Deep Neural Networks
Convolutional Networks III

Bhiksha Raj
Fall 2023
Outline

• Quick recap
• Back propagation through a CNN
  • Modifications: Transposition, scaling, rotation and deformation invariance
• Segmentation and localization
• Some success stories
• Some advanced architectures
  – Resnet
  – Densenet
Story so far

- Pattern classification tasks such as “does this picture contain a cat”, or “does this recording include HELLO” are best performed by scanning for the target pattern.

- Scanning an input with a network and combining the outcomes is equivalent to scanning with individual neurons hierarchically:
  - First level neurons scan the input
  - Higher-level neurons scan the “maps” formed by lower-level neurons
  - A final “decision” unit or layer makes the final decision
  - Deformations in the input can be handled by “pooling”

- For 2-D (or higher-dimensional) scans, the structure is called a convnet
- For 1-D scan along time, it is called a Time-delay neural network
Recap: The general architecture of a convolutional neural network

- A convolutional neural network comprises of “convolutional” and optional “pooling” layers
- Followed by an MLP with one or more layers
Recap: A convolutional layer

- The computation of each output map has two stages
  - Computing an affine map, by convolution of a filter (representing a pattern of weights) over maps in the previous layer
    - Each affine map has, associated with it, a learnable filter
  - An activation that operates point-wise on the output of the convolution
Recap: A convolutional layer

- The computation of each output map has two stages
  - Computing an *affine* map, by *convolution* of a *filter* (representing a pattern of weights) over maps in the previous layer
    - Each affine map has, associated with it, a *learnable filter*
  - An *activation* that operates *point-wise* on the output of the convolution
Recap: Convolution

- Each affine output map is computed from multiple input maps simultaneously.
- There are as many weights (for each output map) as \( \text{size of the filter} \times \text{no. of maps in previous layer} \).

Caveat: 0-based indexing
Recap: Convolution

Each affine output is computed from multiple input maps simultaneously.

There are as many weights (for each output map) as
\[ \text{size of the filter} \times \text{no. of maps in previous layer} \]

Caveat: 0-based indexing
Recap: Convolution

- Each affine output is computed from multiple input maps simultaneously
- There are as many weights (for each output map) as $\text{size of the filter} \times \text{no. of maps in previous layer}$

$$z(l, n, x, y) = \sum_{m} \sum_{i=0}^{2} \sum_{j=0}^{2} w_l(m, n, i, j)y(l - 1, m, x + i, y + j) + b_l(n)$$
Recap: Convolution

- Each affine output is computed from multiple input maps simultaneously.
- There are as many weights (for each output map) as

\[ \sum_{m}^{l-1} \sum_{i=0}^{2} \sum_{j=0}^{2} w_l(m, n, i, j)y(l-1, m, x+i, y+j) + b_l(n) \]

**size of the filter x no. of maps in previous layer**
Recap: Convolution

- Each affine output is computed from multiple input maps simultaneously.
- There are as many weights (for each output map) as
  \[ z(l, n, x, y) = \sum_{m} \sum_{i=0}^{2} \sum_{j=0}^{2} w_l(m, n, i, j)y(l - 1, m, x + i, y + j) + b_l(n) \]

  \[ \text{size of the filter} \times \text{no. of maps in previous layer} \]
Recap: Convolution

- Each affine output is computed from multiple input maps simultaneously
- There are as many weights (for each output map) as the size of the filter x no. of maps in previous layer
Recap: Convolution

• Each affine output is computed from multiple input maps simultaneously
• There are as many weights (for each output map) as

\[ z(l, n, x, y) = \sum_{m} \sum_{i=0}^{2} \sum_{j=0}^{2} w_l(m, n, i, j)y(l - 1, m, x + i, y + j) + b_l(n) \]
Recap: Convolution

- Each affine output is computed from multiple input maps simultaneously.
- There are as many weights (for each output map) as
  \( \text{size of the filter} \times \text{no. of maps in previous layer} \)

\[
z(l, n, x, y) = \sum_{m} \sum_{i=0}^{2} \sum_{j=0}^{2} w_l(m, n, i, j) y(l - 1, m, x + i, y + j) + b_l(n)
\]
Recap: Convolution

- Each affine output is computed from multiple input maps simultaneously.
- There are as many weights (for each output map) as \( \text{size of the filter} \times \text{no. of maps in previous layer} \).

\[
z(l, n, x, y) = \sum_{m} \sum_{i=0}^{2} \sum_{j=0}^{2} w_l(m, n, i, j)y(l - 1, m, x + i, y + j) + b_l(n)
\]
Recap: Convolution

- Each affine output is computed from multiple input maps simultaneously.
- There are as many weights (for each output map) as the \textit{size of the filter} \text{ x } \textit{no. of maps in previous layer}.

\[
z(l, n, x, y) = \sum_{m} \sum_{i=0}^{2} \sum_{j=0}^{2} w_l(m, n, i, j)y(l - 1, m, x + i, y + j) + b_l(n)
\]
Recap: Convolution

- Each affine output is computed from multiple input maps simultaneously
- There are as many weights (for each output map) as the product of the size of the filter and the number of maps in the previous layer
Recap: A convolutional layer

- The computation of each output map has two stages
  - Computing an affine map, by convolution of a filter (representing a pattern of weights) over maps in the previous layer
    - Each affine map has, associated with it, a learnable filter
  - An activation that operates on the output of the convolution

\[ y(l, i, x, y) = f(z(l, i, x, y)) \]
Convolution layer: A more explicit illustration

- Input maps $Y(l - 1, \cdot)$ are convolved with several filters to generate the affine maps $Z(l, \cdot)$
  - Each filter consists of a set of square patterns of weights, with one set for each map in $Y(l - 1, \cdot)$
  - We get one affine map per filter
- A point-wise activation function $f(z)$ is applied to each map in $Z(l, \cdot)$ to produce the activation maps $Y(l, \cdot)$
Pseudocode: Vector notation

The weight $W(l,j)$ is a 3D $D_{l-1} \times K_{l} \times K_{l}$ tensor

$Y(0) = $ Image

for $l = 1:L$  # layers operate on vector at $(x,y)$

    for $x = 1:W_{l-1}-K_{l}+1$
        for $y = 1:H_{l-1}-K_{l}+1$
            for $j = 1:D_{l}$
                segment = $Y(l-1,:,x:x+K_{l}-1,y:y+K_{l}-1)$  #3D tensor
                $z(l,j,x,y) = W(l,j).segment + b(l,j)$  #tensor prod.
                $Y(l,j,x,y) = \text{activation}(z(l,j,x,y))$

$Y = \text{softmax}( \{Y(L,:,:,:)\} )$

Pseudocode has 1-based indexing
Select all true statements about a convolution layer.

- The number of “channels” in any filter equals the number of input maps (output maps from the previous layer)
- The number of “channels” in any filter equals the number of output maps (affine maps output by the layer)
- The number of filters equals the number of input maps
- The number of filters equals the number of output maps
Select all true statements about a convolution layer.

- The number of “channels” in any filter equals the number of input maps (output maps from the previous layer)
- The number of “channels” in any filter equals the number of output maps (affine maps output by the layer)
- The number of filters equals the number of input maps
- The number of filters equals the number of output maps
• Convolutional (and activation) layers are followed intermittently by “pooling” layers
  – Often, they alternate with convolution, though this is not necessary
Recall: Max pooling

- Max pooling selects the largest from a pool of elements
- Pooling is performed by “scanning” the input with a “max-pooling filter”
Recap: Pooling and downsampling layer

- Input maps $Y(l - 1,*)$ are operated on individually by pooling operations to produce the pooled maps $Y(l,*)$.
Recap: Max Pooling layer at layer $l$

Max pooling

for $j = 1:D_1$
  for $x = 1:W_{l-1} - K_1 + 1$
    for $y = 1:H_{l-1} - K_1 + 1$
      $\text{pidx}(l,j,x,y) = \text{maxidx}(Y(l-1,j,x:x+K_1-1,y:y+K_1-1))$
      $u(l,j,x,y) = Y(l-1,j,\text{pidx}(l,j,m,n))$

a) Performed separately for every map ($j$).
   *) Not combining multiple maps within a single max operation.

b) Keeping track of location of max
Recall: Mean pooling

- Mean pooling computes the *mean* of the window of values
  - As opposed to the max of max pooling
Recap: Mean Pooling layer at layer $l$

Mean pooling
for $j = 1:D_l$

for $x = 1:W_{l-1}-K_l+1$
  for $y = 1:H_{l-1}-K_l+1$
    $u(l,j,x,y) = \text{mean}(Y(l-1,j,x:x+K_l-1,y:y+K_l-1))$

a) Performed separately for every map ($j$)
Recap: Resampling

• We can also proportionately decrease or increase the size of the maps by dropping or inserting zeros
  – Downsampling: Drop S-1 rows/columns between rows/columns
    • Reduces the size of the maps by S on each side
  – Upsampling: Insert S-1 rows/columns of zeros between adjacent entries
    • Increases the size of the map by S on each side
The Downsampling Layer

- A *downsampling* layer simply “drops” $S - 1$ of $S$ rows and columns for every map in the layer
  - Effectively reducing the size of the map by factor $S$ in every direction
The Upsampling Layer

- A *upsampling* (or dilation) layer simply introduces $S - 1$ rows and columns for every map in the layer
  - Effectively *increasing* the size of the map by factor $S$ in every direction
- Used explicitly to increase the map size by a uniform factor
• In practice, the downsampling is combined with the layers just before it by performing the operations with a stride > 1
  – Could be convolutional or pooling layers
Convolution with downsampling

The weight $W(l,j)$ is now a 4D $D_1 \times D_{l-1} \times K_1 \times K_1$ tensor.

