Machine Learning Department
School of Computer Science
Carnegie Mellon University

Latent Diffusion Model + Diffusion Transformer + Prompt to Prompt

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Lecture 14
Oct. 20, 2025

Reminders

- Homework 3: Applying and Adapting LLMs
  - Out: Sat, Oct 4
  - Due: Thu, Oct 23 at 11:59pm
- Quiz 4
  - In-class, Mon, Oct 27
  - lectures 12 (only the text-to-image topics) – 15
- Homework 4: Multimodal Foundation Models
  - Out: Thu, Oct 23
  - Due: Mon, Nov 3 at 11:59pm

CONDITIONAL IMAGE GENERATION

Image Generation

- Class-conditional generation
- Super resolution
- Image Editing
- Style transfer
- Text-to-image (TTI) generation

Figure from Razavi et al. (2019)

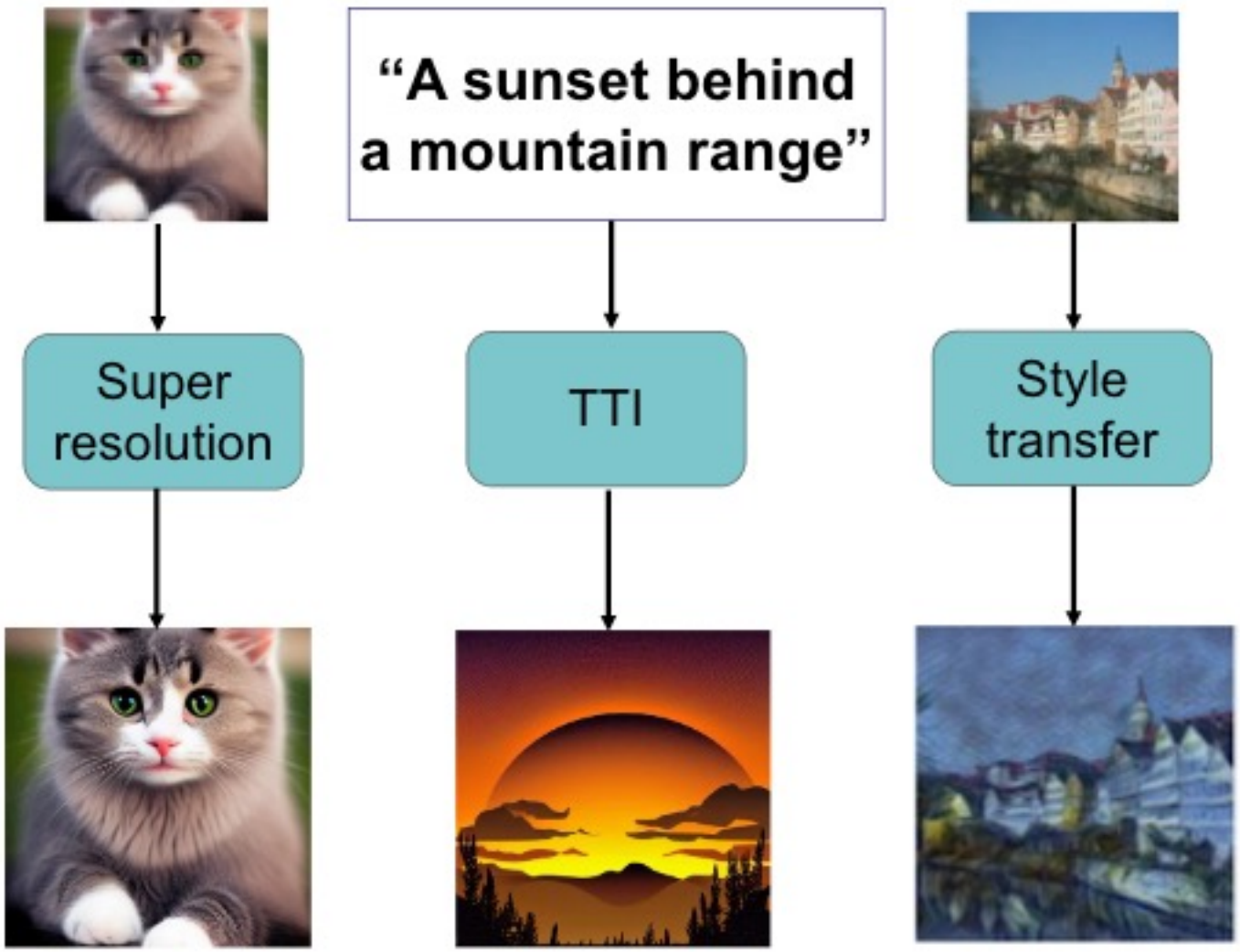


Figure from Bie et al. (2023)

Image Editing

A variety of tasks involve automatic editing of an image:

- **Inpainting** fills in the (pre-specified) missing pixels
- **Colorization** restores color to a greyscale image
- **Uncropping** creates a photo-realistic reconstruction of a missing side of an image

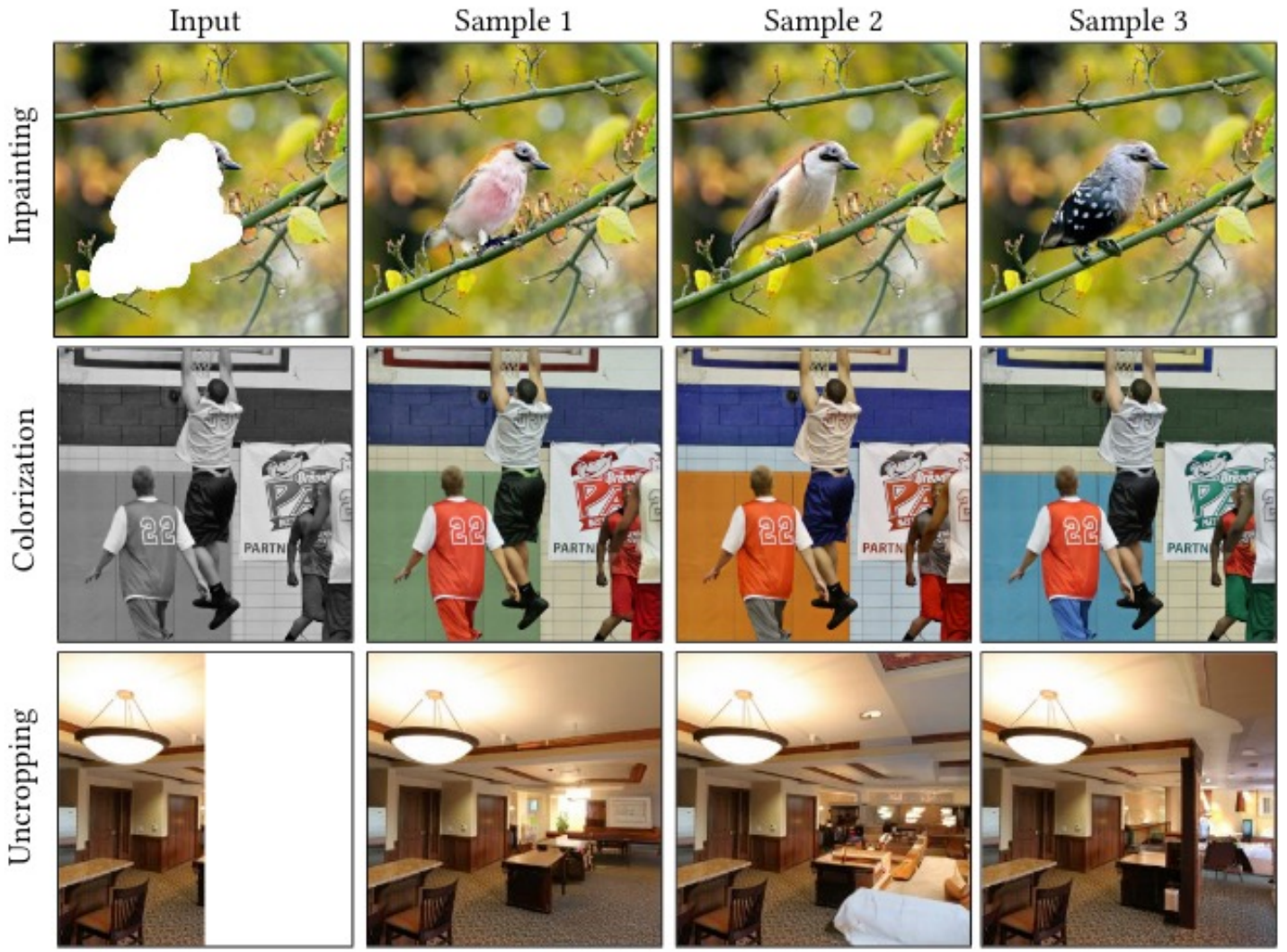
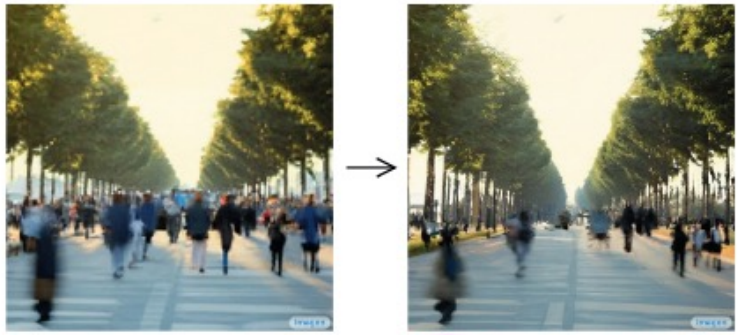


Figure from Saharia et al. (2022)

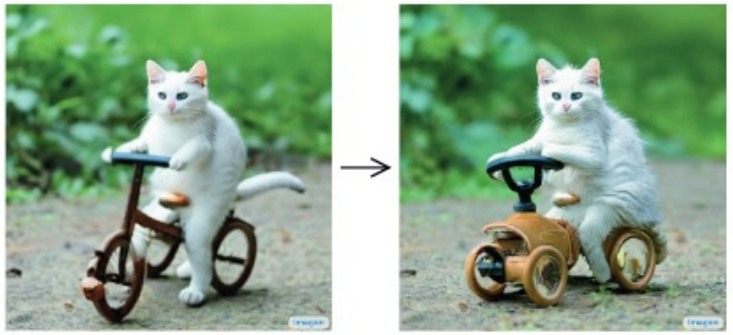
Editing Images with Text

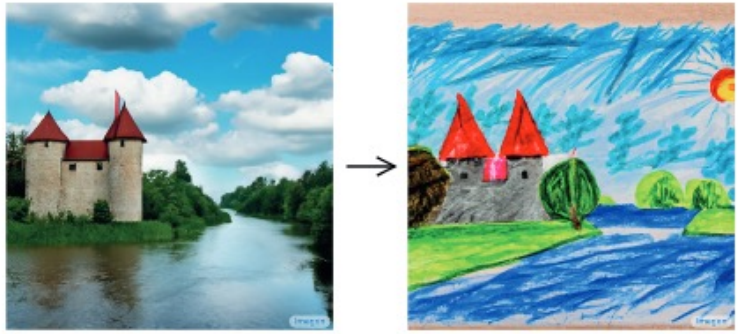
prompt-to-prompt can edit one generated image simply by adjusting the prompt

down-weight existing descriptor in the prompt



swap one word for another





phrase insertion for style change

phrase insertion for content change

LATENT DIFFUSION MODEL (LDM)

Latent Diffusion Model

Motivation:

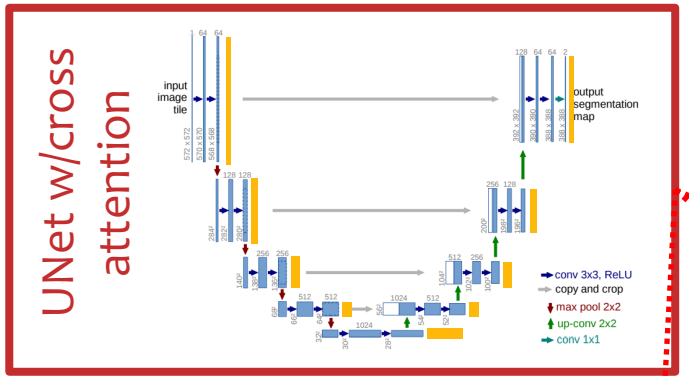
- diffusion models typically operate in pixel space
- yet, training typically takes hundreds of GPU days
  - 150 – 1000 V100 days [Guided Diffusion] (Dhariwal & Nichol, 2021)
  - 256 TPU-v4s for 4 days = 1000 TPU days [Imagen] (Sharia et al., 2022)
- inference is also slow
  - 50k samples in 5 days on A100 GPU [Guided Diffusion] (Dhariwal & Nichol, 2021)
  - 15 seconds per image

Key Idea:

- train an autoencoder (i.e. encoder-decoder model) that learns an efficient latent space that is perceptually equivalent to the data space
- keeping the autoencoder fixed, train a diffusion model on the latent representations of real images z_0 = encoder(x)
  - forward model: latent representation z_0 → noise z_T
  - reverse model: noise z_T → latent representation z_0
- to generate an image:
  - sample noise z_T
  - apply reverse diffusion model to obtain a latent representation z_0
  - decode the latent representation to an image x
- condition on prompt via cross attention in latent space

Latent Diffusion Model

Latent Diffusion Model (LDM)



prompt space

latent space

pixel space

$\widehat{\mathbf{y}}$

τ_θ

LLM

$\mathbf{y}$

orange cat

$p_\theta(\mathbf{z}_T)$

$p_\theta(\mathbf{z}_{T-1} \mid \mathbf{z}_T, \widehat{\mathbf{y}})$

$p_\theta(\mathbf{z}_t \mid \mathbf{z}_{t+1}, \widehat{\mathbf{y}})$

$p_\theta(\mathbf{z}_0 \mid \mathbf{z}_1, \widehat{\mathbf{y}})$

z_T z_{T-1} ... z_{t+1} z_t ... z_1 z

$\mathcal{D}$

Decoder

$\widetilde{\mathbf{x}}$

$\mathcal{E}$

Encoder

$\mathbf{x}$

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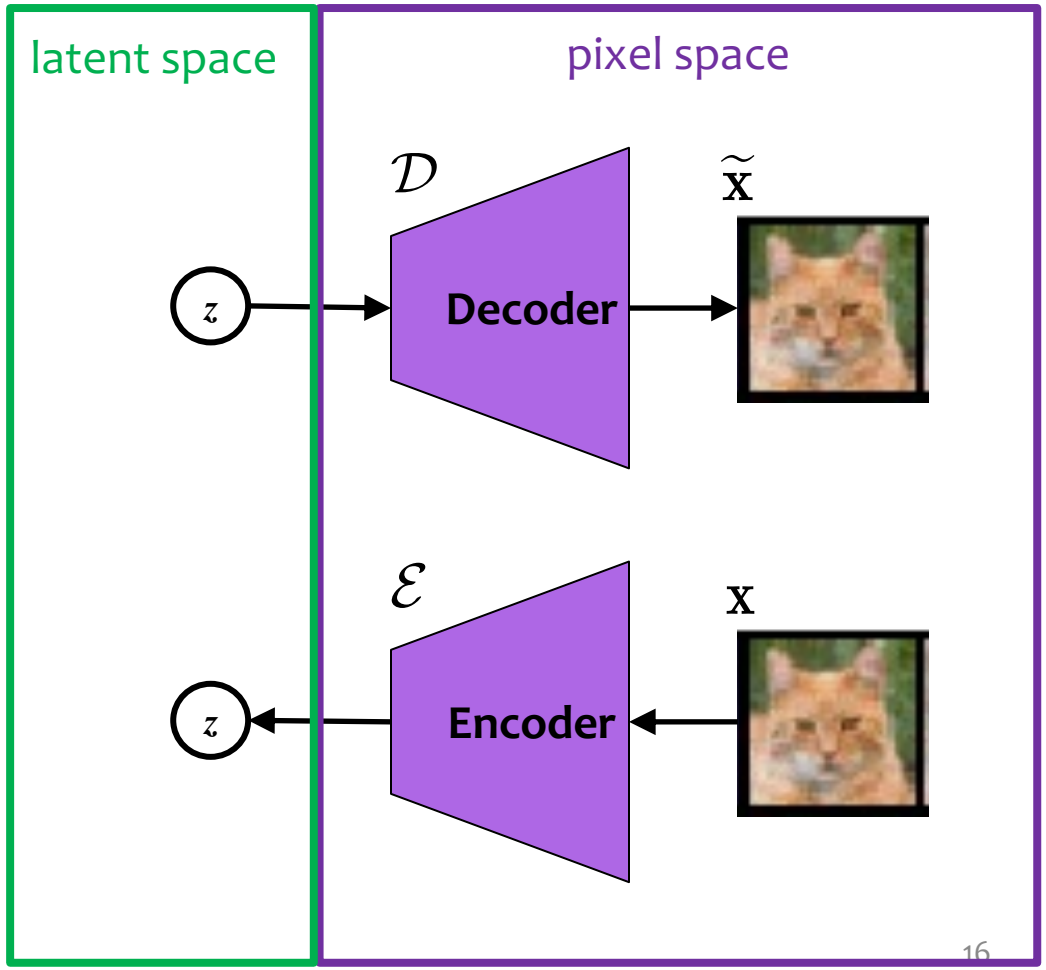
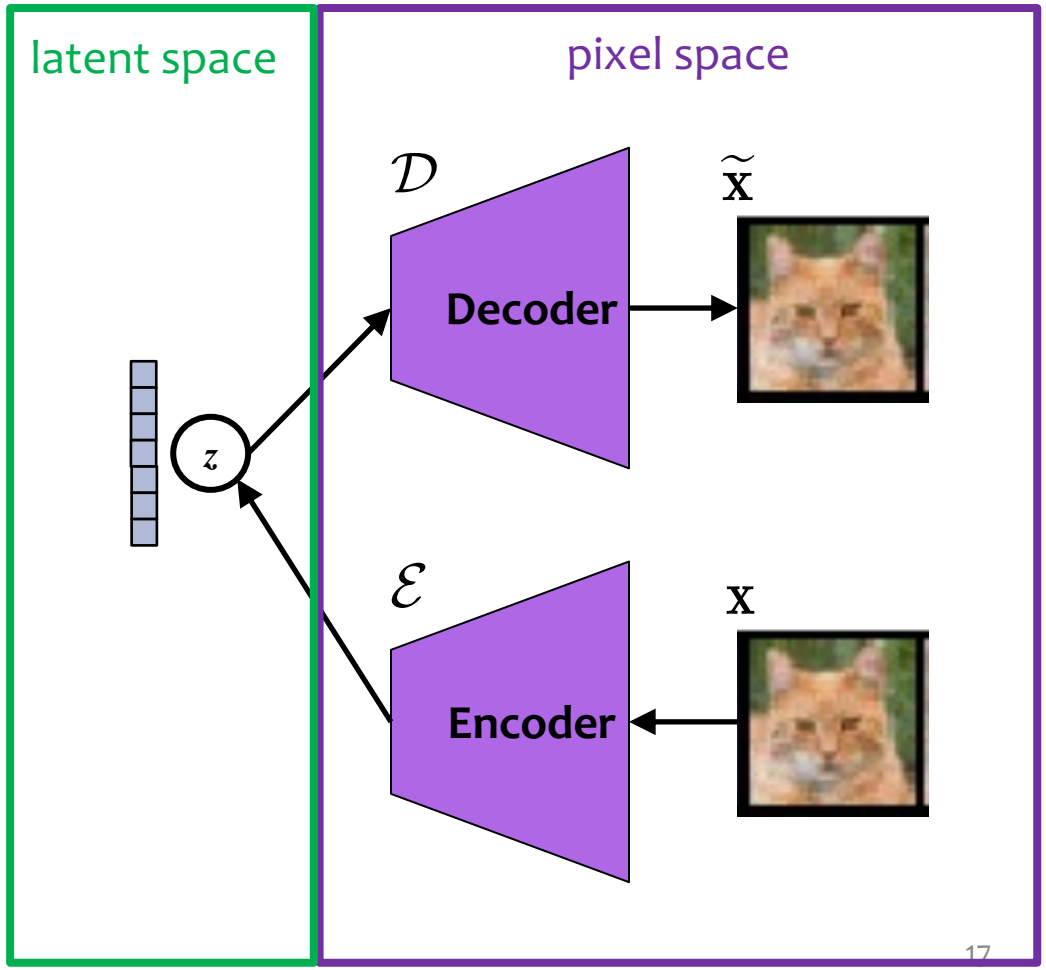
LDM: Autoencoder

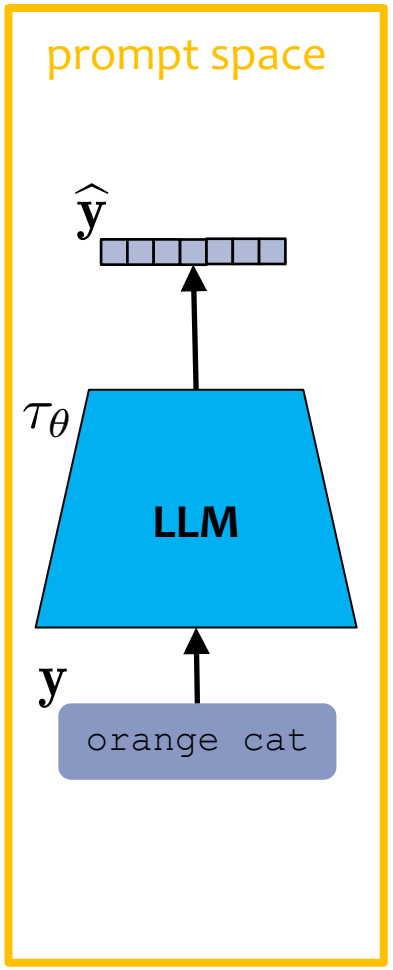


LDM: Autoencoder

- The autoencoder is chosen so that it can project high dimensional images (e.g. 1024x1024) down to low dimensional **latent space** and **faithfully** project back up to **pixel space**
- The original LDM paper considers two options:
  1. a VAE-like model (regularizes the noise towards a Gaussian)
  2. a VQGAN (performs vector quantization in the decoder; i.e., it uses a discrete codebook)
- This model is trained ahead of time just on raw images (no text prompts) and then frozen
- The frozen encoder-decoder can be reused for all subsequent LDM training

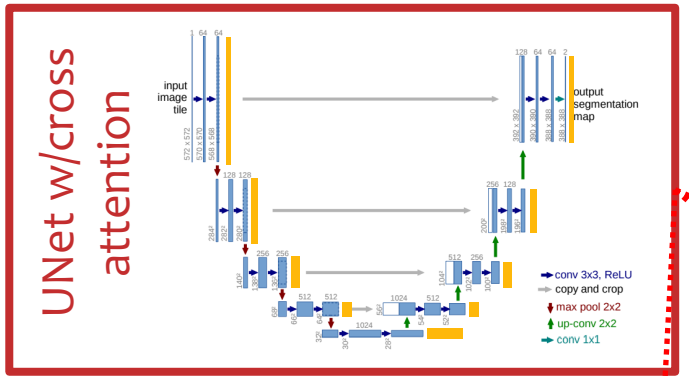


LDM: the Prompt Model



- The prompt model is just a Transformer LM
- We learn its parameters alongside the diffusion model
- The goal is to build up good representations of the text prompts such that they inform the latent diffusion process

LDM: with DDPM



prompt space

latent space

$\widehat{\mathbf{y}}$

τ_θ

LLM

$\mathbf{y}$

orange cat

$p_\theta(\mathbf{z}_T)$

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$p_\theta(\mathbf{z}_0 \mid \mathbf{z}_1, \widehat{\mathbf{y}})$

z_T z_{T-1} ... z_{t+1} z_t ... z_1 z

$q_\phi(\mathbf{z}_T \mid \mathbf{z}_{T-1})$

$q_\phi(\mathbf{z}_{t+1} \mid \mathbf{z}_t)$

$q_\phi(\mathbf{z}_1 \mid \mathbf{z}_0)$

LDM: with DDPM

Noise schedule:

We choose α_t to follow a fixed schedule s.t. $q_\phi(\mathbf{x}_T) \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, just like $p_\theta(\mathbf{x}_T)$.

