# Image-Editing Specialists: A Multi-Objective Approach for Diffusion Models

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## Abstract

*this is the abstract of my paper. have you ever dreamed of a model that can edit you image in a style that you define through another image rather than through a text prompt? this way it can capture all of the nuances withouht having to spend hours writing a long precise sentence that might not capture all of the specifics*

## 1. Introduction

go harder on the alignment this, having better structural and semantic alignment is a human alignment issue Text-to-image (T2I) generative models have achieved remarkable success in creating visually appealing images based on text prompts [23, 41, 44], largely due to advancements in aligning captions with images [1, 39].

Beyond the remarkable generative capabilities of T2I models, instructional image editing has become one of the most practical approach to semantic modification [11, 51]. Unlike traditional image editing [12, 20, 26, 30, 35, 60], which necessitates descriptive captions for both the input and modified images, instruction-based image editing requires only natural-language instructions. This method is more straightforward, as it requires specifying only the elements that need alteration in the original image, without involving the remaining unrelated elements (and attributes). Although it has gained popularity in consumer applications, its generated samples have yet to show true reusability as data augmentation in downstream model training.

Simple-to-generate synthetic samples have shown to serve as pretraining data to teach early-training features [7, 8, 25]. Recently, some studies focused on leveraging T2I models as sources of high quality data augmentation. Some works generate diverse samples by applying naive perturbation to the noisy latents [59, 74], the conditioning embeddings [76] or throughout the denoising process [18]. Others do so by designing, optimizing, or reformulating prompts [6, 16, 48, 53, 54, 70]. Others like Azizi et al. [3] finetune a T2I model to reduce the gap between real data from a specific domain real and class-conditional generated samples. Still, none leverage instructional editing for highly specific and user-controlled & aligned data augmentation in niche domains. In our work, we focus on a method to train instruction-based diffusion models to generate samples that are of high quality and can serve as augmentation, particularly in data-scarce domains, where the collection might be costly or timely.

To become truly useful for downstream applications, we identify two key criteria that an image-editing model should satisfy.

**Structural Alignment:** It should ensure high-fidelity preservation of content in the initial image that is unrelated to the editing request. Current state-of-the-art image-editing models without segmentation or semantic masks in the forward pass struggle to perform precise edits on the subject specified by the text prompt, while leaving unrelated areas of the image intact. Notably, the training data for InstructPix2Pix was created with the Prompt-to-Prompt method [20]. Hence, it suffers from the same limitations as Prompt-to-Prompt, including imperfect preservation of background pixels. pas ouf comme section

**Semantic Alignment:** It should enable fine-grained control over the visual aspects of desired modifications. One effective approach is to utilize both textual and image prompts to express nuanced stylistic preferences. This strategy captures subtleties that are difficult to articulate with text alone and may elude language models. While a text prompt can convey the broad theme of an edit, specifying the precise nuances of its interpretation proves more challenging and impractical. Consequently, it is preferable to enhance user alignment with their envisioned edits without resorting to lengthy prompts, which contradicts the essence of instruction-based systems. Most works on visual prompting for image generation have been targeted at style transfer, where an image's style is edited across the whole frame [21, 55, 62]. Other recent studies have focused on finetuning pre-trained T2I models for subject-driven editing from a set of reference images [19, 46]. However their methods require unique identifiers to capture the edit nuance. In our work, we bring our attention to localized edits conditioned on a visual prompt, and limit the complexity of our text prompts to simple instructions.

The standard diffusion model training objective presents inherent challenges for image editing because it enforces uniformly reconstructing the entire image, without distinguishing between regions that require preservation and those that need modification. Achieving this balance with a standard reconstruction loss necessitates an oracle to generate precise input-output pairs. However, such oracles are often biased, lack scalability, or produce low-quality samples that require further pruning using various filtering techniques [11, 13, 51, 71]. To address these limitations, we frame the problem as an alignment issue, leveraging the capabilities of the InstructPix2Pix model [11]. Although this model can generate edits, it requires refined training to better align with human semantic and structural preferences, especially in complex scene edits. Our reinforcement learning (RL) framework enhances this alignment and circumvents the need for an oracle, as the method is based on self-play. By achieving closer alignment with human preferences, the model is more likely to generate natural-looking edits with better visual appeal, making it a suitable method for high-quality data augmentation.

