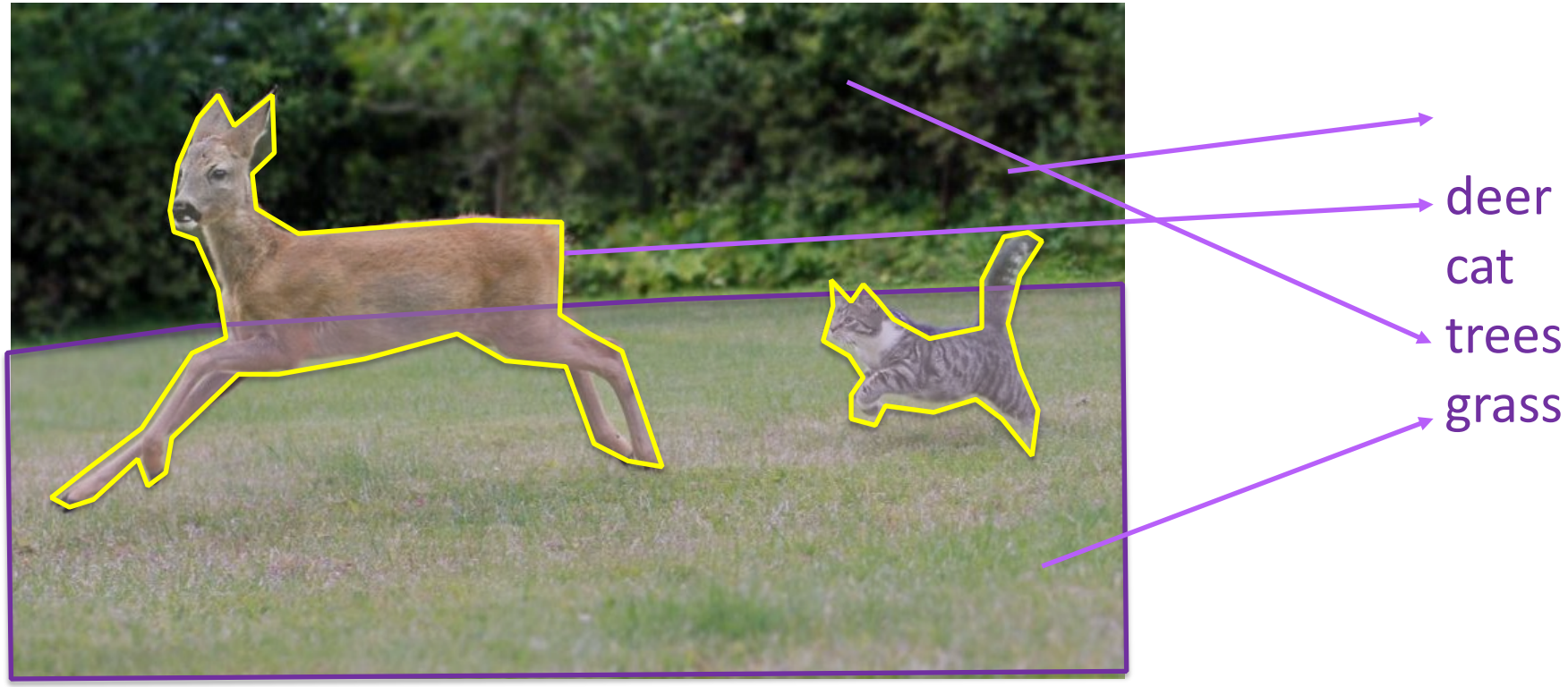
Deep Learning for Vision & Language

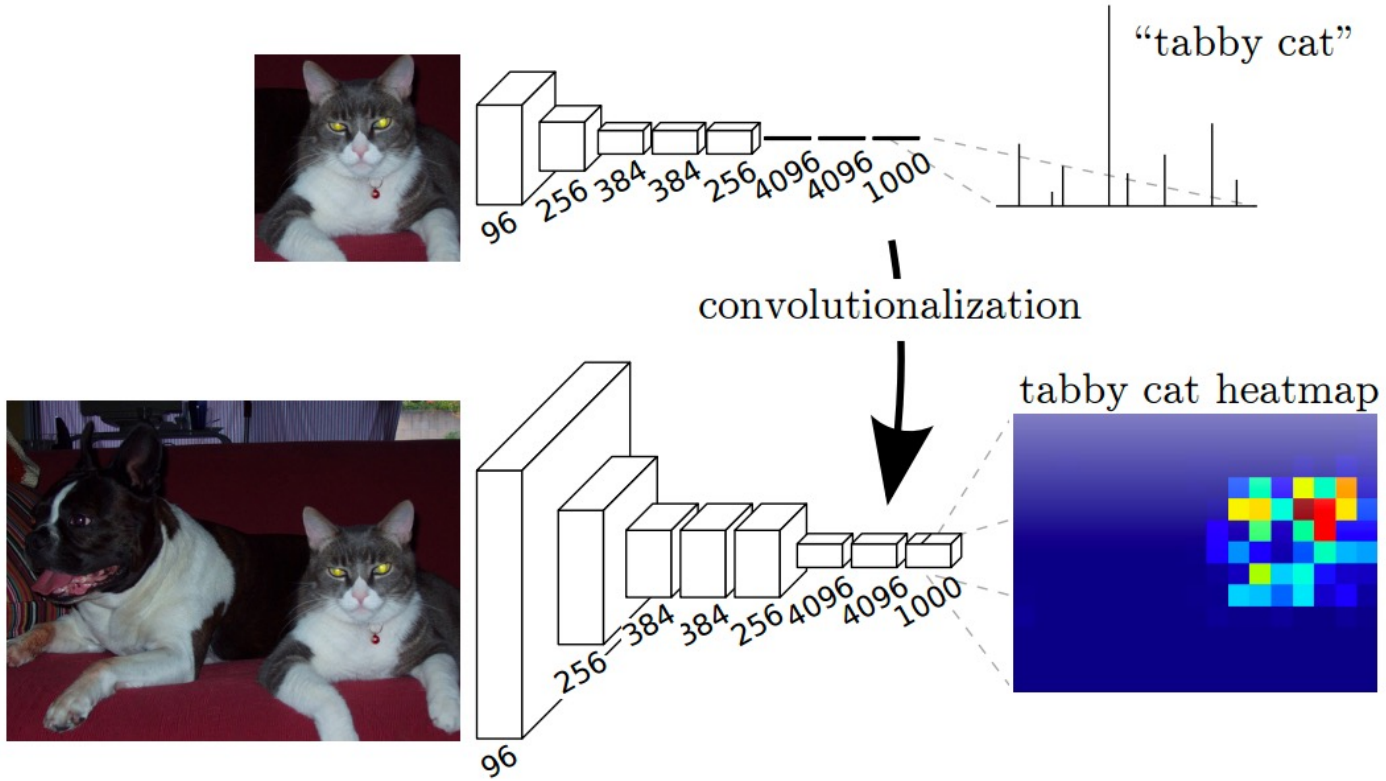
Continuation of Segmentation, AutoEncoders, Variational AutoEncoders, Introduction to Diffusion Models

RICE UNIVERSITY

Semantic Segmentation / Image Parsing



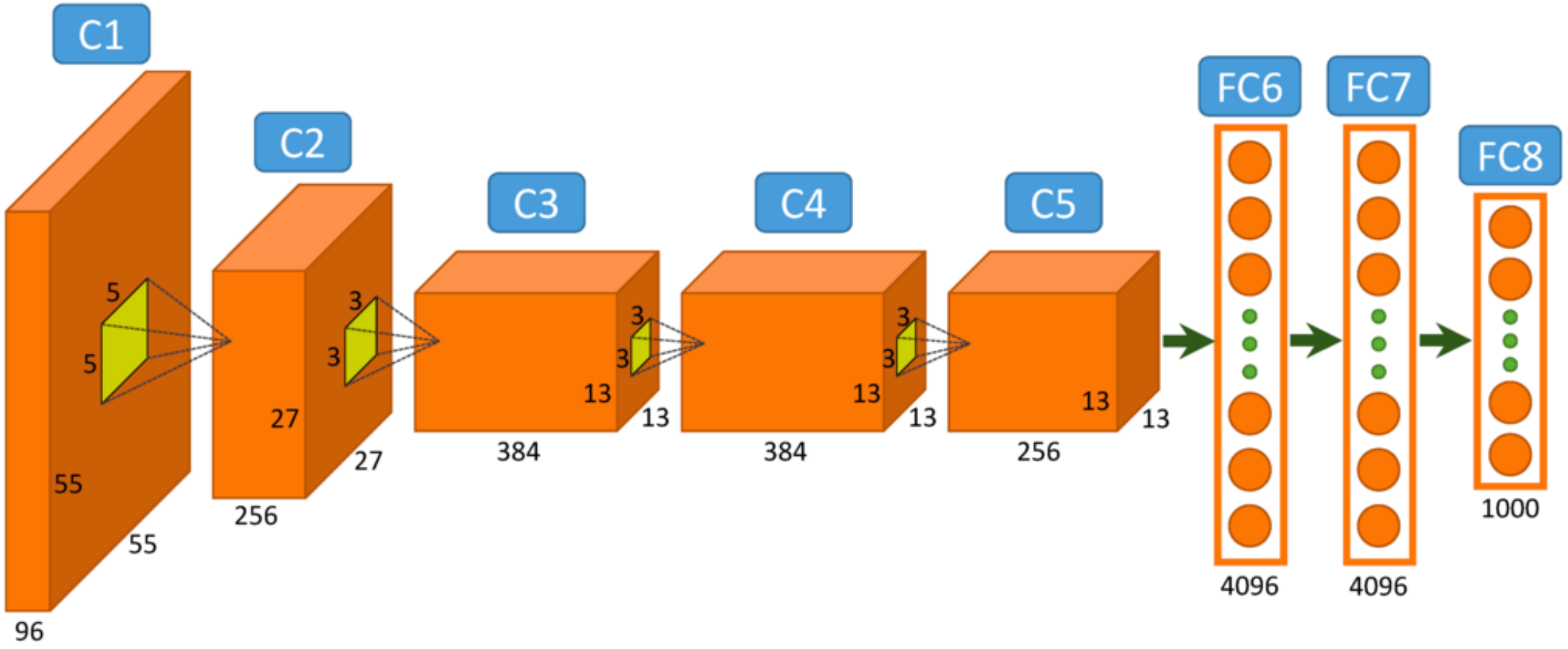
Idea 1: Convolutionalization



However resolution of the segmentation map is low.

