

Text to image

- 60-90 min: Non-technical
 - Try out different models
 - Prompting
 - Bias, limitations and controversy
- 150-180 min: Understand how some of the models work behind the scenes
 - Diffusion
 - Conditioned models
 - Stable Diffusion
 - CLIP
 - U-Net
 - Textual Inversion
 - InstructPix2Pix

Live Course

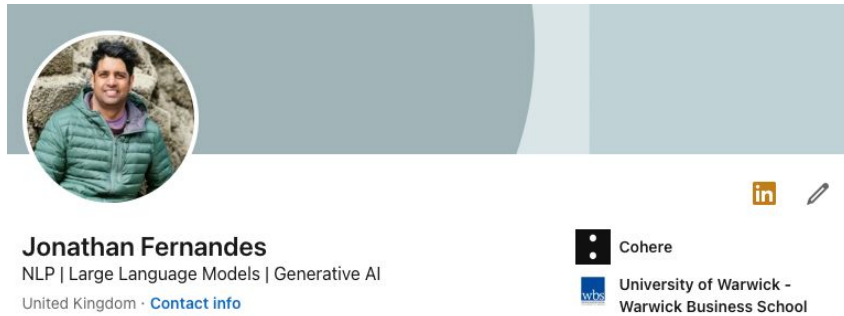


Fundamentals of Large Language Models: A hands-on approach

With Jonathan Fernandes

5pm BST 📅 May 31

Next iteration of this course will include the latest AI generation



What is diffusion?

Text to image - try it out (Colab notebook)

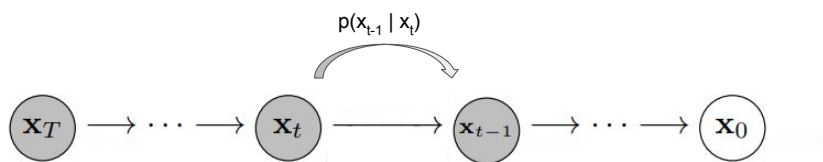
- Start with pipeline. Show the components of the pipeline like Edan Meyer
- 2015 paper chap from STanford (images with gas is very nice)
- Using words only to edit your video. You don't need to have graphic editing skills.
- You can imagine a movie / ad and have it come out. Human creativity at a new level.
- Diffusion process is agnostic (audio, video). Anything that you can add noise to will work.
- Lady Gaga lyrics in the style of Iron Maiden.
- Video / 3-D.
- Human movement - text conditioned. SOmeone picking up a box.

What is diffusion?

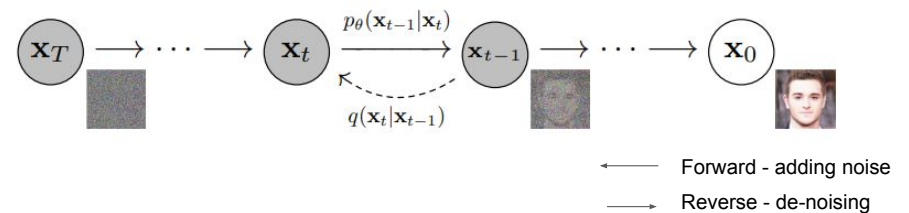
What if we could reverse this process?

Markov chains

A Markov chain is a mathematical system that experiences transitions from one state to another according to certain probabilistic rules. The probability of transitioning to any particular state is dependent solely on the current state and time elapsed.



Diffusion model



Source: Denoising Diffusion Probabilistic Models (Ho et al)

3 key components

- Pipelines - high-level wrappers that make it easy to use the functions.

3 key components

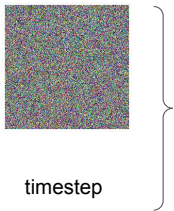
- Pipelines - high-level wrappers that make it easy to use the functions.
- Models - UNet

3 key components

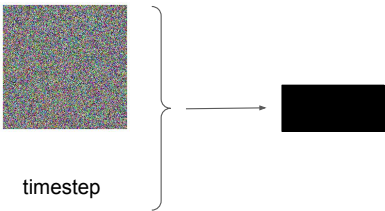
- Pipelines - high-level wrappers that make it easy to use the functions.
- Models - UNet
- Schedulers - the method for iteratively adding noise to an image
 - Why different schedulers?

