Building Blocks

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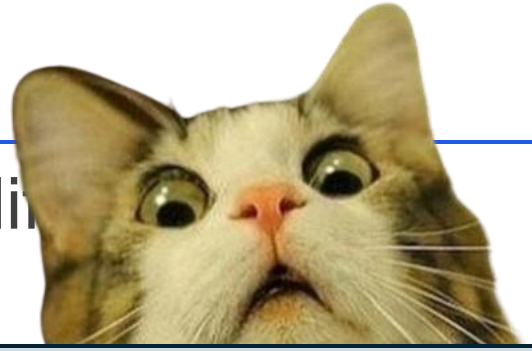
Building Blocks

Here is the algorithm for di



Algorithm 1 Training

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

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

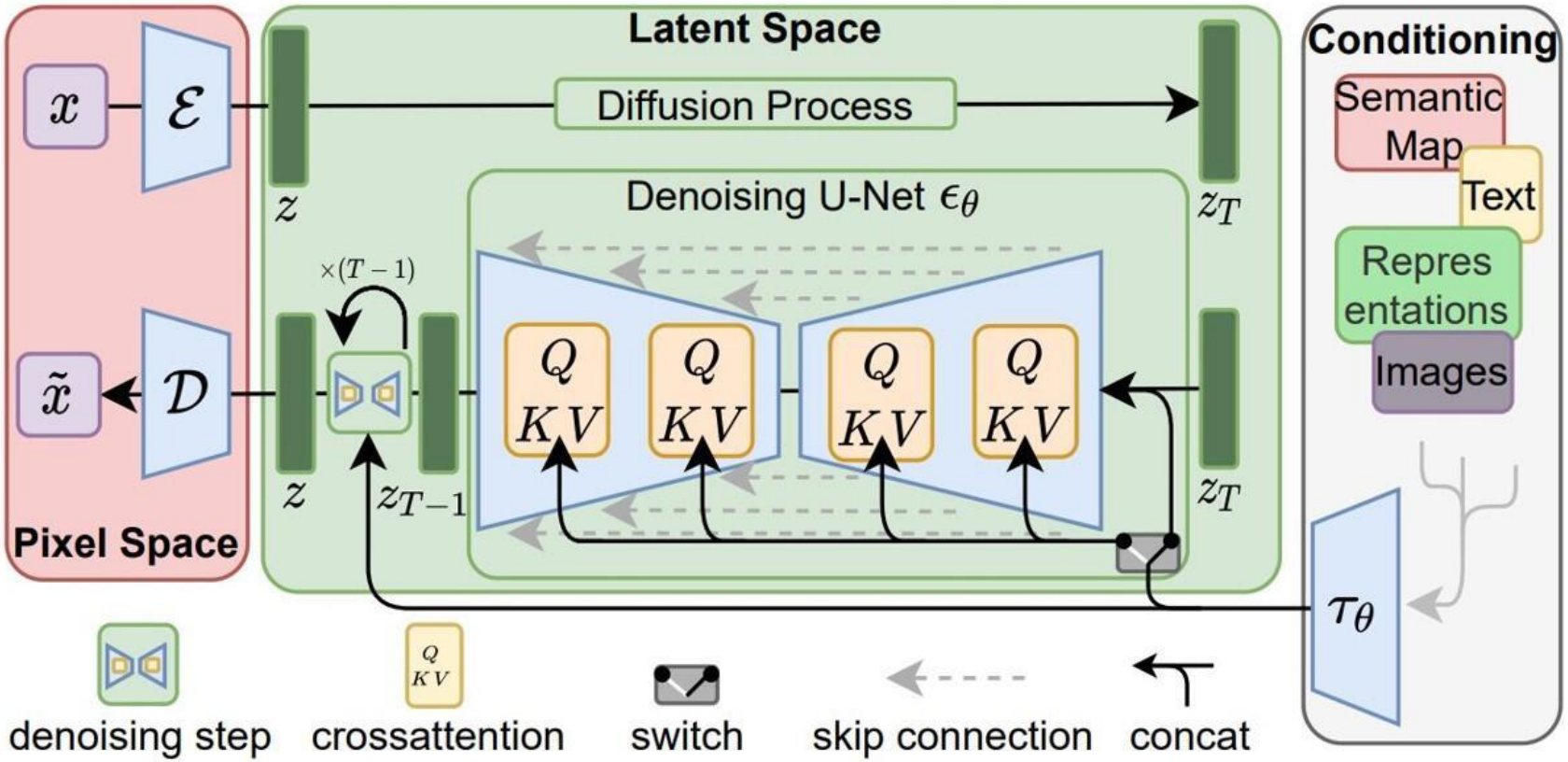
until converged

Algorithm 2 Sampling

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

Building Blocks

Perhaps this makes more sense…



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Building Blocks

Aims of this section:

- By the end of the session we want to be able to understand the architecture.
- We start with the architecture:
  - Variational Autoencoders
  - UNet
  - CLIP
- And some common operations in deep learning:
  - Convolution
  - Normalization
  - Pooling
  - Residual connections
  - Upsampling

