Deep Learning for Computer Vision

Convolutional Neural Networks: An Introduction

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Homework Exercises

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \text{BN}_{\gamma,\beta}(x_i)\}$

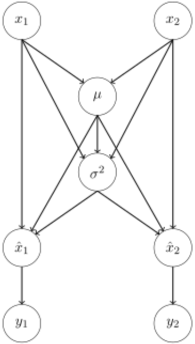
$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \text{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Forward propagation is straight-forward:



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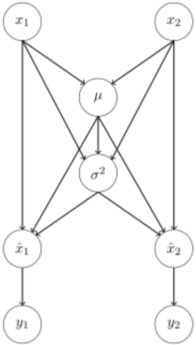
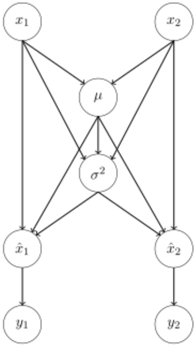


Backprop?

Image Credit: *Aditya Agrawal*

Homework: Backprop in Batch Normalization



$$\frac{\partial L}{\partial \beta} = \frac{\partial L}{\partial y_1}\frac{\partial y_1}{\partial \beta} + \frac{\partial L}{\partial y_2}\frac{\partial y_2}{\partial \beta}$$

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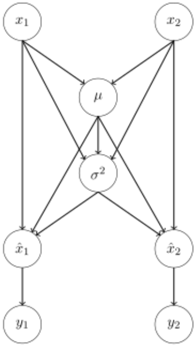

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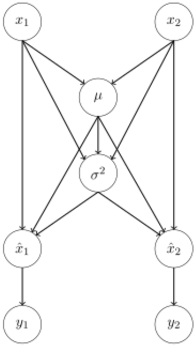

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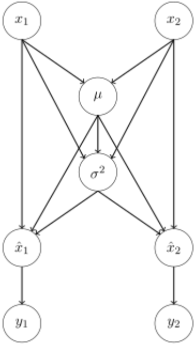

$$\frac{\partial L}{\partial \sigma^2} = \frac{\partial L}{\partial \hat{x}_1}\frac{\partial \hat{x}_1}{\partial \sigma^2} + \frac{\partial L}{\partial \hat{x}_2}\frac{\partial \hat{x}_2}{\partial \sigma^2} = \sum_{i=1}^{2} \frac{\partial L}{\partial \hat{x}_i}\frac{\partial \hat{x}_i}{\partial \sigma^2}$$

$$= \sum_{i=1}^{2} \frac{\partial L}{\partial \hat{x}_i}(x_i - \mu)\frac{-1}{2}(\sigma^2 + \epsilon)^{-3/2}$$

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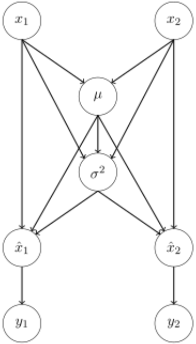
Homework: Backprop in Batch Normalization



$$
\begin{aligned}
\frac{\partial L}{\partial \mu} &= \frac{\partial L}{\partial \hat{x}_1}\frac{\partial \hat{x}_1}{\partial \mu} + \frac{\partial L}{\partial \hat{x}_2}\frac{\partial \hat{x}_2}{\partial \mu} + \frac{\partial L}{\partial \sigma^2}\frac{\partial \sigma^2}{\partial \mu} \\
&= \sum_{i=1}^{2} \frac{\partial L}{\partial \hat{x}_i}\frac{\partial \hat{x}_i}{\partial \mu} + \frac{\partial L}{\partial \sigma^2}\frac{\partial \sigma^2}{\partial \mu} \\
&= \sum_{i=1}^{2} \frac{\partial L}{\partial \hat{x}_i}\frac{-1}{\sqrt{\sigma^2+\epsilon}} + \frac{\partial L}{\partial \sigma^2}\frac{-2(x_1-\mu) \; - 2(x_2-\mu)}{2} \\
&= \sum_{i=1}^{2} \frac{\partial L}{\partial \hat{x}_i}\frac{-1}{\sqrt{\sigma^2+\epsilon}} + \frac{\partial L}{\partial \sigma^2}\frac{\sum_{i=1}^{2} -2(x_i-\mu)}{2}
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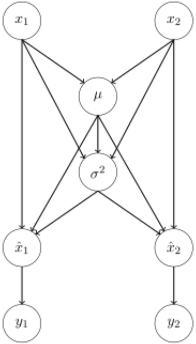

$$\frac{\partial L}{\partial x_1} = \frac{\partial L}{\partial \hat{x}_1}\frac{\partial \hat{x}_1}{\partial x_1} + \frac{\partial L}{\partial \sigma^2}\frac{\partial \sigma^2}{\partial x_1} + \frac{\partial L}{\partial \mu}\frac{\partial \mu}{\partial x_1}$$

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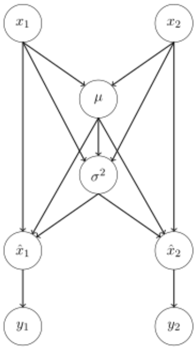

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$$\frac{\partial L}{\partial x_i} = \frac{\partial L}{\partial \hat{x}_i}\frac{1}{\sqrt{\sigma^2+\epsilon}} + \frac{\partial L}{\partial \sigma^2}\frac{2(x_i-\mu)}{m} + \frac{\partial L}{\partial \mu}\frac{1}{m}$$

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Acknowledgements

- This lecture's content is largely based on **Lecture 11** of **CS7015** course taught by Mitesh Khapra at IIT Madras

Review: Convolution Operation

- **Convolution** is a mathematical way of combining two signals to form a third signal

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- **Convolution** is a mathematical way of combining two signals to form a third signal
- As we saw in Part 5 of Week 1, it is one of the most important techniques in signal processing
- In case of 2D data (grayscale images), the convolution operation between a filter $W^{k \times k}$ and an image $X^{N_1 \times N_2}$ can be expressed as:

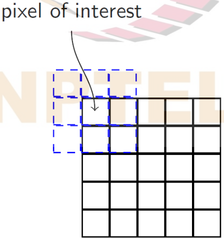
$$Y(i,j) = \sum_{u=-k}^{k} \sum_{v=-k}^{k} W(u,v) X(i-u, j-v)$$

Convolution Operation

- More generally, given a $K_1 \times K_2$ filter W, we can write it as:

$$Y(i,j) = \sum_{a=\lfloor -\frac{K_1}{2} \rfloor}^{\lfloor \frac{K_1}{2} \rfloor} \sum_{b=\lfloor -\frac{K_2}{2} \rfloor}^{\lfloor -\frac{K_2}{2} \rfloor} X(i-a, j-b) W\left(\frac{K_1}{2} + a, \frac{K_2}{2} + b\right)$$

- This allows kernel to be **centered** on pixel of interest

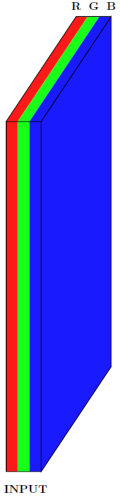


Pause and Ponder

- In the 1D case, we slide a one-dimensional filter over a one-dimensional input
- In the 2D case, we slide a two-dimensional filter over a two-dimensional input
- What would happen in the 3D case where your images are in color (RGB)?

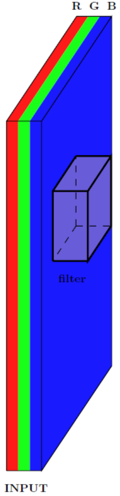
Convolution Operation

- What would a 3D filter look like?



Convolution Operation

- What would a 3D filter look like?
- It will be in 3D too and we will refer to it as a volume



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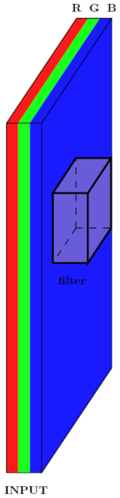

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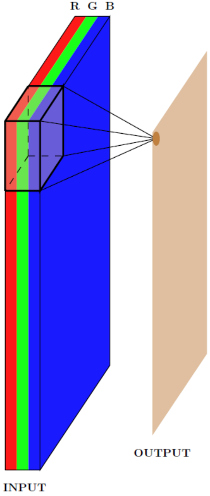

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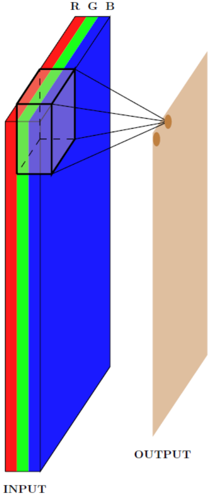

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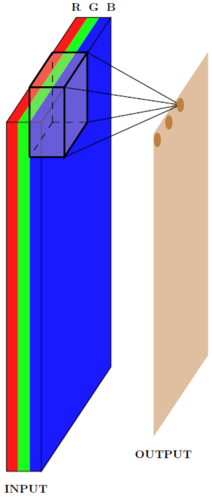

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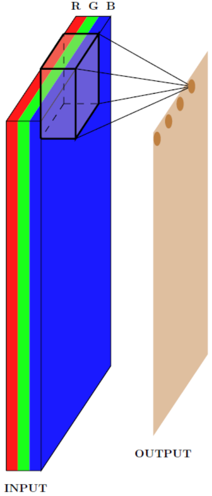

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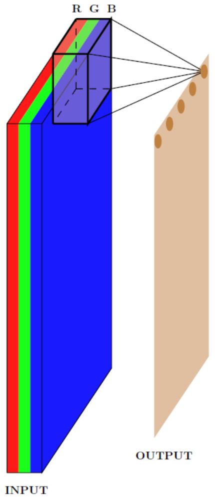

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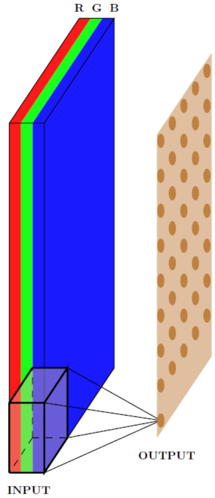

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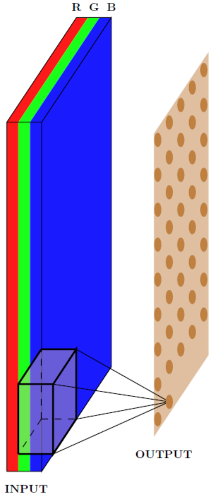

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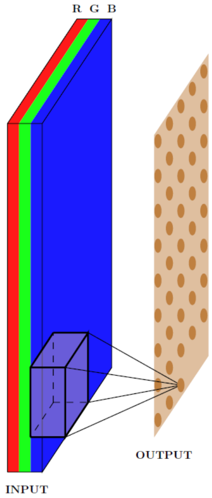