Accordingly, we introduce XXX, an novel RL approach designed to train image editing models that produce edits with styles highly aligned with visual prompts while accurately preserving the original structure in non-pertinent areas of the image. These models are tailored to specialize in specific niche domains, enhancing quality at the expense of diversity. reformulate this, we don't kill diversity, but we specify the concept meant in the prompt to a certain visual aspect. (actually, check what zero-shot is on a model trained for a certain tgt, and then infered on another tgt (ex, train on sparse, infer on dense snow) Unlike traditional reinforcement learning with human feedback (RLHF) methods, our approach bypasses the need for human annotators by employing AI models to provide feedback that accurately simulates human preferences in terms of structure and semantics. We demonstrate XXX's effectiveness in editing complex scenes, such as outdoor city street environments for autonomous driving applications, and its utility in data augmentation for downstream robot manipulation policy training. Our experiments show that XXX surpasses current state-of-the-art methods regarding edit alignment and structural preservation metrics.

Our contributions are summarized as follow: (see the last slide of my presentation?)

1. Designed a framework to train image editing models with RLAIF
2. Crafted a custom objective tailored to learning nuances beyond prompts
3. Improved SOTA models on specific domains with ¡1% of their original dataset size

**We are the first to develop a method combining instructional text and visual prompts in parallel (Also, to the best of our knowledge, there does not exist an instructional editing method that also leverages visual prompting to guide the generation process.), and we are the first to showcase the ability to train an image-editing model with RLAIF**

Future work includes (keep here in case i improve one of those i can plug it back into the contributions):

1. Improve semantic supervision to be better aligned with human judgment
2. Refine supervision beyond simple ranking
3. Showcase usefulness in data-scarce domains like robot learning

## 2. Related Works

**Text-guided Image Editing.** In prior work, text-guided image editing methods fall in three categories: architectural tricks that require no training ((seg/sem mask methods require training of additional model plugged onto diffusion)) , few-steps optimization for each sample, and large scale finetuning. In the first category, Prompt-to-Prompt (P2P) [20] manipulates attention maps in the diffusion model to control the layout and content of the editing. Plug-and-Play (PNP) [60] injects self-attention maps and spatial features to improve the structure. Still, these remain limited in their ability to edit complex scenes. Others leverage a segmentation mask [2, 12, 31, 37, 52, 63, 65] or semantic mask [34, 36, 69, 72] during the forward pass, which imposes a greater inconvenience on users by requiring them to supply these additional masks.

In the second category, Null-Text Inversion [35] optimizes the null-text embedding during the inversion of an input image. Imagic [26] finetunes model weights and embeddings to align with the input image and the edit text prompt. RB-Modulation [45] leverages stochastic optimal controller to align content and style with visual prompts. Still, these are slow at inference because optimization is requires for each generation.

Lastly, other methods adopt the standard reconstruction training. like [11, 13, 50, 51, 71]. InstructPix2Pix [11] generates a large synthetic dataset of image pairs with P2P, coupled with instruction-based text prompts. Similarly, Emu Edit [51] expands the dataset with P2P, screens training samples with semantic and structural filters techniques, and leverages multi-task training. SuTI [13] leverages finetuned experts version of Imagen [47] to create high quality samples for the editing model to learn from. MagicBrush [71] assembles an image editing dataset synthesized with DALL-E 2 [41] and manually prune samples. Alchemist [50] uses a rendering tool targeted to modifying material attributes. However, these methods require an oracle to gen-

(a) Caption for image 1 (b) Caption for image 2 (c) Caption for image 3

Figure 1. Combined caption for all images

(a) Caption for image 1 (b) Caption for image 2 (c) Caption for image 3

Figure 2. Combined caption for all images

erate images, which requires some curation, and may still infuse its limitations see what i wrote in the intro section

None leverage the style of tgt except for rbModulation, which needs optimization for each sample None become really good generators in a certain type of data to make them reusable into another pipeline. not sure about that from hive: Our work follows the same direction as InstructPix2Pix[7] and leverages human feedback to address the misalignment between editing instructions and resulting edited images.

