

# Prompt to Prompt

## Image Editing with Cross-Attention Control

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# Content

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- Motivation & Recap
- Prompt-to-Prompt
- Extensions

# Prompt-to-Prompt Image Editing with Cross Attention Control

## Motivation

Text-2-image editing is sensitive to text prompts

- text influence the high level semantic only



photo of a cat riding a bike



photo of a cat on a bike

A spatial mask to localize the edit

- hard to draw and
- ignoring the original structure & content

## Toward Mask-free Text-2-Image Editing 😊



Origin



Mask



Inpainting Example

Prompt: girl with red hair

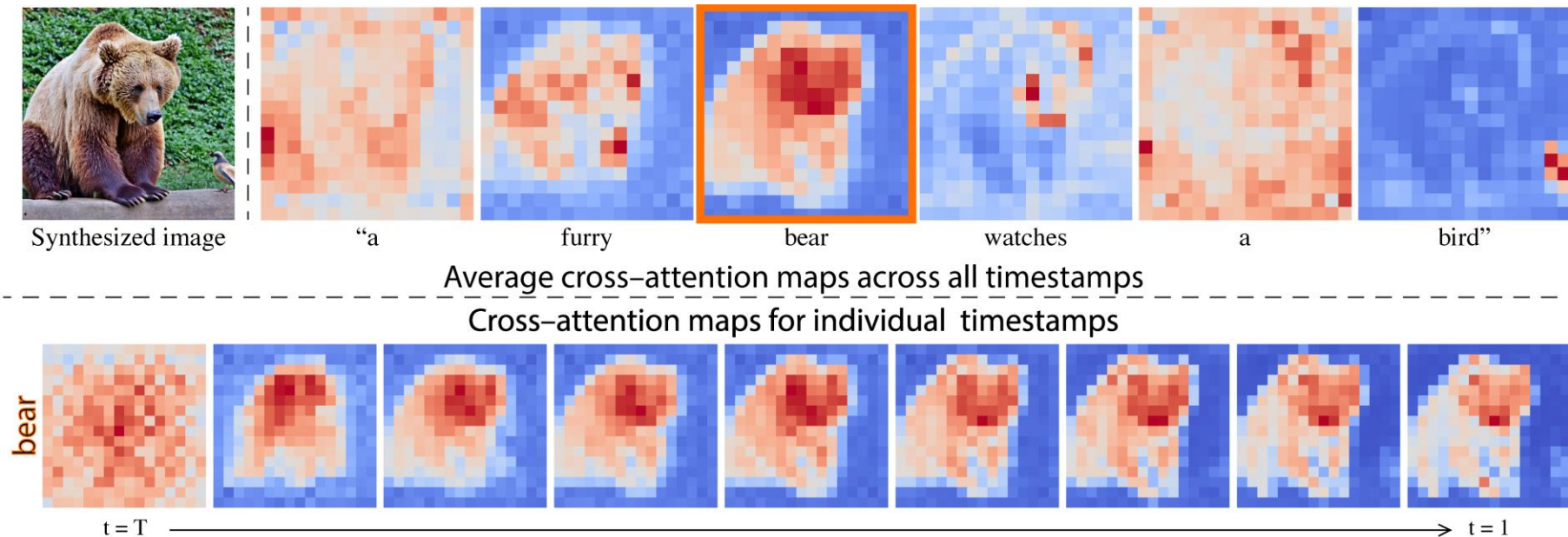
[Prompt-to-Prompt](#)

[Prompt-to-Prompt Image Editing with Cross-Attention Control | OpenReview](#)

[Attend-and-Excite/explain.ipynb at main · AttendAndExcite/Attend-and-Excite \(github.com\)](#)

