

SUPPLEMENTARY INFORMATION

Corresponding to:

Determination of the Dzyaloshinskii-Moriya interaction using pattern recognition and machine learning

Masashi Kawaguchi^{1†}, Kenji Tanabe^{2†*}, Keisuke Yamada³, Takuya Sawa²,
Shun Hasegawa¹, Masamitsu Hayashi^{1**}, and Yoshinobu Nakatani^{4***}

¹Department of Physics, The University of Tokyo, Tokyo, 113-0033, Japan

²Toyota Technological Institute, Nagoya, 468-8511, Japan

³Department of Chemistry and Biomolecular Science, Faculty of Engineering,
Gifu University, Gifu, 501-1193, Japan

⁴University of Electro-Communications, Chofu, 182-8585, Japan

† Equally contributed

Corresponding authors:

* *tanabe@toyota-ti.ac.jp*

** *hayashi@phys.s.u-tokyo.ac.jp*

*** *nakatani@cs.uec.ac.jp*

Supplementary Note 1: Images from micromagnetic simulations

Exemplary images from micromagnetic simulations are presented in Supplementary Figure 1 to illustrate the difference in the magnetic domain patterns generated under same material parameters but with different initial condition and different patterns of the magnetic anisotropy distribution (temperature (T) is set to 300 K). In Supplementary Figure 1(a), five images generated with $D_{\text{set}} = 0.5 \text{ mJ m}^{-2}$ and $\sigma = 0$ are shown. Here the initial condition (random pattern of magnetization) is varied. Energy minimization is used to find the equilibrium state at $T = 300 \text{ K}$. Supplementary Figure 1(b) shows five images with $D_{\text{set}} = 0.5 \text{ mJ m}^{-2}$ and $\sigma = 0.15$. Since σ is non-zero, in addition to the initial condition, patterns of the magnetic anisotropy distribution are varied. Clearly, the magnetic domain size and the domain patterns are different for Supplementary Figures 1(a) and 1(b).

The estimated DM exchange constant using machine learning are denoted at the top of each image. Although the domain patterns are significantly different, the machine learning returns values that are in good agreement with the set value.

Supplementary Note 2: Summary of reported DM exchange constant

The DM exchange constant (D) for Pt/Co/oxide heterostructures reported in the literature are summarized in Supplementary Table 1.

Supplementary Table 1. DM exchange constant (D) of Pt/Co(t)/oxide based heterostructures estimated using different methods [1]. Since D depends on the thickness (t) of the Co layer (units in nanometer), $D_s \equiv D t$ is shown together. BLS stands for Brillouin light scattering. BLS exploits asymmetry in spin wave propagation to study the DM exchange constant.

Material system (nm)	Method	D (mJ m ⁻²)	D_s (pJ m ⁻¹)	Ref.
Pt/Co(0.9)/MgO	Field driven motion of DWs	1.2	1.1	This work
Pt/Co(0.8)/AlO _x	Field driven motion of DWs	1.6~1.9	1.3~1.5	[2]

Pt/Co(0.8)/AlO _x	Field driven motion of DWs	0.33	0.27	[3]
Pt/Co(0.6)/AlO _x	Field driven domain nucleation	2.2	1.3	[4]
Pt/Co(0.5)/MgO	Field driven domain nucleation	0.48	0.24	[5]
Pt/Co(0.93)/AlO _x	Current induced motion of DWs	0.54	0.5	[6]
Pt/Co(1)/MgO	Current induced magnetization switching	2.64	2.64	[7]
Pt/Co(0.6-1.2)/AlO _x	BLS	1.6-2.7	1.6-1.9	[8]
Pt/Co(1.06)/MgO	BLS	2.05	2.17	[9]
Pt/Co(1)/MgO	BLS	1.59	1.59	[10]
Pt/Co(0-2)/AlO _x	BLS	0.8-1.2	1.2-1.8	[11]

Supplementary Note 3: Characteristics of machine learning

We have studied the dependence of the machine learning performance on the number of training data set. The effects of data augmentation and cross validation are studied together. We use images from micromagnetic simulations to generate the training and the testing data sets. The number of the testing images is fixed to 1/10 of the training images. For a given training data set, four machines are developed (since the order of the learning process is randomized, the results can be different even though the training data set used is the same). The material parameters estimated from the four machines are used to obtain the mean value and standard deviation. The convolutional neural network (CNN) system is used, except noted otherwise, for machine learning.