Here we let $\mathbf{z}_0 = \mathbf{z}$, the output of the encoder from our autoencoder

Forward Process:

$$q_\phi(\mathbf{z}_{1:T}) = q(\mathbf{z}_0) \prod_{t=1}^{T} q_\phi(\mathbf{z}_t \mid \mathbf{z}_{t-1})$$

$$q(\mathbf{z}_0) = \text{data distribution}$$

$$q_\phi(\mathbf{z}_t \mid \mathbf{z}_{t-1}) \sim \mathcal{N}(\sqrt{\alpha_t}\mathbf{z}_{t-1}, (1-\alpha_t)\mathbf{I})$$

(Learned) Reverse Process:

$$p_\theta(\mathbf{z}_{1:T}) = p_\theta(\mathbf{z}_T) \prod_{t=1}^{T} p_\theta(\mathbf{z}_{t-1} \mid \mathbf{z}_t, \tau_\theta(y))$$

$$p_\theta(\mathbf{z}_T) \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

$$p_\theta(\mathbf{z}_{t-1} \mid \mathbf{z}_t, \tau_\theta(y)) \sim \mathcal{N}(\mu_\theta(\mathbf{z}_t, t, \tau_\theta(y)), \mathbf{\Sigma}_\theta(\mathbf{z}_t, t))$$

LDM: with DDPM

Noise schedule:

We choose α_t to follow a fixed schedule s.t. $q_\phi(\mathbf{x}_T) \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, just like $p_\theta(\mathbf{x}_T)$.

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Forward Process:

$$q_\phi(\mathbf{z}_{1:T}) = q(\mathbf{z}_0) \prod_{t=1}^{T} q_\phi(\mathbf{z}_t \mid \mathbf{z}_{t-1})$$

$$q(\mathbf{z}_0) = \text{data}$$

$$q_\phi(\mathbf{z}_t \mid \mathbf{z}_{t-1}) \sim \mathcal{N}(\sqrt{$$

Question: How do we define the mean to condition on the prompt representation?

(Learned) Reverse Process:

$$p_\theta(\mathbf{z}_{1:T}) = p_\theta(\mathbf{z}_T) \prod_{t=1}^{T} p_\theta(\mathbf{z}_{t-1} \mid \mathbf{z}_t, \tau_\theta(y))$$

$$p_\theta(\mathbf{z}_T) \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

$$p_\theta(\mathbf{z}_{t-1} \mid \mathbf{z}_t, \tau_\theta(y)) \sim \mathcal{N}(\mu_\theta(\mathbf{z}_t, t, \tau_\theta(y)), \mathbf{\Sigma}_\theta(\mathbf{z}_t, t))$$

Properties of forward and *exact* reverse process

Recall...

Property #1:

$$q(\mathbf{x}_t \mid \mathbf{x}_0) \sim \mathcal{N}(\sqrt{\bar{\alpha}_t}\mathbf{x}_0, (1-\bar{\alpha}_t)\mathbf{I})$$

$$\text{where } \bar{\alpha}_t = \prod_{s=1}^{t} \alpha_s$$

$\Rightarrow$ we can sample $\mathbf{x}_t$ from $\mathbf{x}_0$ at any timestep t efficiently in closed form

$\Rightarrow$ $\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + (1-\bar{\alpha}_t)\boldsymbol{\epsilon}$ where $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$

Property #2: Estimating $q(\mathbf{x}_{t-1} \mid \mathbf{x}_t)$ is intractable because of its dependence on $q(\mathbf{x}_0)$. However, conditioning on $\mathbf{x}_0$ we can efficiently work with:

$$q(\mathbf{x}_{t-1} \mid \mathbf{x}_t, \mathbf{x}_0) = \mathcal{N}(\tilde{\mu}_q(\mathbf{x}_t, \mathbf{x}_0), \sigma_t^2\mathbf{I})$$

$$\begin{aligned}\text{where } \tilde{\mu}_q(\mathbf{x}_t, \mathbf{x}_0) &= \frac{\sqrt{\bar{\alpha}_t}(1-\alpha_t)}{1-\bar{\alpha}_t}\mathbf{x}_0 + \frac{\sqrt{\alpha_t}(1-\bar{\alpha}_t)}{1-\bar{\alpha}_t}\mathbf{x}_t \\ &= \alpha_t^{(0)}\mathbf{x}_0 + \alpha_t^{(t)}\mathbf{x}_t\end{aligned}$$

$$\sigma_t^2 = \frac{(1-\bar{\alpha}_{t-1})(1-\alpha_t)}{1-\bar{\alpha}_t}$$

Property #3: Combining the two previous properties, we can obtain a different parameterization of $\tilde{\mu}_q$ which has been shown empirically to help in learning p_θ.

Rearranging $\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + (1-\bar{\alpha}_t)\boldsymbol{\epsilon}$ we have that:

$$\mathbf{x}_0 = (\mathbf{x}_0 + (1-\bar{\alpha}_t)\boldsymbol{\epsilon}) / \sqrt{\bar{\alpha}_t}$$

Substituting this definition of $\mathbf{x}_0$ into property #2's definition of $\tilde{\mu}_q$ gives:

$$\begin{aligned}\tilde{\mu}_q(\mathbf{x}_t, \mathbf{x}_0) &= \alpha_t^{(0)}\mathbf{x}_0 + \alpha_t^{(t)}\mathbf{x}_t \\ &= \alpha_t^{(0)}\left((\mathbf{x}_0 + (1-\bar{\alpha}_t)\boldsymbol{\epsilon}) / \sqrt{\bar{\alpha}_t}\right) + \alpha_t^{(t)}\mathbf{x}_t \\ &= \frac{1}{\sqrt{\alpha_t}}\left(\mathbf{x}_t - \frac{(1-\alpha_t)}{\sqrt{1-\bar{\alpha}_t}}\boldsymbol{\epsilon}\right)\end{aligned}$$

Parameterizing the *learned* reverse process

Recall...

Recall: $p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t) \sim \mathcal{N}(\mu_\theta(\mathbf{x}_t, t), \mathbf{\Sigma}_\theta(\mathbf{x}_t, t))$

Later we will show that given a training sample $\mathbf{x}_0$, we want

$$p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t)$$

to be as close as possible to

$$q(\mathbf{x}_{t-1} \mid \mathbf{x}_t, \mathbf{x}_0)$$

Intuitively, this makes sense: if the *learned* reverse process is supposed to subtract away the noise, then whenever we're working with a specific $\mathbf{x}_0$ it should subtract it away exactly as *exact* reverse process would have.

Idea #1: Rather than learn $\Sigma_\theta(\mathbf{x}_t, t)$ just use what we know about $q(\mathbf{x}_{t-1} \mid \mathbf{x}_t, \mathbf{x}_0) \sim \mathcal{N}(\tilde{\mu}_q(\mathbf{x}_t, \mathbf{x}_0), \sigma_t^2 \mathbf{I})$:

$$\Sigma_\theta(\mathbf{x}_t, t) = \sigma_t^2 \mathbf{I}$$

Idea #2: Choose μ_θ based on $q(\mathbf{x}_{t-1} \mid \mathbf{x}_t, \mathbf{x}_0)$, i.e. we want $\mu_\theta(\mathbf{x}_t, t)$ to be close to $\tilde{\mu}_q(\mathbf{x}_t, \mathbf{x}_0)$. Here are three ways we could parameterize this:

Option C: Learn a network that approximates the $\boldsymbol{\epsilon}$ that gave rise to $\mathbf{x}_t$ from $\mathbf{x}_0$ in the forward process from $\mathbf{x}_t$ and t:

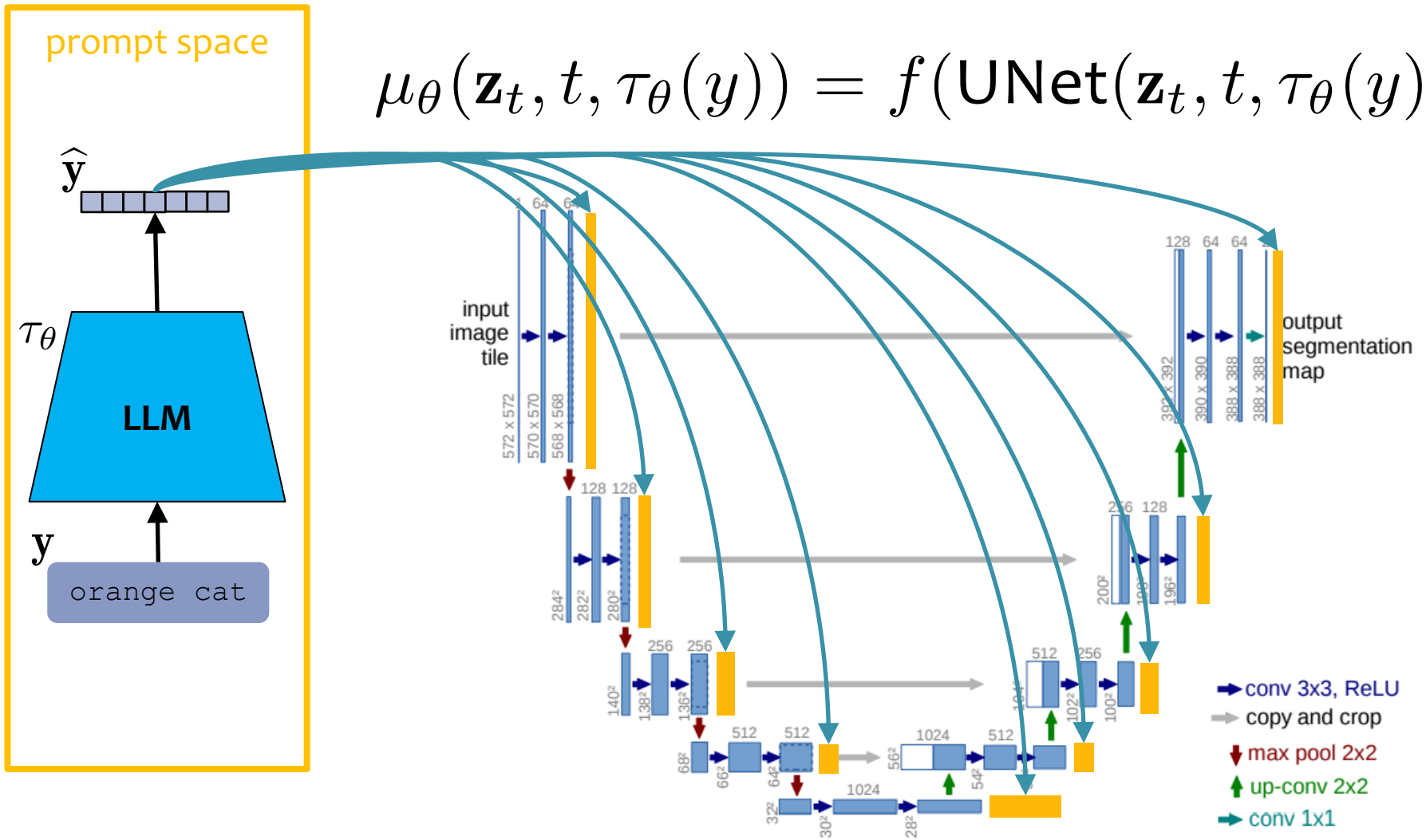
$$\mu_\theta(\mathbf{x}_t, t) = \alpha_t^{(0)} \mathbf{x}_\theta^{(0)}(\mathbf{x}_t, t) + \alpha_t^{(t)} \mathbf{x}_t$$

where $\mathbf{x}_\theta^{(0)}(\mathbf{x}_t, t) = (\mathbf{x}_0 + (1 - \bar{\alpha}_t)\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)) / \sqrt{\bar{\alpha}_t}$

where $\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t) = \text{UNet}_\theta(\mathbf{x}_t, t)$

LDM: Noise Model

$$\mu_\theta(\mathbf{z}_t, t, \tau_\theta(y)) = f(\text{UNet}(\mathbf{z}_t, t, \tau_\theta(y)))$$



- The noise model includes **cross attention** (yellow boxes) to the representation of the prompt text
- During training we optimize both the parameters of the UNet noise model and the parameters of the LLM simultaneously

LDM: Learning the Diffusion Model + LLM

Given a training sample $\mathbf{z}_0$, we want

$$p_\theta(\mathbf{z}_{t-1} \mid \mathbf{z}_t, \tau_\theta(y))$$

to be as close as possible to

$$q(\mathbf{z}_{t-1} \mid \mathbf{z}_t, \mathbf{z}_0)$$

Intuitively, this makes sense: if the *learned* reverse process is supposed to subtract away the noise, then whenever we're working with a specific $\mathbf{z}_0$ it should subtract it away exactly as *exact* reverse process would have.

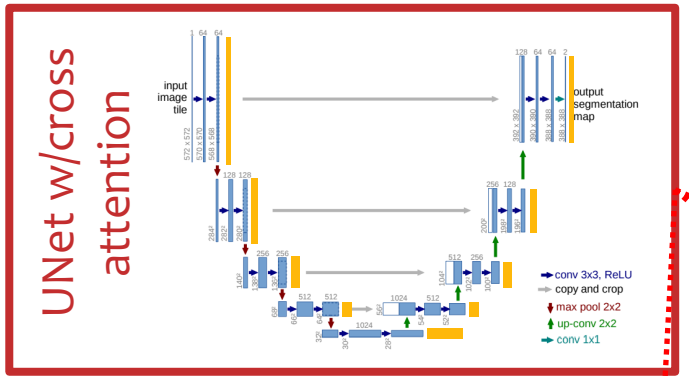
Objective Function:

$$L_{LDM} := \mathbb{E}_{\mathcal{E}(x),y,\epsilon\sim\mathcal{N}(0,1),t}\left[\|\epsilon - \epsilon_\theta(z_t, t, \tau_\theta(y))\|_2^2\right]$$

Algorithm 1 Training

1: initialize θ
2: **for** $e \in \{1, \ldots, E\}$ **do**
3: **for** $x_0, y \in \mathcal{D}$ **do**
4: $t \sim \text{Uniform}(1, \ldots, T)$
5: $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
6: $\mathbf{x}_t \leftarrow \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}$
7: $\ell_t(\theta) \leftarrow \|\boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t, \tau_\theta(\mathbf{y}))\|^2$
8: $\theta \leftarrow \theta - \nabla_\theta \ell_t(\theta)$

Latent Diffusion Model (LDM)



prompt space

latent space

pixel space

$\widehat{\mathbf{y}}$

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LLM

$\mathbf{y}$

orange cat

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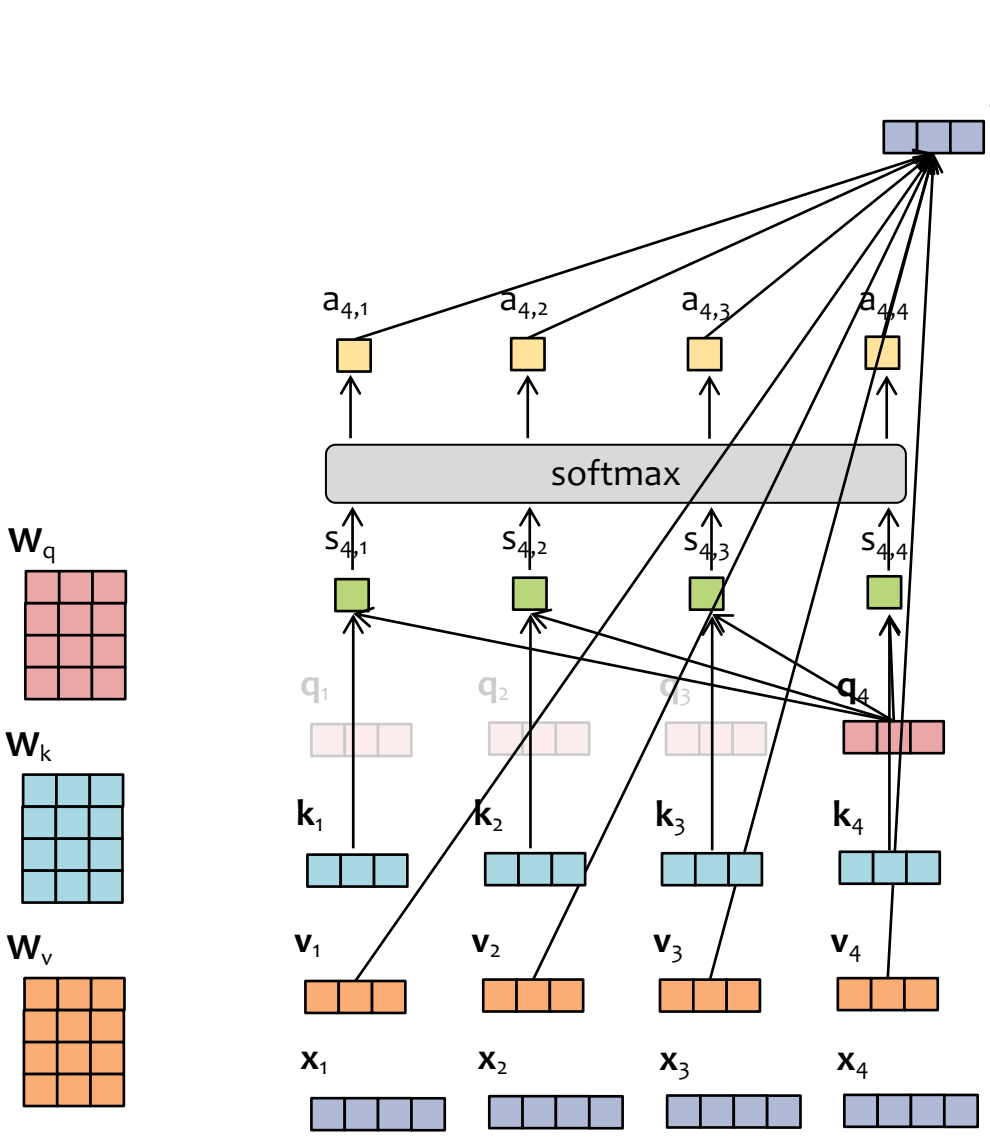
CROSS-ATTENTION