Variational Autoencoders

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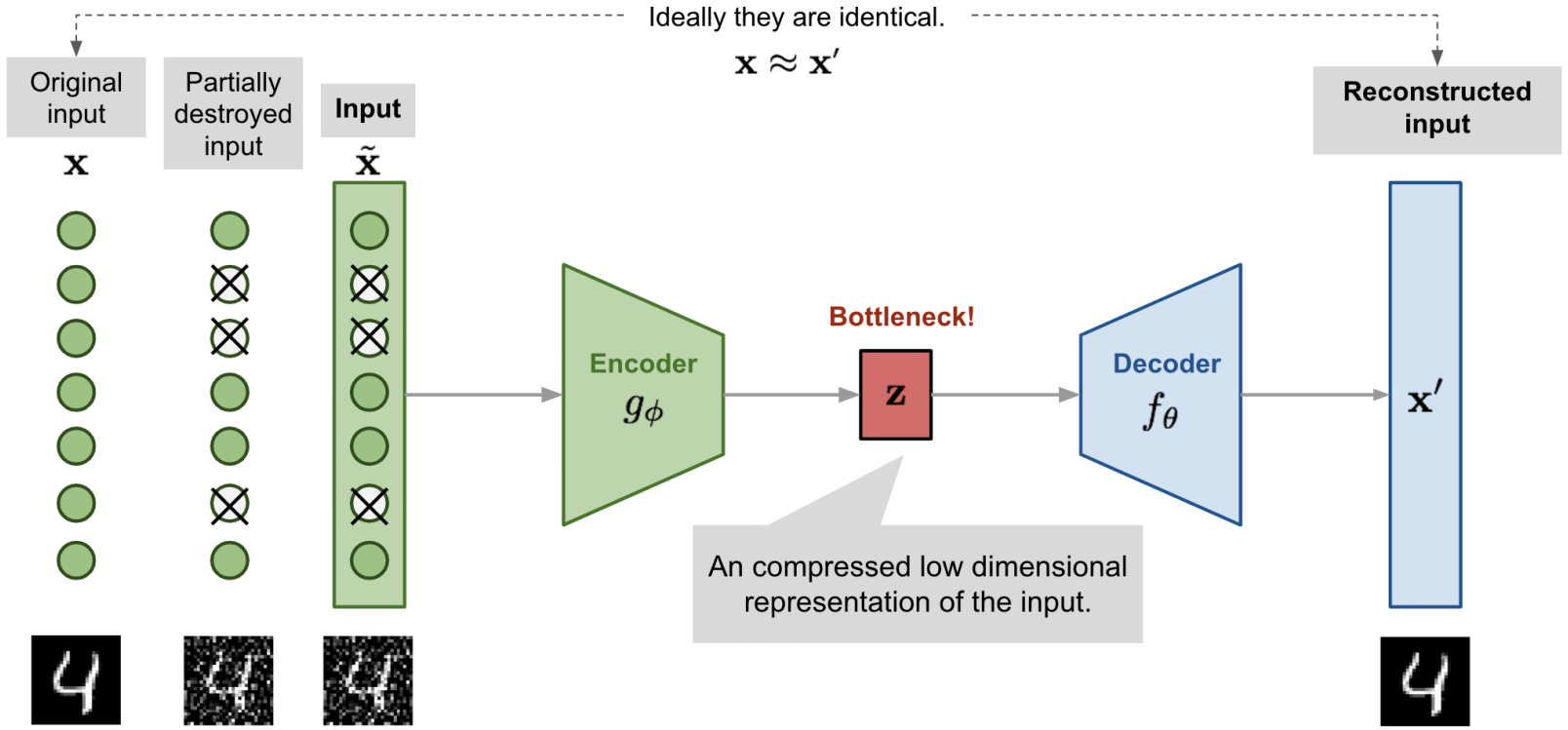
VAEs

A simple example…

- Suppose you want to create a neural network that denoises images.
- One way of doing this is by using an autoencoder…



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VAEs

But there are some issues with using this kind of autoencoder…

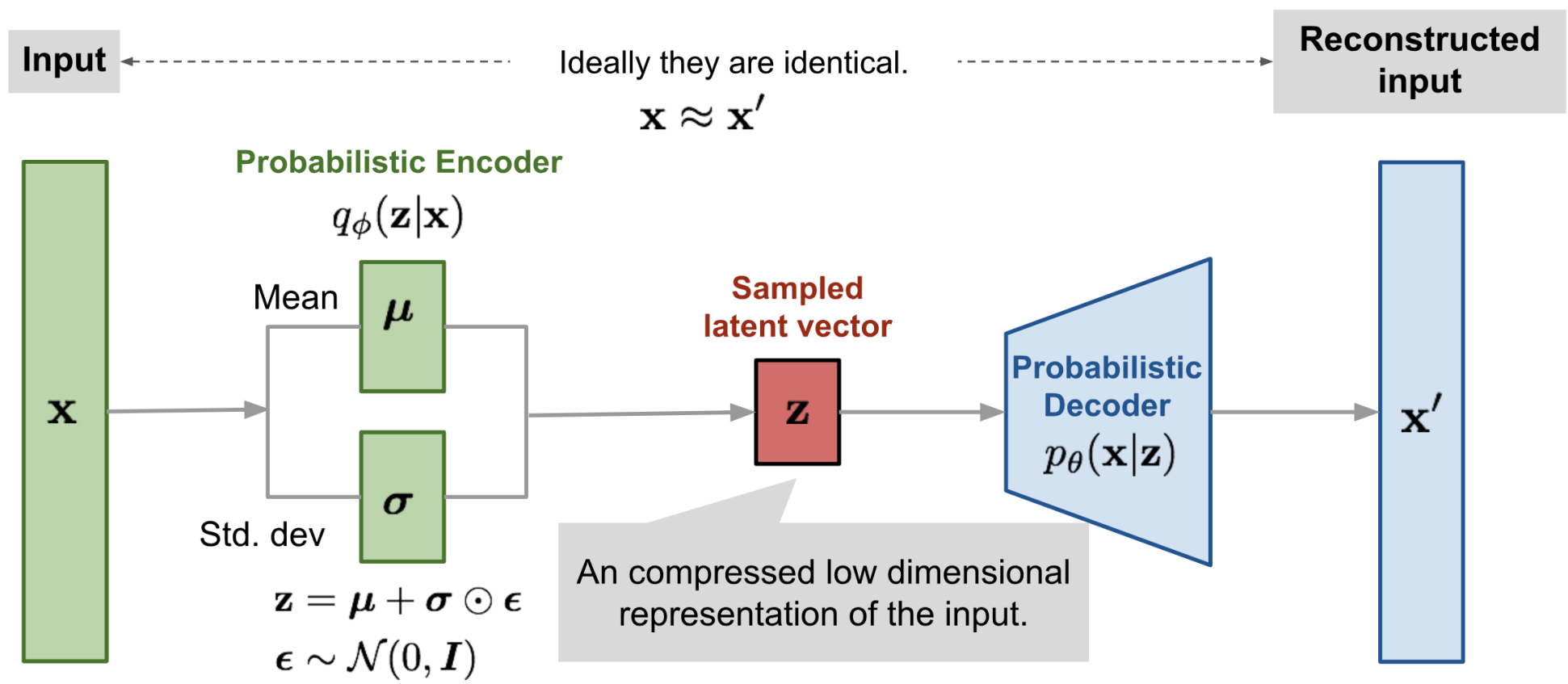
- Gaps between latent points, where the model doesn't really know what is supposed to be there
- It is deterministic – the encoder will map input data to a single point in latent space and then decode it back to the original space.
- This mapping limits the ability to generate samples
- They are not really trying to model the underlying data distribution