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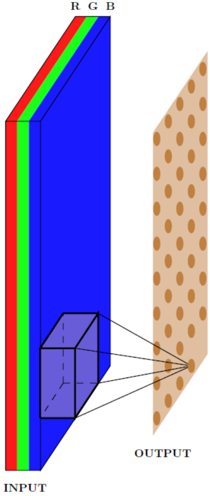

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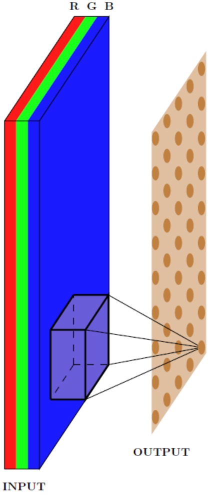
- We assume that the filter always extends to the depth of the image
- In effect, we are doing a 2D convolution operation on a 3D input (because the filter moves along the height and the width but not along the depth)



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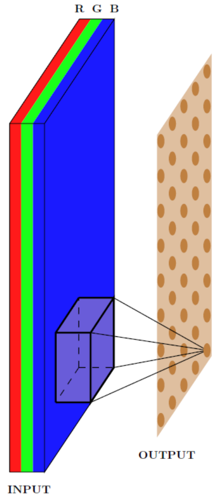

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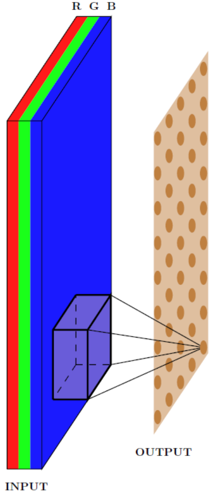
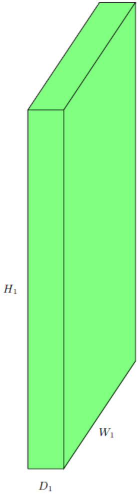
- As a result the output will be 2D (only width and height, no depth)
- We can apply multiple filters to get multiple feature maps



Convolution: Understanding the (Hyper)Parameters

- Input dimensions: Width (W_1) × Height (H_1) × Depth (D_1)



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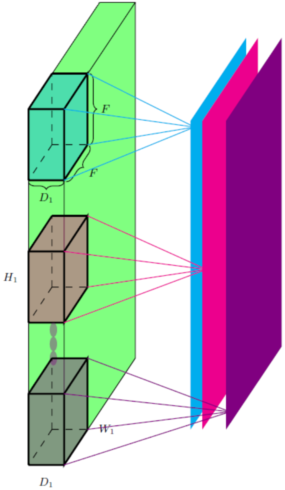
- Input dimensions: Width $(W_1) \times$ Height $(H_1) \times$ Depth (D_1)
- Spatial extent (F) of each filter (the depth of each filter is same as the depth of input)
- Output dimensions is $W_2 \times H_2 \times D_2$ (we will soon see a formula for computing W_2, H_2 and D_2)



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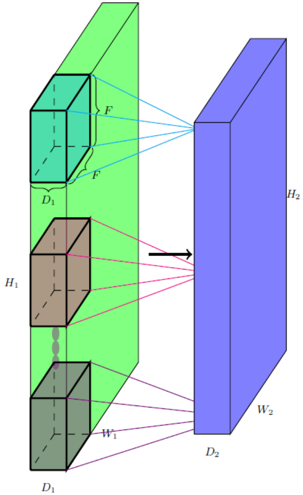
- Stride (S) (explained in following slides)
- Number of filters K



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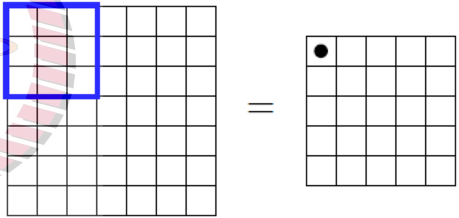

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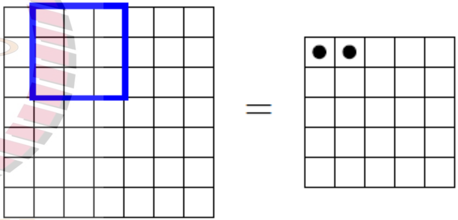

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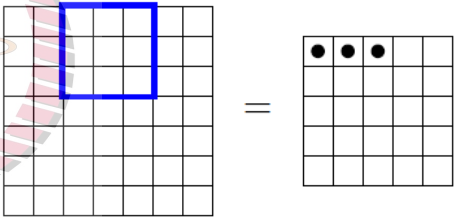

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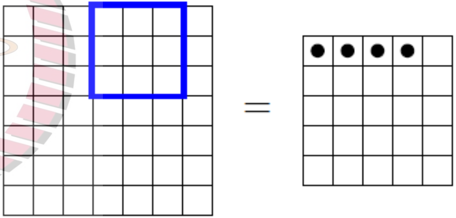

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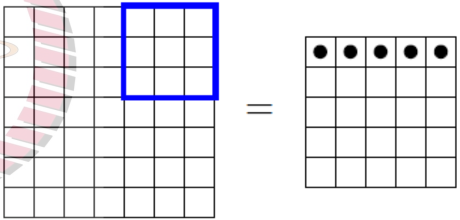

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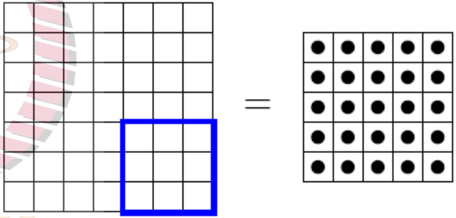
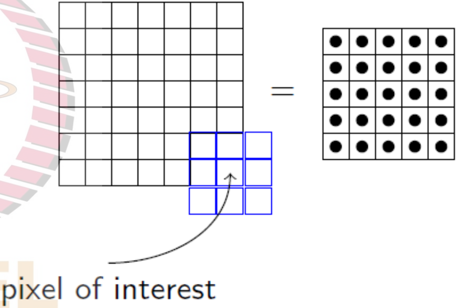


Convolution: Understanding the (Hyper)Parameters

- Let us compute dimensions (W_2, H_2) of output
- Recall that we can't place the kernel at corners as it will cross the input boundary



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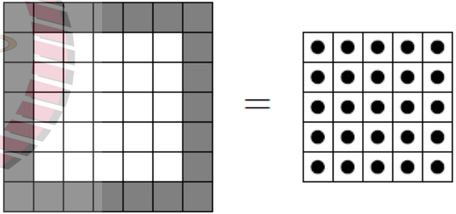
- This is true for all shaded points (the kernel crosses the input boundary)



Convolution: Understanding the (Hyper)Parameters

- Let us compute dimensions (W_2, H_2) of output
- Recall that we can't place the kernel at corners as it will cross the input boundary
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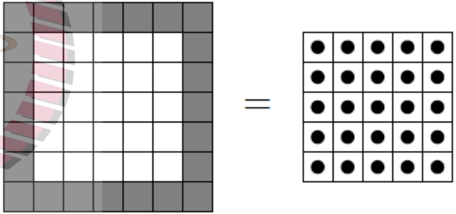
- This results in an output which is of smaller dimensions than input



Convolution: Understanding the (Hyper)Parameters

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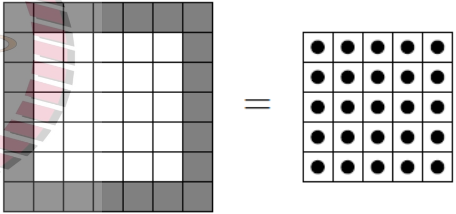

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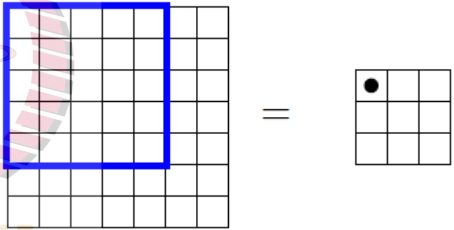

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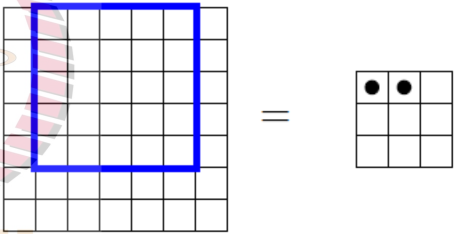

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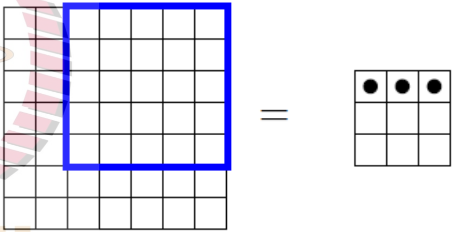

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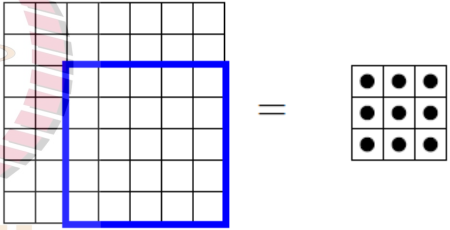

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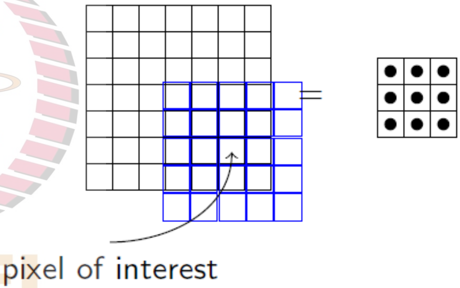

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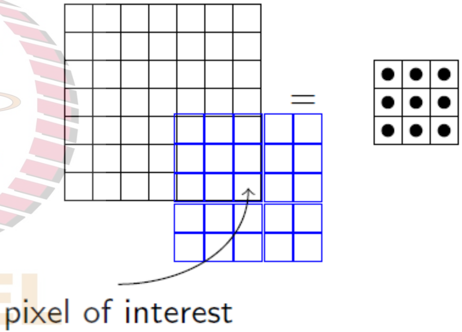

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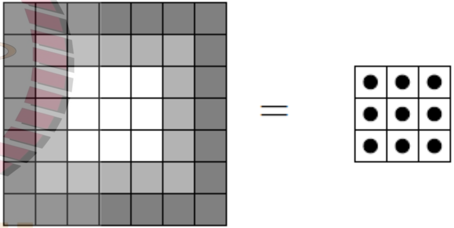

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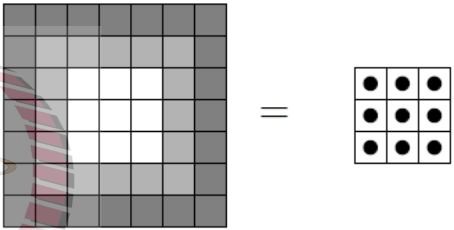

In general,

$$W_2 = W_1 - F + 1$$
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We will refine this formula further

