

EEP 596: LLMs: From Transformers to GPT || Lecture 14

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Deep Learning and Transformers References

Deep Learning

Great reference for the theory and fundamentals of deep learning: Book by Goodfellow and Bengio et al [Bengio et al](#)

[Deep Learning History](#)

Embeddings

[SBERT and its usefulness](#)

[SBert Details](#)

[Instacart Search Relevance](#)

[Instacart Auto-Complete](#)

Attention

[Illustration of attention mechanism](#)

Generative AI References

Prompt Engineering

Prompt Design and Engineering: Introduction and Advanced Methods

Retrieval Augmented Generation (RAG)

Toolformer

RAG Toolformer explained

Misc GenAI references

Time-Aware Language Models as Temporal Knowledge Bases

Generative AI references

Stable Diffusion

The Original Stable Diffusion Paper

Reference: CLIP

Diffusion Explainer: Visual Explanation for Text-to-image Stable Diffusion

The Illustrated Stable Diffusion

Previous Lecture

- Auto Encoder and their use-cases
- De-noising Auto-Encoder

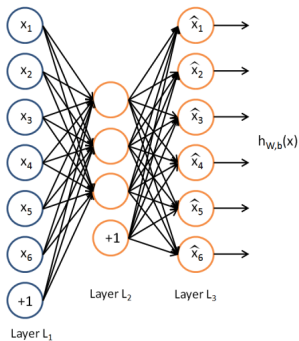
This Lecture

- Stable Diffusion Architecture
- De-noising AutoEncoders in Stable Diffusion

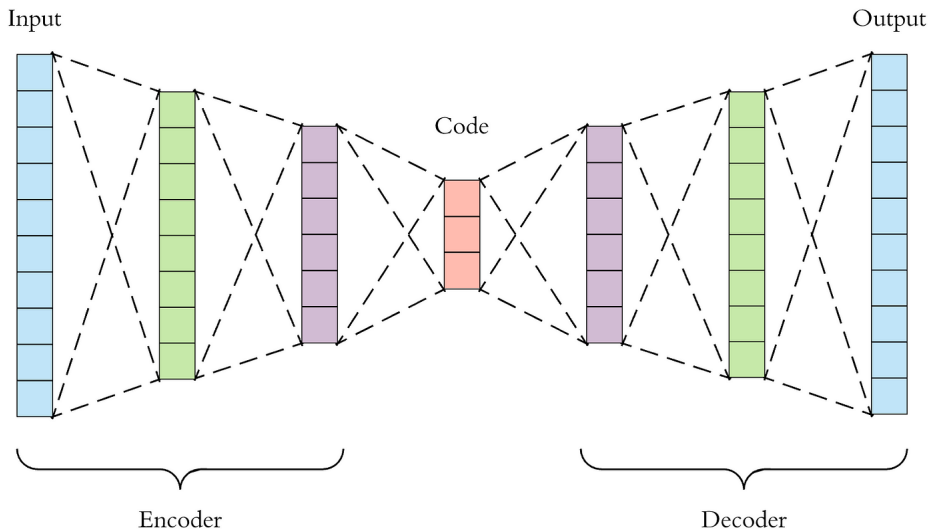
Stable Diffusion Explained

- Based on the concept of “de-noising auto encoders” and the use of text prompt to *guide the de-noising*
- Stable diffusion is also trained to successfully de-noise and increase the resolution of the image using text guidance

Auto Encoders



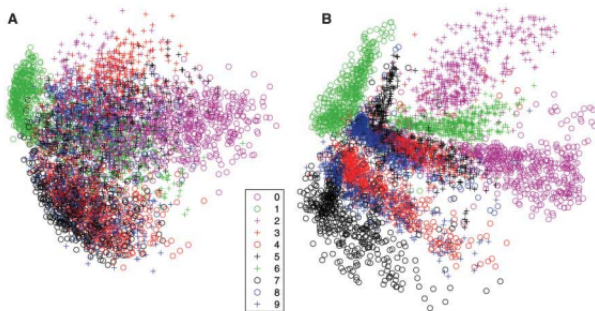
Deep Auto Encoders



AutoEncoders and Dimensionality Reduction

Reading Reference for AE Dimensionality Reduction

Fig. 3. (A) The two-dimensional codes for 500 digits of each class produced by taking the first two principal components of all 60,000 training images. (B) The two-dimensional codes found by a 784-1000-500-250-2 autoencoder. For an alternative visualization, see (B).



AutoEncoders Summary

- 1 Auto-Encoders are a method for dimensionality reduction and can do better than PCA for visualization

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- ① Auto-Encoders are a method for dimensionality reduction and can do better than PCA for visualization
- ② Use Neural Networks architecture and hence can encode non-linearity in the embeddings

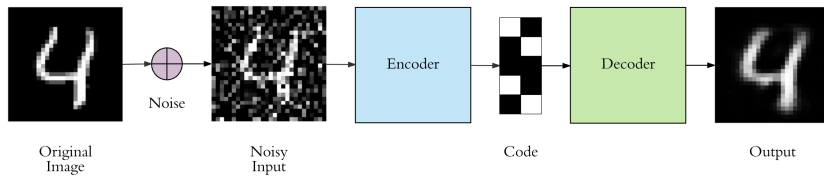
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- ③ Anything else?