# Prompt-to-Prompt Image Editing with Cross Attention Control

**Key Observation:** spatial information in the cross-attention maps

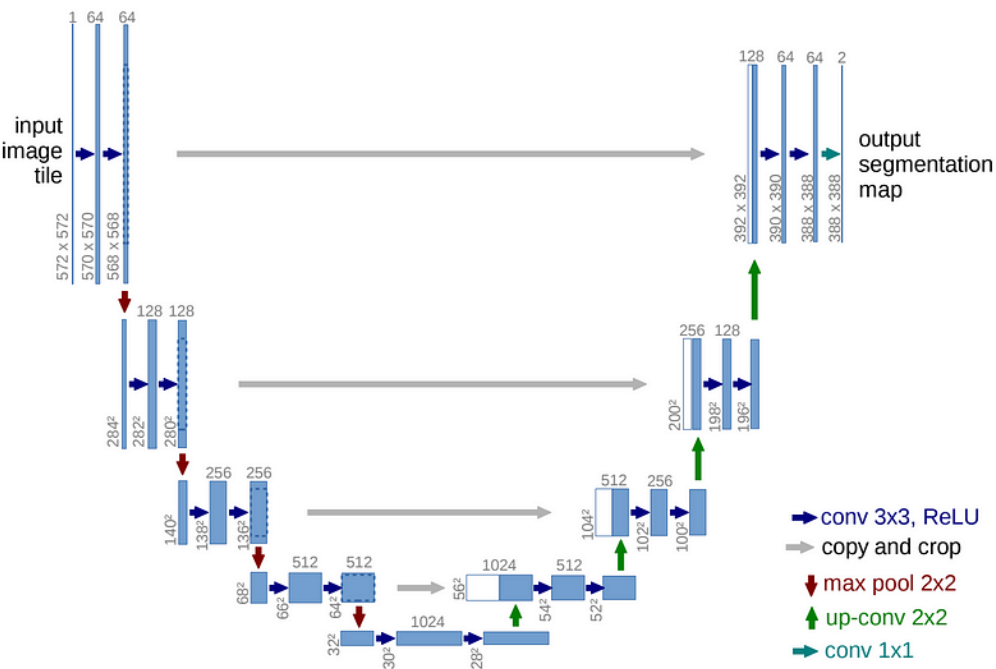


# Prompt-to-Prompt Image Editing with Cross Attention Control

## Model Architecture & Location of Cross Attention

UNET\_CONFIG:

```
target: ldm.modules.diffusionmodules.openaimodel.UNetModel
```



```
for level, mult in enumerate(channel_mult):  
    for _ in range(num_res_blocks):  
        layers = [ ResBlock(...) ]  
        ch = mult * model_channels  
        if ds in attention_resolutions:  
            layers.append(SpatialTransformer(...))
```



```
1 assert use_spatial_transformer, 'Fool!! \  
2 You forgot to use the spatial transformer \  
3 for your cross-attention conditioning...'
```

<https://github.com/CompVis/stable-diffusion/blob/main/ldm/modules/diffusionmodules/openaimodel.py#L541>

# Prompt-to-Prompt Image Editing with Cross Attention Control

**Attentions in stable diffusion**

```
from ldm.modules.attention import SpatialTransformer
```

```
SpatialTransformer → [BasicTransformerBlock(...) for d in range(depth)]
```

```
def _forward(self, x, context=None):  
    x = self.attn1(self.norm1(x), context=context if self.disable_self_attn else None) + x  
    x = self.attn2(self.norm2(x), context=context) + x  
    x = self.ff(self.norm3(x)) + x  
    return x
```

→ self  
→ cross

```
# x.shape = b (h w) c  
# context.shape = b n_token dim
```

