A. Evaluating Additional Editing Technique

Most of the presented results consist of applying our method with the editing technique of Prompt-to-Prompt [4]. However, we demonstrate that our method is not confined to a specific editing approach, by showing it improves the results of the SDEdit [7] editing technique.

In Fig. 1 (top), we measure the fidelity to the original image using LPIPS perceptual distance [13] (lower is better), and the fidelity to the target text using CLIP similarity [8] (higher is better) over 100 examples. We use different values of the SDEdit parameter $t_0$ (marked on the curve), i.e., we start the diffusion process from different $t = t_0 \cdot T$ using a correspondingly noised input image. This parameter controls the trade-off between fidelity to the input image (low $t_0$) and alignment to the text (high $t_0$). We compare the standard SDEdit to first applying our inversion and then performing SDEdit while replacing the null-text embedding with our optimized embeddings. As shown, our inversion significantly improves the fidelity to the input image.

This is visually demonstrated in Fig. 1 (bottom). Since the parameter $t_0$ controls a reconstruction-editability trade-off, we have used a different parameter for each method (SDEdit with and without our inversion) such that both achieve the same CLIP score. As can be seen, when using our method, the true identity of the baby is well preserved.

B. Limitations

While our method works well in most scenarios, it still faces some limitations. The most notable one is inference time. Our approach requires approximately one minute on GPU for inverting a single image. Then, infinite editing operations can be made, each takes only ten seconds. This is not enough for real-time applications. Other limitations come from using Stable Diffusion [9] and Prompt-to-Prompt editing [4]. First, the VQ auto-encoder produces artifacts in some cases, especially when human faces are involved. We consider the optimization of the VQ decoder as out of scope here, since this is specific to Stable Diffusion and we aim for a general framework. Second, we observe that the generated attentions maps of Stable Diffusion are less accurate compared to the attention maps of Imagen [10], i.e., words might not relate to the correct region, indicating inferior text-based editing capabilities. Lastly, complicated structure modifications are out of reach for Prompt-to-Prompt, such as changing a seating dog to a standing one as in [6]. Our inversion approach is orthogonal to the specific model and editing techniques, and we believe that these will be improved in the near future.
C. Societal Impact

Our work suggests a new editing technique for manipulating real images using state-of-the-art text-to-image diffusion models. This modification of real photos might be exploited by malicious parties to produce fake content in order to spread disinformation. This is a known problem, common to all image editing techniques. However, research in identifying and preventing malicious editing is already making significant progress. We believe our work would contribute to this line of work, since we provide an analysis of the inversion and editing procedures using text-to-image diffusion models.

D. Ablation Study

Additional visual results for our ablation study are presented in Fig. 5 and 6, showing our method converges to high-quality reconstruction more efficiently. We now turn to provide additional results for specific experiments.

Robustness to different input captions. In Fig. 7 (top) we demonstrate our robustness to different input captions by successfully inverting an image using multiple captions. Yet, the edited parts should be included in the source caption in order to produce semantic attention maps for these (Fig. 7 bottom). For example, to edit the print on the shirt, the source caption should include a "shirt with a drawing" term or a similar one.

DDIM Inversion. To validate our selection of the guidance scale parameter of \( w = 1 \) during the DDIM Inversion (see Algorithm 1, line 3, in the main text), we conduct the DDIM inversion with different values of \( w \) from 1 to 8 using the same data as in Section 4. For each inversion, we measure the log-likelihood of the result latent image \( z_T^w \in \mathbb{R}^{64 \times 64 \times 4} \) under the standard multivariate normal distribution. Intuitively, to achieve high edibility we would like to maximize this term since during training \( z_T^w \) distributes normally. The mean log-likelihood as a function of \( w \) is plotted in Fig. 2a. In addition, we measure the reconstruction with respect to the ground truth input image using the PSNR metric. As can be seen in Fig. 2b, increasing the value of \( w \) results in less editable latent vector \( z_T^w \) and poorer initial reconstruction for our optimization, and therefore we use \( w = 1 \).

Textual inversion with a pivot. We consider performing textual inversion around a pivot, i.e., similar to our pivotal inversion but optimizing the conditioned embedding. This results in a comparable reconstruction to ours, as demonstrated in Fig. 8 (bottom), but with poor editability. We analyze the attention maps (Fig. 8, top), observing that these are less accurate than ours. For example, using our NULL-text optimization, the attention referring to "goats" is much more local, and attention referring to "desert" is more accurate. Consequently, editing the "desert" results in artifacts over the goats (Fig. 8, bottom).