**Reinforcement Learning for Diffusion.** Aligning model outputs with human preferences has seen a wide success in the field of language modeling. For objectives that are complex to define explicitly, a popular strategy is reinforcement learning with human feedback (RLHF) [4, 15, 38, 56], where we first teach a reward function to capture output preferences, and leverage reinforcement learning algorithms like proximal policy optimization [49] to finetune models with such rewards.

In the field of diffusion models, several works study the use of human feedback for T2I generation. [28] collects human annotations, and perform maximum likelihood training where the reward is naively used as a weight. [64] designs a reward model that better captures finegrained human preferences. [9, 17] show that diffusion models can be trained with RL using a reward model judging images' aesthetics [66]. Specific to instructional image-editing, HIVE [73] extends large-dataset supervised training by collecting human feedback on edits and performing off-policy RLHF training. However, these methods need a reward model trained on large-scale human annotation. Not only is this process cumbersome, but it also provides supervision of limited quality. First, it quickly becomes hard for humans to evaluate at a finegrained level the preservation faithfulness of pixels unrelated to the edit instruction. Second, semantic alignment remains vague as it is only compared to the short instruction prompts, where different individuals could easily disagree on the specific interpretation.

Inspired by advances with RLAIF [5, 27], we alleviate the need for humans-in-the-loop and opt for a method where AI models provide the preference supervision tailored to solving the two issues above. Further, we train on-policy by leveraging the framework established by D3PO [67], positing that using online samples would lead to better results. should i be more clear with the fact that i use ai models tailored to improving the two flaws that i identified with generalist reward models based on human preference? so one depth model for structure, and one encoding alignment with the visual prompt for semantic alignment

## 3. Method

In this section, we describe the custom objective designed to obtain parallel supervision for the semantic and structural alignment. In Sec. 3.1, we describe how to alleviate the need for a reward model. Then, we explain in Sec. 3.2 how we design our two separate objectives. Finally, in Sec. 3.3, we present the modified architecture to intake the additional visual prompt conditioning and its modified score estimate formulation for classifier-free guidance with three conditionings.

### 3.1. Reinforcement Learning Training of Diffusion Models

Our model should learn from a reward that captures the structural and semantic alignment. For such, the reward function must intake the input image to be edited $I_{og}$, the instruction prompt $c_T$, the target style image $I_{sty}$, and compare those to the generated edit $I_{gen}$.

Most RLHF methods train a reward model to then train a downstream model. However, Direct Preference Optimization (DPO) [40] showed that preference ranking can be used to train language models and circumvent reward models. [61] showed that this could be extended to diffusion models. In our work, we leverage the framework introduced by D3PO [67], which expands that of DPO into a multi-step Markov Decision Process (MDP).

Given a pair of outputs $(y_1, y_2) \sim \pi_{\text{ref}}(y|x)$ generated from a reference pre-trained model $\pi_{\text{ref}}$, we denote the preference as $y_w \succ y_l|x$ and store the raking tuple $(x, y_w, y_l)$ in dataset $\mathcal{D}$, where $y_w$ and $y_l$ are the prefered and dispreferred samples respectively. Following the Bradley-Terry model [10], the human preference distribution $p^*$ can be expressed by using a reward function $r^*$ as:

$$p^*(y_1 \succ y_2 \mid x) = \frac{\exp(r^*(x, y_1))}{\exp(r^*(x, y_1)) + \exp(r^*(x, y_2))} \quad (1)$$

A parametrized reward model $r_\phi$ can then be trained via maximum likelihood estimation to approximate $r^*$ with:

$$\mathcal{L}_R(r_\phi, \mathcal{D}) = -\mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}} \left[\log \rho(r_\phi(x, y_w) - r_\phi(x, y_l))\right] \quad (2)$$

where $\rho$ is the logistic function. Prior works in RL have for objective to optimize a distribution such that its associated reward is maximized, allthewhile regularizing this distribution with the KL divergence to remain similar to its initial reference distribution:

$$\max_{\pi_\theta} \mathbb{E}_{x\sim\mathcal{D}, y\sim\pi_\theta(y|x)} \left[r_\phi(x, y)\right] - \beta\mathbb{D}_{\text{KL}} \left[\pi_\theta(y|x) \parallel \pi_{\text{ref}}(y|x)\right] \quad (3)$$

where $\beta$ controls the deviation between $\pi_\theta$ and $\pi_{\text{ref}}$. This distribution takes the following for optimal solution:

$$\pi_r(y \mid x) = \frac{1}{Z(x)} \pi_{\text{ref}}(y \mid x) \exp\left(\frac{1}{\beta} r(x, y)\right) \quad (4)$$

where $Z(x) = \sum_y \pi_{\text{ref}}(y|x) \exp\left(\frac{1}{\beta} r(x, y)\right)$ is the partition function. Reorganizing Eq. 4, we obtain the expression for the reward as a function of its associated optimal policy.

