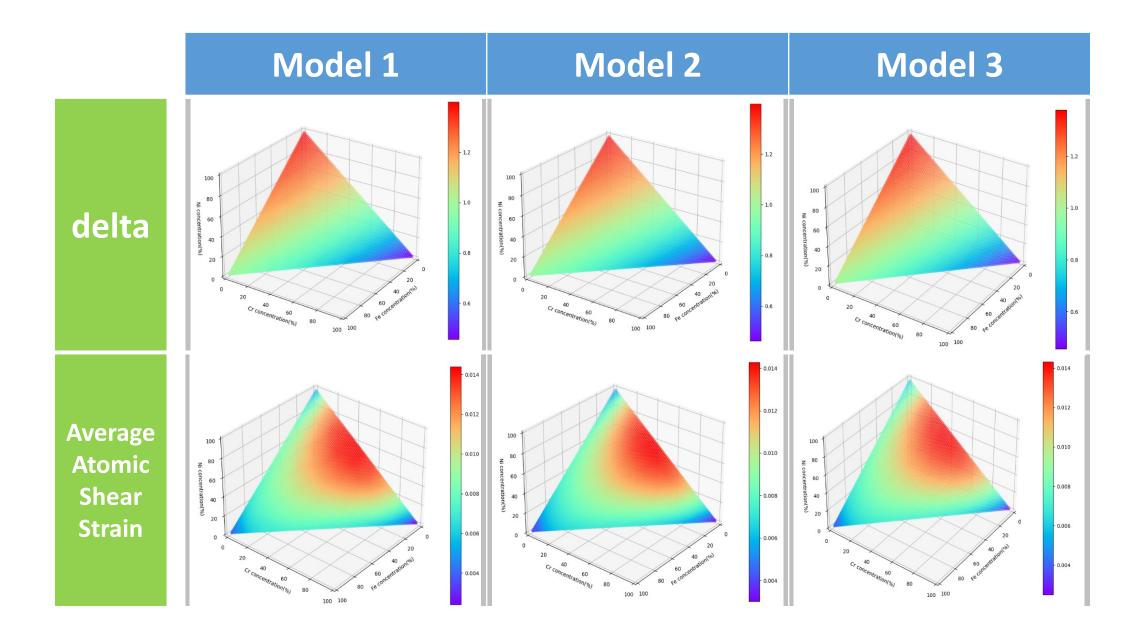
Solve - validation result

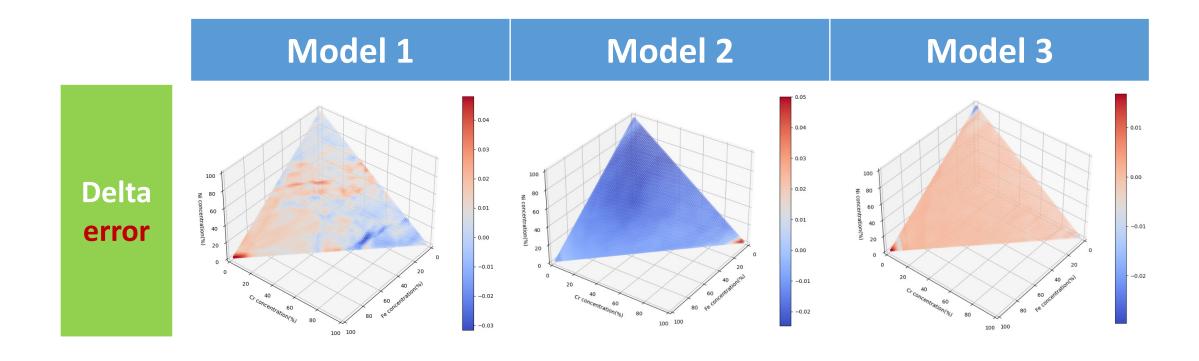


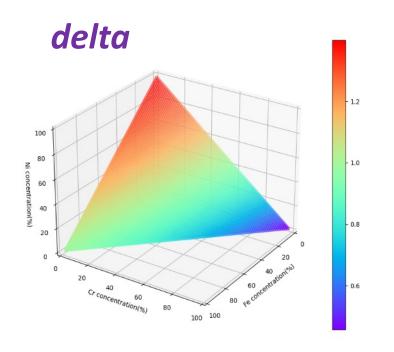
Solve - training database (add)