Colab notebook - diffusion

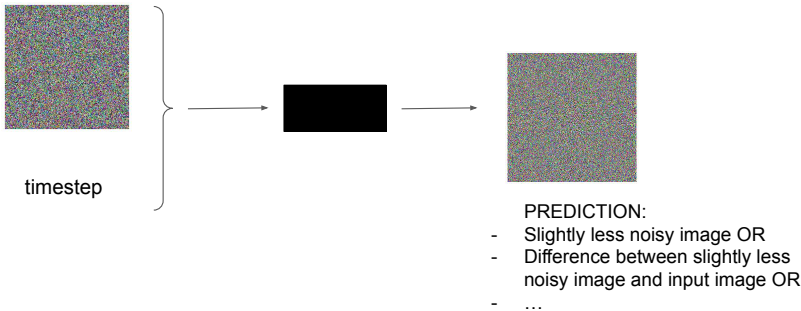
Diffusion models (inference)



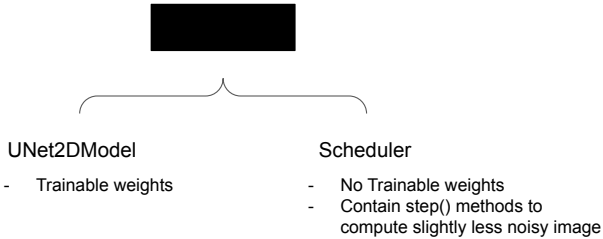
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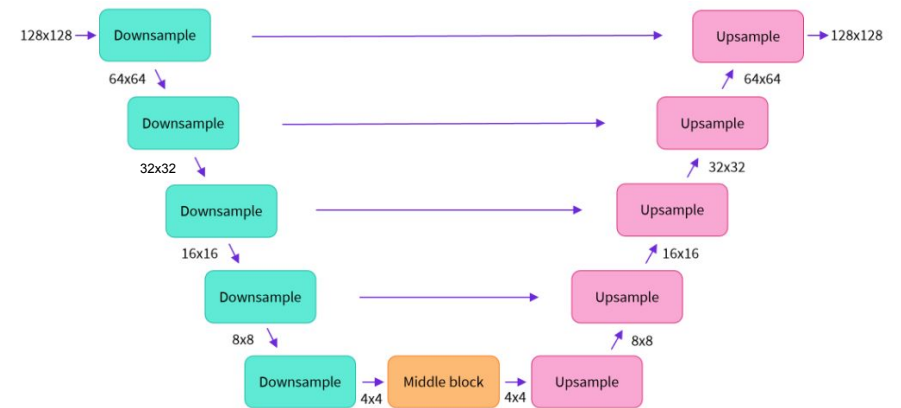


Diffusion models (inference)



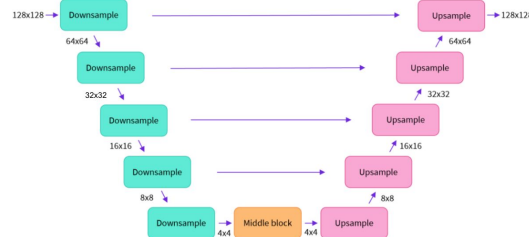
U-Net model

U-Net model



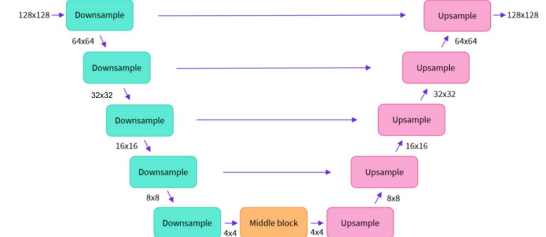
U-Net

- Predicts images of the same size as the input



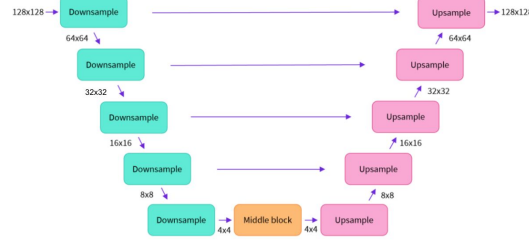
U-Net

- Predicts images of the same size as the input
- Has the same number of downsampling blocks as upsampling blocks



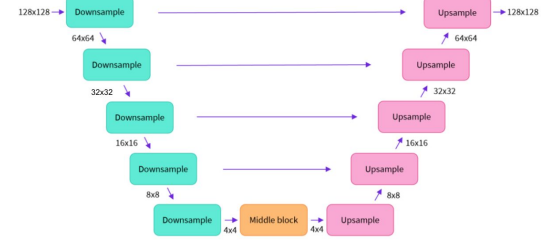
U-Net

- Predicts images of the same size as the input
- Has the same number of downsample blocks as upsample blocks
- Downsample and Upsample are several blocks of ResNet layers



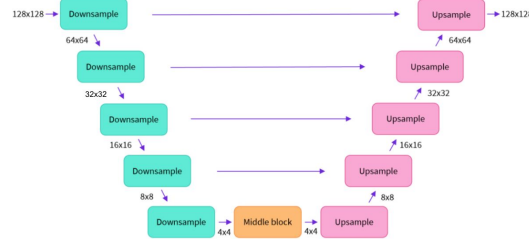
U-Net

- Predicts images of the same size as the input
- Has the same number of downsample blocks as upsample blocks
- Downsample and Upsample are several blocks of ResNet layers
- Downsample - halve the image sizes
- Upsample - double the image sizes



