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

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Abstract

Test-time adaptation harnesses test inputs to improve the accuracy of a model trained on source data when tested on shifted target data. Existing methods update the source model by (re-)training on each target domain. While effective, re-training is sensitive to the amount and order of the data and the hyperparameters for optimization. We instead update the target data, by projecting all test inputs toward the source domain with a generative diffusion model. Our diffusion-driven adaptation method, DDA, shares its models for classification and generation across all domains. Both models are trained on the source domain, then fixed during testing. We augment diffusion with image guidance and self-ensembling to automatically decide how much to adapt. Input adaptation by DDA is more robust than prior model adaptation approaches across a variety of corruptions, architectures, and data regimes on the ImageNet-C benchmark. With its input-wise updates, DDA succeeds where model adaptation degrades on too little data in small batches, dependent data in non-uniform order, or mixed data with multiple corruptions.

1 Introduction

Deep networks achieve state-of-the-art performance for visual recognition [1, 2, 3, 4], but can still falter when there is a shift between the source data for training a recognition model and the target data for testing [5]. Shift can result from corruption [6, 7]; adversarial attack [8]; or natural shifts between simulation and reality, different locations and times, and other such differences [9, 10]. To cope with shift, adaptation and robustness techniques update inference to improve accuracy on target data. In this work we examine two key axes of adaptation, when to adapt—during training or testing—and what to adapt—the model or the input, and propose a uniquely test-time input adaptation method driven by a generative diffusion model.

The dominant paradigm for adaptation is to update the model during training by joint optimization over source and target [11, 12, 13, 14, 15]. However train-time adaptation faces a fundamental issue: not knowing how the data may differ during testing. While train-time updates can cope with known target domains, what if new and different shifts should arise during deployment? In this case, test-time updates are needed to adapt the model (1) without the source data and (2) without halting inference. Source-free adaptation [16, 17, 18, 19, 20, 21] satisfies (1) by re-training the model on new targets without access to the source. Test-time adaptation [22, 16, 23, 24] satisfies (1) and (2) by iteratively updating the model while making predictions. Updating the model during testing makes inference more robust to shift, but with some additional disadvantages. Model updates could be too computationally intense to scale to many targets, which each need their own model, and the updates

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Our adaptation method, DDA, projects inputs from all target domains to the source domain by a generative diffusion model. Having trained on the source data alone, our source diffusion model for generation and source classification model for recognition do not need any updating, and therefore scale to multiple target domains without potentially expensive and sensitive re-training optimization.

may be sensitive to different amounts or orders of data from the target(s), in which case it may fail to help or even harm robustness. In summary, existing methods concentrate on updating the source model.

We propose to update the target data during testing instead. To update the data, we project test inputs back to the source domain by generative diffusion modeling. Our diffusion-driven adaptation method, DDA, learns a diffusion model of the source data during training, then projects inputs from all targets during testing. Figure 1 shows how just one generative model of source enables adaptation from multiple targets. DDA trains a diffusion model to replace the source data, for source-free adaptation, and adapts target inputs while making predictions, for test-time adaptation. Figure 2 illustrates how DDA adapts the input then applies the source classifier without model adaptation.

Our experiments measure robustness to input corruption to compare and contrast input updates and model updates. For input updates, we evaluate and ablate our proposed DDA method. For model updates, we evaluate entropy minimization methods (Tent [23] and MEMO [24]), which are the state-of-the-art for fully test-time online updates, and BUFR [25], which is the state-of-the-art for source-free offline updates. DDA achieves higher robustness than MEMO in all cases, and helps where Tent degrades due to limited, ordered, or mixed data. As a model-agnostic input adaptation method, DDA improves across standard (ResNet-50) and state-of-the-art convolutional (ConvNeXt [4]) and attentional (Swin Transformer [3]) architectures without re-tuning.

Our contributions:

- We propose the first diffusion modeling approach for test-time adaptation to corruption, DDA, and propose a novel self-ensembling scheme to select how much to adapt.
- We identify and empirically confirm weak points of test-time model updates—small batches, ordered data, and mixed domains—and highlight our test-time input updates to address these natural but currently challenging regimes.
- We experiment on the ImageNet-C benchmark to show that our DDA improves over test-time model adaptation across corruptions, architectures, and data regimes.

