Consolidating Attention Features for Multi-view Image Editing

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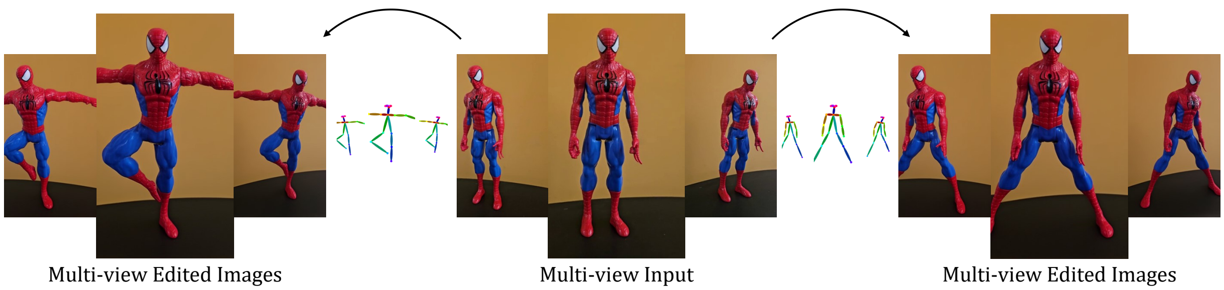

Fig. 1. Given an object-centric multi-view image set (center), we edit all images simultaneously (left and right), using 3D geometric control, such as changing the body skeleton. To promote consistency across different views, we leverage an image diffusion model and introduce QNeRF, a query feature space neural radiance field, to progressively consolidate attention features during the generation process.

Large-scale text-to-image models enable a wide range of image editing techniques, using text prompts or even spatial controls. However, applying these editing methods to multi-view images depicting a single scene leads to 3D-inconsistent results. In this work, we focus on spatial control-based geometric manipulations and introduce a method to consolidate the editing process across various views. We build on two insights: (1) maintaining consistent features throughout the generative process helps attain consistency in multi-view editing, and (2) the queries in self-attention layers significantly influence the image structure. Hence, we propose to improve the geometric consistency of the edited images by enforcing the consistency of the queries. To do so, we introduce QNeRF, a neural radiance field trained on the internal query features of the edited images. Once trained, QNeRF can render 3D-consistent queries, which are then softly injected back into the self-attention layers during generation, greatly improving multi-view consistency. We refine the process through a progressive, iterative method that better consolidates queries across the diffusion timesteps. We compare our method to a range of existing techniques and demonstrate that it can achieve better multi-view consistency and higher fidelity to the input scene. These advantages allow us to train NeRFs with fewer visual artifacts, that are better aligned with the target geometry.

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1 INTRODUCTION

The advent of large-scale text-to-image models has led to rapid advancements in image editing techniques. Commonly, such techniques are used to modify a *single* image by leveraging the rich visual and semantic prior found in a pre-trained text-to-image diffusion model. However, when considering *sets* of images depicting a shared scene, naïve applications of such methods lead to inconsistent edits across the set (see Figure 3).

In the realm of multi-view editing, where the image set depicts a single object observed from multiple directions, a recent line of work proposes to leverage the inherent consistency of 3D representations as a means to consolidate the edits into a more 3D-consistent set [Haque et al. 2023]. In practice, existing methods assume that the edits performed are small enough that the underlying 3D representation can successfully average over inconsistent changes. This assumption holds well for simpler texture or appearance changes,

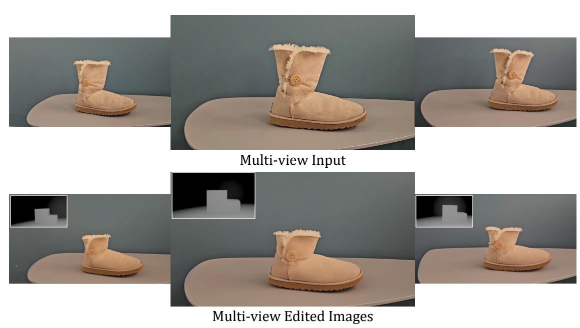

Fig. 2. Editing multi-view images of a boot, with a loose depth map [Bhat et al. 2023]. We show a sample of three images from the set.

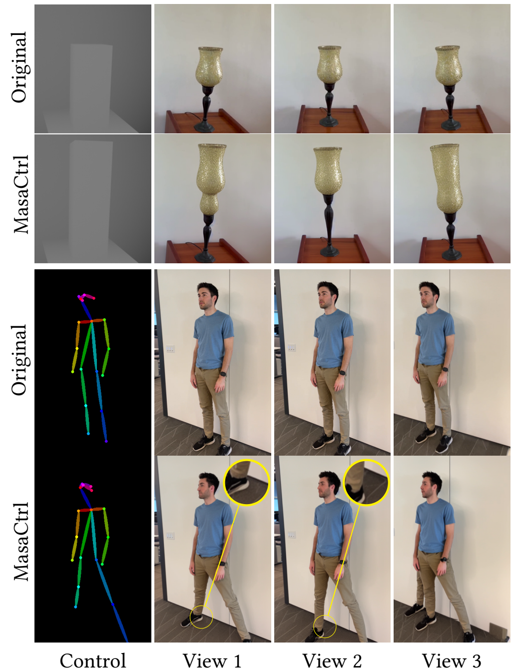

Fig. 3. The first and third rows show images captured from different viewpoints. When these are individually edited using ControlNet and MasaCtrl, inconsistencies arise. Note the shape of the lamp (top) or the distance of the foot from the wall (bottom). Images were edited using 2D controls projected from a shared 3D model (skeleton, box). The leftmost column shows controls corresponding to view 1.

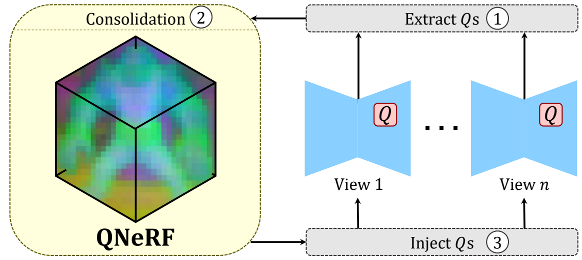

Fig. 4. We simultaneously generate multi-view edited images with a diffusion model. To consolidate the images, along the denoising process we (1) extract self-attention queries from the network, (2) train a NeRF (termed QNeRF) on the extracted queries and render consolidated queries, and (3) softly inject the rendered queries back to the network for each view. We repeat these steps throughout the denoising process.

but not for more complex geometric changes. As such, these methods can turn a person's portrait into a painting, but they struggle to make him raise his hands.