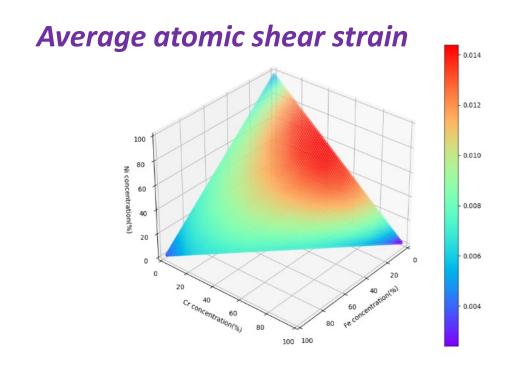








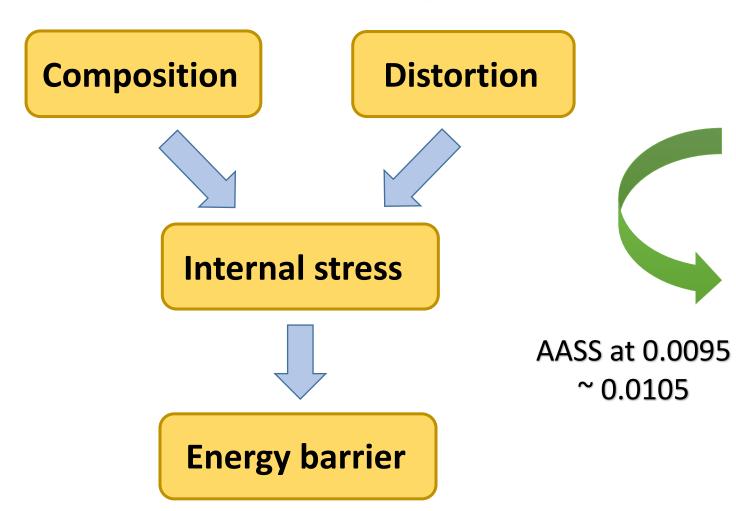


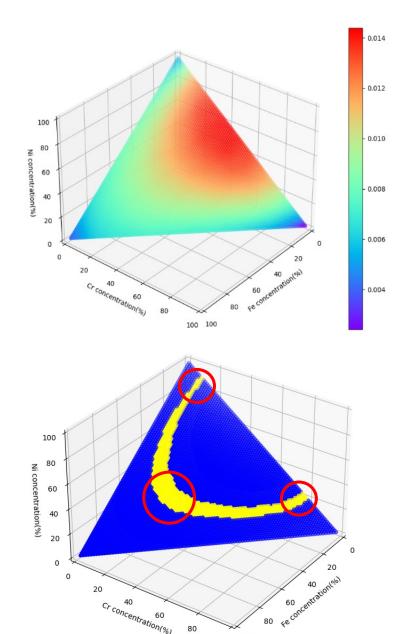


- ① Zhang, Y., Zhou, Y. J., Lin, J. P., Chen, G. L., & Liaw, P. K. (2008). Solid-Solution Phase Formation Rules for Multi-component Alloys.

 Advanced Engineering Materials, 10(6), 534–538. doi:10.1002/adem.200700240 原子半徑
- ② GUO, S., & LIU, C. T. (2011). Phase stability in high entropy alloys: Formation of solid-solution phase or amorphous phase. Progress in Natural Science: Materials International, 21(6), 433–446. doi:10.1016/s1002-0071(12)60080-x 原子半徑、電子性質
- ③ Dai, F.-Z., Sun, Y., Wen, B., Xiang, H., & Zhou, Y. (2020). Temperature Dependent Thermal and Elastic Properties of High Entropy (Ti0.2Zr0.2Hf0.2Nb0.2Ta0.2)B2: Molecular Dynamics Simulation by Deep Learning Potential. Journal of Materials Science & Technology. 用AASS去衡量高熵二硼化物的lattice distortion

Application on dislocation energy barrier calculation ...





End