2 Related Work

We relate our uniquely generative test-time input adaptation method to existing methods for model and input adaptation. We also highlight diffusion modeling as the key approach for our generative modeling of the source data.

Model Adaptation Model adaptation aims to update the source model on target data to improve accuracy. While myriad varieties exist, we focus on source-free adaptation—not needing the source
Source-free adaptation \cite{20, 19, 21, 16} makes it possible to respect practical deployment constraints on computation, bandwidth, and privacy. Nevertheless, most methods involve a certain amount of complexity and computation by altering training \cite{20, 19, 21, 16} and interrupting testing by re-training their model(s) offline on each target \cite{20, 19, 21, 25}. DDA is source-free, as it replaces the source data with source diffusion modeling. However, it differs by adapting the data and not its diffusion model or recognition model. Furthermore, it does not alter training of the recognition model, as it can train the diffusion model in isolation. By keeping its models fixed, DDA handles multiple targets without halting testing for model re-training, as source-free model adaptation must. Test-time adaptation \cite{16, 22, 23, 26} updates the model without holding up inference. (Fully test-time methods are more extreme still, and do so without any access to training or source data.) Such test-time model updates can be sensitive to their optimization hyperparameters along with the size, order, and diversity of the test data. On the contrary, DDA updates the data, which makes it independent across inputs, and thereby invariant to the batching, order, or mixture of the test data. DDA can even adapt to a single test input without augmentation, unlike test-time model adaptation.

Input Adaptation  Input adaptation aims to translate data between source and target. DDA carries out test-time input adaptation from target to source by diffusion. Prior methods adapt during testing, but differ in their purpose and technique, or adapt during training, but cannot handle new target domains during testing. When testing, translation goes from target to source, allowing direct application of the source model without having to (re-)train it for target, as done by diffusion-driven defense \cite{27} for robustness to attack. When training, translation goes from source to target—real or synthesized—to provide additional data or auxiliary losses, as done by style transfer \cite{28, 29, 30, 31}, conditional image synthesis \cite{32, 15, 34, 35, 36, 37}, or adversarial generation \cite{38} for robustness to shift. A key work in this line is CyCADA \cite{15}, which translates from source to target with generative modeling by CycleGAN \cite{32}. While CyCADA is generative like DDA, CycleGAN requires paired source and target data for training, and so it cannot adapt to multiple and varied targets during testing. In contrast, DDA only requires source data during training, and can adapt to multiple target domains with a single model.

Diffusion Modeling  Diffusion \cite{39, 40, 41, 42, 43, 44, 40} is an emerging approach to generative modeling that operates on the input space by iteratively refining samples. In essence, diffusion models learn to “reverse” noise to generate an image by gradient updates w.r.t. the input. The type of noise matters, and standard diffusion models rely on Gaussian noise. In this work, we investigate how a strong diffusion model can project corrupted target data to the source data distribution, which involves corruptions that are highly non-Gaussian. We apply the denoising diffusion probabilistic model (DDPM) \cite{45} in this new role of diffusion-driven adaptation. Guided diffusion models improve generation by optimization based on class labels \cite{46, 47}, text \cite{48, 49} and images \cite{50}, but test-time adaptation denies the necessary data for their use. While diffusion has been applied to adversarial defense \cite{27}, we are the first to adopt it for test-time adaptation to corruptions. Diffusion is key to our source-free and test-time adaptation method, in replacing the source data with source diffusion, and in updating target data without needing to update the model across batches or target domains. We apply diffusion in this fashion to propose a source-free adaptation method that uniquely scales to multiple target domains without the addition or optimization of parameters.

3  Test-Time Diffusion-Driven Adaptation

We propose diffusion-driven adaptation (DDA) for test-time input adaptation by generative modeling with diffusion. During training, we train a generative diffusion model on the source domain data, and train a discriminative classification model on the source domain data and annotations. During testing, given a test input from the target domain, the diffusion model projects it to the source domain, and then the classification model makes its prediction from the original and translated input. Figure 2 illustrates inference with DDA through projection, classification, and ensembling of the predictions over the target and source-projected inputs.