$$r(x, y) = \beta \log \frac{\pi_r(y \mid x)}{\pi_{\text{ref}}(y \mid x)} + \beta \log Z(x) \quad (5)$$

Substituting the parametrized reward function and policy for their optimal counterparts, we reintegrate that expression into Eq. 2. With the change of variables, the loss function is now expressed over policies rather than over reward functions. This closed form avoids having to train a reward model, but rather allows us to directly optimize the model.

$$\mathcal{L}_{\text{DPO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}} \left[\log \rho \left(\beta \log \frac{\pi_\theta(y_w|x)}{\pi_{\text{ref}}(y_w|x)} - \beta \log \frac{\pi_\theta(y_l|x)}{\pi_{\text{ref}}(y_l|x)}\right)\right] \quad (6)$$

Extending this to diffusion models, we note a key difference to the described framework. The output is not generated from a single forward pass, but rather a sequential process. To address this, we pose the $T$-horizon MDP formulation, adapted from [57], for the $T$-timesteps long denoising process.

$$\begin{aligned}
&\boldsymbol{s}_t = (\boldsymbol{x}_{T-t}, \boldsymbol{c}, t) \qquad P_0(s_0) = (\mathcal{N}(\boldsymbol{0}, \boldsymbol{I}), p(\boldsymbol{c}), \delta_0) \\
&\boldsymbol{a}_t = \boldsymbol{x}_{T-t-1} \qquad P(\boldsymbol{s}_{t+1} \mid \boldsymbol{s}_t, \boldsymbol{a}_t) = (\delta_{\boldsymbol{x}_{T-t-1}}, \delta_c, \delta_{t+1}) \\
&r(\boldsymbol{s}_t, \boldsymbol{a}_t) = r((\boldsymbol{x}_{T-t}, \boldsymbol{c}, t), \boldsymbol{x}_{T-t-1}) \\
&\pi(\boldsymbol{a}_t \mid s_t) = p_\theta(\boldsymbol{x}_{T-t-1} \mid \boldsymbol{x}_{T-t}, \boldsymbol{c}, t)
\end{aligned}$$

where $p_\theta(\boldsymbol{x}_{0:T}|\cdot)$ is a T2I diffusion model, $\delta$ is the Dirac delta distribution, and $\boldsymbol{c}$ is the conditioning distributed according to $p(\boldsymbol{c})$. Note that we disregard $r$ as our method circumvents it. With such, we treat the denoising process as a sequence of observations and actions: $\sigma = \{s_0, a_0, s_1, a_1, ..., s_{T-1}, a_{T-1}\}$. Since we can only judge the denoised output, we would need to update $\pi_\theta(\sigma) = \prod_t^T \pi_\theta(s_t, a_t)$, which is intractable. Following [67], we assume that if the final output of a sequence is preferred over that of another sequence, then any state-action pair of the winning sequence is preferred over that of the losing sequence. Hence, we determine the preferred sequence by sampling an initial state $s_0 = s_0^w = s_0^l$, generating two independent sequences, and ranking their output. Accordingly, we express the objective at a certain timestep as:

$$\mathcal{L}_t(\pi_\theta) = -\mathbb{E}_{(s_t,\sigma_w,\sigma_l)} \left[\log \rho \left(\beta \log \frac{\pi_\theta(a_t^w|s_t^w)}{\pi_{\text{ref}}(a_t^w|s_t^w)} - \beta \log \frac{\pi_\theta(a_t^l|s_t^l)}{\pi_{\text{ref}}(a_t^l|s_t^l)}\right)\right] \quad (7)$$

### 3.2. Multi-objective Joint Training

Now that we know how a preference ranking is converted into a loss that can train our diffusion model, we explain how we rank two generated sample based off their structural alignment with the input image, and their semantic alignment with the text and visual prompts. Our approach splits each objective into two separate scores.