NULL-text optimization without pivotal inversion. Optimizing the null-text embedding fails without the efficient pivotal inversion. This is demonstrated in Fig. 5 and 6, where the non-pivotal NULL-text optimization produces low-quality reconstruction (2nd row).

E. Additional results

Additional editing results of our method are provided in Fig. 3 and additional comparisons are provided in Fig. 9.

Inference time comparison. As can be seen in Tab. 1, SDEdit is the fastest since an inversion is not employed, but as a result, it fails to preserve the details of the original image. Our method is more efficient than Text2Live [1]. VQ-
GAN+CLIP [3] and Imagic [6], as it provides an accurate reconstruction in $\sim 1$ minute, while also allowing multiple editing operations after a single inversion.

| Input   | red velvet couch | leather couch | unicorn couch |
|---------|------------------|---------------|--------------|
| Input   | giraffe $\rightarrow$ goat | giraffe $\rightarrow$ robot | bucket $\rightarrow$ basket |
| Input   | fish cake | avocado cake | Lego cake |
| Input   | apples $\rightarrow$ puppies | apples $\rightarrow$ cookies | cardboard basket |
| Input   | street $\rightarrow$ beach | snowy street | street $\rightarrow$ forest |
| Input   | branch $\rightarrow$ rainbow | Lego birds | origami birds |

Figure 3. Additional real image editing results for our method.

Comparison to Imagic Quantitative comparison to Imagic is presented in Fig. 4, using the unofficial Stable Diffusion implementation. According to these measures, our method achieves better preservation of the original de-
tails (lower LPIPS). This is also supported by the visual results in Fig. 11, as Imagic struggles to accurately retain the background. Furthermore, we observe that Imagic is quite sensitive to the interpolation parameter $\alpha$, as a high value reduces the fidelity to the image and a low value reduces the fidelity to the text guidance, while a single value cannot be applied to all examples. Moreover, the authors of Imagic apply their method on the same three images, presented in Fig. 11, using the parameters $\alpha = 0.93, 0.86, 1.08$. This results in much better quality, however, still the background is not preserved, the model is sensitive to $\alpha$, and fine-tuning per editing operation is required.

F. Implementation details

In all of our experiments, we employ the Stable Diffusion [9] using a DDIM sampler with the default hyperparameters: number of diffusion steps $T = 50$ and guidance scale $w = 7.5$. Stable diffusion utilizes a pre-trained CLIP network as the language model $\psi$. The null-text is tokenized into start-token, end-token, and 75 non-text padding tokens. Notice that the padding tokens are also used in CLIP and the diffusion model since both models do not use masking.

All inversion results except the ones in the ablation study were obtained using $N = 10$ (See Algorithm 1 in the main paper) and a learning rate of 0.01. We have used an early stop parameter of $\epsilon = 1e - 5$ such that the total inversion for an input image and caption took $40s - 120s$ on a single A100 GPU. Namely, for each timestamp $t$, we stop the optimization when the loss function value reaches $\epsilon = 1e - 5$.

Baseline Implementations. For the comparisons in section 5, we use the official implementation of Text2Live* [1]

*https://github.com/omerbt/Text2LIVE
and VQGAN+CLIP. We have implemented the SDEdit method over Stable Diffusion based on the official implementation. We also compare our method to Imagic using an unofficial implementation (see Appendix E).

**Global Null-text Inversion.** The algorithm for optimizing only a single Null-text embedding $\varnothing$ for all timestamps is presented in algorithm 2. In this case, since the optimization of $\varnothing$ in a single timestamp affects all other timestamps, we change the order of the iterations in Algorithm 1. That is, we perform $N$ iterations in each we optimize $\varnothing$ for all the diffusion timestamps by iterating over $t$. As shown in Section 4, the convergence of this optimization is much slower than our final method. More specifically, we found that only after 7500 optimization steps (about 30 minutes) the global null-text inversion accurately reconstruct the input image.