DDA does not need any target data during training, and in principle it can handle an arbitrary number of target domains during testing. Of course, its ability to effectively project a given input to the source domain may vary for each target. DDA can adapt a single test input at a time, making it an episodic
method, which does not require batching or cumulative updates. In contrast, existing test-time model adaptation methods, such as Tent [23] and BUFR [25], degrade on on too little data (small batches), on dependent data (in non-random order), or on mixed data across different target domains (with multiple corruptions) See Sec. 4.3 for our comparison of input and model adaptation. By not relying on the batching or ordering of the data, our DDA approach can better address practical settings that require inference as the data arrives, such as perception for autonomous driving.

3.1 Background: Diffusion for Image Generation

Diffusion models are a class of latent variable generative models that have recently demonstrated state-of-the-art performance for image synthesis. Given a clean image sampled from the real image distribution \( x_0 \sim q(x_0) \), the forward process of the diffusion model defines a fixed Markov chain, to gradually add Gaussian noise to the clean image \( x_0 \) over \( T \) time steps, producing a sequence of noised images \( x_1, x_2, \ldots, x_T \). Mathematically, the forward process is defined as

\[
q(x_{1:T}|x_0) := \prod_{t=1}^{T} q(x_t | x_{t-1}), \quad q(x_t | x_{t-1}) := N \left( x_t; \sqrt{1 - \beta_t} x_{t-1}, \beta_t I \right),
\]

where the sequence, \( \beta_1, ..., \beta_T \), is a fixed variance schedule to control the step sizes of the noise.

On the other hand, given the noise sampled from a Gaussian distribution \( X_T \sim N(0, I) \), the reverse process of the diffusion model iteratively removes the noise to generate a clean image in \( T \) time steps. The reverse process is formulated as a Markov chain with parameterized Gaussian transitions

\[
p(x_{0:T}) := p(x_T) \prod_{t=1}^{T} p(x_{t-1} | x_t), \quad p_\theta(x_{t-1} | x_t) := N \left( x_{t-1}; \mu_\theta(x_t, t), \sigma^2_t(x_t, t) I \right).
\]

In denoising diffusion probabilistic models (DDPM) [45], we set \( \sigma_t(x_t, t) = \sigma_I \) to time-dependent constants. \( \mu_\theta \) is parameterized into a linear combination of \( x_t \) and \( \epsilon_\theta(x_t, t) \), where \( \epsilon_\theta(x_t, t) \) is a function that predicts the noise component of a noised sample \( x_t \). The parameters of \( \mu_\theta(x_t, t) \) are learned by optimizing the variational bound of negative log-likelihood \( \mathbb{E}[- \log p_\theta(x_0)] \). With the above parameterization and following DDPM [45], the training objective \( \mathcal{L}_{\text{simple}} \) simplifies to the mean-squared error loss between the actual noise \( \epsilon \sim N(0, I) \) in \( x_t \) and the predicted noise:

\[
\mathcal{L}_{\text{simple}} := ||\epsilon_\theta(x_t, t) - \epsilon||^2.
\]

Since the training objective is derived from the variational bound on the negative log-likelihood \( \mathbb{E}[- \log p_\theta(x_0)] \) of the data, the diffusion model learns a generative model of the source data distribution.

3.2 Diffusion-Driven Input Adaptation

Here we detail the key step of our diffusion-driven adaptation approach: the projection of target test inputs to the source data distribution by diffusion. Specifically, we project the test image to the source domain by running the forward process followed by the reverse process of the diffusion model. Note that our approach is orthogonal to the choice of diffusion model as long as the chosen model can be
trained on the source data. Equipped with a diffusion model of the source data, our approach applies this single model to the projection of single/multiple/mixed target domain data to the source domain.

We describe the steps of our method and highlight each as it is illustrated in Fig. 2. Given an input image $x_0$ from the target domain and an unconditional diffusion model trained on the source domain, First the forward process (Eq. 1 of the diffusion model, the green arrow, perturbs the image with Gaussian noise. We denote the image sequence derived by $N$ iterative forward steps as $x_0, x_1, \ldots, x_N$, where $N$ is a hyper-parameter controlling the amount of noise added to the input image. We name $N$ as “diffusion range” for simplicity. Then the reverse process (Eq. 2, the red dotted arrow, iteratively removes noise for $N$ steps to generate the denoised image sequence $x^g_0, x^g_1, \ldots, x^g_N$. Since the diffusion model is trained on the source domain, the generated image $x^g_0$ should have higher likelihood under the source data distribution than the test image $x_0$, in so much as the diffusion model is fit to the domain.