In this work, we present an approach for consistent multi-view image editing, focusing on articulations and shape changes, as shown in Figures 1 and 2. An important point to consider is the close relation between multi-view image editing and 3D editing. Multi-view edited images can be used to deduce a 3D edited model, and conversely, from a 3D edited model, corresponding edited views can be rendered. Similar to previous works [Chan et al. 2023; Höllein et al. 2024], we opt to present our method as multi-view image editing, since our editing method directly operates on images using a 2D generative model, without explicitly reconstructing the 3D scene.

We use ControlNet [Zhang et al. 2023], which was trained to take rough spatial controls (*e.g.*, body skeletons or loose depth maps [Bhat et al. 2023]) as an input, and synthesize images aligned with them. Conditioning the generation of the images on these rough controls provides the model with a preliminary understanding of the edited image's coarse geometry. However, relying solely on this coarse geometry signal falls short of attaining high consistency among the edited images.

Our key idea is to encourage the features of ControlNet to be consistent during the generation of the multi-view edited images. As shown by recent works [Geyer et al. 2023], increasing the consistency of internal features can help improve the consistency of edited frames in video generation. In particular, we observe that the queries of the self-attention layers within the diffusion model significantly influence the structure of the output image. Hence, we propose consolidating the queries of all generated images into a 3D-consistent shared representation, by training a neural field in query feature space, which we term QNeRF. We then use the queries rendered from the QNeRF to guide the generation of the edited images, increasing the consistency of the edited multi-view images. The process of training the QNeRF and using the rendered queries is a progressive process interleaved during the denoising process. As illustrated in Figure 4, the updated QNeRF is trained with the extracted queries, and the rendered queries guide the features of the generated images within the diffusion network.

We demonstrate that our approach enables a wide range of articulation and shape-based modifications, while achieving greater visual quality than alternative consistency-preserving approaches. These results are validated through qualitative evaluations, as well as automated metrics and user preference scores. Finally, we demonstrate that the underlying geometry of NeRFs trained on our results exhibits better alignment with the target controls.

2 RELATED WORK

Image Editing with Diffusion Models. Advancements in large-scale diffusion models have significantly enhanced image editing techniques [Brack et al. 2023; Brooks et al. 2022; Huberman-Spiegelglas et al. 2023; Kawar et al. 2023; Meng et al. 2022]. Specifically, the manipulation of internal representations within the diffusion model during the denoising process has been shown to enable high-quality and semantic edits [Epstein et al. 2023; Ge et al. 2023; Geyer et al. 2023; Hertz et al. 2022; Parmar et al. 2023; Patashnik et al. 2023; Tumanyan et al. 2023]. Notably, some recent works focus on self-attention layers, and leverage the roles of queries, keys, and values within self-attention to obtain various edits [Alaluf et al. 2023; Cao et al. 2023; Hertz et al. 2023b]. While the above works focus on editing a *single* image, we build on the functionality of self-attention components to achieve consistent multi-view image editing.

Neural Field Editing. With the rapid advancement in implicit 3D representations [Kerbl et al. 2023; Mildenhall et al. 2020], various methods for editing these representations have been developed [Haque et al. 2023; Liu et al. 2021; Yang et al. 2021; Yuan et al.

2022]. Some approaches focus on altering the appearance of NeRFs by stylizing them [Fan et al. 2022; Haque et al. 2023; Huang et al. 2022; Lee and Kim 2023; Nguyen-Phuoc et al. 2022; Wang et al. 2022; Zhang et al. 2022] or changing the colors of specific objects within the scene [Kobayashi et al. 2022; Wang et al. 2021a]. Other methods move objects within the scene [Yang et al. 2021], or entirely remove them [Kobayashi et al. 2022]. Most related to our work are methods that deform the geometry of a given NeRF [Bao and Yang et al. 2022; Chen et al. 2023b; Peng et al. 2022; Xu and Harada 2022; Yuan et al. 2022, 2023]. These methods typically extract an explicit 3D representation (*e.g.*, mesh) from the NeRF [Bao and Yang et al. 2022], edit it with classical geometric processing techniques, and then deform the NeRF accordingly. While these methods provide fast means for 3D deformation, they may struggle with complex scenes that include backgrounds. Furthermore, as they do not employ a generative prior, they cannot hallucinate new details or modify existing ones.

Leveraging 2D Prior for NeRF Synthesis and Editing. The rich prior embedded in large-scale image diffusion models, has prompted efforts to distill it for synthesizing and editing NeRFs [Haque et al. 2023; Liu et al. 2023; Poole et al. 2022]. Poole *et al.* [2022] introduced the SDS loss, to generate a NeRF with the guidance of a text-to-image model. This technique has been extensively developed [Katzir et al. 2024; Lin et al. 2023; Wang et al. 2023; Zhu and Zhuang 2023], applied to multiple settings [Chen et al. 2023a; Lin et al. 2023; Liu et al. 2023; Metzer et al. 2022; Shi et al. 2024; Wang and Shi 2023], and has also been adopted for editing purposes [Hertz et al. 2023a; Koo et al. 2023; Park et al. 2024; Zhuang et al. 2024, 2023]. Another approach leverages the 2D prior of text-to-image models for NeRF editing through iterative updates of the dataset used to train some initial NeRF [Haque et al. 2023]. This method, first proposed in Instruct-NeRF2NeRF, has been widely adopted in follow-up works [Khalid et al. 2023; Kim et al. 2023; Shum et al. 2023; Song et al. 2023; Weber et al. 2023]. Instead of editing a given dataset, a recent work [Wu et al. 2023] reconstructs a scene from a few images by generating 3D-consistent fake views. A common theme in such works, is the use of an underlying 3D representation (*i.e.*, the NeRF) as a means to consolidate the inconsistently-generated images across the different views. Our work also employs a NeRF to consolidate images edited from different views. However, we focus on geometric manipulations which pose a distinct challenge. There, iterative dataset updates can lead to considerable artifacts because the underlying geometry is no longer consistent across the set's frames. Instead, we consolidate geometries by training NeRFs on self-attention query features, and then inject the consolidated features into the model throughout the denoising process.