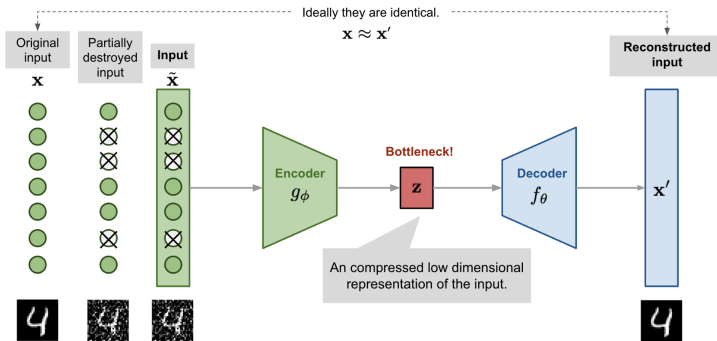
AutoEncoders Summary

- 1 Auto-Encoders are a method for dimensionality reduction and can do better than PCA for visualization
- 2 Use Neural Networks architecture and hence can encode non-linearity in the embeddings
- 3 Anything else?
- 4 Auto Encoders can learn convolutional layers instead of dense layers - Better for images! More flexibility!!

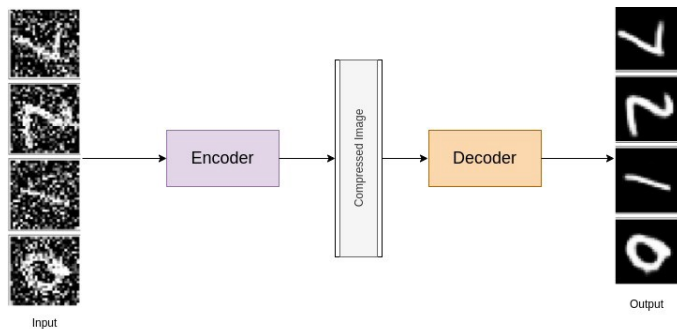
De-noising Auto Encoders



De-noising Auto Encoders



De-noising Auto Encoders



De-noising Auto Encoders

Details

- Just like an Auto Encoder

De-noising Auto Encoders

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- Difference: Noise is injected in the inputs on purpose but output is a clean data point.

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- This forces the Auto Encoder to “de-noise” data, esp. useful for images!

De-noising Auto Encoders

Details

- Just like an Auto Encoder
- Difference: Noise is injected in the inputs on purpose but output is a clean data point.
- This forces the Auto Encoder to “de-noise” data, esp. useful for images!
- Esp. useful for a category of objects or images (e.g. digit recognition or face recognition, etc)

Stable Diffusion High-Level



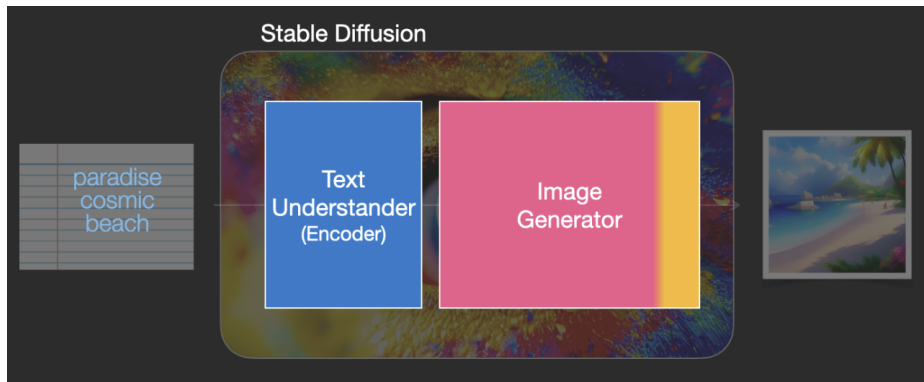
Reference: The Illustrated Stable Diffusion

Stable Diffusion High-Level



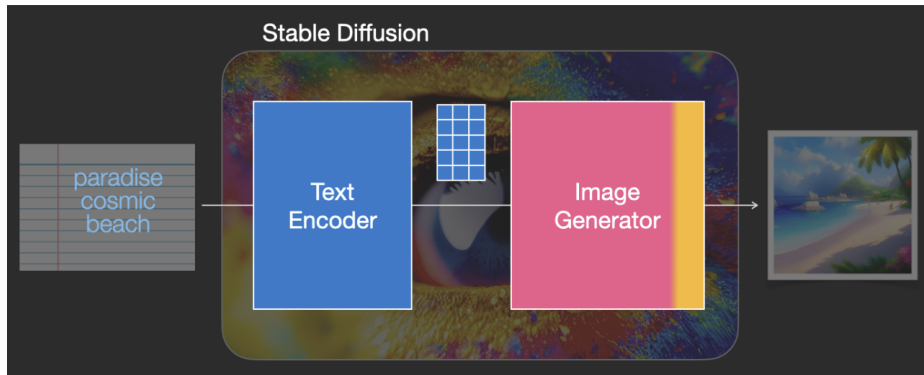
Reference: [The Illustrated Stable Diffusion](#)

Stable Diffusion Components



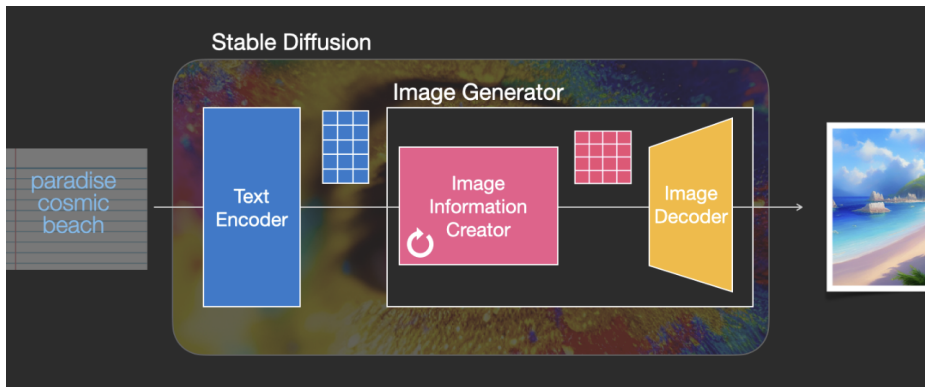
Reference: The Illustrated Stable Diffusion