Convolution: Understanding the (Hyper)Parameters

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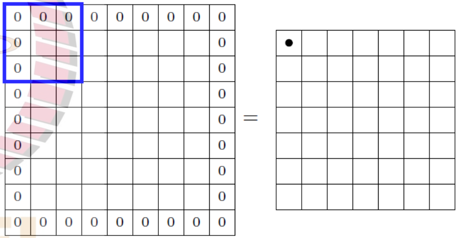

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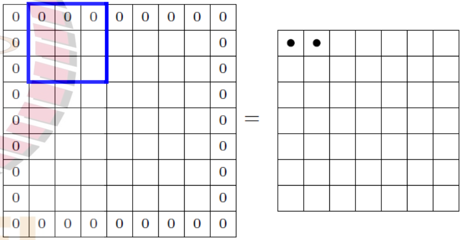

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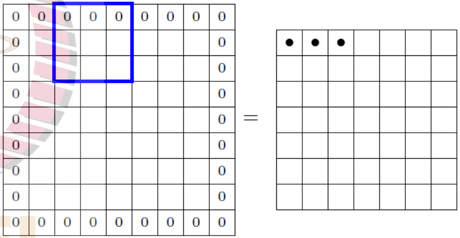

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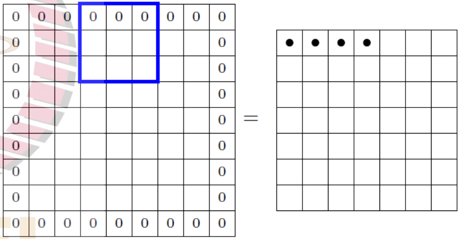

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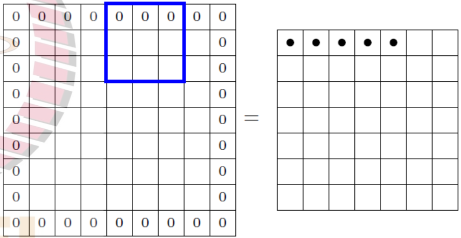

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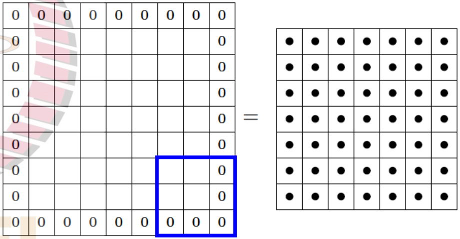

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We now have:

$$W_2 = W_1 - F + 2P + 1$$
$$H_2 = H_1 - F + 2P + 1$$

We will refine this formula further

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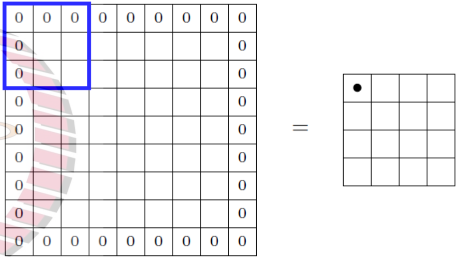

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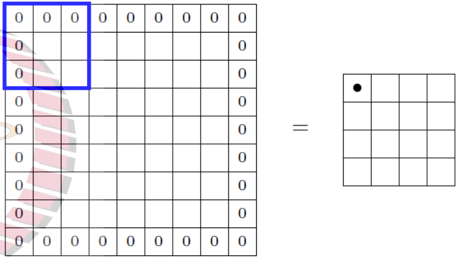

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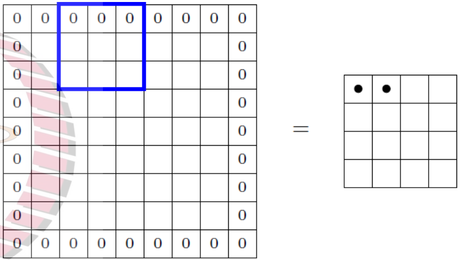

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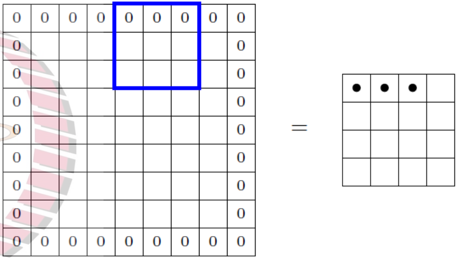

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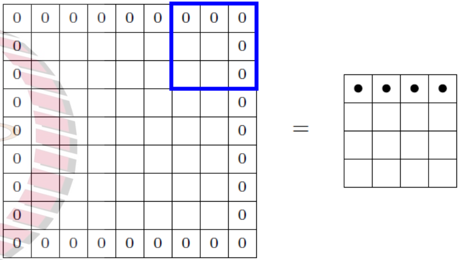

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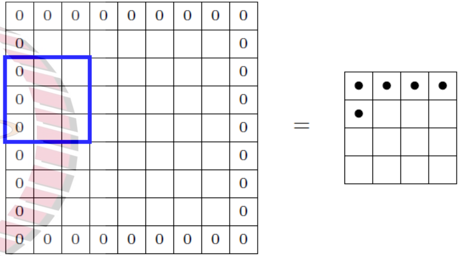

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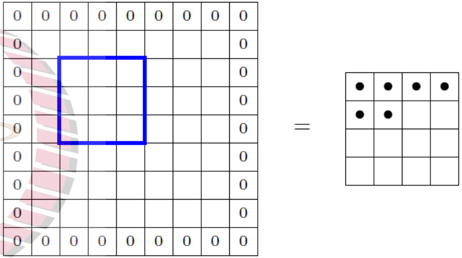

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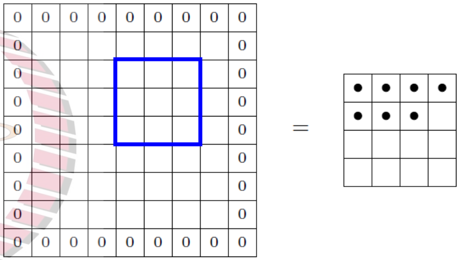

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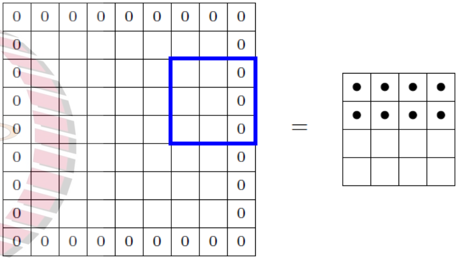

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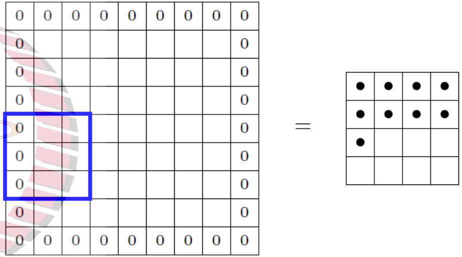

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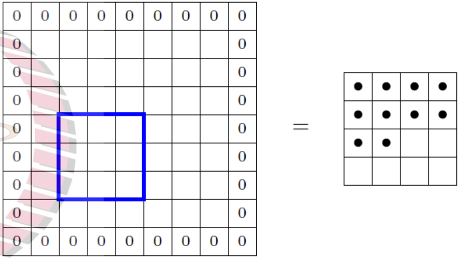

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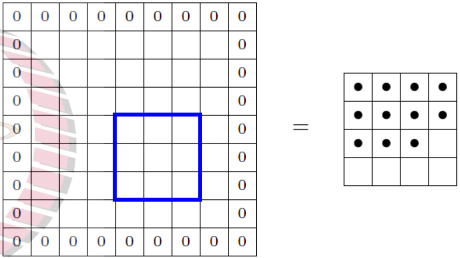

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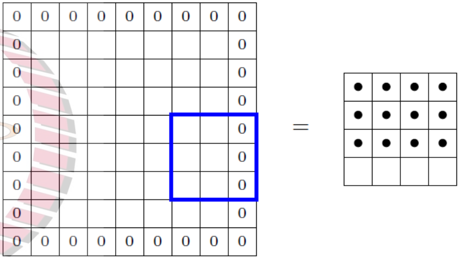

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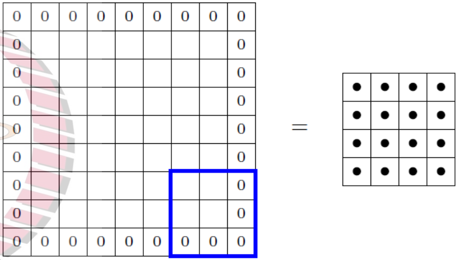

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So our final formula should mostly look like,

$$W_2 = \frac{W_1 - F + 2P}{S} + 1$$

$$H_2 = \frac{H_1 - F + 2P}{S} + 1$$

Not done yet, we will refine this formula further!

Convolution: Understanding the (Hyper)Parameters

- Finally, coming to depth of output

Convolution: Understanding the (Hyper)Parameters

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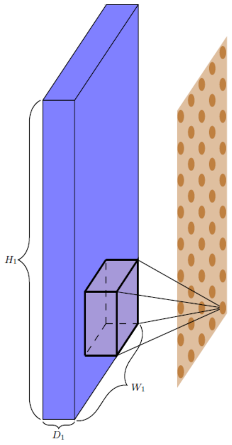
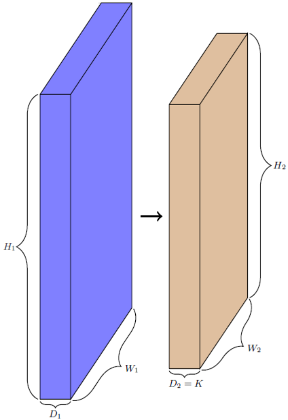
- Each filter gives us one 2D output



Convolution: Understanding the (Hyper)Parameters

- Finally, coming to depth of output
- Each filter gives us one 2D output
- K filters will give us K such 2D outputs
- We can think of resulting output as $K \times W_2 \times H_2$ volume
- Thus $D_2 = K$



$$W_2 = \frac{W_1 - F + 2P}{S} + 1$$

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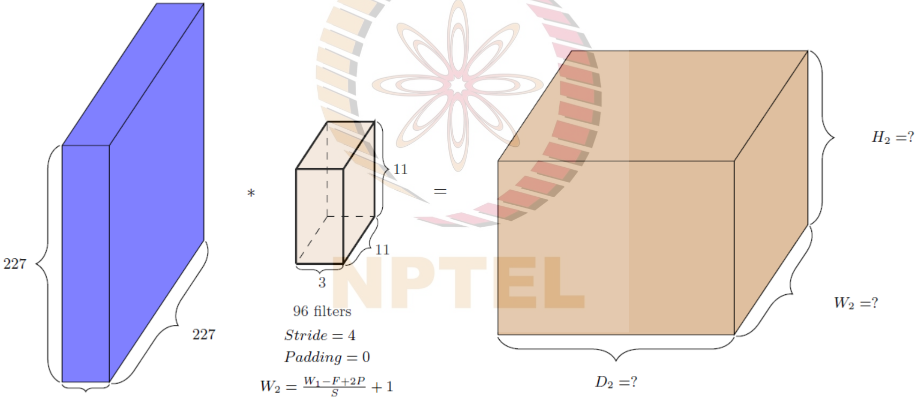
$$D_2 = K$$

Quick Exercise

Work out output dimensions for the setting below!



