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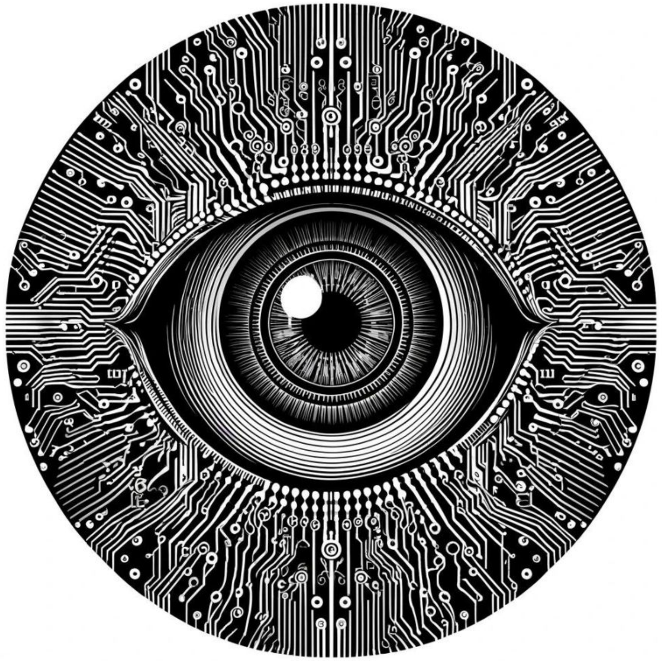
Skip Connections



Antonio Rueda-Toicen