VAEs

Instead of trying to build a latent space encoding, why not try and model a distribution…

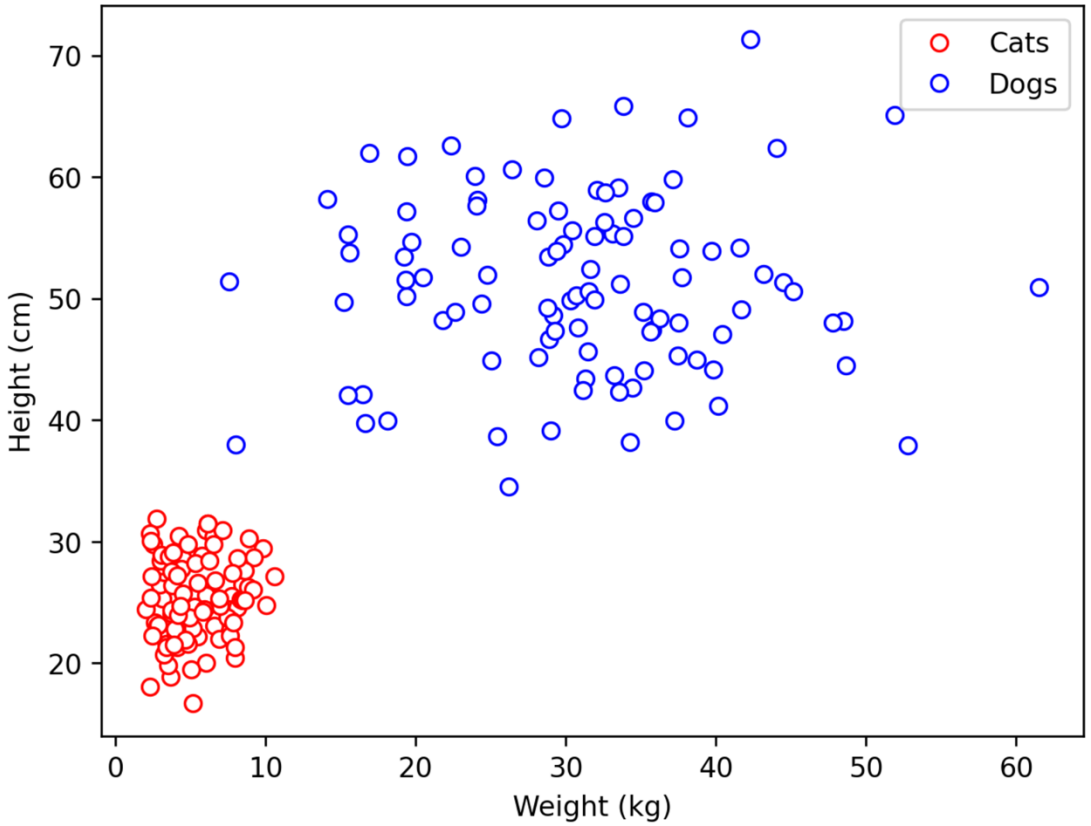
- We should try and map the input space to a latent *distribution* rather than a single point in space
- We should therefore have a continuous and dense latent space
- This will enable smooth interpolation between points
- We impose restrictions on the latent space to force it to map the input data to the distribution that we want.
- This distribution is the normal distribution. This is because we can draw from it easily, and computing gradients is also easy.