https://people.eecs.berkeley.edu/~jonlong/long_shelhamer_fcn.pdf

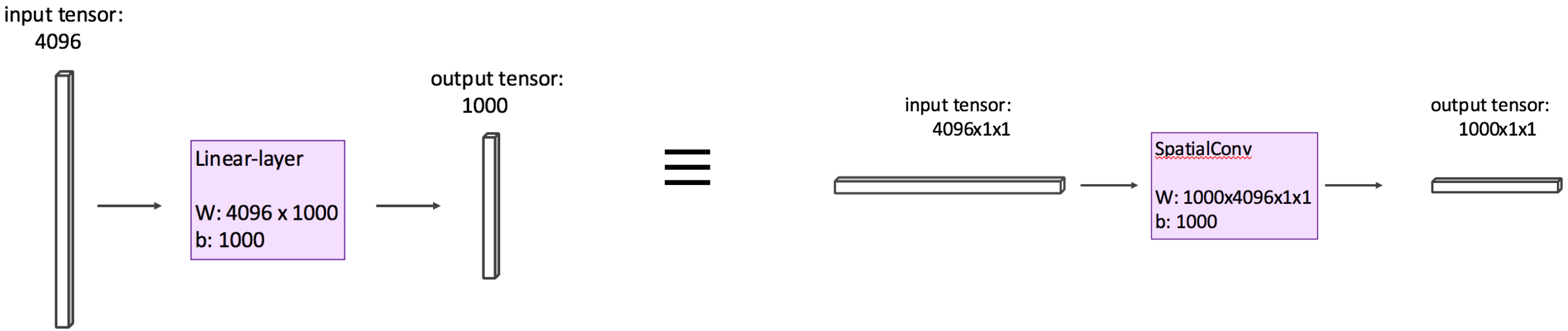
Alexnet



https://www.saagie.com/fr/blog/object-detection-part1

Idea 1: Convolutionalization

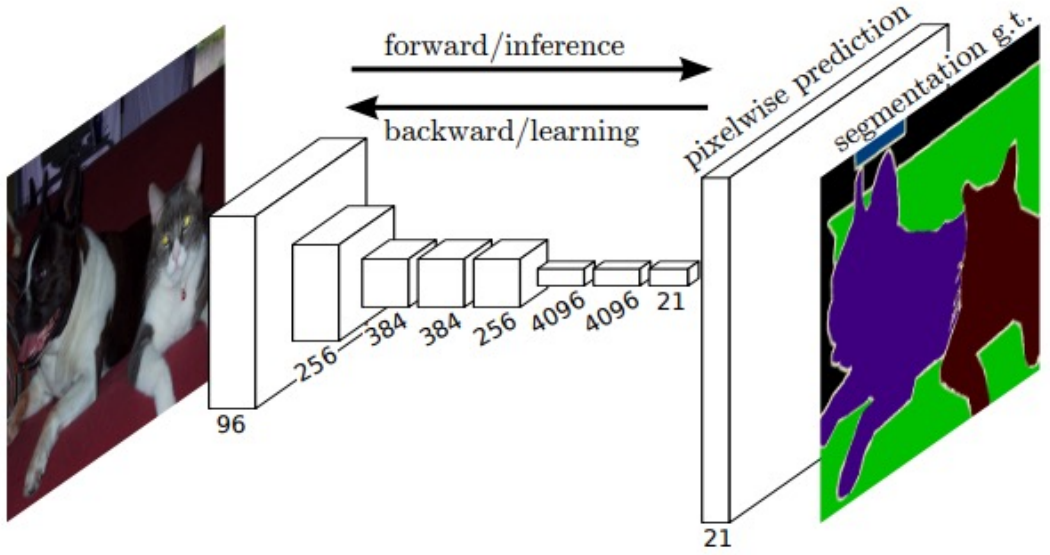
nn.Linear(4096, 1000) == nn.Conv2D(4096, 1000, kernel_size = 1, stride = 1)



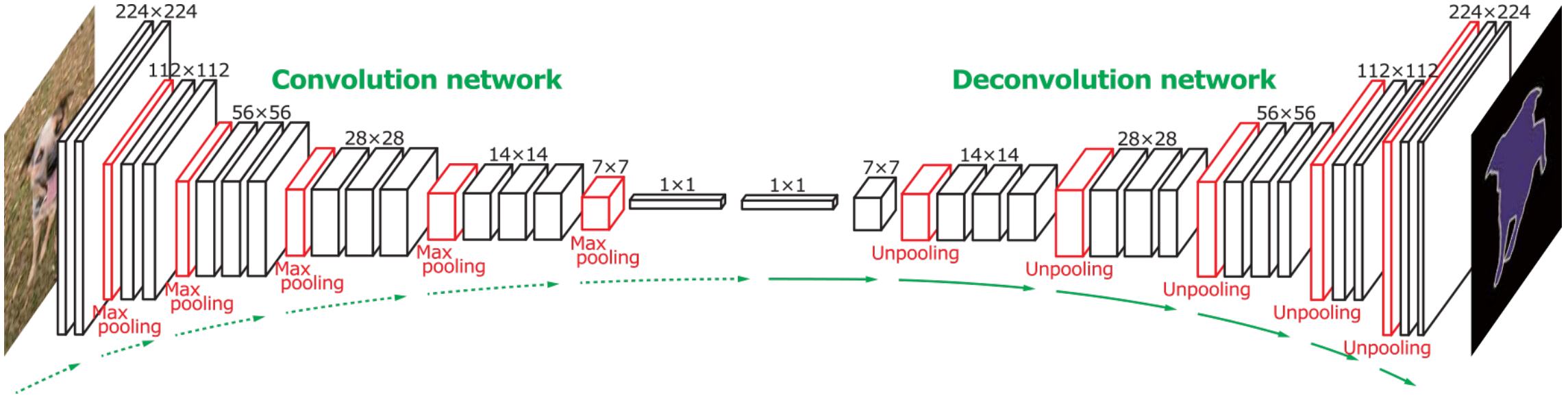
Fully Convolutional Networks (CVPR 2015)

Fully Convolutional Networks for Semantic Segmentation

Jonathan Long* Evan Shelhamer* Trevor Darrell
UC Berkeley
{jonlong,shelhamer,trevor}@cs.berkeley.edu



Idea 2: Up-sampling Convolutions or ”Deconvolutions”

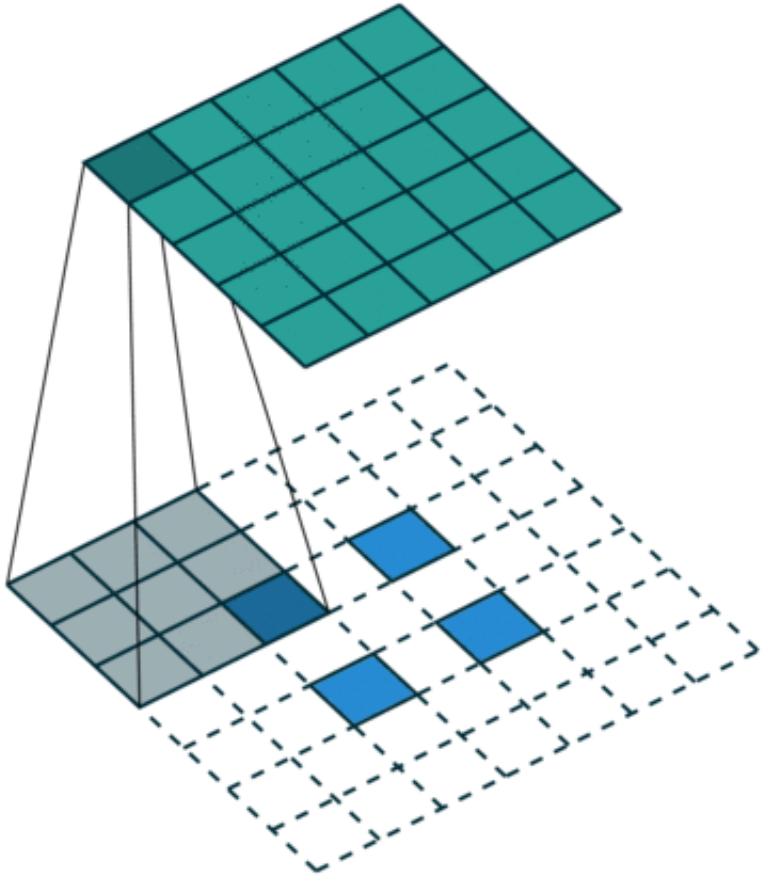


Learning Deconvolution Network for Semantic Segmentation

Hyeonwoo Noh Seunghoon Hong Bohyung Han
Department of Computer Science and Engineering, POSTECH, Korea
{hyeonwoonoh_,maga33,bhhan}@postech.ac.kr

http://cvlab.postech.ac.kr/research/deconvnet/

Idea 2: Up-sampling Convolutions or ”Deconvolutions”



https://github.com/vdumoulin/conv_arithmetic

Idea 2: Up-sampling Convolutions or ”Deconvolutions”