Stable Diffusion Components



Reference: [The Illustrated Stable Diffusion](#)

Image Information Creator



Reference: The Illustrated Stable Diffusion

Image Decoder

Stable Diffusion

Text
Encoder
(CLIPText)

Image
Information
Creator
(UNet + Scheduler)

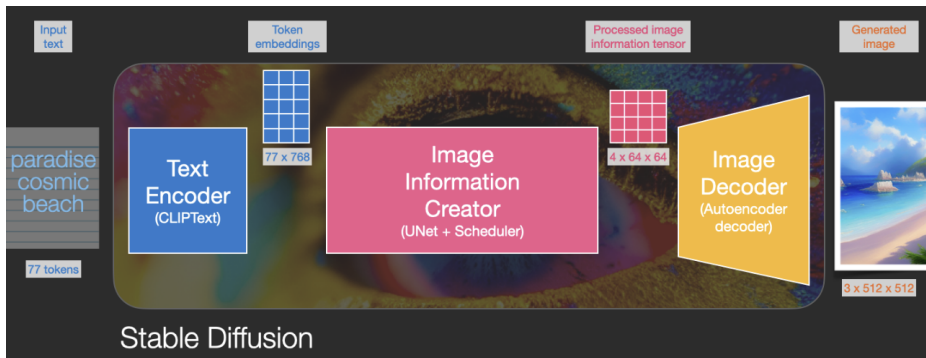
Image
Decoder
(Autoencoder
decoder)

Reference: The Illustrated Stable Diffusion

Stable Diffusion - Break down of components

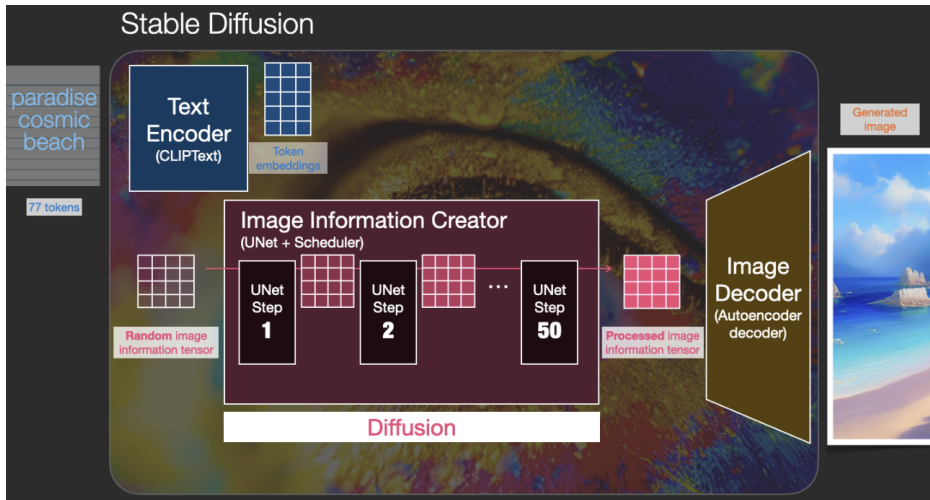
- 1 **Text Encoding:** Uses ClipText
- 2 **Image diffusion process:** Take in a text embedding and generate an image embedding that can then be converted to an image.
- 3 **Image Decoder:** This is an AutoEncoder-Decoder that takes in an Image embedding and returns an image in a pixel format (512x512x3)

High-level



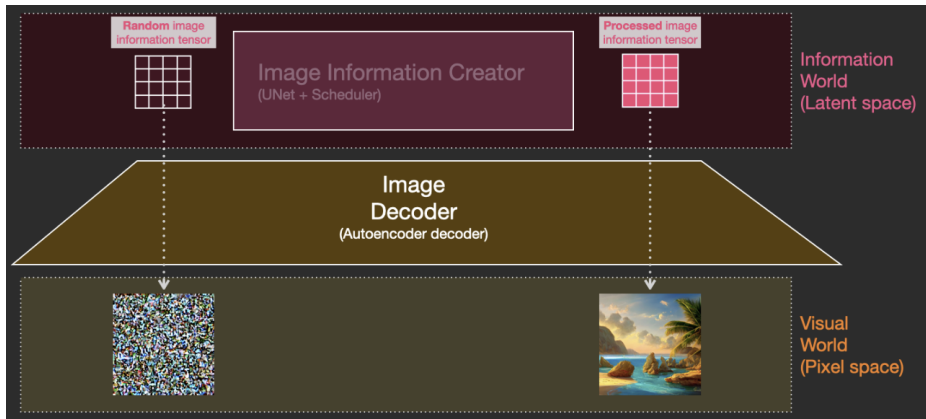
Reference: The Illustrated Stable Diffusion

Understanding Diffusion



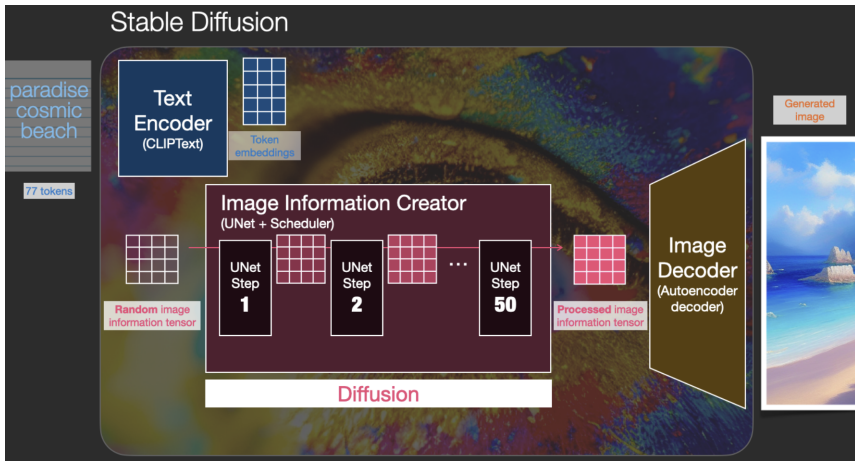
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Understanding Diffusion