Scaled Dot-Product Attention



$$\mathbf{a}_4 = \text{softmax}(\mathbf{s}_4)$$ attention weights

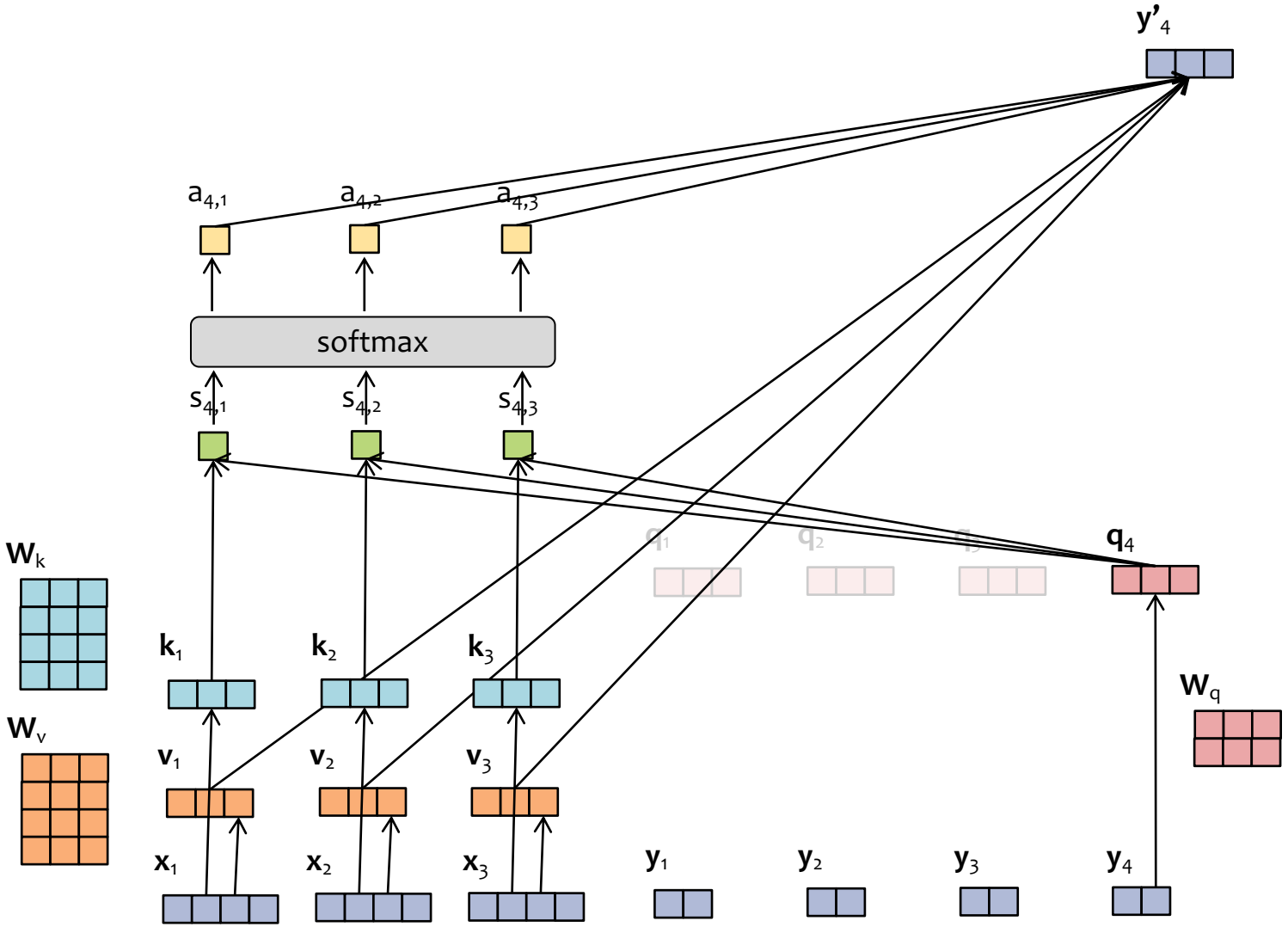
$$s_{4,j} = \mathbf{k}_j^T \mathbf{q}_4 / \sqrt{d_k}$$ scores

$$\mathbf{q}_j = \mathbf{W}_q^T \mathbf{x}_j$$ queries

$$\mathbf{k}_j = \mathbf{W}_k^T \mathbf{x}_j$$ keys

$$\mathbf{v}_j = \mathbf{W}_v^T \mathbf{x}_j$$ values

Cross Attention



$$\mathbf{y}'_t = \sum_{j=1}^{m} a_{t,j}\mathbf{v}_j, \forall t$$

$$\mathbf{a}_t = \text{softmax}(\mathbf{s}_t), \forall t$$ attention weights

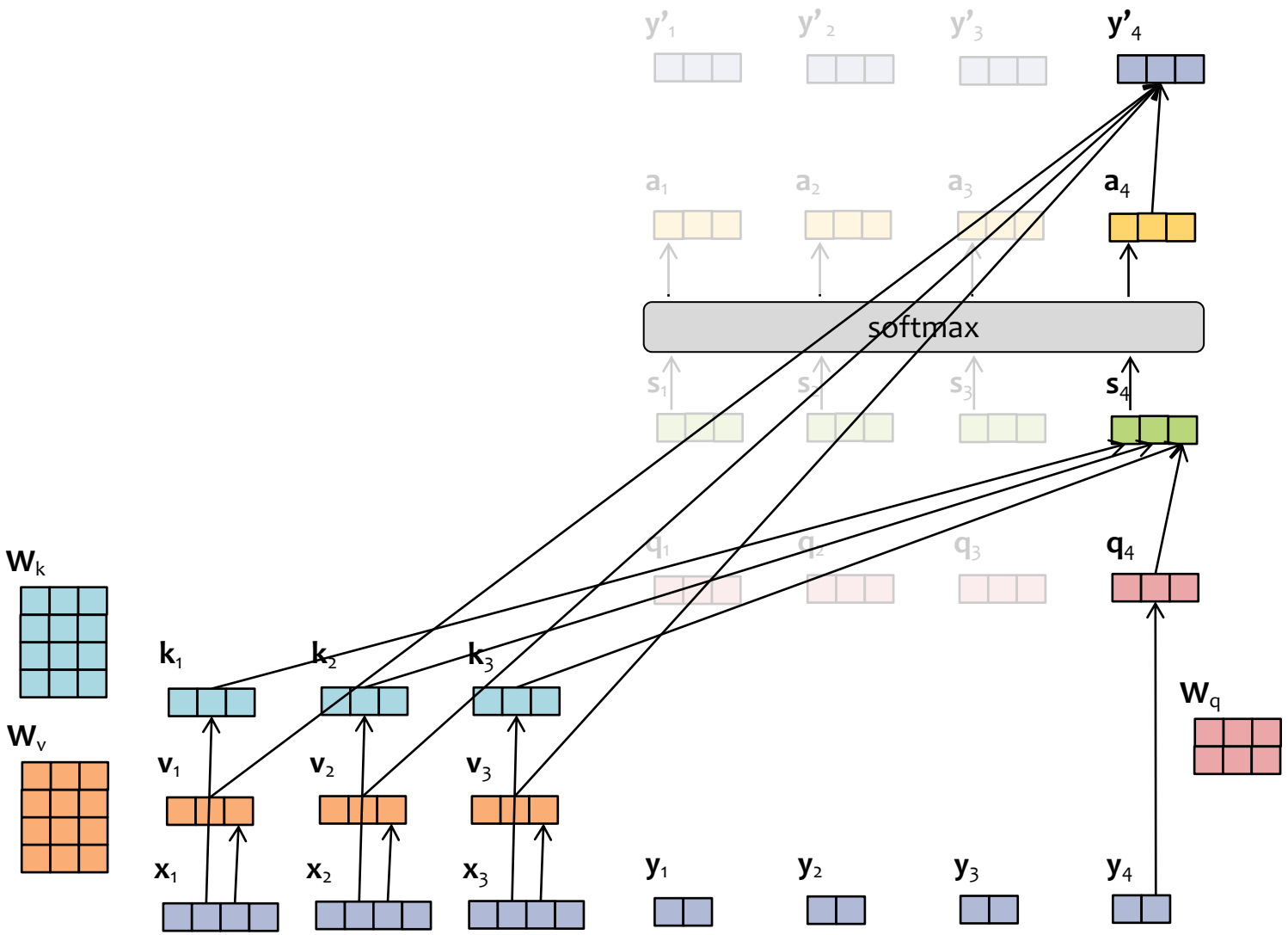
$$s_{t,j} = \mathbf{k}_j^T \mathbf{q}_t / \sqrt{d}, \forall j, t$$ scores

$$\mathbf{q}_t = \mathbf{W}_q^T \mathbf{y}_t, \forall t \in \{1, \ldots, n\}$$ queries

$$\mathbf{k}_j = \mathbf{W}_k^T \mathbf{x}_j, \forall j \in \{1, \ldots, m\}$$ keys

$$\mathbf{v}_j = \mathbf{W}_v^T \mathbf{x}_j, \forall j \in \{1, \ldots, m\}$$ values

Cross Attention



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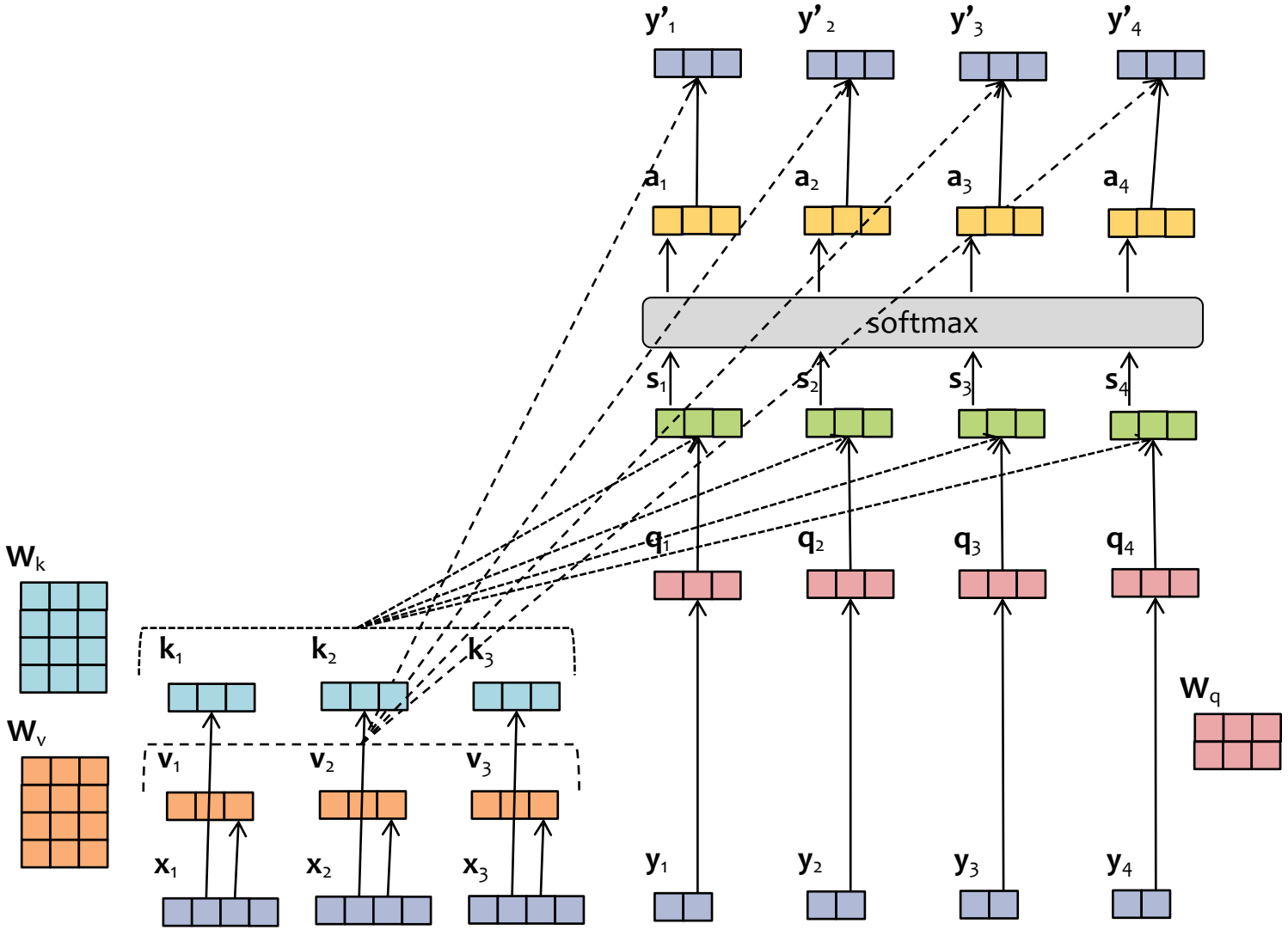
Cross Attention



$$\mathbf{Y} = \mathbf{A}\mathbf{V} = \text{softmax}(\mathbf{Q}\mathbf{K}^T/\sqrt{d})\mathbf{V}$$

$$\mathbf{A} = \text{softmax}(\mathbf{S})$$ attention weights

$$\mathbf{S} = \mathbf{Q}\mathbf{K}^T/\sqrt{d} \in \mathbb{R}^{n\times m}$$ scores

$$\mathbf{Q} = \mathbf{Y}\mathbf{W}_q \in \mathbb{R}^{n\times d}$$ queries

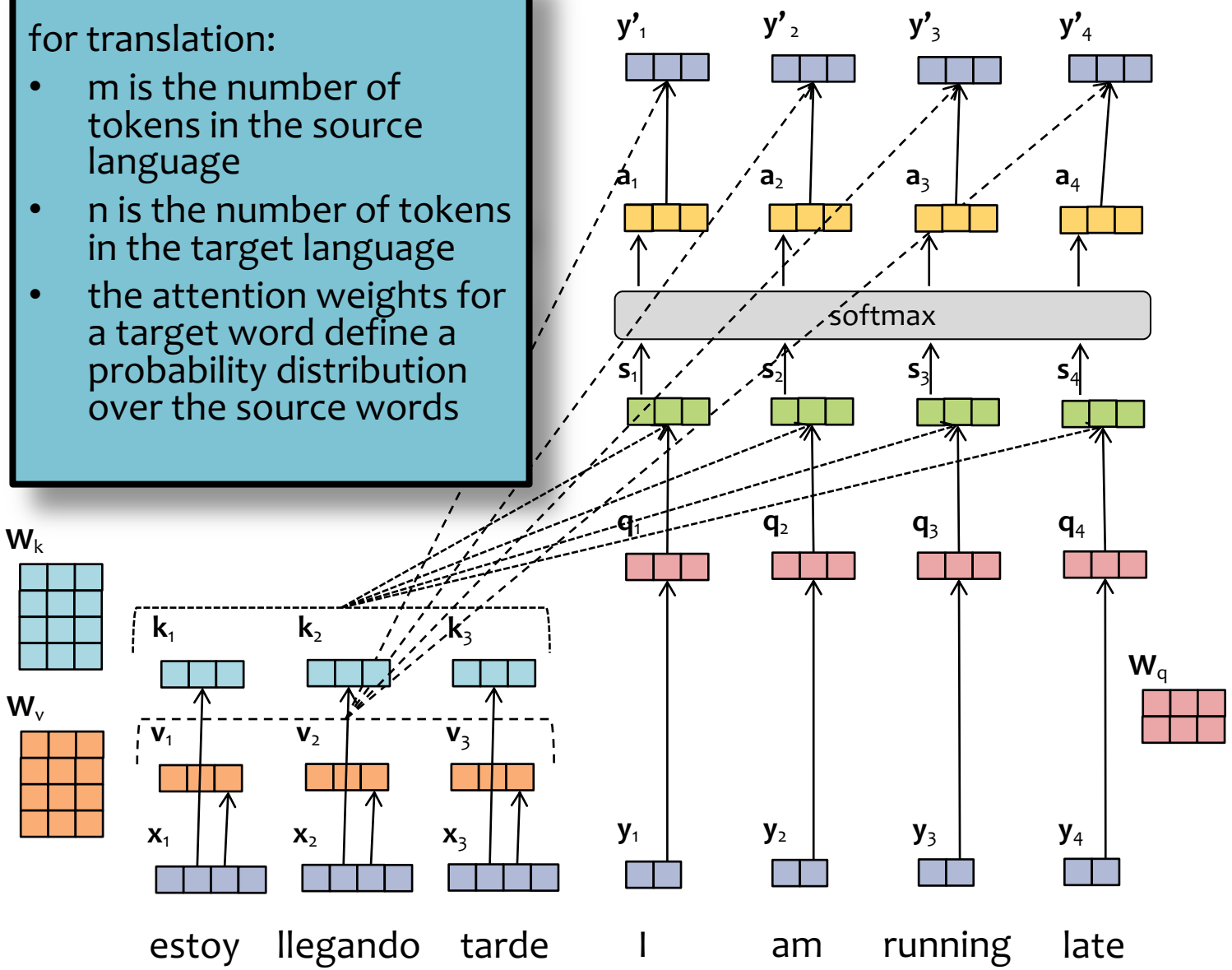
$$\mathbf{K} = \mathbf{X}\mathbf{W}_k \in \mathbb{R}^{m\times d}$$ keys

$$\mathbf{V} = \mathbf{X}\mathbf{W}_v \in \mathbb{R}^{m\times d}$$ values

Example: Cross Attention for Translation

for translation:

- m is the number of tokens in the source language
- n is the number of tokens in the target language
- the attention weights for a target word define a probability distribution over the source words



$$\mathbf{Y} = \mathbf{AV} = \text{softmax}(\mathbf{QK}^T/\sqrt{d})\mathbf{V}$$

$\mathbf{A} = \text{softmax}(\mathbf{S})$ attention weights

$\mathbf{S} = \mathbf{QK}^T/\sqrt{d} \in \mathbb{R}^{n \times m}$ scores

$\mathbf{Q} = \mathbf{YW}_q \in \mathbb{R}^{n \times d}$ queries

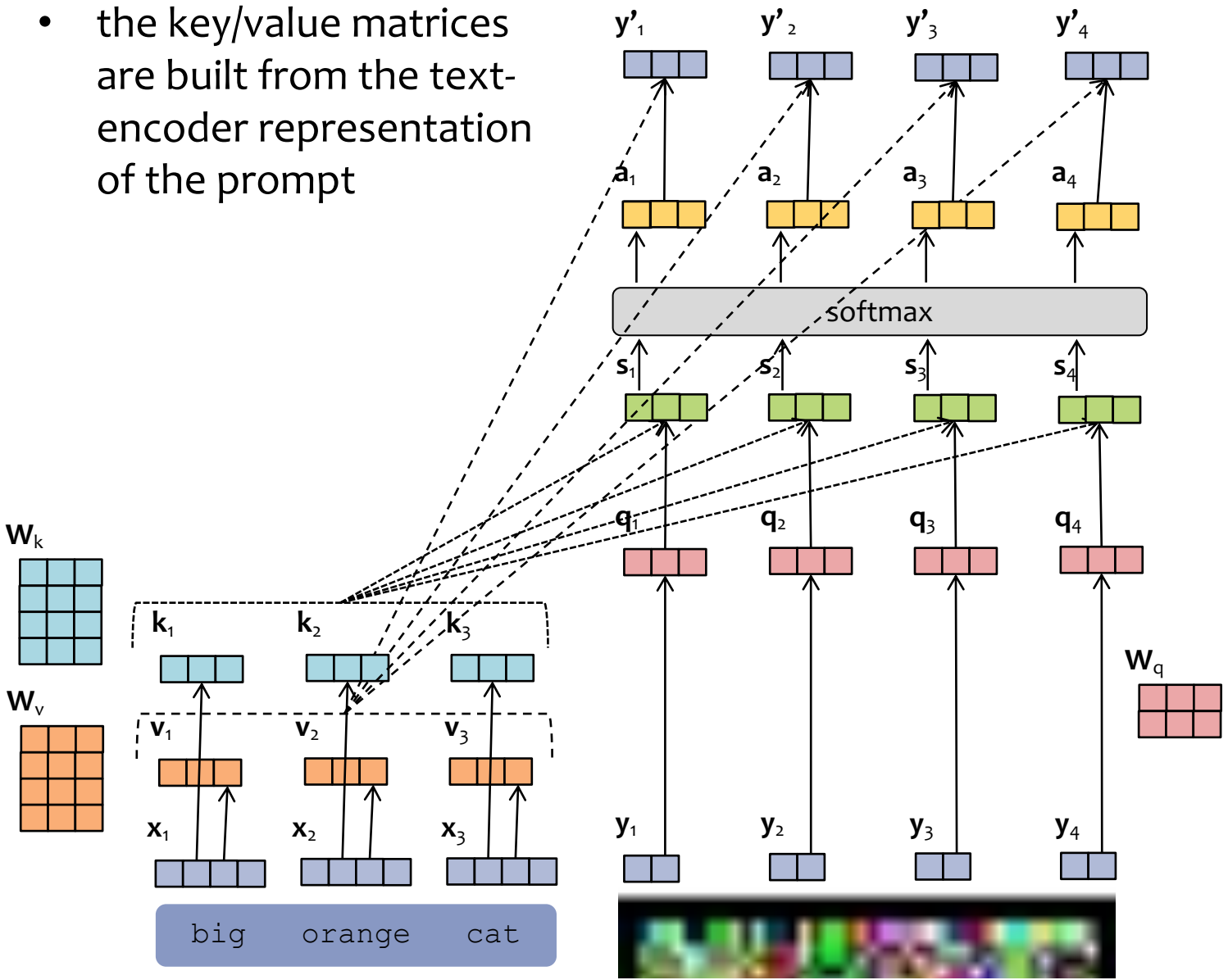
$\mathbf{K} = \mathbf{XW}_k \in \mathbb{R}^{m \times d}$ keys