# Prompt-to-Prompt Image Editing with Cross Attention Control

$$M = \text{Softmax} \left( \frac{QK^T}{\sqrt{d}} \right)$$

# x.shape = b (h w) c --> b h\*w inner\_dim

# context.shape = b n\_token dim --> b n\_token inner\_dim

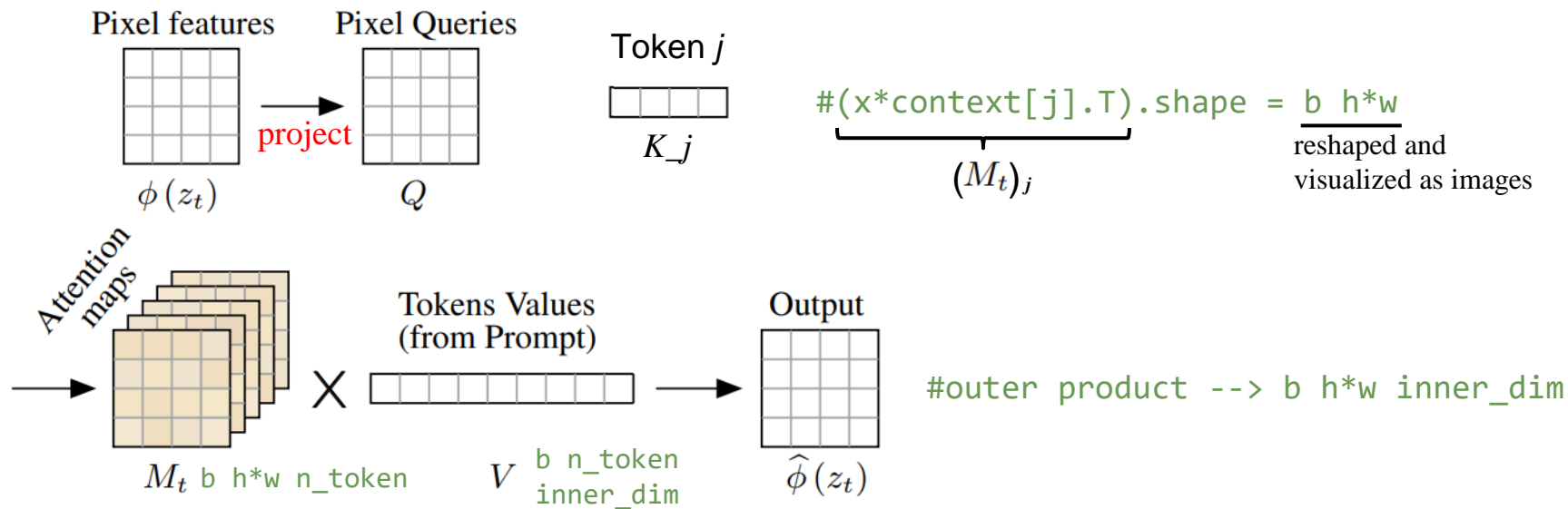
# attention, what we cannot get enough of

`sim = einsum('b i d, b j d -> b i j', q, k) * self.scale`

`attn = sim.softmax(dim=-1)` # normalizes values along axis -1 (j)

`out = einsum('b i j, b j d -> b i d', attn, v)`

**cross-attention**



# Content

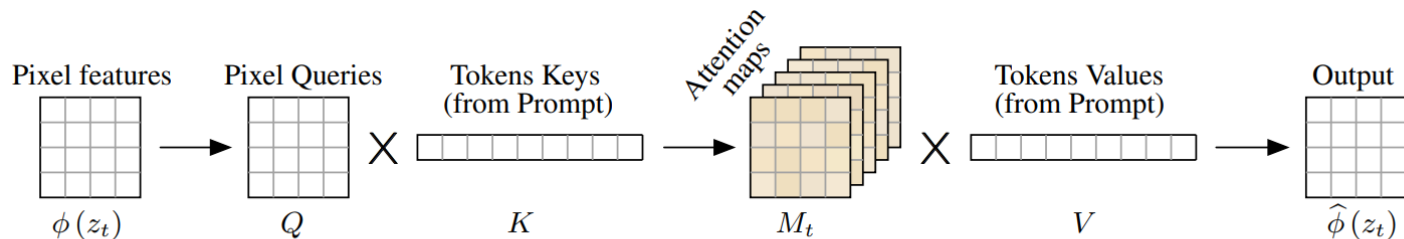
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- Motivation & Recap
- Prompt-to-Prompt
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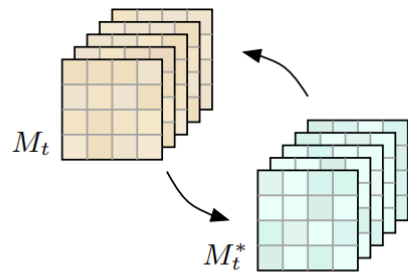


# Prompt-to-Prompt Image Editing with Cross Attention Control

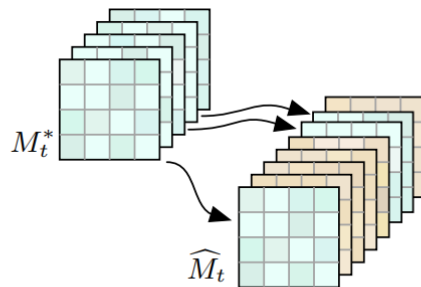
$M = \text{Softmax} \left( \frac{QK^T}{\sqrt{d}} \right)$  we can inject the attention maps  $M$  that were obtained from the generation with the original prompt  $P$ , into a second generation with the modified prompt  $P^*$



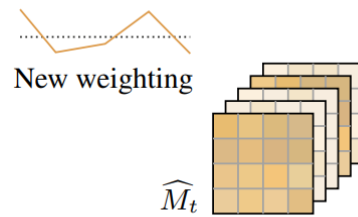
Text to Image Cross Attention  
Cross Attention Control



Word Swap



Adding a New Phrase



Attention Re-weighting

# Prompt-to-Prompt Image Editing with Cross Attention Control

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## Algorithm 1: Prompt-to-Prompt image editing