**Structural score.** To obtain a score for how well the structure of the input image has been preserved, we leverage monocular depth estimation models [68]. Given a pair of input and edited images, we compute the depth map of each image independently, and define our structural score as the $L_1$ distance between the two resulting depth maps.

$$\mathcal{L}_{struct} = \frac{1}{h \cdot w} \sum_{i,j}^{h,w} |f_\phi(I_{og})_{i,j} - f_\phi(I_{gen})_{i,j}|$$

where $f_\phi$ is the depth model. With this metric, we capture any missing, additional or deformed elements in the edit compared to the input.

**Semantic score.** Contrary to the structural score, the semantic alignment should only be measured inside the region of the generated image where the edit is expected. Accordingly, we isolate the relevant regions with a text-conditioned segmentation model to locate the element to be edited. Here, we use grounded-SAM2 [32, 42, 43]. Same goes for the visual prompt, whose style may not be covering the entire frame. Subsequently, we determine the semantic alignment score by computing the distance between the embeddings of relevant patches in the generated and target style images. Additionally, we find that adding the standard pixel-space reconstruction objective on the instruction-irrelevant pixels, which should remain identical, enforces better localization and sharper bounds of the region of the image that must be edited. This serves as a regularizer to prevent the style from spreading over the whole generated frame to unrelated regions. Accordingly, our semantic score is:

$$\begin{aligned}\mathcal{L}_{sem} = & D(m_{og} \odot I_{og},\ m_{sty} \odot I_{sty},\ f_\theta) \\ & + \lambda \cdot (1 - m_{og}) \odot \|I_{og} - I_{gen}\|_2\end{aligned}$$

where $D(\cdot)$ is a distance metric, $m_{og}$ and $m_{sty}$ are the binary segmentation map obtained from the input and style images respectively, $\odot$ defines the element-wise multiplication, here the cosine distance, $f_\theta$ is an encoder, and $\lambda$ is a hyperparameter to weigh the influence of the pixel reconstruction objective relative to the semantic one. We find empirically that $\lambda = 0.05$ achieves the ideal balance.

Similar to [75], we obtain *advantages* [58] by normalizing the scores on a per-batch basis using the mean and variance of each training batch. We then combine the distinct advantages into a unique score, with their relative contribution weighed by a hyperparameter $\alpha$.

$$\mathcal{L}_{total} = \hat{A}_{struct} + \alpha \cdot \hat{A}_{sem} \text{ , where } \hat{A} = \frac{\mathcal{L} - \mu_{\mathcal{L}}}{\sqrt{\sigma_{\mathcal{L}}^2 + \epsilon}}$$

Finally, we rank two sequences according to the score of their respective output.

### 3.3. Architecture for Multiple Conditionings

Our architecture is based on that of InstructPix2Pix [11], itself is adapted from Stable Diffusion [44] with one main architecture modification. That is, they add input channels to the first convolutional layer to intake the encoded input image. We extend this and add more input channels to the first convolutional layer to intake both the input and style images. The weights that operate on the newly added input channels are initialized to zero, don't even need to explain? otherwise the generated output would be unrealistic and our supervising AI models would fail to provide any meaningful signal In practice, we find that applying a cross-attention layer before feeding the visual prompt improves performance, as it helps identify regions of both images relevant to the instruction. Here, the query is the linear projection of the concatenation of $\mathcal{E}(I_{og})$ and $\mathcal{E}(I_{sty})$, and the key and query are obtained by projecting the CLIP encoding of the instruction prompt.