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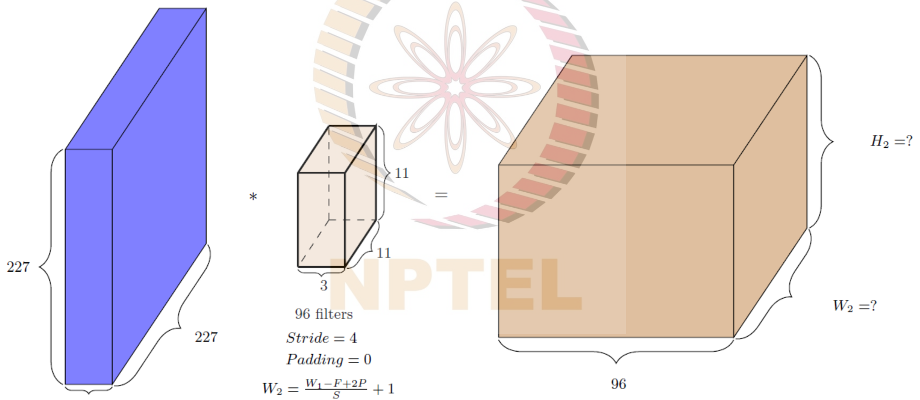

$Stride = 4$

$Padding = 0$

$W_2 = \frac{W_1 - F + 2P}{S} + 1$

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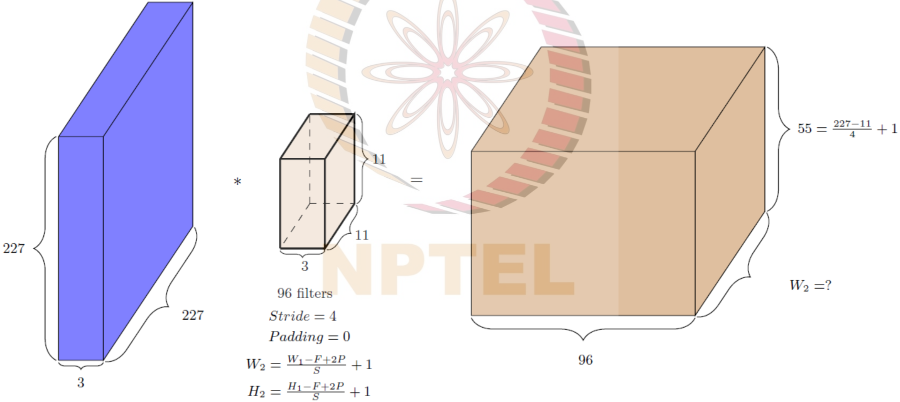

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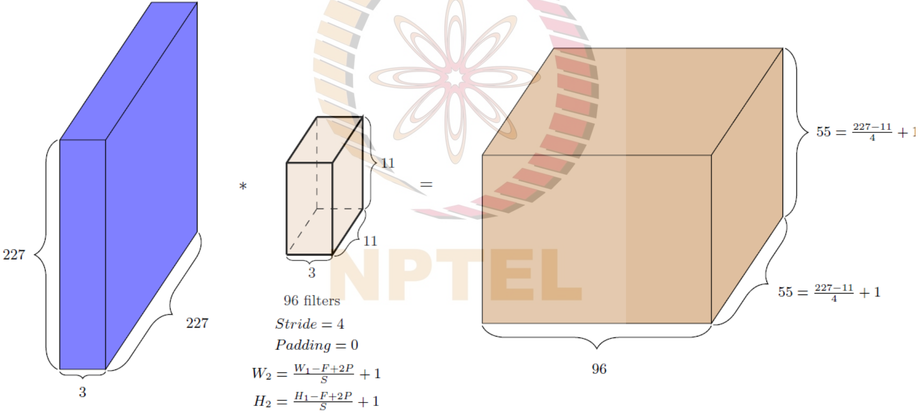
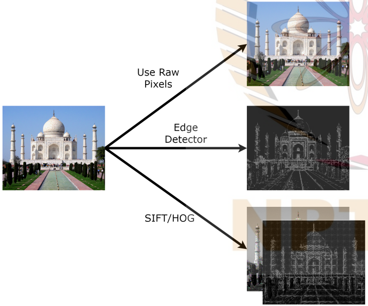


Pause and Ponder

- What is the connection between convolution and neural networks? Won't feedforward neural networks do?
- We will try to understand this by considering the task of "image classification"

Traditional Machine Learning for Vision

- Traditional ML-based computer vision solutions involve static feature engineering from images (e.g. recall SIFT, LBP, HoG, etc)
- Though effective, static feature engineering was a bottleneck of pre-DL vision solutions



Static Feature Engineering (No Learning)

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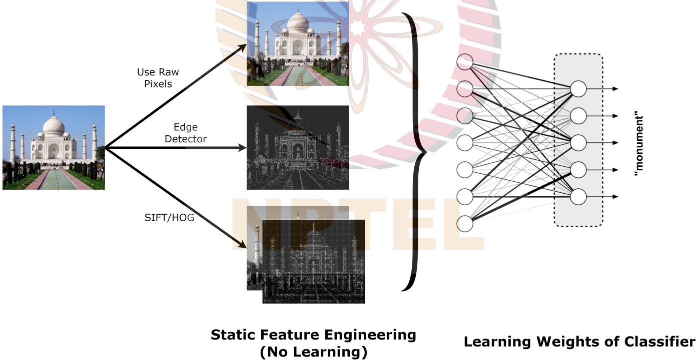
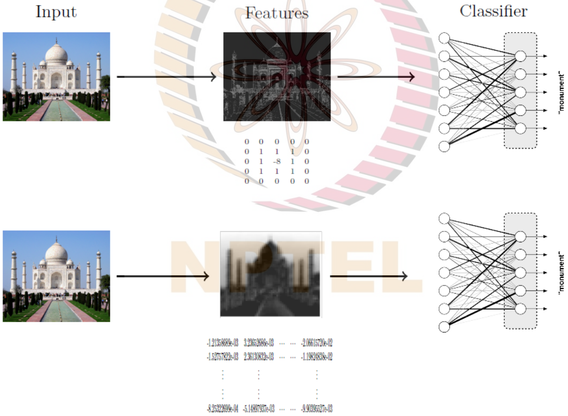


Beyond Static Feature Engineering

- Instead of using handcrafted kernels such as edge detectors can we **learn meaningful kernels/filters** in addition to learning the weights of the classifier?



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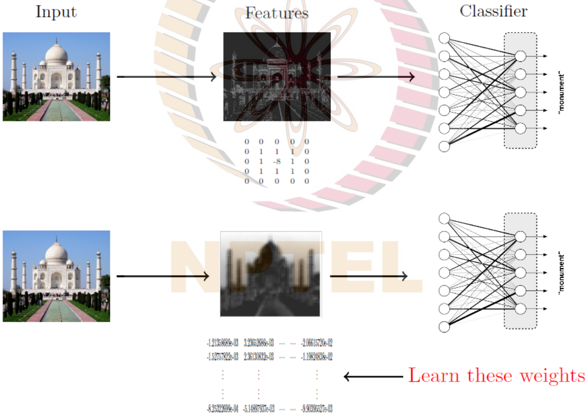
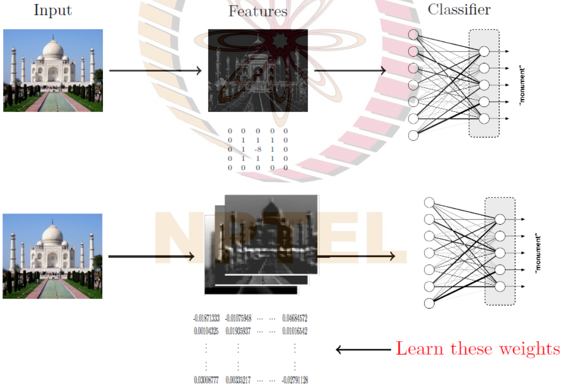


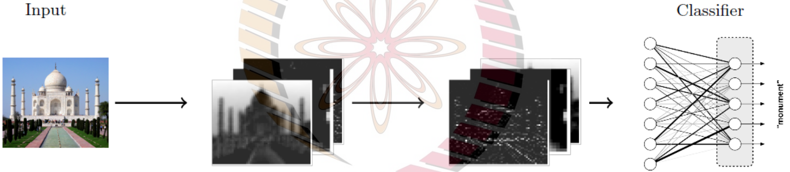
Beyond Static Feature Engineering

- **Even better:** Instead of using handcrafted kernels such as edge detectors can we **learn** **multiple meaningful kernels/filters** in addition to learning the weights of the classifier?



Beyond Static Feature Engineering

- Can we learn multiple layers of meaningful kernels/filters in addition to learning the weights of the classifier?



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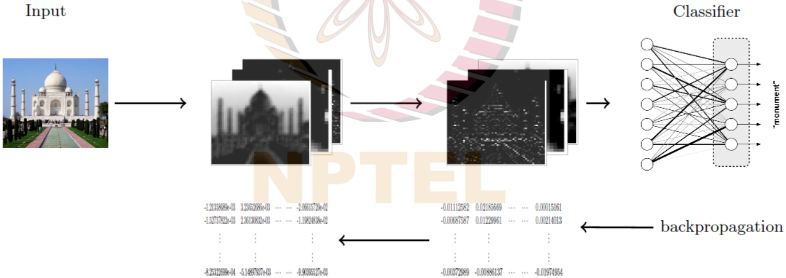
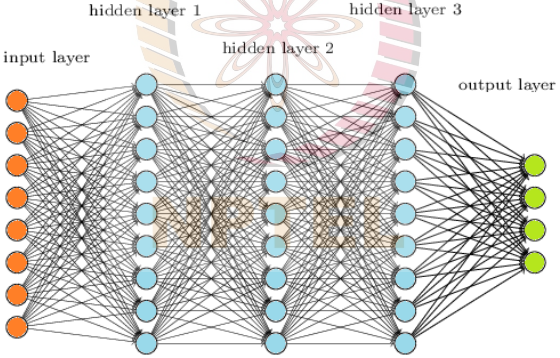


- Such a network is called a **Convolutional Neural Network!**

Pause and Ponder

- Learning kernels/filters by treating them as parameters definitely is interesting
- But why not directly use flattened images with fully connected neural networks (or feedforward neural networks, FNNs) instead?