Multi-view Image Synthesis ad Editing. Rather than generating or optimizing a 3D representation, some works opt to directly generate sets of multi-view images [Chan et al. 2021a, 2023; Höllein et al. 2024; Kulhánek et al. 2022; Nguyen-Phuoc et al. 2019; Or-El et al. 2022; Tseng et al. 2023; Watson et al. 2022]. Commonly, such methods employ additional conditions to provide a signal about the 3D world, *i.e.*, per-view camera parameters. Often, they further employ a 3D representation within the model's feature space to ensure consistency across different views. Our work is similar to these works, in that we directly edit a set of multi-view images by leveraging an internal 3D representation, rather than creating a 3D model. For applications requiring a 3D representation (*e.g.*, fabrication), one can then construct a 3D model (*e.g.*, NeRF) from the multi-view images.

Feature NeRFs. Previous works showed that NeRFs can represent not only RGB images but also semantic latent features. Some works [Kerr et al. 2023; Kobayashi et al. 2022; Tschernezki et al. 2022] distill semantic 2D features into NeRFs, allowing one to obtain semantic 3D information. Other works [Chan et al. 2021b; Niemeyer and Geiger 2021] show that features rendered from NeRFs can be employed for consistent multi-view image generation. In this work, we distill the attention features of a diffusion model into a NeRF and use rendered features during the denoising process to achieve multi-view editing.

3 PRELIMINARIES

Self-Attention in Diffusion Models. Recent diffusion models are typically implemented as a UNet [Ronneberger et al. 2015] consisting of cross-attention, self-attention, and convolutional layers. Previous works studied the roles of these components, focusing on attention layers. In our work, we focus on the queries, keys, and values of *self-attention* layers. Specifically, it has been shown that each query in self-attention layers determines the semantic meaning of the pixel that corresponds to it [Alaluf et al. 2023; Cao et al. 2023]. Hence, the queries are associated with the structure of the generated image. Moreover, the keys and values of self-attention layers determine the appearance of the image, and by using the keys and values of one image in the denoising process of another image, the appearance is transferred [Alaluf et al. 2023]. In particular, in MasaCtrl [Cao et al. 2023], non-rigid edits are applied to an image. To preserve the appearance of the original image, they inject keys and values of self-attention layers from the original image into the generated one. In our method, we employ this technique to preserve the appearance of the original scene.

Neural Radiance Fields. Neural Radiance Field (NeRF) is an implicit 3D representation, parameterized by a network. Given a spatial location $\mathbf{x}$ and a viewing direction $\mathbf{d}$, the network outputs the density $\sigma(\mathbf{x})$ and the RGB value of that location $c(\mathbf{x}, \mathbf{d})$. These can then be used to render an image from a desired viewing direction, using classical volume rendering techniques [Max 1995; Mildenhall et al. 2020]. Specifically, given a camera ray $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}$, the expected color $C(\mathbf{r})$ is given by

$$C(\mathbf{r}) = \int_{t_n}^{t_f} T(t)\sigma(\mathbf{r}(t))c(\mathbf{r}(t), \mathbf{d})dt, \quad (1)$$

where

$$T(t) = \exp\left(-\int_{t_n}^{t} \sigma(\mathbf{r}(s))ds\right). \quad (2)$$

In this work, we train a NeRF on latent representations rather than on RGB values. Following previous works [Kerr et al. 2023; Kobayashi et al. 2022], we use the same volumetric rendering approach to render latent representations.

4 METHOD

Our method operates on a set of posed images $\{x^v\}_{v=1}^n$ depicting the same scene from multiple viewpoints, along with a set of 2D

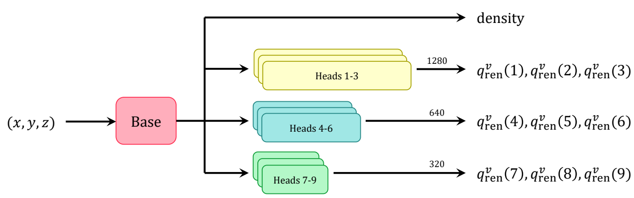

Fig. 5. The architecture of QNeRF. Nine heads are attached to the base network, to produce queries corresponding to nine self-attention layers of the diffusion model. Each group of heads corresponds to a self-attention layer of a certain resolution, and the number displayed above the arrow represents the number of channels in that group (1280, 640, 320).

spatial controls $\{c^v\}_{v=1}^n$ loosely specifying the target geometry of the main object from each view (Figures 1, 2). These controls are the projection of a low-dimensional 3D model that is easy to manipulate, such as a skeleton or a box. We elaborate on the process of obtaining the edited controls in the supplementary materials.

Given these controls, we simultaneously edit all the input images to generate output images $\{\hat{x}^v\}_{v=1}^n$. These output images should depict the same scene as the input images, with the subject's geometry changed to align with the provided controls. To edit the images, we leverage a pre-trained Stable Diffusion model [Rombach et al. 2021], and the MasaCtrl [Cao et al. 2023] approach. There, the images are first inverted with DDIM [Song et al. 2021]. Then, they are re-synthesized following a given control, while preserving the appearance of the original scene by injecting the keys and values of self-attention layers from the original image into the edited one. However, this approach considers each image in isolation, and so the corresponding edit outputs are inconsistent between viewpoints. Our key idea to overcome this hurdle, is to consolidate the edits by improving their multiview consistency in the attention feature space. Specifically, we notice that the inconsistencies are largely in the object shapes. Hence, we propose to align the shapes by consolidating the self-attention queries between the different views. We do so by training a NeRF on the queries during the denoising process, which we term QNeRF.

A conceptual overview of the consolidation process is illustrated in Figure 4. There, we depict the parallel networks, each of which denoises a single view. Query features are extracted from the networks and used to train the QNeRF, which consolidates them into a 3D-consistent representation. The consolidated query features are then softly-injected (Section 4.2) back into the denoising network, improving the multi-view consistency of the edited images.

In practice, we perform the denoising process in intervals. In each interval, we interleave consolidation steps with steps that allow the features to evolve. All consolidation steps in a single interval employ the same trained QNeRF. Additionally, we inject the self-attention keys and values in all steps to preserve the original scene appearance [Cao et al. 2023]. The details of our QNeRF, feature injection approach, and the structure of intervals are provided below.