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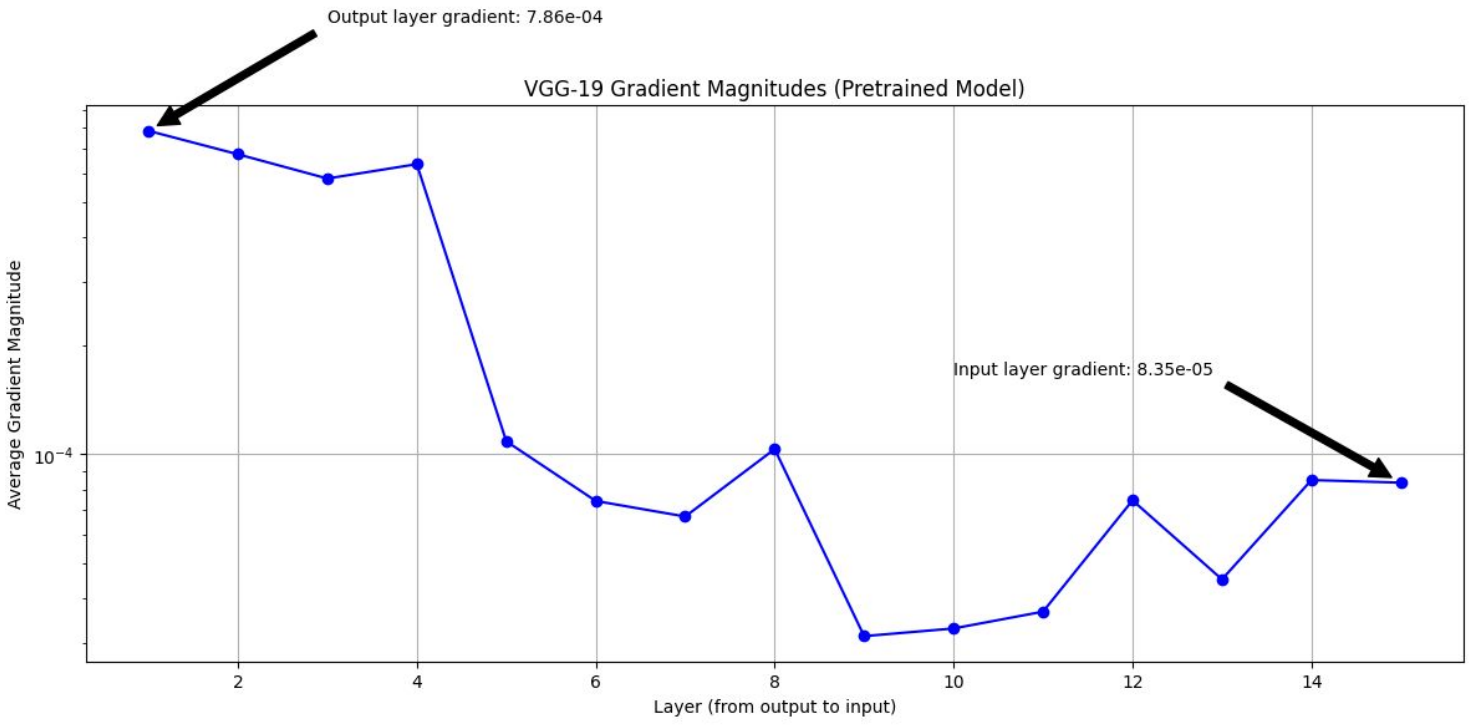
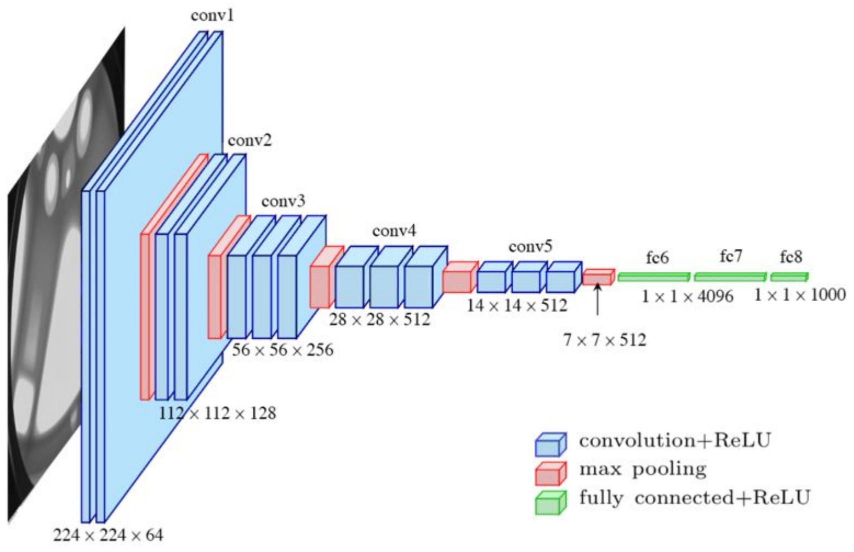
Learning goals