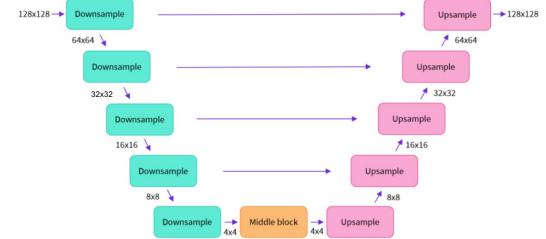
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- Skip connects - connect downsample to corresponding upsample
- What is the purpose of the "middle block"?
- What is the purpose of skip connections?



Go to colab

Train a model

Training Steps

- Take a batch of images
- Forward pass
- Calculate loss of network on batch
- Update weights of the neural network

```
#Big picture
num_epochs = 10
losses = []

for epoch in range(num_epochs):
    for step, batch in enumerate(train_dataloader):
        noisy_images = ...
        timesteps = ...
        noise_pred = model(noisy_images, timesteps)
        # loss calculations
        loss = F.mse_loss(noise_pred, noise)
        loss.backward()
        losses.append(loss.item())
        # Update optimizer
        optimizer.step()
        optimizer.zero_grad()
```

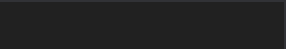
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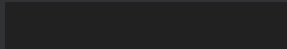

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Training a diffusion model

Load a batch of training images

Training a diffusion model

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Add a random amount of noise

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Input to model : noisy version of inputs

Training a diffusion model

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Add a random amount of noise

Input to model : noisy version of inputs

Use the loss to determine how well the model does at de-noising the inputs

Update the model weights

Training a diffusion model

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Training a diffusion model

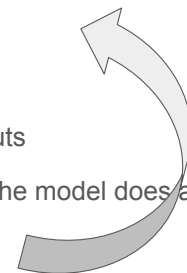
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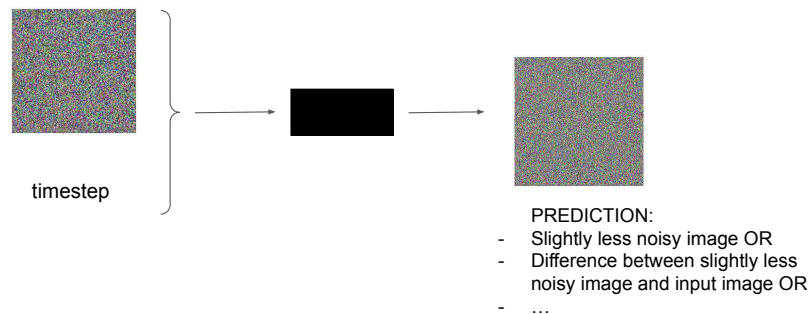
Update the model weights



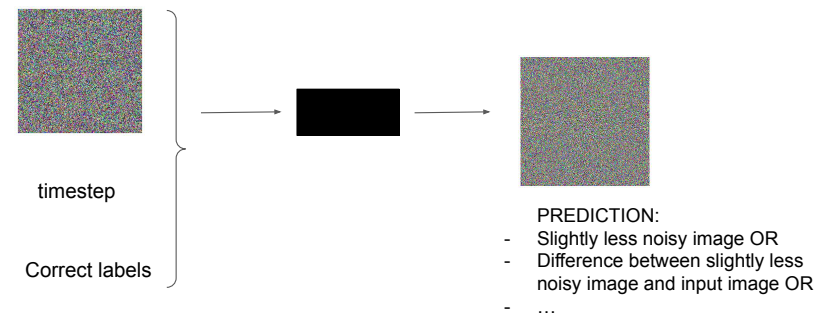
Train a model (colab notebook)

Conditioned models

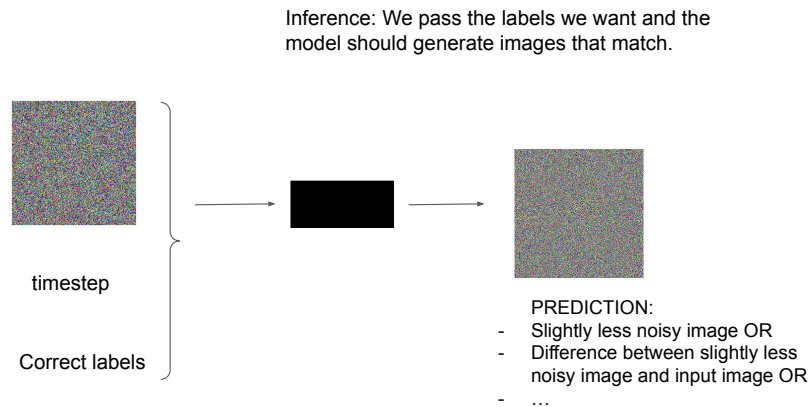
Diffusion models (training)