4.1 QNeRF

The centerpiece of our approach is the QNeRF – a NeRF [Mildenhall et al. 2020] trained on query features extracted from the diffusion model during the denoising process. The inherent 3D consistency of the QNeRF drives the consolidation of the queries. Specifically, at the last step of each of our intervals (Section 4.3), we extract the self-attention queries from the diffusion model along all UNet decoder layers with resolutions $\in (16, 32, 64)$. These yield a total of 9 query sets per denoised-image at a given denoising timestep. These comprise the training set on which we train our QNeRF.

The QNeRF itself is a depth-nerfacto [Deng et al. 2022; Müller et al. 2022; Tancik et al. 2023], with a series of adaptations to better fit our use case. First, rather than producing an RGB value for each input coordinate, we output 9 query values corresponding to the 9 extracted query layers. We do so by adding 9 heads to the base nerfacto network, where each head is optimized to output the queries of a specific self-attention layer. Hence, the dimension of each head's output is set to the number of channels in the respective layer's queries. The base nerfacto network predicts the density at each point, as in the original nerfacto architecture. By sharing the density between the different queries, we can better share cross-layer information and stabilize the geometry. Additionally, we omit the dependence of the QNeRF on the viewing direction. This choice embodies the fact that the queries represent geometry, which is not dependent on the viewing direction. The full architecture of our QNeRF is presented in Figure 5. To train it, we employ the q-loss:

$$\mathcal{L}_q = \sum_{\mathbf{r}\in\mathcal{R}} \sum_{l} \|\hat{\mathbf{Q}}_l(\mathbf{r}) - q^{\mathbf{r}}(l)\|, \tag{3}$$

where $\mathcal{R}$ are sampled rays, $q^{\mathbf{r}}(l)$ are the extracted queries corresponding to ray $\mathbf{r}$ and layer l. $\hat{\mathbf{Q}}_l(\mathbf{r})$ is defined similarly to $C(\mathbf{r})$ in Equation 1, where we replace RGB value, c, with a self-attention query value, q. Additionally, we use the depth-loss $\mathcal{L}_{\text{depth}}$ proposed by Deng *et al.* [2022], and our final loss for training the QNeRF is written as $\mathcal{L} = \mathcal{L}_q + \mathcal{L}_{\text{depth}}$.

Once trained, we can use the QNeRF to render consolidated queries to guide the denoising process. We do so using the standard volumetric rendering technique [Max 1995; Mildenhall et al. 2020]. Finally, since we do not expect the geometry to significantly change between intervals, we initialize each QNeRF from the one trained at the prior interval.

4.2 Query Guidance

With the QNeRF in hand, we wish to use consolidated queries produced by it to guide the denoising process. Consider the editing process of a specific frame with a given camera viewpoint. The direct way to use our QNeRF would be to render the queries for this particular viewpoint, and use them to replace the queries naturally created by the UNet during the denoising steps. However, in our initial experiments, we observed that such direct replacement can lead to visual artifacts in the edited frames. Instead, we propose a "soft-guidance" mechanism inspired by previous works [Chefer et al. 2023; Dhariwal and Nichol 2021; Epstein et al. 2023; Parmar et al. 2023]. At each query-guided denoising step, we first do a single forward pass through the UNet and extract all the naturally generated queries. We then perform a single optimization step on the input latents themselves, with the goal of minimizing the distance between these generated queries and the ones rendered from the QNeRF. Formally, the query guidance is defined as:

$$z_t^v \leftarrow z_t^v - \alpha \nabla_{z_t^v} \sum_l \|q^v(l) - q^v_{\text{ren}}(l)\|^2, \tag{4}$$

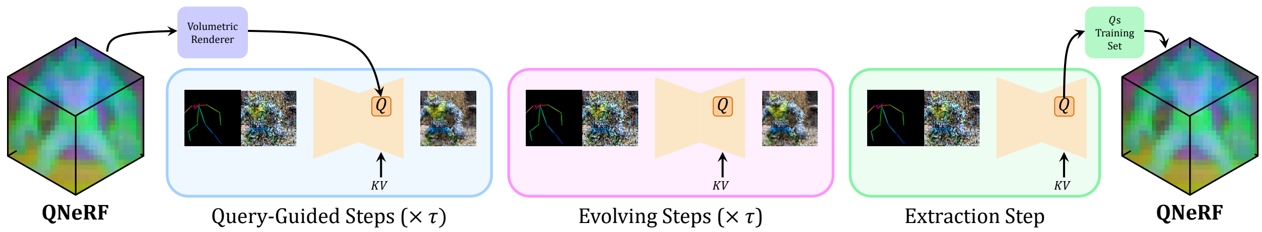

Fig. 6. In each multi-view denoising interval, we apply τ query-guided steps, followed by τ evolving steps where no guidance is applied. In the ending step of the interval, we extract the generated queries and use them to train the QNeRF that provides guidance for the next interval. In query-guided steps, we consolidate the geometry across the different views. We do so by altering the noisy latent code with an objective of proximity between the self-attention queries generated by the latent code, and queries rendered from the QNeRF. The evolving steps ensure the denoising process progresses, in the sense that the generated features match the current timestep. To preserve the appearance of the original image, we inject their keys and values self-attention features.

where z_t^v is the noisy latent code corresponding to viewpoint v at timestep t, and $q^v(l), q^v_{\text{ren}}(l)$ are the generated and rendered self-attention queries of layer l, respectively. After this update step, a DDIM [Song et al. 2021] denoising step is applied to obtain z^v_{t-1}.

4.3 Multi-view Image Denoising Interval

As previously noted, rather than training a QNeRF for every denoising step, we employ an interval-based approach. The structure of each interval is motivated by two observations. On the one hand, it has been observed that in a standard denoising process, the internal UNet features of adjacent denoising timesteps are similar [Li et al. 2023], to the extent that their computation can often be skipped and reused. Hence, we expect that guiding several adjacent timesteps with the same query features should not degrade the quality of the results. On the other hand, if we continue to reuse the same queries over an extended number of timesteps, we leave no room for the gradual change that does occur in the diffusion features. In an extreme case, using the same query-guidance for all timesteps would lead to the same queries being used across the entire diffusion path. Ideally, our mechanism should allow the queries to evolve freely along the denoising process.