The product in blue is a tensor inner product with a scalar output:

$Y(0) = \text{Image}$

for $l = 1:L$  # layers operate on vector at $(x,y)$

```
import numpy as np

m = 1
for x = 1:S:W_{l-1}-K_l+1
  n = 1
  for y = 1:S:H_{l-1}-K_l+1
    segment = Y(l-1,:,x:x+K_{l-1},y:y+K_{l-1})  # 3D tensor
    z(l,:,m,n) = W(l) \cdot \text{segment}  # tensor inner prod.
    Y(l,:,m,n) = \text{activation}(z(l,:,m,n))
    n++
  n++
m++
```

Downsampled indices

$Y = \text{softmax}( \{ Y(L,:, :) \} )$
Max Pooling with Downsampling

Max pooling

for j = 1:D_1

    m = 1
    for x = 1:stride(l):W_{l-1}-K_l+1
        n = 1
        for y = 1:stride(l):H_{l-1}-K_l+1
            pidx(l,j,m,n) = maxidx(Y(l-1,j,x:x+K_l-1,y:y+K_l-1))
            Y(l,j,m,n) = Y(l-1,j,pidx(l,j,m,n))
            n = n+1
        m = m+1
    end
end
Mean Pooling with Downsampling

Mean pooling

for \( j = 1:D_1 \)

\[
\begin{align*}
m & = 1 \\
\text{for } x = 1: \text{stride}(l):W_{l-1}-K_1+1 \\
\hspace{1cm} n & = 1 \\
\text{for } y = 1: \text{stride}(l):H_{l-1}-K_1+1 \\
\hspace{2cm} Y(l,j,m,n) & = \text{mean}(Y(l-1,j,x:x+K_1-1,y:y+K_1-1)) \\
\hspace{1cm} n & = n+1 \\
m & = m+1
\end{align*}
\]
A *upsampling* layer is generally followed by a CNN layer

- It is not useful to follow it by a pooling layer
- It is also not useful as the *final* layer of a CNN
The Upsampling Layer

- Upsampling layers followed by a convolutional layer are also often viewed as convolving with a fractional stride
  - Upsampling by factor $S$ is the same as striding by factor $1/S$
- Also called “transpose convolutions” for reasons we won’t get into here
* with resampling

- Although the resampling operation is generally merged with convolutions or pooling (by changing their stride) in the forward pass in practical implementations...
- ...It is more convenient to think of the two as separate operations in the backward pass
  - More on this later...
Recap: A CNN, end-to-end

• Typical image classification task
  – Assuming maxpooling..

• Input: RGB images
  – Will assume color to be generic
Recap: A CNN, end-to-end

- Several convolutional and pooling layers.
- The output of the last layer is “flattened” and passed through an MLP.

$W_m: 3 \times L \times L$
$m = 1 \ldots K_1$

$W_m: K_2 \times L_3 \times L_3$
$m = 1 \ldots K_3$
• Parameters to be learned:
  – The weights of the neurons in the final MLP
  – The (weights and biases of the) filters for every convolutional layer
Recap: Learning the CNN

• Training is as in the case of the regular MLP
  – The *only* difference is in the *structure* of the network

• Training examples of (Image, class) are provided

• Define a loss:
  – Define a divergence between the desired output and true output of the network in response to any input
  – The loss aggregates the divergences of the training set

• Network parameters are trained to minimize the loss
  – Through variants of gradient descent
  – Gradients are computed through backpropagation
Defining the loss

- The loss for a single instance

\[ W_m: 3 \times L \times L \]
\[ m = 1 \ldots K_1 \]

\[ W_m: K_2 \times L_3 \times L_3 \]
\[ m = 1 \ldots K_3 \]

- Input: \( x \)

- **Div()**

- **Div (y(x), d(x))**
Recap: Problem Setup

• Given a training set of input-output pairs \((X_1, d_1), (X_2, d_2), \ldots, (X_T, d_T)\)

• The divergence on the \(i^{th}\) instance is \(\text{div}(Y_i, d_i)\)

• The aggregate Loss

\[
\text{Loss} = \frac{1}{T} \sum_{i=1}^{T} \text{div}(Y_i, d_i)
\]

• Minimize \(\text{Loss}\) w.r.t \(\{W_m, b_m\}\)
  – Using gradient descent
Recap: The derivative

Total training loss:

\[ \text{Loss} = \frac{1}{T} \sum_i \text{Div}(Y_i, d_i) \]

- Computing the derivative

Total derivative:

\[ \frac{d\text{Loss}}{dw} = \frac{1}{T} \sum_i \frac{d\text{Div}(Y_i, d_i)}{dw} \]
Recap: The derivative

Total training loss:

\[ \text{Loss} = \frac{1}{T} \sum_i \text{Div}(Y_i, d_i) \]

- Computing the derivative

Total derivative:

\[ \frac{d\text{Loss}}{dw} = \frac{1}{T} \sum_i \frac{d\text{Div}(Y_i, d_i)}{dw} \]
Backpropagation: Final flat layers

• For each training instance: First, a forward pass through the net
• Then the backpropagation of the derivative of the divergence

• Backpropagation continues in the usual manner until the computation of the derivative of the divergence w.r.t the inputs to the first “flat” layer
  – Important to recall: the first flat layer is only the “unrolling” of the maps from the final convolutional layer

\[ \nabla_{Y(L)} \text{Div}(Y(X), d(X)) \]
Backpropagation: Convolutional and Pooling layers

• Backpropagation from the flat MLP requires special consideration of:
  – The shared computation in the convolution layers
  – The pooling layers
Backpropagating through the convolution

- **Convolution layers:**
  - We already have the derivative w.r.t (all the elements of) activation map $Y(l, \ast)$
    - Having backpropagated it from the divergence
  - We must backpropagate it through the activation to compute the derivative w.r.t. $Z(l, \ast)$ and further back to compute the derivative w.r.t the filters and $Y(l - 1, \ast)$
Backprop: Pooling layer

- **Pooling layers:**
  - We already have the derivative w.r.t $Y(l,*)$
    - Having backpropagated it from the divergence
  - We must compute the derivative w.r.t $Y(l - 1,*)$
Backpropagation: Convolutional and Pooling layers

• **Assumption:** We already have the derivatives w.r.t. the elements of the maps output by the final convolutional (or pooling) layer
  – Obtained as a result of backpropagating through the flat MLP

• **Required:**
  – **For convolutional layers:**
    • How to compute the derivatives w.r.t. the affine combination $Z(l)$ maps from the activation output maps $Y(l)$
    • How to compute the derivative w.r.t. $Y(l - 1)$ and $w(l)$ given derivatives w.r.t. $Z(l)$
  – **For pooling layers:**
    • How to compute the derivative w.r.t. $Y(l - 1)$ given derivatives w.r.t. $Y(l)$
Backpropagation: Convolutional and Pooling layers

• **Assumption:** We already have the derivatives w.r.t. the elements of the maps output by the final convolutional (or pooling) layer
  - Obtained as a result of backpropagating through the flat MLP

• **Required:**
  
  — **For convolutional layers:**
    • How to compute the derivatives w.r.t. the affine combination $Z(l)$ maps from the activation output maps $Y(l)$
    • How to compute the derivative w.r.t. $Y(l - 1)$ and $w(l)$ given derivatives w.r.t. $Z(l)$

  — **For pooling layers:**
    • How to compute the derivative w.r.t. $Y(l - 1)$ given derivatives w.r.t. $Y(l)$
• **Assumption:** We already have the derivatives w.r.t. the elements of the maps output by the final convolutional (or pooling) layer
  – Obtained as a result of backpropagating through the flat MLP

• **Required:**
  – **For convolutional layers:**
    • How to compute the derivatives w.r.t. the affine combination $Z(l)$ maps from the activation output maps $Y(l)$
    • How to compute the derivative w.r.t. $Y(l - 1)$ and $w(l)$ given derivatives w.r.t. $Z(l)$
  – **For pooling layers:**
    • How to compute the derivative w.r.t. $Y(l - 1)$ given derivatives w.r.t. $Y(l)$
• **Forward computation:** The activation maps are obtained by point-wise application of the activation function to the affine maps

\[ y(l, m, x, y) = f(z(l, m, x, y)) \]

- The affine map entries \( z(l, m, x, y) \) have already been computed via convolutions over the previous layer
Backpropagating through the activation

- **Backward computation:** For every map $Y(l, m)$ for every position $(x, y)$, we already have the derivative of the divergence w.r.t. $y(l, m, x, y)$
  - Obtained via backpropagation
- We obtain the derivatives of the divergence w.r.t. $z(l, m, x, y)$ using the chain rule:
  $$\frac{d\text{Div}}{dz(l, m, x, y)} = \frac{d\text{Div}}{dy(l, m, x, y)} f'(z(l, m, x, y))$$
  - Simple component-wise computation
Backpropagation: Convolutional and Pooling layers

- **Assumption:** We already have the derivatives w.r.t. the elements of the maps output by the final convolutional (or pooling) layer
  - Obtained as a result of backpropagating through the flat MLP

- **Required:**
  - **For convolutional layers:**
    - How to compute the derivatives w.r.t. the affine combination $Z(l)$ maps from the activation output maps $Y(l)$
    - How to compute the derivative w.r.t. $Y(l-1)$ and $w(l)$ given derivatives w.r.t. $Z(l)$
  - **For pooling layers:**
    - How to compute the derivative w.r.t. $Y(l-1)$ given derivatives w.r.t. $Y(l)$
Backpropagating through affine map

• Forward affine computation:
  – Compute affine maps $z(l, n, x, y)$ from previous layer maps $y(l - 1, m, x, y)$ and filters $w_l(m, n, x, y)$

• Backpropagation: Given $\frac{dDiv}{dz(l,n,x,y)}$
  – Compute derivative w.r.t. $y(l - 1, m, x, y)$
  – Compute derivative w.r.t. $w_l(m, n, x, y)$
Backpropagating through affine map

• Forward affine computation:
  – Compute affine maps $z(l, n, x, y)$ from previous layer maps $y(l - 1, m, x, y)$ and filters $w_l(m, n, x, y)$

• Backpropagation: Given $\frac{dDiv}{dz(l,n,x,y)}$
  – Compute derivative w.r.t. $y(l - 1, m, x, y)$
  – Compute derivative w.r.t. $w_l(m, n, x, y)$
Backpropagating through the affine map

