Deep Learning

Chapter 6: Modern Convolutional Neural Networks

Mina Rezaei

Department of Statistics – LMU Munich

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LECTURE OUTLINE

From LeNet to AlexNet

Networks Using Blocks (VGG)

- VGG Blocks
- VGG Network

Network in Network (NiN)

- NiN Blocks
- NiN Model

Networks with Parallel Concatenations (GoogLeNet)

- Inception Blocks
- GoogLeNet Architecture

Residual Networks (ResNet)

- Residual Block
- ResNet Model

Densely Connected Networks (DenseNet)

- Dense Blocks
- DenseNet Model

From LeNet to AlexNet

LENET ARCHITECTURE

- Pioneering work on CNNs by Yann Lecun in 1998[**?**].
- Applied on the MNIST dataset for automated handwritten digit recognition.
- Consists of convolutional, "subsampling" and dense layers.
- Complexity and depth of the net was mainly restricted by limited computational power back in the days.

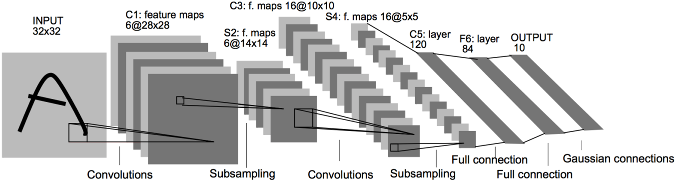


Figure: LeNet architecture: two conv layers with subsampling, followed by dense layers and a 'Gaussian connections' layer.

LENET ARCHITECTURE

- A neuron in a subsampling layer looks at a 2×2 region of a feature map, sums the four values, multiplies it by a trainable coefficient, adds a trainable bias and then applies a sigmoid activation.
- A stride of 2 ensures that the size of the feature map reduces by about a half.
- The 'Gaussian connections' layer has a neuron for each possible class.
- The output of each neuron in this layer is the (squared) Euclidean distance between the activations from the previous layer and the weights of the neuron.

ALEXNET

- AlexNet, which employed an 8-layer CNN, won the ImageNet Large Scale Visual Recognition Challenge 2012 by a phenomenally large margin.
- The network trained in parallel on two small GPUs, using two streams of convolutions which are partly interconnected.
- The architectures of AlexNet and LeNet are very similar, but there are also significant differences:
- First, AlexNet is much deeper than the comparatively small LeNet5. AlexNet consists of eight layers: five convolutional layers, two fully-connected hidden layers, and one fully-connected output layer.
- Second, AlexNet used the ReLU instead of the sigmoid as its activation function.

ALEXNET

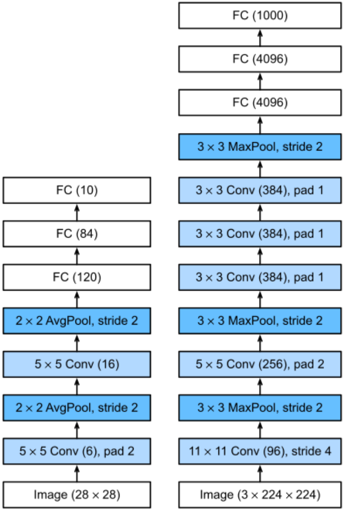
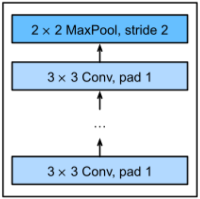


Figure: From LeNet (left) to AlexNet (right).

Networks Using Blocks (VGG)

VGG BLOCKS

- The block composed of convolutions with 3×3 kernels with padding of 1 (keeping height and width) and 2×2 max pooling with stride of 2 (halving the resolution after each block).
- The use of blocks leads to very compact representations of the network definition.
- It allows for efficient design of complex networks.