Deconvolutional Layers

Upconvolutional Layers

Backwards Strided
Convolutional Layers

Fractionally Strided
Convolutional Layers

Transposed
Convolutional Layers

Spatial Full
Convolutional Layers

Pytorch

Docs > torch.nn > ConvTranspose2d

CONVTRANSPOSE2D

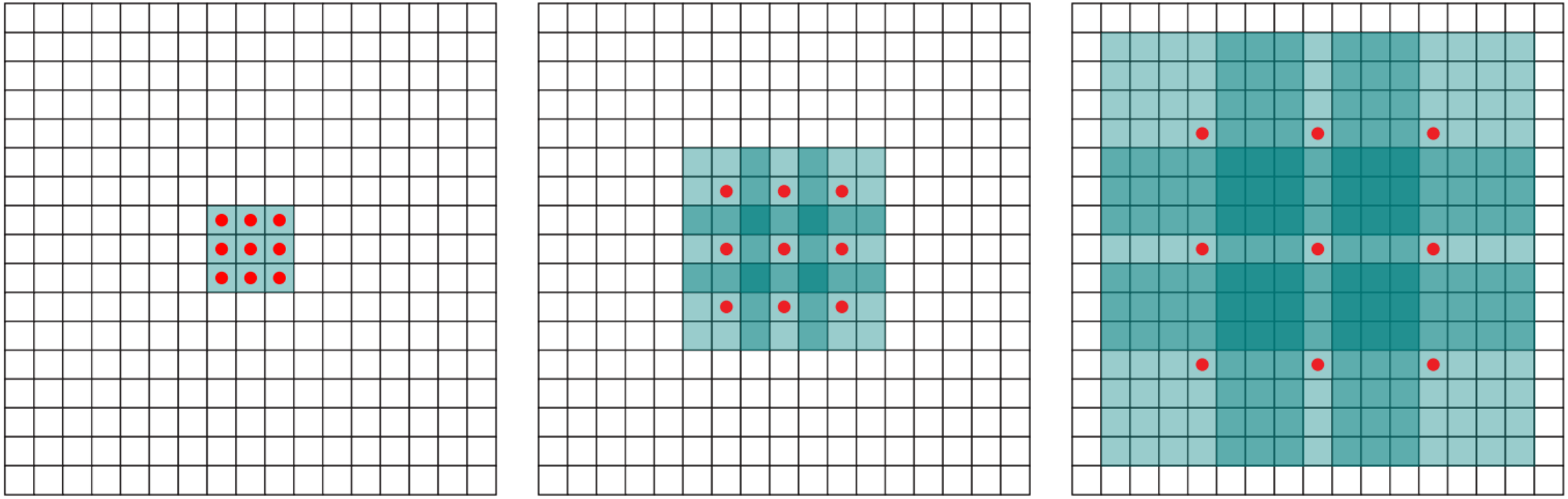
CLASS torch.nn.ConvTranspose2d(*in_channels*, *out_channels*, *kernel_size*, *stride=1*, *padding=0*, *output_padding=0*, *groups=1*, *bias=True*, *dilation=1*, *padding_mode='zeros'*, *device=None*, *dtype=None*) [SOURCE]

Applies a 2D transposed convolution operator over an input image composed of several input planes.

This module can be seen as the gradient of Conv2d with respect to its input. It is also known as a fractionally-strided convolution or a deconvolution (although it is not an actual deconvolution operation as it does not compute a true inverse of convolution). For more information, see the visualizations here and the Deconvolutional Networks paper.

This module supports TensorFloat32.

