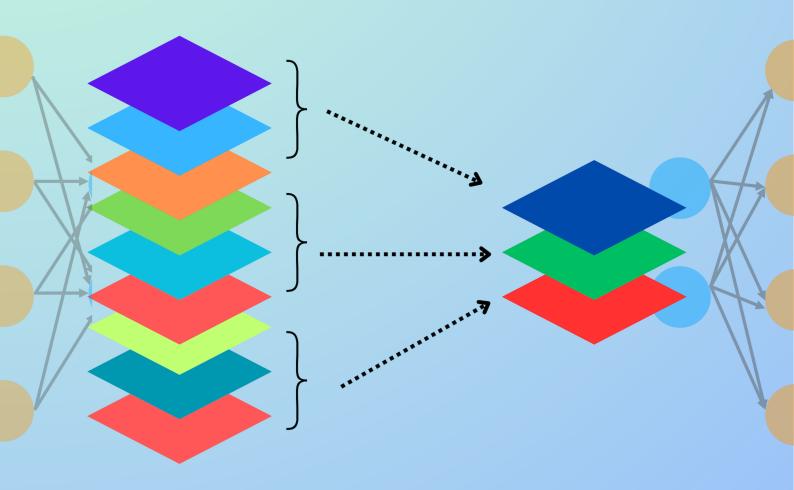
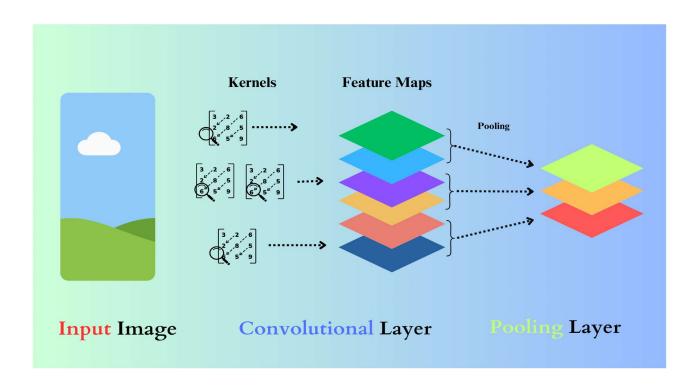
FUNDAMENTALS OF DEEP LEARNING

Pooling in Convolutional Neural Networks



Shivang Kainthola

Pooling in Convolutional Neural Networks



Background

- → Kernels are the **key element** of convolutional neural networks, which are applied on images and extract key features.
- → The output of the application of kernels to images, called the convolution operation are **feature maps**.
- \rightarrow Feature maps are the neural network's understanding of different features within the image.

What is Pooling?

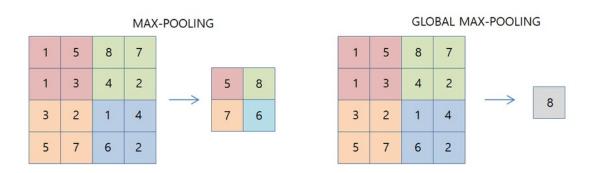
- → Corresponding to how kernels extract features from the image into feature maps, pooling is then done on the generated feature maps.
- → The idea behind pooling is to extract the information from feature maps, and shrink their size, but compiling information within a distinct patch of the feature map, often a rectangular or square region.
- → It is carried out in a pooling layer, and since it works on feature maps, it is placed after the convolution layers.

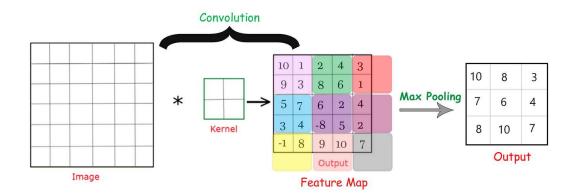
Pooling Operations

- → Pooling is often carried out for **patches or windows of values** of the feature maps, which is rectangular or square.
- → The 'patch' or 'window' is like a kernel, and the values coming within the patch are summarized, by whichever type of pooling method is used. The stride of this filter is often equal to the size of the filter, as no values are overlapped.
- → Overall, pooling focuses on a small window of the feature map and summarizes the information within that region, making it less sensitive to small positional variations.
- $\ensuremath{\longrightarrow}$ There are different methods of pooling that can be used.

1) Max Pooling / Global Max Pooling

- → In Max Pooling, each distinct patch is represented by the maximum of the covered values.
- \rightarrow In Global Max Pooling, the maximum of an entire feature map is considered.
- \rightarrow It is often used at the end of the network for dimensionality reduction before fully-connected layers.

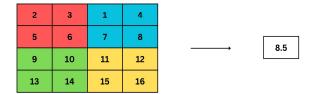


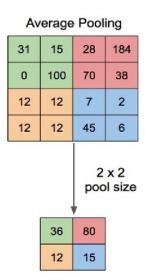


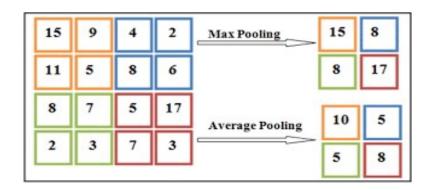
2) Average Pooling / Global Average Pooling

- → In average pooling, each distinct patch of the feature map is represented by the average of its values.
- → While, with global average pooling, average of the entire feature map values are taken.
- → Helpful when trying to extract information about the overall feature distribution.

Global Average Pooling







3) Sum Pooling

- → Instead of taking the average or maximum, sum pooling finds the sum of the values in the distinct patches.
- \rightarrow The values added up might become large, which can be a disadvantage.
- → It is useful when spare feature maps are obtained, which may have many 0 values, in which case sum pooling ensures that the information obtainable only from non-zero values is retained.
- \rightarrow Not used very often.

2	3	1	4
1	7	0	2
9	6	3	4
2	8	1	7

2	3	1	4
1	7	0	2
9	6	3	4
2	8	1	7

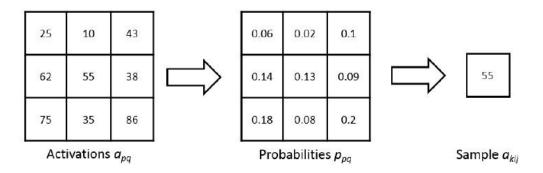
2	3	1	4
1	7	0	2
9	6	3	4
2	8	1	7

2	3	1	4
1	7	0	2
9	6	3	4
2	8	1	7

32 **30** 37 **38**

4) Stochastic Pooling

- → Stochastic pooling differs from other methods like max and average pooling.
- → The network <u>calculates a probability for each element (activation)</u> within the region.
- → Using a multinomial distribution, the network randomly selects a single activation from the region/patch based on the calculated probabilities. The selected activation value becomes the output of the pooling operation for that region.
- → It can potentially reduce overfitting, but due to its random nature, can lead to information loss, and require further hyperparameter tuning.



Thank You!

If you found this article helpful, please do leave a like and comment any feedback you feel I could use.

While I'm working on the next project, I'll be over at:



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