Challenges of Applying FNNs to Images

MNIST Dataset

On a reasonably *simple* dataset like MNIST, we can get about 2% error (or even better) using FNNs, but

- Ignores spatial (2-D) structure of input images – unroll each 28×28 image into a 784-D vector
  - Pixels that are spatially separate are treated the same way as pixels that are adjacent
- No obvious way for networks to learn same features (e.g. edges) at different places in the input image
- Can get computationally expensive for large images
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How do Convolutional Neural Networks Solve these Challenges?

- **Local receptive fields**, in which hidden units are connected to local patches of the layer below, serve two purposes:
  - Capture local spatial relationships in pixels (which would not be captured by FNNs)
  - Greatly reduces number of parameters in the model
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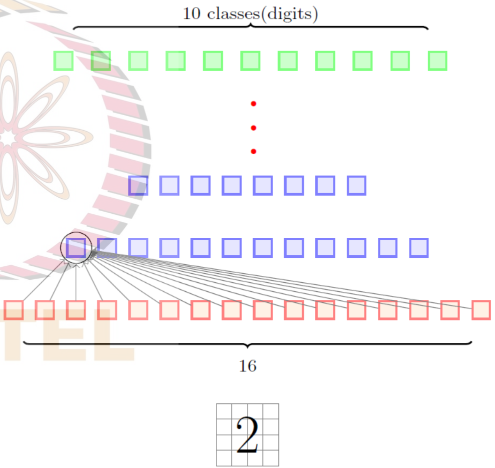
- **Pooling** which condenses information from previous layer, serves two purposes:
  - Aggregates information, especially minor variations
  - Reduces size of output of a previous layer, which reduces number of computations in later layers

Credit: Steve Renals

Local Receptive Fields

- This is what a regular feedforward neural network will look like
- There are many dense connections here



Local Receptive Fields

- This is what a regular feedforward neural network will look like
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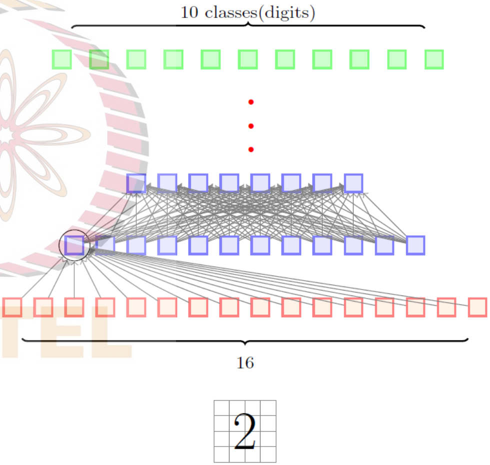
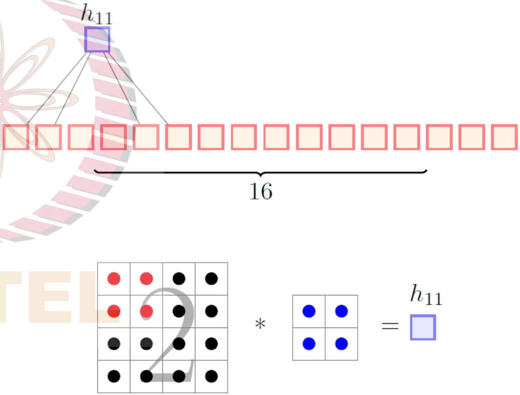
- All 16 input neurons are contributing to computation of h_{11}
- Let us contrast this to what happens in case of convolution



Local Receptive Fields

- Only a few local neurons participate in computation of h_{11}
- E.g. only pixels 1, 2, 5, 6 contribute to h_{11}



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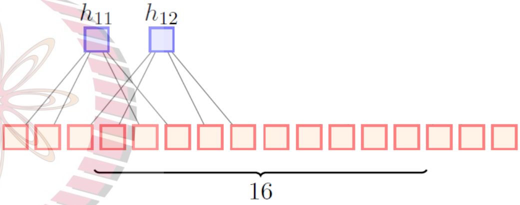

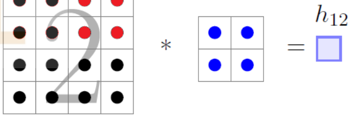

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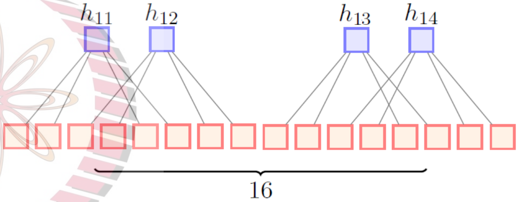

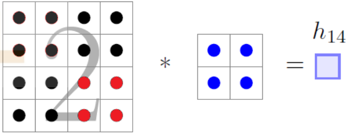

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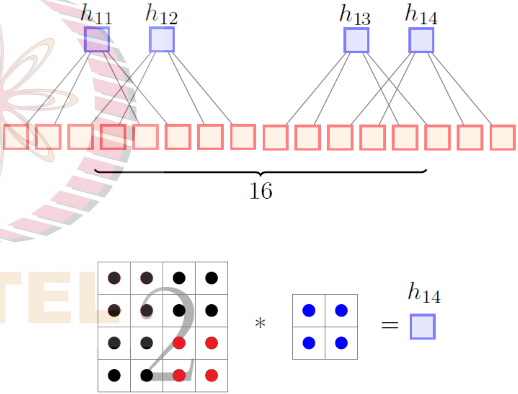

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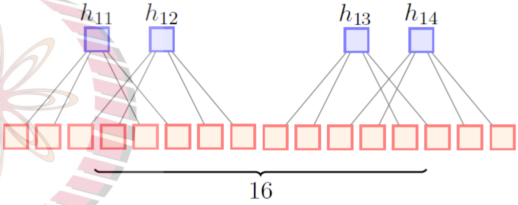
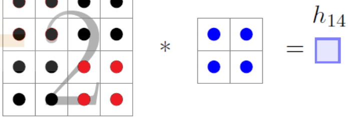
- This **sparse connectivity** reduces the number of parameters in the model
- We are taking advantage of the structure of the image (interactions between neighboring pixels are interesting in images)





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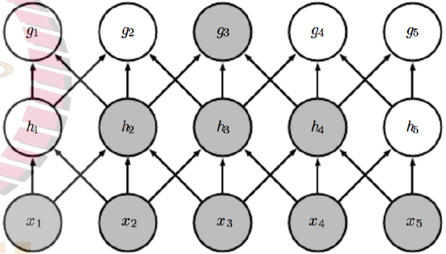

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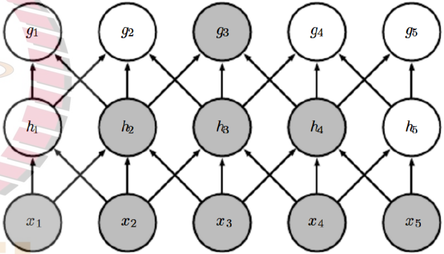

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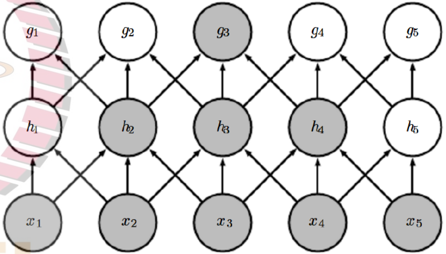
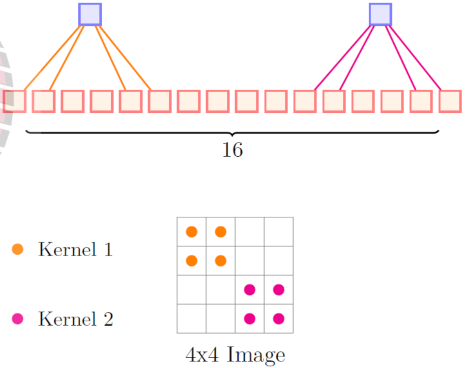
- Well, not really
- The two highlighted neurons ($x_1 x_5$) do not interact in layer 1
- But they indirectly contribute to the computation of g_3 and hence interact indirectly



Weight Sharing

- Consider the following network; do we want the kernel weights to be different for different parts of the image?



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- Consider the following network; do we want the kernel weights to be different for different parts of the image?
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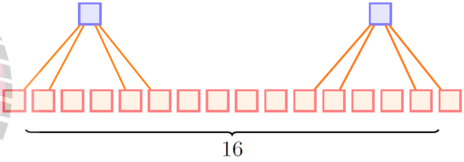

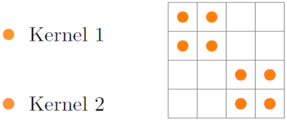

4x4 Image

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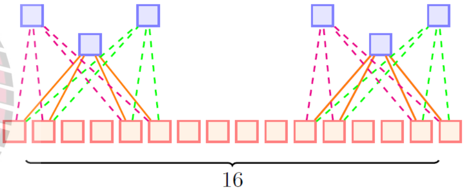
- We can have as many different kernels to capture different kinds of artifacts, but each one is intended to give the same response on all parts of the image
- This is called **weight sharing**



Convolutional Neural Network

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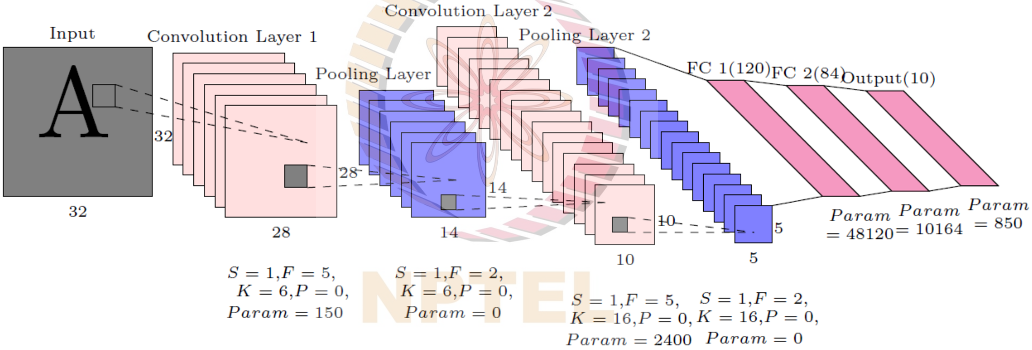