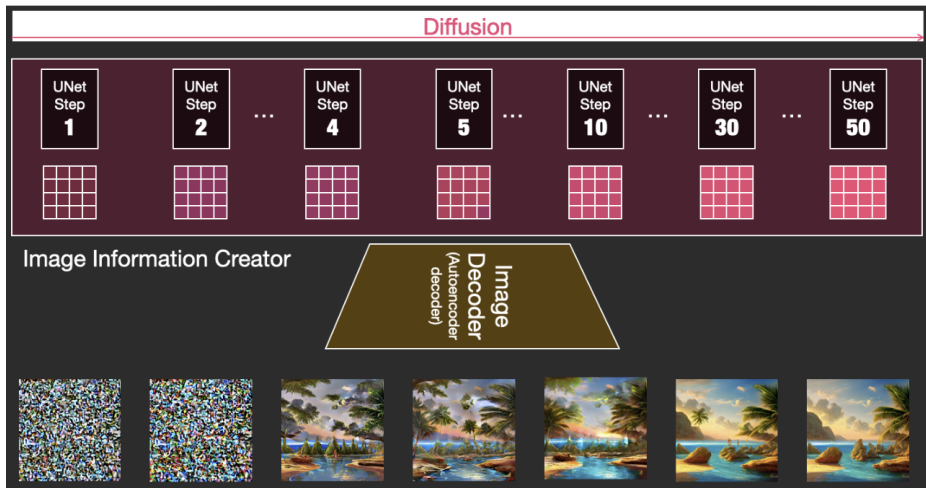
Reference: The Illustrated Stable Diffusion

Understanding Diffusion



Reference: The Illustrated Stable Diffusion

Understanding Diffusion



Reference: The Illustrated Stable Diffusion

Generating Training Examples with Noise Addition

Training examples are created by generating **noise** and adding an **amount** of it to the images in the training dataset (forward diffusion)

1
Pick an image

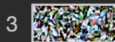


2
Generate some
random **noise**



Noise sample 1

3
Pick an amount
of **noise**



4
Add **noise** to
the image in
that **amount**



Reference: The Illustrated Stable Diffusion

Generating Training Examples with Noise Addition

Generating a 2nd training example with a different image, **noise sample** and **noise amount** (forward diffusion)

1
Pick an image

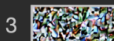
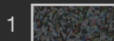


2
Generate some
random noise



Noise sample 2

3
Pick an amount
of noise

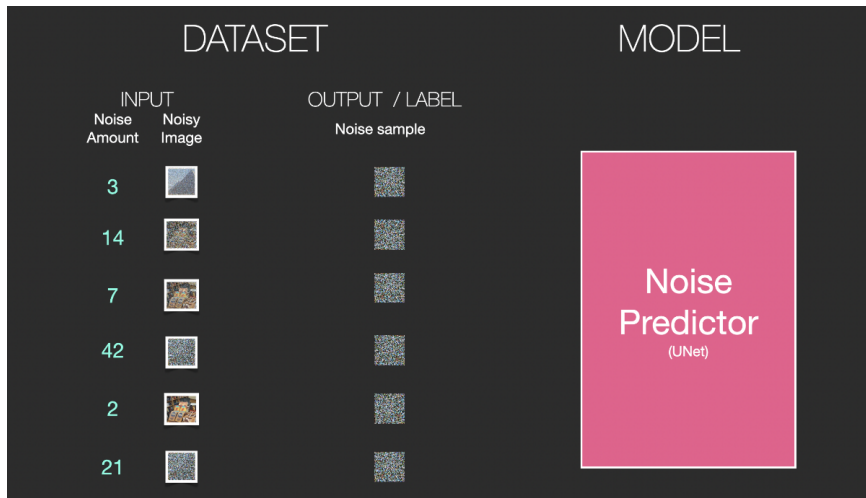


4
Add **noise** to
the image in
that **amount**



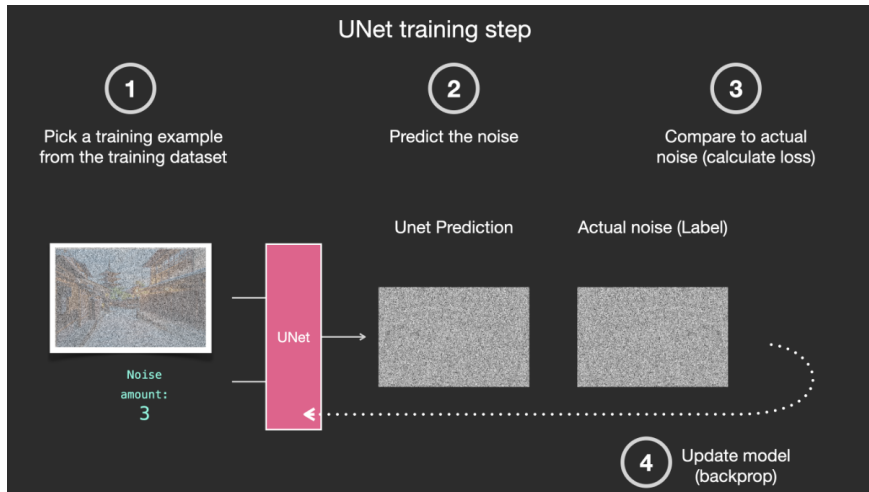
Reference: The Illustrated Stable Diffusion