**Algorithm 2:** Global NULL-text inversion

1. **Input:** A source prompt $P$ and input image $I$.
2. **Output:** Noise vector $z_T$ and an optimized embedding $\varnothing$.
3. Set guidance scale $w = 1$;
4. Compute the intermediate results $z_T, \ldots, z_0$ of DDIM inversion for image $I$;
5. Set guidance scale $w = 7.5$;
6. Initialize $\varnothing \leftarrow \psi(w)$;
7. for $j = 0, \ldots, N - 1$ do
8. Set $\varnothing_T \leftarrow \varnothing_T^+$;
9. for $t = T, T - 1, \ldots, 1$ do
10. Set $\varnothing_T \leftarrow \varnothing_T^+$;
11. $\varnothing \leftarrow \varnothing - \eta \nabla_{\varnothing} \|z_{T-1} - z_{t-1}(\varnothing, \varnothing, C)\|_2^2$;
12. $z_{t-1} \leftarrow z_{t-1}(\varnothing, \varnothing, C)$;
13. end
14. end
15. Return $\varnothing_T, \varnothing$

**G. Additional Background - Diffusion Models**

Diffusion Denoising Probabilistic Models (DDPM) [5, 11] are generative latent variable models that aim to model a distribution $p_0(x_0)$ that approximates the data distribution $q(x_0)$ and easy to sample from. DDPMs model a “forward process” in the space of $x_0$ from data to noise. This is called “forward” due to its procedure progressing from $x_0$ to $x_T$. Note that this process is a Markov chain starting from $x_0$, where we gradually add noise to the data to generate the latent variables $x_1, \ldots, x_T$ in $X$. The sequence of latent variables, therefore, follows $q(x_1, \ldots, x_T \mid x_0) = \prod_{t=1}^{T} q(x_t \mid x_{t-1})$, where a step in the forward process is defined as a Gaussian transition $q(x_t \mid x_{t-1}) := N(x_t; \sqrt{1 - \beta_t} x_{t-1}, \beta_t I)$ parameterized by a schedule $\beta_0, \ldots, \beta_T \in (0, 1)$. When $T$ is large enough, the last noise vector $x_T$ nearly follows an isotropic Gaussian distribution.

An interesting property of the forward process is that one can express the latent variable $x_t$ directly as the following linear combination of noise and $x_0$ without sampling intermediate latent vectors:

$$x_t = \sqrt{\alpha_t} x_0 + \sqrt{1 - \alpha_t} w, \quad w \sim N(0, I),$$

where $\alpha_t := \prod_{k=1}^{t} (1 - \beta_k)$.

To sample from the distribution $q(x_0)$, we define the dual “reverse process” $p(x_{t-1} \mid x_t)$ from isotropic Gaussian noise $x_T$ to data by sampling the posteriors $q(x_{t-1} \mid x_t)$. Since the intractable reverse process $q(x_{t-1} \mid x_t)$ depends on the unknown data distribution $q(x_0)$, we approximate it with a parameterized Gaussian transition network $p_\theta(x_{t-1} \mid x_t) := N(x_{t-1} \mid \mu_\theta(x_t, t), \Sigma_\theta(x_t, t))$. The $\mu_\theta(x_t, t)$ can be replaced [5] by predicting the noise $\varepsilon_\theta(x_t, t)$ added to $x_0$ using equation 1.

Under this definition, we use Bayes’ theorem to approximate

$$\mu_\theta(x_t, t) = \frac{1}{\sqrt{\alpha_t}} \left(x_t - \frac{\beta_t}{\sqrt{1 - \alpha_t}} \varepsilon_\theta(x_t, t)\right).$$

Once we have a trained $\varepsilon_\theta(x_t, t)$, we can using the following sample method

$$x_{t-1} = \mu_\theta(x_t, t) + \sigma_t z, \quad z \sim N(0, I).$$

We can control $\sigma_t$ of each sample stage, and in DDIMs [12] the sampling process can be made deterministic using $\sigma_t = 0$ in all the steps. The reverse process can finally be trained by solving the following optimization problem:

$$\min_\theta L(\theta) := \min_\theta \mathbb{E}_{x_0 \sim q(x_0), w \sim N(0, I), t} \|w - \varepsilon_\theta(x_t, t)\|_2^2,$$

teaching the parameters $\theta$ to fit $q(x_0)$ by maximizing a variational lower bound.

**H. User-Study**

An illustration of our user study is provided in Fig. 12

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Input caption: “A black dinning room table sitting in a yellow dinning room.”

Figure 5. Ablation study. We show the inversion results for an increasing number of optimization iterations. Our method achieves high-quality reconstruction with fewer optimization steps.
**Input caption:** “Two people riding elephants in dirty deep water.”

