# Back to the Source: Diffusion-Driven Adaptation to Test-Time Corruption

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## **Corruption Happens, and Corruption Hurts**



## **Corruption Happens, and Corruption Hurts**



ImageNet-C benchmark:



#### **Corruption Happens, and Corruption Hurts**



ImageNet-C benchmark:





testing data varies in many ways yet our models stay the same and fail to generalize



How to adapt to multiple shifts?



How to adapt to multiple shifts?

Update model for each shift



How to adapt to multiple shifts?

Update model for each shift

Update input for all shifts



How to adapt to multiple shifts?

Update model for each shift

Update input for all shifts

how do model and input updates compare?

#### **Too Little Data**



large batch

VS.



small batch

#### **Too Little Data**



large batch

VS.



small batch

#### **Dependent Data**





independent

VS.



dependent

#### **Too Little Data**



large batch

VS.



small batch

#### **Dependent Data**





independent

VS.



dependent

#### **Mixed Data**



same/single shift







mixed/multiple shifts

#### **Too Little Data**



large batch

#### **Dependent Data**





independent

#### **Mixed Data**



same/single shift

VS.



small batch

VS.



dependent





mixed/multiple shifts

# Input updates can help!

## **Input Updates by Diffusion-Driven Adaptation**



#### DDA projects target inputs back to the source domain.

Adapting the input enables direct use of the source classifier without model adaptation.

- add noise by perturbing the corrupted input with gaussian noise
- iteratively update by applying the reverse process of the diffusion model
- refine by guiding updates to match image structure

For reliability, we ensemble predictions with and without input adaptation weighted by confidence.

### Input Updates Improve on Model Updates for Episodic Adaptation

DDA **input updates improve** on MEMO model updates. MEMO can hurt without tuning to the architecture, because model optimization can be sensitive to its hyperparameters.

	IN	ImageNet-C Accuracy			
Model	Acc.	Source-Only	MEMO	DiffPure	DDA
ResNet-50	76.6	18.7	24.7	16.8	29.7
Swin-T	81.2	33.1	29.5	24.8	40.0
ConvNeXt-T	82.1	39.3	37.8	28.8	44.2
Swin-B	83.4	40.5	37.0	28.9	44.5
ConvNeXt-B	83.9	45.6	45.8	32.7	49.4

DDA is architecture agnostic—although model adaptation can apply to different architectures, it may need tuning.

#### Input Updates are Insensitive to Batch Size and Order

**DDA is episodic** so batching & ordering do not matter. For Tent, not so! Online model updates are sensitive.



DDA can adapt on inputs one-by-one in whatever order.

### **Diffusing Inputs to Defuse Corruptions**



successes

### **Diffusing Inputs to Defuse Corruptions**



#### successes

#### failures

why we need self-ensemble to choose how much to adapt

### **DDA Helps across Corruption Types**

**DDA reliably helps** due to self-ensembling and refinement. Diffusion alone can hurt when the projection fails.



### Is It Time To Update our Opinion of Model Updates?

While input updates shine in certain settings small batches, ordered data, and mixed corruptions model and input updates are complementary

More adaptation is needed to make the best of both kinds of updates-take the next steps with us!

Come check out the poster and see our

- poster #399 on day 2: WED-AM session (WED-AM-339)
- demo #11 on day 1: Tue. June 20, 2023
- arxiv https://arxiv.org/abs/2207.03442
- code <u>https://github.com/shiyegao/DDA</u>

Thanks!