- Understand the vanishing gradient as a numerical problem
- Implement skip connections as element-wise addition or concatenation of activation maps

The vanishing gradient

$$w_{ij} = w_{ij} - \left(\text{learning rate} * \frac{dL}{dw_{ij}}\right)$$

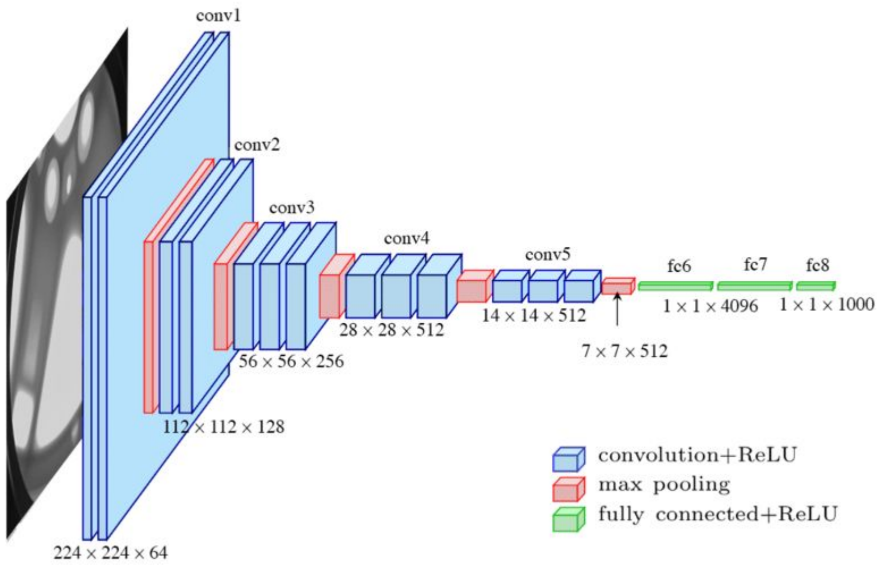




VGG-19 network (source)