Generating Training Examples with Noise Addition



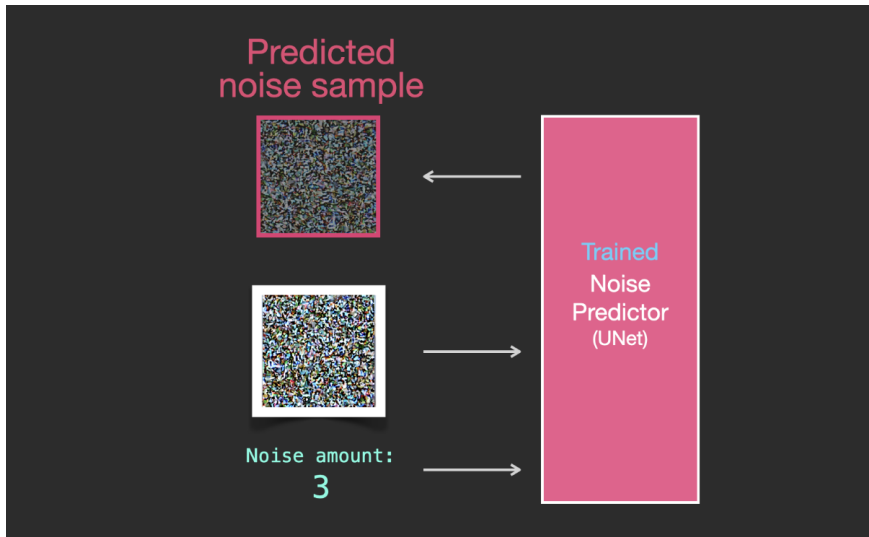
Reference: The Illustrated Stable Diffusion

Training Process

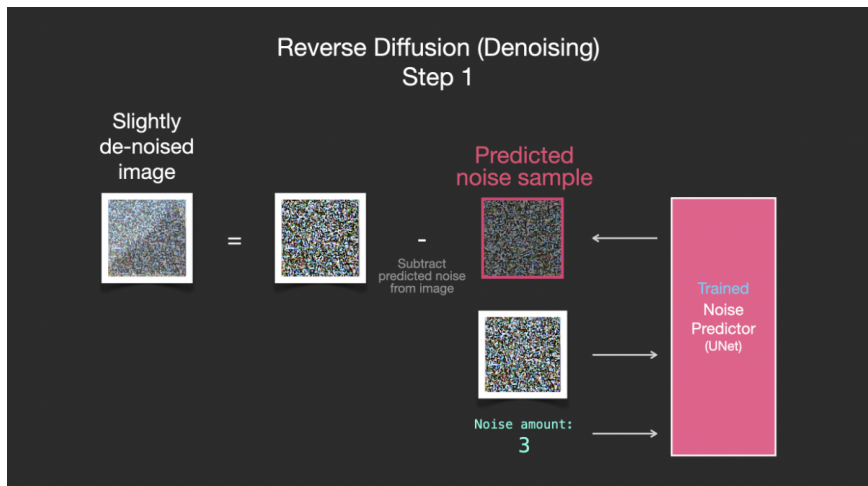


Reference: The Illustrated Stable Diffusion

Predicting noise and Noise Removal

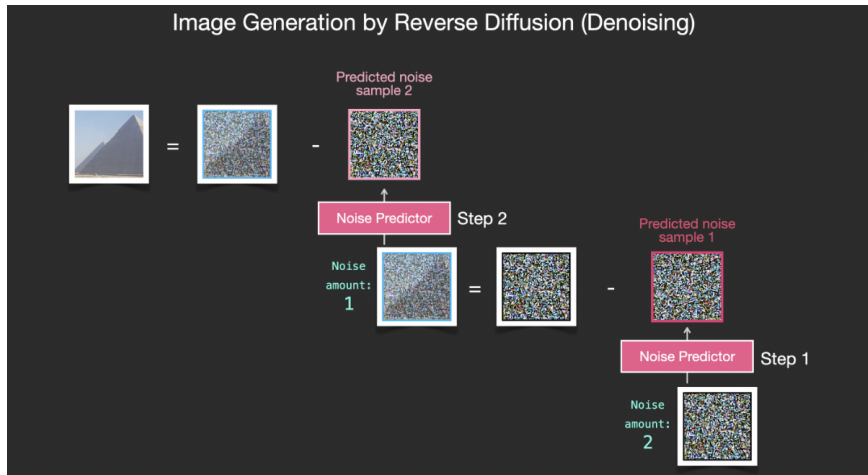


Predicting noise and Noise Removal



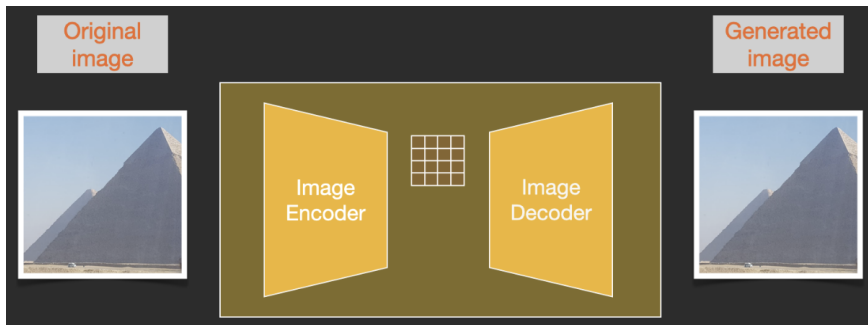
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Predicting noise and Noise Removal