While this projection can adapt the input, a trade-off arises when choosing the diffusion range $N$. Too little diffusion, when $N$ is small, fails to project outside of the target domain back to the source. However, too much diffusion, when $N$ is large, fails to project inside of the same class across domains. Our ideal goal is to adapt the input from the target domain to the source domain while preserving its discriminative content for the classification task. The issue is that domain and class information may be interdependent, which makes it difficult to identify the optimal trade-off between domain adaptation and class preservation.

Based on our observation that the class information can relate strongly to the structure (low-frequency signal) of an image, we regularize diffusion to better preserve this structure. Inspired by ILVR [50], we adopt an iterative latent refinement process, the purple dotted arrow, which conditions on the input image in the reverse process. This refinement enforces the structural, and therefore class, alignment between the generated image and the input image. In particular, we adopt a linear low-pass filtering operation implemented by $\phi_D(\cdot)$, a sequence of downsampling and upsampling operations by a scaling factor of $D$. The low-pass filtered image represents the structural information of an image. At each time step $t$ in the reverse process, we force $\phi_D(x^g_t)$ to be identical to $\phi_D(x_t)$. Mathematically, we add a latent refinement operation after sampling $\hat{x}^g_{t-1}$ based on $x^g_t$.

$$\hat{x}^g_{t-1} \sim p_{\theta} \left( x^g_{t-1} \mid x^g_t \right), \quad x^g_{t-1} = \phi_D(x_{t-1}) + (I - \phi_D)(\hat{x}^g_{t-1}).$$  \hspace{1cm} (4)

The latent refinement is conducted when $t \geq M$, where $M$ is a hyper-parameter named “refinement range”.

In summary, we first perturb the input image from the target domain with noise by the forward process of the diffusion model, and then run the reverse process with iterative latent refinement to carry out input adaptation with minimal alteration of class-dependent information. In this way, we generate an image in the style of the source domain that preserves the class identity of the given target image. Algorithm 1 outlines our approach for projecting the target image to the source domain with diffusion.

### 3.3 Selecting How Much to Adapt by Self-Ensembling

Once we have adapted the target domain inputs to the source domain by diffusion, our source-trained classification model can make predictions on the adapted images. In most cases, diffusion preserves enough discriminative information in the adapted inputs for correct classification. However, diffusion may occasionally generate imperfect or ambiguous images that are more like source data but result in misclassification. In such cases, the classification model may be more accurate on the original, unadapted input, even with its domain shift.

Motivated by these failure cases for diffusion, we propose a self-ensembling scheme to aggregate the predictions over the original and adapted inputs. Specifically, as we have both the original test image $x_0$ and generated image $x^g_0$ from diffusion, we first apply the classification model to both inputs. The confidence of the $C$ classification predictions on the original, unadapted and generated, adapted input are denoted as $p \in \mathbb{R}^C$ and $p^g \in \mathbb{R}^C$, respectively. The ensembled prediction fuses the predictions based on the average confidence, i.e., $\arg \max_c \frac{1}{2} (p_c + p^g_c)$, where $c \in \{1, \ldots, C\}$.

This self-ensembling scheme automatically selects how much to rely on the adapted and unadapted inputs. Selecting in this way increases the robustness of adaptation by rejecting unsuitable results of generative modeling.
**Algorithm 1** Diffusion-Driven Input Adaptation

1: **Input**: Reference image $x_0$
2: **Output**: Generated image $x_0^g$
3: $M$: refinement range for the iterative latent refinement
4: $N$: diffusion range
5: Sample $x_N \sim q(x_N \mid x_0)$  
6: $x_N^g \leftarrow x_N$  
7: **for** $t \leftarrow N \ldots 1$ **do**
8: $x_{t-1}^g \sim p_\theta (x_{t-1}^g \mid x_t^g)$  
9: **if** $t > M$ **then**
10: $x_{t-1} \sim q(x_{t-1} \mid x_0)$  
11: $x_{t-1}^g \leftarrow \phi_D (x_{t-1}) + (I - \phi_D) (x_{t-1}^g)$  
12: **else**
13: $x_{t-1}^g \leftarrow \hat{x}_{t-1}^g$
14: **end if**
15: **end for**
16: return $x_0^g$