$\mathbf{V} = \mathbf{XW}_v \in \mathbb{R}^{m \times d}$ values

LDM: Cross-Attention

Cross-Attention in LDM:

- the query matrix is built from a layer of UNet
- the key/value matrices are built from the text-encoder representation of the prompt



$$\mathbf{Y} = \mathbf{AV} = \text{softmax}(\mathbf{QK}^T/\sqrt{d})\mathbf{V}$$

$$\mathbf{A} = \text{softmax}(\mathbf{S})$$

$$\mathbf{S} = \mathbf{QK}^T/\sqrt{d} \in \mathbb{R}^{n\times m}$$

$$\mathbf{Q} = \mathbf{YW}_q \in \mathbb{R}^{n\times d}$$

$$\mathbf{K} = \mathbf{XW}_k \in \mathbb{R}^{m\times d}$$

$$\mathbf{V} = \mathbf{XW}_v \in \mathbb{R}^{m\times d}$$

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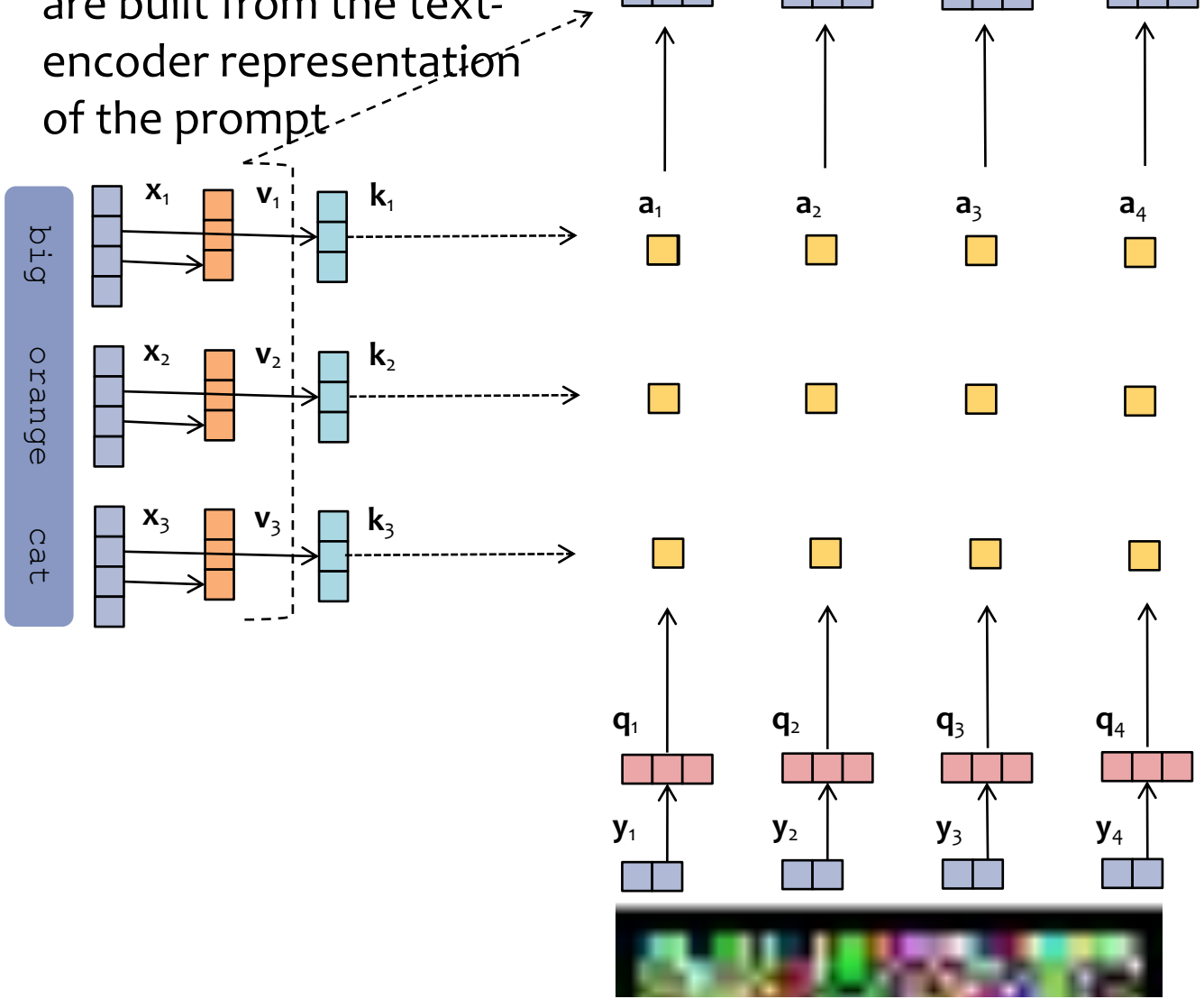
Cross-Attention in LDM:

- the query matrix is built from a layer of UNet
- the key/value matrices are built from the text-encoder representation of the prompt



$$\mathbf{Y} = \mathbf{AV} = \text{softmax}(\mathbf{QK}^T/\sqrt{d})\mathbf{V}$$

$$\mathbf{A} = \text{softmax}(\mathbf{S}) \qquad \text{(attention weights)}$$

$$\mathbf{S} = \mathbf{QK}^T/\sqrt{d} \in \mathbb{R}^{n\times m}$$

$$\mathbf{Q} = \mathbf{YW}_q \in \mathbb{R}^{n\times d}$$

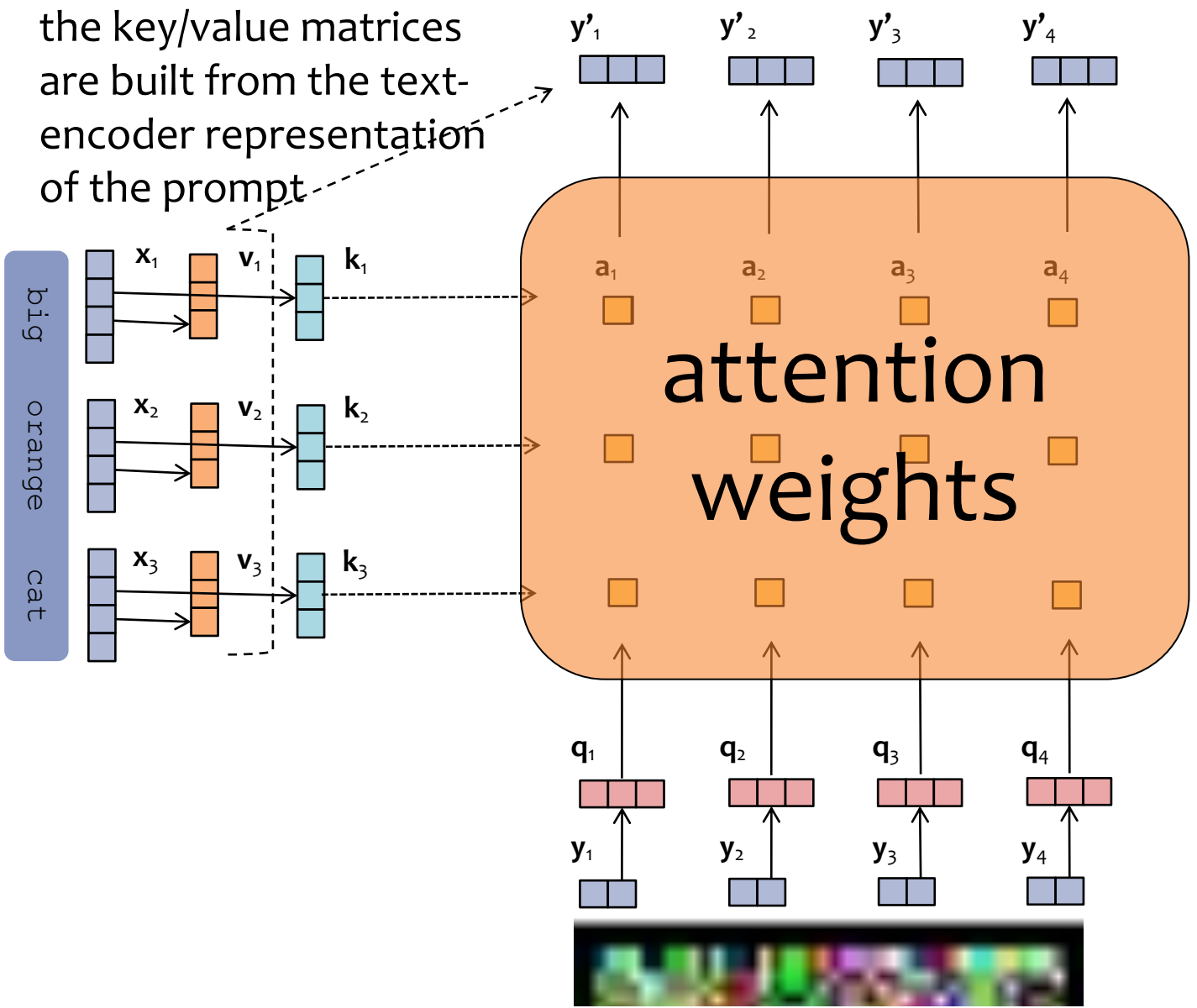
$$\mathbf{K} = \mathbf{XW}_k \in \mathbb{R}^{m\times d}$$

$$\mathbf{V} = \mathbf{XW}_v \in \mathbb{R}^{m\times d}$$

LDM: Cross-Attention

Cross-Attention in LDM:

- the query matrix is built from a layer of UNet
- the key/value matrices are built from the text-encoder representation of the prompt



$$\mathbf{Y} = \mathbf{AV}$$

$$\mathbf{A} = \text{soft}$$

$$\mathbf{S} = \mathbf{QK}^T$$

$$\mathbf{Q} = \mathbf{YW}$$

$$\mathbf{K} = \mathbf{XW}$$

$$\mathbf{V} = \mathbf{XW}$$

for LDM:

- m is the number of tokens in the text prompt
- n is the number of dimensions in the latent space (if we have compression)
- n would be the number of pixels in the image (if we had no compression)
- the attention weights for a (latent) pixel define a probability distribution over the prompt tokens

The actual attention and cross-attention blocks are **multi-head**

LDM: Cross-Attention in Noise Model

- The cross-attention is placed within a larger Transformer layer

Transformer Layer inside UNet

input	$\mathbb{R}^{h \times w \times c}$
LayerNorm	$\mathbb{R}^{h \times w \times c}$
Conv1x1	$\mathbb{R}^{h \times w \times d \cdot n_h}$
Reshape	$\mathbb{R}^{h \cdot w \times d \cdot n_h}$
$\times T$ { SelfAttention	$\mathbb{R}^{h \cdot w \times d \cdot n_h}$
$\times T$ { MLP	$\mathbb{R}^{h \cdot w \times d \cdot n_h}$
$\times T$ { CrossAttention	$\mathbb{R}^{h \cdot w \times d \cdot n_h}$
Reshape	$\mathbb{R}^{h \times w \times d \cdot n_h}$
Conv1x1	$\mathbb{R}^{h \times w \times c}$

- The cross-attention modifies the keys and values to be the prompt representation
- The queries are the current layer of UNet

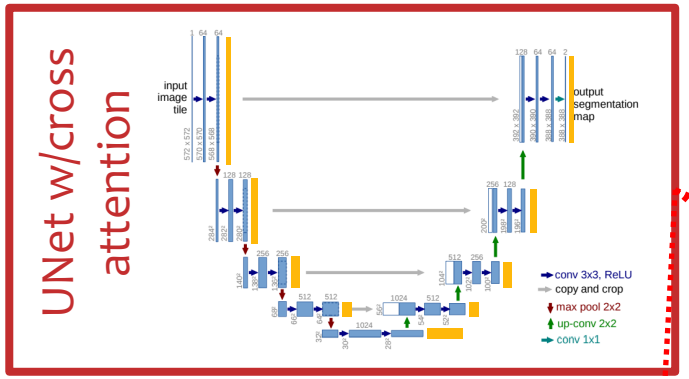
$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right) \cdot V, \text{ with}$$

$$Q = W_Q^{(i)} \cdot \varphi_i(z_t),\ K = W_K^{(i)} \cdot \tau_\theta(y),\ V = W_V^{(i)} \cdot \tau_\theta(y).$$

Here, $\varphi_i(z_t) \in \mathbb{R}^{N \times d_\epsilon^i}$ denotes a (flattened) intermediate representation of the UNet implementing ϵ_θ and $W_V^{(i)} \in \mathbb{R}^{d \times d_\epsilon^i}$, $W_Q^{(i)} \in \mathbb{R}^{d \times d_\tau}$ & $W_K^{(i)} \in \mathbb{R}^{d \times d_\tau}$ are learnable projection matrices [36, 97]. See Fig. 3 for a visual depiction.

Figure from http://arxiv.org/abs/2112.10752

Latent Diffusion Model (LDM)



prompt space

latent space

pixel space

$\widehat{\mathbf{y}}$

τ_θ

LLM

$\mathbf{y}$

orange cat

$p_\theta(\mathbf{z}_T)$

$p_\theta(\mathbf{z}_{T-1} \mid \mathbf{z}_T, \widehat{\mathbf{y}})$

$p_\theta(\mathbf{z}_t \mid \mathbf{z}_{t+1}, \widehat{\mathbf{y}})$

$p_\theta(\mathbf{z}_0 \mid \mathbf{z}_1, \widehat{\mathbf{y}})$

z_T z_{T-1} ... z_{t+1} z_t ... z_1 z

$\mathcal{D}$

Decoder

$\widetilde{\mathbf{x}}$

$\mathcal{E}$

Encoder

$\mathbf{x}$

$q_\phi(\mathbf{z}_T \mid \mathbf{z}_{T-1})$

$q_\phi(\mathbf{z}_{t+1} \mid \mathbf{z}_t)$

$q_\phi(\mathbf{z}_1 \mid \mathbf{z}_0)$

LDM Results

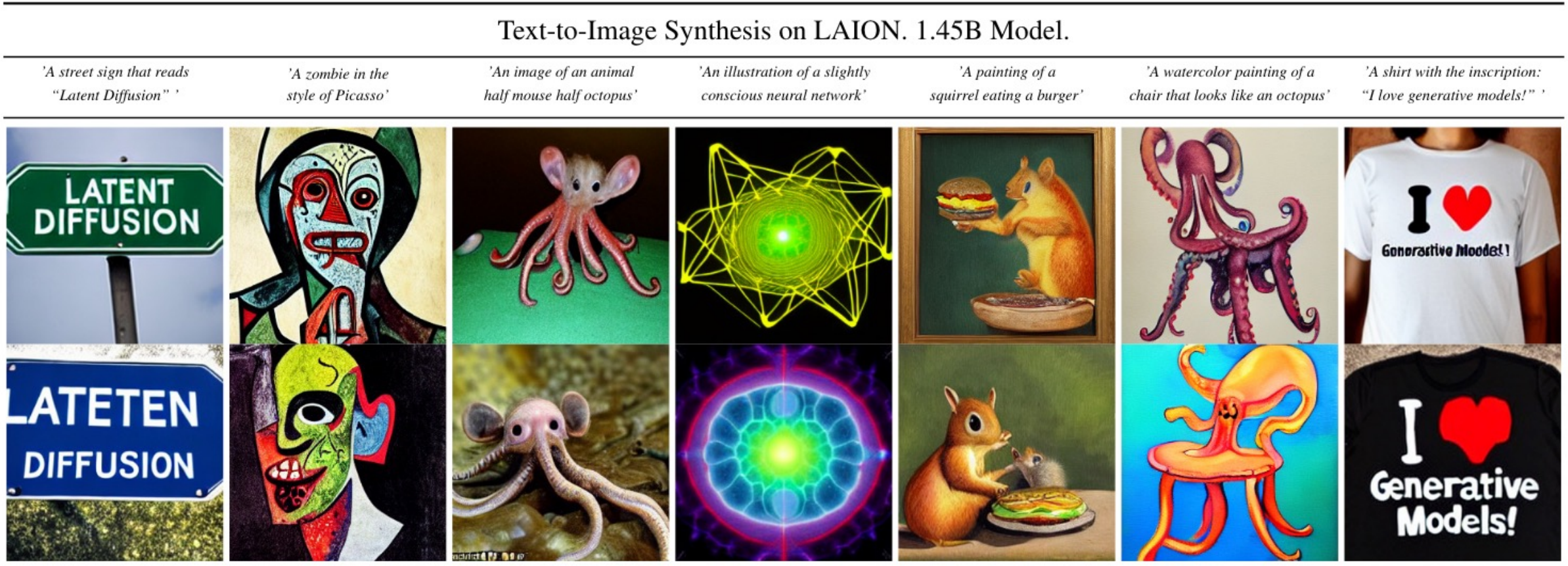


Figure 5. Samples for user-defined text prompts from our model for text-to-image synthesis, *LDM-8 (KL)*, which was trained on the LAION [78] database. Samples generated with 200 DDIM steps and $\eta = 1.0$. We use unconditional guidance [32] with $s = 10.0$.

Figure from http://arxiv.org/abs/2112.10752

LDM Results

- The result models obtain very high quality FID / IS scores with many fewer parameters than competing models
- The models are much more efficient than vanilla diffusion models because the most computationally intensive step happens in low dimensional latent space, instead of high dimensional pixel space

Text-Conditional Image Synthesis				
Method	FID ↓	IS↑	N_{params}	
CogView† [17]	27.10	18.20	4B	self-ranking, rejection rate 0.017
LAFITE† [109]	26.94	<u>26.02</u>	75M	
GLIDE* [59]	<u>12.24</u>	-	6B	277 DDIM steps, c.f.g. [32] $s = 3$
Make-A-Scene* [26]	**11.84**	-	4B	c.f.g for AR models [98] $s = 5$
LDM-KL-8	23.31	$20.03_{\pm 0.33}$	1.45B	250 DDIM steps
*LDM-KL-8-G**	12.63	$\mathbf{30.29}_{\pm \mathbf{0.42}}$	1.45B	250 DDIM steps, c.f.g. [32] $s = 1.5$

Table 2. Evaluation of text-conditional image synthesis on the 256×256-sized MS-COCO [51] dataset: with 250 DDIM [84] steps our model is on par with the most recent diffusion [59] and autoregressive [26] methods despite using significantly less parameters. †/*:Numbers from [109]/ [26]

Figure from http://arxiv.org/abs/2112.10752

CLASSIFIER-FREE GUIDANCE

Classifier-free Guidance

- Diffusion models (unlike GANs) are great at generating diverse samples
- But when diffusion is conditioned on some input (text, label, etc.) that diversity may cause it to stray away from the prompt
- **Classifier-free guidance** helps diffusion to adhere to the prompt, yielding higher quality images

Motivation:

- CFG steers generation to increase:

$$\log p(\mathbf{c} \mid \mathbf{z}_0) \propto \log p(\mathbf{z}_0 \mid \mathbf{c}) - \log p(\mathbf{z}_0)$$
$$\text{where } \nabla_{\mathbf{z}_0} \log p(\mathbf{c} \mid \mathbf{z}_0) \propto \nabla_{\mathbf{z}_0} \log p(\mathbf{z}_0 \mid \mathbf{c}) - \nabla_{\mathbf{z}_0} \log p(\mathbf{z}_0)$$

- Define $\log p(\mathbf{z}_0)$ through $\boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t) = \boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t, \emptyset)$ where $\emptyset$ is given a null embedding and otherwise shares parameters with $\boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t, \mathbf{c})$
- So we guide the DDPM sampling to high $p(\mathbf{c} \mid \mathbf{z}_0)$ by:

$$\begin{aligned}\boldsymbol{\epsilon}_\theta &\leftarrow \boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t, \emptyset) + w \cdot \nabla_{\mathbf{z}_0} \log p(\mathbf{z}_0 \mid \mathbf{c}) \\ &\propto \boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t, \emptyset) + w \cdot \boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t, \mathbf{c})\end{aligned}$$

where $w > 1$ is the scale of the guidance and $w = 1$ gives standard sampling

- Larger $w \Rightarrow$ higher $p(\mathbf{c} \mid \mathbf{z}_0)$, lower diversity.