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```

1 Input: A source prompt  $\mathcal{P}$ , a target prompt  $\mathcal{P}^*$ , and a random seed  $s$ .
2 Optional for local editing:  $w$  and  $w^*$ , words in  $\mathcal{P}$  and  $\mathcal{P}^*$ , specifying the editing region.
3 Output: A source image  $x_{src}$  and an edited image  $x_{dst}$ .
4  $z_T \sim N(0, I)$  a unit Gaussian random variable with random seed  $s$ ;
5  $z_T^* \leftarrow z_T$ ;
6 for  $t = T, T-1, \dots, 1$  do
7    $z_{t-1}, M_t \leftarrow DM(z_t, \mathcal{P}, t, s)$ ;
8    $M_t^* \leftarrow DM(z_t^*, \mathcal{P}^*, t, s)$ ;
9    $\widehat{M}_t \leftarrow Edit(M_t, M_t^*, t)$ ;
10   $z_{t-1}^* \leftarrow DM(z_t^*, \mathcal{P}^*, t, s) \{M \leftarrow \widehat{M}_t\}$ ;
11  if local then
12     $\alpha \leftarrow B(\overline{M}_{t,w}) \cup B(\overline{M}_{t,w^*}^*)$ ;
13     $z_{t-1}^* \leftarrow (1 - \alpha) \odot z_{t-1} + \alpha \odot z_{t-1}^*$ ;
14  end
15 end
16 Return  $(z_0, z_0^*)$ 

```

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## Word Swap

$$Edit(M_t, M_t^*, t) := \begin{cases} M_t^* & \text{if } t < \tau \\ M_t & \text{otherwise} \end{cases}$$

## Adding a New Phrase

$$(Edit(M_t, M_t^*, t))_{i,j} := \begin{cases} (M_t^*)_{i,j} & \text{if } A(j) = \text{None} \\ (M_t)_{i,A(j)} & \text{otherwise.} \end{cases}$$

$i$ : pixel value;  $j$ : text token

## Attention Re-weighting

$$(Edit(M_t, M_t^*, t))_{i,j} := \begin{cases} c \cdot (M_t)_{i,j} & \text{if } j = j^* \\ (M_t)_{i,j} & \text{otherwise} \end{cases}$$

# Prompt-to-Prompt Image Editing with Cross Attention Control

## How to implement?

[https://github.com/google/prompt-to-prompt/blob/main/ptp\\_utils.py#L173](https://github.com/google/prompt-to-prompt/blob/main/ptp_utils.py#L173)

```
### prompt to prompt setup
controller = _setup_attention_controller(attention_control_type, prompts,
                                         cross_replace_steps=cross_replace_steps, self_replace_steps=self_replace_steps,
                                         LocalBlend_pair=LocalBlend_pair,
                                         Reweightwords=Reweightwords, Reweight_scales=Reweight_scales,
                                         sampling_steps=steps, tokenizer=model.cond_stage_model.tokenizer)
ptp_utils.register_attention_control(model, controller)

def register_recr(net_, count, place_in_unet):
    ## modify the forward function of the cross attention module
    if net_.__class__.__name__ == 'CrossAttention':
        net_.forward = ca_forward(net_, place_in_unet)
        return count + 1
```

# Prompt-to-Prompt Image Editing with Cross Attention Control

```
ca_forward: sim = einsum('2 i d, 2 j d -> 2 i j', q, k) * self.scale
            attn = sim.softmax(dim=-1)      # normalizes values along axis -1 (j)
            attn = controller(attn, is_cross, place_in_unet) https://github.com/google/prompt-to-prompt/blob/main/ptp\_utils.py#L203
            out = einsum('2 i j, 2 j d -> 2 i d', attn, v)
```

```
### forward method of controller
def forward(self, attn, is_cross: bool, place_in_unet: str):
    super(AttentionControlEdit, self).forward(attn, is_cross, place_in_unet)
    if is_cross or (self.num_self_replace[0] <= self.cur_step < self.num_self_replace[1]):
        h = attn.shape[0] // (self.batch_size)
        attn = attn.reshape(self.batch_size, h, *attn.shape[1:])
        attn_base, attn_repalce = attn[0], attn[1:]
        if is_cross:
            alpha_words = self.cross_replace_alpha[self.cur_step]
            attn_repalce_new = self.replace_cross_attention(attn_base, attn_repalce) * alpha_words \
                               + (1 - alpha_words) * attn_repalce
            attn[1:] = attn_repalce_new
        else:
            attn[1:] = self.replace_self_attention(attn_base, attn_repalce)
        attn = attn.reshape(self.batch_size * h, *attn.shape[2:])
    return attn
```

# Prompt-to-Prompt Image Editing with Cross Attention Control

## How to implement?

[https://github.com/google/prompt-to-prompt/blob/main/ptp\\_utils.py#L74](https://github.com/google/prompt-to-prompt/blob/main/ptp_utils.py#L74)