Idea 3: Dilated Convolutions



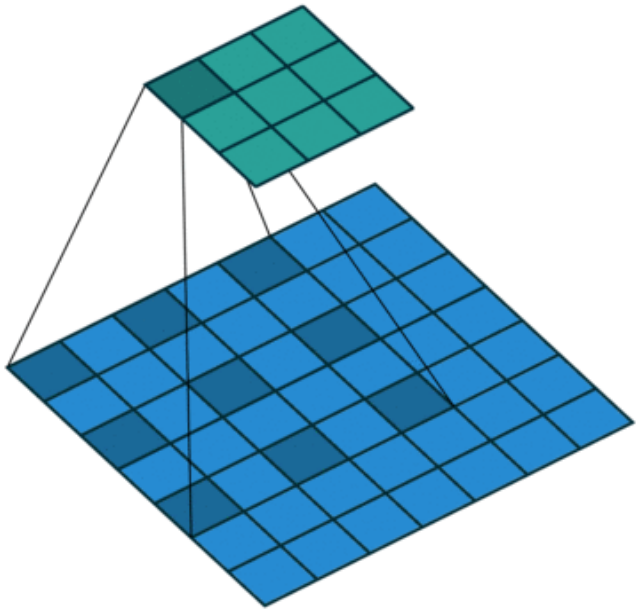
MULTI-SCALE CONTEXT AGGREGATION BY DILATED CONVOLUTIONS

Fisher Yu
Princeton University

Vladlen Koltun
Intel Labs

ICLR 2016

Idea 3: Dilated Convolutions



MULTI-SCALE CONTEXT AGGREGATION BY DILATED CONVOLUTIONS

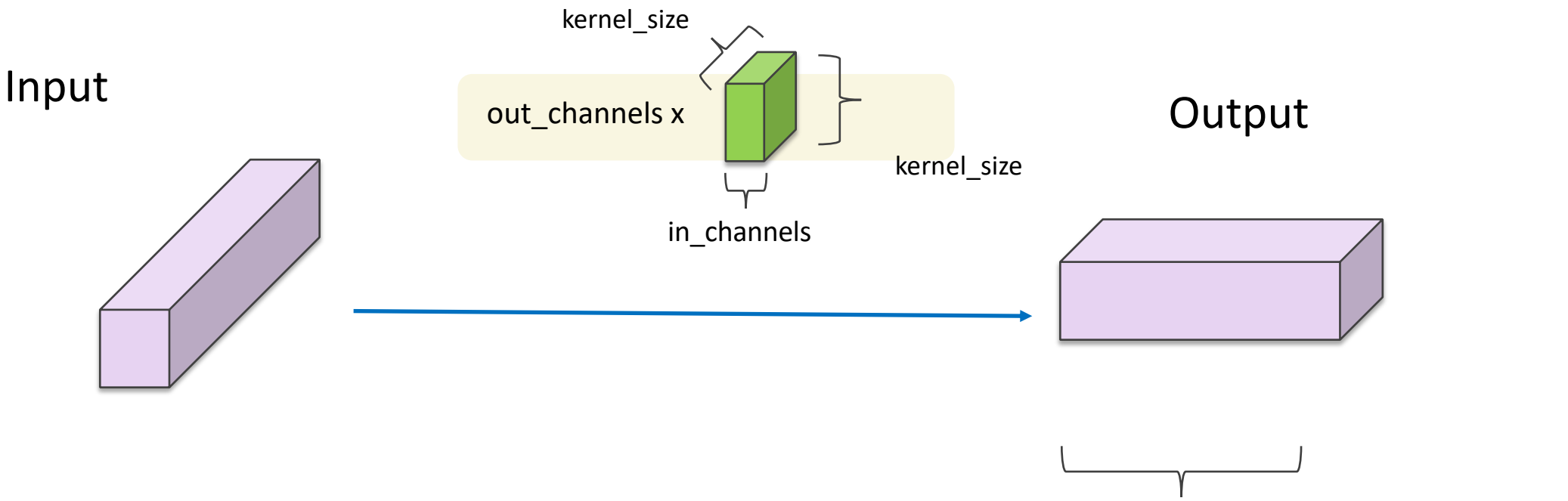
Fisher Yu
Princeton University

Vladlen Koltun
Intel Labs

ICLR 2016

Convolutional Layer in pytorch

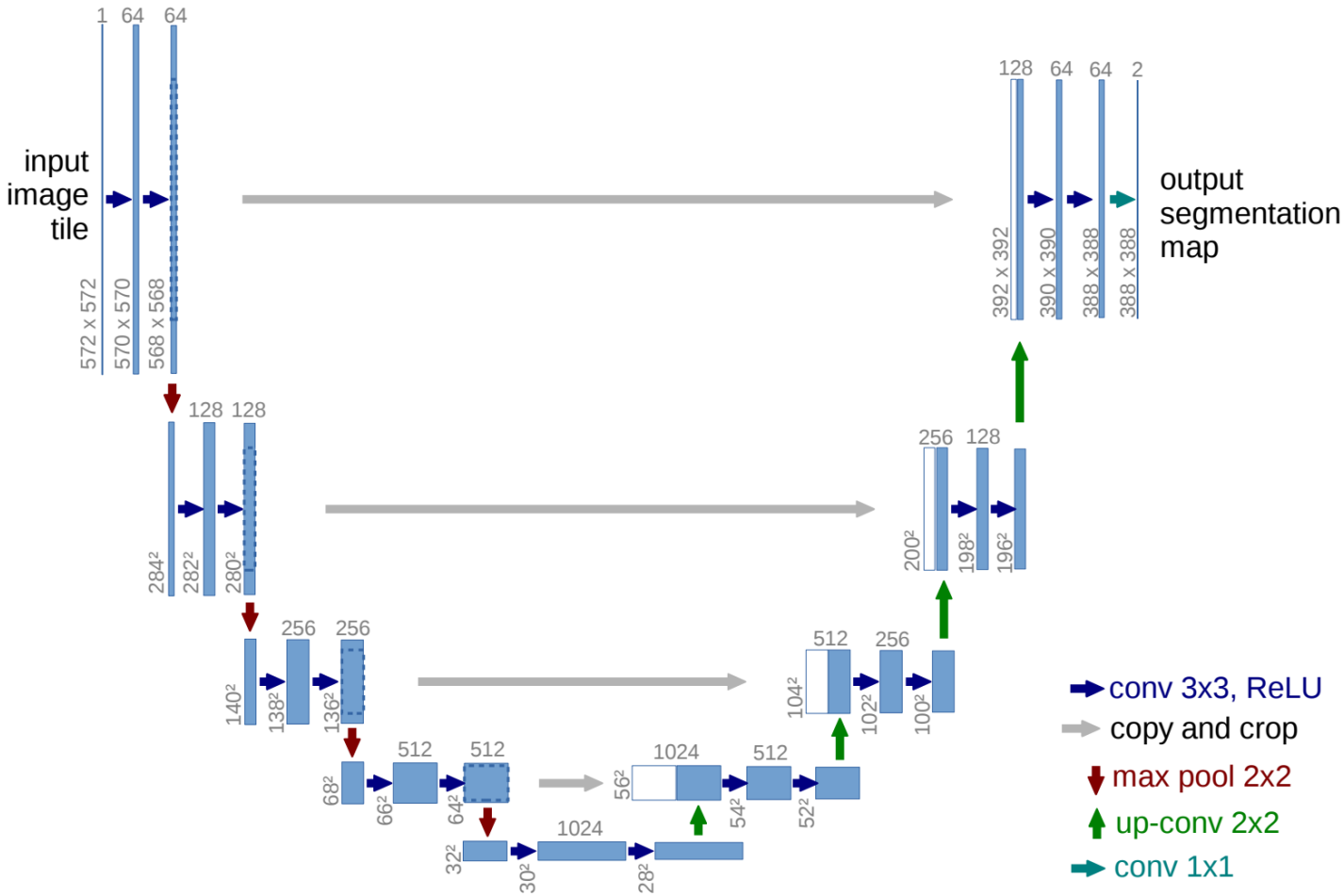
```
class torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1,
groups=1, bias=True)  [source]
```



U-Net: Convolutional Networks for Biomedical Image Segmentation

Olaf Ronneberger, Philipp Fischer, and Thomas Brox

Computer Science Department and BIOSS Centre for Biological Signalling Studies,
University of Freiburg, Germany



https://arxiv.org/abs/1505.04597

https://github.com/milesial/Pytorch-UNet

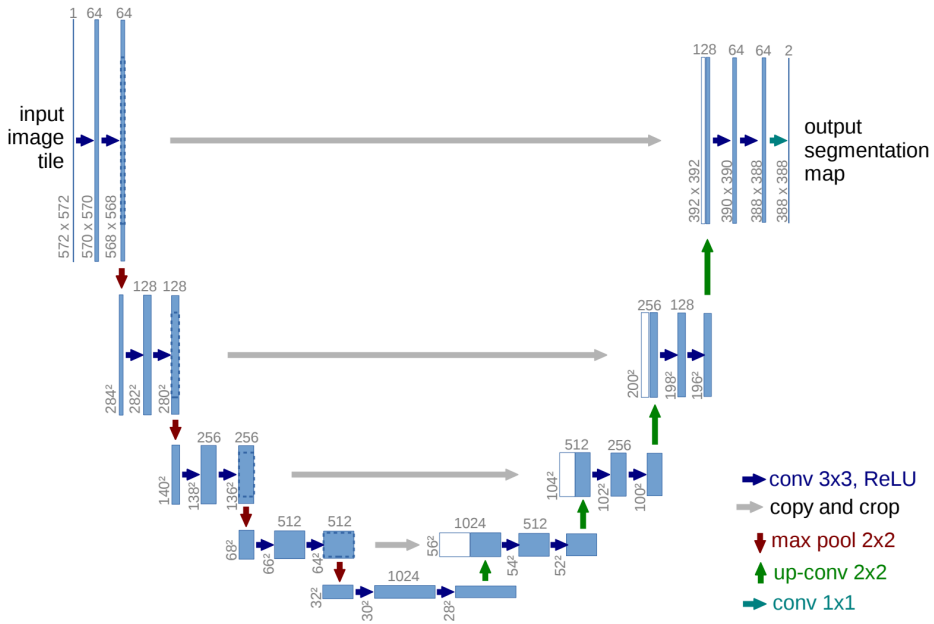
https://github.com/usuyama/pytorch-unet

UNet in Pytorch

```
from .unet_parts import *


class UNet(nn.Module):
    def __init__(self, n_channels, n_classes, bilinear=False):
        super(UNet, self).__init__()
        self.n_channels = n_channels
        self.n_classes = n_classes
        self.bilinear = bilinear

        self.inc = (DoubleConv(n_channels, 64))
        self.down1 = (Down(64, 128))
        self.down2 = (Down(128, 256))
        self.down3 = (Down(256, 512))
        factor = 2 if bilinear else 1
        self.down4 = (Down(512, 1024 // factor))
        self.up1 = (Up(1024, 512 // factor, bilinear))
        self.up2 = (Up(512, 256 // factor, bilinear))
        self.up3 = (Up(256, 128 // factor, bilinear))
        self.up4 = (Up(128, 64, bilinear))
        self.outc = (OutConv(64, n_classes))

    def forward(self, x):
        x1 = self.inc(x)
        x2 = self.down1(x1)
        x3 = self.down2(x2)
        x4 = self.down3(x3)
        x5 = self.down4(x4)
        x = self.up1(x5, x4)
        x = self.up2(x, x3)
        x = self.up3(x, x2)
        x = self.up4(x, x1)
        logits = self.outc(x)
        return logits
```

https://github.com/milesial/Pytorch-UNet/blob/master/unet/unet_model.py

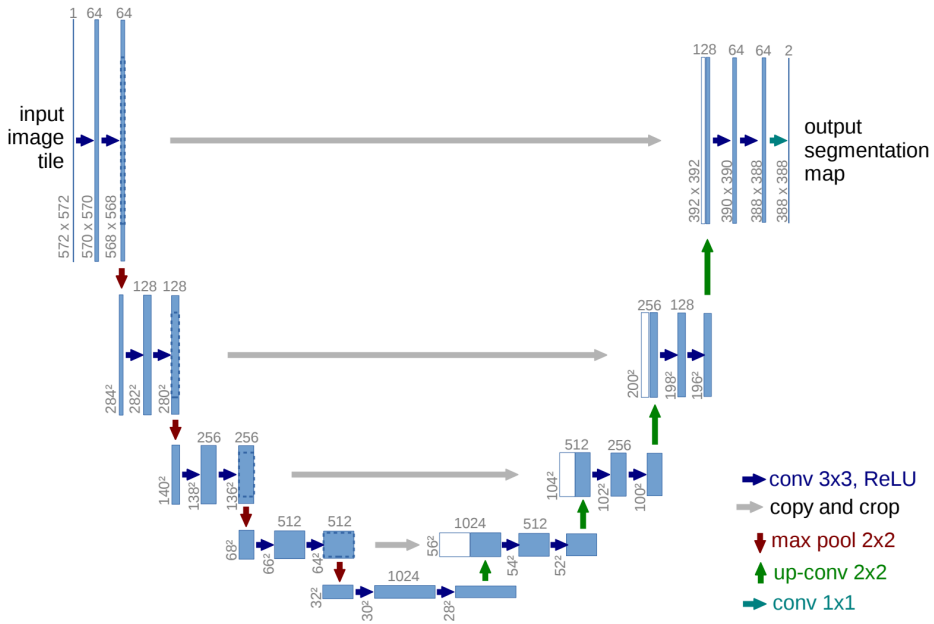
Chair segmentation - Training



Chair Segments: A Compact Benchmark for the Study of Object Segmentation

Leticia Pinto-Alva[‡†], Ian K. Torres[♮*], Rosangel Garcia[§*], Ziyan Yang[†], Vicente Ordonez[†]
[‡]Universidad Católica San Pablo, [♮]University of Massachusetts, Amherst, [§]Le Moyne College, [†]University of Virginia
lp2rv@virginia.edu, zy3cx@virginia.edu, vicente@virginia.edu