4 Experiments

4.1 Setup

**Dataset**  
ImageNet-C [6] is a standard robustness benchmark for large-scale 1000-way image classification. It consists of synthetic but natural corruptions (e.g., natural noise and blur, digital artifact, and different weather conditions) applied to the ImageNet [51] validation set of 50,000 images. It includes 15 corruption types at 5 levels of severity. We measure robustness as the top-1 accuracy of predictions on the most severe corruptions (level 5) on ImageNet-C. We evaluate DDA with the same hyperparameters in all experiments, except as noted for ablation and analysis.

**Adaptation Settings**  
We consider adaptation with and without separation of the target domains/corruption types. The first *independent adaptation*: this is the standard setting for robustness experiments on ImageNet-C, where adaptation and evaluation are done independently for each corruption type. The second *joint adaptation*: this is a more natural and difficult setting, where adaptation and evaluation are done jointly over all corruptions by combining their data. The settings are equivalent for “episodic” methods that make independent predictions across test inputs. Note that the regular source-only model is episodic, as is our DDA method. However, many model adaptation methods are not—Tent [23] and BUFR [25] included—because model updates on one input alter predictions on other inputs. Experimenting with both settings allows for standardized comparison with existing work and exploration of adaptation without knowledge of the target domains.

**Classification Models**  
We experiment with multiple classification architectures to ensure general improvement. We select ResNet-50 [1] for a common architecture to standardize on, RedNet-26 [52] for a compact architecture, plus Swin [3] and ConvNeXt [4] to evaluate the state-of-the-art in attentional and convolutional architectures. Experimenting with Swin and ConvNeXt sharpens our evaluation of adaptation as these architectures already improve robustness. Table 1 lists their FLOPS, number of parameters, and accuracy on the source data.

4.2 Benchmark Evaluation: Independent Adaptation

**Input updates are more robust than model updates with episodic adaptation.** We begin by evaluating source-only inference (without adaptation), model adaptation with MEMO, and input adaptation with our DDA. Each method is episodic, in making separate predictions for each input, for fair comparison. MEMO adapts by augmentation and entropy minimization: it minimizes the entropy of the predictions w.r.t. the model parameters over different augmentations of the input. By relying on data augmentation, MEMO avoids trivial solutions to optimizing so many parameters on a single input. DDA circumvents this issue by not updating the model at all, and instead updating the input itself. Table 1 summarizes each source classifier and compares the robustness of each method.
Table 1: **Input adaptation is more robust in the episodic setting of image-wise adaptation.**
Episodic inference is independent across inputs, which includes source-only prediction without adaptation and model updates by MEMO or input updates by DDA (ours). We evaluate standard accuracy on ImageNet and robustness to corruption on ImageNet-C with maximum severity (level 5). All results are top-1 accuracies (higher is better).

| Architecture  | Data/ FLOPs/ Params | ImageNet Acc. | Source-Only Acc. | MEMO Acc. | DDA Acc. |
|---------------|--------------------|---------------|------------------|----------|----------|
| RedNet-26     | 1K/224² 1.7/9.2    | 76.0          | 15.0             | 20.6     | 25.0     |
| ResNet-50     | 1K/224² 4.1/25.6   | 76.6          | 18.7             | 24.7     | 27.3     |
| Swin-T        | 1K/224² 4.5/28.3   | 81.2          | 33.1             | 29.5     | 37.0     |
| ConvNeXt-T    | 1K/224² 4.5/28.6   | 81.7          | 39.3             | 37.8     | 41.4     |

Figure 3: **DDA reliably improves robustness across corruption types.** We compare the source-only model, diffusion-only adaptation, and DDA with diffusion and self-ensembling. DDA is the best on average, and reliably improves over diffusion-only inference with few exceptions. Self-ensembling with DDA prevents catastrophic drops (on fog or contrast, for example).

