

### Abstract

We propose a method that enables us to use miscellaneous data collected under various conditions directly for deep learning. When we train a model using miscellaneous data, the model's performance is often degraded by "Information to be Ignored," which disturbs correct recognition. Our proposed method dramatically improves the model's performance by estimating the "Information to be Ignored" and training the model not to be affected by it. Our technique will make it possible to easily utilize miscellaneous data for learning and will contribute to expanding AI services into fields where deploying deep learning has been challenging.

### Learning from miscellaneous data

Deep learning using data collected under various conditions

Use Directly → Model

### Difficulty

Information to be Taken in and to be Ignored

- Information to be Taken in: Essential for recognition
- Information to be Ignored: Disturbs recognition (e.g. back ground)

Model recognizes the query based on Information to be Ignored. **Failed!**

### Self-supervised adaptive learning to capture Information to be Taken in

**Estimate Information to be Ignored and train the model not to be affected by them.**

**Point 1.**  
Destruct Information to be Taken in; then capture Information to be Ignored by self-supervised learning

Destruct Information to be Taken in to make object recognition impossible

- Information to be Ignored is reserved.
- e.g. Image data: Shuffle Pixel Blocks

Self-Supervised Learning

- Capture Information to be Ignored remaining in the data

Estimator

estimate

**Point 2.**  
Train the model to capture Information to be Taken in and not to capture Information to be Ignored

Train the model not to capture the estimated Information to be Ignored

Model

Train the model to capture Information to be Taken in using ground truth data

Information to be Ignored

Ground truth

Performance	Visual explanations	Visualization of feature embeddings						
<p>Ours achieves high recognition accuracy.</p> <ul style="list-style-type: none"> <li>Previous method degrades model performance due to Information to be Ignored.</li> </ul> <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th>Methods</th> <th>Accuracy[%]</th> </tr> </thead> <tbody> <tr> <td>Previous</td> <td>3.6</td> </tr> <tr> <td>Ours</td> <td>77.4</td> </tr> </tbody> </table>	Methods	Accuracy[%]	Previous	3.6	Ours	77.4	<p>Our method focuses on targets.</p> <p>Previous</p> <p>Ours</p>	<p>Ours forms clusters based on ground truths.</p> <p>Previous</p> <p>Ours</p> <p>Features with different ground truths are mixed.</p> <p>Features are separated per ground truths.</p>
Methods	Accuracy[%]							
Previous	3.6							
Ours	77.4							

### References

[1] Y. Mitsuzumi, G. Irie, D. Ikami, T. Shibata, "Generalized Domain Adaptation," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021.

[2] R. Tobias, R. Stiefelhagen, "Adaptiope: A Modern Benchmark for Unsupervised Domain Adaptation," in *Proc. IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, 2021.

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