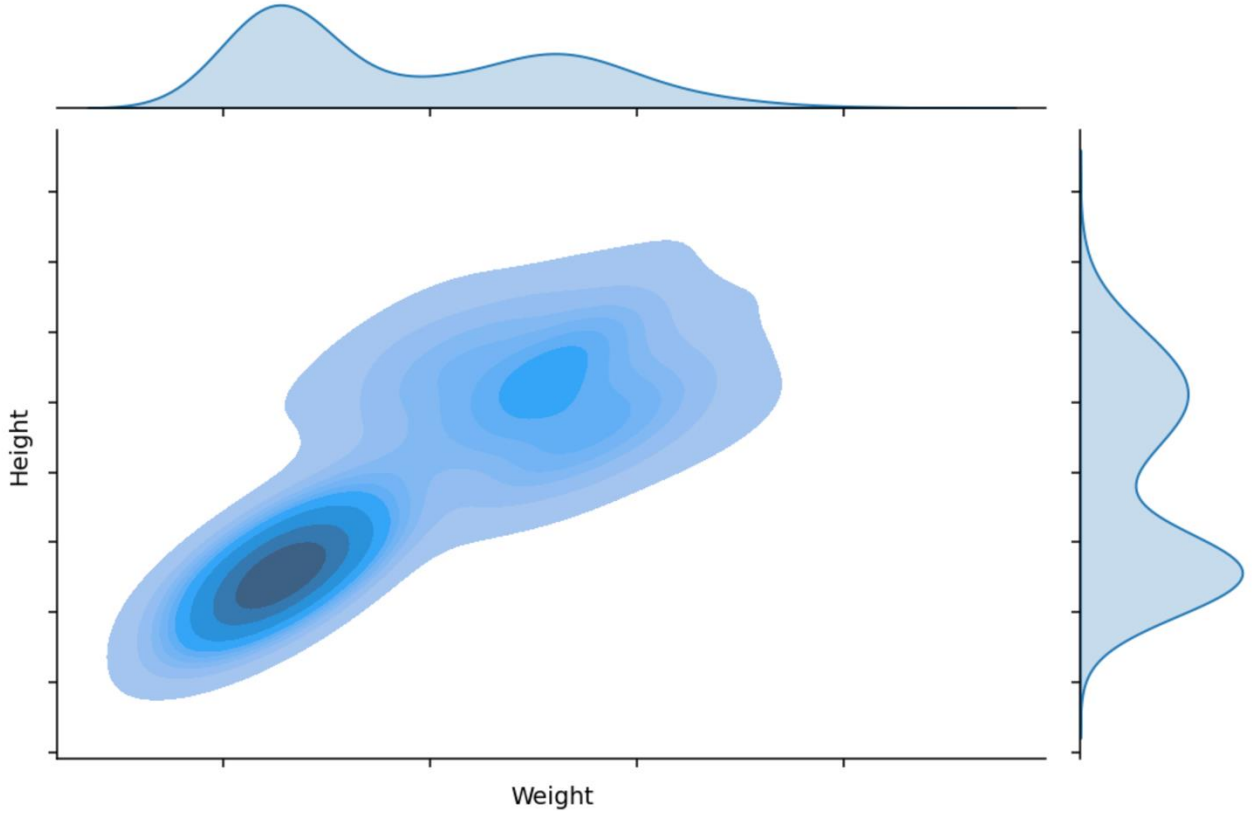
VAEs


Input
Ideally they are identical.
$\mathbf{x} \approx \mathbf{x}'$
Reconstructed input
Probabilistic Encoder
$q_\phi(\mathbf{z}|\mathbf{x})$
Mean
μ
σ
Std. dev
$\mathbf{x}$
$\mathbf{z} = \mu + \sigma \odot \epsilon$
$\epsilon \sim \mathcal{N}(0, I)$
Sampled latent vector
$\mathbf{z}$
An compressed low dimensional representation of the input.
Probabilistic Decoder
$p_\theta(\mathbf{x}|\mathbf{z})$
$\mathbf{x}'$

VAEs

Back to cats and dogs…





VAEs

Latent variables

- Latent variables represent the underlying factors that generate our observed data x (height and weight).
- The latent variable z can represent whether the animal is a cat or dog – the data example has small height and weight **because** it is a cat, and vice versa
- In a VAE, we assume that these latent variables follow a standard Gaussian:

$$p_\theta(z) = \mathcal{N}(0, I)$$

- We initially do not distinguish between cats and dogs, and assume that all latent variables are drawn from the same distribution.
- This distribution is the **prior** – it is an assumption we make about how the values in our latent variables are distributed.

VAEs

Decoder

- The decoder says given some latent z, what should my height and weight (i.e. x) be. This is given by:

$$p_\theta(x|z)$$

- If z is a cat, then the decoder will give measurements that (hopefully) fall within the cat cluster.
- In other words:

  "Given that z is a cat, generate a height and weight that fits within the cat Gaussian cluster."
- This is the **Likelihood**.

VAEs

Posterior

- The true posterior $p_\theta(z|x)$ gives the probability of the example being a cat (or dog), given the height and weight that you have shown me.
- To calculate this value, we can use Bayes' Theorem:

$$p_\theta(z|x) = \frac{p_\theta(x|z)p_\theta(z)}{p_\theta(x)}$$ Problem!

- This bottom term asks: what's the probability of this particular height and weight…but this is a problem:

$$p_\theta(x) = \int p_\theta(x|z)p_\theta(z)\,dz$$ We cannot solve this!

VAEs

So what do we do?

- We approximate it.
- Use a neural network to find $q_\phi(z|x) \approx p_\theta(z|x)$
- But remember, we want to force the latent space distribution to be as close as possible to Normal. In other words we want to learn:

$$q_\phi(z|x) \sim \mathcal{N}(E_\phi, \sigma_\phi(x)^2 I)$$

- Now we want to do 2 things:
  - Enforce the latent space to take on the same structure as our prior distribution
  - Ensure that the output of the decoder is as close as possible to the original input.
- But we also wanted to force this **learned** distribution to be as close to the **true** distribution as possible.

$$L = -\mathbb{E}_{q(Z|X)}[\log p_\theta(x|z)] + \beta D_{KL}\big(q_\phi(z|x) \| p_\theta(z)\big)$$

U-Net

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U-Net

U-Net is a classic neural network architecture

- U-Net was originally developed for biomedical image segmentation.
- The original paper *U-Net: Convolutional Networks for Biomedical Image Segmentation* was presented at MICCAI in 2015, and now has nearly 85k citations!

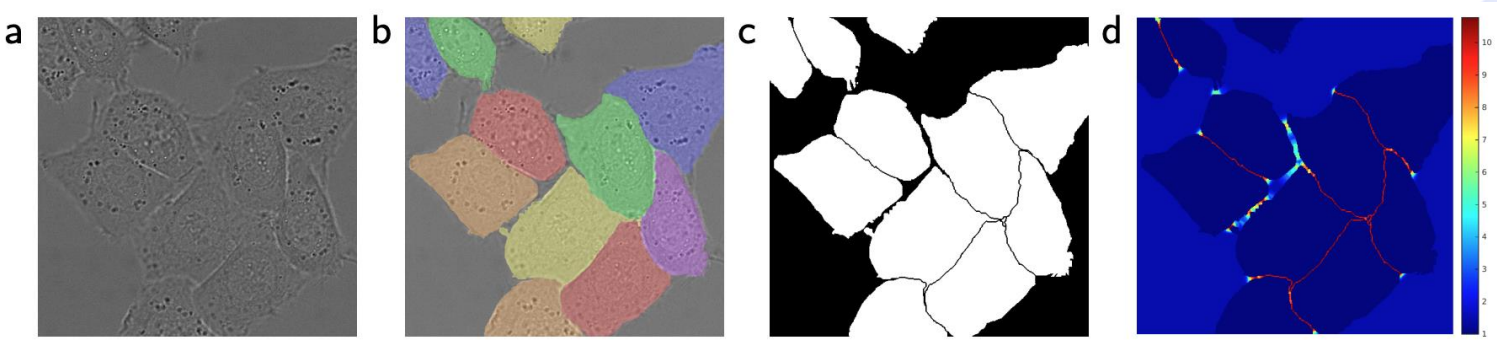

Fig. 3. HeLa cells on glass recorded with DIC (differential interference contrast) microscopy. (**a**) raw image. (**b**) overlay with ground truth segmentation. Different colors indicate different instances of the HeLa cells. (**c**) generated segmentation mask (white: foreground, black: background). (**d**) map with a pixel-wise loss weight to force the network to learn the border pixels.

U-Net

U-Net was originally designed for semantic segmentation

- The input data consists of the original image
- For the label data, each corresponding pixel is given a label.