- We already have the derivative w.r.t \( Z(l,\ast) \)
  - Having backpropagated it past \( Y(l,\ast) \)
• We already have the derivative w.r.t $Z(l, \ast)$
  – Having backpropagated it past $Y(l, \ast)$

• We must compute the derivative w.r.t $Y(l - 1, \ast)$
Dependency between $Z(l,n)$ and $Y(l-1,*)$

- Each $Y(l-1,m)$ map/channel influences $Z(l,n)$ through the $m$th “plane” (channel) of the $n$th filter $w_l(m,n)$
Dependency between $Z(l,n)$ and $Y(l-1,\ast)$

- Each $Y(l-1,m)$ map/channel influences $Z(l,n)$ through the $m$th “plane” (channel) of the $n$th filter $w_l(m,n)$
Dependency between $Z(l,*)$ and $Y(l-1,*)$

- Each $Y(l-1,m)$ map/channel influences $Z(l,n)$ through the $m$th “plane”(channel) of the $n$th filter $w_l(m,n)$
Dependency between $Z(l,*)$ and $Y(l-1,*)$

Each $Y(l-1,m)$ map/channel influences $Z(l,n)$ through the $m$th “plane” (channel) of the $n$th filter $w_l(m,n)$
Each $Y(l-1, m)$ map/channel influences $Z(l, n)$ through the $m$th “plane” (channel) of the $n$th filter $w_l(m, n)$

$Y(l-1, m, *, *)$ influences the divergence through all $Z(l, n, *, *)$ maps
Dependency diagram for a single map

\[ \nabla_{Y(l-1)} \text{Div}() \]

\[ \nabla_{Z(l)} \text{Div}() \]

\[ \nabla_{Y(l-1,m)} \text{Div}(.) = \sum_{n} \nabla_{Z(l,n)} \text{Div}(.) \nabla_{Y(l-1,m)} Z(l,n) \]

- Need to compute \( \nabla_{Y(l-1,m)} Z(l,n) \), the derivative of \( Z(l,n) \) w.r.t. \( Y(l-1,m) \) to complete the computation of the formula
Dependency diagram for a single map

\[ \nabla_{Y(l-1)} \text{Div}() \quad \nabla_{Z(l)} \text{Div}() \]

\[ Y(l-1,1) \quad \vdots \quad Y(l-1,m) \quad \vdots \quad Y(l-1,D_{l-1}) \]

Consider a specific \( Z(l,n) \)

\[ \nabla_{Y(l-1,m)} \text{Div}(.) = \sum_{n} \nabla_{Z(l,n)} \text{Div}(.) \nabla_{Y(l-1,m)}Z(l,n) \]

- Need to compute \( \nabla_{Y(l-1,m)}Z(l,n) \), the derivative of \( Z(l,n) \) w.r.t. \( Y(l-1,m) \) to complete the computation of the formula
BP: Convolutional layer

- Each $Y(l-1,m)$ affects several $z(l,n,x',y')$ terms
• Each $Y(l-1, m, x, y)$ affects several $z(l, n, x', y')$ terms
BP: Convolutional layer

- Each $Y(l-1, m, x, y)$ affects several $z(l, n, x', y')$ terms
  - Affects terms in all $l^{th}$ layer $Z$ maps

$N = \text{No. of filters}$
BP: Convolutional layer

\[
\frac{d\text{Div}}{dY(l-1,m,x,y)} = \sum_n \sum_{x',y'} \frac{d\text{Div}}{dz(l,n,x',y')} \frac{dz(l,n,x',y')}{dY(l-1,m,x,y)}
\]

Summing over all Z maps

N = No. of filters
BP: Convolutional layer

\[ Y(l-1, m) \]

Summing over all Z maps

\[
\frac{dY(l-1, m, x, y)}{dY(l-1, m, x, y)} = \sum_n \sum_{x', y'} \frac{dDiv}{dz(l, n, x', y')} \frac{dz(l, n, x', y')}{dY(l-1, m, x, y)}
\]

N = No. of filters

What is this?
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

- Compute how each $x, y$ in $Y$ influences various locations of $z$

Assuming indexing begins at 0
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

$$z(l, n, 0,0) += Y(l - 1, m, 2,2) w_l(m, n, 2,2)$$

- **Note:** The coordinates of $z(l, n)$ and $w_l(m, n)$ sum to the coordinates of $Y(l - 1, m)$

$$z(l, n, x', y') += Y(l - 1, m, 2,2) w_l(m, n, 2 - x', 2 - y')$$
How a single $Y(l-1, m, x, y)$ influences $z(l, n, x', y')$

$$z(l, n, 1,0) \ += \ Y(l-1, m, 2,2) w_l(m, n, 1,2)$$

- **Note:** The coordinates of $z(l, n)$ and $w_l(m, n)$ sum to the coordinates of $Y(l-1, m)$

$$z(l, n, x', y') \ += \ Y(l-1, m, 2,2) w_l(m, n, 2-x', 2-y')$$
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$ 

$z(l, n, 2, 0) += Y(l - 1, m, 2, 2)w_l(m, n, 0, 2)$

- **Note:** The coordinates of $z(l, n)$ and $w_l(m, n)$ sum to the coordinates of $Y(l - 1, m)$

$z(l, n, x', y') += Y(l - 1, m, 2, 2)w_l(m, n, 2 - x', 2 - y')$
How a single \( Y(l - 1, m, x, y) \) influences \( z(l, n, x', y') \)

\[
z(l, n, 0, 1) \oplus Y(l - 1, m, 2, 2)w_l(m, n, 2, 1)
\]

- **Note:** The coordinates of \( z(l, n) \) and \( w_l(m, n) \) sum to the coordinates of \( Y(l - 1, m) \)

\[
z(l, n, x', y') \oplus Y(l - 1, m, 2, 2)w_l(m, n, 2 - x', 2 - y')
\]
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

$$z(l, n, 1,1) += Y(l - 1, m, 2,2)w_l(m, n, 1,1)$$

- **Note:** The coordinates of $z(l, n)$ and $w_l(m, n)$ sum to the coordinates of $Y(l - 1, m)$

$$z(l, n, x', y') += Y(l - 1, m, 2,2)w_l(m, n, 2 - x', 2 - y')$$
How a single \( Y(l - 1, m, x, y) \) influences \( z(l, n, x', y') \)

\[
Z(l, n, 2, 1) \rightarrow Y(l - 1, m, 2, 2)w_l(m, n, 0, 1)
\]

- **Note:** The coordinates of \( z(l, n) \) and \( w_l(m, n) \) sum to the coordinates of \( Y(l - 1, m) \)

\[
z(l, n, x', y') \rightarrow Y(l - 1, m, 2, 2)w_l(m, n, 2 - x', 2 - y')
\]
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

$z(l, n, 0, 2) = Y(l - 1, m, 2, 2)w_l(m, n, 2, 0)$

- **Note:** The coordinates of $z(l, n)$ and $w_l(m, n)$ sum to the coordinates of $Y(l - 1, m)$

$z(l, n, x', y') = Y(l - 1, m, 2, 2)w_l(m, n, 2 - x', 2 - y')$
How a single $Y(l-1, m, x, y)$ influences $z(l, n, x', y')$

\[ z(l, n, 1,2) = Y(l-1, m, 2,2)w_l(m, n, 2,1) \]

- **Note:** The coordinates of $z(l, n)$ and $w_l(m, n)$ sum to the coordinates of $Y(l-1, m)$

\[ z(l, n, x', y') = Y(l-1, m, 2,2)w_l(m, n, 2-x', 2-y') \]
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

\[ z(l, n, 2,2) + = Y(l - 1, m, 2,2)w_l(m, n, 0,0) \]

- **Note:** The coordinates of $z(l, n)$ and $w_l(m, n)$ sum to the coordinates of $Y(l - 1, m)$

\[ z(l, n, x', y') + = Y(l - 1, m, 2,2)w_l(m, n, 2 - x', 2 - y') \]
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

$z(l, n, x', y') \pm Y(l - 1, m, x, y)w_l(m, n, x - x', y - y')$

**Note:** The coordinates of $z(l, n)$ and $w_l(m, n)$ sum to the coordinates of $Y(l - 1, m)$
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

$z(l, n, x', y') \equiv Y(l - 1, m, x, y)w_l(m, n, x - x', y - y')$

$$\frac{dz(l, n, x', y')}{dY(l - 1, m, x, y)} = w_l(m, n, x - x', y - y')$$
BP: Convolutional layer

\[ \frac{d\text{Div}}{dY(l-1,m,x,y)} = \sum_n \sum_{x',y'} \frac{d\text{Div}}{dz(l,n,x',y')} \frac{dz(l,n,x',y')}{dY(l-1,m,x,y)} \]

Summing over all Z maps
BP: Convolutional layer

Summing over all Z maps

\[
\frac{dDiv}{dY(l-1, m, x, y)} = \sum_n \sum_{x', y'} \frac{dDiv}{dZ(l, n, x', y')} w_l(m, n, x - x', y - y')
\]
In order to compute the derivative at a single affine element \( Y(l,m,x,y) \), we must consider the contributions of *every* position of *every* affine map at the next layer: True or false

- True
- False

The derivative for a single affine element \( Y(l,m,x,y) \) will require summing over *every* position of *every* \( Z \) map in the next layer: True or false

- True
- False
In order to compute the derivative at a single affine element $Y(l,m,x,y)$, we must consider the contributions of every position of every affine map at the next layer: True or false

- True
- False

The derivative for an single affine element $Y(l,m,x,y)$ will require summing over every position of every $Z$ map in the next layer: True or false

- True
- False
Computing derivative for $Y(l - 1, m, *, *)$

• The derivatives for every element of every map in $Y(l - 1)$ by direct implementation of the formula:

$$\frac{d\text{Div}}{dY(l - 1, m, x, y)} = \sum_n \sum_{x', y'} \frac{d\text{Div}}{dz(l, n, x', y')} w_i(m, n, x - x', y - y')$$