Accordingly, we adapt the score estimate formulation as follows. Classifier-free guidance (CFG) [22] shifts probability mass where an implicit classifier assigns high likelihood to the conditioning, improving visual quality and faithfulness of samples. The standard CFG estimate is:

$$\tilde{e}_\theta(z_t, c) = e_\theta(z_t, \varnothing) + s \cdot (e_\theta(z_t, c) - e_\theta(z_t, \varnothing))$$

InstructPix2Pix adds a conditioning on the input image to be edited on top of the text instruction, further disentangling the score estimate yields:

$$\begin{aligned}\tilde{e}_\theta(z_t, c_I, c_T) = & \ e_\theta(z_t, \varnothing, \varnothing) \\ & + s_I \cdot (e_\theta(z_t, c_I, \varnothing) - e_\theta(z_t, \varnothing, \varnothing)) \\ & + s_T \cdot (e_\theta(z_t, c_I, c_T) - e_\theta(z_t, c_I, \varnothing))\end{aligned}$$

In our case, we find it beneficial to extend CFG with respect to the additional visual prompt, and use the following (see Appendix 6.1 for the complete derivation):

$$\begin{aligned}\tilde{e}_\theta(z_t, c_{I_{og}}, c_{I_{tgt}}, c_T) = & \ e_\theta(z_t, \varnothing, \varnothing, \varnothing) \\ & + s_{I_{og}} \cdot (e_\theta(z_t, c_{I_{og}}, \varnothing, \varnothing) - e_\theta(z_t, \varnothing, \varnothing, \varnothing)) \\ & + s_{I_{tgt}} \cdot (e_\theta(z_t, c_{I_{og}}, c_{I_{tgt}}, \varnothing) - e_\theta(z_t, c_{I_{og}}, \varnothing, \varnothing)) \\ & + s_T \cdot (e_\theta(z_t, c_{I_{og}}, c_{I_{tgt}}, c_T) - e_\theta(z_t, c_{I_{og}}, c_{I_{tgt}}, \varnothing))\end{aligned}$$

## 4. Experiments

Thiss ection rpesents the rexperimental results and ablation studies of our technical choices, demonstrating the effectiveness of our method. We apply the default guidance scale parameters ($s_{I_{og}}$ and $s_T$) from InstructPix2Pix for a fair comparison.

### 4.1. Complex Scene Editing

We first showcase the ability of our model to perform local edits in complex scenes. We choose autonomous vehicle road images from Oxford RobotCar dataset[33] as our initial images to be edited and train our model to edit the weather in these scenes. This combination captures the intricacies of image editing well. First, models trained in supervised learning methods are most likely to have biases, snow could be falling, rain could be falling, snow and rain might look a certain way, thickness, sparseness, color etc.

Table 1. Weather Edits Performance Comparison

| Method | Snow | Night | Rain |
|---|---|---|---|
| InstructPix2Pix | 0.4161 | 0.4591 | 0.4895 |
| MagicBrush | 0.4687 | 0.4707 | 0.4714 |
| Ours | **0.3577** | **0.3878** | **0.4570** |

We train over 20 steps (or hours, nb samples) with a batch size of 512.

We report quantitative results of our semantic alignment cosine distance, and comparison with InstructPix2Pix [11], and MagicBrush [71] on these weather domains. We argue that this is a better loss to evaluate image edits, as it exclusively considers the region of interest, rather than what other metrics do when they encode the entire image. We argue that disentangling the reported metrics between the pixels that should be edited and the ones that should not, better highlights the precision of the edit. For instance, EmuEdit and MagicBrush report the L1 and L2 scores for the whole image, stating that a lower score is better. This makes sense to quantify how well regions in the image that are unrelated to the instruction prompt have been preserved. However, it is counterintuitive to measure the quality of the pixels that are expected to have been edited with such metric, as a lower score would indicate a lower strength of editing. As in the presented method, we rely on grounded SAM2 to produce those masks. We find that it produces high quality masks that often surpass the contour precision of objects compared to human-made masks provided in public benchmarks [71].

Add depth of ip2p and Magicbrush, L1 & L2 inside mask (↑) and outside mask (↓) add hive?