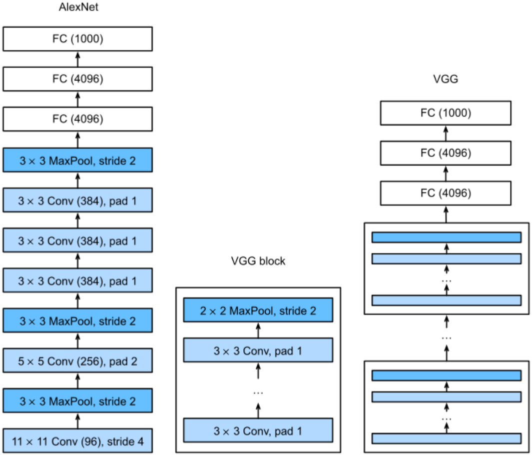
credit : D2DL

Figure: VGG block.

VGG NETWORK

- Architecture introduced by Simonyan and Zisserman, 2014 [**?**] as “Very Deep Convolutional Network”.
- A deeper variant of the AlexNet.
- Basic ide is to have small filters and Deeper networks
- Mainly uses many convolutional layers with a small kernel size 3x3.
- Stack of three 3x3 conv (stride 1) layers has same effective receptive field as one 7x7 conv layer.
- Performed very well in the ImageNet Challenge 2014.
- Exists in a small version (VGG16) with a total of 16 layers and a larger version (VGG19) with 19 layers.

VGG NETWORK



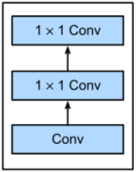
credit : D2DL

Figure: From AlexNet to VGG that is designed from building blocks.

Network in Network (NiN)

NIN BLOCKS

- The NiN block consists of one convolutional layer followed by two 1×1 convolutional layers that act as per-pixel fully-connected layers with ReLU activations.
- The convolution window shape of the first layer is typically set by the user. The subsequent window shapes are fixed to 1×1.



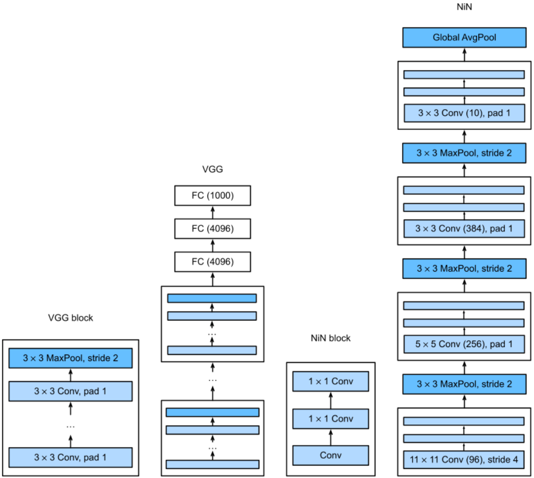
credit : D2DL

Figure: NiN block.

NETWORK IN NETWORK (NIN)

- NiN uses blocks consisting of a convolutional layer and multiple 1×1 convolutional layers. This can be used within the convolutional stack to allow for more per-pixel nonlinearity.
- NiN removes the fully-connected layers and replaces them with global average pooling (i.e., summing over all locations) after reducing the number of channels to the desired number of outputs (e.g., 10 for Fashion-MNIST).
- Removing the fully-connected layers reduces overfitting. NiN has dramatically fewer parameters.
- The NiN design influenced many subsequent CNN designs.

NETWORK IN NETWORK (NIN)



credit : D2DL

Figure: Comparing architectures of VGG and NiN, and their blocks.

Networks with Parallel Concatenations (GoogLeNet)

INCEPTION MODULES

- The Inception block is equivalent to a subnetwork with four paths.
- It extracts information in parallel through convolutional layers of different window shapes and max-pooling layers.
- 1×1 convolutions reduce channel dimensionality on a per-pixel level. Max-pooling reduces the resolution.