• But this is actually a convolution!
  – Let’s see how
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

$z(l, n, 0, 0) \pm= Y(l - 1, m, 2, 2) w_l(m, n, 2, 2)$

$$\frac{dDiv}{dY(l - 1, m, 2, 2)} \pm= \frac{dDiv}{dz(l, n, 0, 0)} w_l(m, n, 2, 2)$$
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

\[ z(l, n, 1, 0) += Y(l - 1, m, 2, 2)w_l(m, n, 1, 2) \]

\[ \frac{d\text{Div}}{dY(l - 1, m, 2, 2)} += \frac{d\text{Div}}{dz(l, n, 1, 0)}w_l(m, n, 1, 2) \]
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

$$z(l, n, 2,0) + = Y(l - 1, m, 2,2) w_l(m, n, 0,2)$$

$$\frac{dDiv}{dY(l - 1, m, 2,2)} + = \frac{dDiv}{dz(l, n, 2,0)} w_l(m, n, 0,2)$$
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

$z(l, n, 0,1) += Y(l - 1, m, 2,2)w_l(m, n, 2,1)$

$$\frac{dDiv}{dY(l - 1, m, 2,2)} + = \frac{dDiv}{dz(l, n, 0,1)}w_l(m, n, 2,1)$$
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

$z(l, n, 1,1) + = Y(l - 1, m, 2,2)w_l(m, n, 1,1)$

$$\frac{dDiv}{dY(l - 1, m, 2,2)} + = \frac{dDiv}{dz(l, n, 1,1)}w_l(m, n, 1,1)$$
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

$$z(l, n, 2, 1) = Y(l - 1, m, 2, 2)w_l(m, n, 0, 1)$$

$$\frac{dDiv}{dY(l - 1, m, 2, 2)} + \frac{dDiv}{dz(l, n, 2, 1)}w_l(m, n, 0, 1)$$
How a single \( Y(l - 1, m, x, y) \) influences \( z(l, n, x', y') \)

\[
\begin{align*}
   z(l, n, 0,2) & = Y(l - 1, m, 2,2) w_l(m, n, 2,0) \\
   \frac{dDiv}{dY(l - 1, m, 2,2)} & = \frac{dDiv}{dz(l, n, 0,2)} w_l(m, n, 2,0)
\end{align*}
\]
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

<table>
<thead>
<tr>
<th></th>
<th>0,0</th>
<th>1,0</th>
<th>2,0</th>
</tr>
</thead>
<tbody>
<tr>
<td>0,1</td>
<td>1,1</td>
<td>2,1</td>
<td></td>
</tr>
<tr>
<td>0,2</td>
<td>1,2</td>
<td>2,2</td>
<td></td>
</tr>
</tbody>
</table>

$w_l(m, n, *, *)$

$$z(l, n, 1, 2) += Y(l - 1, m, 2, 2)w_l(m, n, 2, 1)$$

$$\frac{dDiv}{dY(l - 1, m, 2, 2)} += \frac{dDiv}{dz(l, n, 1, 2)}w_l(m, n, 1, 0)$$
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$

$$z(l, n, 2,2) \mp Y(l - 1, m, 2,2)w_l(m, n, 0,0)$$

$$\frac{dDiv}{dY(l - 1, m, 2,2)} \mp \frac{dDiv}{dz(l, n, 2,2)} w_l(m, n, 0,0)$$
How a single $Y(l - 1, m, x, y)$ influences $z(l, n, x', y')$ 

\[
\frac{d\text{Div}}{dY(l - 1, m, 2, 2)} = \sum_{x', y'} \frac{d\text{Div}}{dz(l, n, x', y')} w_l(m, n, 2 - x', 2 - y')
\]

- The derivative at $Y(l - 1, m, 2, 2)$ is the sum of component-wise product of the filter elements (shown by color) and the elements of the derivative at $z(l, m, ..)$
Derivative at $Y(l - 1, m, x, y)$ from a single $Z(l, n)$ map

$z(l, n, x', y') = Y(l - 1, m, x, y)w(l, m, x - x', y - y')$

\[
\frac{dDiv}{dY(l - 1, m, x, y)} = \sum_{x', y'} \frac{dDiv}{dz(l, n, x', y')} w_l(m, n, x - x', x - y')
\]

Contribution of the entire $n$th affine map $z(l, n, *, *)$
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]

Zero pad with K-1 rows and cols on every side

$w_i(m, n, *, *)$
Derivative at \( Y(l - 1, m) \) from a single \( Z(l, n) \) map

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')} 
\]
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

$$\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}$$
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map
Derivative at $Y(l-1,m)$ from a single $Z(l,n)$ map
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

$$\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}$$
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map
Derivative at $Y(\ell - 1, m)$ from a single $Z(\ell, n)$ map
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

$$\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}$$
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

$\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}$
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

$$\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}$$
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

$$\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}$$
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map.

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map.

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = w_i(m, n, *, *)
\]

\[
\frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]

$w_l(m, n, *, *)$
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

$\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}$
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = w_i(m, n, *, *)
\]

\[
\frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map
Derivative at $Y(l - 1, m)$ from a single $Z(l, n)$ map

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]
BP: Convolutional layer

Summing over all Z maps

\[
\frac{dDiv}{dY(l-1,m,x,y)} = \sum_n \sum_{x',y'} \frac{dDiv}{dz(l,n,x',y')} w_l(m,n,x-x',y-y')
\]
The actual convolutions

- The $D_l$ affine maps are produced by convolving with $D_l$ filters
The actual convolutions

- The $D_l$ affine maps are produced by convolving with $D_l$ filters
- The $m^{th}$ $Y$ map always convolves the $m^{th}$ plane of the filters
- The derivative for the $m^{th}$ $Y$ map will invoke the $m^{th}$ plane of all the filters
In reality, the derivative at each \((x,y)\) location is obtained from \textit{all} \(z\) maps.

\[ \frac{\partial \text{Div}}{\partial y(l-1,m,x,y)} \]

\[ w_l(m,n,x,y) \]

\[ n = 1 \]

\[ n = 2 \]

\[ \vdots \]

\[ n = D_l \]
In reality, the derivative at each (x,y) location is obtained from all z maps.
\[
\frac{\partial \text{Div}}{\partial y(l-1, m, x, y)} = \frac{d\text{Div}}{dY(l-1, m, x, y)} = \sum_n \sum_{x', y'} \frac{d\text{Div}}{dZ(l, n, x', y')} w_l(m, n, x - x', y - y')
\]

\[
\frac{\partial \text{Div}}{\partial z(l, n, x', y')} = w_l(m, n, K + 1 - x, K + 1 - y)
\]
\[
\frac{\partial \text{Div}}{\partial y(l-1, m, x, y)} = \sum_n \sum_{x', y'} \frac{\partial \text{Div}}{\partial z(l, n, x', y')} w_l(m, n, x - x', y - y') w_l(m, n, K + 1 - x, K + 1 - y)
\]
\[ \frac{\partial \text{Div}}{\partial y(l-1, m, x, y)} = \sum_{n} \sum_{x', y'} \frac{\partial \text{Div}}{\partial z(l, n, x', y')} w_l(m, n, x' - x, y' - y) \]

\[ w_l(m, n, K + 1 - x, K + 1 - y) \]

\[ n = 1 \]

\[ n = 2 \]

\[ n = D_l \]
\[
\frac{\partial \text{Div}}{\partial y(l-1, m, x, y)} = \sum_n \sum_{x, y'} \frac{\partial \text{Div}}{\partial z(l, n, x', y')} w_l(m, n, x - x', y - y')
\]

\[
\frac{\partial \text{Div}}{\partial z(l, n, x', y')} w_l(m, n, K + 1 - x, K + 1 - y)
\]
\[ \frac{\partial \text{Div}}{\partial y(l-1,m,x,y)} = \sum_n \sum_{x',y'} \frac{\partial \text{Div}}{\partial z(l,n,x',y')} w_l(m,n,x-x',y-y') \]

\[ w_l(m,n,K+1-x,K+1-y) \]
$w_l(m, n, x, y)$

$n = 1$

$n = 2$

$n = D_l$

$w_l(m, n, K + 1 - x, K + 1 - y)$

$\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)}$

$\frac{d\text{Div}}{dY(l - 1, m, x, y)} = \sum_n \sum_{x', y'} \frac{d\text{Div}}{dz(l, n, x', y')} w_l(m, n, x - x', y - y')$

$\frac{\partial \text{Div}}{\partial z(l, n, x', y')}$
\[ \frac{\partial \text{Div}}{\partial y(l-1, m, x, y)} = \sum_n \sum_{x, y} \frac{\partial \text{Div}}{\partial z(l, n, x', y')} w_l(m, n, x'-x, y'-y) \]

\[ w_l(m, n, K+1-x, K+1-y) \]
\( w_l(m, n, x, y) \)

\( n = 1 \)

\( n = 2 \)

\( n = D_l \)

\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \sum_n \sum_{x',y'} \frac{\partial \text{Div}}{\partial z(l, n, x', y')} w_l(m, n, x - x', y - y')
\]

\[
\frac{\partial \text{Div}}{\partial z(l, n, x', y')} = w_l(m, n, K + 1 - x, K + 1 - y)
\]
\[ w_l(m, n, x, y) \]

\[ n = 1 \]

\[ n = 2 \]

\[ n = D_l \]

\[ \frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} \]

\[ \frac{d\text{Div}}{dy(l - 1, m, x, y)} = \sum_n \sum_{x', y'} \frac{d\text{Div}}{dz(l, n, x', y')} w_l(m, n, x - x', y - y') \]

\[ w_l(m, n, K + 1 - x, K + 1 - y) \]
\[ w_l(m, n, x, y) \]

\[ n = 1 \]

\[ n = 2 \]

\[ n = D_l \]

\[ w_l(m, n, K + 1 - x, K + 1 - y) \]

\[ \frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \sum_n \sum_{x, y'} \frac{d\text{Div}}{dz(l, n, x', y')} w_l(m, n, x - x', y - y') \]

\[ \frac{d\text{Div}}{dY(l - 1, m, x, y)} = \sum_n \sum_{x, y'} \frac{d\text{Div}}{dz(l, n, x', y')} w_l(m, n, x - x', y - y') \]
\( w_l(m, n, x, y) \)