Numerical underflow in neural networks

```python
import numpy as np
from scipy.signal import convolve2d

# Example data (any image or 2D array)
image = np.ones((8,8), dtype=np.float32)

# A 3×3 kernel with sum=0.8
kernel = np.array([[0.05, 0.10, 0.05],
                   [0.10, 0.20, 0.10],
                   [0.05, 0.10, 0.05]], dtype=np.float32)

for i in range(1000):
   image = convolve2d(image, kernel, mode='same', boundary='fill', fillvalue=0)
   # Underflow can show up when values drop below np.finfo(np.float32).tiny
   if (image > 0).sum() == 0:
       print("All values underflowed to 0 at iteration", i)
       break
```



VGG-19 network (source)

Numerical underflow

```python
import numpy as np

a = 1e-8 # Equal to 1 x 10 ** -8
b = 2

print(np.float32(a) ** b)  # Gives a value close to 1e-16
print(np.float16(a) ** b)  # Underflows to 0.0
```

$$(0.00000001)^2 = (1 \times 10^{-8})^2 = 10^{-16}$$

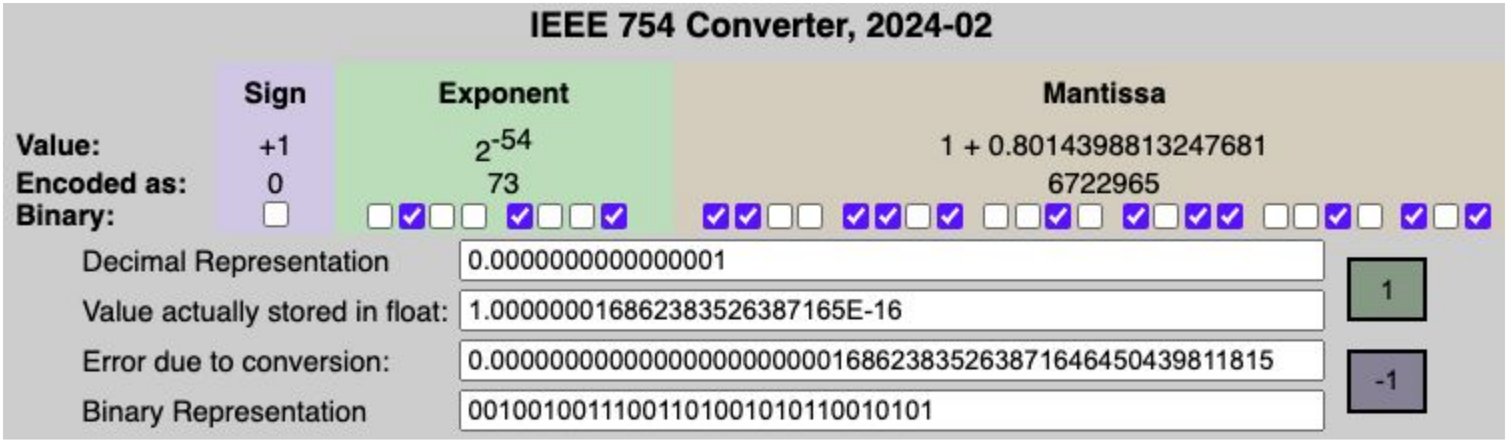
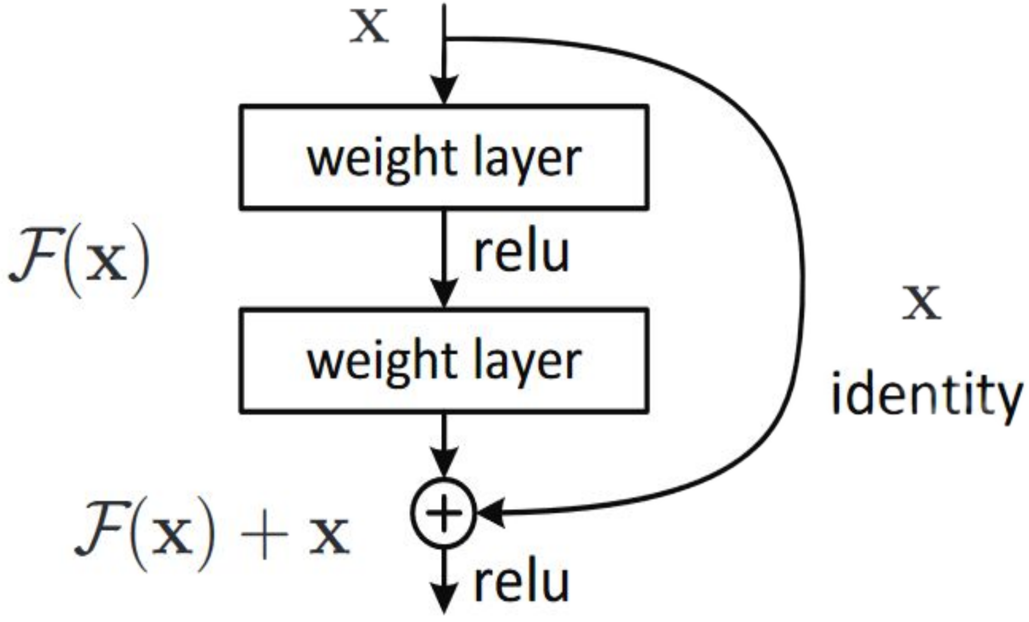