The data size dependence of the machine learning performance (i.e. estimation error of the DM exchange constant) is shown in Supplementary Figure 2. Here we compare results with and without cross validation. For

both cases, the estimation error saturates as the number of images used for training approaches 100,000 images. These results justify the data size used to develop the machine described in the main text.

Cross validation is carried out by splitting the images, generated from the simulations, into eleven groups with equal number of images (e.g. for 110,000 images, each group has 10,000 images). We use ten groups for training and the remaining one for testing to acquire the estimation error. This process is repeated 11 times: the group used for testing is changed each time. Since we develop 4 machines for a given training data set, the total number of machines for image recognition with and without cross validation is 44 and 4, respectively. The effect of cross validation is displayed in Supplementary Figure 2. The average estimation error with and without cross validation for 100,000 training images is $\sim 0.045 \text{ mJ m}^{-2}$ and $\sim 0.046 \text{ mJ m}^{-2}$, respectively. We thus find that cross validation does not significantly improve the estimation error.

The impact of data augmentation is shown by the colored symbols in Supplementary Figure 3. Here we use image rotation, shifting, and combination of rotation and shifting. The black solid circles show results without data augmentation. For each data point, we show average results from the four machines and cross validation (total machine number is 44).

Data augmentation with rotation is performed by taking a quarter of the images obtained from the simulations and create images that are rotated 90, 180 and 270 degrees. For example, among the 100,000 (10,000) training (testing) images output from the simulations, 25,000 (2,500) images are randomly selected and rotated 90, 180 and 270 degrees to generate a total of 100,000 (10,000) images. The estimation error of the DM exchange constant using such data augmentation (rotation) is shown by the red squares in Supplementary Figure 3.

The procedure for data augmentation with shifting is schematically sketched in Supplementary Figure 4. In micromagnetic simulations, we use a periodic boundary condition, which mimics the experimental condition (experimentally, $\sim 2 \mu\text{m} \times 2 \mu\text{m}$ size images are taken from samples that has a dimension of $\sim 10 \text{ mm} \times 10 \text{ mm}$). The periodic boundary condition employed in the simulations allows data augmentation with shifting. The dimension of images used in the simulations is $2.048 \mu\text{m} \times 2.048 \mu\text{m}$. The shifting process is carried out by cutting the image into two pieces, shifting one half and displacing the other half in opposite directions. For vertical shifting (Supplementary Figure 4(a)), the bottom half of the image ($2.048 \mu\text{m} \times 1.024 \mu\text{m}$) is shifted by $1.024 \mu\text{m}$ along the y -axis. The top half of the image ($2.048 \mu\text{m} \times 1.024 \mu\text{m}$) is displaced by $-1.024 \mu\text{m}$ along the y -axis. Similar procedure is performed for the horizontal shifting, which is displayed in Supplementary Figure 4(b). In addition, we augment data with a “vertical + horizontal” shifting, a combination of vertical and horizontal shifting: the process is sketched in Supplementary Figure 4(c). Using vertical, horizontal and vertical + horizontal shifting, three additional images are produced from

the original image. Similar to data augmentation with rotation, we take a quarter of the images obtained from the simulations and create images that are shifted. The estimation error of the DM exchange constant is shown using the blue up triangles in Supplementary Figure 3.