\( n = 1 \)

\( n = 2 \)

\( n = D_l \)

\[ \frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \sum_n \sum_{x, y} \frac{\partial \text{Div}}{\partial z(l, n, x', y')} w_l(m, n, x - x', y - y') \]

\[ \frac{\partial \text{Div}}{\partial z(l, n, x', y')} \]
\[ w_l(m, n, x, y) \]

\[ n = 1 \]

\[ \text{flip} \]

\[ n = 2 \]

\[ \vdots \]

\[ n = D_l \]

\[ w_l(m, n, K + 1 - x, K + 1 - y) \]

\[ \frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} \]

\[ \frac{d\text{Div}}{dY(l - 1, m, x, y)} = \sum_n \sum_{x', y'} \frac{d\text{Div}}{dz(l, n, x', y')} w_l(m, n, x - x', y - y') \]

\[ \frac{\partial \text{Div}}{\partial z(l, n, x', y')} \]
\[
\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \sum_n \sum_{x,y} \frac{\partial \text{Div}}{dz(l, n, x', y')} w_l(m, n, x - x', y - y')
\]

\[
\frac{\partial \text{Div}}{\partial z(l, n, x', y')} = w_l(m, n, K + 1 - x, K + 1 - y)
\]
\[
\frac{\partial \text{Div}}{\partial Y(l-1,m,x,y)} = \sum_n \sum_{x',y'} \frac{\partial \text{Div}}{\partial z(l,n,x',y')} w_l(m,n,x-x',y-y')
\]

\[
\frac{\partial \text{Div}}{\partial z(l,n,x',y')} = w_l(m,n,K+1-x,K+1-y)
\]
\[
\frac{\partial \text{Div}}{\partial y(l-1, m, x, y)}
\]

\[
\frac{d\text{Div}}{dY(l-1, m, x, y)} = \sum_n \sum_{x', y'} \frac{d\text{Div}}{dz(l, n, x', y')} w_l(m, n, x - x', y - y')
\]

\[
\frac{\partial \text{Div}}{\partial z(l, n, x', y')}
\]
\[ w_l(m, n, x, y) \]

\[ n = 1 \]

\[ n = 2 \]

\[ n = D_l \]

\[ d \text{Div} \]

\[ \frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} \]

\[ d \text{Div} \]

\[ \frac{d \text{Div}}{dY(l - 1, m, x, y)} = \sum_n \sum_{x_l, y_l} \frac{d \text{Div}}{dZ(l, n, x', y')} w_l(m, n, x - x', y - y') \]

\[ w_l(m, n, K + 1 - x, K + 1 - y) \]
\[
\frac{\partial D\text{iv}}{\partial y(l - 1, m, x, y)} = \sum_n \sum_{x', y'} \frac{\partial D\text{iv}}{\partial z(l, n, x', y')} w_l(m, n, x - x', y - y')
\]
\[ w_l(m, n, x, y) \]

\[ n = 1 \]

\[ n = 2 \]

\[ n = D_l \]

\[ w_l(m, n, K + 1 - x, K + 1 - y) \]

\[ \frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} \]

\[ \frac{d\text{Div}}{dY(l - 1, m, x, y)} = \sum_n \sum_{x',y'} \frac{d\text{Div}}{dz(l, n, x', y')} w_l(m, n, x - x', y - y') \]
\[
\frac{\partial \text{Div}}{\partial y(l-1, m, x, y)} = \sum_{n} \sum_{x', y'} \frac{\partial \text{Div}}{\partial z(l, n, x', y')} w_l(m, n, x - x', y - y') \]

\[
w_l(m, n, K + 1 - x, K + 1 - y) = n = 1
\]

\[
n = 2
\]

\[
n = D_l
\]
$$w_l(m, n, x, y)$$

$$n = 1$$

$$n = 2$$

$$n = D_l$$

$$w_l(m, n, K + 1 - x, K + 1 - y)$$

$$\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)}$$

$$\frac{d\text{Div}_{Y(l-1,m,x,y)}}{dY(l-1,m,x,y)} = \sum_{n} \sum_{x',y'} \frac{d\text{Div}_{Z(l,n,x',y')}}{dz(l,n,x',y')} w_l(m,n,x-x',y-y')$$
\[ w_l(m, n, x, y) \]

\[ n = 1 \]

\[ n = 2 \]

\[ n = D_l \]

\[ \frac{\partial \text{Div}}{\partial y(l-1, m, x, y)} \]

\[ \frac{d\text{Div}}{dy(l-1, m, x, y)} = \sum_{n} \sum_{x', y'} \frac{d\text{Div}}{dz(l, n, x', y')} w_l(m, n, x-x', y-y') \]

\[ w_l(m, n, K+1-x, K+1-y) \]
$$w_l(m, n, x, y)$$

$$n = 1$$

$$n = 2$$

$$n = D_l$$

$$w_l(m, n, K + 1 - x, K + 1 - y)$$

$$\frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)}$$

$$\frac{d\text{Div}}{dy(l - 1, m, x, y)} = \sum_{n\ x, y} \frac{d\text{Div}}{dz(l, n, x', y')} w_l(m, n, x - x', y - y')$$
\[ w_l(m, n, x, y) \]

\[ n = 1 \]

\[ n = 2 \]

\[ n = D_l \]

\[ w_l(m, n, K + 1 - x, K + 1 - y) \]

\[ \frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} \]

\[ \frac{d \text{Div}}{dY(l - 1, m, x, y)} = \sum_n \sum_{x_l y_l} \frac{d \text{Div}}{dz(l, n, x', y')} w_l(m, n, x - x', y - y') \]

\[ \frac{\partial \text{Div}}{\partial z(l, n, x', y')} \]
\[ w_l(m, n, x, y) \]

\[ n = 1 \]

\[ n = 2 \]

\[ \ldots \]

\[ n = D_l \]

\[ w_l(m, n, K + 1 - x, K + 1 - y) \]

\[ \frac{\partial \text{Div}}{\partial z(l, n, x', y')} \]

\[ \frac{\partial \text{Div}}{\partial y(l - 1, m, x, y)} = \sum_n \sum_{x, y'} \frac{\partial \text{Div}}{\partial z(l, n, x', y')} w_l(m, n, x - x', y - y') \]

\[ f(l, n, x, y) = \sum_{x, y'} \frac{\partial \text{Div}}{\partial z(l, n, x', y')} w_l(m, n, x - x', y - y') \]
Computing the derivative for \( Y(l - 1, m) \)

- This is just a convolution of the zero-padded maps by the transposed and flipped filter
  - After zero padding it first with \( K - 1 \) zeros on every side
The size of the Y-derivative map

- We continue to compute elements for the derivative $Y$ map as long as the (flipped) filter has at least one element in the (unpadded) derivative Zmap
  - i.e. so long as the $Y$ derivative is non-zero

- The size of the $Y$ derivative map will be $(H + K - 1) \times (W + K - 1)$
  - $H$ and $W$ are height and width of the Zmap

- This will be the size of the actual $Y$ map that was originally convolved
The size of the Y-derivative map

• If the Y map was zero-padded in the forward pass, the derivative map will be the size of the zero-padded map
  – The zero padding regions must be deleted before further backprop
Select all statements that are true about how to compute the derivative of the divergence w.r.t lth layer activation maps by backpropagation

- To compute the derivative w.r.t. the mth activation map of the lth convolutional layer, we must select the mth “planes” of all the (l+1)th layer filters
- The selected filter planes must be flipped left-right and up-down
- They must convolve the derivative (maps) for the (l+1)th layer affine values
- The output of the convolution must be flipped back left-right and up-down
Select all statements that are true about how to compute the derivative of the divergence w.r.t lth layer activation maps by backpropagation

- To compute the derivative w.r.t. the mth activation map of the lth convolutional layer, we must select the mth “planes” of all the (l+1)th layer filters
- The selected filter planes must be flipped left-right and up-down
- They must convolve the derivative (maps) for the (l+1)th layer affine values
- The output of the convolution must be flipped back left-right and up-down
Overall algorithm for computing derivatives w.r.t. $Y(l - 1)$

- Given the derivatives $\frac{d\text{Div}}{dz(l,n,x,y)}$

- Compute derivatives using:

$$\frac{d\text{Div}}{dY(l - 1, m, x, y)} = \sum_n \sum_{x', y'} \frac{d\text{Div}}{dz(l, n, x', y')} w_l(m, n, x - x', y - y')$$

Can be computed by convolution with flipped filter
Derivatives for a single layer $l$:

Vector notation

# The weight $W(l,m)$ is a 3D $D_{l-1} \times K_1 \times K_1$
# Assuming dz has already been obtained via backprop

dzpad = zeros($D_1 \times (H_1+2(K_1-1)) \times (W_1+2(K_1-1))$)  # zeropad
for j = 1:$D_1$
    for i = 1:$D_{l-1}$  # Transpose and flip
        Wflip(i,j,:) = flipLeftRight(flipUpDown(W(l,i,j,:)))
        dzpad(j,K_1:K_1+H_1-1,K_1:K_1+W_1-1) = dz(l,j,:)  #center map
    end
for j = 1:$D_{l-1}$
    for x = 1:$W_{l-1}$
        for y = 1:$H_{l-1}$
            segment = dzpad(:, x:x+K_1-1, y:y+K_1-1)  #3D tensor
            dy(l-1,j,x,y) = Wflip.segment  #tensor inner prod.
Backpropagating through affine map

• Forward affine computation:
  – Compute affine maps $z(l, n, x, y)$ from previous layer maps $y(l - 1, m, x, y)$ and filters $w_l(m, n, x, y)$