Conditioned Diffusion models (training)



Conditioned Diffusion models (inference)



Conditioned models

- Add additional channels in the input to the Unet
- Add cross-attention layers that can attend to a sequence passed.
 - Conditioning is text
 - Stable Diffusion uses this

Add additional channels in the input to the Unet

- UNet2DModel with additional input channels

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Conditioned models - adding additional
channels
(colab notebook)

Add additional channels in the input to the Unet

- UNet2DModel with additional input channels
- Map class labels to a learned vector (embedding layer)
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REVIEW: This is what we have done in the notebook

Stable Diffusion

Model and training details

What makes this different to other text to image solutions?

- DALL-E
- DALLE-2
- Imagen

Can run on commodity hardware

Model

Text encoder - CLIP ViT-L/14

UNet = 860M parameter model

Autoencoder - downsampling factor of 8.

The model was pretrained on 256x256 images and then finetuned on 512x512 images.

Training time

- Hardware Type: A100 PCIe 40GB
- Hours used: 150000

Training data

The core dataset was trained on LAION-Aesthetics, a soon to be released subset of LAION 5B.

LAION-Aesthetics was created with a new CLIP-based model that filtered LAION-5B based on how “beautiful” an image was, building on ratings from the alpha testers of Stable Diffusion.

Controversy

- Image regurgitation
- Copying artist styles
 - Getty Images
 - Shutterstock

Cost



Jack Clark @jackclarkSF · 28 Aug

...

Stable Diffusion: \$600k to train.

I'm impressed and somewhat surprised - I figured it'd have cost a bunch more.

Also, AI is going to proliferate and change the world quite quickly if you can train decent generative models with less than \$1m.



Emad @EMostaque · 28 Aug

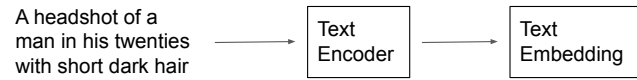
Replying to @KennethCassel

We actually used 256 A100s for this per the model card, 150k hours in total so at market price \$600k

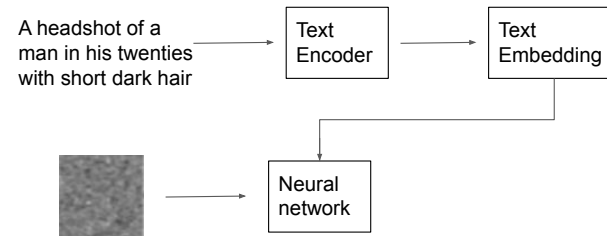
Applications

https://www.reddit.com/r/StableDiffusion/comments/wyduk1/show_rstablediffusion_integrating_sd_in_photoshop/

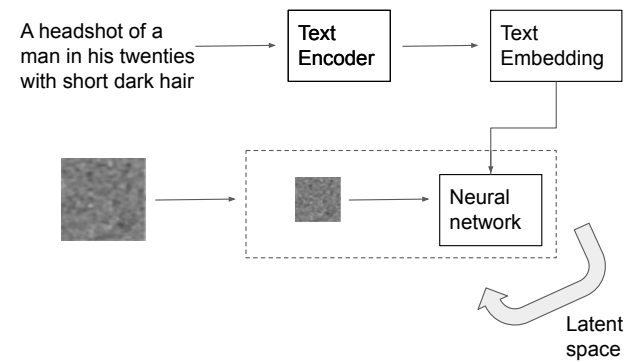
What components do we need?



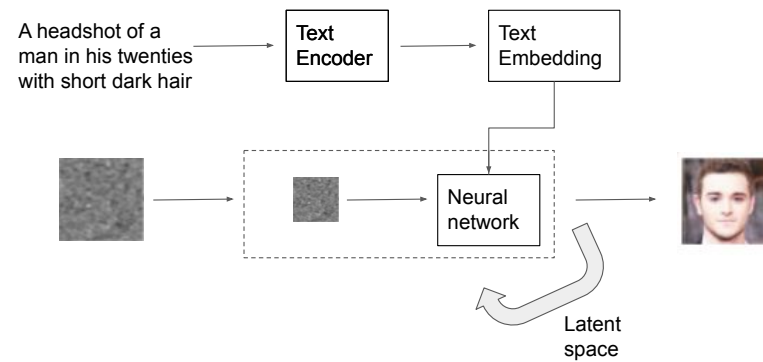
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What components do we need?



What components do we need?



The key difference between latent and standard diffusion is that latent diffusion model is trained to generate latent (compressed) representations of the images

What 3 components do we need for latent diffusion?