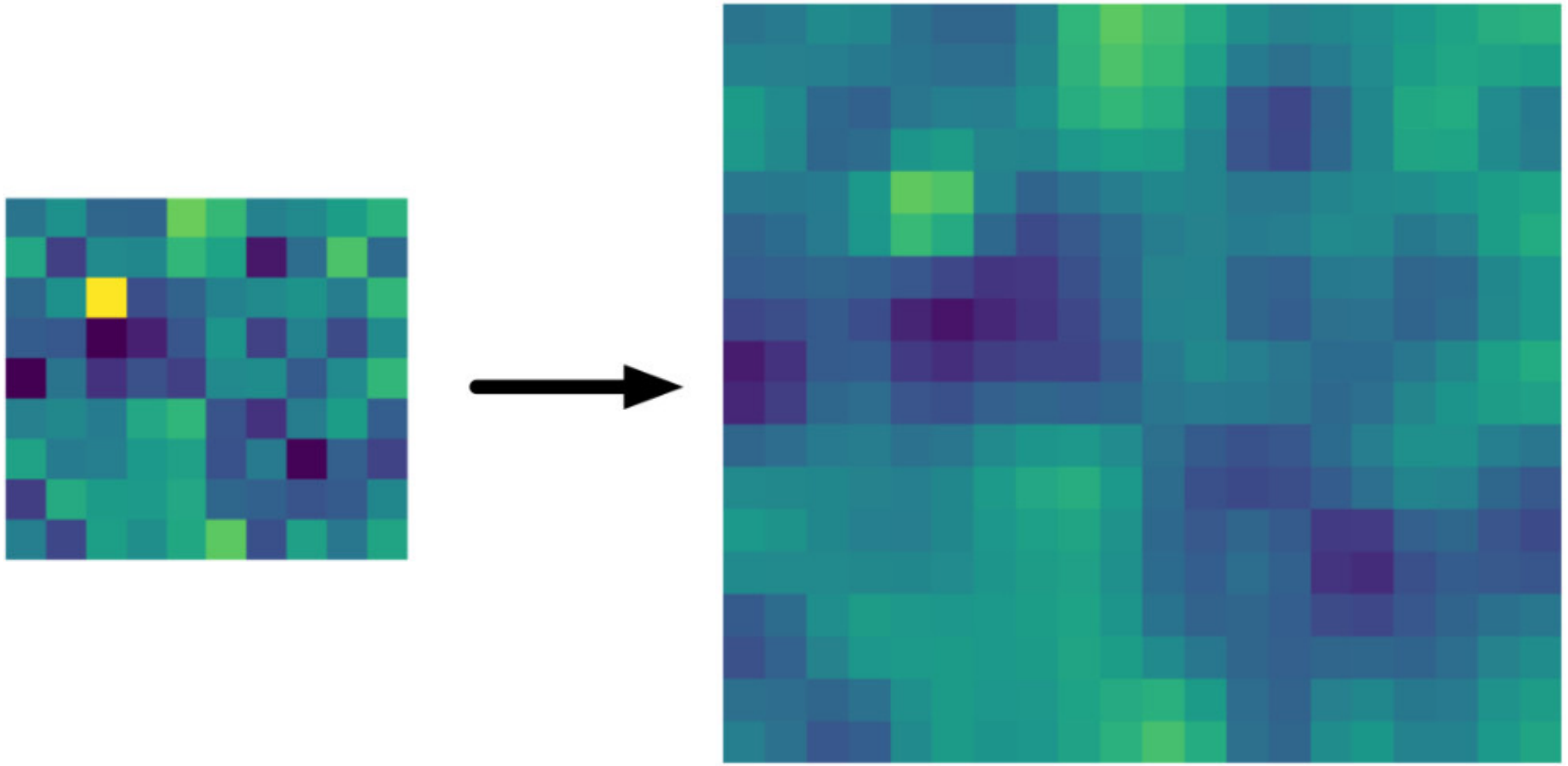
Chair segmentation - Prediction



Chair Segments: A Compact Benchmark for the Study of Object Segmentation

Leticia Pinto-Alva[‡†], Ian K. Torres[♮*], Rosangel Garcia[§*], Ziyan Yang[†], Vicente Ordonez[†]
[‡]Universidad Católica San Pablo, [♮]University of Massachusetts, Amherst, [§]Le Moyne College,
[†]University of Virginia
lp2rv@virginia.edu, zy3cx@virginia.edu, vicente@virginia.edu

Bilinear Upsampling Layer

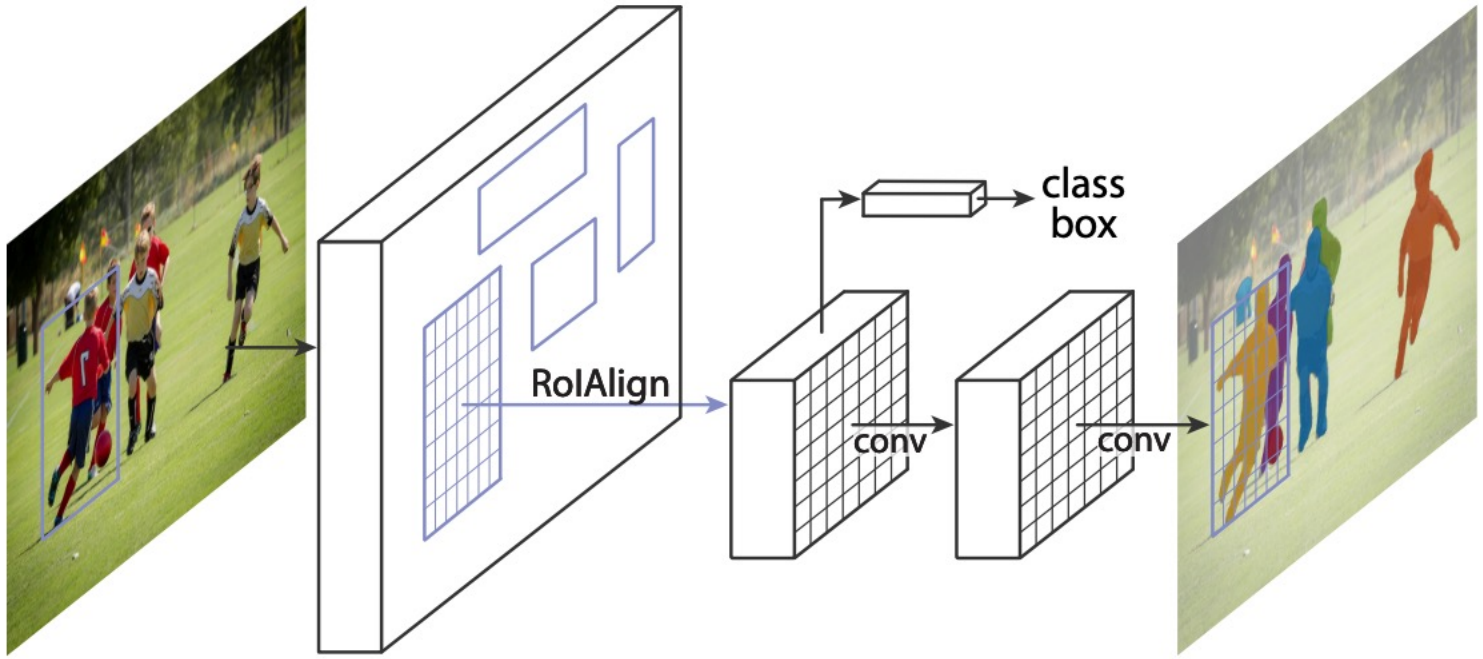


https://machinethink.net/blog/coreml-upsampling/

Mask R-CNN

Kaiming He Georgia Gkioxari Piotr Dollár Ross Girshick

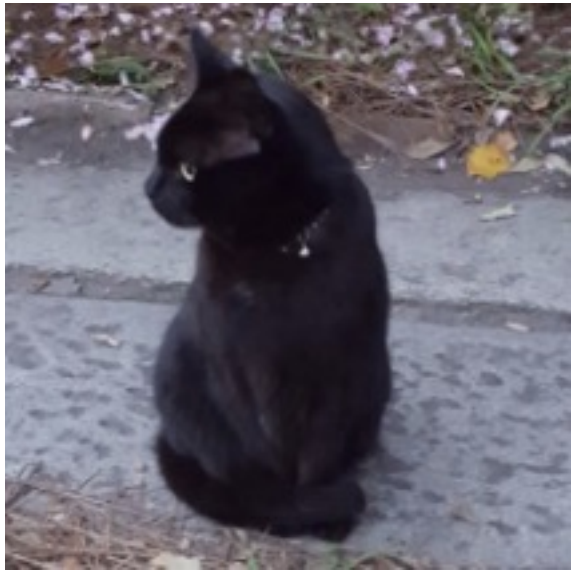
Facebook AI Research (FAIR)