DDA is consistently more robust, and applies across architectures without tuning, to even boost state-of-the-art architectures (the Swin-T transformer & ConvNeXt-T convnet) where MEMO hurts.

**DDA consistently improves across corruption types and prevents catastrophic failure.** Figure 3 analyzes the robustness of DDA across each corruption type individually. Diffusion without self-ensembling improves over source-only inference on most but not all corruptions. In general, diffusion helps on local/high-frequency corruptions like noise, but fails on more global/low-frequency corruptions like fog and contrast. Our proposed self-ensembling automatically selects how much to adapt to avoid such failure cases to consistently improve or maintain accuracy.

**DDA is not sensitive to small batches or ordered data.** The amount and order of the data for each corruption type may vary in practical settings. For the amount, source-free methods use the entire test set at once, while test-time methods may choose different batch sizes. For the order of the target data, it is commonly shuffled (as done by Tent and other test-time methods). We evaluate at different batch sizes and with and without shuffling to understand the effect of these data regimes. Figure 4 plots sensitivity these factors. DDA and MEMO are totally unaffected, as episodic methods, but Tent is extremely sensitive. Controlling the amount and order of data during deployment may not always be possible, but Tent requires it to ensure improvement (and not failure).

### 4.3 Challenge Exploration: Joint Adaptation

The joint adaptation setting, in which the data for all corruption types is combined, presents a new challenge. In this new setting, the amount, order, and mixture of the data can be varied to further complicate adaptation for methods that depend on batching or ordering of the domains. As episodic methods, which adapt to each input independently, MEMO and DDA can both address small batches,
Batch Size | Accuracy
---|---

Tent, random order | MEMO: 20.6% | DDA: 25.0%
Tent, class order | MEMO: 24.7% | DDA: 27.3%

(a) RedNet-26

(b) ResNet-50

(c) Swin-Tiny

(d) ConvNeXt-Tiny

Figure 4: **DDA is invariant to batch size and data order while Tent is extremely sensitive.** To analyze sensitivity to the amount and order of the data we measure the average robustness of independent adaptation across corruption types. DDA does not depend on these factors and consistently improves on MEMO. Tent fails on class-ordered data without shuffling and degrades at small batch sizes.

Table 2: **DDA is reliably more robust when the target data is limited, ordered, or mixed.** To explore different deployment regimes, we measure accuracy while varying batch size and whether or not the data is ordered by class or mixed across corruption types. We compare episodic adaptation by input updates with DDA (ours) and by model updates with MEMO against cumulative adaptation with Tent. DDA and MEMO are invariant to these differences in the data. However, Tent is highly sensitive to batch size and order, and fails in the more natural data regimes.

| Method | Mixed Classes | Mixed Types | Batch Size | RedNet-26 | ResNet-50 | Swin-T | ConvNeXt-T |
|---|---|---|---|---|---|---|---|
| Source-Only | N/A | N/A | 15.0 | 18.7 | 33.1 | 39.3 |
| MEMO [24] | N/A | N/A | 20.6 | 24.7 | 29.5 | 37.8 |
| DDA (ours) | ✓ | ✓ | 1 / 64 | 0.8 / 0.2 | 0.1 / 0.4 | 2.8 / 2.3 | 10.5 / 9.6 |
| | ✓ | ✓ | 1 / 64 | 0.8 / 0.3 | 0.1 / 0.3 | 8.0 / 2.2 | 18.8 / 6.5 |
| | ✓ | ✓ | 1 / 64 | 0.8 / 7.7 | 0.1 / 22.6 | 3.0 / 41.0 | 11.0 / 50.1 |
| | ✓ | ✓ | 1 / 64 | 0.8 / 3.4 | 0.1 / 6.5 | 8.5 / 36.9 | 18.9 / 47.4 |

ordered data, and mixed domains. On the other hand, non-episodic methods, such as model adaptation with cumulative updates across inputs, are sensitive to these data regimes.