- A text encoder (CLIP's Text Encoder)

What 3 components do we need for latent diffusion?

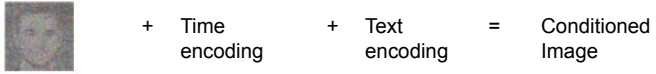
- A text encoder - CLIP's Text Encoder
- Neural network - UNet

U-Net



+ Time
encoding

U-Net

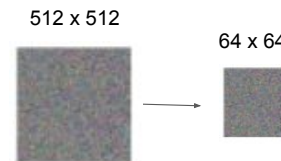


What 3 components do we need for stable diffusion?

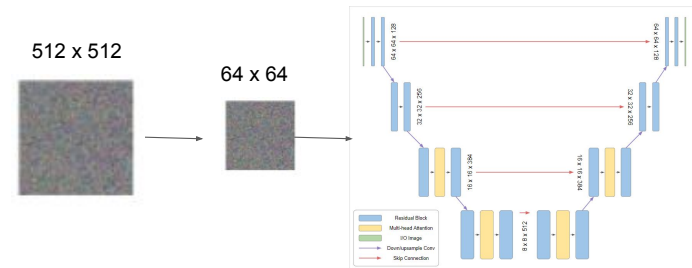
- A text encoder - CLIP's Text Encoder
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- Autoencoder

Autoencoder

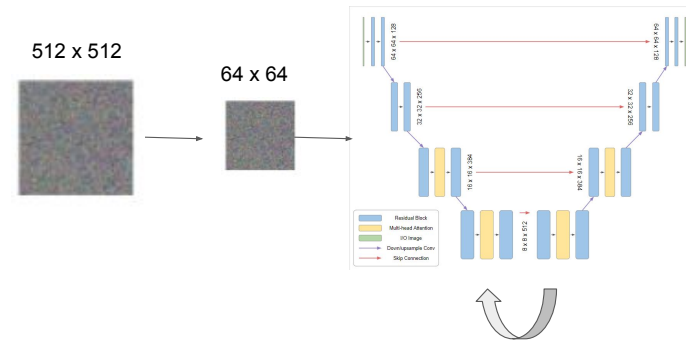
Autoencoder



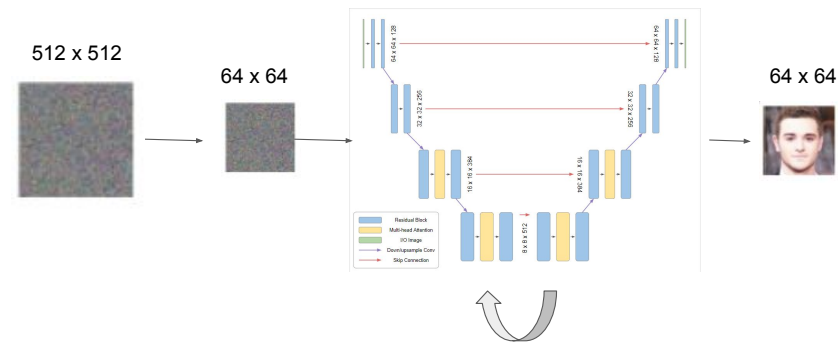
Autoencoder



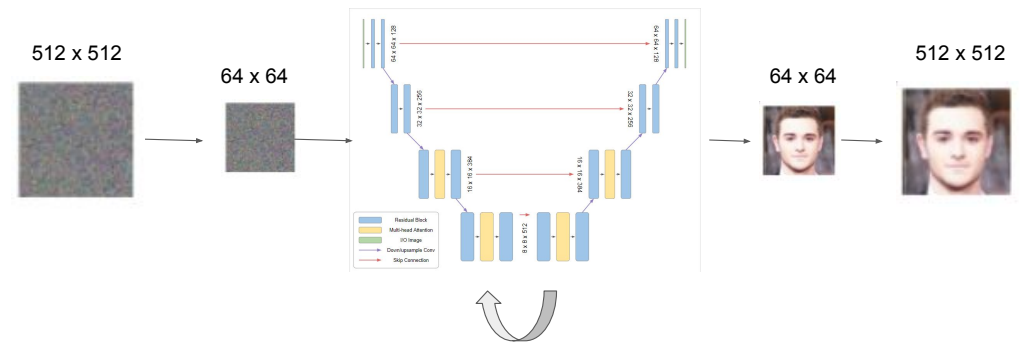
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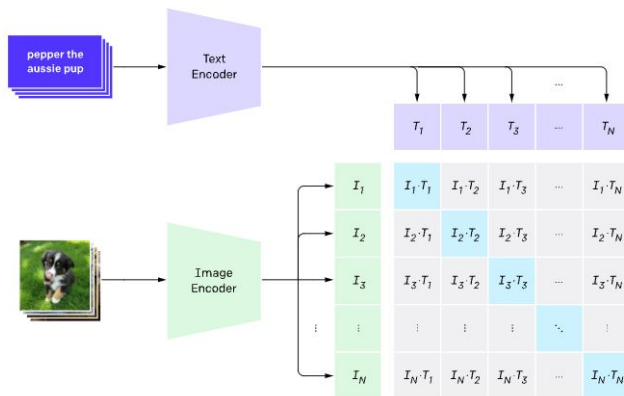
Autoencoder