Image from [IEEE-754 Floating Point Converter]

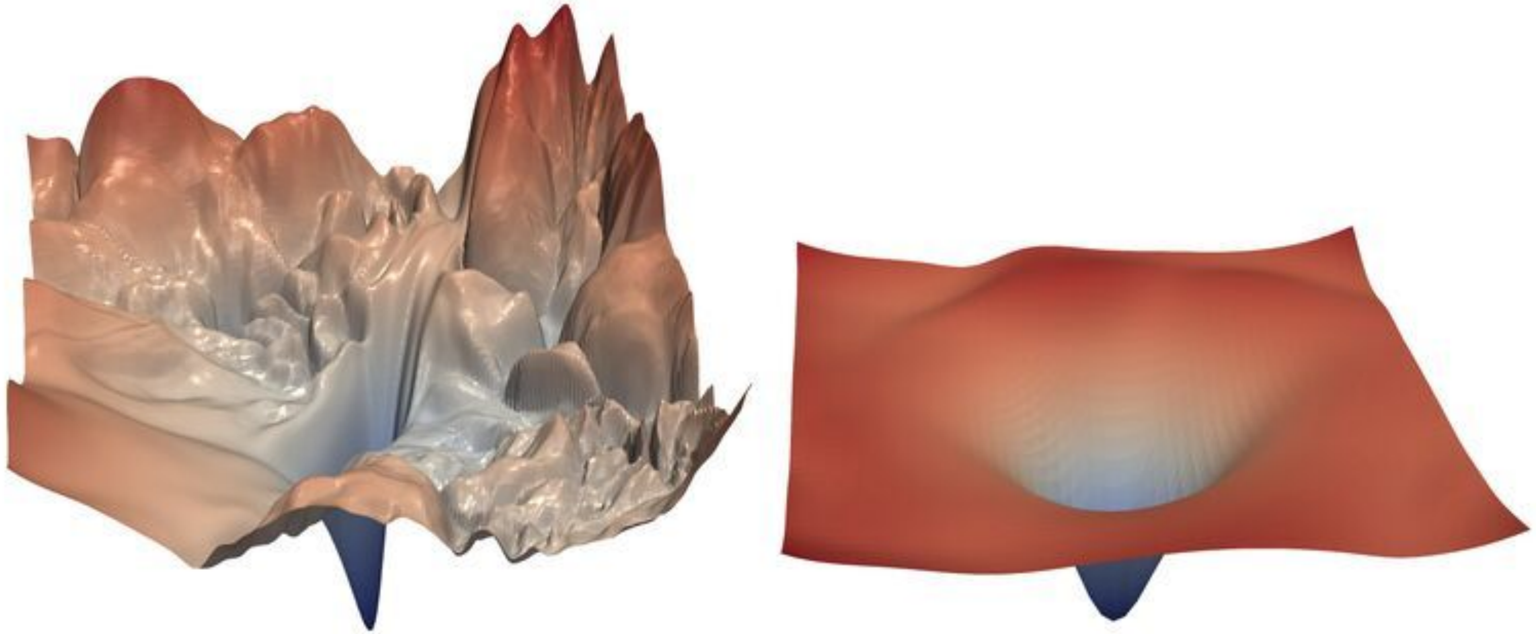
Skip connections on Resnet

```python
import torch.nn as nn

class ResidualBlock(nn.Module):
    def __init__(self, channels):
        super().__init__()
        # Main path - "city route"
        self.conv1 = nn.Conv2d(channels, channels, kernel_size=3, padding=1)
        self.bn1 = nn.BatchNorm2d(channels)
        self.conv2 = nn.Conv2d(channels, channels, kernel_size=3, padding=1)
        self.bn2 = nn.BatchNorm2d(channels)
        self.relu = nn.ReLU()

    def forward(self, x):
        # Save input for skip connection - "highway route / checkpoint"
        identity = x

        # Main path through convolutions
        out = self.conv1(x)
        out = self.bn1(out)
        out = self.relu(out)
        out = self.conv2(out)
        out = self.bn2(out)

        # Add skip connection - "merging highway with city route (adding checkpoint)"
        out += identity

        # Final activation
        out = self.relu(out)

        return out
```