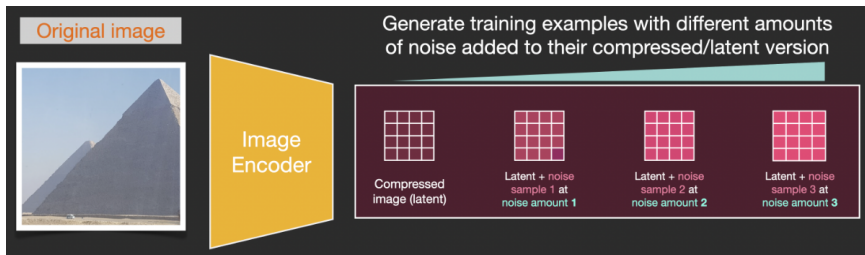
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Speeding up Stable Diffusion



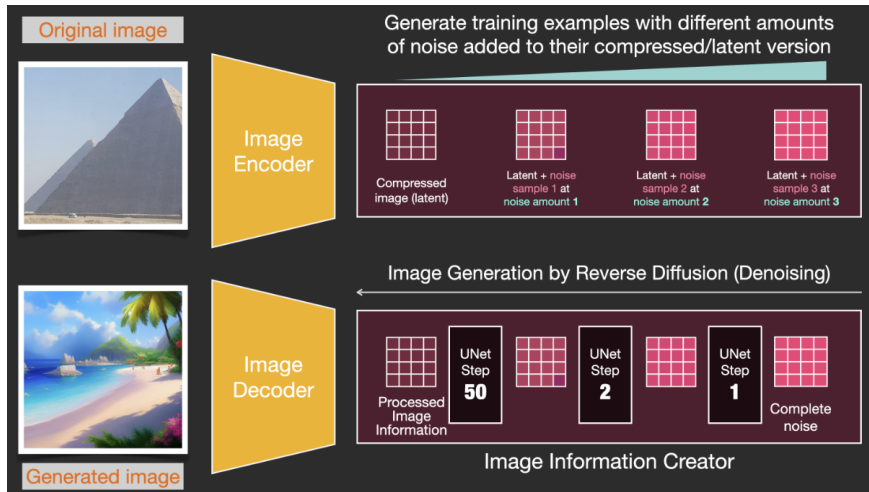
Reference: The Illustrated Stable Diffusion

Speeding up Stable Diffusion



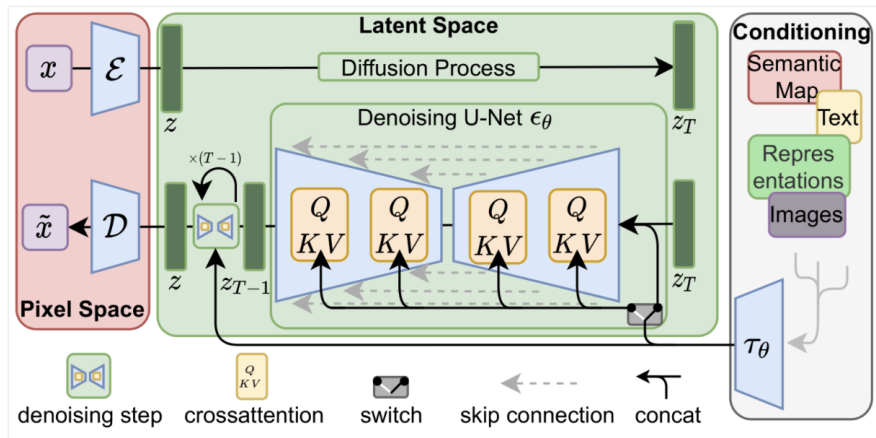
Reference: The Illustrated Stable Diffusion

Speeding up Stable Diffusion



Reference: The Illustrated Stable Diffusion

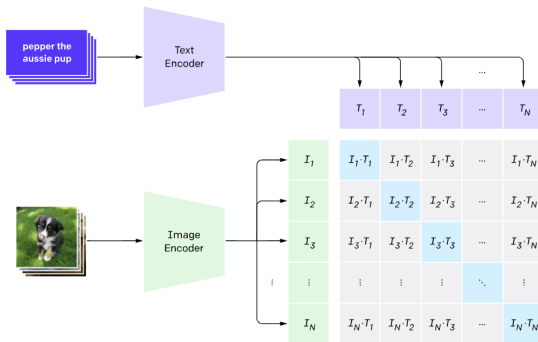
Stable Diffusion Full Architecture



Reference: [The Illustrated Stable Diffusion](#)

Clip Pre-Training Architecture

1. Contrastive pre-training

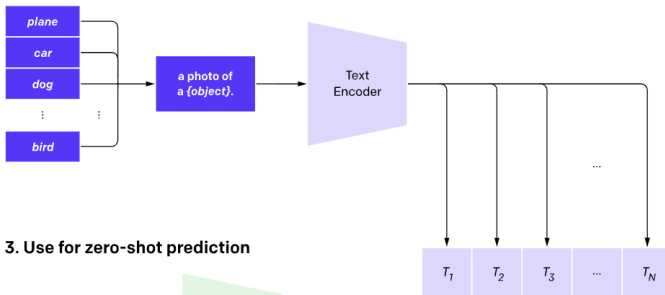


CLIP pre-trains an image encoder and a text encoder to predict which images were paired with which texts in our dataset. We then use this behavior to turn CLIP into a zero-shot classifier. We convert all of a dataset's classes into captions such as "a photo of a dog" and predict the class of the caption CLIP estimates best pairs with a given image.

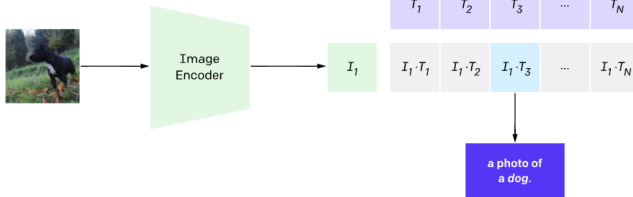
Reference: CLIP

Clip Zero-Shot Prediction Process

2. Create dataset classifier from label text



3. Use for zero-shot prediction



Reference: CLIP

ICE #1

What pre-trained encoders would CLIP probably have used for text and image encodings?