Colab notebook - autoencoder

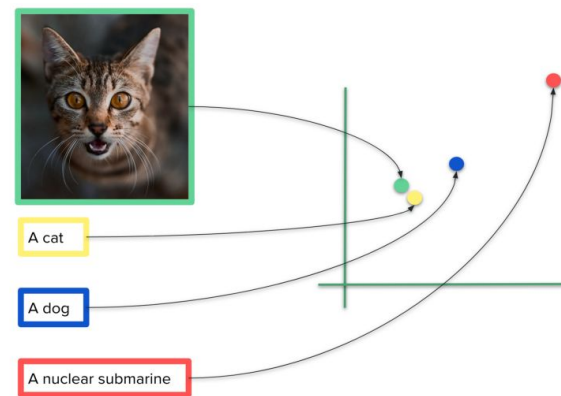
Text encoder - CLIP

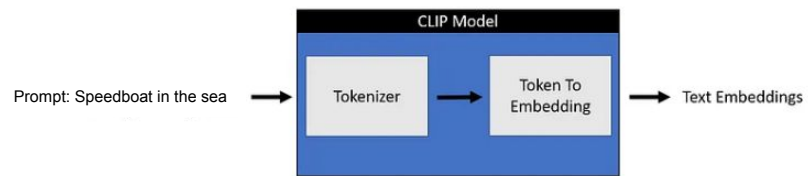
CLIP - Contrastive pre-training



Source: <https://openai.com/blog/clip/>

CLIP





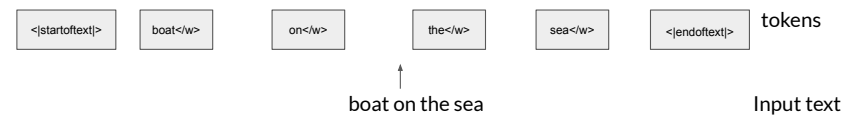
Colab - CLIP Model

Colab - tokenizers

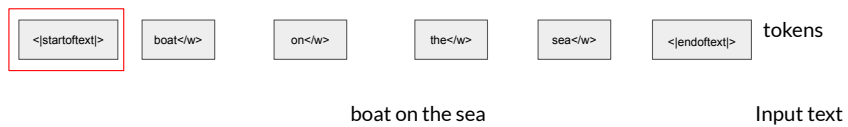
Text encoders

boat on the sea

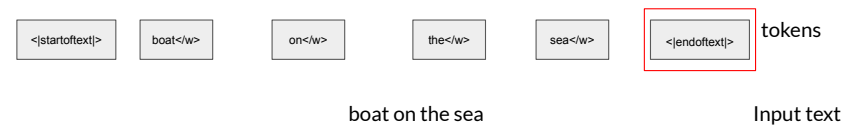
CLIPTextModel



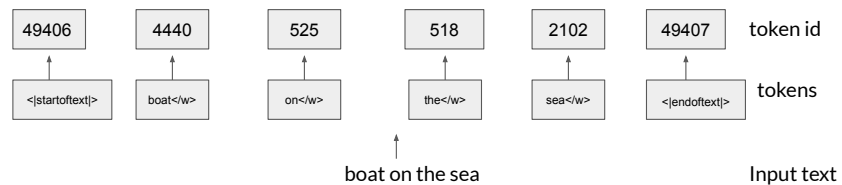
CLIPTextModel



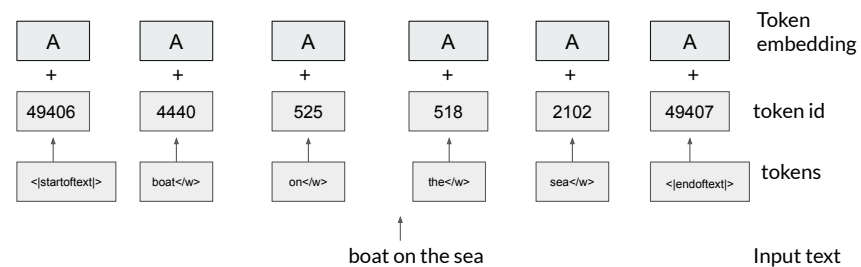