Finally, we can combine image rotation and shifting to generate images for data augmentation. From one image, we generate three additional images from rotation (90, 180, 270 deg) and another three additional images from shifting (vertical, horizontal, vertical + horizontal), which add up to total of 16 images (including the original image). The estimation error of the DM exchange constant using the augmented data of combined rotation and shifting is shown in Supplementary Figure 3, green down triangles.

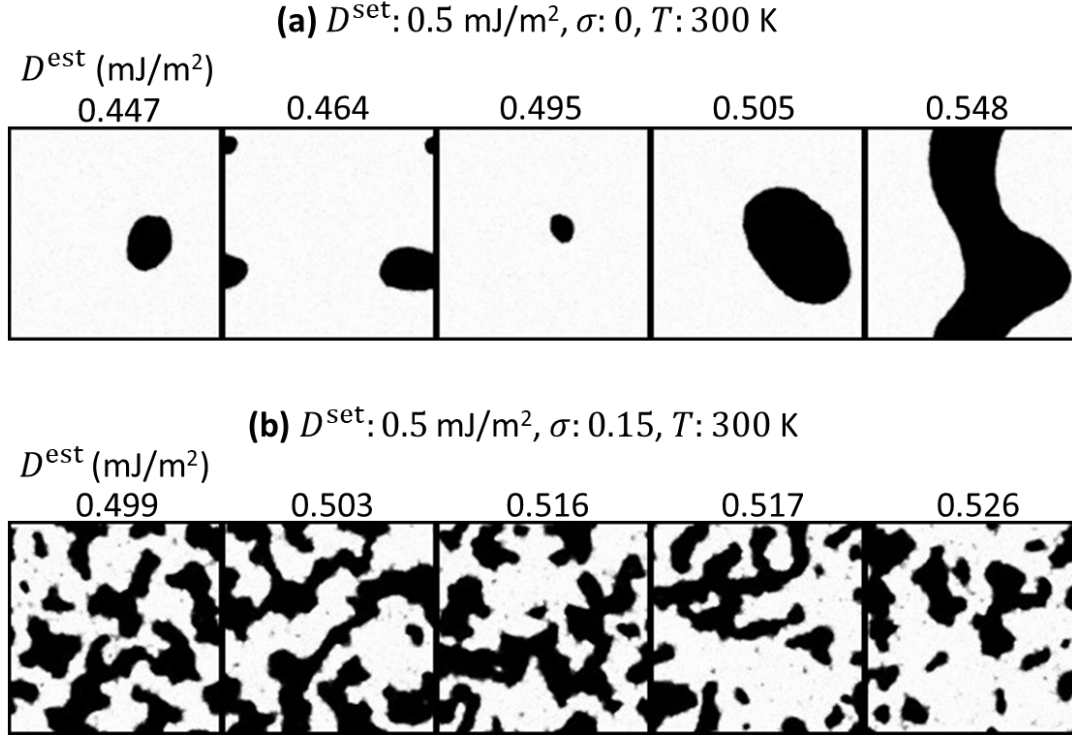
The results shown in Supplementary Figure 3 suggest that data augmentation is effective in generating images for pattern recognition. For all three methods (rotation, shifting, rotation + shifting), the estimation error does not significantly increase from the data set without data augmentation. Using data augmentation with rotation + shifting, one may reduce the training/testing data size by a factor of 16.

In addition to the CNN system describe in the main text, a simple residual network (RN) system (<https://dl.sony.com/project/>, search by technique, ResNet, tutorial.basics.12_residual_learning) has been tested for comparison. In Supplementary Figure 3, the average estimation error for 100,000 training images without cross validation was $\sim 0.045 \text{ mJ m}^{-2}$. Under the same condition, the RN system provides an estimation error of $\sim 0.032 \text{ mJ m}^{-2}$. As an initial screening, the RN system seems to perform better, however, with the cost of computation time, which is nearly two times larger using our computing resources.