We thus propose an interleaved process, which breaks image generation into several overlapping intervals. Consider one such interval (illustrated in Figure 6), starting at diffusion timestep T_i and spanning 2τ steps. We begin the interval by taking τ QNeRF-guided steps, using a QNeRF obtained from the end of the previous interval. We store the noisy latents obtained at this point $(T_i - \tau)$ for future use. Following these τ steps, we take another τ steps where we perform vanilla MasaCtrl editing, without any query guidance. These steps thus allow the queries to evolve freely, matching the more advanced step. At the end of these unguided steps, we extract the updated query features, and use them to optimize a new QNeRF. Finally, we retrieve the latents stored at $T_i - \tau$ and begin a new interval starting from this point, using the updated QNeRF for guidance.

In the special case of the first interval, we do not have a QNeRF at hand. Hence, we perform unguided-editing for 2τ steps (*i.e.*, until $T - 2\tau$), train a QNeRF from features extracted at this step, and begin the next interval at $T - \tau$.

4.4 Progressive Consolidation

The consolidation of the queries along the denoising process is done progressively, by training the QNeRF on-the-fly during intermediate steps of the generation. Specifically, the queries used to train the QNeRF at each interval, are affected by the consolidated queries rendered from the prior interval's QNeRF. By combining this approach with the scheduling within each interval, we provide the model with room to freely develop the queries, while ensuring that any injected queries are still the result of consolidated queries formed at the end of the previous interval. Crucially, this prevents the queries from drifting apart too far before they are re-consolidated.

5 EXPERIMENTS

Next, we evaluate our method qualitatively and quantitatively, and compare it to other baseline methods. We show results on eight multi-view image sets, of 200-500 images each. Additional details regarding the datasets are provided in the supplementary materials.

5.1 Ablation Studies

We begin with a study of the importance of the main components of our method. We consider the following configurations: (i) Independently editing the images with MasaCtrl [Cao et al. 2023], (ii) directly injecting the rendered queries instead of our soft-injection mechanism, and (iii) using a non-progressive consolidation process. There, we first edit all the images independently using MasaCtrl and cache their self-attention queries along different timesteps. We then train QNeRFs on these queries, and finally re-create the edits with soft Q-injections. Qualitative results are presented in Figure 7. As can be seen, independent image editing (second row) leads to inconsistent results. For example, the subject's feet are located in different positions with respect to the wooden deck (second column compared to third column). Additionally, the legs differ in their shapes (rightmost column) and the height of the deck varies between the images. Directly injecting the rendered queries (third row) makes the images consistent, but they diverge too much from the original images, cutting the legs and increasing the height of the deck. Training the QNeRFs with a non-progressive approach (fourth row) can lead to more artifacts, such as the missing leg in the fourth column. In the last row, the legs are consistently positioned, and their shape does not vary between different images. Additionally, the shape of the deck remains as in the original images.

5.2 Qualitative Comparisons

We compare our method to three types of methods: (i) Geometric NeRF editing methods that deform the NeRF according to the deformation of a mesh extracted from the NeRF, (ii) ControlNet-based

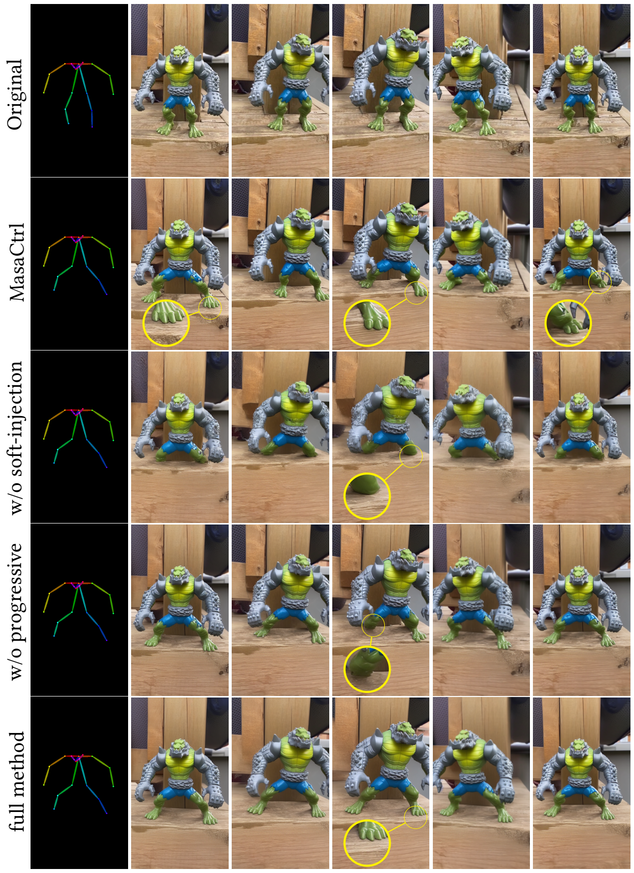

Fig. 7. Ablation study results. Our full method creates more consistent images, while accurately preserving the original scene.

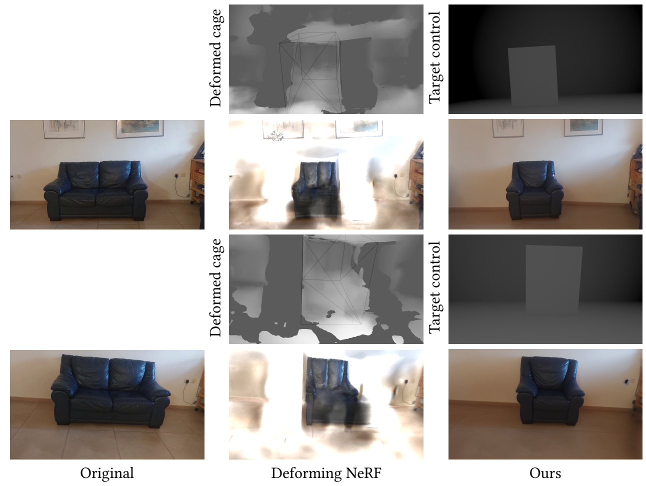

Fig. 8. Note that Deforming-NeRF retains both pillows when squeezing the sofa, resulting in an unnatural appearance, while our method transforms it into a single-pillow sofa, better suited to its size.

multi-image editing methods, and (iii) text-based editing methods. More qualitative results of our method are shown in Figures 12, 13, and 14 and in the supplemental. Additionally, we provide a supplemental video that includes NeRFs trained on our edited images.