Classifier-free Guidance

- Diffusion models (unlike GANs) are great at generating diverse samples
- But when diffusion is conditioned on some input (text, label, etc.) that diversity may cause it to stray away from the prompt
- **Classifier-free guidance** helps diffusion to adhere to the prompt, yielding higher quality images

Algorithm 1 Sampling from DDPM with Classifier-free Guidance

$w = 7.5$

$\mathbf{c} = \texttt{tokenize("a cat with green eyes")}$

$\mathbf{c}' = \texttt{tokenize("")}$

$\mathbf{z}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$

for $t \in \{T, \ldots, 1\}$ **do**

  $\boldsymbol{\epsilon}_\theta \leftarrow (1+w)\boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t, \mathbf{c}) - w\boldsymbol{\epsilon}_\theta(\mathbf{z}_t, t, \mathbf{c}')$

  $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$

  $\hat{\mathbf{z}}_0 \leftarrow \left(\mathbf{z}_t - \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}_\theta\right) / \sqrt{\bar{\alpha}_t}$

  $\hat{\boldsymbol{\mu}}_t \leftarrow \alpha_t^{(0)}\hat{\mathbf{z}}_0 + \alpha_t^{(t)}\mathbf{z}_t$

  $\mathbf{z}_{t-1} \leftarrow \hat{\boldsymbol{\mu}}_t + \sigma_t^2\boldsymbol{\epsilon}$

return $\mathbf{x}_0$

Classifier-free Guidance

- Increasing guidance scale yields samples that more closely adhere to the class label
- Guidance scale *w* increases from the left block of samples to the right block of samples

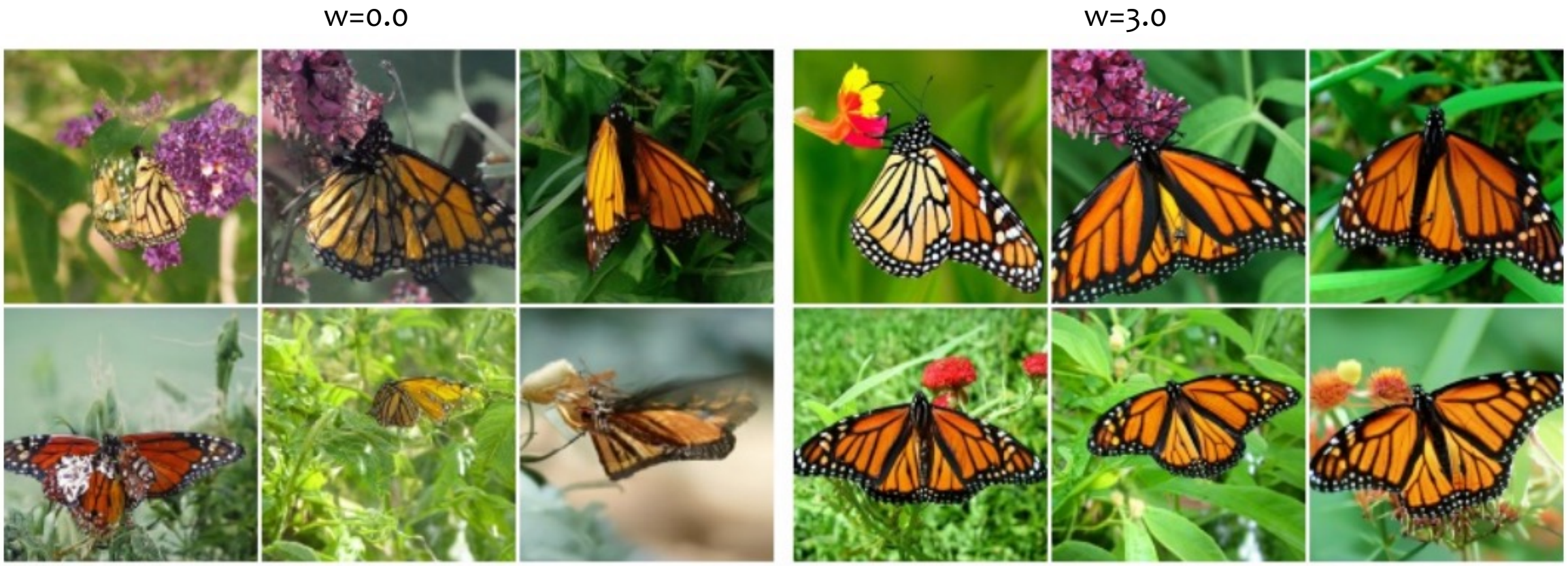


Figure from https://arxiv.org/pdf/2207.12598

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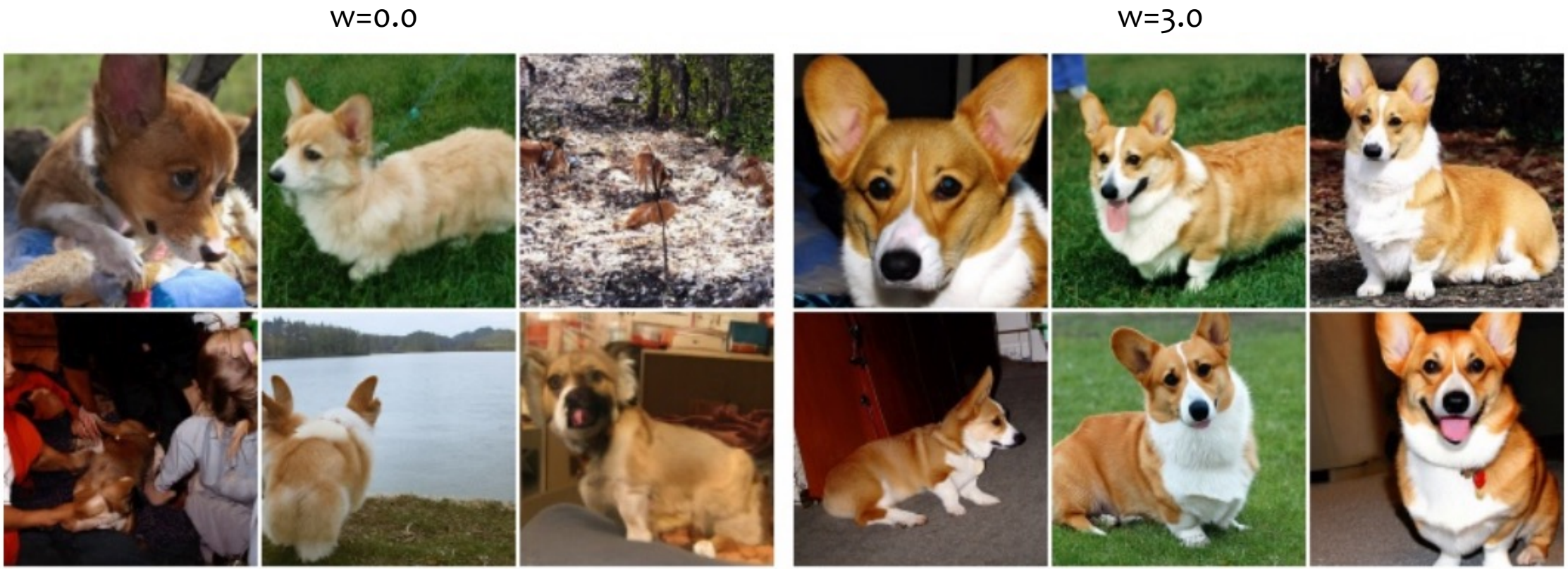


Figure from https://arxiv.org/pdf/2207.12598

DIFFUSION WITH TRANSFORMERS

Diffusion Transformer (DiT)

2015
- UNet introduced for medical image segmentation

2016-2018
- Numerous UNet variants used to good effect
- pixel-level autoregressive models
- conditional GANs
- Pixel-CNN++ set the standard variant

2020
- UNet used by Ho et al. for DDPM to good effect

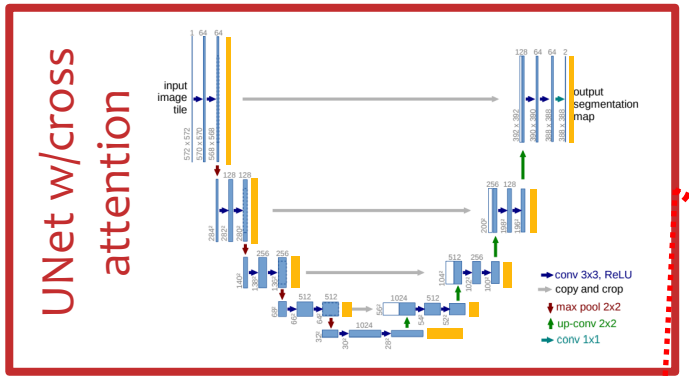
2021
- Dhariwal & Nichol include conditional information via Transformer block

2022-2023
- Everyone continues using UNet for diffusion models because it seems to work well

May 2023
- Diffusion Transformer shows we don't actually need UNet

Figure from https://arxiv.org/pdf/2212.09748

Latent Diffusion Model (LDM) with UNet backbone



prompt space

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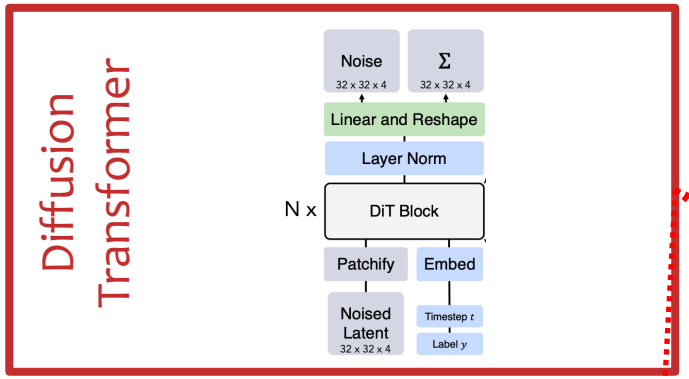
Latent Diffusion Model (LDM) with Diffusion Transformer backbone



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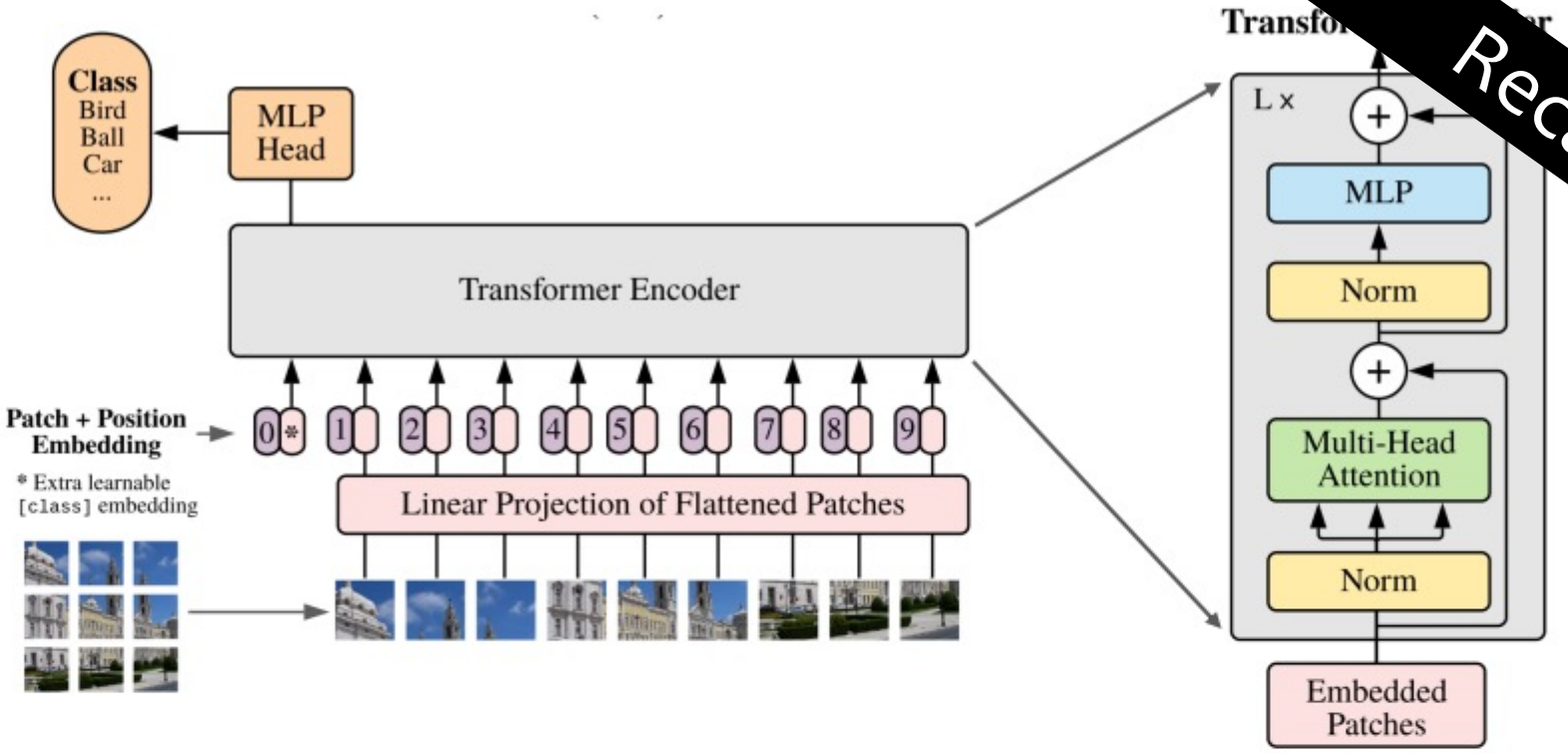
DiT figure from https://arxiv.org/pdf/2212.09748

Vision Transformer (ViT)



Recall...

- Instead of words as input, the inputs are $P \times P$ pixel *patches*
- Each patch is embedded linearly into a vector of size 1024
- Uses 1D positional embeddings
- Pre-trained on a large, supervised dataset (e.g., ImageNet 21K, JFT-300M)

Source: https://arxiv.org/pdf/2010.11929

Diffusion Transformer (DiT)

Diffusion Transformer

- DiT backbone is essentially a Vision Transformer (ViT) with some tweaks
- Input is a noisy latent, a timestep, and a label (or other conditional information)
- Output is a mean and covariance output, each of fixed size
- After a final layer norm, a linear layer is used to convert from a sequence of T token embeddings to fixed size output

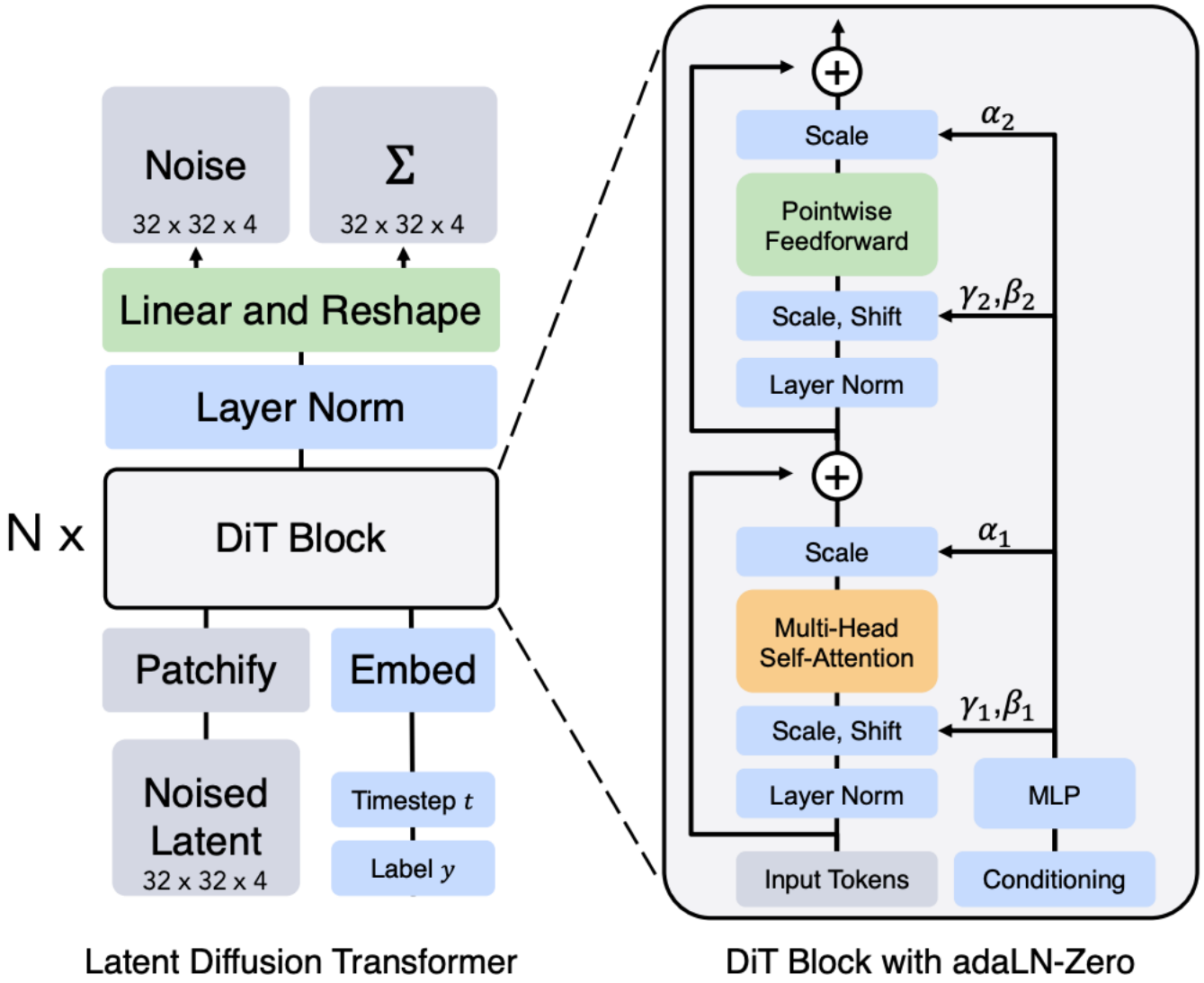
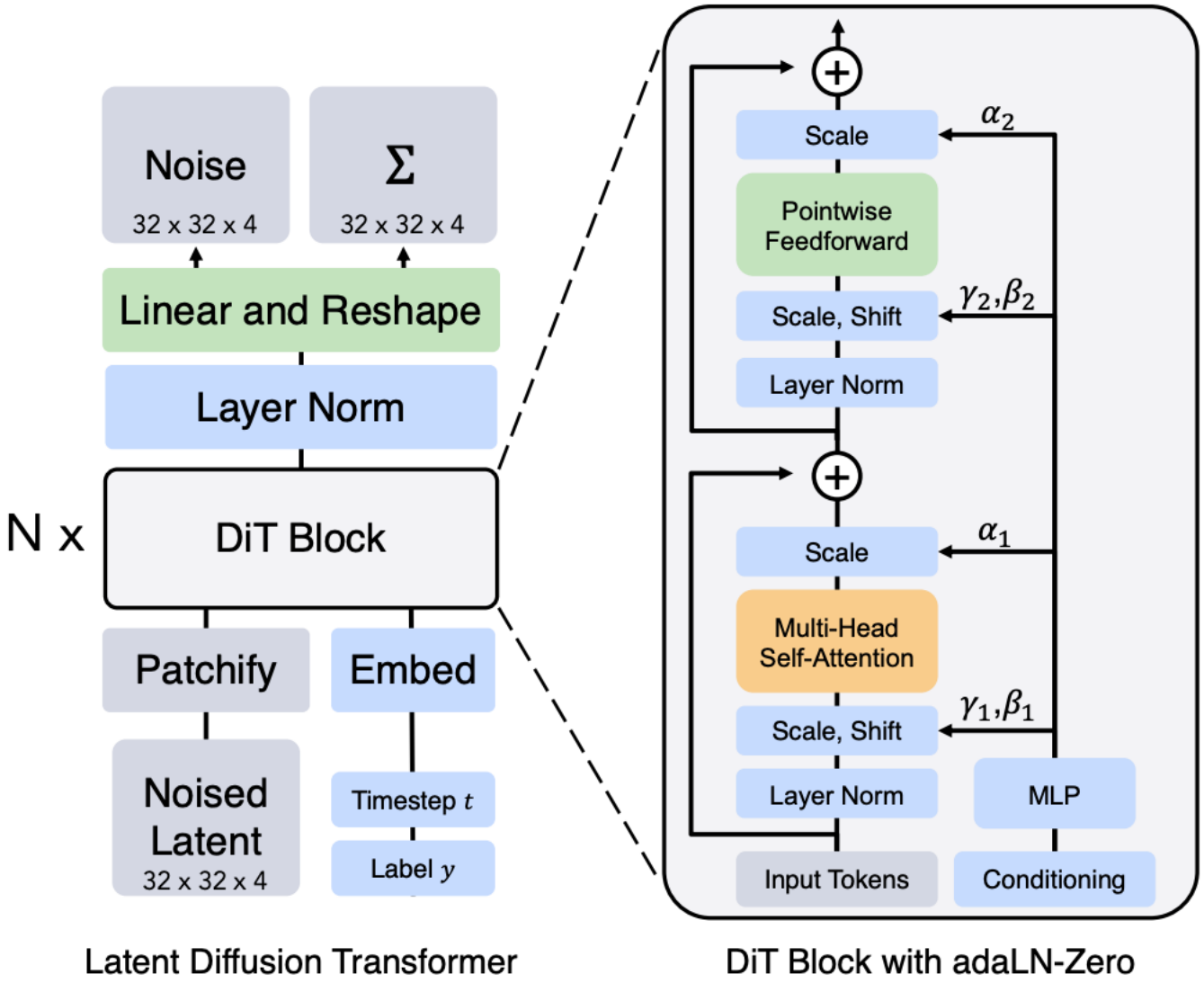