Supplementary References

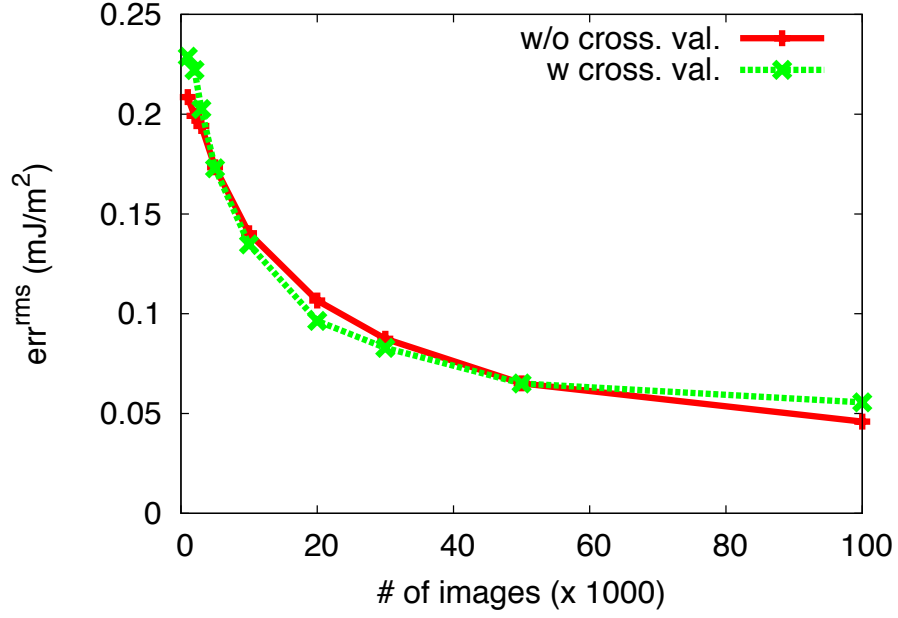
- [1] Kuepferling, M. et al. Measuring interfacial dzyaloshinskii-moriya interaction in ultra thin films. *arXiv:2009.11830* (2020).
- [2] Pham, T. H. et al. Very large domain wall velocities in Pt/Co/GdOx and Pt/Co/Gd trilayers with Dzyaloshinskii-Moriya interaction. *Europhys. Lett.* **113**, 67001 (2016).
- [3] Benitez, M. J. et al. Magnetic microscopy and topological stability of homochiral Néel domain walls in a Pt/Co/AlOx trilayer. *Nat. Commun.* **6**, 8957 (2015).
- [4] Pizzini, S. et al. Chirality-Induced Asymmetric Magnetic Nucleation in Pt/Co/AlOx Ultrathin Microstructures. *Phys. Rev. Lett.* **113**, 047203 (2014).
- [5] Kim, S. et al. Correlation of the Dzyaloshinskii–Moriya interaction with Heisenberg exchange and orbital asphericity. *Nat. Commun.* **9**, 1648 (2018).
- [6] Conte, R. Lo. et al. Ferromagnetic layer thickness dependence of the Dzyaloshinskii-Moriya interaction and spin-orbit torques in Pt/Co/AlOx *AIP Adv.* **7**, 065317 (2017).
- [7] Pai, C.-F., Mann, M., Tan, A. J. & Beach, G. S. D. Determination of spin torque efficiencies in heterostructures with perpendicular magnetic anisotropy. *Phys. Rev. B* **93**, 144409 (2016).
- [8] Belmeguenai, M. et al. Interfacial dzyaloshinskii-moriya interaction in perpendicularly magnetized Pt/Co/AlOx ultrathin films measured by brillouin light spectroscopy. *Phy. Rev. B* **91**, 180405 (2015).
- [9] Boulle, O. et al. Room-temperature chiral magnetic skyrmions in ultrathin magnetic nanostructures. *Nat. Nanotechnol.* **11**, 449 (2016).
- [10] Ma, X. et al. Interfacial Dzyaloshinskii-Moriya Interaction: Effect of 5d Band Filling and Correlation with Spin Mixing Conductance. *Phys. Rev. Lett.* **120**, 157204 (2018).
- [11] Cho, J. et al. Thickness dependence of the interfacial Dzyaloshinskii–Moriya interaction in inversion symmetry broken systems. *Nat. Commun.* **6**, 7635 (2015).

