



Analysis of high-resolution transmission electron microscopy images by deep learning:

Example of AgCo nanoalloys

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Convolutional neural networks for HRTEM analysis

Image classification, regression, or denoising

requires large number of examples with known categories, values, perfect images

```
3681796691
6757863485
2179712845
4819018894
4819018894
4819018894
7592658197
2658197
222234480
7128769861
```

Proc. of the IEEE 86, 2278 (1998)

Nanosystems

realistic large-scale data thanks to simulations

inverse problems: structure determination from experimental characterization techniques

machine learning can add value: reduction of search space when informed by physical models

Advantages: fast, enables thus statistical analysis

Disadvantages: limited scope of applicability, requires validation

Why nanoalloys, why HRTEM?

Nanoalloys

- catalysis
- plasmonics
- magnetic particles for biomedical applications

Advantages

- new properties due to alloy effect
- reduced cost
- encapsulation of toxic elements



PdPt nanoalloy Faraday Discuss., **181**, 19 (2015)

HRTEM

- analysis of individual objects
- atomic resolution

Difficulties

- image noise, long exposure may affect objects
- aberrations, defocus, Z-insensitivity

Dataset generation: Molecular dynamics

Interatomic model

Tight-binding second moment approximation for Ag-Co J. Comput. Theor. Nanosci. **6**, 841 (2009)

Random system size (up to 1000 atoms), and composition

Rapid quench

- Core-shell: gas mixture 7500 K to 300 K
- Janus: droplets 800 K to 300 K

Thermalization at 300K

200.000 simulations, side effect: enables statistical analysis





Dataset generation: HRTEM images

Multi-slice technique

several software packages available, here Dr. Probe Ultramicroscopy **193**, 1 (2018)

200 keV electrons, 20 slices resolution: ~23 px/nm

Variability

- random defocus and aberration coefficients
- random position and orientation
- addition of shot noise

5 images per configuration \rightarrow 2M images

→ realism and diversity are key

Pairs of clean and noisy images





Core-shell





Janus

Classification in terms of chemical ordering

Network architecture



Output value

- **class:** core-shell or Janus
- **size:** number of atoms
- composition: N_{Ag}/N_{tot}

Influence of dataset size



Evaluation of classification accuracy



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Estimation of particle size and composition

Number of atoms



Average error: ±33 atoms

Particle composition





Image denoising

Autoencoder network



noisy
ground truth
prediction

Image: Second seco

→ almost perfect noise suppression perspective: super-resolution

Conclusion and perspectives

Results

- Classification in terms of chemical ordering: 81%
- Size estimation of particles: \pm 33 atoms
- Almost perfect noise suppression

Outlook

- Application to images from experiments
- Other types of analysis, e.g. estimation of microscopy parameters
- Other experimental characterization techniques, such as HAADF STEM, X-ray diffraction, Raman spectroscopy



Many thanks to our collaboration









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Thank you for your attention

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Convolutional neural networks

Convolutional layer



Convolutional neural networks

Max. pooling layer



Convolutional neural networks

For training: compare output to labeled chirality minimize cost function via gradient descent (10⁶ params) X