Intuitive Explanation of Skip Connections in Deep Learning

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Deep Learning

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1. What is the vanishing gradient problem?

The vanishing gradient problem is a challenge that arises in training deep neural networks. During the training process, the backpropagation algorithm is used to adjust the network's weights by calculating gradients (the rate of change of the loss function with respect to the weights). However, in very deep networks, these gradients often shrink as they are propagated backward through the layers.

This happens because activation functions like sigmoid or tanh compress their input values into a small range (e.g. 0 to 1 for sigmoid), leading to derivatives that are less than 1. When gradients are multiplied across many layers, they get smaller and smaller, potentially approaching zero. This means that the weights in earlier layers of the network barely get updated, effectively "freezing" them and making it hard for the network to learn useful features in those layers.

The issue is more pronounced in deeper networks because there are more layers where gradients can shrink. This results in a network that cannot fully utilize its depth to learn complex patterns in data, limiting its performance. The vanishing gradient problem is one of the reasons why older deep networks struggled with very deep architectures.

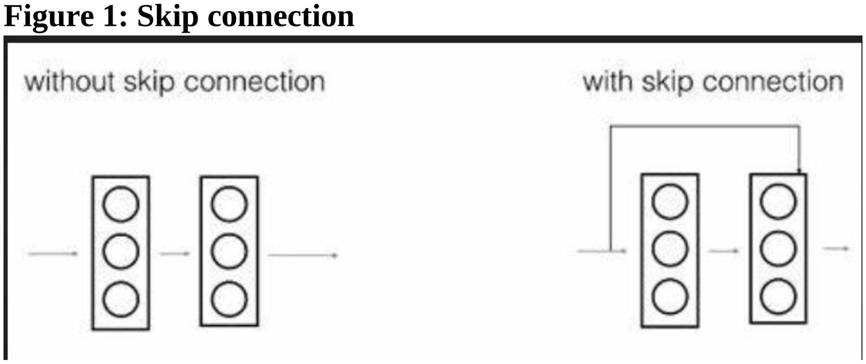
2. What is the skip connection?

A skip connection is a technique used in modern deep learning architectures, such as ResNet, to help overcome problems like the vanishing gradient. The idea is simple: instead of letting the input to a layer pass through all the intermediate layers and transformations, it is also directly added to the output of that layer, effectively "skipping" over some layers.

Here's how it works: consider a layer H(x) that represents a transformation (like a set of convolutions, activations, and other operations). With a skip connection, the input x is added directly to H(x) , making the output F(x)=H(x)+x. This creates a shortcut path that allows the gradient to flow directly through the skipped layers during backpropagation, reducing the chances of gradients vanishing. Please refer Figure 1

Skip connections also allow the network to focus on learning residual mappings (the difference between the input and output) rather than the full transformation, making training easier and faster. They preserve important information from earlier layers and make it possible to train much deeper networks effectively.

Figure 1: Skip connection



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3. Summarize the UNet model and how it makes use of skip connections.

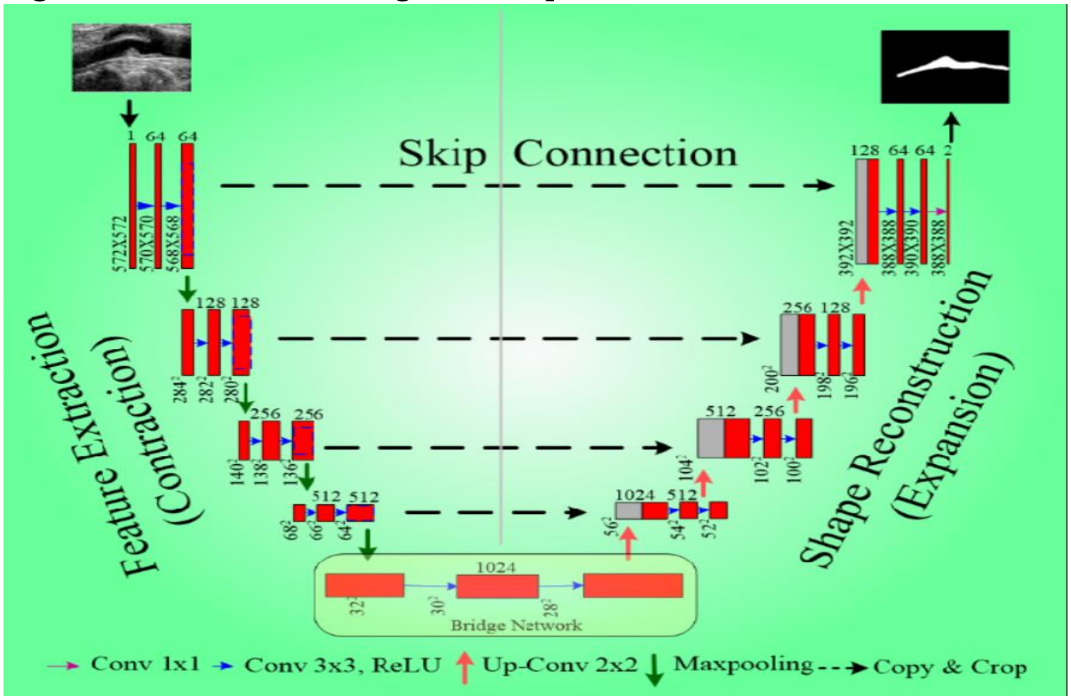
The UNet model is a deep learning architecture originally designed for biomedical image segmentation. It's widely used in tasks where the goal is to classify each pixel of an image, such as identifying tumors in medical scans. Its name comes from its U-shaped architecture, which consists of two main parts:

1. **Encoder (Contracting Path):** This part captures the context of the image by progressively reducing its spatial dimensions (using operations like convolution and pooling). As it goes deeper, the encoder extracts increasingly abstract features, but some spatial details are lost.
2. **Decoder (Expanding Path):** This part restores the spatial dimensions by up sampling, aiming to produce a segmentation map that matches the original input size. It combines abstract features with spatial details to localize objects.

Skip connections play a crucial role in UNet by directly connecting the feature maps from the encoder to corresponding layers in the decoder. These connections allow the model to retain fine-grained spatial details that might otherwise be lost in the encoder. The feature maps from the encoder (which contain high-resolution details) are concatenated with the up sampled feature maps in the decoder, enabling the network to combine low-level (fine detail) and high-level (contextual) information.

This strategy ensures better segmentation accuracy, as the decoder can use both global context and precise localization information. Without skip connections, the decoder would struggle to reconstruct high-resolution details, leading to less accurate segmentations. UNet's use of skip connections is one of the reasons it has become a popular choice for segmentation tasks.

Figure 2: UNet model making use of skip connections



References

AI Summer. (n.d.). *Skip connections in deep learning: A detailed guide*. Retrieved November 23, 2024, from https://theaisummer.com/skip-connections/