- ① CNN for both
- ② Word2Vec and CNN
- ③ Transformer and Vi Transformer
- ④ Glove and CNN

Clip Implementation Pseudo-code

```
# image_encoder - ResNet or Vision Transformer
# text_encoder - CBOW or Text Transformer
# I[n, h, w, c] - minibatch of aligned images
# T[n, l] - minibatch of aligned texts
# W_i[d_i, d_e] - learned proj of image to embed
# W_t[d_t, d_e] - learned proj of text to embed
# t - learned temperature parameter

# extract feature representations of each modality
I_f = image_encoder(I) #[n, d_i]
T_f = text_encoder(T) #[n, d_t]

# joint multimodal embedding [n, d_e]
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

# scaled pairwise cosine similarities [n, n]
logits = np.dot(I_e, T_e.T) * np.exp(t)

# symmetric loss function
labels = np.arange(n)
loss_i = cross_entropy_loss(logits, labels, axis=0)
loss_t = cross_entropy_loss(logits, labels, axis=1)
loss = (loss_i + loss_t)/2
```

Figure 3. Numpy-like pseudocode for the core of an implementation of CLIP.

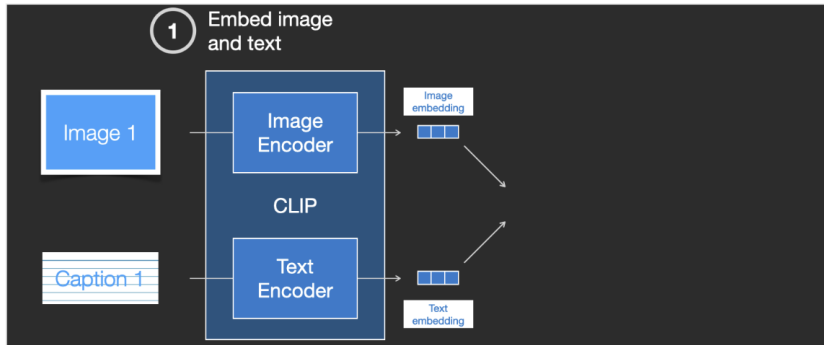
Reference: CLIP

Clip Training Examples

IMAGE			
			
CAPTION	Photo pour Japanese pagoda and old house in Kyoto at twilight - image libre de droit	Soaring by Peter Eades	far cry 4 concept art is the reason why it 39 s a beautiful game vg247. Black Bedroom Furniture Sets. Home Design Ideas

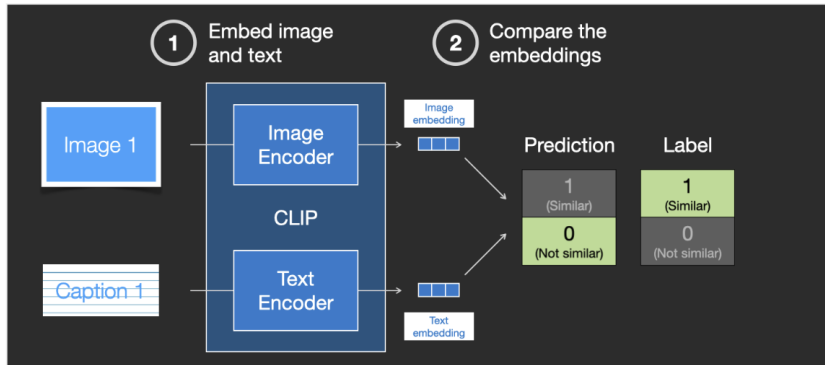
Question: How many examples used for Training? **Reference:** [The Illustrated Stable Diffusion](#)

Clip Training Process



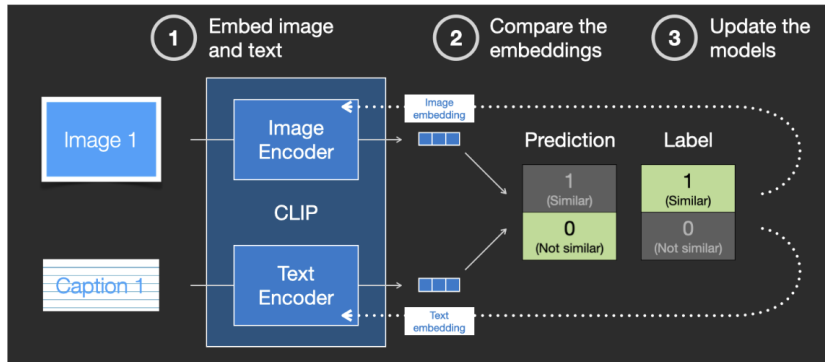
Reference: The Illustrated Stable Diffusion

Clip Training Process



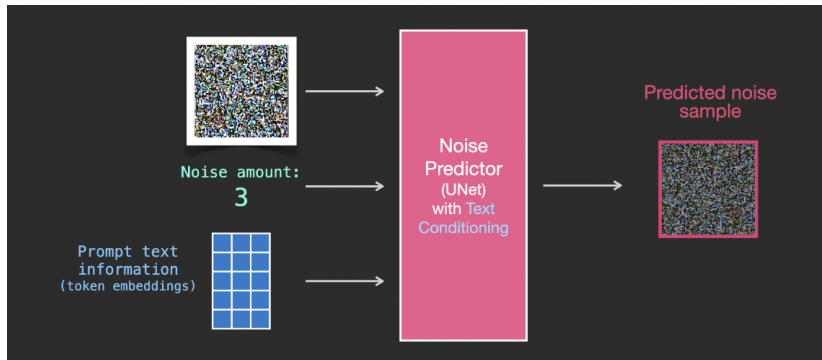
Reference: The Illustrated Stable Diffusion