Figure from https://arxiv.org/pdf/2212.09748

Adaptive LayerNorm

Diffusion Transformer

- Within the **DiT Block,** the interesting part is how we condition on the label
- Original DiT paper tries out various approaches:
  - In-context conditioning
  - Cross-attention block
  - Adaptive layer norm (adaLN) block
  - Adaptive layer norm with zero initialization strategy (adaLN-Zero)
- adaLN-Zero is the best approach empirically
  - key insight: learn an MLP that outputs the scale and shift parameters for LayerNorm and residual connections



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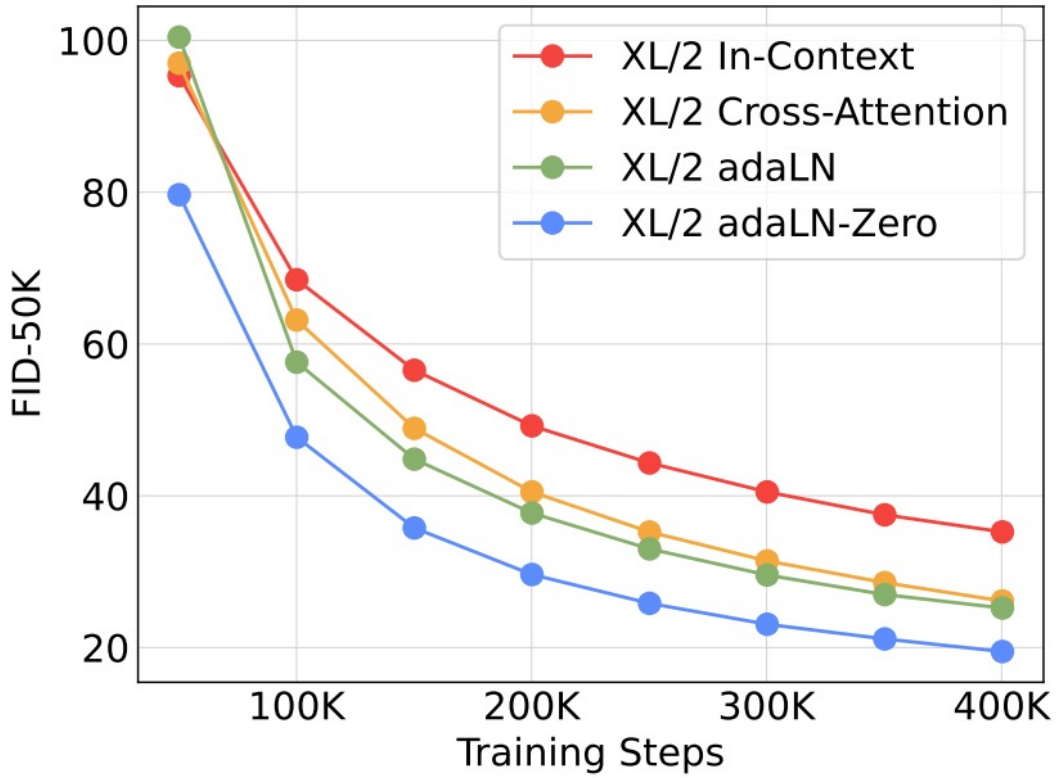

Figure 5. **Comparing different conditioning strategies.** adaLN-Zero outperforms cross-attention and in-context conditioning at all stages of training.

Figure from https://arxiv.org/pdf/2212.09748

GFLOPS and FID

GFLOPS

Definition: GFLOPS are a hardware-independent measure of the computation cost of a model

- A FLOP is one floating-point operation (like a single addition, multiplication, etc. on real numbers).
- 1 GFLOP = 10^9 FLOPs.
- GFLOPs measure how much computation a model requires for one forward pass (or sometimes per image/sample)

FID

Definition: **Fréchet Inception Distance:** a standard metric used to evaluate the **quality of generated images**

- **To compute:**
  1. Pass both real and generated images through a pretrained Inception-v3 network.
  2. Collect the activations (features) from a mid-level layer (often the pool3 layer)
  3. Model these feature sets as multivariate Gaussians with means μ_r, μ_g and covariances Σ_r, Σ_g
  4. Compute the Fréchet distance between the two Gaussians:

$$\mathrm{FID} = \|\mu_r - \mu_g\|_2^2 + \mathrm{Tr}\left(\Sigma_r + \Sigma_g - 2(\Sigma_r\Sigma_g)^{1/2}\right)$$

- **Interpretation:**
  - Lower FID → generated images are more similar to real images (better quality and diversity).
  - Higher FID → larger gap between generated and real distributions (worse quality).

Diffusion Transformer

- Decreasing the patch size of a DiT increases the GFLOPs even though it does not increase the number of parameters
- So DiT studies the relationship between FID performance and GFLOPs (rather than FID and # of param.s)
- **Question:** How much does the total computation increase if we drop the patch size from p=4 to p=2?

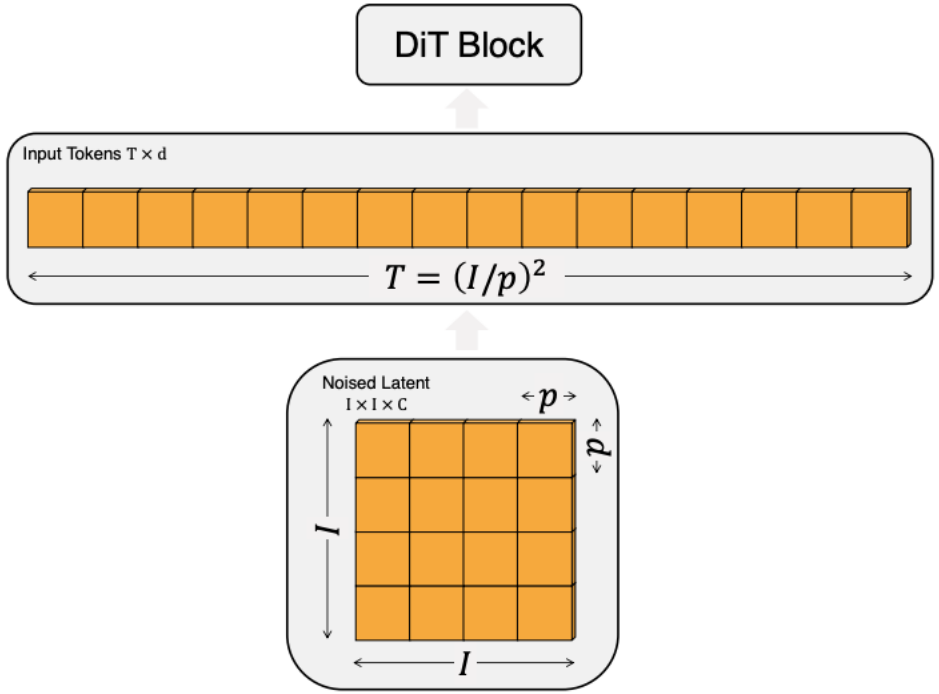

Figure 4. **Input specifications for DiT.** Given patch size $p \times p$, a spatial representation (the noised latent from the VAE) of shape $I \times I \times C$ is "patchified" into a sequence of length $T = (I/p)^2$ with hidden dimension d. A smaller patch size p results in a longer sequence length and thus more Gflops.

Results: Diffusion Transformer

- Decreasing the patch size of a DiT increases the GFLOPs even though it does not increase the number of parameters
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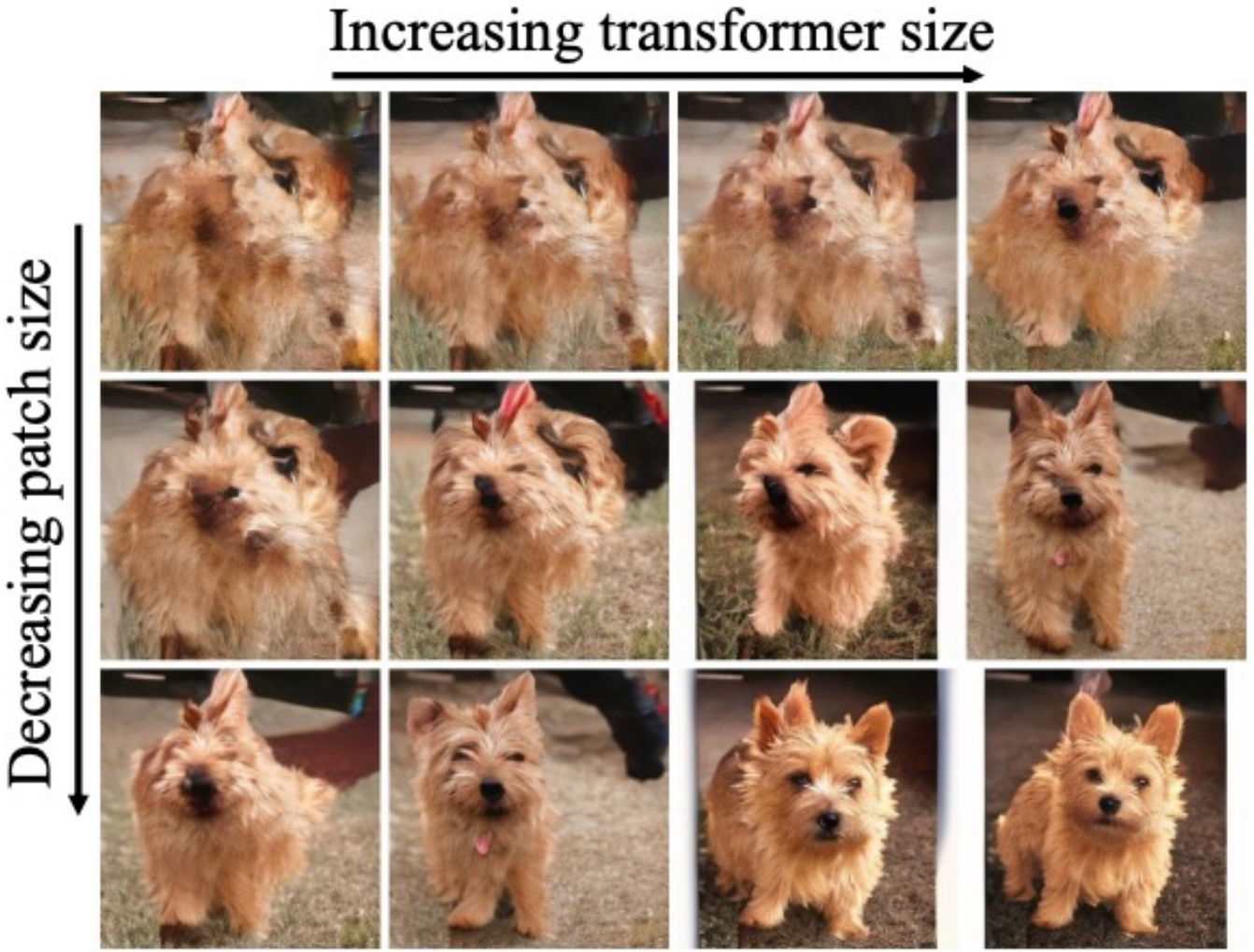
- Of course, we can also increase the number of model parameters just by increasing the size of the Transformer



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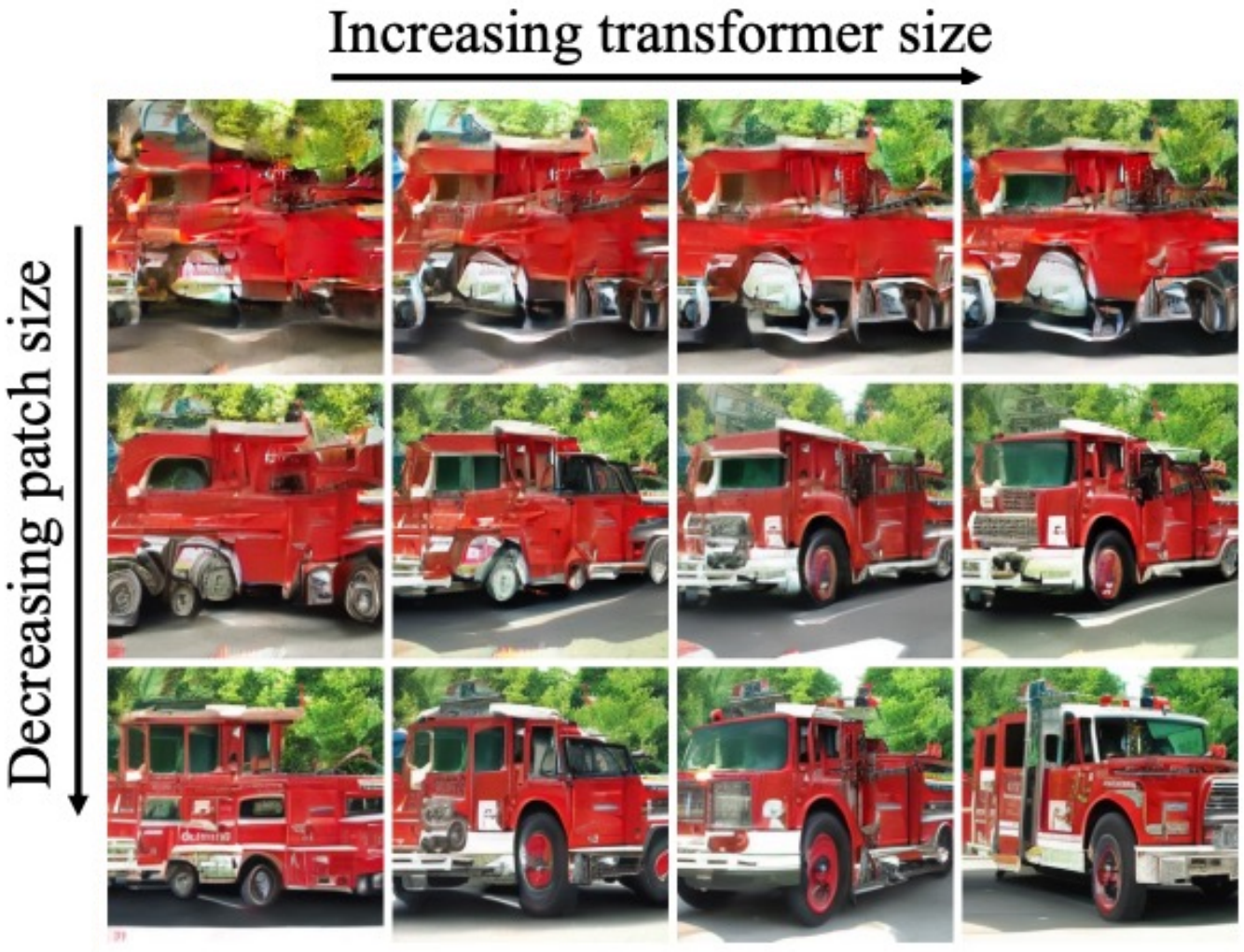

Results: Diffusion Transformer

Scaling results:

1. **GFLOPs and FID are strongly correlated (i.e. if we increase GFLOPs then we get better FID score)**
2. Larger DiT models are more compute efficient than smaller DiT models during training (i.e., if we use the same amount of training computation for both, the larger DiT does better at test time than the smaller DiT)
3. The DiT beats a latent diffusion model (LDM) with a UNet backbone even at the same amount of compute:
   - LDM-4 (103.6 Gflops)
   - DiT-XL/2 (118.6 Gflops)

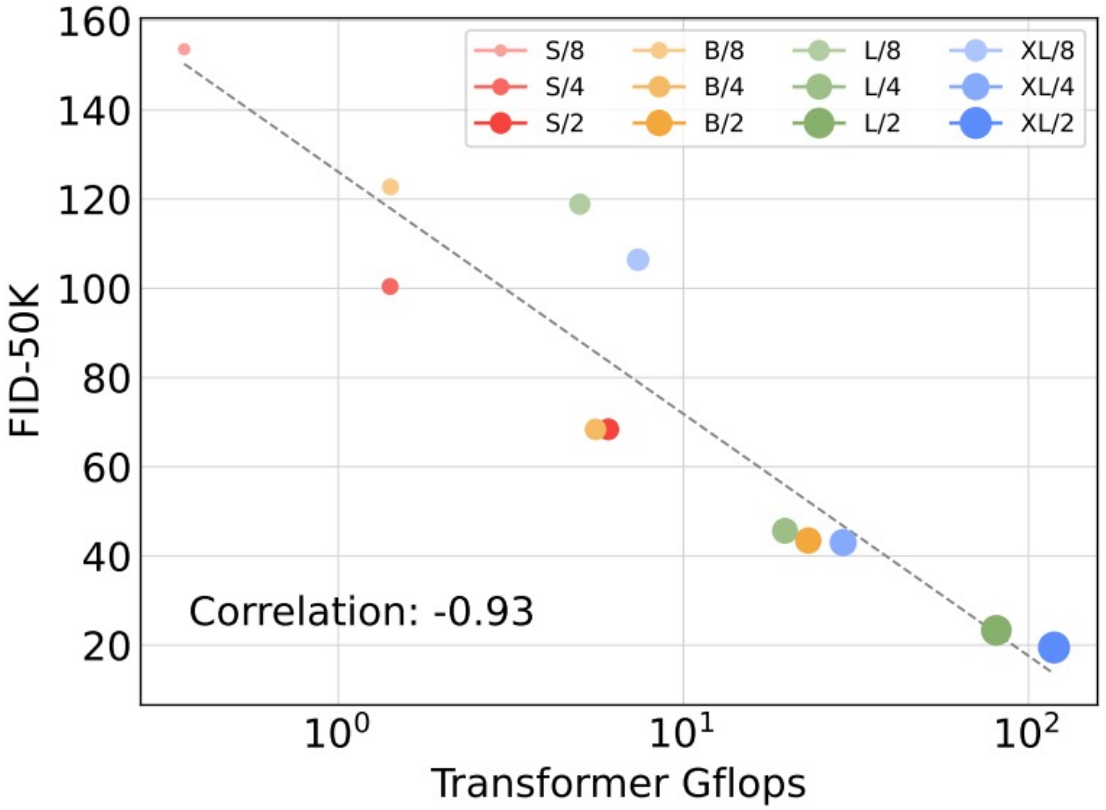

Figure 8. **Transformer Gflops are strongly correlated with FID.** We plot the Gflops of each of our DiT models and each model's FID-50K after 400K training steps.

Results: Diffusion Transformer

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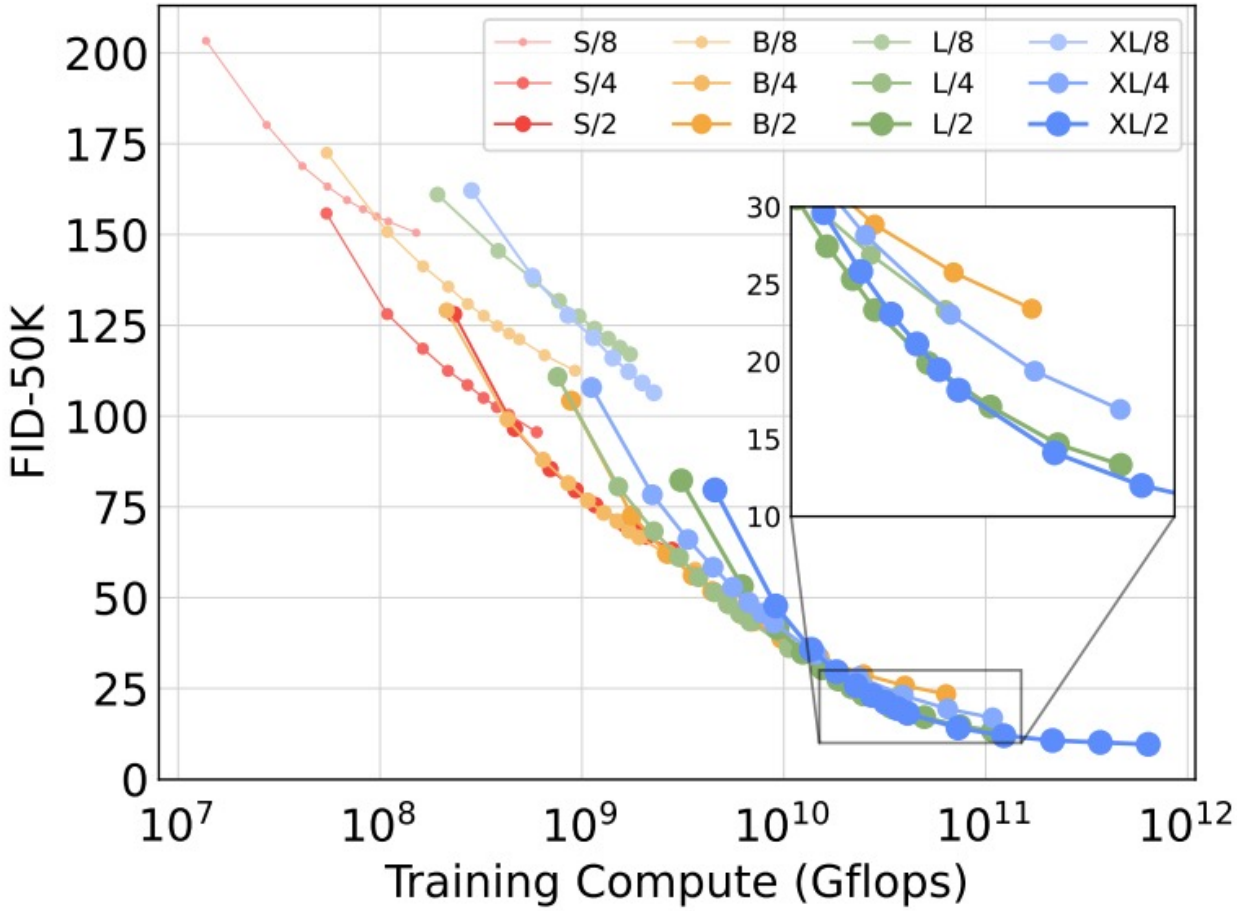

Figure 9. **Larger DiT models use large compute more efficiently.** We plot FID as a function of total training compute.