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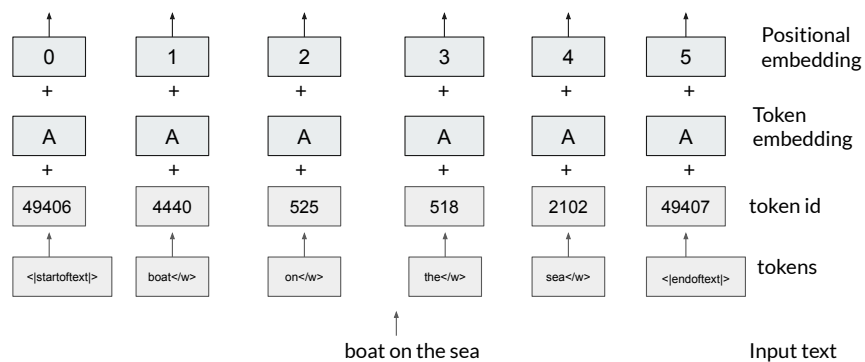
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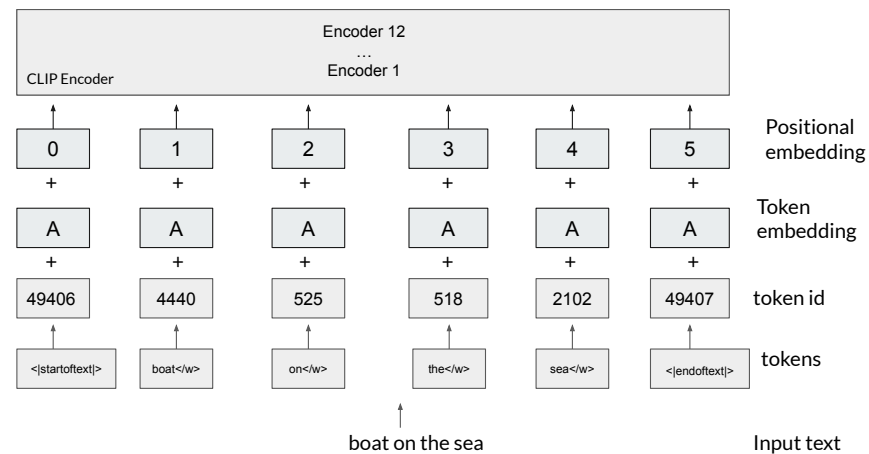
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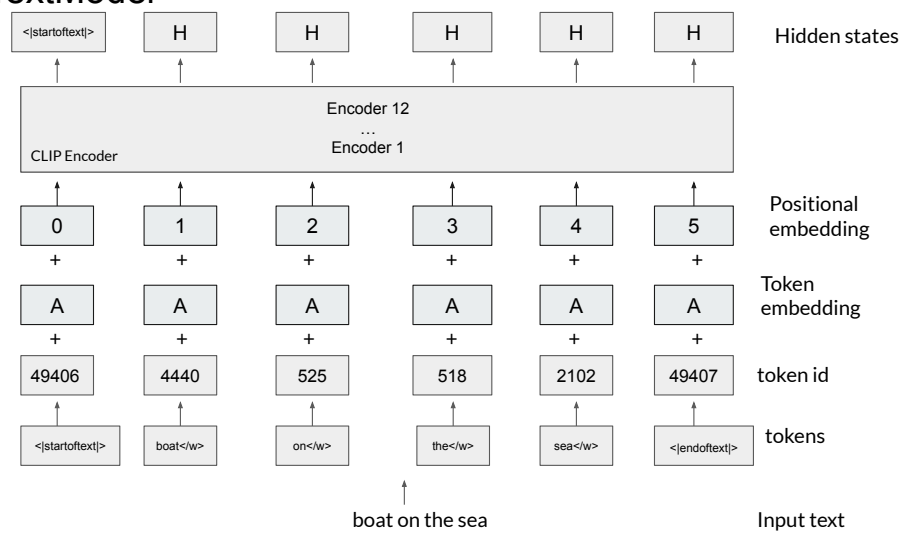
CLIPTextModel



CLIPTextModel



CLIPTextModel

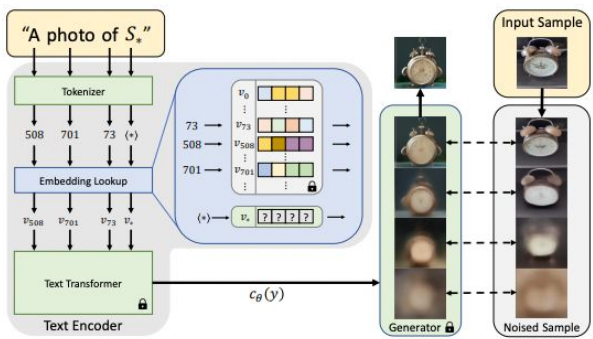


Colab - text encoders

Textual Inversion

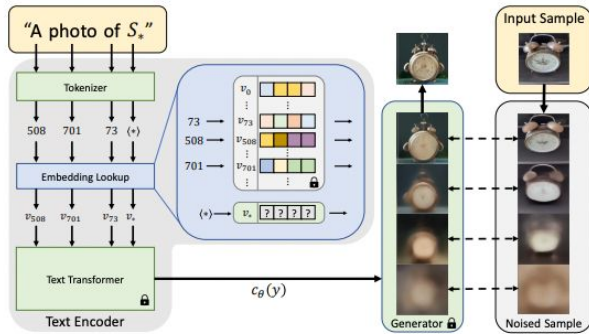
- Capture concepts from a small number of example images to control text-to-image pipelines