0.54	0.64	0.36	0.58	0.48
0.90	0.89	0.91	0.87	0.89
0.91	0.90	0.85	0.89	0.90
0.46	0.48	0.59	0.56	0.47
0.54	0.64	0.36	0.58	0.48

grass	grass	grass	grass	grass
road	road	road	road	road
road	road	road	road	road
grass	grass	grass	grass	grass
grass	grass	grass	grass	grass

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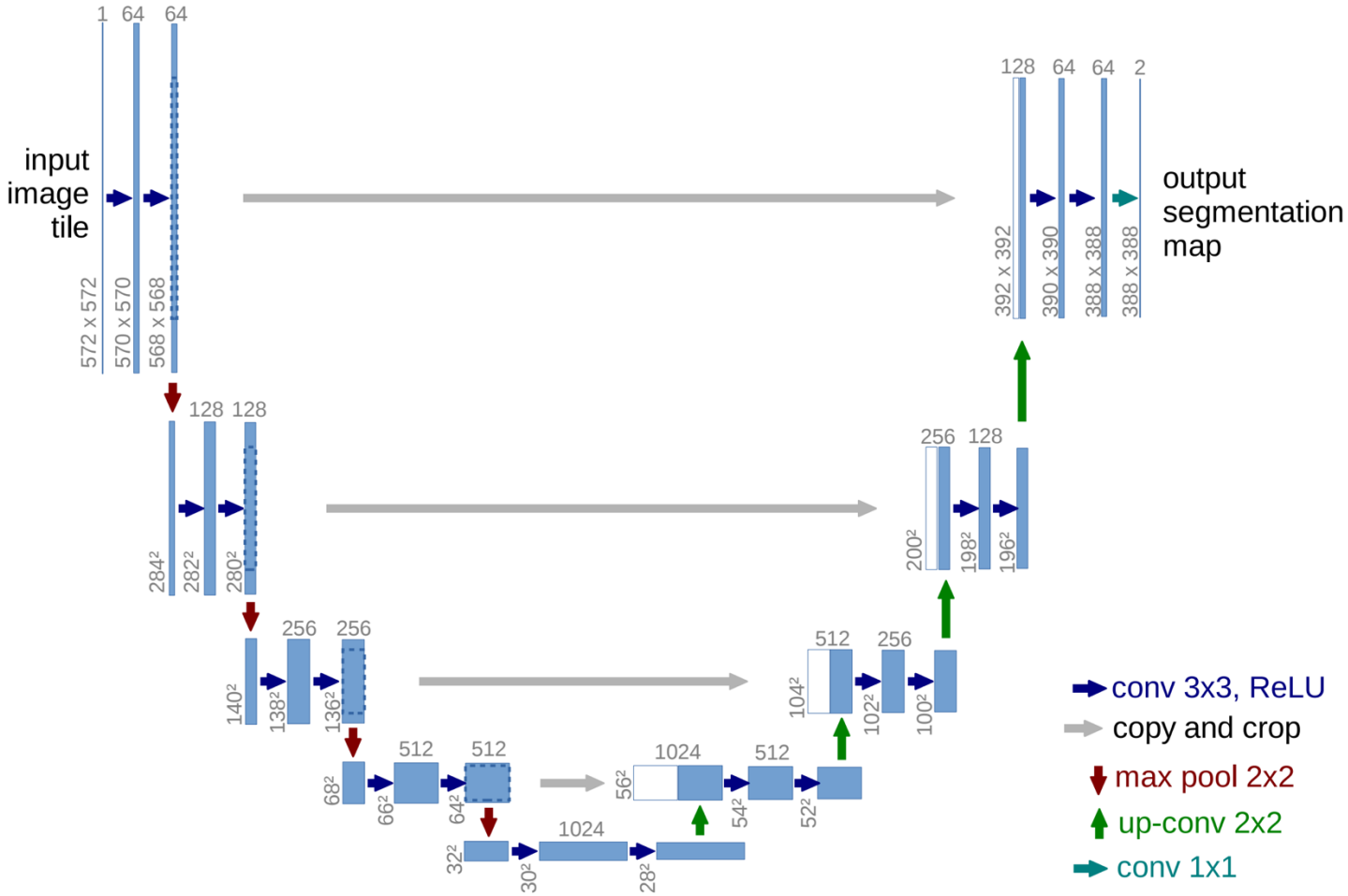
U-Net

Perhaps unsurprisingly, U-Net has a distinctive U-shaped architecture…



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U-Net

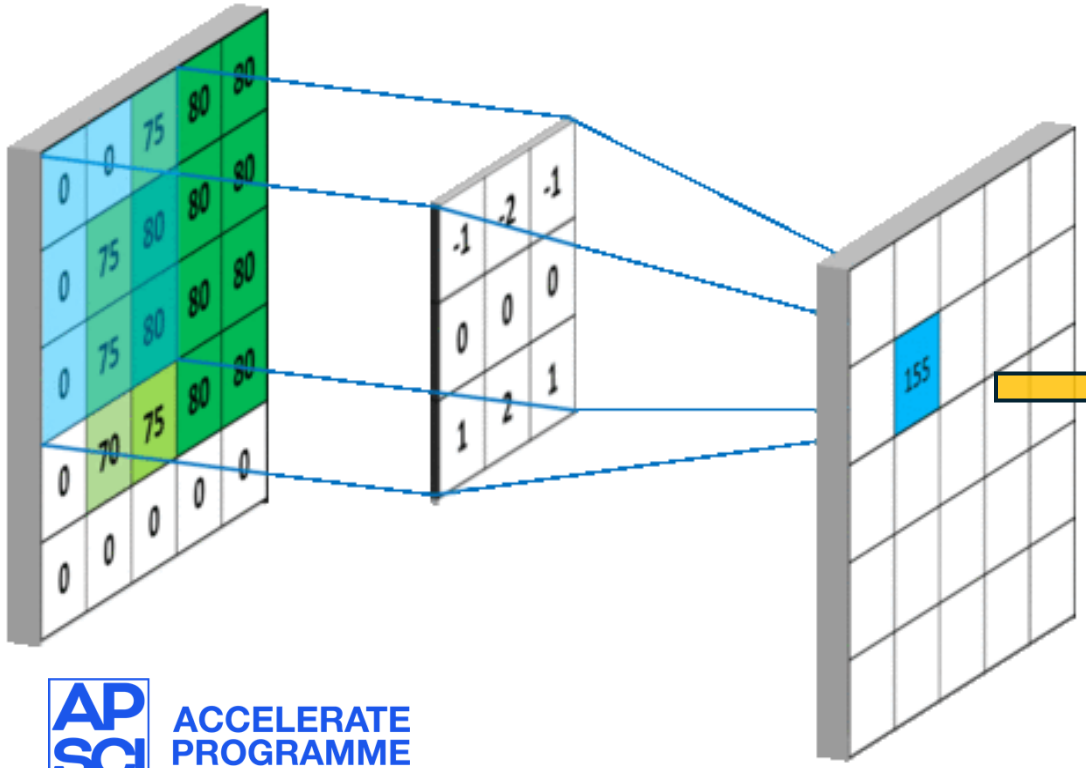
There are some key components of U-Net that are worth going over…