### 4.2. Ablation Study

**Depth-Only Reward** we first evaluate cc, c,c ,c

**clip-prompt alignment -¿ biases don't mimick tgt** we first evaluate cc, c,c ,c

**clip-image all patches -¿ spreads over all image** we first evaluate cc, c,c ,c

**cfg score** we first evaluate cc, c,c ,c

**different encoders (dreamsim vs clip vs dino vs sam** we first evaluate cc, c,c ,c

### 4.3. Sim2Real Edits

We now showcase the ability for our model to produce edits that can be reused in a downstream model training. Robotics policies are known to be very brittle and perform poorly out-of-distribution. Further, due to the complexity of collecting real-world data in those robot learning tasks, many works use a simulation environment to collect large-scale data to pre-train their robot policy [29]. Still, the gap between the simulation domain and real domain is generally large. Hence, models often require a layer of finetuning on real-world data to perform correctly, which still requires costly and lengthy data collection in real-world. Here, we aim to train our diffusion model to perform image editing to modify said simulation images into samples closely resemble the real-world domain. This requires only a *few images* from the real world to serve as target style conditioning for the editing process, rather than *tens of thousands*. We select a robot manipulation task referred to as Push-T, first introduced in [14], where a T-shaped block is placed randomly on a surface and a autonomous arm must push it to align its pose with that of a target, drawn somewhere else on that same surface.

## 5. Conclusion

in this section, i tell you that my results are great and that my method is unique because it has not been done before

While our method demonstrates impressive performance, we have also identified limitations inherent to its training method. Types of edits are limited to local ones, where a clear segmentation can be drawn around the shape of the region to be edited. Further, the edits are limited to ones that do not modify the global shape of the element to be modified, but rather modify its texture or surface. Some interesting future work could include adding some more flexible bounds in the masking and depth alignment operations (by ignoring the top quantile for depth, or voluntarily enlarging the segmentation mask for semantics) to allow for edits that involve adding, removing, or modifying the shape of objects a bit. another limitation is that the semantic alignment is dependent on what the encoder can capture. Also, the method relies on the zero-shot performance of the base model. Hence, the biases of such encoder and diffusion model might be infused in the final outputs. Nevertheless, these limitations can be addressed by substituting the encoder or generative prior with suitable alternatives in a plug-and-play fashion.

## 6. Appendix

### 6.1. Derivation for Classifier-free Guidance with Three Conditionings

We introduce separate guidance scales like ip2p to enable separately trading off the strength of each conditioning. The modified score estimate for our model is derived as follows. Our generative model learns $P(z|c_T,\ c_{I_{tgt}},\ c_{I_{og}})$, which corresponds to the probability distribution of the image latents $z = \mathcal{E}(x)$ conditioned on an input original image $c_{I_{og}}$, a target style image $c_{I_{tgt}}$, and a text instruction $c_T$. We arrive at our particular classifier-free guidance formulation by expressing the conditional probability as follows:

$$\begin{aligned} P(z|c_T,\ c_{I_{tgt}},\ c_{I_{og}}) &= \frac{P(z, c_T,\ c_{I_{tgt}},\ c_{I_{og}})}{P(c_T,\ c_{I_{tgt}},\ c_{I_{og}})} \\ &= \frac{P(c_T|c_{I_{tgt}}, c_{I_{og}}, z)P(c_{I_{tgt}}|c_{I_{og}}, z)P(c_{I_{og}}|z)P(z)}{P(c_T,\ c_{I_{tgt}},\ c_{I_{og}})} \end{aligned} \tag{8}$$

Diffusion models estimate the score [24] of the data distribution, i.e. the derivative of the log probability. Taking the logarithm of the expression above yields the following:

$$\begin{aligned} \log(P(z|c_T,\ c_{I_{tgt}},\ c_{I_{og}})) =\ & \log(P(c_T|c_{I_{tgt}}, c_{I_{og}}, z)) \\ & + \log(P(c_{I_{tgt}}|c_{I_{og}}, z)) \\ & + \log(P(c_{I_{og}}|z)) \\ & + \log(P(z)) \\ & - \log(P(c_T,\ c_{I_{tgt}},\ c_{I_{og}})) \end{aligned} \tag{9}$$

Taking the derivative and rearranging, we obtain:

$$\begin{aligned} \nabla_z \log(P(z|c_T,\ c_{I_{tgt}},\ c_{I_{og}})) =\ & \nabla_z \log(P(z)) \\ & + \nabla z \log(P(c_{I_{og}}|z)) \\ & + \nabla z \log(P(c_{I_{tgt}}|c_{I_{og}}, z)) \\ & + \nabla_z \log(P(c_T|c_{I_{tgt}}, c_{I_{og}}, z)) \end{aligned} \tag{10}$$