```
img, pred_x0 = self.p_sample_ddim(...)
### apply local_blend to img
if controller:
    img = controller.step_callback(img)
```

```
1 class LocalBlend:
2     def __call__(self, x_t, attention_store):
3         k = 1
4         maps = attention_store["down_cross"][2:4] + attention_store["up_cross"][:3]
5         maps = [item.reshape(self.alpha_layers.shape[0], -1, 1, 16, 16, MAX_NUM_WORDS) for item in maps]
6         maps = torch.cat(maps, dim=1)
7         maps = (maps * self.alpha_layers).sum(-1).mean(1)
8         mask = nnf.max_pool2d(maps, (k * 2 + 1, k * 2 + 1), (1, 1), padding=(k, k))
9         mask = nnf.interpolate(mask, size=(x_t.shape[2:]))
10        mask = mask / mask.max(2, keepdims=True)[0].max(3, keepdims=True)[0]
11        mask = mask.gt(self.threshold)
12        mask = (mask[:1] + mask[1:]).float()
13        x_t = x_t[:1] + mask * (x_t - x_t[:1]) # x_t[1:] = mask * x_t[1:] + (1-mask) * x_t[:1]
14        return x_t
```

# Prompt-to-Prompt Image Editing with Cross Attention Control

a small girl with blue shirt sitting in front of a mirror, red hair

original



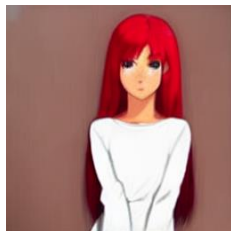
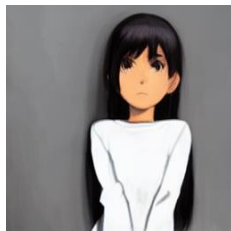
w/o ptp



w/ ptp



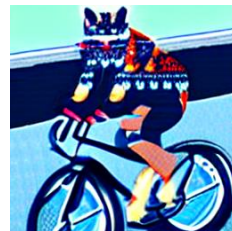
girl, red hair



a cat(lion) with a hat is lying on a beach chair.



photo of a cat riding a bike(car)



# Prompt-to-Prompt Image Editing with Cross Attention Control

photo of a cat on a bike(car)

cross\_replace\_steps  
self\_replace\_steps

0.5/0.5



0.8/0.2



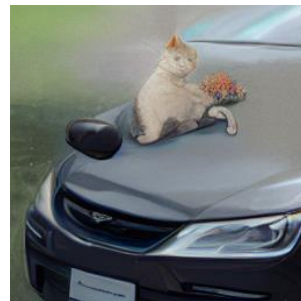
0.8/0.3



0.8/0.4



0.8/0.5



0.0/0.0



0.8/0.6



0.5/0.4



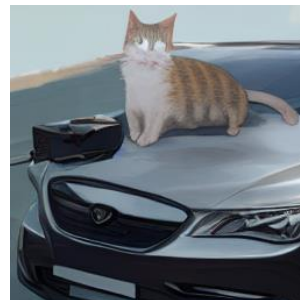
0.6/0.4



0.7/0.4



0.8/0.4



w/o LocalBlend

# Prompt-to-Prompt Image Editing with Cross Attention Control

## Conclusions

### Pros:

- ✓ Training free
- ✓ Mask free
- ✓ Flexible