Results: Diffusion Transformer

Scaling results:

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Class-Conditional ImageNet 256×256					
Model	FID↓	sFID↓	IS↑	Precision↑	Recall↑
BigGAN-deep [2]	6.95	7.36	171.4	0.87	0.28
StyleGAN-XL [53]	2.30	4.02	265.12	0.78	0.53
ADM [9]	10.94	6.02	100.98	0.69	0.63
ADM-U	7.49	5.13	127.49	0.72	0.63
ADM-G	4.59	5.25	186.70	0.82	0.52
ADM-G, ADM-U	3.94	6.14	215.84	0.83	0.53
CDM [20]	4.88	-	158.71	-	-
LDM-8 [48]	15.51	-	79.03	0.65	0.63
LDM-8-G	7.76	-	209.52	0.84	0.35
LDM-4	10.56	-	103.49	0.71	0.62
LDM-4-G (cfg=1.25)	3.95	-	178.22	0.81	0.55
LDM-4-G (cfg=1.50)	3.60	-	247.67	**0.87**	0.48
DiT-XL/2	9.62	6.85	121.50	0.67	**0.67**
DiT-XL/2-G (cfg=1.25)	3.22	5.28	201.77	0.76	0.62
DiT-XL/2-G (cfg=1.50)	**2.27**	**4.60**	**278.24**	0.83	0.57

PROMPT-TO-PROMPT

Background: Image Editing

- Fixing the Random Seed:
  - A simple baseline for image editing with text: change part of the prompt, **keep the random seed fixed** (e.g. the noise at the start of diffusion), and then run diffusion sampler
  - Problem: the entire **structure** of the image may **change dramatically**
  - Doesn't feel like "editing" at all, more like generation of **unrelated images**

Figure from http://arxiv.org/abs/2208.01626

- Mask-based Image Editing:
  - standard approaches to text-based image editing typically **require an image mask** as well
  - the **mask** specifies which part of the image should remain **unchanged**
  - then the **text prompt** informs how the **unmasked part** should be adapted (e.g. by a diffusion model)
  - (Example: Blended Diffusion)

Figure from http://arxiv.org/abs/2111.14818

Background: Image Editing

- Fixing the Random Seed:
  - A simple baseline for image editing with text: change part of the prompt, **keep the random seed fixed** (e.g. the noise at the start of diffusion), and then run
  - Problem: image ma
  - Doesn't f… like…

the composition is inconsistent in various ways: the background, whole cake vs. single slice, how much cake is in view

Figure from http://arxiv.org/abs/2208.01626

- Mask-based Image Editing:
  - standard approaches to text-based image editing typically **require an image mask** as well
  - the **mask** specifies which part of the … main **unchanged**
  - **…ompt** informs how **…art** should be … diffusion model) …ded …ffusion)

here the composition remains consistent across images

Figure from http://arxiv.org/abs/2111.14818

Prompt-to-Prompt

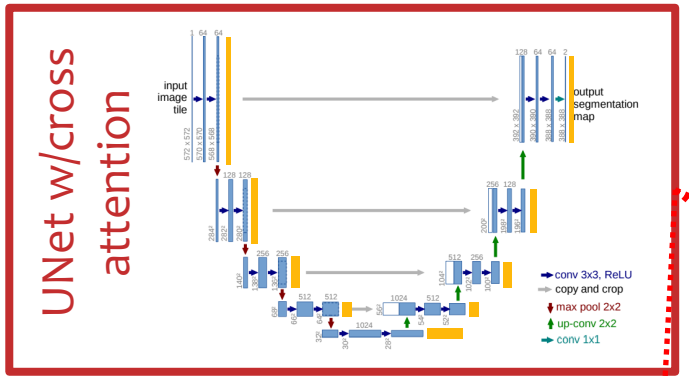
Prompt-to-Prompt:

- **Goal:** edit images with text only and do not require the user to provide a mask
- **Key Idea:**
  - **given** pre-trained latent diffusion model
  - run diffusion model with **original prompt** and **store** the attention weights and cross-attention weights (from the pixels back to the text)
  - re-run diffusion with **edited prompt,** but (carefully) **copy in** the cross-attention weights from the previous run
  - exactly *how* to copy in the attention weights depends on the type of edit
- **Inference only:** no training is involved! we only modify how the samples are drawn from the pre-trained latent diffusion model

the composition remains consistent across images, but with only the text for guidance (no mask)

Figure from http://arxiv.org/abs/2208.01626

Latent Diffusion Model (LDM)



Prompt-to-prompt: (1) assumes we have a pretrained latent diffusion model and (2) does no parameter estimation

prompt space

latent space

pixel space

$\widehat{\mathbf{y}}$

τ_θ

LLM

$\mathbf{y}$

orange cat

$p_\theta(\mathbf{z}_T)$

$p_\theta(\mathbf{z}_{T-1} \mid \mathbf{z}_T, \widehat{\mathbf{y}})$

$p_\theta(\mathbf{z}_t \mid \mathbf{z}_{t+1}, \widehat{\mathbf{y}})$

$p_\theta(\mathbf{z}_0 \mid \mathbf{z}_1, \widehat{\mathbf{y}})$

z_T z_{T-1} ... z_{t+1} z_t ... z_1 z

$\mathcal{D}$

Decoder

$\widetilde{\mathbf{x}}$

$\mathcal{E}$

Encoder

$\mathbf{x}$

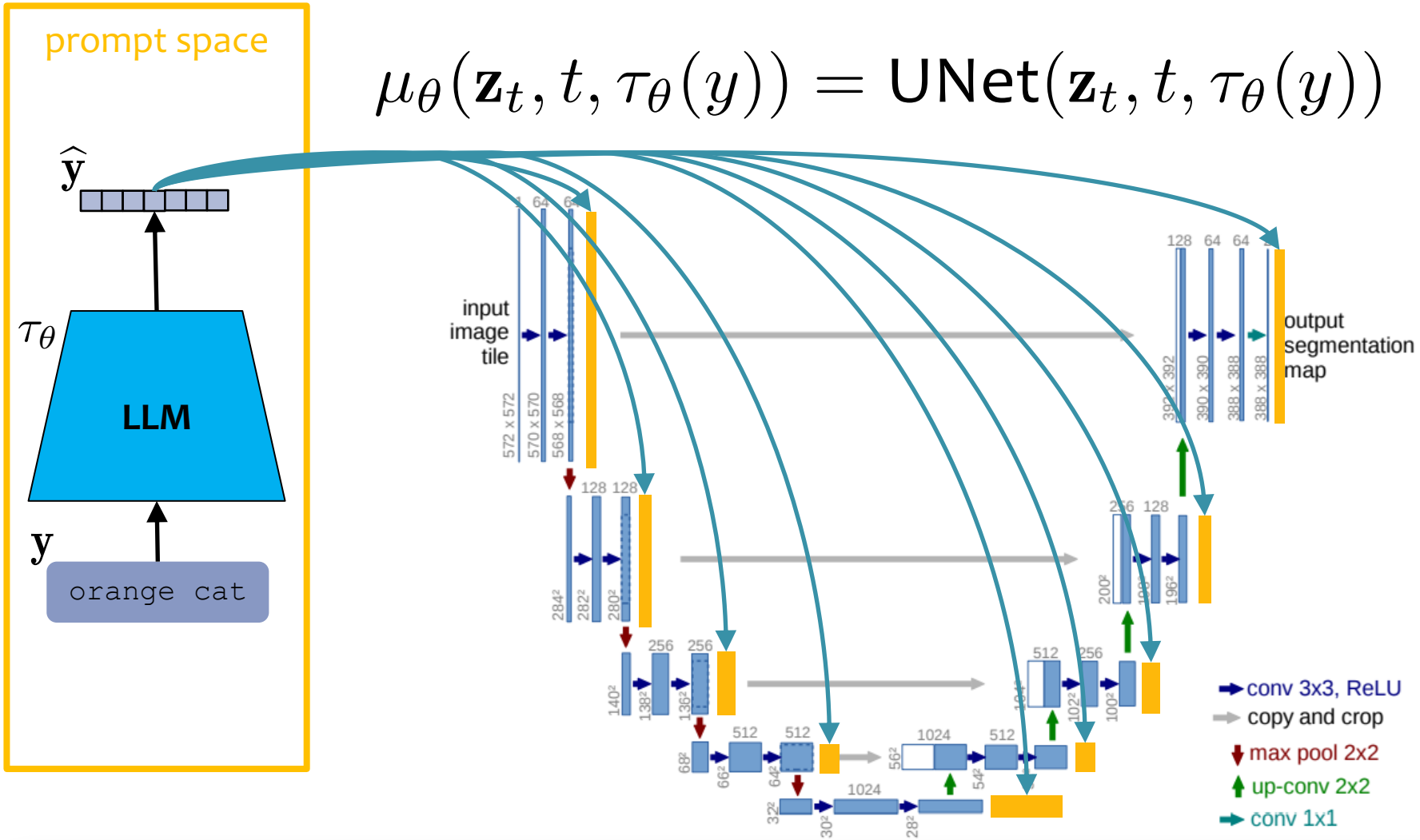
$q_\phi(\mathbf{z}_T \mid \mathbf{z}_{T-1})$

$q_\phi(\mathbf{z}_{t+1} \mid \mathbf{z}_t)$

$q_\phi(\mathbf{z}_1 \mid \mathbf{z}_0)$

LDM: Noise Model

$$\mu_\theta(\mathbf{z}_t, t, \tau_\theta(y)) = \text{UNet}(\mathbf{z}_t, t, \tau_\theta(y))$$



- The noise model includes **cross attention** (yellow boxes) to the representation of the prompt text
- During training we optimize both the parameters of the UNet noise model and the parameters of the LLM simultaneously

Prompt-to-prompt modifies the cross attention in LDM, which looks at both the text encoding and the (latent) representation of the image

Prompt-to-Prompt: Editing Cross Attention

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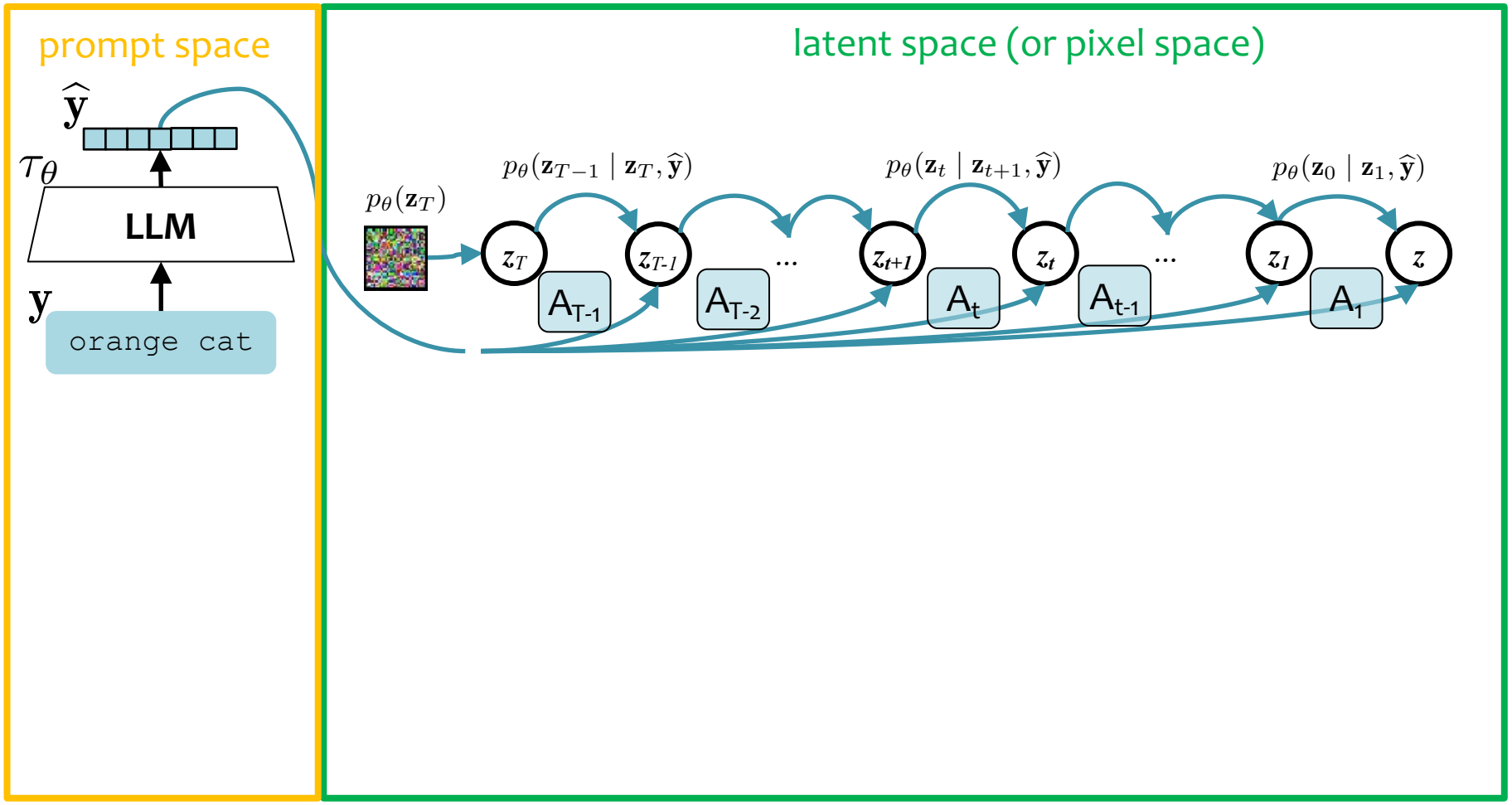
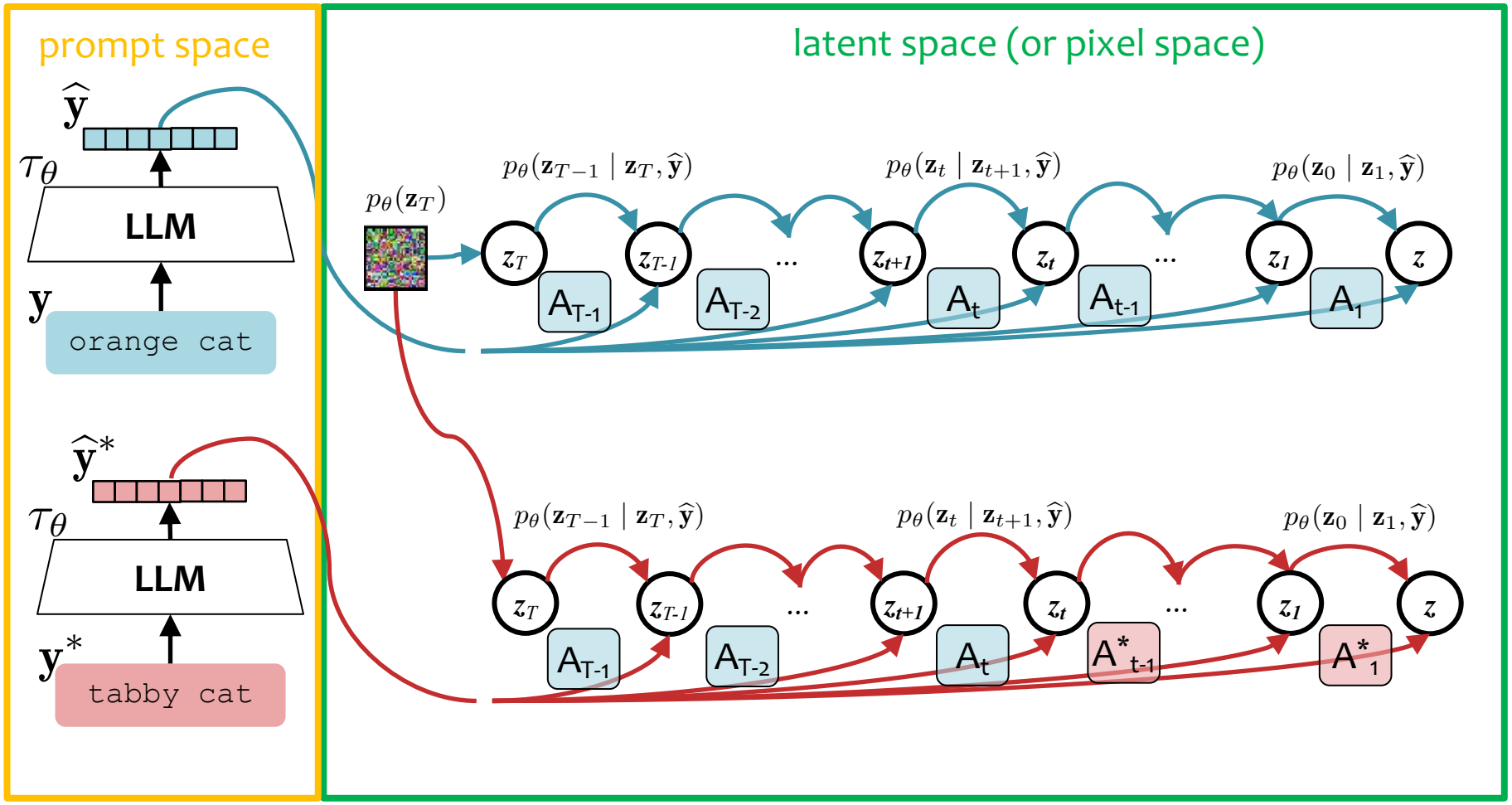
Figure from http://arxiv.org/abs/2208.01626

Prompt-to-Prompt: Editing Cross Attention

1. encode the original prompt y
2. run diffusion on y and obtain attention weights $A_{T-1},\dots,A_1$



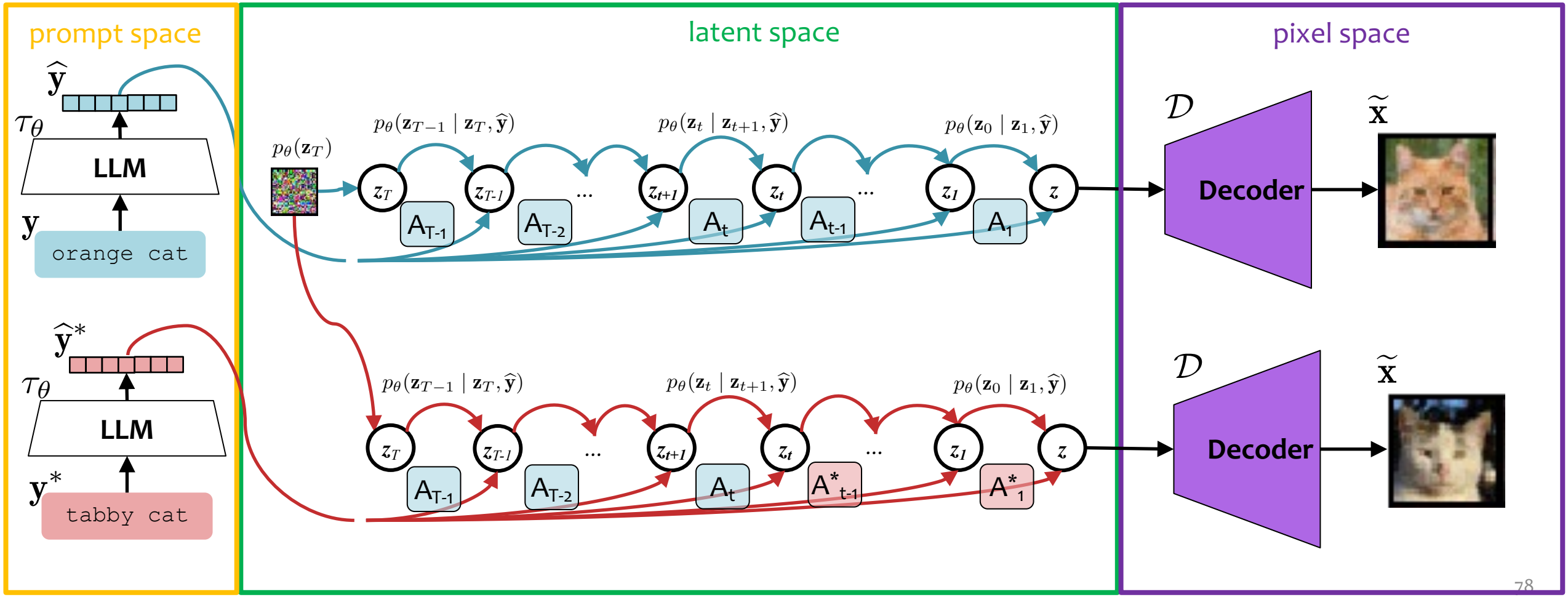
Prompt-to-Prompt: Editing Cross Attention