• Backpropagation: Given $\frac{dDiv}{dz(l,n,x,y)}$
  - Compute derivative w.r.t. $y(l - 1, m, x, y)$
  - Compute derivative w.r.t. $w_l(m, n, x, y)$
The derivatives for the weights

\[ Y(l - 1, m) \otimes w_l(m, n) \]

\[ Z(l, n) \]

\[ z(l, n, x, y) = \sum_m \sum_{x', y'} w_l(m, n, x', y') y(l - 1, m, x + x', y + y') + b_l(n) \]

- Each **weight** \( w_l(m, n, x', y') \) affects several \( z(l, n, x, y) \) but only within a **single** affine \( (z(l, n,*,*) \) map/channel
  
  - And is also linked to several \( y(l - 1, m, x, y) \) but only within a single previous-layer output map/channel \( y(l - 1, m,*,*) \)
    
    * \( w_l(m, n,*,*) \) connects \( y(l - 1, m,*,*) \) to \( z(l, n,*,*) \)

- Consider the contribution of one filter components: \( w_l(m, n, i, j) \) (e.g. \( w_l(m, n, 1,2) \)) in the above animation for illustration
Convolution: the contribution of a single weight

- Each affine output is computed from multiple input maps simultaneously.
- Each weight \( w_l(m, n, i, j) \) affects several \( z(l, n, x, y) \) within the \( n \)th output affine map.

\[
z(l, n, x, y) = \sum_m \sum_{x'=0}^{2} \sum_{y'=0}^{2} w_l(m, n, x', y')y(l - 1, m, x + x', y + y') + b_l(n)
\]
Convolution: the contribution of a single weight

Each weight $w_l(m, n, i, j)$ affects several $z(l, n, x, y)$ in the $n$th output affine map

- Consider the contribution of one filter components: e.g. $w_l(m, n, 1,2)$

$$z(l, n, 0,0) = w_l(m, n, 1,2)y(l - 1, m, 1,2) + \cdots$$

$$z(l, n, x, y) = \sum_{m} \sum_{x' = 0}^{2} \sum_{y' = 0}^{2} w_l(m, n, x', y')y(l - 1, m, x + x', y + y') + b_l(n)$$
Convolution: the contribution of a single weight

- Each weight $w_l(m, n, i, j)$ affects several $z(l, n, x, y)$ in the $n$th output affine map
  - Consider the contribution of one filter components: e.g. $w_l(m, n, 1,2)$
Convolution: the contribution of a single weight

Each weight $w_l(m, n, i, j)$ affects several $z(l, n, x, y)$ in the $n$th output affine map.

- Consider the contribution of one filter components: e.g. $w_l(m, n, 1,2)$

$$z(l, n, x, y) = \sum_{m} \sum_{x' = 0}^{2} \sum_{y' = 0}^{2} w_l(m, n, x', y')y(l - 1, m, x + x', y + y') + b_l(n)$$
Convolution: the contribution of a single weight

- Each weight $w_l(m, n, i, j)$ affects several $z(l, n, x, y)$ in the $n$th output affine map
  - Consider the contribution of one filter components: e.g. $w_l(m, n, 1,2)$
Convolution: the contribution of a single weight

\[ Y(l - 1, m) \]

\[ Z(l, n) \]

\[ z(l, n, x, y) = \sum_{m} \sum_{x'=0}^{2} \sum_{y'=0}^{2} w_l(m, n, x', y')y(l - 1, m, x + x', y + y') + b_l(n) \]

- Each weight \( w_l(m, n, i, j) \) affects several \( z(l, n, x, y) \) in the \( n \)th output affine map
  - Consider the contribution of one filter components: e.g. \( w_l(m, n, 1,2) \)
Convolution: the contribution of a single weight

- Each weight $w_l(m,n,i,j)$ affects several $z(l,n,x,y)$ in the $n$th output affine map
  - Consider the contribution of one filter components: e.g. $w_l(m,n,1,2)$
Convolution: the contribution of a single weight

\[
z(l, n, 0,0) = w_l(m, n, 1,2)y(l - 1, m, 1,2) + \cdots
\]
\[
z(l, n, 1,0) = w_l(m, n, 1,2)y(l - 1, m, 2,2) + \cdots
\]
\[
z(l, n, 2,0) = w_l(m, n, 1,2)y(l - 1, m, 3,2) + \cdots
\]
\[
z(l, n, 0,1) = w_l(m, n, 1,2)y(l - 1, m, 1,3) + \cdots
\]
\[
z(l, n, 1,1) = w_l(m, n, 1,2)y(l - 1, m, 2,3) + \cdots
\]
\[
z(l, n, 2,1) = w_l(m, n, 1,2)y(l - 1, m, 3,3) + \cdots
\]
\[
z(l, n, 0,2) = w_l(m, n, 1,2)y(l - 1, m, 1,4) + \cdots
\]

- Each weight \( w_l(m, n, i, j) \) affects several \( z(l, n, x, y) \) in the \( n \)th output affine map
  - Consider the contribution of one filter components: e.g. \( w_l(m, n, 1,2) \)
Convolution: the contribution of a single weight

Each weight $w_l(m, n, i, j)$ affects several $z(l, n, x, y)$ in the $n$th output affine map

- Consider the contribution of one filter components: e.g. $w_l(m, n, 1,2)$

$$z(l, n, x, y) = \sum_{m} \sum_{x' = 0}^{2} \sum_{y' = 0}^{2} w_l(m, n, x', y') y(l - 1, m, x + x', y + y') + b_l(n)$$

$$z(l, n, 0,0) = w_l(m, n, 1,2) y(l - 1, m, 1,2) + \ldots$$
$$z(l, n, 1,0) = w_l(m, n, 1,2) y(l - 1, m, 2,2) + \ldots$$
$$z(l, n, 2,0) = w_l(m, n, 1,2) y(l - 1, m, 3,2) + \ldots$$
$$z(l, n, 0,1) = w_l(m, n, 1,2) y(l - 1, m, 1,3) + \ldots$$
$$z(l, n, 1,1) = w_l(m, n, 1,2) y(l - 1, m, 2,3) + \ldots$$
$$z(l, n, 2,1) = w_l(m, n, 1,2) y(l - 1, m, 3,3) + \ldots$$
$$z(l, n, 0,2) = w_l(m, n, 1,2) y(l - 1, m, 1,4) + \ldots$$
$$z(l, n, 1,2) = w_l(m, n, 1,2) y(l - 1, m, 2,4) + \ldots$$
Convolution: the contribution of a single weight

- Each weight $w_l(m, n, i, j)$ affects several $z(l, n, x, y)$ in the $n$th output affine map
  - Consider the contribution of one filter components: e.g. $w_l(m, n, 1,2)$

$$z(l, n, 0,0) = w_l(m, n, 1,2)y(l - 1, m, 1,2) + \cdots$$
$$z(l, n, 1,0) = w_l(m, n, 1,2)y(l - 1, m, 2,2) + \cdots$$
$$z(l, n, 2,0) = w_l(m, n, 1,2)y(l - 1, m, 3,2) + \cdots$$
$$z(l, n, 0,1) = w_l(m, n, 1,2)y(l - 1, m, 1,3) + \cdots$$
$$z(l, n, 1,1) = w_l(m, n, 1,2)y(l - 1, m, 2,3) + \cdots$$
$$z(l, n, 2,1) = w_l(m, n, 1,2)y(l - 1, m, 3,3) + \cdots$$
$$z(l, n, 0,2) = w_l(m, n, 1,2)y(l - 1, m, 1,4) + \cdots$$
$$z(l, n, 1,2) = w_l(m, n, 1,2)y(l - 1, m, 2,4) + \cdots$$
$$z(l, n, 2,2) = w_l(m, n, 1,2)y(l - 1, m, 3,4) + \cdots$$

$$z(l, n, x, y) = \sum_{m} \sum_{x'=0}^{2} \sum_{y'=0}^{2} w_l(m, n, x', y')y(l - 1, m, x + x', y + x') + b_l(n)$$
Convolution: the contribution of a single weight

- Each weight $w_l(m, n, i, j)$ affects several $z(l, n, x, y)$ in the $n$th output affine map
  - Consider the contribution of one filter components: e.g. $w_l(m, n, 1,2)$
Convolution: the contribution of a single weight

Each weight $w_l(m, n, i, j)$ affects several $z(l, n, x, y)$ in the $n$th output affine map
- Consider the contribution of one filter components: e.g. $w_l(m, n, 1,2)$
Convolution: the contribution of a single weight

\[
\begin{align*}
z(l, n, 0, 0) &= w_l(m, n, 1, 2)y(l - 1, m, 1, 2) + \cdots \\
z(l, n, 1, 0) &= w_l(m, n, 1, 2)y(l - 1, m, 2, 2) + \cdots \\
z(l, n, 2, 0) &= w_l(m, n, 1, 2)y(l - 1, m, 3, 2) + \cdots \\
z(l, n, 0, 1) &= w_l(m, n, 1, 2)y(l - 1, m, 1, 3) + \cdots \\
z(l, n, 1, 1) &= w_l(m, n, 1, 2)y(l - 1, m, 2, 3) + \cdots \\
z(l, n, 2, 1) &= w_l(m, n, 1, 2)y(l - 1, m, 3, 3) + \cdots \\
z(l, n, 0, 2) &= w_l(m, n, 1, 2)y(l - 1, m, 1, 4) + \cdots \\
z(l, n, 1, 2) &= w_l(m, n, 1, 2)y(l - 1, m, 2, 4) + \cdots \\
z(l, n, 2, 2) &= w_l(m, n, 1, 2)y(l - 1, m, 3, 4) + \cdots \\
\end{align*}
\]

\[
\begin{align*}
z(l, n, x, y) &= w_l(m, n, 1, 2)y(l - 1, m, x + 1, y + 2) + \cdots \\
z(l, n, x, y) &= w_l(m, n, i, j)y(l - 1, m, x + i, y + j) + \cdots \\
\end{align*}
\]

\[
\frac{dz(l, n, x, y)}{dw_l(m, n, i, j)} = y(l - 1, m, x + i, y + j)
\]
The derivative for a single weight