Geometric NeRF Editing. Here, we compare with NeRF-Editing [Yuan et al. 2022] and Deforming-NeRF [Xu and Harada 2022]. These methods extract a mesh of the main object in the scene, construct a cage, and deform the NeRF according to the deformation inferred by the cage. The differences between these two methods lie primarily in the implementation details of the NeRF used and in the techniques for cage construction and deformation. For NeRF-Editing, we utilize the official implementation and obtain the cage through dilation of the extracted mesh. For Deforming-NeRF, we manually construct a coarse cage with a low polygon count. Further details on the mesh processing are provided in the supplementary materials. The comparison results are presented in Figures 8, 10, and in the supplementary materials. For the sofa example, we compare only with Deforming-NeRF, as NeuS [Wang et al. 2021b], which is used in NeRF-Editing, struggles to extract the mesh for this example.

As seen in the results, both of these methods cannot generate details not apparent in the original scene, and hence struggle to handle backgrounds. In NeRF-Editing, the imperfection of the foreground-background separation is apparent as spurious unrelated regions from the background distort the foreground object. In Deforming-NeRF, squeezing the sofa or moving Spiderman's legs results in void regions. Moreover, the realism of the sofa degrades when scaling it. Unlike our method, which turns the sofa into a single-pillow sofa that better fits its size, Deforming-NeRF retains two pillows, making the sofa appear less realistic. Conversely, our method, which utilizes a generative model, generates semantically coherent images according to the edit conditions. Overall, these NeRF deformation methods and our generative approach represent two conceptually different paradigms, each with its own strengths and weaknesses.

Multi-image Editing With ControlNet. Next, we compare our method to prior art addressing multi-image editing, evaluating three methods employing different approaches to ensure multi-image consistency. First, we compare with InstructNeRF2NeRF (IN2N) [Haque et al. 2023], a dataset update technique. Second, we compare with CSD [Kim et al. 2023] which performs a collaborative score distillation sampling (SDS) process. We follow the authors and integrate CSD with IN2N, where the image-editing step itself is replaced with a CSD-based multi-view editing step. Finally, we compare with TokenFlow [Geyer et al. 2023], a recent text-based video editing method that improves cross-frame consistency through a flow-based approach. Here, we concatenate the initial image set into a single video which we then edit.

The above methods utilize text-based editing interfaces. We integrate them with ControlNet, enabling spatial control for specifying target edits. Specifically, we replace the InstructPix2Pix editor with MasaCtrl [Cao et al. 2023] in IN2N and CSD, denoted as IN2N-CN and CSD-CN, respectively. For TokenFlow, we make use of their ControlNet version. Notably, TokenFlow constructs its flow based on patch-similarity in the original video, which may not match with the changed geometry in our case. We observe a significant performance improvement when using the frame-by-frame MasaCtrl edited images rather than unedited ones to build the flow, and thus evaluate this variant of the model. For a fair comparison between IN2N and CSD with TokenFlow and our method, we train a NeRF on the outputs of TokenFlow and our method.

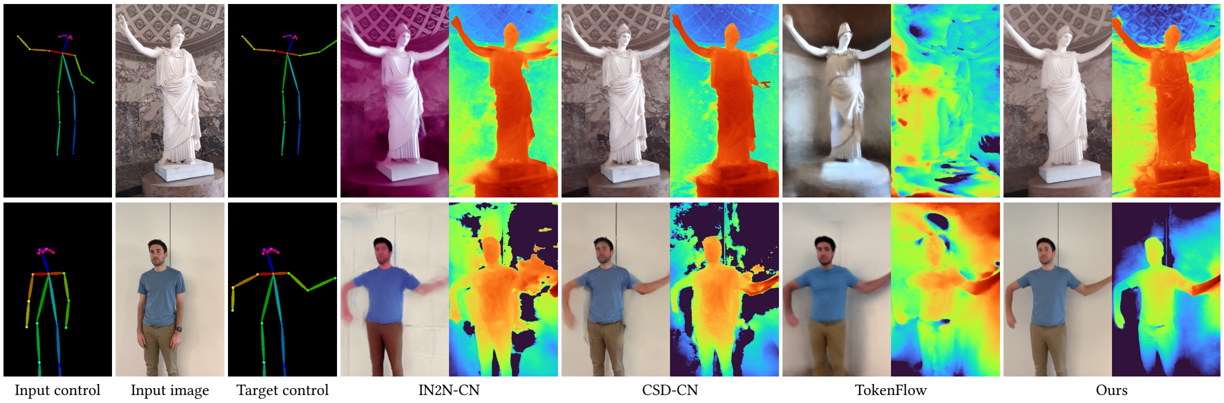

Fig. 9. Qualitative comparison of our approach with baseline methods. Techniques relying on "dataset update", such as IN2N-CN and CSD-CN, struggle to alter the geometry. This can be seen in the noisy depth of the statue's right arm when using IN2N-CN, and the ghostly right arm of the statue with CSD-CN. TokenFlow struggles to preserve the appearance of the original image, and tends to produce noisy geometry, suggesting a lack of consistency between the edited frames. Our method preserves the appearance of the original images while changing the geometry consistently.

Rendered images of these methods are shown in Figures 9 and 11. Both IN2N and CSD rely on partial dataset updates, assuming that gradual edits and averaging over partially-edited views will result in a consistent NeRF. However, this assumption is valid for appearance edits but not for shape changes like articulations. For example, moving a person's arms in parts of the dataset can lead to a NeRF with partial arms in both source and target locations, resulting in artifacts like ghostly limbs. This issue is observed in the last row of Figure 9, where original arms are visible in both RGB and depth images of CSD. In the case of IN2N, the original arms are visible in the depth image, while the new right arm has noisy geometry. TokenFlow edits all images without a-priori averaging through a NeRF. Hence, it better aligns with the desired shape and avoids the ghostly-limb artifacts. However, geometric edits still violate its flow-consistency assumptions, leading to visual artifacts. Moreover, its feature injection approach struggles to match MasaCtrl's in faithfulness to the original frames. Our approach successfully overcomes the artifacts that arise with gradual dataset updates over an existing NeRF, while still retaining high similarity to the original frame.