![Input image DDIM inversion VQAE](image)

**Figure 6.** Ablation study. We show the inversion results for an increasing number of optimization iterations. Our method achieves high-quality reconstruction with fewer optimization steps.
Figure 7. **Robustness to the input caption.** We can invert an input image (top) using different input captions (first column). Naturally, the selection of the caption affects the editing abilities with Prompt-to-Prompt, as can be seen in the visualization of the cross-attention map (bottom). Yet, our method is not particularly sensitive to the exact wording of the prompt.
Figure 8. **Ablation study - Textual inversion with a pivot.** We compare our method to replacing the text-NULL optimization with optimizing the conditional (textual) embedding while still applying pivotal inversion. As can be seen (top), this results in less accurate attention maps, and thus, in less accurate editing capabilities. In particular, textual inversion with a pivot achieves high-fidelity reconstruction ("Inversion (T+P)"), but goat heads distort (bottom) when editing is applied due to the inaccurate attention maps.
| Input | Our Inversion | Text2LIVE | VQGAN+CLIP | SDEdit | Our Editing |
|-------|---------------|-----------|------------|--------|-------------|
| ![Input](image1) | ![Our Inversion](image2) | ![Text2LIVE](image3) | ![VQGAN+CLIP](image4) | ![SDEdit](image5) | ![Our Editing](image6) |
| **"A girl dog sitting on the grass and holding a ball"** |
| ![Input](image7) | ![Our Inversion](image8) | ![Text2LIVE](image9) | ![VQGAN+CLIP](image10) | ![SDEdit](image11) | ![Our Editing](image12) |
| **"A blue bicycle is parking on the side of the street"** |
| ![Input](image13) | ![Our Inversion](image14) | ![Text2LIVE](image15) | ![VQGAN+CLIP](image16) | ![SDEdit](image17) | ![Our Editing](image18) |
| **"A child monkey is climbing on a tree"** |
| ![Input](image19) | ![Our Inversion](image20) | ![Text2LIVE](image21) | ![VQGAN+CLIP](image22) | ![SDEdit](image23) | ![Our Editing](image24) |
| **"A Landscape of Snowy mountains"** |
| ![Input](image25) | ![Our Inversion](image26) | ![Text2LIVE](image27) | ![VQGAN+CLIP](image28) | ![SDEdit](image29) | ![Our Editing](image30) |
| **"A Landscape of mountains Tuscany"** |

Figure 9. Additional comparison results. See also Fig. 10
| Input                                                                 | Our Inversion | Text2LIVE      | VQGAN+CLIP     | SDEdit | Our Editing |
|----------------------------------------------------------------------|---------------|----------------|----------------|--------|-------------|
| ![Input](image1)                                                     | ![Our Inversion](image2) | ![Text2LIVE](image3) | ![VQGAN+CLIP](image4) | ![SDEdit](image5) | ![Our Editing](image6) |
| "a bridge over a **frozen** waterfall"                               |               |                |                |        |             |
| ![Input](image7)                                                     | ![Our Inversion](image8) | ![Text2LIVE](image9) | ![VQGAN+CLIP](image10) | ![SDEdit](image11) | ![Our Editing](image12) |
| "A **golden** bridge over a waterfall"                               |               |                |                |        |             |
| ![Input](image13)                                                   | ![Our Inversion](image14) | ![Text2LIVE](image15) | ![VQGAN+CLIP](image16) | ![SDEdit](image17) | ![Our Editing](image18) |
| "A **spinach moss** cake on a table"                                 |               |                |                |        |             |
| ![Input](image19)                                                   | ![Our Inversion](image20) | ![Text2LIVE](image21) | ![VQGAN+CLIP](image22) | ![SDEdit](image23) | ![Our Editing](image24) |
| "A **birthday** cake on a table"                                     |               |                |                |        |             |

Figure 10. **Additional comparison results.**
Figure 11. **Comparison to Imagic** [6]. We first employ the unofficial Imagic implementation for Stable Diffusion and present the results for different values of the interpolation parameter $\alpha = 0.6, 0.7, 0.8, 0.9$ (left to right). This parameter is used to interpolate between the target text embedding and the optimized one [6], where a larger value of $\alpha$ increases the fidelity to the target text. In addition, the Imagic authors apply their method using the Imagen model over the same images, using the following parameters $\alpha = 0.93, 0.86, 1.08$ (from top to bottom row). As can be seen, Imagic produces highly meaningful editing, especially when the Imagen model is involved. However, Imagic struggles to preserve the original details, such as the identity of the baby (1st row) or cups in the background (2nd row). Furthermore, we observe that each example requires a separate tuning of the $\alpha$ parameter. Lastly, recall that each Imagic editing requires a separate tuning of the model.
Which image below better applies the requested edit to the input image on top, while preserving most of the details from the input image?

![Input Image](image)

**Edit instruction:** couch $\rightarrow$ unicorn pattern couch

- Image 1
- Image 2
- Image 3
- Image 4

Figure 12. User study print screen.