1. encode the original prompt y
2. run diffusion on y and obtain attention weights $A_{T-1},\dots,A_1$
3. encode the modified prompt y*
4. run diffusion again
   a) reuse the noise z_T from the original run
   b) use the attention weights from the original run until timestep τ $A_{T-1},\dots,A_t$
   c) then switch to using attention weights from this current run $A^*_{t-1},\dots,A^*_1$
   d) regardless of which attention weights, you still attend to y*

Prompt-to-Prompt: Editing Cross Attention

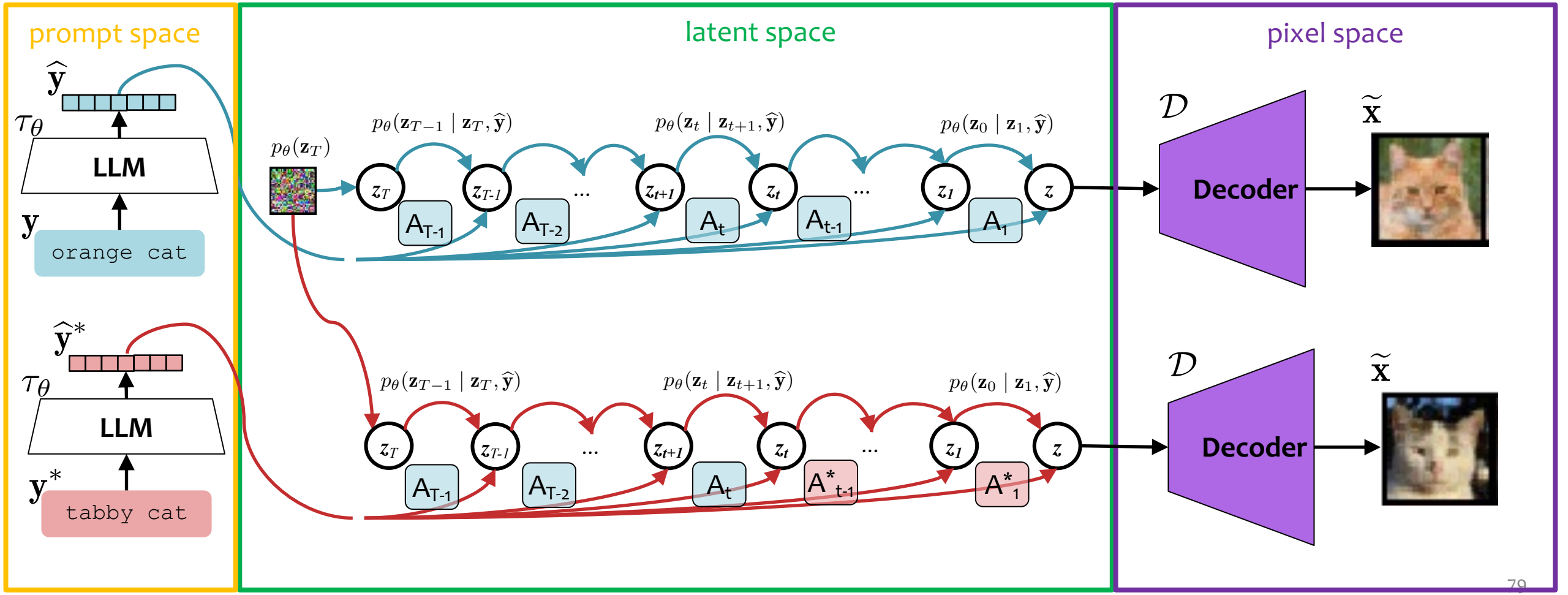
5. if running in latent space, then use decoder to recover pixel space representation



Question:

Why do we use from the original attention weights for a while before swapping to the new attention weights?

Answer:



Prompt-to-Prompt: Editing Cross Attention

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Algorithm 1 Prompt-to-Prompt image editing

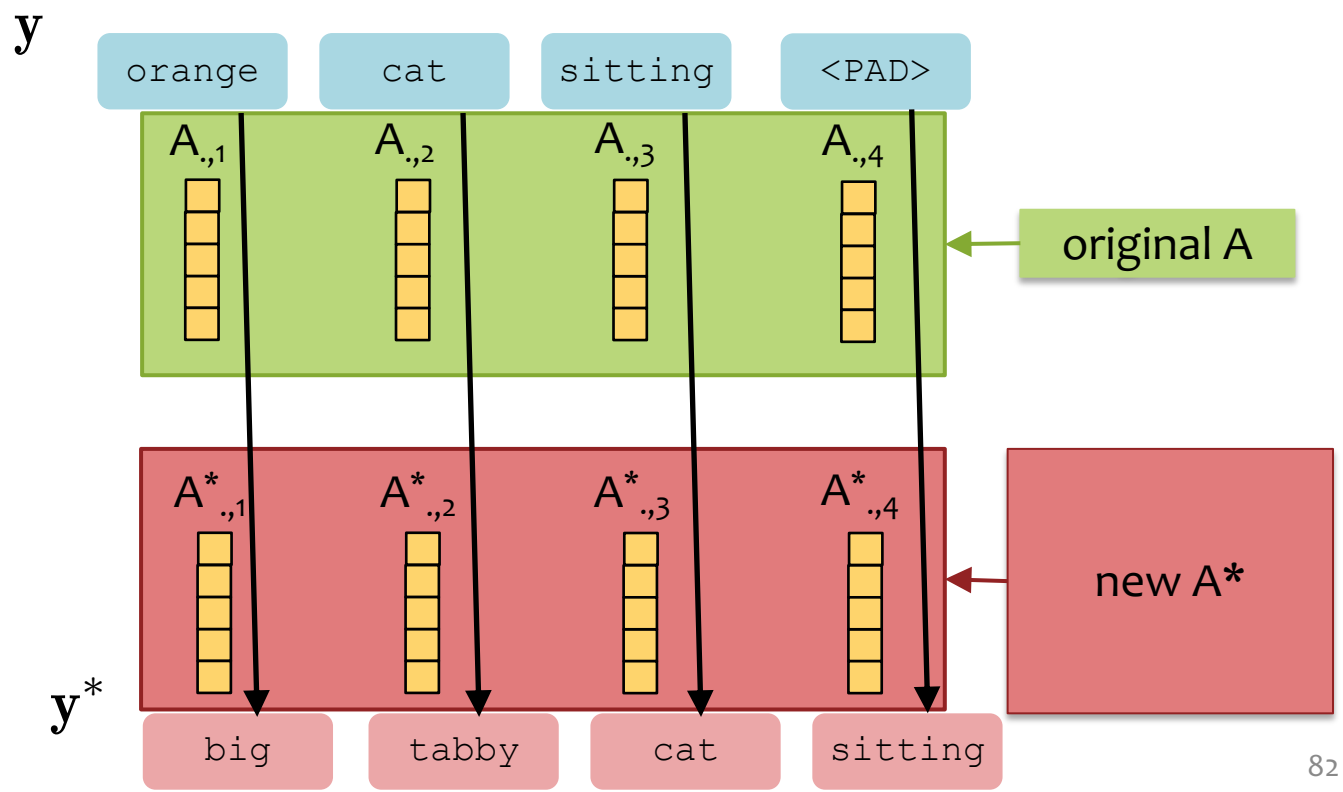
Input: A source prompt $\mathbf{y}$, a target prompt $\mathbf{y}^*$, and a random seed s.
Output: A source image x_{src} and an edited image x_{dst}.
$\mathbf{z}_T \sim \mathcal{N}(0, I)$ a unit Gaussian random variable with random seed s;
$\mathbf{z}_T^* \leftarrow \mathbf{z}_T'$;
for $t = T, T-1, \ldots, 1$ **do**
    $\mathbf{z}_{t-1}, \mathbf{A}_t \leftarrow DM(\mathbf{z}_t, \mathbf{y}, t, s)$;
    $\mathbf{A}_t^* \leftarrow DM(\mathbf{z}_t^*, \mathbf{y}^*, t, s)$;
    $\widehat{\mathbf{A}}_t \leftarrow \text{Edit}(\mathbf{A}_t, \mathbf{A}_t^*, t)$;
    $\mathbf{z}_{t-1}^* \leftarrow DM(\mathbf{z}_t^*, \mathbf{y}^*, t, s, t)\{\mathbf{A} \leftarrow \widehat{\mathbf{A}}_t\}$;
return $(\mathbf{z}_0, \mathbf{z}_0^*)$

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

Figure from http://arxiv.org/abs/2208.01626

Attention Swapping

- Problem: What if A_t and A^*_t are not the same shape?
- Solution: Swap in just the appropriate parts!
  - The dimension in latent space will always remain constant (e.g. 1024)
  - The dimension in text prompt space also remain constant if we use a fixed length encoder
    - e.g. length = 77, if we use CLIP encoder
    - orange cat sitting <PAD> <PAD> … <PAD>
  - However, the words might not align properly!
- Example:
  - we replace "orange" with "big tabby"
  - then copy the attention weights for "orange" to both "big" and "tabby" in the new attention weights



CLIP (the text encoder for Prompt to Prompt)

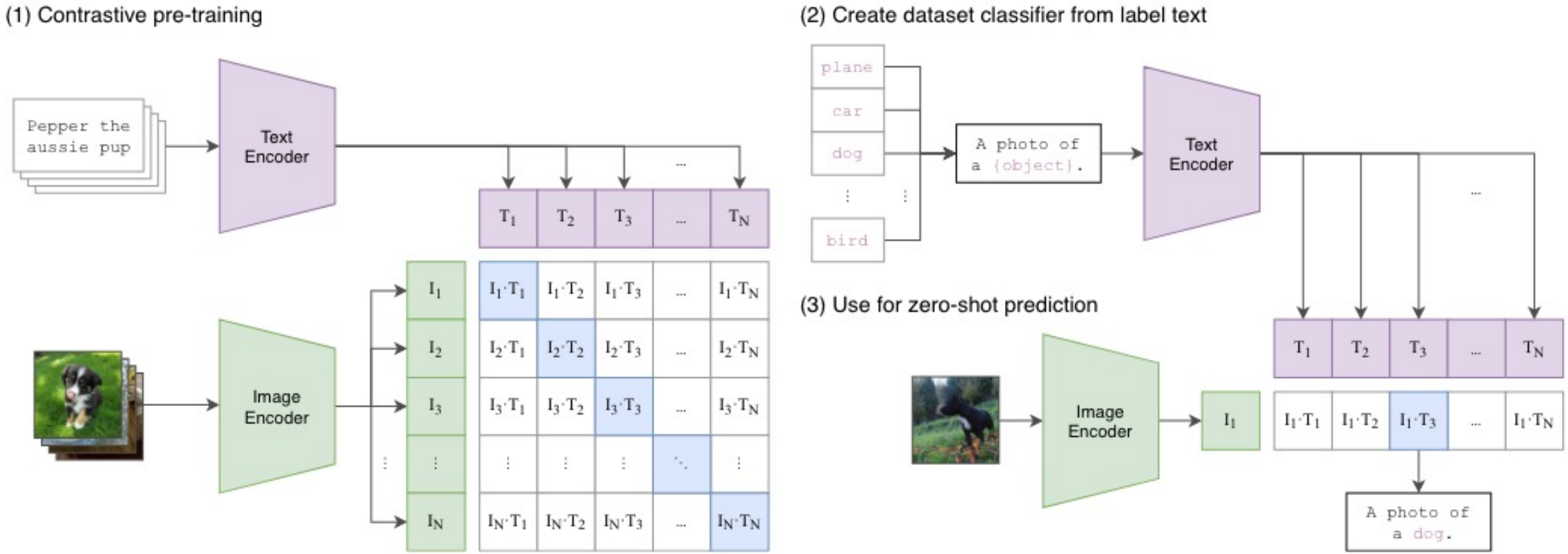


Figure 1. Summary of our approach. While standard image models jointly train an image feature extractor and a linear classifier to predict some label, CLIP jointly trains an image encoder and a text encoder to predict the correct pairings of a batch of (image, text) training examples. At test time the learned text encoder synthesizes a zero-shot linear classifier by embedding the names or descriptions of the target dataset's classes.

Figure from Radford et al. (2021)

Attention Swapping

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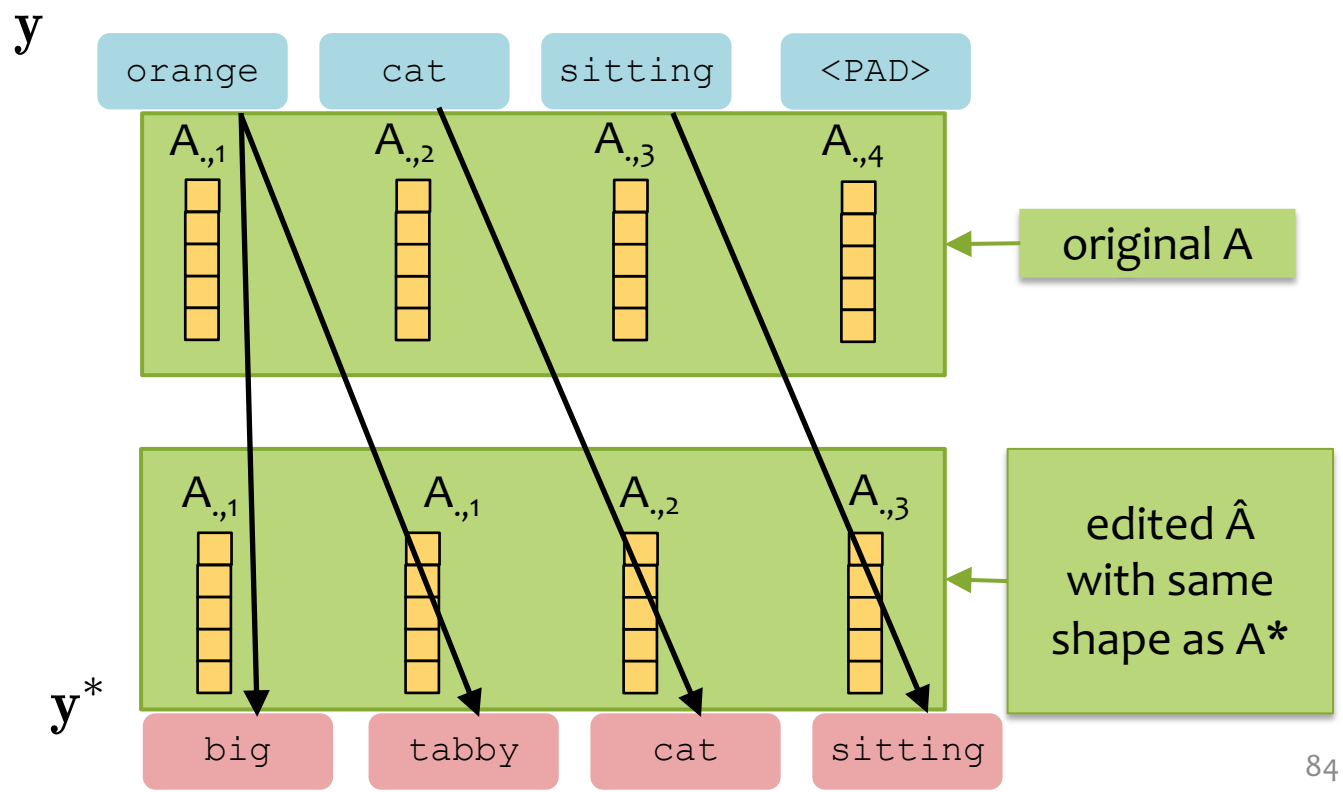

Prompt-to-Prompt Results

- word/phrase cross-attention swapping automatically identifies the regions of the image that need to remain constant and those that should be adapted

Figure 5: Object preservation. By injecting only the attention weights of the word "butterfly", taken from the top-left image, we can preserve the structure and appearance of a single item while replacing its context. Note how the butterfly sits on top of all objects in a very plausible manner.

Figure from http://arxiv.org/abs/2208.01626

Prompt-to-Prompt Results

- varying the moment of the attention swap to A* allows us to see the effect of our cross-attention manipulation

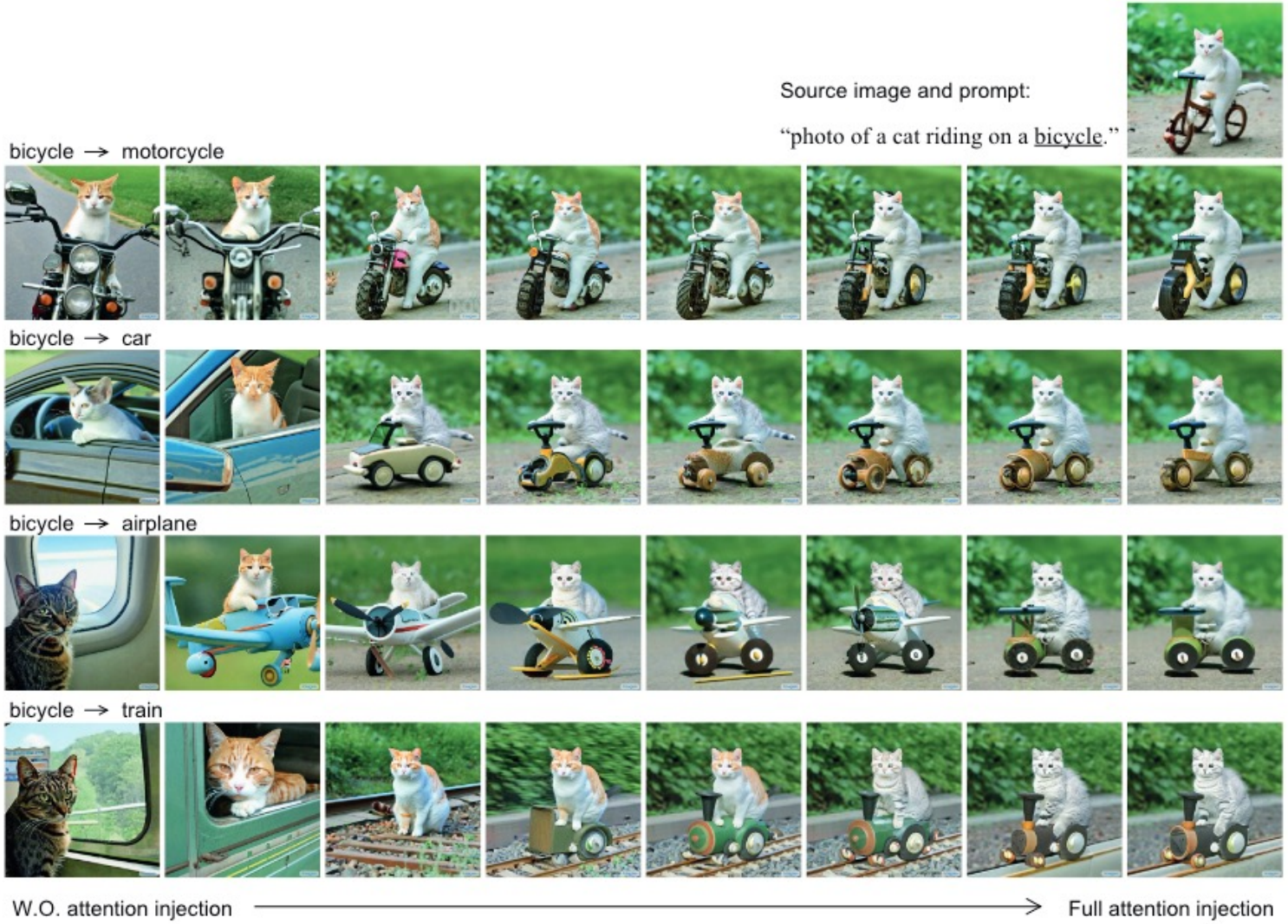

Figure 6: Attention injection through a varied number of diffusion steps. On the top, we show the source image and prompt. In each row, we modify the content of the image by replacing a single word in the text and injecting the cross-attention maps of the source image ranging from 0% (on the left) to 100% (on the right) of the diffusion steps. Notice that on one hand, without our method, none of the source image content is guaranteed to be preserved. On the other hand, injecting the cross-attention throughout all the diffusion steps may over-constrain the geometry, resulting in low fidelity to the text prompt, e.g., the car (3rd row) becomes a bicycle with full cross-attention injection.

Figure from http://arxiv.org/abs/2208.01626

Prompt-to-Prompt Results

- So far we've focused on swapping one word/phrase for another
- Prompt-to-prompt supports different types of edits
- Different types of edits are achieved through different manipulations of cross-attention weights

Figure from http://arxiv.org/abs/2208.01626