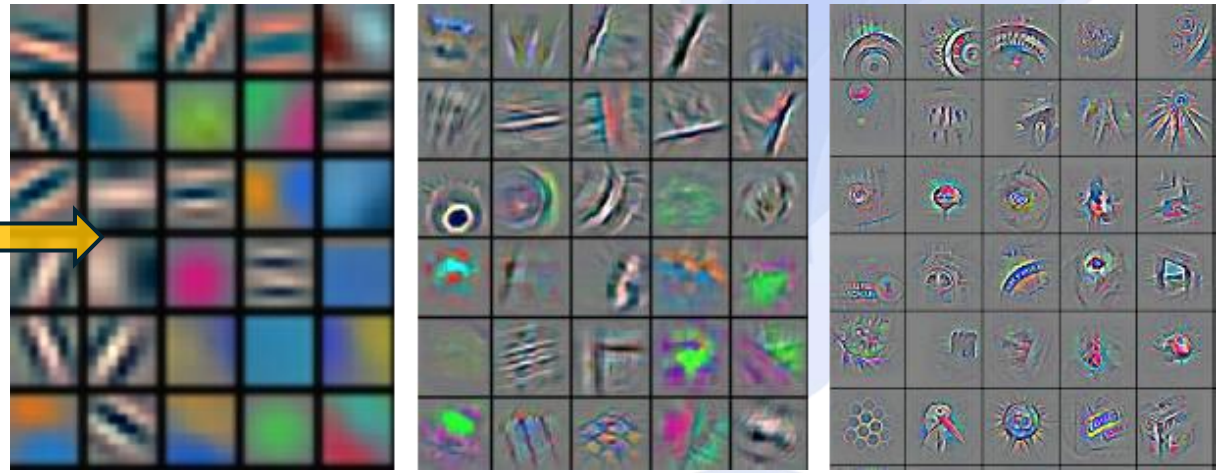
- Convolution
- Residuals
- Upsampling
- Pooling
- Normalization

U-Net

Convolution was a major advancement in machine vision

- *Gradient-based Learning Applied to Document Recognition*, 1998, LeCun et al, ~65k citations
- *ImageNet Classification with Deep Convolutional Neural Networks*, 2012, Krizhevsky et al, ~130k citations





Zeiler, Matthew D., and Rob Fergus. "Visualizing and understanding convolutional networks." Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part I 13. Springer International Publishing, 2014.

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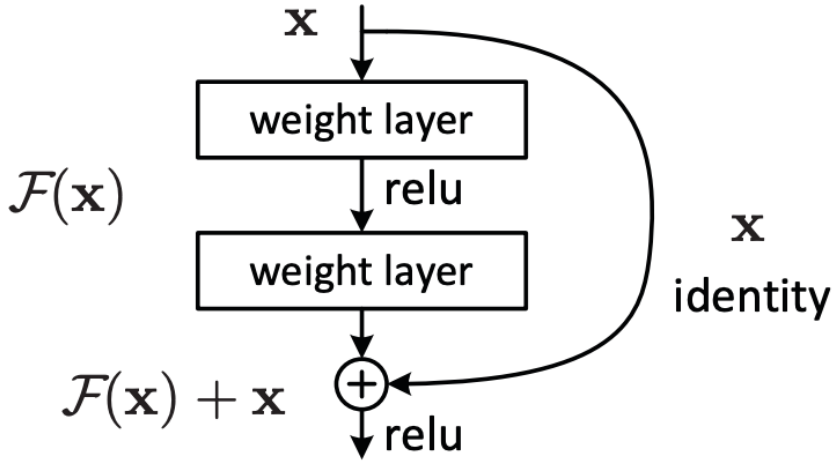
U-Net

Like CNNs, residual neural networks were a major step forward for deep learning.

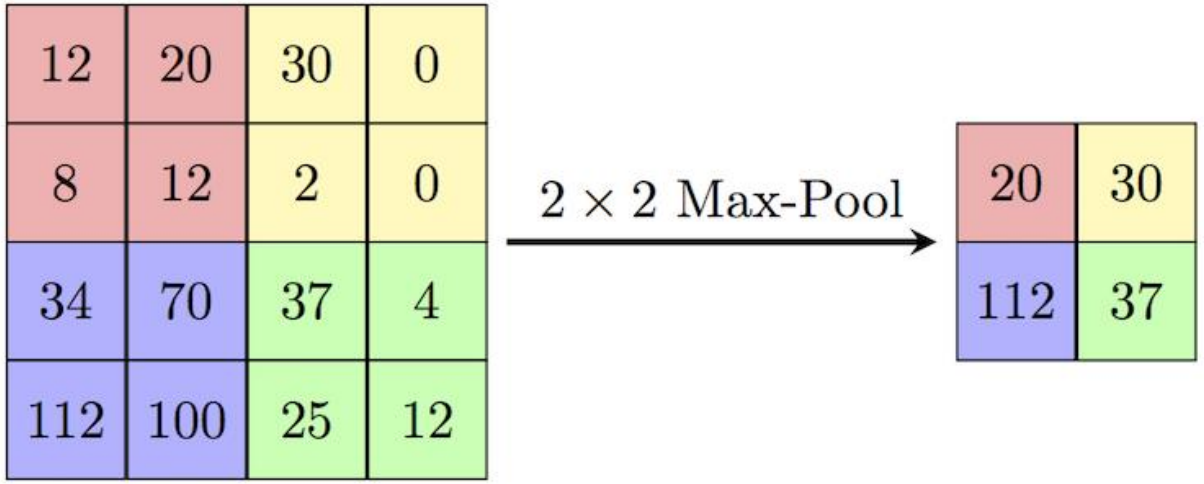
- *Deep Residual Learning for Image Recognition*, He et al, Microsoft Research, 2015 ~210k citations
- Most neural networks now use residual connections.
- After AlexNet, the main idea was simply to make the neural network bigger.
- However, after a certain point, error appeared to increase that was not attributable to overfitting.
- Instead of trying to learn a complicated function to transform the inputs directly to the outputs, we learn: “what do we need to change in order to transform the inputs to the outputs”
- The trick is to add skip connections:



U-Net

Pooling

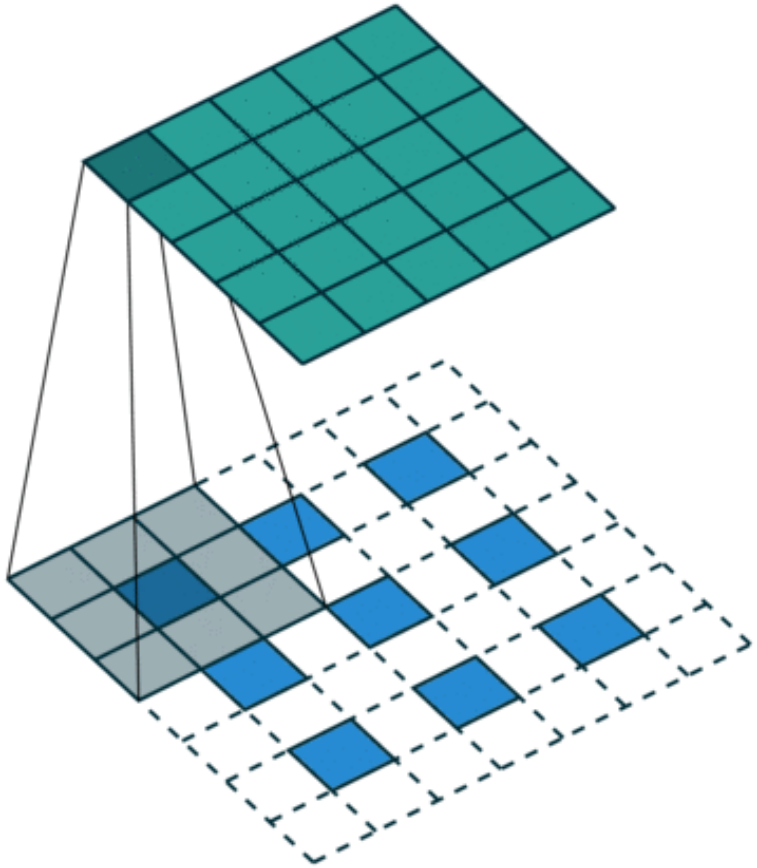
- Yamaguchi et al. "A neural network for speaker-independent isolated word recognition." 1990
- It’s a very simple concept:



- Pass a window across the filter and take the maximum value
- The maxpool operation is defined by the stride and the filter size
- It preserves important features and downscales to make computation less intense
- Makes the networks somewhat equivariant.