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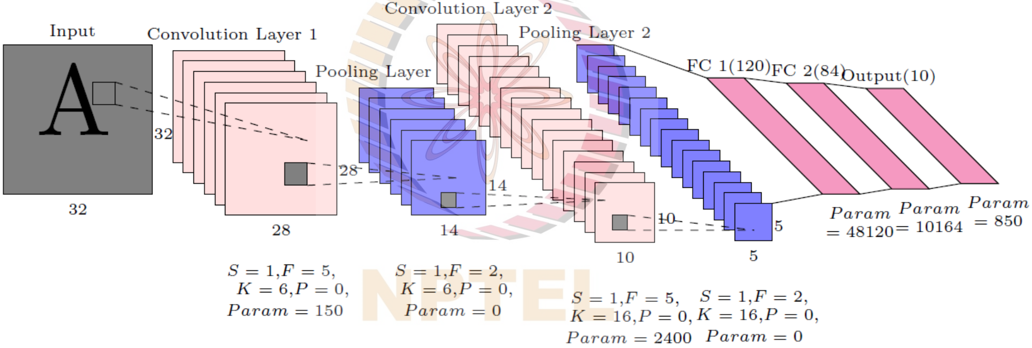
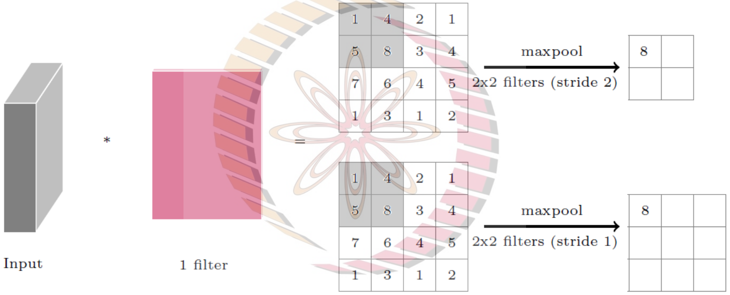


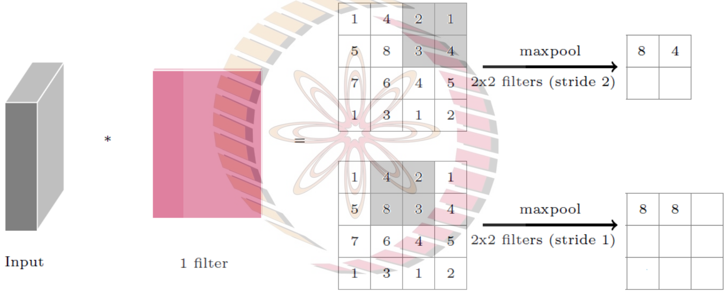
- It has alternate convolution and pooling layers
- What do pooling layers do?

Pooling Layer



- **Pooling** is a parameter-free down sampling operation

Pooling Layer



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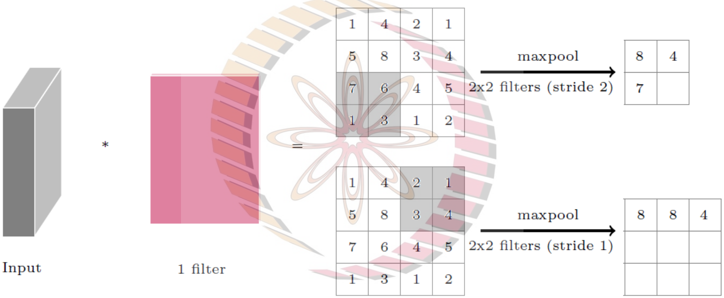

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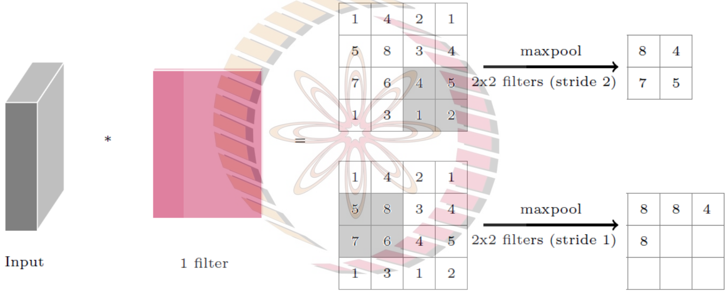

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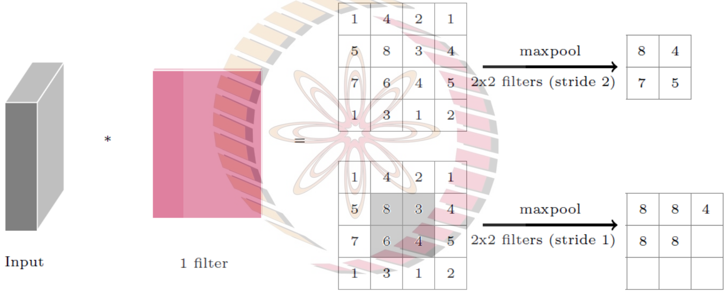

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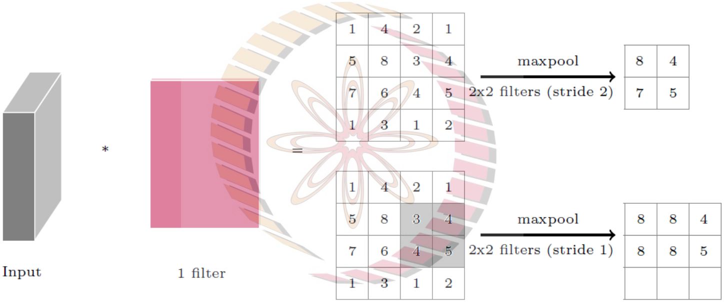

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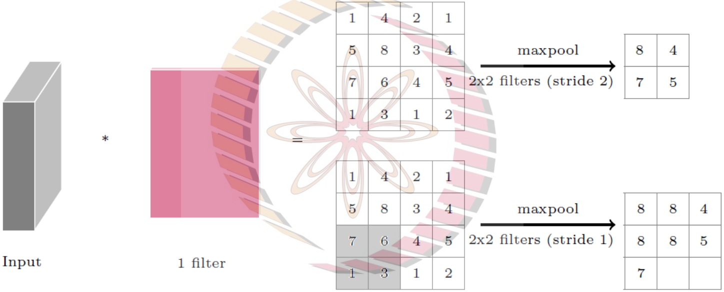

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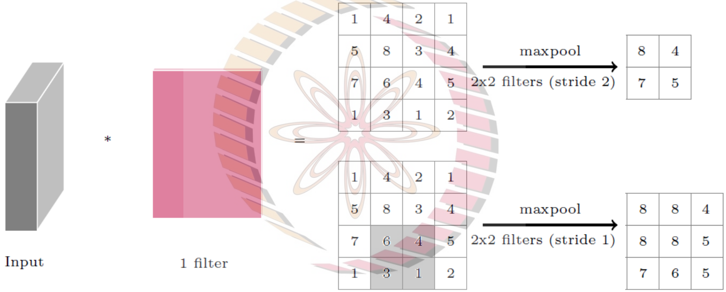

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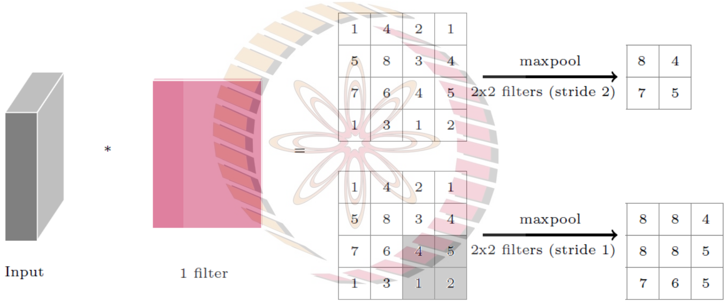

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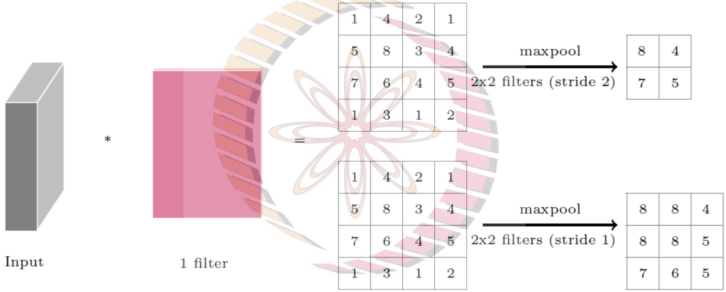

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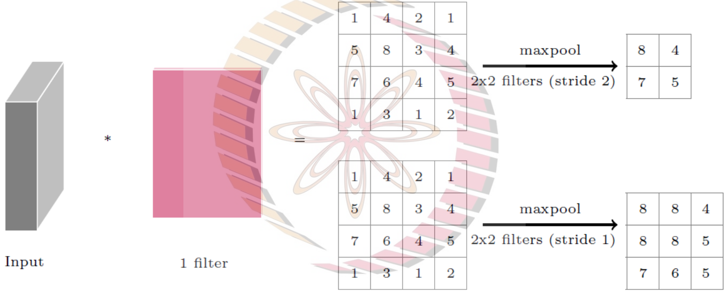

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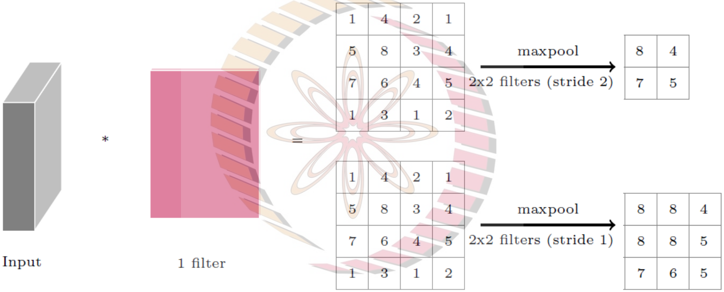

- **Pooling** is a parameter-free down sampling operation
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- Other notable mentions: Mixed Pooling (combines max and average pooling), Spatial Pyramid Pooling, Spectral Pooling - we'll see some of these in later lectures

Other Variants of Convolution: Dilated Convolution

- Introduces another parameter to convolutional layer called **dilation rate**

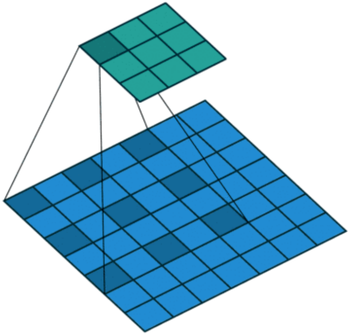

Image Credit: Vincent Dumoulin

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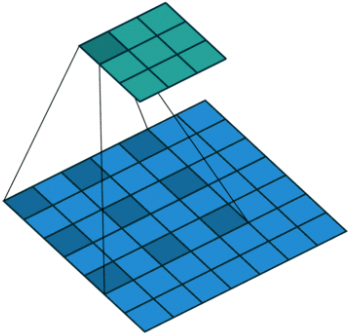

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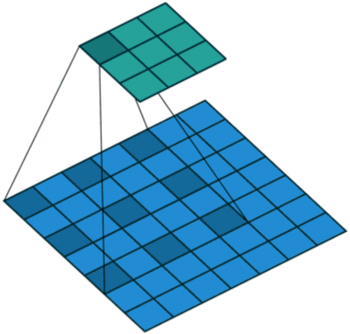