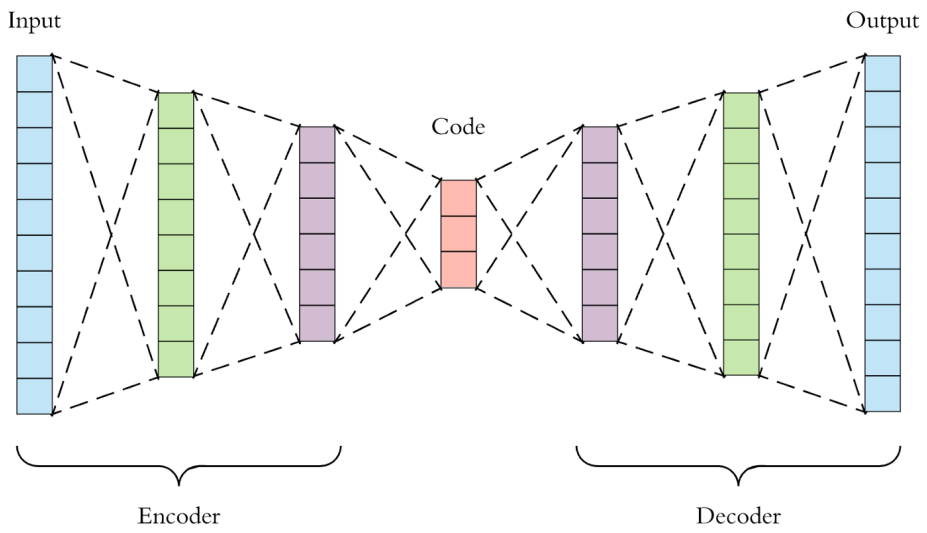


https://github.com/facebookresearch/detectron2

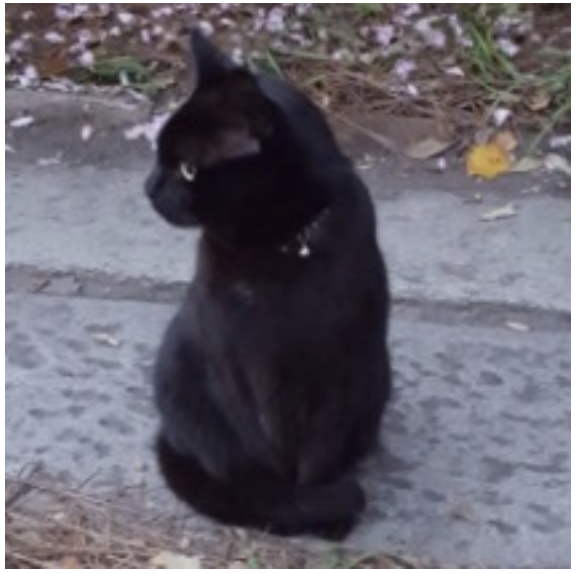
https://arxiv.org/abs/1703.06870

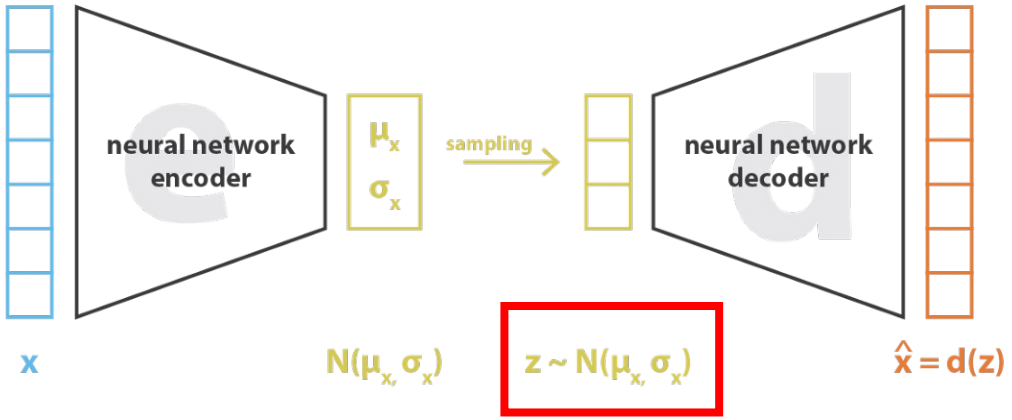
AutoEncoder Models (Downsample, Upsample)





Variational AutoEncoders (VAE)





$$\text{loss} = \|x - \hat{x}\|^2 + KL[\, N(\mu_x, \sigma_x), N(0, I)\,]$$

https://pytorch.org/docs/stable/generated/torch.normal.html

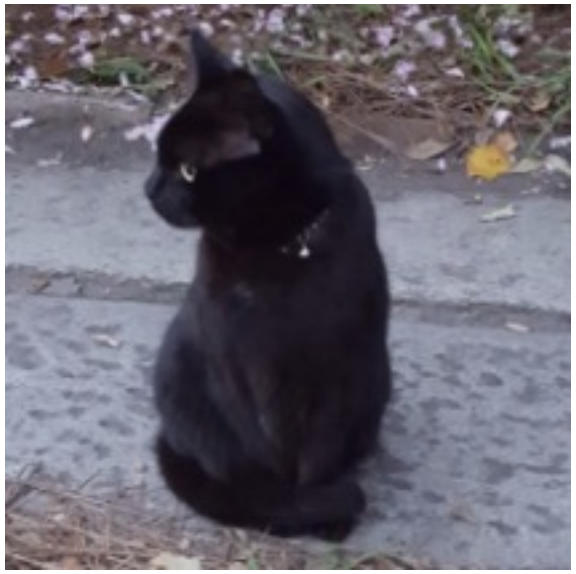
https://ai.stackexchange.com/questions/30176/are-mean-and-standard-deviation-in-variational-autoencoders-unique

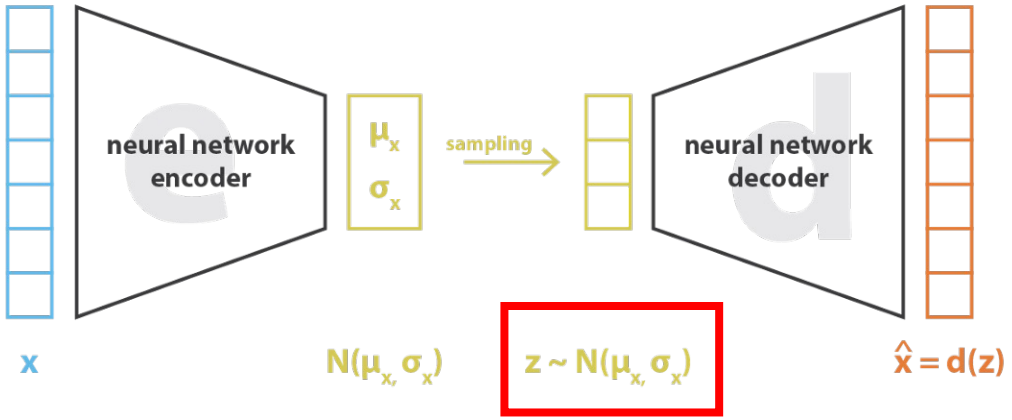
Reparameterization “trick”

$$z = z\_mean + sigma * epsilon$$

$$sigma = exp(z\_log\_var/2)$$

$$\varepsilon \sim Normal(0,1)$$





$$loss = \| x - \hat{x} \|^2 + KL[\, N(\mu_x, \sigma_x), N(0, I) \,]$$

https://pytorch.org/docs/stable/generated/torch.normal.html

https://ai.stackexchange.com/questions/30176/are-mean-and-standard-deviation-in-variational-autoencoders-unique

Kullback-Leibler Divergence

$$D_{\mathrm{KL}}(P \parallel Q) = \sum_{x \in \mathcal{X}} P(x) \log\left(\frac{P(x)}{Q(x)}\right)$$

KLDIVLOSS

KLDivLoss

KLDivLoss

CLASS torch.nn.KLDivLoss(*size_average=None*, *reduce=None*, *reduction='mean'*, *log_target=False*) [SOURCE]

The Kullback-Leibler divergence loss.

For tensors of the same shape y_{pred}, y_{true}, where y_{pred} is the `input` and y_{true} is the `target`, we define the **pointwise KL-divergence** as

$$L(y_{\text{pred}},\ y_{\text{true}}) = y_{\text{true}} \cdot \log \frac{y_{\text{true}}}{y_{\text{pred}}} = y_{\text{true}} \cdot (\log y_{\text{true}} - \log y_{\text{pred}})$$

To avoid underflow issues when computing this quantity, this loss expects the argument `input` in the log-space. The argument `target` may also be provided in the log-space if `log_target` = *True*.

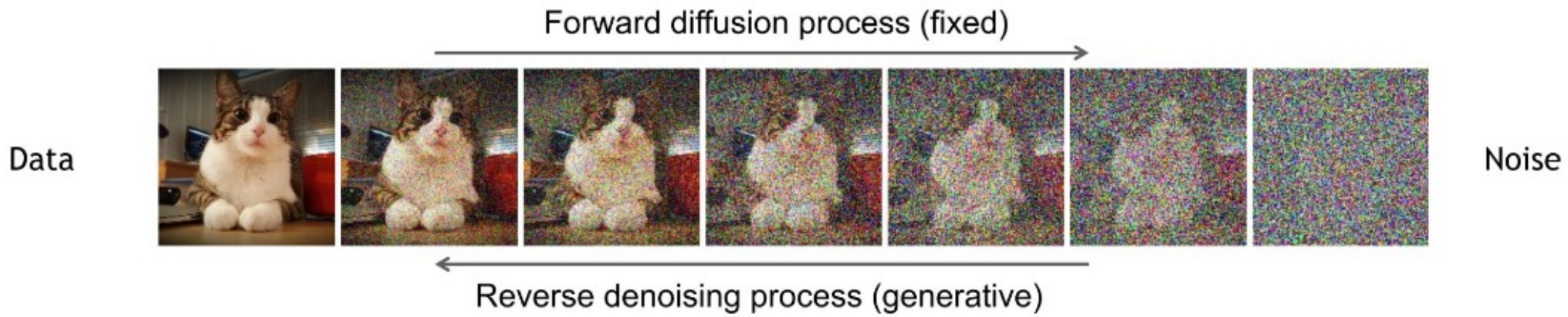
To summarise, this function is roughly equivalent to computing

```
if not log_target: # default
    loss_pointwise = target * (target.log() - input)
else:
    loss_pointwise = target.exp() * (target - input)
```

Denoising Diffusion Probabilistic Models (DDPM)

Forward diffusion: Markov chain of diffusion steps to slowly add gaussian noise to data

Reverse diffusion: A model is trained to generate data from noise by iterative denoising