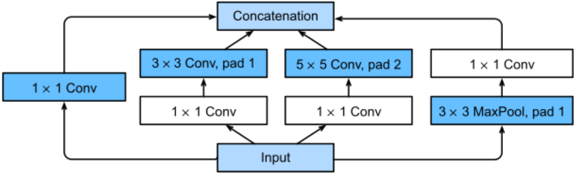
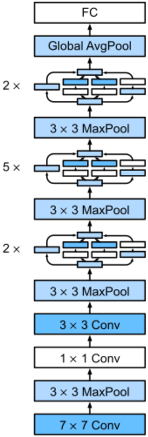


Figure: Inception Block.

GOOGLENET ARCHITECTURE

- GoogLeNet connects multiple well-designed Inception blocks with other layers in series.
- The ratio of the number of channels assigned in the Inception block is obtained through a large number of experiments on the ImageNet dataset.
- GoogLeNet, as well as its succeeding versions, was one of the most efficient models on ImageNet, providing similar test accuracy with lower computational complexity.

GOOGLENET ARCHITECTURE



credit : D2DL

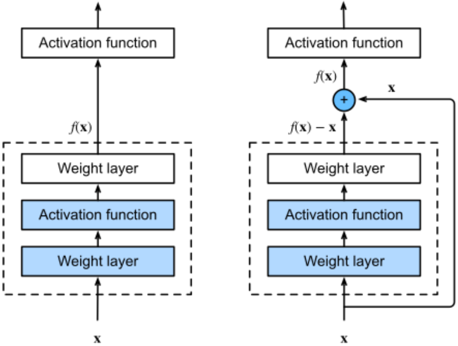
Figure: The GoogLeNet architecture.

Residual Networks (ResNet)

RESIDUAL BLOCK (SKIP CONNECTIONS)

- Problem setting: theoretically, we could build infinitely deep architectures as the net should learn to pick the beneficial layers and skip those that do not improve the performance automatically.
- But: this skipping would imply learning an identity mapping $\mathbf{x} = \mathcal{F}(\mathbf{x})$. It is very hard for a neural net to learn such a 1:1 mapping through the many non-linear activations in the architecture.
- Solution: offer the model explicitly the opportunity to skip certain layers if they are not useful.
- Introduced in [He et. al , 2015] and motivated by the observation that stacking evermore layers increases the test- as well as the train-error ($\neq$ overfitting).

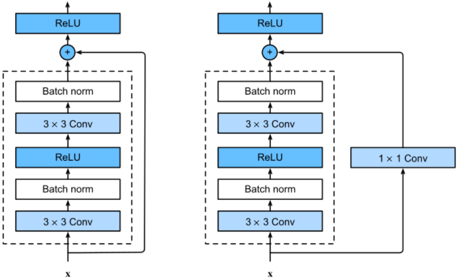
RESIDUAL BLOCK (SKIP CONNECTIONS)



credit : D2DL

Figure: A regular block (left) and a residual block (right).

RESIDUAL BLOCK (SKIP CONNECTIONS)



credit : D2DL

Figure: ResNet block with and without 1×1 convolution.The information flows through two layers and the identity function. Both streams of information are then element-wise summed and jointly activated.

RESIDUAL BLOCK (SKIP CONNECTIONS)

- Let $\mathcal{H}(\mathbf{x})$ be the optimal underlying mapping that should be learned by (parts of) the net.
- $\mathbf{x}$ is the input in layer l (can be raw data input or the output of a previous layer).
- $\mathcal{H}(\mathbf{x})$ is the output from layer l.
- Instead of fitting $\mathcal{H}(\mathbf{x})$, the net is ought to learn the residual mapping $\mathcal{F}(\mathbf{x}) := \mathcal{H}(\mathbf{x}) - \mathbf{x}$ whilst $\mathbf{x}$ is added via the identity mapping.
- Thus, $\mathcal{H}(\mathbf{x}) = \mathcal{F}(\mathbf{x}) + \mathbf{x}$, as formulated on the previous slide.
- The model should only learn the **residual mapping** $\mathcal{F}(\mathbf{x})$
- Thus, the procedure is also referred to as **Residual Learning**.