5.3 Quantitative Comparisons

We quantitatively evaluate our method against ControlNet-based methods across the "statue", "person" and "alligator-toy" scenes. CSD method failed to update enough images in the "alligator-toy" scenario, even after a week of training on an H100 GPU, so we omit it from automated evaluations. Since we do not have access to ground-truth images or detailed geometry matching the edits, we opt for measuring quality in three ways: (1) Output image quality, measured by the Kernel Inception Distance (KID) [Bińkowski et al. 2018] between edited results and original images. (2) Quality of the final 3D representation, measured through a user study.

To evaluate image quality, we calculate the Kernel Inception Distance (KID) between each method's outputs and the original scene images for each scene and edit. We report the average score across all edits. KID is related to the Frćhet Inception Distance (FID), but is designed to smaller datasets (fewer than 50, 000 images). For completeness, we also include FID. The results are provided in Table 1. Across all scenarios, our method achieves enhanced visual fidelity, maintaining fidelity to the original scene with fewer visual artifacts compared to the baselines.

Metric	IN2N-CN	CSD-CN	TokenFlow	Ours
KID (↓)	0.280	0.090	0.440	**0.072**
FID (↓)	201	87	295	**73**
Depth User Study Rank (↓)	2.26	2.12	3.70	**1.90**
Depth User Study Win-rate (↑)	14.16%	34.16%	0.83%	**50.83%**
RGB User Study Rank (↓)	2.90	2.33	3.42	**1.35**
RGB User Study Win-rate (↑)	5.00%	22.50%	0.83%	**71.67%**

Table 1. Quantitative evaluation metrics. Our method outperforms the baselines both in terms of fidelity, and user-preference.

To evaluate 3D representation quality, we conducted a user study where technical users viewed depth map videos extracted from NeRFs trained for each method. They ranked videos based on alignment with the target pose and quality. Competing methods' depth maps often contained holes and clouds due to inconsistent geometry, likely resulting in lower scores. Similarly, we conducted a user study using RGB videos. We collected 120 responses from 20 unique users. Table 1 presents average ranks and win rates for each method across all scenes and edits. Our method was preferred over baselines in the majority of cases, indicating better alignment with desired edits and higher visual quality.

5.4 Additional Experiments

In the supplementary materials, we offer a comparison with text-based editing methods, specifically IN2N [Haque et al. 2023] and PDS [Koo et al. 2023], demonstrating the challenges of performing geometric edits through a text interface. We further experiment with our method using a text interface instead of geometric controls. We show that our consolidation mechanism can operate effectively even without a geometric prior. We also show results on a 360° scene, and show that our method does not suffer from the Janus problem.

6 CONCLUSIONS, LIMITATIONS, AND FUTURE WORK

We presented a technique to consolidate the results of multi-view editing. We introduce QNeRF as a means to progressively consolidate the attention features of the images throughout the editing process. Our approach is generic, making it applicable to various diffusion-based editing techniques where the image layouts are modified. Here, we demonstrated our approach with two types of controls: articulations, and rough bounding boxes. These conditions are intentionally lenient, offering ease of control.

Our work is based on the generative power of text-to-image models. However, it also inherits their common weaknesses. For example, the model struggles to generate human hands. Similarly, the model may still hallucinate fine details. In our work, we focused on consolidating the shape, however, in highly detailed objects, these fine details are not consistent despite the shared underlying shape. Similar hallucinations can be noticed in detailed background regions which are dis-occluded by the geometric manipulation. These inconsistencies can lead to blurry regions when training a NeRF on the edited multi-view images. See the supplementary for examples.

In our work, we optimize the QNeRF with a black-box optimizer. This may cause it to "average" over outliers, even when it could be more beneficial to filter them out by applying robust statistics techniques. Additionally, we envision exploring alternative means for consolidating features, including the utilization of other three-dimensional representations like Gaussian Splats [Kerbl et al. 2023].

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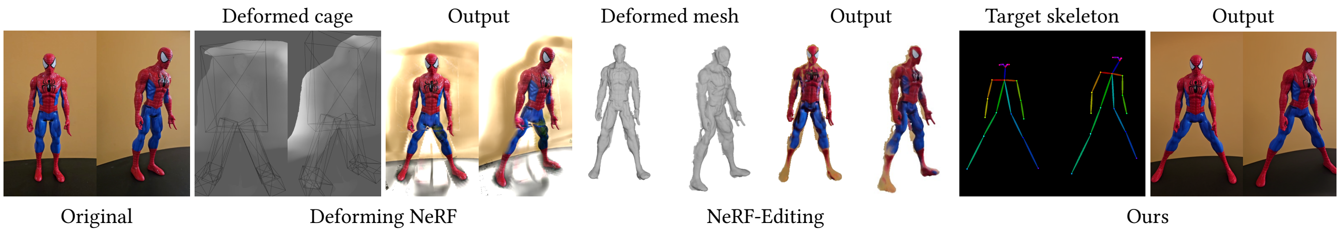

Fig. 10. Comparison of our method with geometric NeRF editing baseline methods. From left to right, we show the original images, the results of Deforming-NeRF, NeRF-Editing, and our method. For each method we show the deforming means (*e.g.*, deformed mesh or skeleton) side-by-side with the output. The baseline methods do not utilize generative priors and hence encounter difficulty generating new details, such as the disoccluded space between Spiderman's legs, resulting in a void region. In NeRF-Editing, we see orange "pieces" of the background attached to the object and leaking onto the object, causing visual artifacts (*e.g.*, on the feet).