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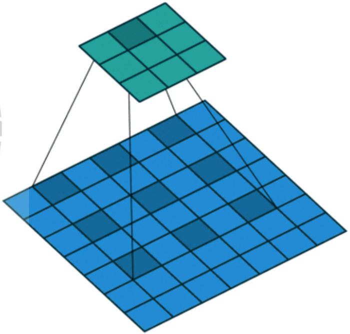

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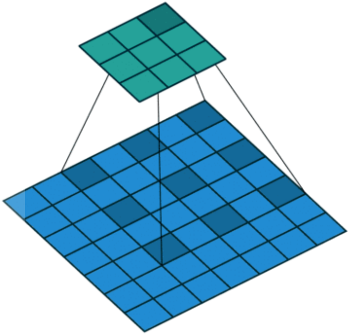

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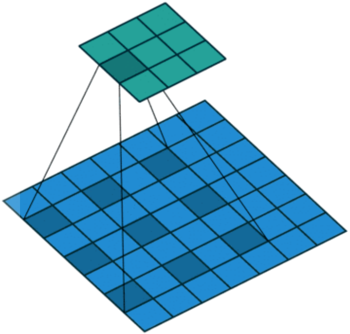

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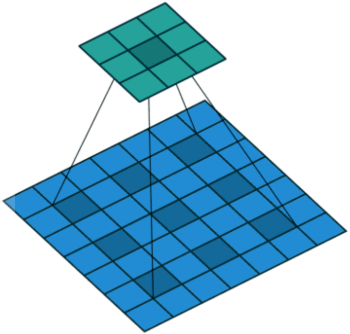

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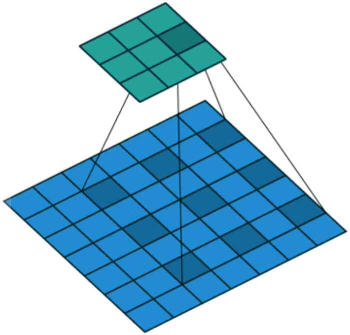

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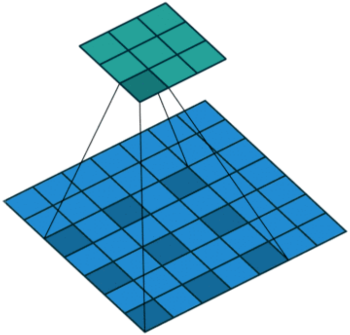

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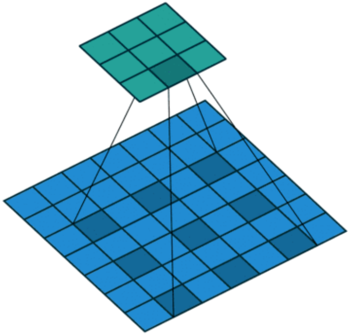

Image Credit: Vincent Dumoulin

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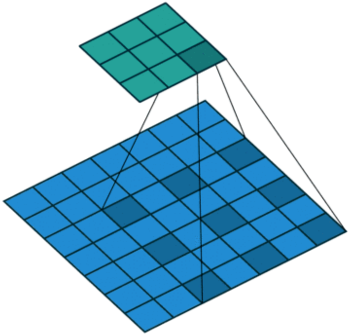

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Other Variants of Convolution: Dilated Convolution

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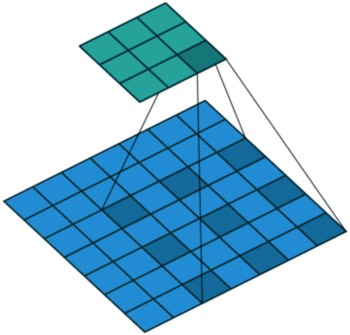
- Figure shows 3×3 kernel with dilation rate 2
- Notice that dilated rate 1 is standard convolution



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- Notice that dilated rate 1 is standard convolution
- A subtle difference between dilated convolution and standard convolution with stride > 1, what is it?

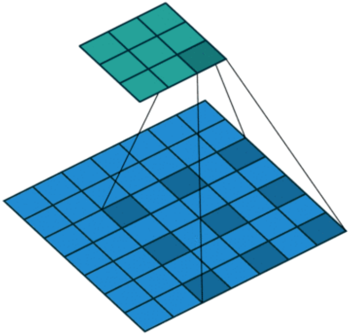

Image Credit: Vincent Dumoulin

Other Variants of Convolution: Transpose Convolution

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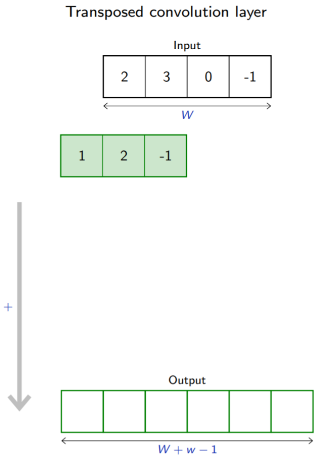

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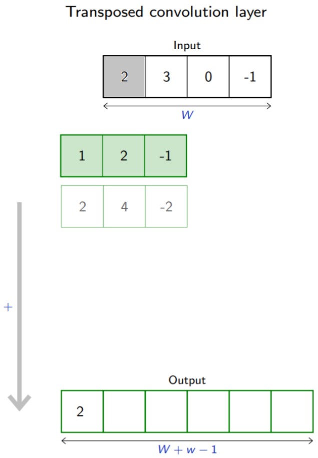

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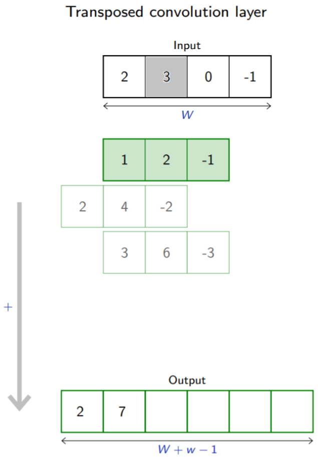

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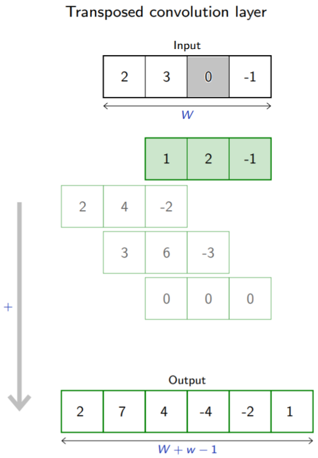

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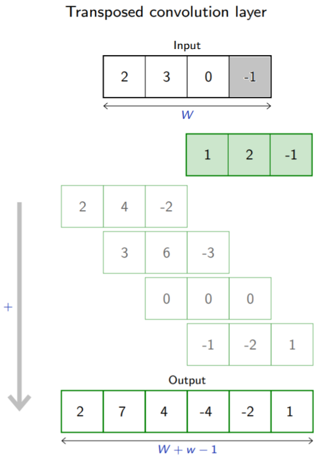

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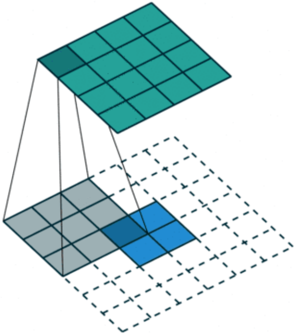
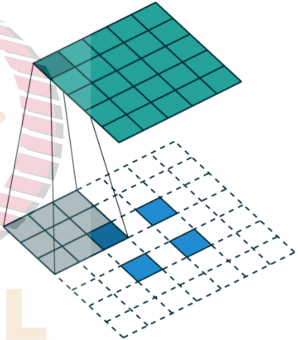


Upsampling 2 × 2 input to a 4 × 4 output



Upsampling 2 × 2 input to a 5 × 5 output

GIF Credit: *Vincent Dumoulin*

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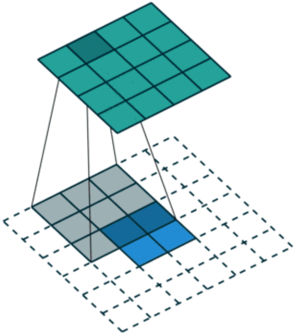

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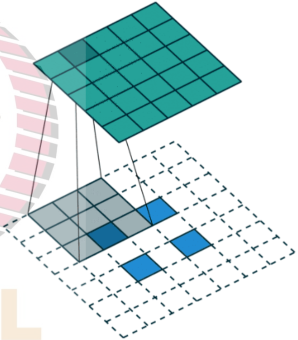

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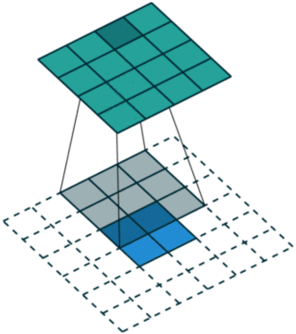

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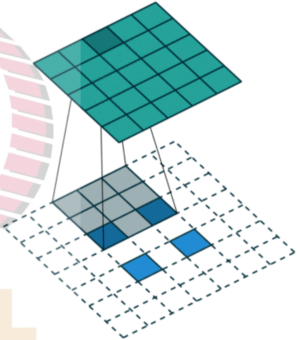

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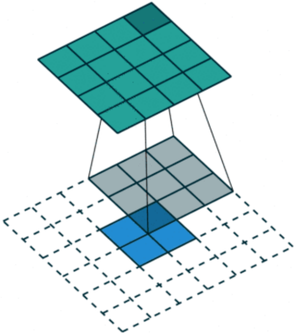

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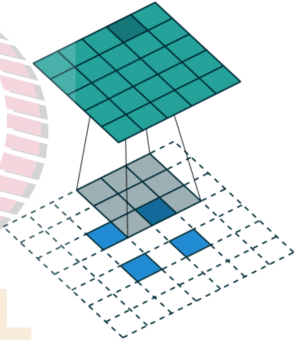

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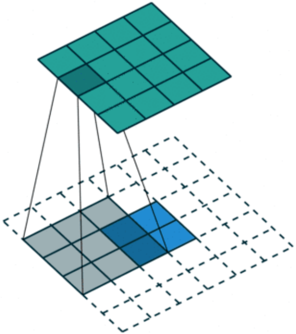

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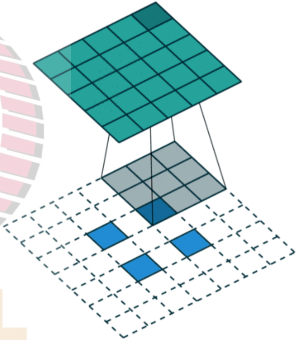

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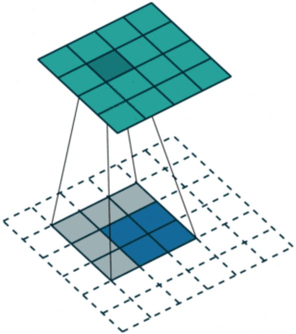