RESIDUAL BLOCK (SKIP CONNECTIONS)

- The element-wise addition of the learned residuals $\mathcal{F}(\mathbf{x})$ and the identity-mapped data **x** requires both to have the same dimensions.
- To allow for downsampling within $\mathcal{F}(\mathbf{x})$ (via pooling or valid-padded convolutions), the authors introduce a linear projection layer W_s .
- W_s ensures that **x** is brought to the same dimensionality as $\mathcal{F}(\mathbf{x})$ such that:

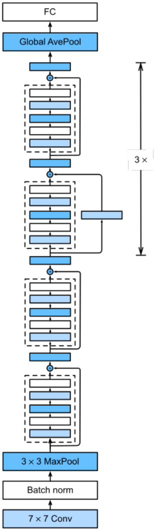
$$y = \mathcal{F}(\mathbf{x}) + W_s\mathbf{x},$$

- y is the output of the skip module and W_s represents the weight matrix of the linear projection (# rows of W_s = dimensionality of $\mathcal{F}(\mathbf{x})$).
- This idea applies to fully connected layers as well as to convolutional layers.

RESNET ARCHITECTURE

- The residual mapping can learn the identity function more easily, such as pushing parameters in the weight layer to zero.
- We can train an effective deep neural network by having residual blocks.
- Inputs can forward propagate faster through the residual connections across layers.
- ResNet had a major influence on the design of subsequent deep neural networks, both for convolutional and sequential nature.

RESNET ARCHITECTURE



credit : D2DL

Figure: The ResNet-18 architecture.

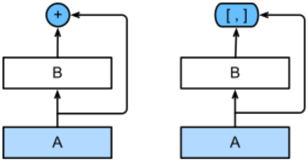
Densely Connected Networks (DenseNet)

FROM RESNET TO DENSENET

- ResNet significantly changed the view of how to parametrize the functions in deep networks.
- DenseNet (dense convolutional network) is to some extent the logical extension of this [Huang et al., 2017].
- Dense blocks where each layer is connected to every other layer in feedforward fashion.
- Alleviates vanishing gradient, strengthens feature propagation, encourages feature reuse.
- To understand how to arrive at it, let us take a small detour to mathematics:
  - Recall the Taylor expansion for functions. For the point $x = 0$ it can be written as:
    $f(x) = f(0) + f'(0)x + \frac{f''(0)}{2!}x^2 + \frac{f'''(0)}{3!}x^3 + \dots .$

FROM RESNET TO DENSENET

- The key point is that it decomposes a function into increasingly higher order terms. In a similar vein, ResNet decomposes functions into : $f(\mathbf{x}) = \mathbf{x} + g(\mathbf{x})$.
- That is, ResNet decomposes f into a simple linear term and a more complex nonlinear one. What if we want to capture (not necessarily add) information beyond two terms? One solution was DenseNet [Huang et al., 2017].



credit : D2DL

Figure: DensNet Block.

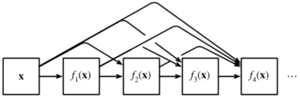
FROM RESNET TO DENSENET

As shown in previous Figure, the key difference between ResNet and DenseNet is that in the latter case outputs are concatenated (denoted by $[,]$) rather than added. As a result, we perform a mapping from x to its values after applying an increasingly complex sequence of functions:

$$\mathbf{x} \to [\mathbf{x}, f_1(\mathbf{x}), f_2([\mathbf{x}, f_1(\mathbf{x})]), f_3([\mathbf{x}, f_1(\mathbf{x}), f_2([\mathbf{x}, f_1(\mathbf{x})])]), \ldots] .$$

In the end, all these functions are combined in MLP to reduce the number of features again. In terms of implementation this is quite simple: rather than adding terms, we concatenate them.
The name DenseNet arises from the fact that the dependency graph between variables becomes quite dense. The last layer of such a chain is densely connected to all previous layers.

FROM RESNET TO DENSENET



credit : D2DL

Figure: The DensNet architecture.

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