U-Net

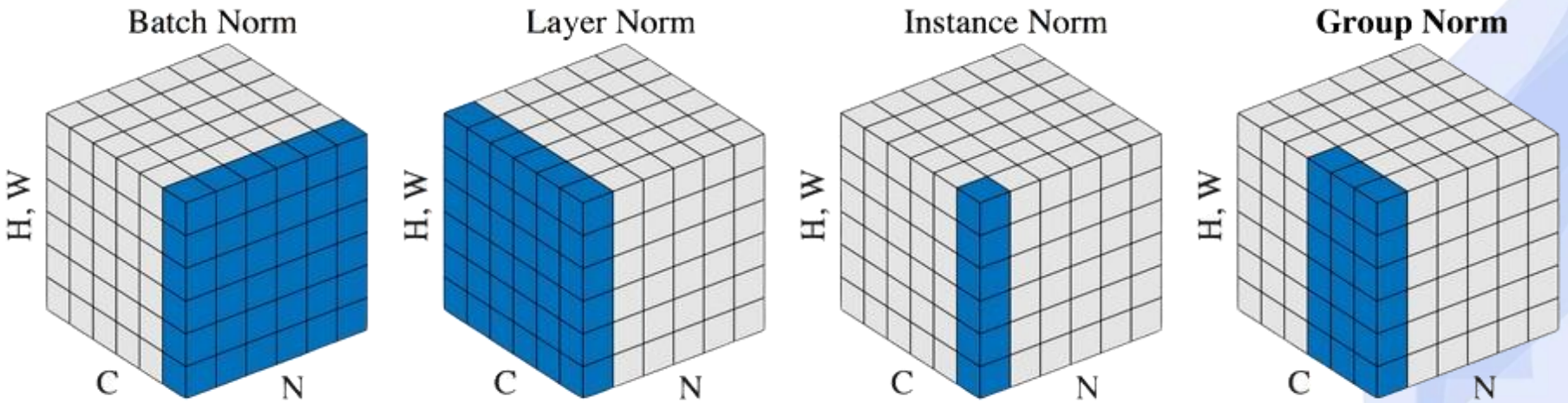
Upsampling



U-Net

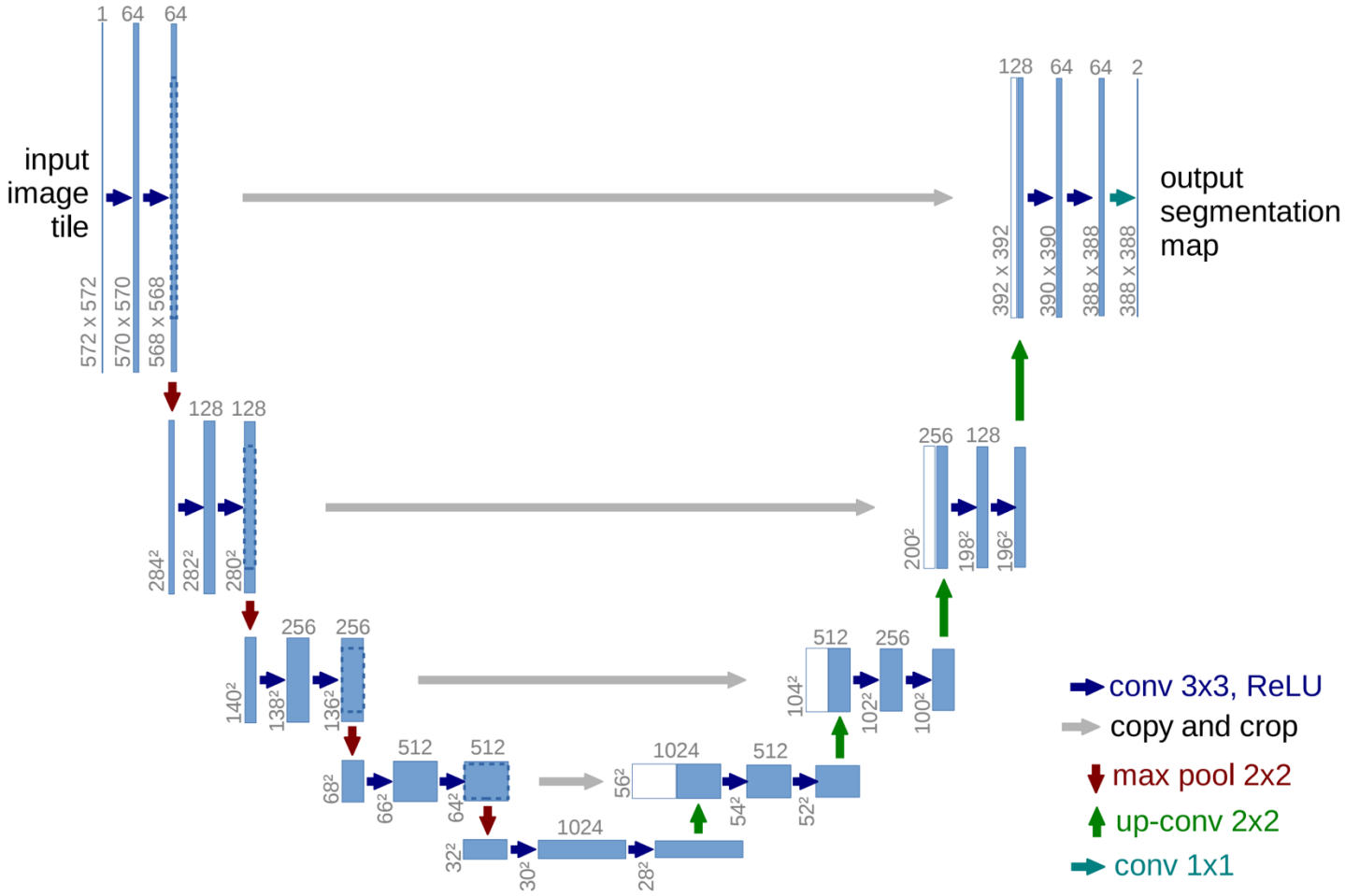
Normalization

- There are a few different types of normalization:



U-Net

Let’s look at the U-Net architecture again…



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CLIP

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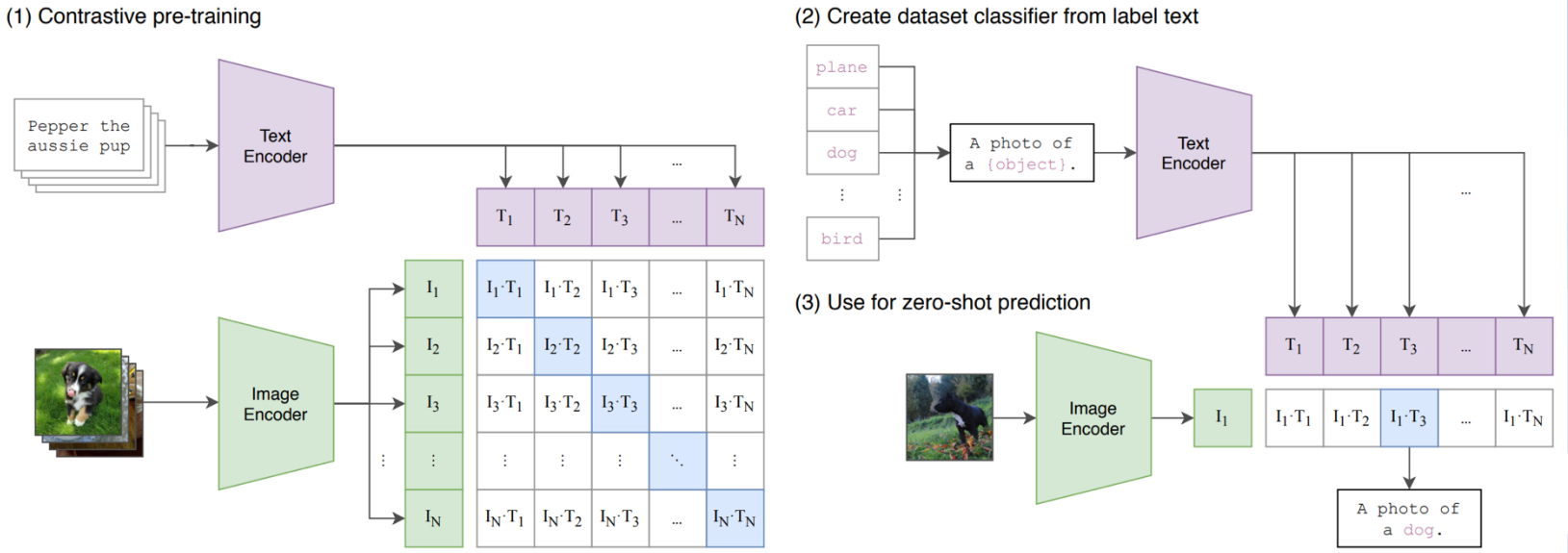
CLIP

Contrastive Language-Image Pre-training

- *Learning Transferable Visual Models for Natural Language Supervision*, Radford et al, 2021, ~17k citations
- Takes in images and texts and connects them together



Radford, Alec, et al. "Learning transferable visual models from natural language supervision." International conference on machine learning. PMLR, 2021.