Supplementary Figure 1



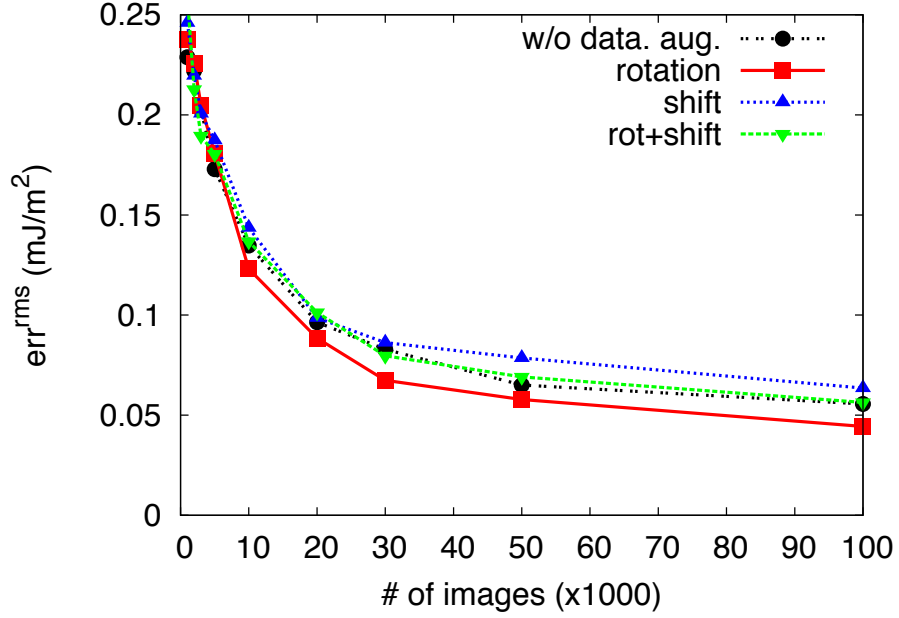
Supplementary Figure 1: Exemplary images from micromagnetic simulations. (a,b) Equilibrium magnetic domain images obtained from micromagnetic simulations using $D^{\text{set}} = 0.5 \text{ mJ m}^{-2}$, $\sigma^{\text{set}} = 0$ (a) and $D^{\text{set}} = 0.5 \text{ mJ m}^{-2}$, $\sigma^{\text{set}} = 0.15$ (b). The system temperature is set to $T = 300 \text{ K}$ and the other material parameters are described in the methods section of the main text (Fig. 4). The initial magnetization configuration (a) and the patterns of the magnetic anisotropy distribution are varied (b). The estimated DM exchange constant (D^{est}) using machine learning and pattern recognition are shown at the top of each image. We use image rotation to augment data (4 images from one original) and feed the images to four machines: we take the average of the 16 D^{est} values.