- Each filter component \( w_l(m, n, i, j) \) affects several \( z(l, n, x, y) \)
  - The derivative of each \( z(l, n, x, y) \) w.r.t. \( w_l(m, n, i, j) \) is given by
    \[
    \frac{dz(l, n, x, y)}{dw_l(m, n, i, j)} = y(l-1, m, x+i, y+j)
    \]

- The final divergence is influenced by every \( z(l, n, x, y) \)
- The derivative of the divergence w.r.t \( w_l(m, n, i, j) \) must sum over all \( z(l, n, x, y) \) terms it influences
  \[
  \frac{d\text{Div}}{dw_l(m, n, i, j)} = \sum_{x,y} \frac{d\text{Div}}{dz(l, n, x, y)} \frac{dz(l, n, x, y)}{dw_l(m, n, i, j)}
  \]
The derivative for a single weight

- Each filter component $w_l(m, n, i, j)$ affects several $z(l, n, x, y)$
- The derivative of each $z(l, n, x, y)$ w.r.t. $w_l(m, n, i, j)$ is given by

$$\frac{dz(l, n, x, y)}{dw_l(m, n, i, j)} = y(l-1, m, x + i, y + j)$$

- The final divergence is influenced by every $z(l, n, x, y)$
- The derivative w.r.t $w_l(m, n, i, j)$ must sum over all $z(l, n, x, y)$ terms it influences
The derivative for a single weight

- Each filter component $w_i(m, n, i, j)$ affects several $z(l, n, x, y)$
  - The derivative of each $z(l, n, x, y)$ w.r.t. $w_i(m, n, i, j)$ is given by
    $$\frac{dz(l, n, x, y)}{dw_i(m, n, i, j)} = y(l - 1, m, x + i, y + j)$$

- The final divergence is influenced by every $z(l, n, x, y)$
- The derivative w.r.t $w_i(m, n, i, j)$ must sum over all $z(l, n, x, y)$ terms it influences
  $$\frac{d\text{Div}}{dw_i(m, n, i, j)} = \sum_{x, y} \frac{d\text{Div}}{dz(l, n, x, y)} \frac{dz(l, n, x, y)}{dw_i(m, n, i, j)}$$

Already computed
The derivative for a single weight

- Each filter component $w_l(m, n, i, j)$ affects several $z(l, n, x, y)$
  - The derivative of each $z(l, n, x, y)$ w.r.t. $w_l(m, n, i, j)$ is given by
    $$\frac{dz(l, n, x, y)}{dw_l(m, n, i, j)} = y(l - 1, m, x + i, y + j)$$

- The final divergence is influenced by every $z(l, n, x, y)$
- The derivative of the divergence w.r.t $w_l(m, n, i, j)$ must sum over all $z(l, n, x, y)$ terms it influences
  $$\frac{d\text{Div}}{dw_l(m, n, i, j)} = \sum_{x, y} \frac{d\text{Div}}{dz(l, n, x, y)} y(l - 1, m, x + i, y + j)$$
The derivative for a single weight

To compute $\frac{d \text{Div}}{dw_l(m,n,1,2)}$

To compute $\frac{d \text{Div}}{dw_l(m,n,0,0)}$
But this too is a convolution

\[
\frac{d \text{Div}}{dw_l (m, n, i, j)} = \sum_{x, y} \frac{d \text{Div}}{dz(l, n, x, y)} y(l - 1, m, x + i, y + j)
\]

- The derivatives for all components of all filters can be computed directly from the above formula
  - To compute the derivative for \( w_l (m, n, i, j) \), “place” the \( \frac{d \text{Div}}{dz(l, n)} \) map on \( y(l - 1, m) \) map positioned at \((i, j)\) and compute the inner product

- In fact, it is just a convolution

\[
\frac{d \text{Div}}{dw_l (m, n, i, j)} = \frac{d \text{Div}}{dz(l, n)} \otimes y(l - 1, m)
\]

- How?
Recap: Convolution

• Forward computation: Each filter produces an affine map

\[ z(l, n, x, y) = \sum_{m}^{2} \sum_{i=0}^{2} \sum_{j=0}^{2} w_l(m, n, i, j)y(l - 1, m, x + i, y + j) + b_l(n) \]
Recap: Convolution

\[
z(l, n, x, y) = \sum_{m}^{2} \sum_{i=0}^{2} \sum_{j=0}^{2} w_l(m, n, i, j) y(l - 1, m, x + i, y + j) + b_l(n)
\]

- \(Y(l - 1, m)\) influences \(Z(l, n)\) through \(w_l(m, n)\)
The filter derivative

- The derivatives of the divergence w.r.t. every element of \( Z(l, n) \) is known
  - Must use them to compute the derivative for \( w_l(m, n, *, *) \)
The filter derivative

- The derivatives of the divergence w.r.t. every element of \( Z(l, n) \) is known
  - Must use them to compute the derivative for \( w_l(m, n, *, *) \)
The filter derivative

- The derivatives of the divergence w.r.t. every element of $Z(l, n)$ is known
  - Must use them to compute the derivative for $w_l(m, n, *, *)$
The filter derivative

• The derivatives of the divergence w.r.t. every element of $Z(l, n)$ is known
  – Must use them to compute the derivative for $w_l(m, n, *, *)$
The filter derivative

- The derivatives of the divergence w.r.t. every element of $Z(l, n)$ is known
  - Must use them to compute the derivative for $w_l(m, n, *, *)^{92}$
The filter derivative

- The derivatives of the divergence w.r.t. every element of $Z(l, n)$ is known
  - Must use them to compute the derivative for $w_l(m, n, *, *)$
The filter derivative

- The derivatives of the divergence w.r.t. every element of $Z(l, n)$ is known
  - Must use them to compute the derivative for $w_l(m, n, *, *)$
The filter derivative

- The derivatives of the divergence w.r.t. every element of $Z(l, n)$ is known
  - Must use them to compute the derivative for $w_l(m, n, *, *)$
The derivatives of the divergence w.r.t. every element of $Z(l, n)$ is known

- Must use them to compute the derivative for $w_l(m, n, *, *)$
The filter derivative

The derivatives of the divergence w.r.t. every element of $Z(l, n)$ is known

- Must use them to compute the derivative for $w_l(m, n, *, *)$
The derivative of the $n^{th}$ affine map $Z(l, n)$ convolves with every output map $Y(l - 1, m)$ of the $(l - 1)^{th}$ layer, to get the derivative for $w_i(m, n)$, the $m^{th}$ “channel” of the $n^{th}$ filter.
The filter derivative

\[
\frac{d\text{Div}}{dz(l, 1, x, y)} = \sum_{x, y} \frac{d\text{Div}}{dz(l, n, x, y)} y(l - 1, m, x + i, y + j)
\]

If \(Y(l - 1, m)\) was zero padded in the forward pass, it must be zero padded for backprop.
Select all statements that are true about how to compute the derivative of the divergence w.r.t lth layer filters using backpropagation

- The derivative for the mth plane of the nth filter is computed by convolving the mth input (l-1th) layer map with the nth output (lth) layer affine derivative map
- The output map must be flipped left-right/up-down before convolution
Select all statements that are true about how to compute the derivative of the divergence w.r.t lth layer filters using backpropagation

- The derivative for the mth plane of the nth filter is computed by convolving the mth input (l-1th) layer map with the nth output (lth) layer affine derivative map
- The output map must be flipped left-right/up-down before convolution
Derivatives for the filters at layer $l$:
Vector notation

# The weight $W(l,j)$ is a 3D $D_{l-1} \times K_1 \times K_1$
# Assuming that derivative maps have been upsampled
#   if stride > 1
# Also assuming y map has been zero-padded if this was
#   also done in the forward pass
# The width and height of the dz map are W and H

for n = 1:D_l
    for x = 1:K_l
        for y = 1:K_l
            for m = 1:D_{l-1}
                \[ dw(l,m,n,x,y) = dz(l,n,:,:,:) \cdot y(l-1,m,x:x+H-1,y:y+W-1) \]
Derivatives through a convolutional layer

• The entire process is simpler if we simply look at it through code
  – Through the reapplication of two simple rules:

• For any computation of the form

\[ y = \sigma(z) \]

  – The loss derivative for \( z \) given the loss derivative of \( y \) is

\[
\frac{dL}{dz} = \frac{dL}{dy} \sigma'(z)
\]

• For any computation in the forward pass

\[ z = wy \]

  – The backward computation to compute loss derivatives for the terms on the right, given loss derivatives to the left is

\[
dL/dy += wdL/dz \ ; \ dL/dw += ydL/dz
\]

  – Since this is “backpropogation”, all computations are reversed
CNN: Forward

\[ Y(0,:,:,:) = \text{Image} \]

for \( l = 1:L \)  \# layers operate on vector at \((x,y)\)
  
  for \( x = 1:W_{l-1}-K_l+1 \)
    
    for \( y = 1:H_{l-1}-K_l+1 \)
      
      for \( j = 1:D_l \)
        
        \[ z(l,j,x,y) = 0 \]
      
      for \( i = 1:D_{l-1} \)
        
        for \( x' = 1:K_l \)
          
          for \( y' = 1:K_l \)
            
            \[ z(l,j,x,y) += w(l,j,i,x',y') Y(l-1,i,x+x'-1,y+y'-1) \]
          
        \end{align*}

      \[ Y(l,j,x,y) = \text{activation}(z(l,j,x,y)) \]
    