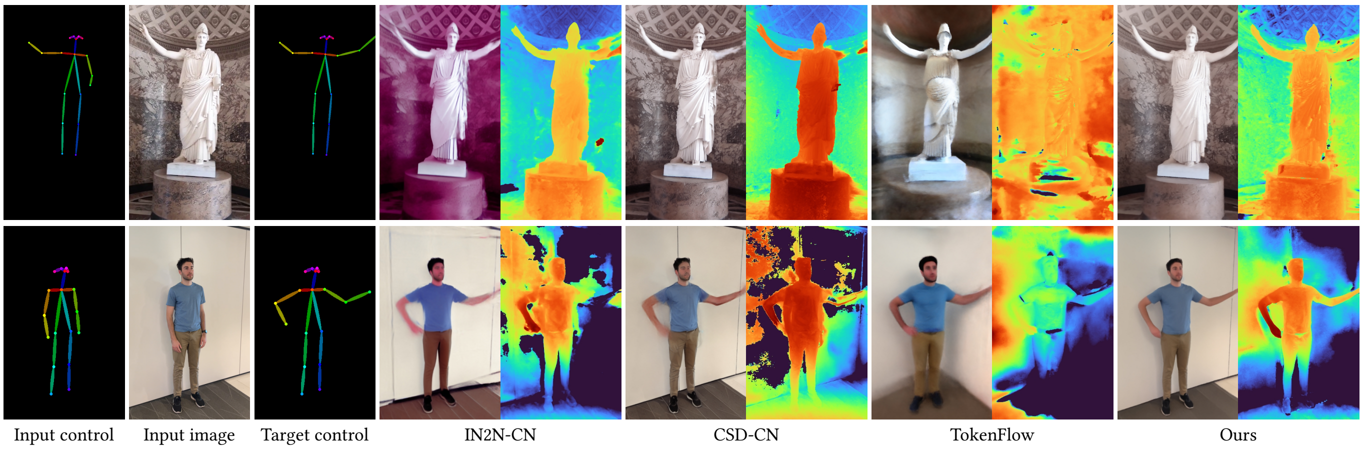

Fig. 11. Qualitative comparison of our approach with baseline methods. We show another view for each of the examples in Figure 9.

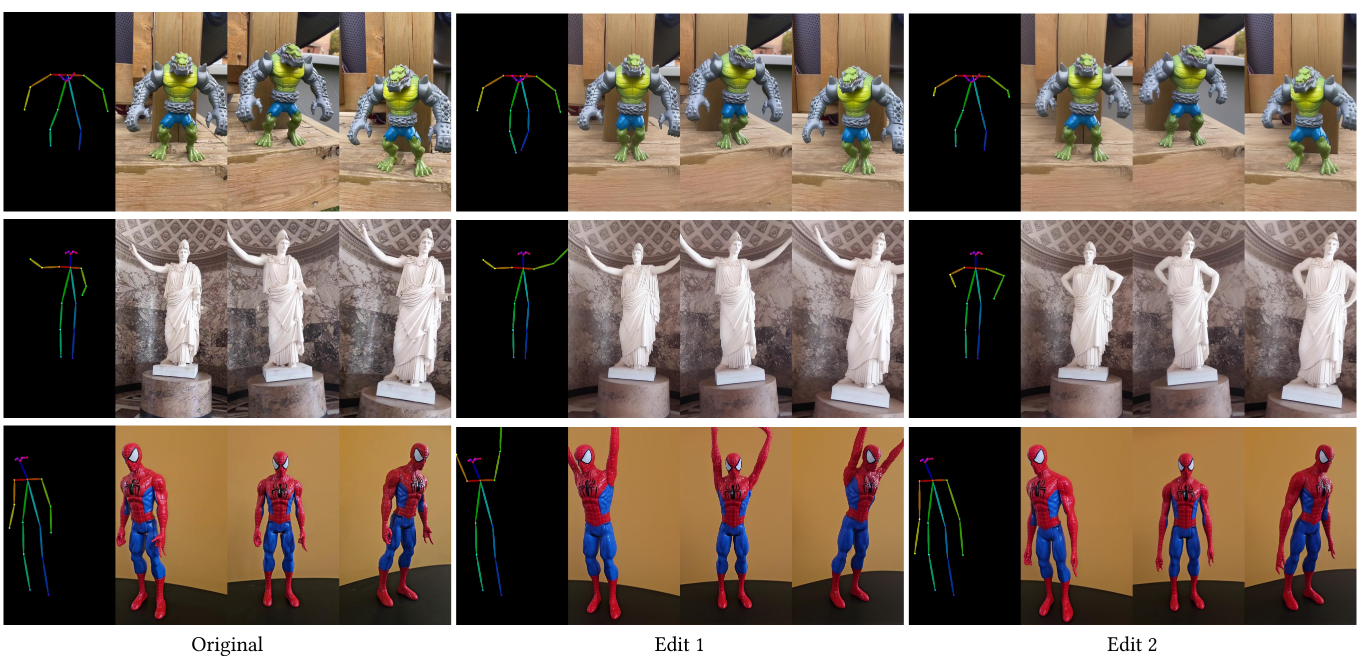

Fig. 12. Qualitative results of our method. Here we edit the images with a skeleton and show a sample of three different views for each example.

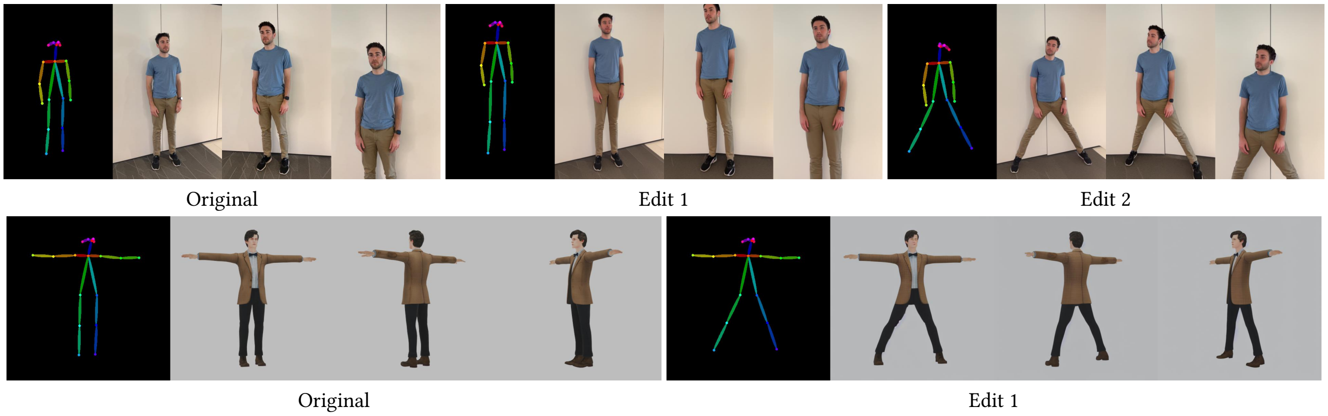

Fig. 13. Qualitative results of our method. Here we edit the images with a skeleton and show a sample of three different views for each example.

Fig. 14. Qualitative results of our method. Here we edit the images with a loose depth map, and show a sample of three different views for each example.

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