Supplementary Figure 2



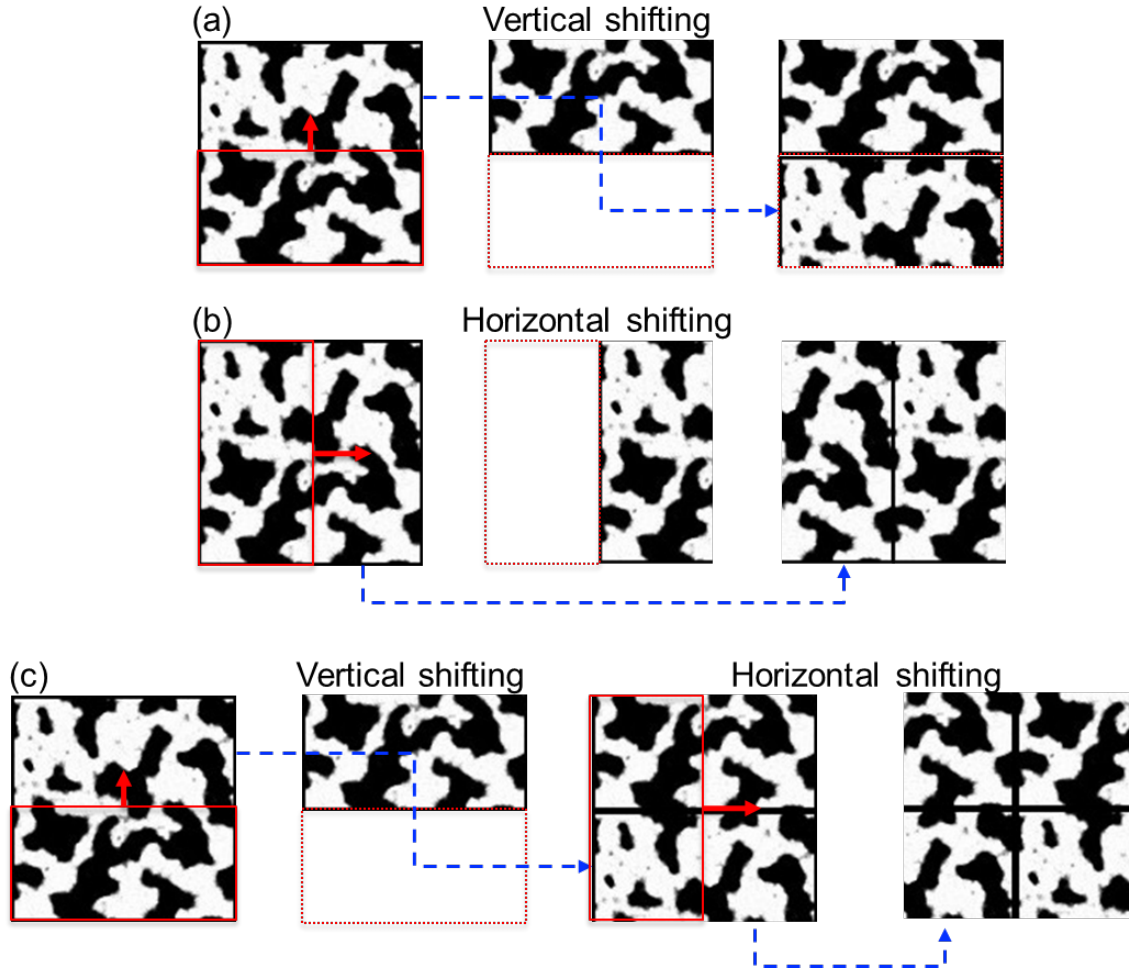
Supplementary Figure 2: Assessment of the impact of cross validation. Number of training images vs. the estimation error of the DM exchange constant (D^{est}). The x axis represents the number of images used for training. Black squares: without cross validation, red circles: with 11-fold cross validation.

Supplementary Figure 3



Supplementary Figure 3: Evaluation of data augmentation. The estimation error of the DM exchange constant (D^{est}) plotted as a function of the number of images used for training. Black squares: without data augmentation, red circles: data augmentation with image rotation, blue up triangles: data augmentation with shifting, green down triangle: data augmentation with shifting + rotation. The 11-fold cross validation is implemented.

Supplementary Figure 4



Supplementary Figure 4: Schematic illustration of the image shifting procedure. (a-c) Vertical (a), horizontal (b) and vertical + horizontal (c) image shifting processes are illustrated. A periodic boundary condition applied to the images in the simulations, allowing image shifting without causing discontinuity from the edges.