  \end{align*}

\[ Y = \text{softmax}( Y(L,:,1,1)..Y(L,:,W-K+1,H-K+1) ) \]
Backward layer $l$

dw(l) = zeros(D_1 \times D_{l-1} \times K_1 \times K_l)
dY(l-1) = zeros(D_{l-1} \times W_{l-1} \times H_{l-1})
for x = W_{l-1} - K_1 + 1 : downto : 1
   for y = H_{l-1} - K_1 + 1 : downto : 1
      for j = D_1 : downto : 1
         dz(l,j,x,y) = dY(l,j,x,y) \cdot f'(z(l,j,x,y))
      for i = D_{l-1} : downto : 1
         for x' = K_1 : downto : 1
            for y' = K_1 : downto : 1
               dY(l-1,i,x+x'-1,y+y'-1) +=
                  w(l,j,i,x',y')dz(l,j,x,y)
               dw(l,j,i,x',y') +=
                  dz(l,j,x,y)Y(l-1,i,x+x'-1,y+y'-1)
Complete Backward (no pooling)

dY(L) = dDiv/dY(L)
for l = L:downto:1  # Backward through layers
    dw(l) = zeros(D_lxD_{l-1}xK_lxK_l)
    dY(l-1) = zeros(D_{l-1}xW_{l-1}xH_{l-1})
    for x = W_{l-1}-K_l+1:downto:1
        for y = H_{l-1}-K_l+1:downto:1
            for j = D_l:downto:1
                dz(l,j,x,y) = dY(l,j,x,y).f'(z(l,j,x,y))
            endfor
            for i = D_{l-1}:downto:1
                for x' = K_l:downto:1
                    for y' = K_l:downto:1
                        dY(l-1,i,x+x'-1,y+y'-1) +=
                        w(l,j,i,x',y')dz(l,j,x,y)
                        dw(l,j,i,x',y') +=
                        dz(l,j,x,y)y(l-1,i,x+x'-1,y+y'-1)
Complete Backward (no pooling)

\[ dY(L) = \frac{dDiv}{dY(L)} \]

for \( l = L : \text{downto}:1 \)  \# Backward through layers

\[ dw(l) = \text{zeros}(D_l \times D_{l-1} \times K_l \times K_l) \]
\[ dY(l-1) = \text{zeros}(D_{l-1} \times W_{l-1} \times H_{l-1}) \]

for \( x = W_{l-1} - K_l + 1 : \text{downto}:1 \)

for \( y = H_{l-1} - K_l + 1 : \text{downto}:1 \)

for \( j = D_l : \text{downto}:1 \)

\[ dz(l,j,x,y) = dY(l,j,x,y) . f'(z(l,j,x,y)) \]

for \( i = D_{l-1} : \text{downto}:1 \)

for \( x' = K_l : \text{downto}:1 \)

for \( y' = K_l : \text{downto}:1 \)

\[ dY(l-1,i,x+x'-1,y+y'-1) += w(l,j,i,x',y') dz(l,j,x,y) \]
\[ dw(l,j,i,x',y') += dz(l,j,x,y) y(l-1,i,x+x'-1,y+y'-1) \]

Multiple ways of recasting this as tensor/ vector operations.

Will not discuss here
Backpropagation: Convolutional layers

For convolutional layers:

1. How to compute the derivatives w.r.t. the affine combination $Z(l)$ maps from the activation output maps $Y(l)$
2. How to compute the derivative w.r.t. $Y(l - 1)$ and $w(l)$ given derivatives w.r.t. $Z(l)$
Backpropagation: Convolutional and Pooling layers

• **Assumption:** We already have the derivatives w.r.t. the elements of the maps output by the final convolutional (or pooling) layer
  – Obtained as a result of backpropagating through the flat MLP

• **Required:**
  – **For convolutional layers:**
    • How to compute the derivatives w.r.t. the affine combination $Z(l)$ maps from the activation output maps $Y(l)$
    • How to compute the derivative w.r.t. $Y(l-1)$ and $w(l)$ given derivatives w.r.t. $Z(l)$

  – **For pooling layers:**
    • How to compute the derivative w.r.t. $Y(l-1)$ given derivatives w.r.t. $Y(l)$
• Pooling “pools” groups of values to reduce jitter-sensitivity
  – Scanning with a “pooling” filter
• The most common pooling is “Max” pooling
Max Pooling

- Max pooling selects the largest from a pool of elements
- Pooling is performed by “scanning” the input

\[ P(l, m, i, j) = \underset{k \in \{i, i+K_{pool}-1\}, n \in \{j, j+K_{pool}-1\}}{\text{argmax}} Y(l-1, m, k, n) \]

\[ Y(l, m, i, j) = Y(l-1, m, P(l, m, i, j)) \]
Max pooling

- Max pooling selects the largest from a pool of elements
- Pooling is performed by “scanning” the input

\[
P(l, m, i, j) = \operatorname{argmax}_{k \in \{i, i+K_{pool} - 1\}, \ n \in \{j, j+K_{pool} - 1\}} Y(l - 1, m, k, n)
\]

\[
Y(l, m, i, j) = Y(l - 1, m, P(l, m, i, j))
\]
Max pooling selects the largest from a pool of elements

Pooling is performed by “scanning” the input

\[
P(l, m, i, j) = \arg\max_{k \in \{i, i+K_{lpool}-1\}, \ n \in \{j, j+K_{lpool}-1\}} Y(l-1, m, k, n)
\]

\[
Y(l, m, i, j) = Y(l-1, m, P(l, m, i, j))
\]
Max pooling

- Max pooling selects the largest from a pool of elements
- Pooling is performed by “scanning” the input

\[ P(l, m, i, j) = \arg\max_{k \in \{i, i+K_{pool}-1\}, \ n \in \{j, j+K_{pool}-1\}} Y(l - 1, m, k, n) \]

\[ Y(l, m, i, j) = Y(l - 1, m, P(l, m, i, j)) \]
Max pooling

- Max pooling selects the largest from a pool of elements
- Pooling is performed by “scanning” the input

\[ P(l, m, i, j) = \arg\max_{k \in \{i, i+K_{pool}-1\}, n \in \{j, j+K_{pool}-1\}} Y(l - 1, m, k, n) \]

\[ Y(l, m, i, j) = Y(l - 1, m, P(l, m, i, j)) \]
Derivative of Max pooling

Max pooling selects the largest from a pool of elements

\[ \frac{dDiv}{dy(l-1,m,k,l)} = \begin{cases} 
\frac{dDiv}{dy(l,m,i,j)} & \text{if } (k,l) = P(l,m,i,j) \\
0 & \text{otherwise}
\end{cases} \]

Max pooling selects the largest from a pool of elements

\[ P(l,m,i,j) = \arg\max_{k \in \{i, i+K_{pool}-1\}, \quad n \in \{j, j+K_{pool}-1\}} Y(l-1,m,k,n) \]

\[ y(l,m,i,j) = y(l-1,m,P(l,m,i,j)) \]
Max Pooling layer at layer $l$

a) Performed separately for every map (j).
   *) Not combining multiple maps within a single max operation.

b) Keeping track of location of max

Max pooling

for $j = 1:D_l$
  for $x = 1:W_{l-1}-K_l+1$
    for $y = 1:H_{l-1}-K_l+1$
      $pidx(l,j,x,y) = \text{maxidx}(y(l-1,j,x:x+K_l-1,y:y+K_l-1))$
      $y(l,j,x,y) = y(l-1,j,pidx(l,j,x,y))$
Derivative of max pooling layer at layer $l$

- a) Performed separately for every map ($j$).
  
  *) Not combining multiple maps within a single max operation.

- b) Keeping track of location of max

Max pooling

$$
\text{dy}(\cdot,\cdot,\cdot) = \text{zeros}(D_1 \times W_1 \times H_1)$$

for $j = 1:D_1$

for $x = 1:W_1$

for $y = 1:H_1$

$$
\text{dy}(l-1,j,\text{pidx}(l,j,x,y)) += \text{dy}(l,j,x,y)
$$

“+” because this entry may be selected in multiple adjacent overlapping windows
Mean pooling

- Mean pooling computes the mean of a pool of elements.
- Pooling is performed by "scanning" the input.

\[ y(l, m, i, j) = \frac{1}{K_{pool}^2} \sum_{k \in \{i, i+K_{pool}-1\},\ n \in \{j, j+K_{pool}-1\}} y(l - 1, m, k, n) \]
The derivative of mean pooling is distributed over the pool

\[ k \in \{i, i + K_{lpool} - 1\}, \quad n \in \{j, j + K_{lpool} - 1\} \]

\[ dy(l - 1, m, k, n) = \frac{1}{K_{lpool}^2} dy(l, m, k, n) \]
Mean Pooling layer at layer $l$

Mean pooling

for $j = 1:D_1$  #Over the maps
  for $x = 1:W_{l-1}-K_1+1$  #$K_1 =$ pooling kernel size
    for $y = 1:H_{l-1}-K_1+1$
      $y(l,j,x,y) = \text{mean}(y(l-1,j,x+K_1-1,y:y+K_1-1))$
Derivative of mean pooling layer at layer $l$

Mean pooling

\[
dy(:, :, :) = \text{zeros}(D_l \times W_l \times H_l)
\]

for $k = 1:D_l$

\[
\text{for } x = 1:W_l
\]

\[
\text{for } y = 1:H_l
\]

\[
\text{for } i = 1:K_{l_{\text{pool}}}
\]

\[
\text{for } j = 1:K_{l_{\text{pool}}}
\]

\[
dy(l-1, k, p, x+i, y+j) += \left(\frac{1}{K_{l_{\text{pool}}}^2}\right)dy(l, k, x, y)
\]

“+=“ because adjacent windows may overlap
Learning the network

- Have shown the derivative of divergence w.r.t every intermediate output, and every free parameter (filter weights)
- Can now be embedded in gradient descent framework to learn the network
- Still missing one component... resampling
  - Next class
Story so far

- The convolutional neural network is a supervised version of a computational model of mammalian vision.
- It includes:
  - Convolutional layers comprising learned filters that scan the outputs of the previous layer.
  - Pooling layers that operate over groups of outputs from the convolutional layer to reduce network size.
- The parameters of the network can be learned through regular back propagation:
  - Maxpooling layers must propagate derivatives only over the maximum element in each pool.
    - Other pooling operators can use regular gradients or subgradients.
  - Derivatives must sum over appropriate sets of elements to account for the fact that the network is, in fact, a shared parameter network.