**DDA is more robust than model adaptation in the joint setting.** We further compare with MEMO and test-time batch normalization [22] (BN) in the joint setting. We evaluate with ResNet-50 because it is a standard architecture for these model adaptation methods. The accuracies are 27.3% for DDA, 24.7% for MEMO, and 10.3% for BN. Although BN is competitive in the independent setting, in the joint setting sharing the mean and variance across all corruption types is insufficient for adaptation. BUFR [25] lacks ResNet-50 results, and we could not tune it to better than source-only accuracy.

**DDA assumes less and succeeds where Tent degrades.** We compare to Tent [23], a representative fully test-time model adaptation method, which cumulatively updates during testing. Tent can help the most when its assumptions of large enough batches and randomly ordered data are met, but may otherwise harm robustness. In contrast, the accuracy of DDA is independent of batch size and data order, and helps robustness in each setting.

### 4.4 Ablation and Analysis of Diffusion-Driven Adaptation

We ablate the different types of diffusion updates. As described in Sec. 3.2, DDA updates the input by its forward process, reverse process, and refinement/guidance. We experiment with three settings: (1) We first run the forward process (i.e., add Gaussian noise) on the input image and then run the reverse process of the diffusion model to denoise, without the iterative refinement module ("forward+reverse"). (2) We start from a random noise and run the reverse process of the diffusion model to denoise, without the iterative refinement module ("reverse"). (3) We run the forward process and then the reverse process of the diffusion model to denoise, with the iterative refinement module ("forward+reverse+refine").
Figure 5: **Ablation of diffusion updates justifies each step.** We ablate the forward, reverse, and refinement updates of our DDA method. We omit self-ensembling from DDA to focus on these input updates. Forward adds noise, reverse denoises by diffusion, and refinement guides the reverse updates. DDA is best with all steps, but forward and reverse or reverse and refinement help on their own.

model with the iterative refinement module as guidance (“reverse+refinement”). (3) Our full method with both, i.e., we run the forward process on the input image and then run the reverse process of the diffusion model with the iterative refinement module as guidance (“DDA”). Figure 5 compares their performance, and demonstrates that each step contributes to robustness.

5 Discussion

DDA mitigates shift by test-time input adaptation with diffusion modeling. Our experiments on ImageNet-C confirm that diffusing target data back to the source domain improves robustness. In contrast to test-time model adaptation, which can struggle with scarce, ordered, and mixed data, our method is able to reliably boost accuracy in these regimes. In contrast to source-free model adaptation, which can require re-training to each target, we are able to scalably adapt from multiple targets by keeping our source models fixed. These practical differences derive from our conceptual shift from model adaptation to input adaptation and our adoption of diffusion modeling.

Having examined whether to adapt by input updates or model updates, we expect that reconciling the two will deliver more robust generalization than either alone.

**Limitations** The strengths and weaknesses of input adaptation complement those of modal adaptation. Although our method can adapt to a single target input, it must adapt from scratch on each input, and so its computation cannot be amortized across deployment. In contrast, model adaptation by TTT [16] or Tent [23] can update on each batch while cumulatively adapting the model more and more. Although diffusion can project many targets to the source data, and does so without expensive model re-training, it can fail on certain shifts. If these shifts arise gradually, then model adaptation could gradually update too [53], but our fixed diffusion model cannot.

We rely on diffusion, and so we are bound to the quality of generation by diffusion. Diffusion does have its failure modes, even though our positive results demonstrate its present use and future potential. In particular, diffusion models may not only translate domain attributes but other image content, given their large model capacity. Our use of image guidance helps avoid this, but at the cost of restraining adaptation on certain corruptions. New diffusion architectures or new guidance techniques specific to adaption could correct these shortcomings.

As-is, diffusion takes more computation time than classification, so ongoing work to accelerate diffusion is needed to reduce prediction latency [54].

**Societal Impact** While our work seeks to mitigate dataset shift, we must nevertheless remain aware of dataset bias. Because our diffusion model is trained entirely on the source data, biases in the data may be reflected or amplified by the learned model. Having learned from biased data, the diffusion model is then liable to project target data to whatever biases are present, and may in the process lose important or sensitive attributes of the target data. While this is a serious concern, diffusion-driven adaptation at least allows for interpretation and monitoring of the translated images, since it adapts the input rather than the model. Even so, making good use of this capacity requires diligence and more research into automated analyses of generated images.
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