Textual Inversion



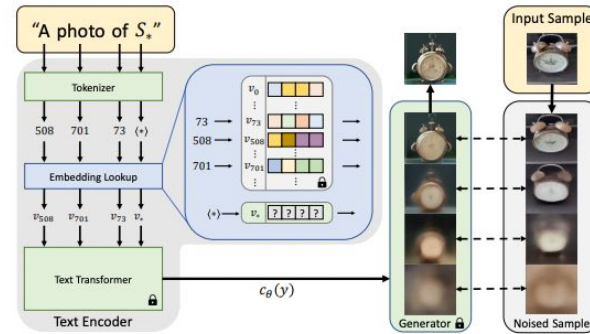
Textual Inversion

- A prompt containing the placeholder word is first converted to tokens



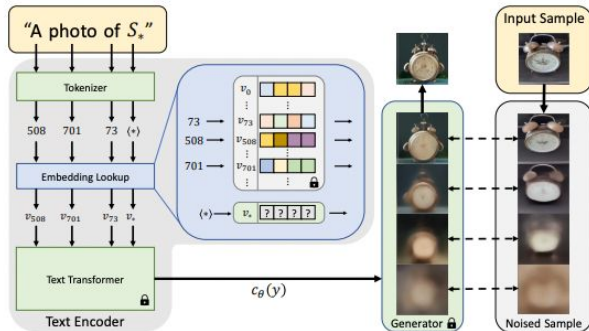
Textual Inversion

- The tokens are converted to embeddings



Textual Inversion

- Finally, the embedding vectors are transformed into a single conditioning code $c_\theta(y)$ which guides the generative model.



InstructPix2Pix

InstructPix2Pix

<https://huggingface.co/spaces/timbrooks/instruct-pix2pix>

“A photograph of a girl riding a horse”



“A photograph of a girl riding a dragon”



Different images generated



With Prompt-to-Prompt
“A photograph of a girl riding a horse”



With Prompt-to-Prompt
“A photograph of a girl riding a dragon”



Training Data Generation



Training Data Generation

	Input LAION caption	Edit instruction	Edited caption
Human-written (700 edits)	Yefim Volkov, Misty Morning	make it afternoon	Yefim Volkov, Misty Afternoon
	girl with horse at sunset	change the background to a city	girl with horse at sunset in front of city
	painting-of-forest-and-pond	Without the water.	painting-of-forest

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Fine-tune GPT-3 to generate a large dataset of text triplets

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GPT-3 generated (>450,000 edits)	Alex Hill, Original oil painting on canvas, Moonlight Bay	in the style of a coloring book	Alex Hill, Original coloring book illustration, Moonlight Bay
	The great elf city of Rivendell, sitting atop a waterfall as cascades of water spill around it	Add a giant red dragon	The great elf city of Rivendell, sitting atop a waterfall as cascades of water spill around it with a giant red dragon flying overhead
	Kate Hudson arriving at the Golden Globes 2015	make her look like a zombie	Zombie Kate Hudson arriving at the Golden Globes 2015

Training Data Generation

(a) Generate text edits:

Input Caption: "photograph of a girl riding a horse" → GPT-3 → Instruction: "have her ride a dragon"
Edited Caption: "photograph of a girl riding a dragon"

(b) Generate paired images:


Input Caption: "photograph of a girl riding a horse" → Stable Diffusion + Prompt2Prompt → 
Edited Caption: "photograph of a girl riding a dragon"

Training Data Generation

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(b) Generate paired images:

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Edited Caption: "photograph of a girl riding a dragon"

(c) Generated training examples:



What have we looked at?

- Non-technical
 - Try out different models
 - Prompting
 - Bias, limitations and controversy
- 180 min: Understand how some of the models work behind the scenes
 - Diffusion
 - Conditioned models
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Next iteration of this course will include the latest AI generation

What have we looked at?

- We've tried out different models
- We've looked at prompting and prompting guides to improve
- Looked at Bias, limitations and controversy with AI generation.
- Diffusion
 - Conditioned models
- Stable Diffusion
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Live Course



Fundamentals of Large Language Models: A hands-on approach

With Jonathan Fernandes

5pm BST 📅 May 31

END