Denoising Diffusion Probabilistic Models

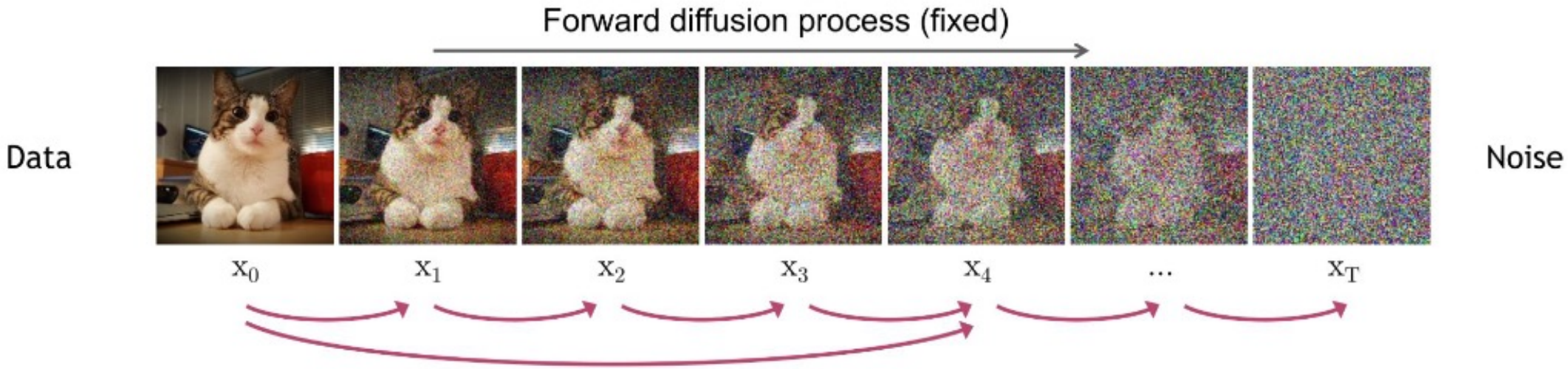
Jonathan Ho
UC Berkeley
jonathanho@berkeley.edu

Ajay Jain
UC Berkeley
ajayj@berkeley.edu

Pieter Abbeel
UC Berkeley
pabbeel@cs.berkeley.edu

https://cvpr2022-tutorial-diffusion-models.github.io/
Slides compiled by my student Aman Shrivastava

DDPM | Forward diffusion



We add a small amount of gaussian noise to a sample $\mathbf{x}_0$ in $\mathbf{T}$ timesteps to produces noised samples, $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T\}$. The steps are controlled by the noise schedule as follows:

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I}) \quad q(\mathbf{x}_{1:T}|\mathbf{x}_0) = \prod_{t=1}^{T} q(\mathbf{x}_t|\mathbf{x}_{t-1})$$

https://cvpr2022-tutorial-diffusion-models.github.io/

Forward diffusion process (fixed)

Data

Noise

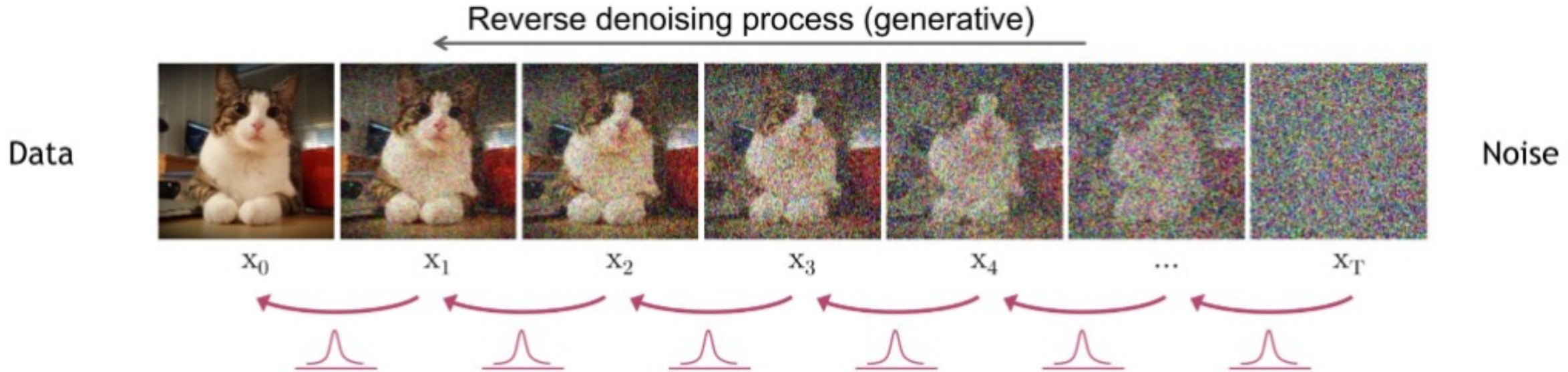
x_0 x_1 x_2 x_3 x_4 ... x_T

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I}) \quad q(\mathbf{x}_{1:T}|\mathbf{x}_0) = \prod_{t=1}^{T} q(\mathbf{x}_t|\mathbf{x}_{t-1})$$

Define $\bar{\alpha}_t = \prod_{s=1}^{t}(1-\beta_s)$ ➡ $q(\mathbf{x}_t|\mathbf{x}_0) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t}\mathbf{x}_0, (1-\bar{\alpha}_t)\mathbf{I}))$ (Diffusion Kernel)

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

DDPM | Reverse Diffusion

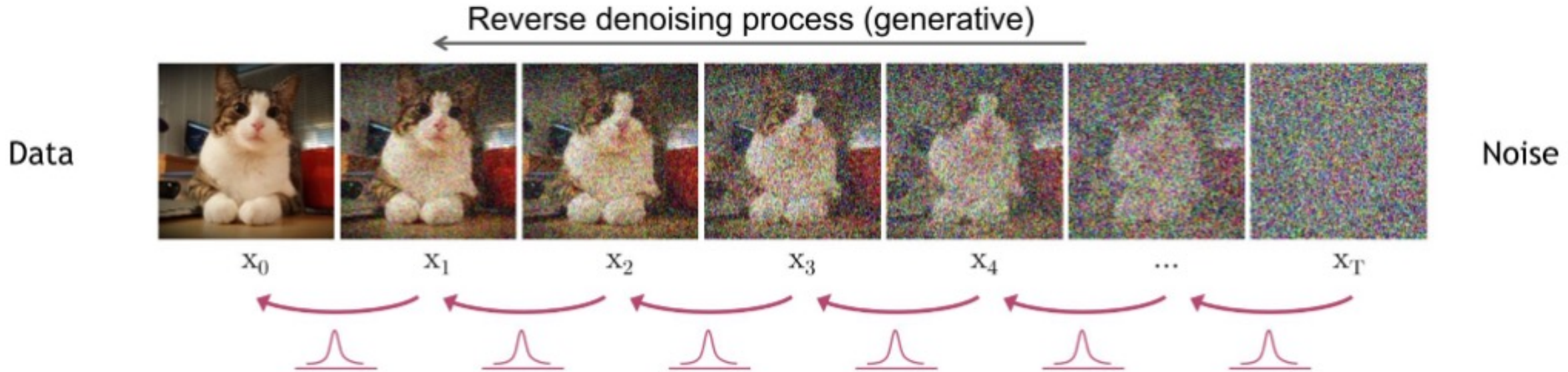


We learn a neural network model **(p_θ)** to approximate these conditional probabilities **$q(x_{(t-1)} \mid x_t)$** in order to run the reverse diffusion process as follows:

$$p_\theta(\mathbf{x}_{0:T}) = p(\mathbf{x}_T) \prod_{t=1}^{T} p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) \quad p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$$

https://cvpr2022-tutorial-diffusion-models.github.io/

DDPM | Reverse Diffusion

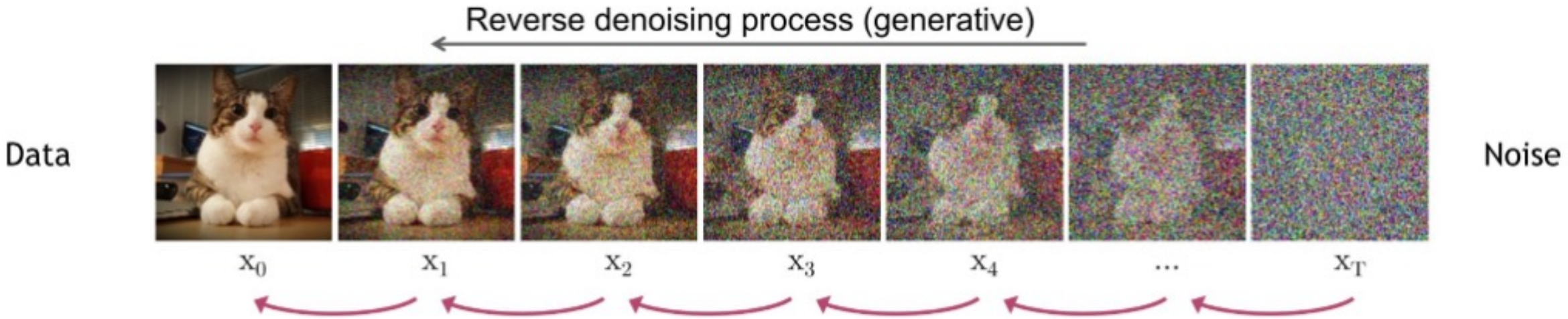


We learn a neural network model **(p_θ)** to approximate these conditional probabilities **$q(x_{(t-1)} \mid x_t)$** in order to run the reverse diffusion process as follows:

$$p_\theta(\mathbf{x}_{0:T}) = p(\mathbf{x}_T) \prod_{t=1}^{T} p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) \quad p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$$

https://cvpr2022-tutorial-diffusion-models.github.io/

How do we train?