Clip Training Process



Reference: The Illustrated Stable Diffusion

Image Generation Process



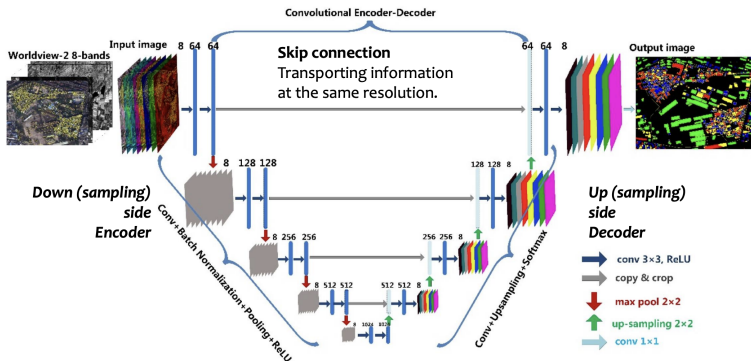
Reference: The Illustrated Stable Diffusion

Image Generation: Training Data

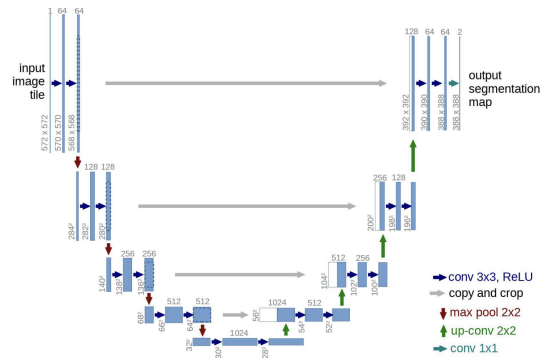


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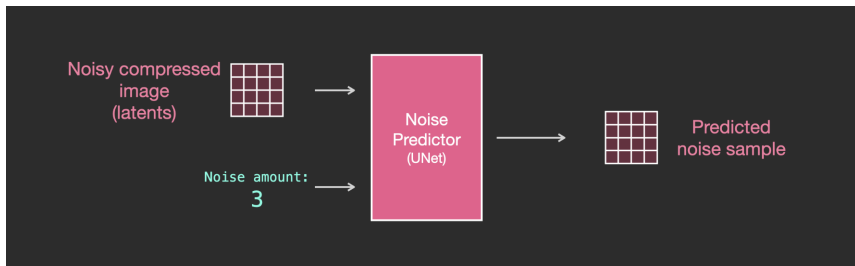
Unet Architecture



Unet Architecture

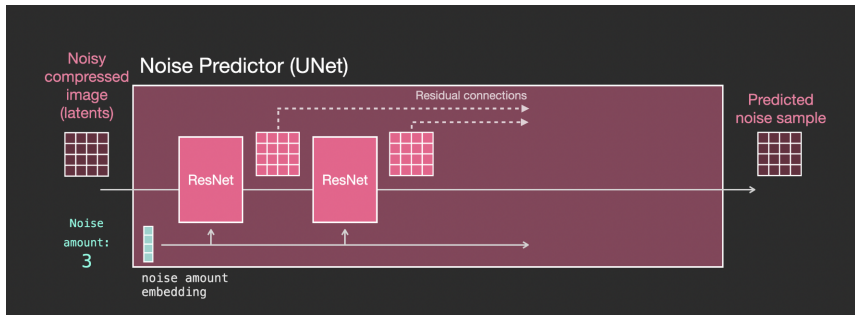


Unet Predictor (Without Text)



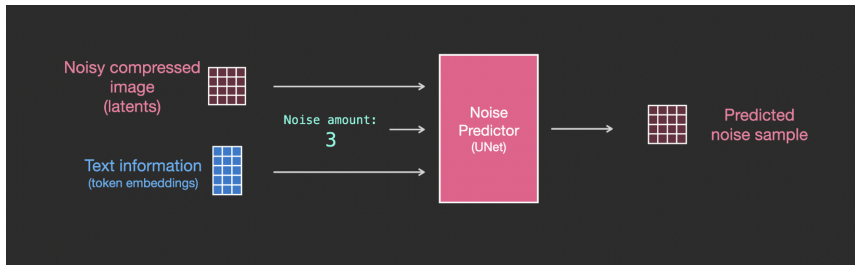
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Unet Predictor (Without Text)



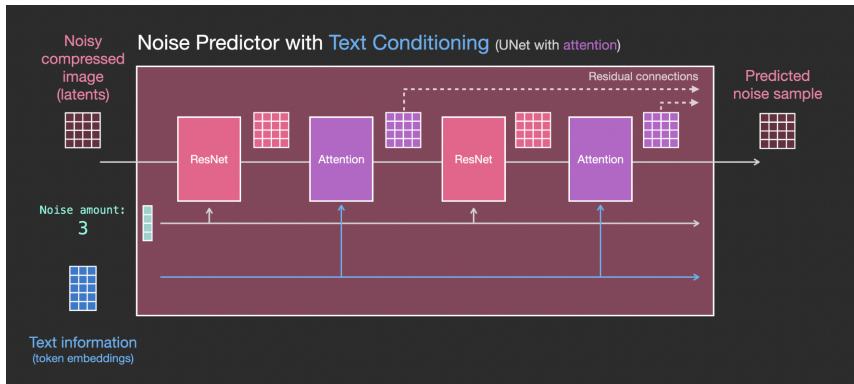
Reference: The Illustrated Stable Diffusion

Unet Predictor (With Text)



Reference: The Illustrated Stable Diffusion

Unet Predictor (With Text)



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