### Cons:

- ✗ Precise control
- ✗ Stable hyper-parameter
- ✗ Natural language instruction!



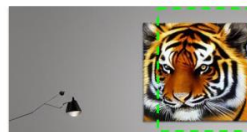
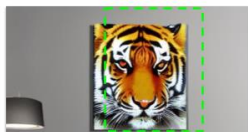
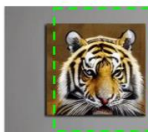
# Content

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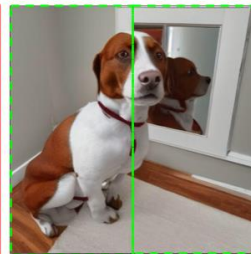
- Motivation & Recap
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# Directed Diffusion: Direct Control of Object Placement through Attention Guidance

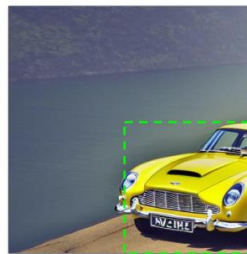
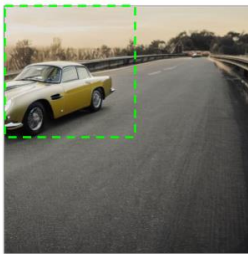
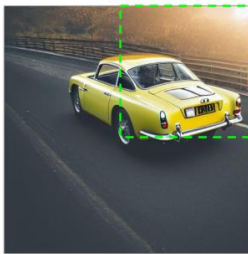
Prompt: A painting of a tiger, on the wall in the living room [, in the upper left of the image]



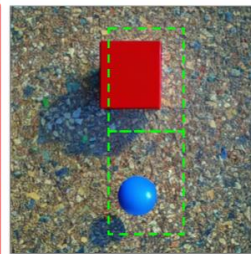
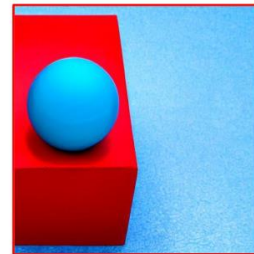
Prompt: A dog sitting next to a mirror



Prompt: A car on a bridge [, in the upper left of the image]



Prompt: A red cube above a blue sphere



SD