Algorithm 1 Training

1: **repeat**
2: $\mathbf{x}_0 \sim q(\mathbf{x}_0)$
3: $t \sim \text{Uniform}(\{1, \dots, T\})$
4: $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
5: Take gradient descent step on

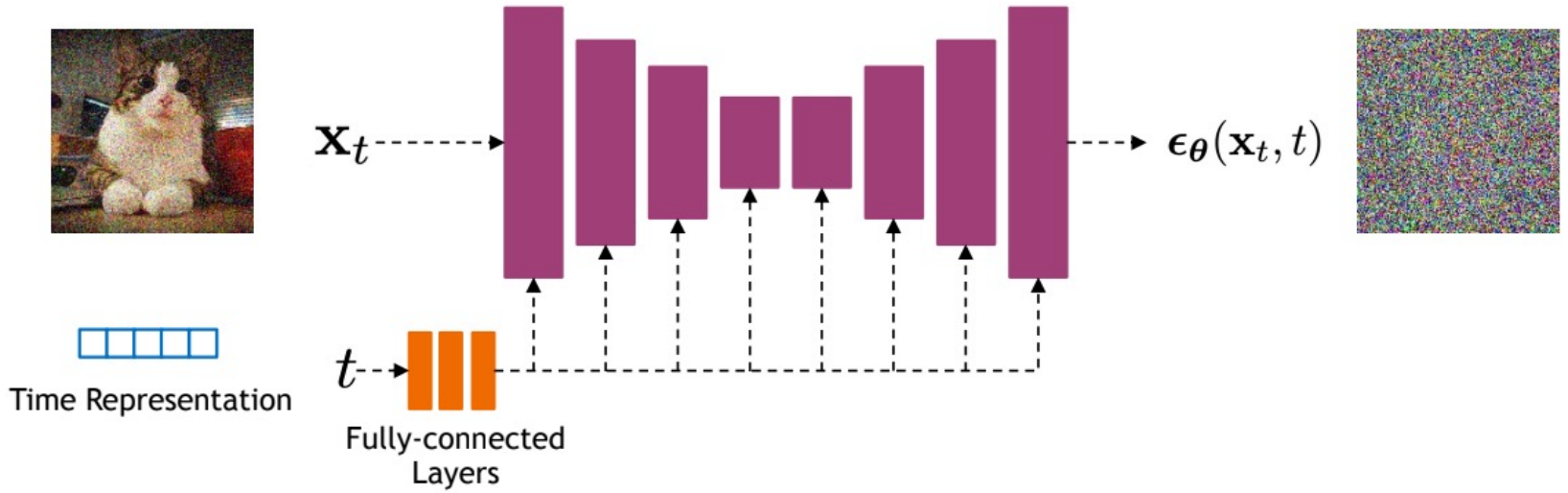
$$\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t) \right\|^2$$

6: **until** converged

https://cvpr2022-tutorial-diffusion-models.github.io/

Unet to model transition

Diffusion models often use U-Net architectures with ResNet blocks and self-attention layers to represent $\epsilon_\theta(\mathbf{x}_t, t)$

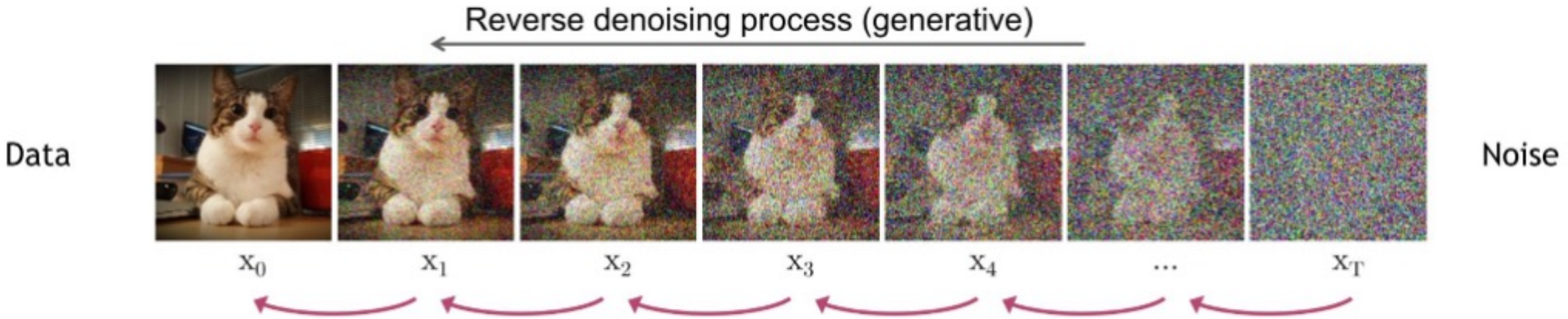


Time representation: sinusoidal positional embeddings or random Fourier features.

Time features are fed to the residual blocks using either simple spatial addition or using adaptive group normalization layers. (see Dharivwal and Nichol NeurIPS 2021)

https://cvpr2022-tutorial-diffusion-models.github.io/

How do we train?

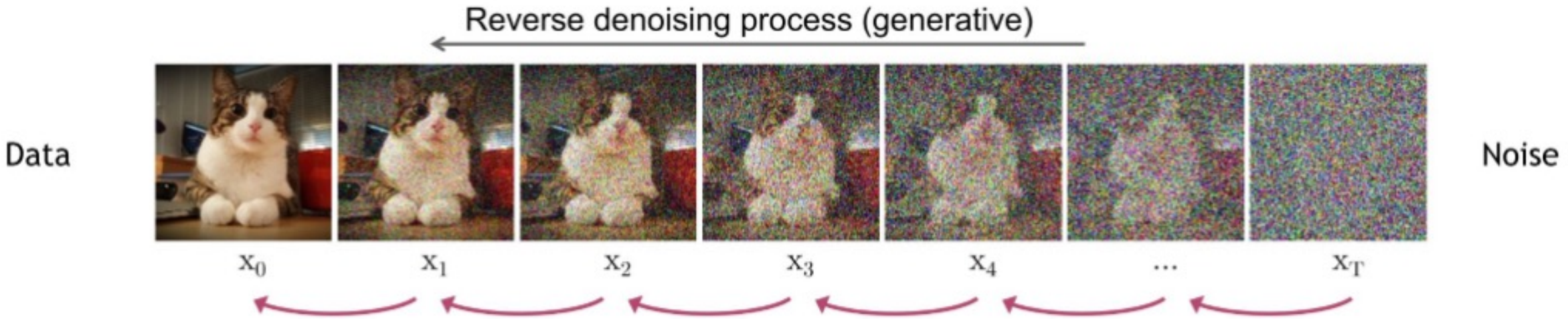


Algorithm 2 Sampling

1: $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
2: **for** $t = T, \ldots, 1$ **do**
3: $\quad \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ if $t > 1$, else $\mathbf{z} = \mathbf{0}$
4: $\quad \mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$
5: **end for**
6: **return** $\mathbf{x}_0$

https://cvpr2022-tutorial-diffusion-models.github.io/

How do we train?



Algorithm 1 Training

1: **repeat**
2: $\mathbf{x}_0 \sim q(\mathbf{x}_0)$
3: $t \sim \text{Uniform}(\{1, \dots, T\})$
4: $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
5: Take gradient descent step on
$$\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t) \right\|^2$$
6: **until** converged

Algorithm 2 Sampling

1: $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
2: **for** $t = T, \dots, 1$ **do**
3: $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ if $t > 1$, else $\mathbf{z} = \mathbf{0}$
4: $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$
5: **end for**
6: **return** $\mathbf{x}_0$

https://cvpr2022-tutorial-diffusion-models.github.io/

Imagen by Google

A cute corgi lives in a house made out of sushi.

A cute sloth holding a small treasure chest. A bright golden glow is coming from the chest.

Imagen by Google

2.2 Diffusion models and classifier-free guidance

Here we give a brief introduction to diffusion models; a precise description is in Appendix A. Diffusion models [63, 28, 65] are a class of generative models that convert Gaussian noise into samples from a learned data distribution via an iterative denoising process. These models can be conditional, for example on class labels, text, or low-resolution images [e.g. 16, 29, 59, 58, 75, 41, 54]. A diffusion model $\hat{\mathbf{x}}_\theta$ is trained on a denoising objective of the form

$$\mathbb{E}_{\mathbf{x},\mathbf{c},\boldsymbol{\epsilon},t}\left[w_t \|\hat{\mathbf{x}}_\theta(\alpha_t \mathbf{x} + \sigma_t \boldsymbol{\epsilon}, \mathbf{c}) - \mathbf{x}\|_2^2\right] \tag{1}$$

where $(\mathbf{x}, \mathbf{c})$ are data-conditioning pairs, $t \sim \mathcal{U}([0,1])$, $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, and α_t, σ_t, w_t are functions of t that influence sample quality. Intuitively, $\hat{\mathbf{x}}_\theta$ is trained to denoise $\mathbf{z}_t := \alpha_t \mathbf{x} + \sigma_t \boldsymbol{\epsilon}$ into $\mathbf{x}$ using a squared error loss, weighted to emphasize certain values of t. Sampling such as the ancestral sampler [28] and DDIM [64] start from pure noise $\mathbf{z}_1 \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ and iteratively generate points $\mathbf{z}_{t_1}, \ldots, \mathbf{z}_{t_T}$, where $1 = t_1 > \cdots > t_T = 0$, that gradually decrease in noise content. These points are functions of the $\mathbf{x}$-predictions $\hat{\mathbf{x}}_0^t := \hat{\mathbf{x}}_\theta(\mathbf{z}_t, \mathbf{c})$.

https://arxiv.org/pdf/2205.11487.pdf

Questions