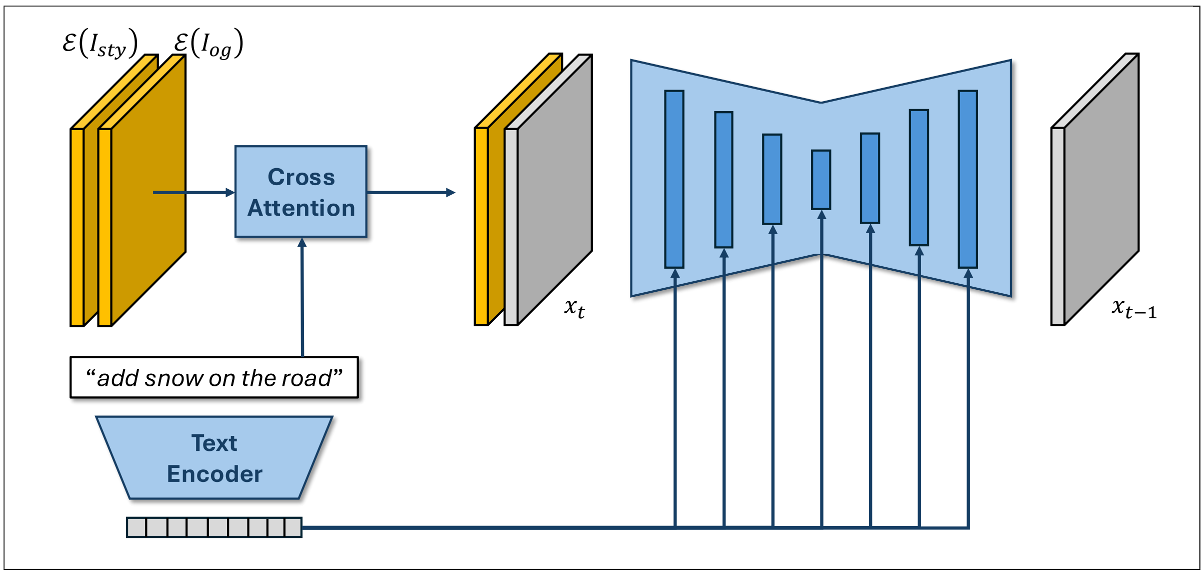


Figure 3. This is my architecture figure.

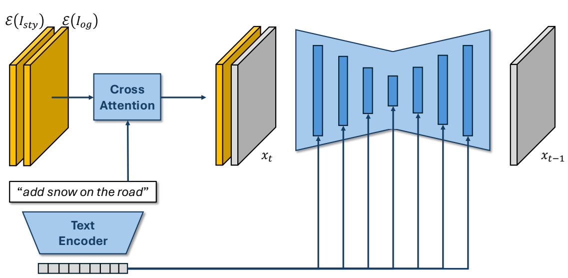


Figure 4. This is my architecture figure.

## Abstract

*THIS IS THE ABSTRACT*

## 7. Introduction

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### 7.1. subsection 1

All manuscripts must be in English.

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coding style: `cvpr.sty` *e.g.*

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### 7.4. Mathematics

Please number all of your sections and displayed equations as in these examples:

$$E = m \cdot c^2 \tag{11}$$

and

$$v = a \cdot t. \tag{12}$$

### 7.5. Blind review

this sentence starts with no indent FAQ

**Q:** list of stuff
**A:** list with line skip

**Q:** dfa

a figure is like this; When placing figures in LaTeX, it's almost always best to use `\includegraphics`, and to specify the figure width as a multiple of the line width as in the example below

```
\usepackage{graphicx} ...
\includegraphics[width=0.8\linewidth]
                   {myfile.pdf}
```

Figure 5. Example of caption. It is set in Roman so that mathematics (always set in Roman: $B \sin A = A \sin B$) may be included without an ugly clash.

| Method | Frobnability |
|---|---|
| Theirs | Frumpy |
| Yours | Frobbly |
| Ours | Makes one's heart Frob |

Table 2. Results. Ours is better.

## 8. Formatting your paper

a footnote looks like this[1].

referencing is like this: To see how our method outperforms previous work, please see Fig. 5 and Tab. 2.It is also possible to refer to multiple targets as once, *e.g.* to Fig. 5 and **??**. You may also return to Sec. 8 or look at Eq. (12).

a centered table is like this

## 9. Experiments

this is where i discuss experiments

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