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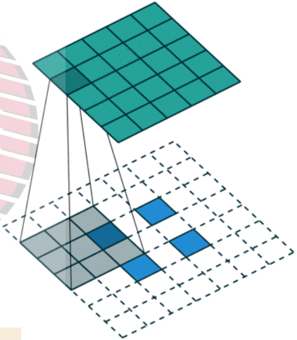

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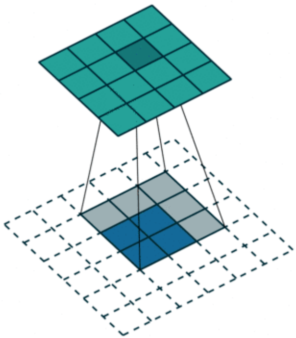

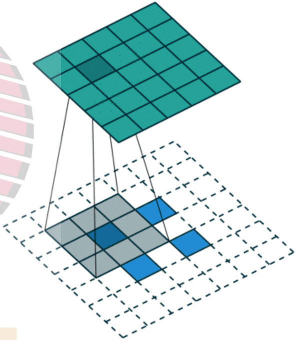

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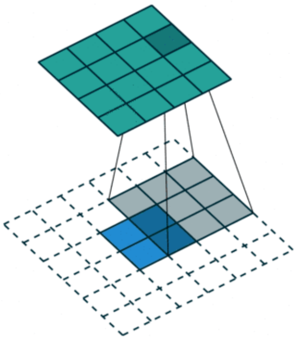

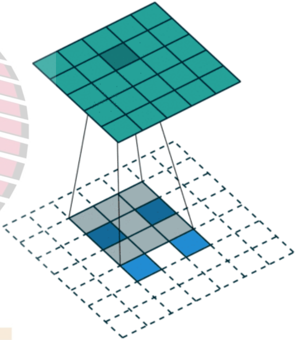

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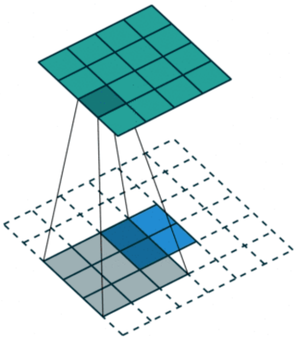

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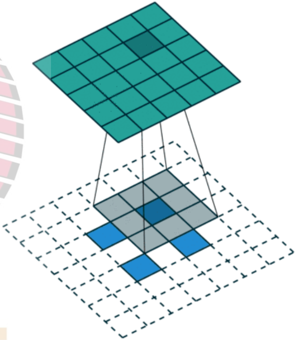

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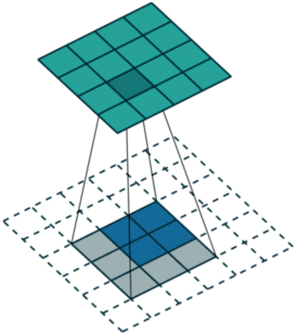

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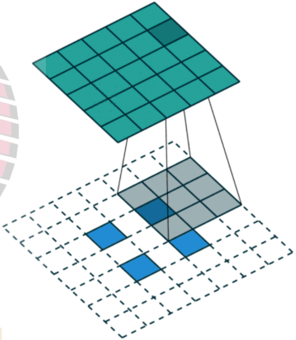

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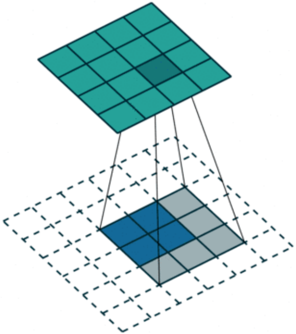

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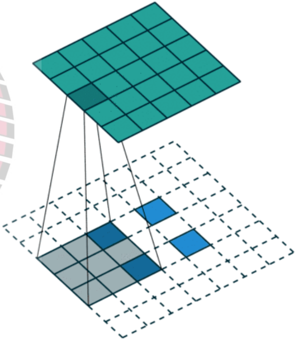

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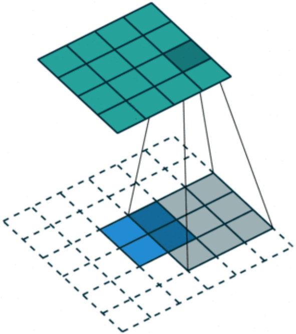

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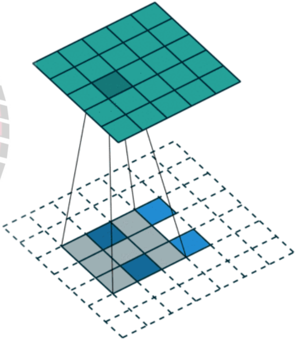

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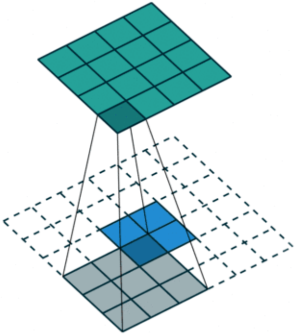

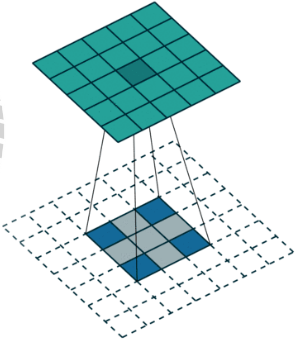

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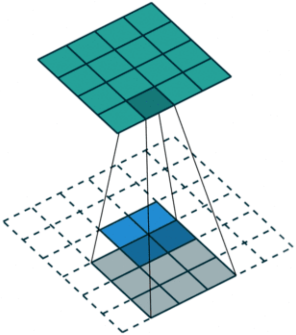

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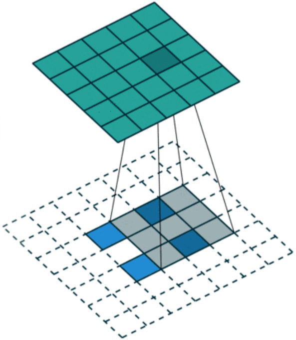

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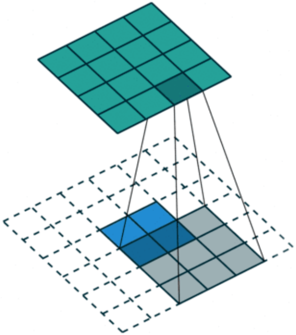

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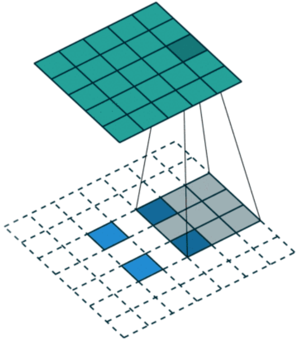

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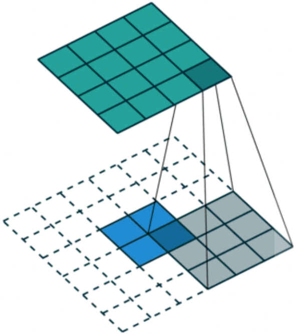

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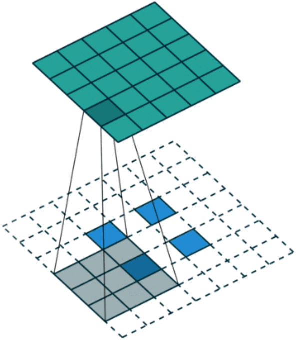

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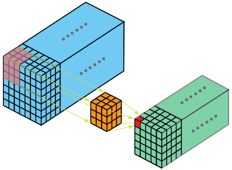
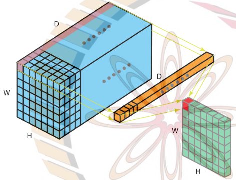
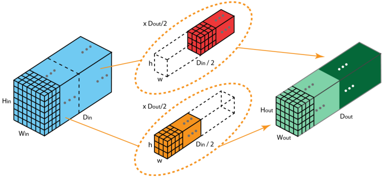


3D Convolution



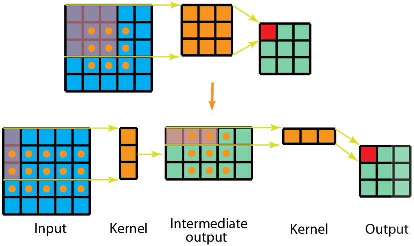
1 × 1 **Convolution**
Pointwise Convolution



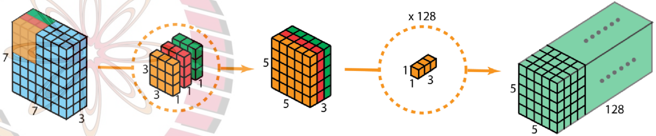
Grouped Convolution

Credit: Illarion Khlestov, Chi-Feng Wang

Other Variants of Convolution



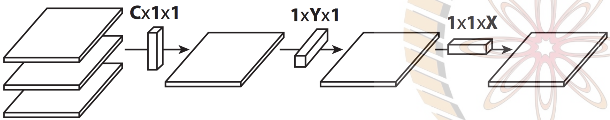
Spatial Separable Convolution



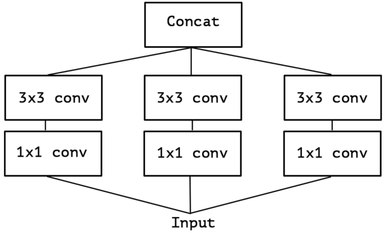
Depthwise Separable Convolution

Credit: Chi-Feng Wang

Other Variants of Convolutions



Flattened Convolutions



Spatial and Cross-Channel Convolutions

Credit: Illarion Khlestov

Homework

Readings

- For an interactive illustration of the convolution operation, visit `https://setosa.io/ev/image-kernels/`
- Read more about deconvolution operation at Distill
- Other good resources:
  - Deep Learning Book: Chapter 9 - Convolutional Networks
  - Stanford CS231n Notes

Questions

- Given a $32 \times 32 \times 3$ image and 6 filters of size $5 \times 5 \times 3$, what will be the dimension of the output volume when a stride of 1 and a padding of 0 is considered?
- Is the max-pooling layer differentiable? How to backpropagate across it?

References

[1] David Lowe. “Distinctive Image Features from Scale-Invariant Keypoints”. In: *International Journal of Computer Vision* 60 (Nov. 2004), pp. 91–110.

[2] Navneet Dalal and Bill Triggs. “Histograms of oriented gradients for human detection”. In: *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’05)* 1 (2005), 886–893 vol. 1.

[3] Svetlana Lazebnik, Cordelia Schmid, and J. Ponce. “Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories”. In: vol. 2. Feb. 2006, pp. 2169 –2178.

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[6] Oren Rippel, Jasper Snoek, and Ryan P. Adams. “Spectral Representations for Convolutional Neural Networks”. In: *NIPS*. 2015.

[7] Nal Kalchbrenner et al. “Neural Machine Translation in Linear Time”. In: *ArXiv* abs/1610.10099 (2016).