DD(1st Q)

DD(2nd Q)

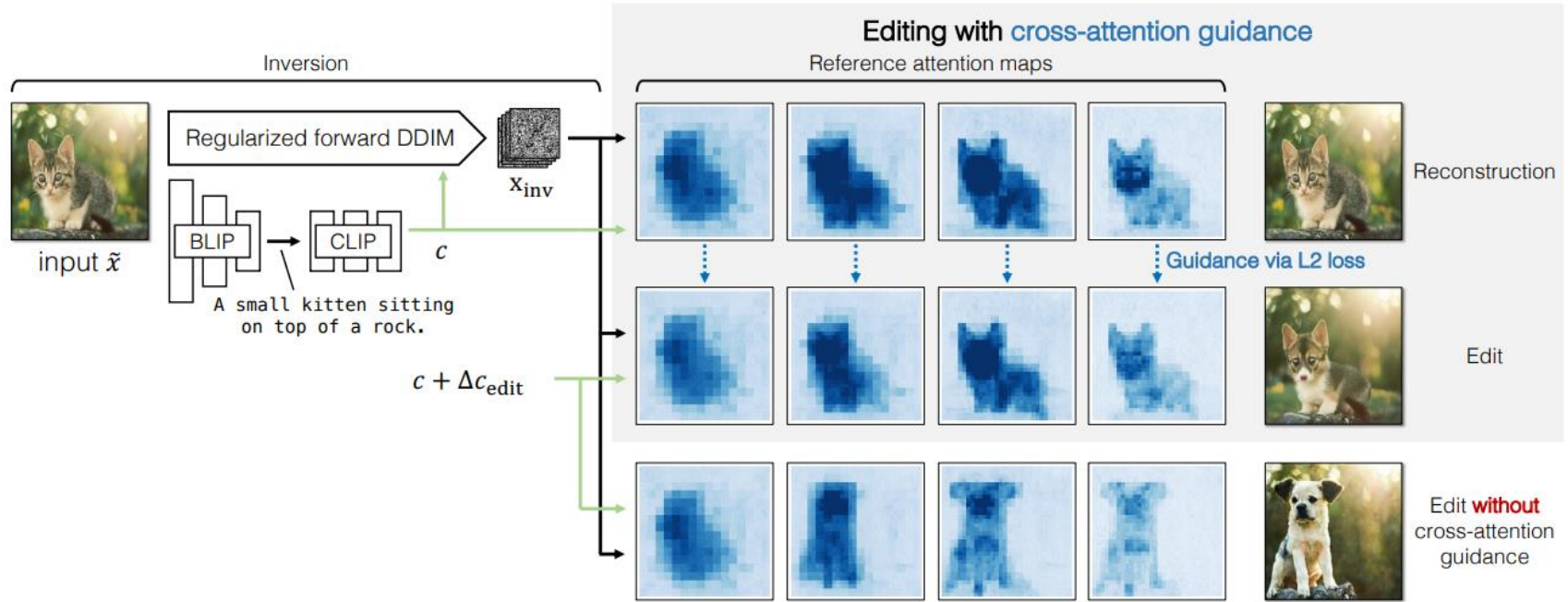
DD(3rd Q)

DD(4th Q)

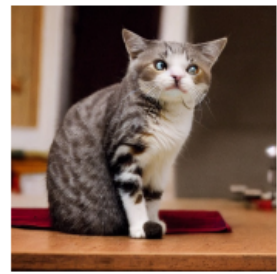
SD

DD

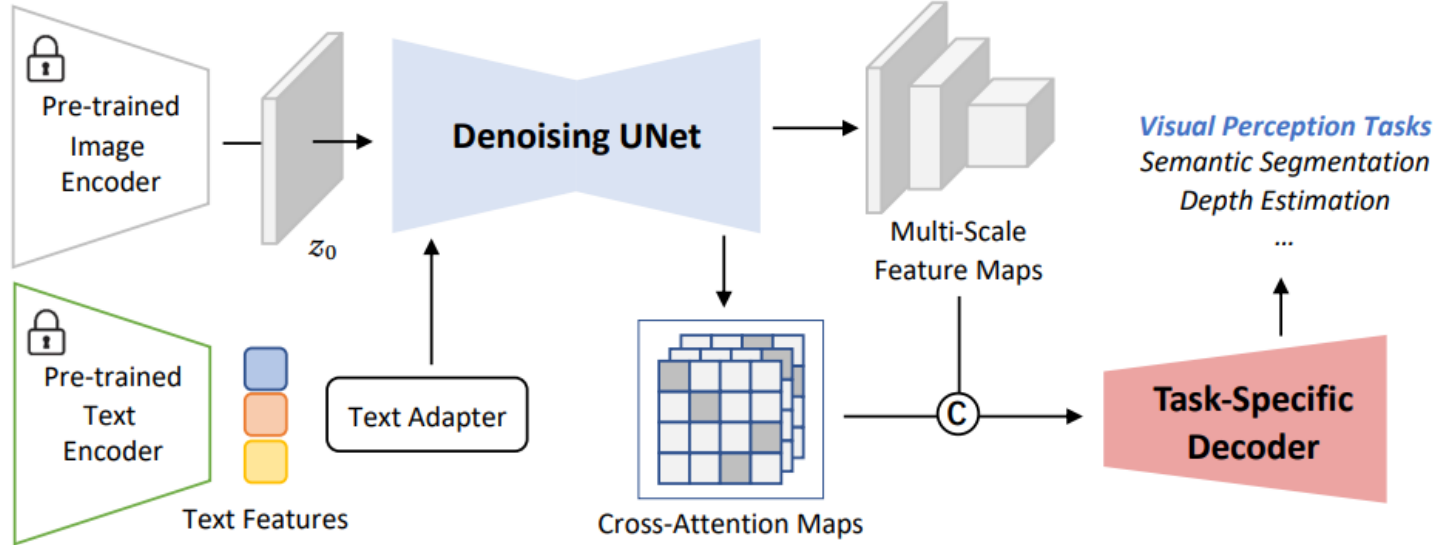
# Zero-shot Image-to-Image Translation



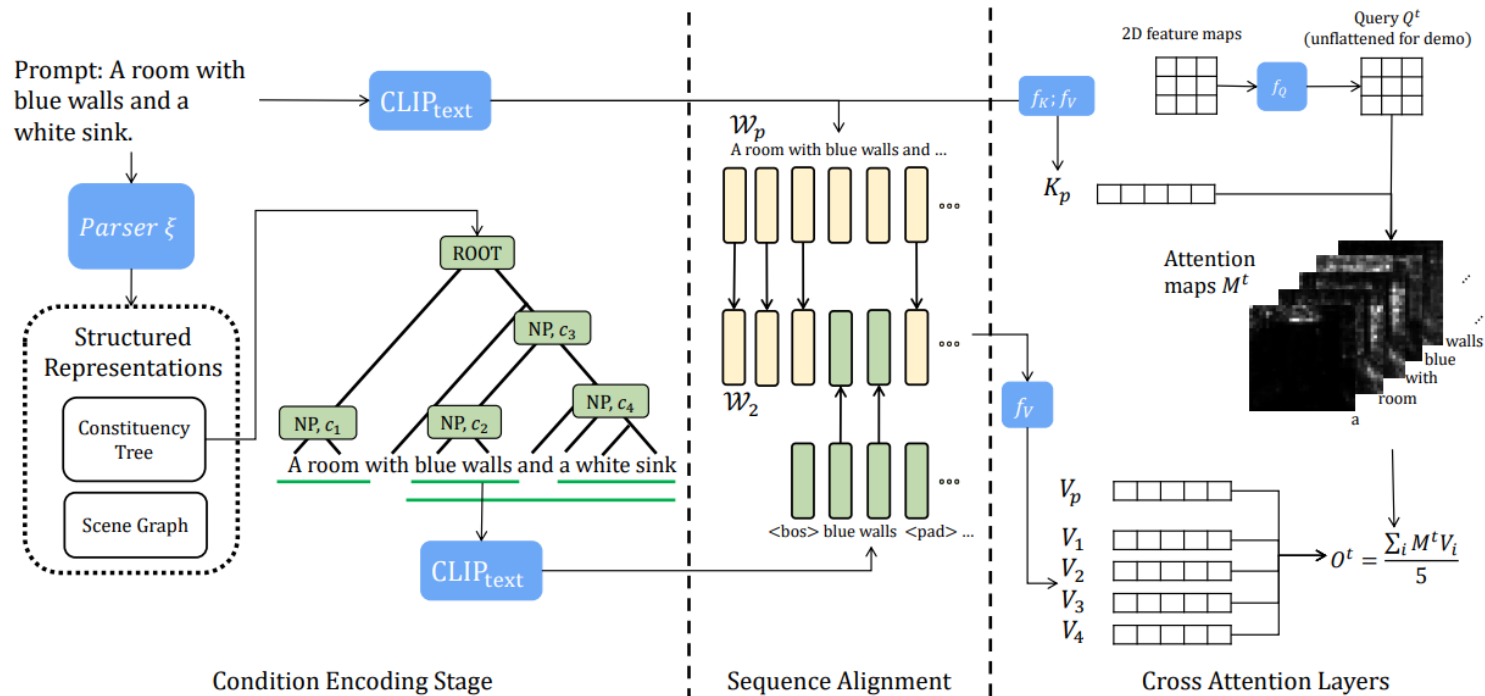
# Unleashing Text-to-Image Diffusion Models for Visual Perception



text prompts  
a photo of a  
<class name>

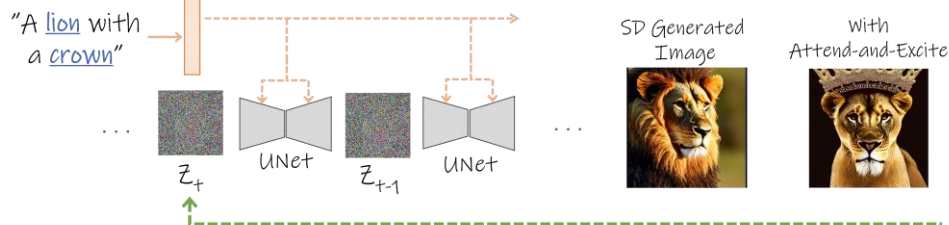


# Training-Free Structured Diffusion Guidance for Compositional Text-to-Image Synthesis

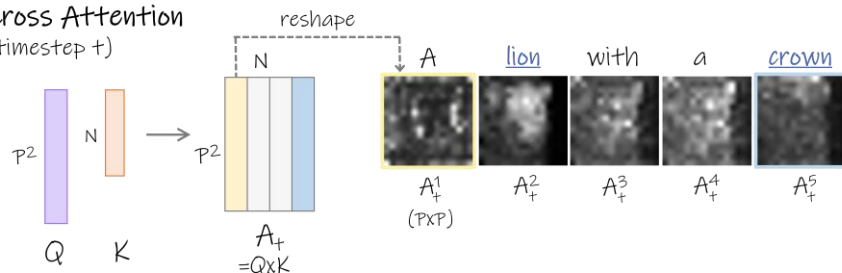


# Attend-and-Excite: Attention-Based Semantic Guidance for Text-to-Image Diffusion Models

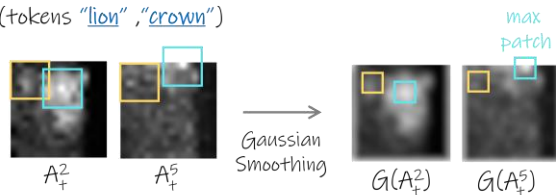
DDPM Process



Cross Attention  
(timestep  $t$ )



Loss Computation  
(tokens "lion", "crown")



$$L_2 = 1 - \max G(A_t^2)$$

$$L_5 = 1 - \max G(A_t^5)$$

$$\text{Loss: } L = \max(L_2, L_5)$$

$$\text{Update: } z'_t = z_t - \alpha \nabla_{z_t} L$$