$$\underbrace{\begin{bmatrix}-0.12 & 0.24\\ 0.35 & -0.25\end{bmatrix}}_{\text{Identity Path (x)}} + \underbrace{\begin{bmatrix}0.25 & -0.14\\ -0.45 & 0.35\end{bmatrix}}_{\text{Main Path (F(x))}} = \underbrace{\begin{bmatrix}0.13 & 0.10\\ -0.10 & 0.10\end{bmatrix}}_{\text{Output (F(x) + x)}}$$

Effects on the loss landscape



(a) without skip connections (b) with skip connections

Figure 1: The loss surfaces of ResNet-56 with/without skip connections. The proposed filter normalization scheme is used to enable comparisons of sharpness/flatness between the two figures.

32nd Conference on Neural Information Processing Systems (NIPS 2018), Montréal, Canada.

Image from [Visualizing the Loss Landscape of Neural Nets]

Relevance on current architectures

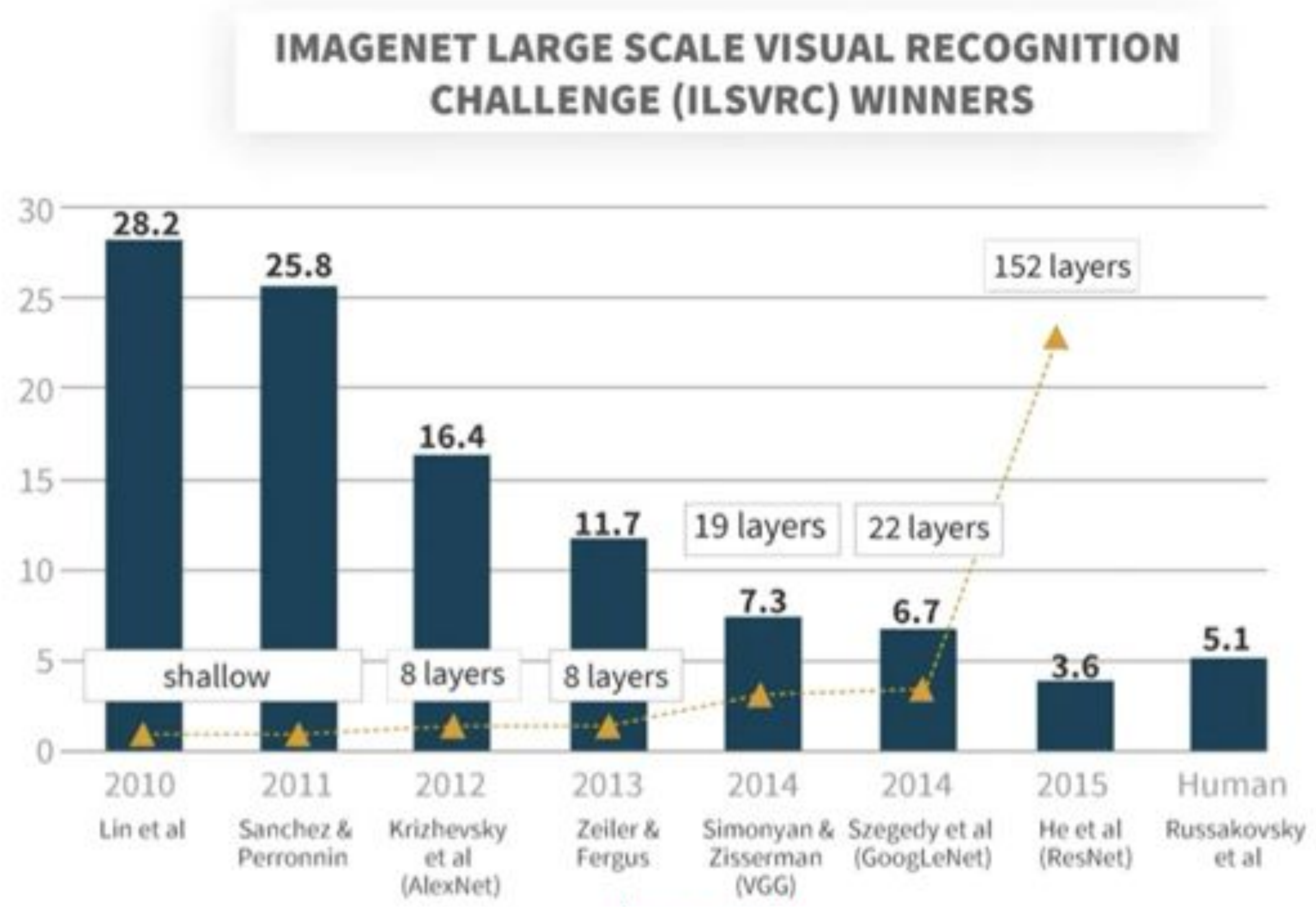
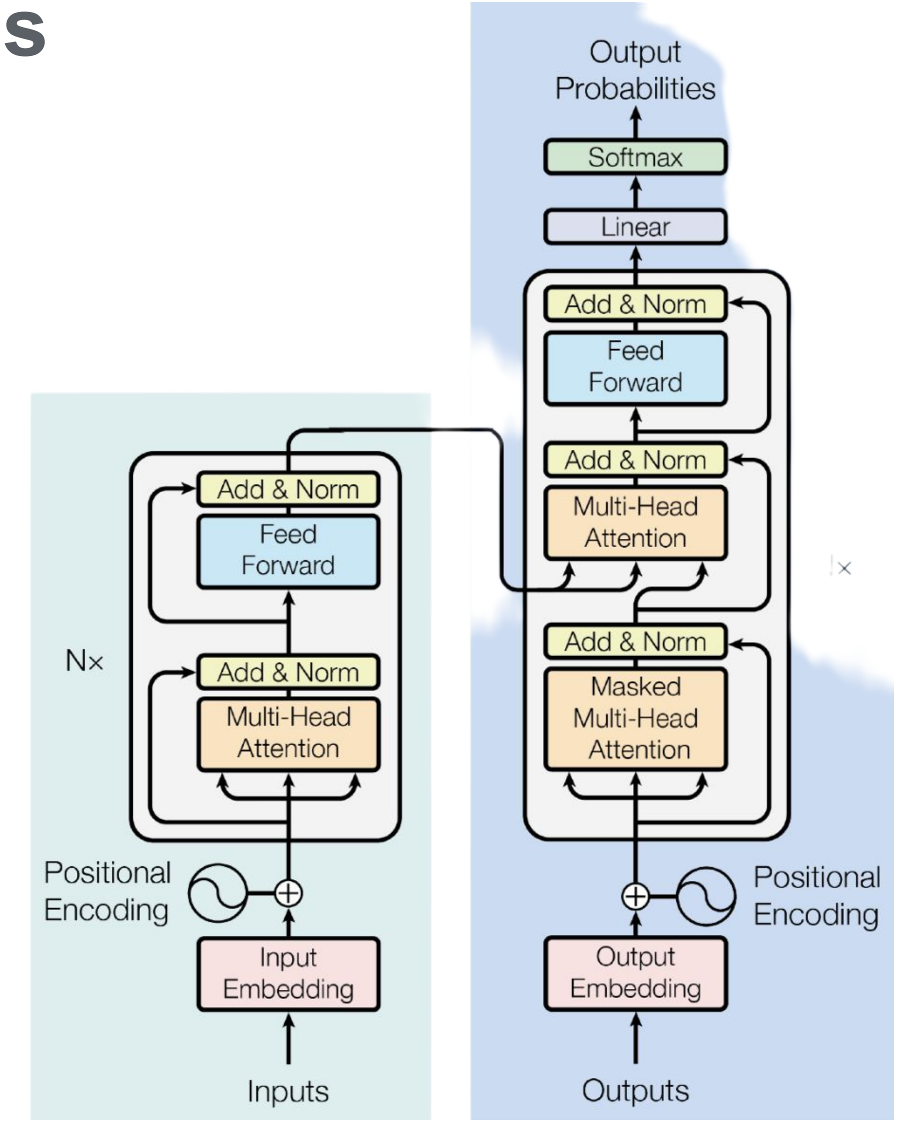


Image source



Transformer architecture from source

Skip connections on Densenet

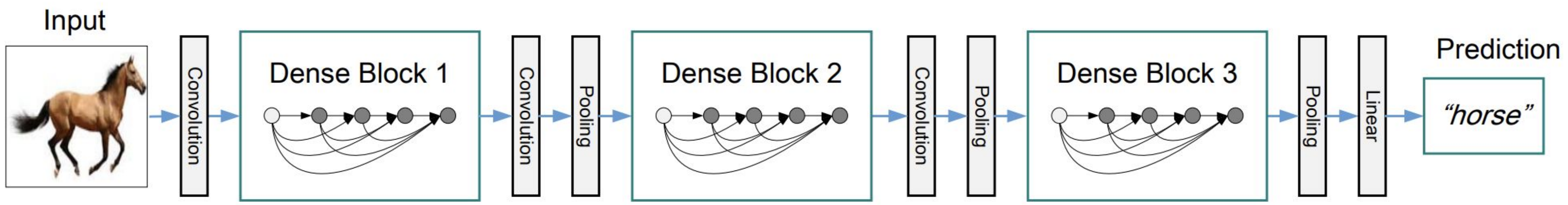
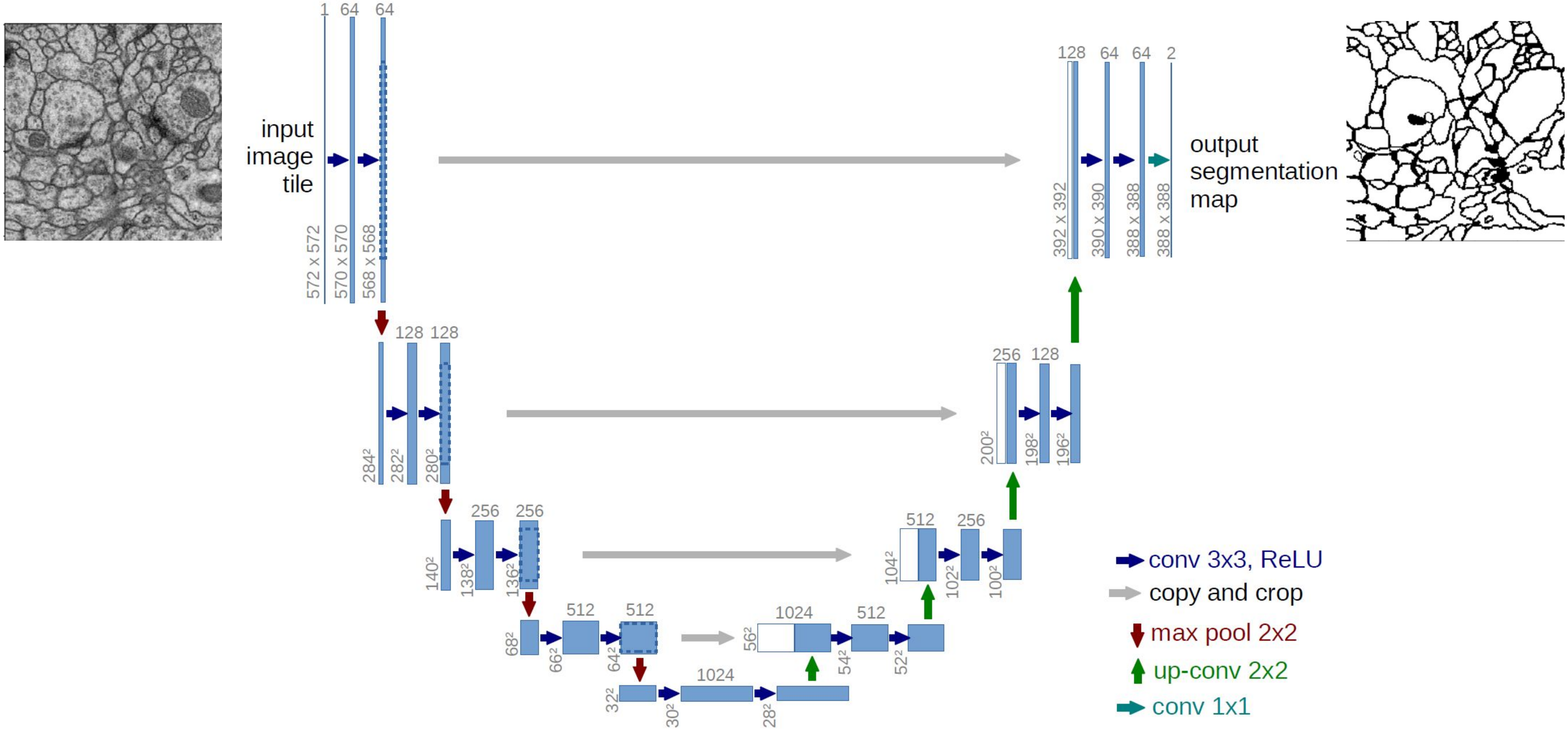


Figure 2: A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

```
# Feature maps are concatenated instead of added
# We can control the number of feature maps by using 1x1 convolutions
torch.cat(features, dim=1)
```

Skip connections on U-net



Summary

The vanishing gradient is a numerical problem

- Computers have limited precision to represent small numbers

Skip connections serve as “checkpoints” for what the model has learned

- A skip connection gives us the chance to preserve information that could have been destroyed due to numerical underflow
- Skip connections are what allow neural networks to be deep and increase their number of parameters while avoiding vanishing gradients

Two types of skip connections: addition and concatenation

- We use either element wise addition or concatenation of feature maps as skip connections

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Further reading and references

Deep Residual Learning for Image Recognition

- **https://arxiv.org/abs/1512.03385**

Densely Connected Convolutional Networks

- https://arxiv.org/abs/1608.06993

Visualizing the Loss Landscape of Neural Nets

- https://arxiv.org/abs/1712.09913

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