Deep Learning

Lecture 7 – Convolutional Neural Networks

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Robotics, Computer Vision, Deep Learning, Machine Learning, System Software

Agenda

7.1 Convolution Layers

7.2 Downsampling

7.3 Upsampling

7.4 Architectures

7.5 Visualization

7.1
Convolution Layers

Representation Learning





Classifier → "bus"?

Gradients → Classifier → "bus"?

Gradients → Histogram → Classifier → "bus"?

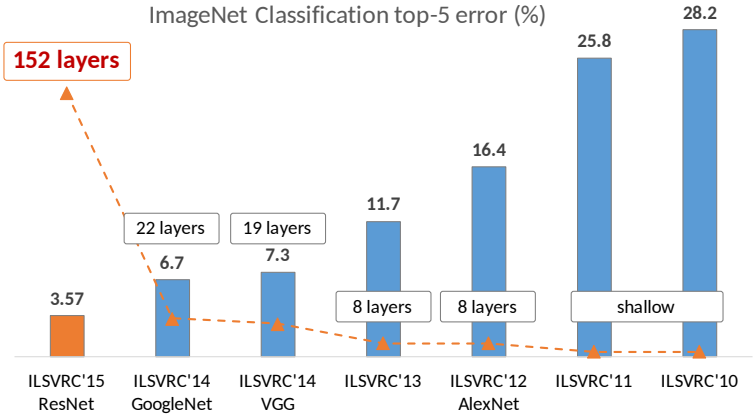
Gradients → Histogram → K-means sparse code FV/VLAD → Classifier → "bus"?

Low-Level Features → Mid-Level Features → High-Level Features → Classifier → "bus"?

Trainable

Hand-Crafted

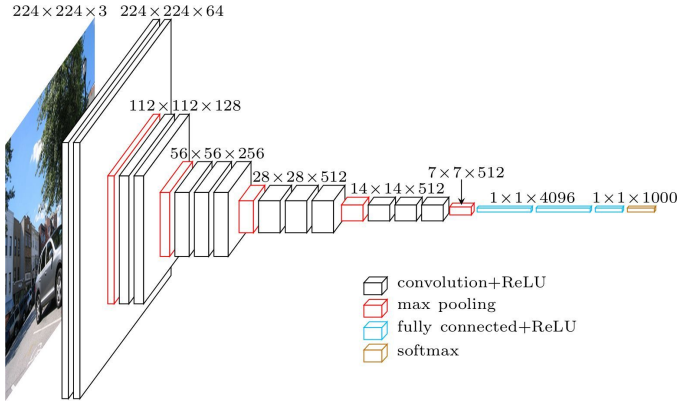
ImageNet Large Scale Visual Recognition Challenge



- Classification into 1000 object categories. Current state-of-the-art: 1.3 %

Russakovsky et al.: ImageNet Large Scale Visual Recognition Challenge. IJCV, 2015.

VGG Network



3 Types of Layers:

- Convolution layers, pooling layers and fully connected layers

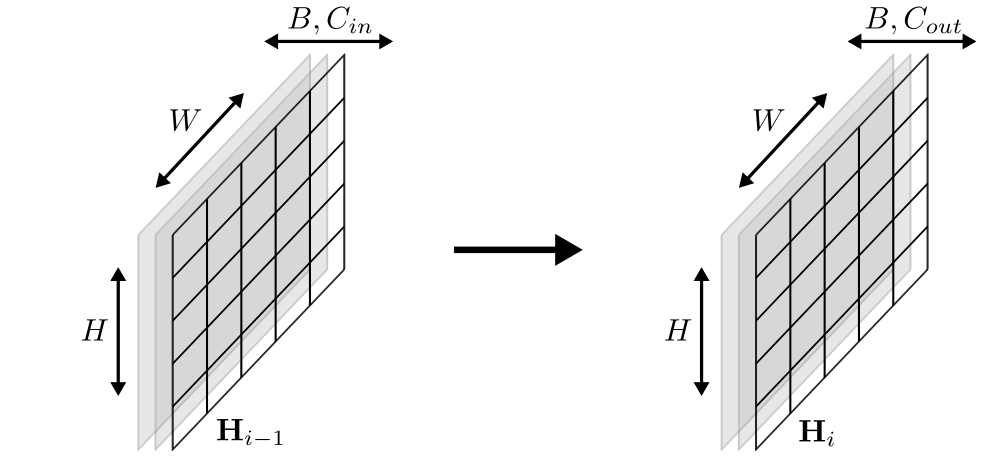
https://www.kaggle.com/code/blurredmachine/vggnet-16-architecture-a-complete-guide/notebook

Notation

We will use the following **notation:**

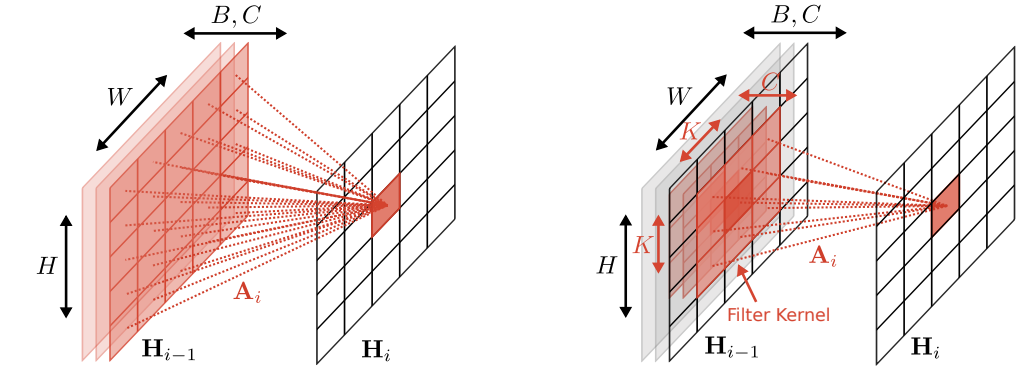
- B: **Batch size**
- W: **Width** of image or feature map
- H: **Height** of image or feature map
- C: Number of feature **channels** (=neurons per pixel)
  - C_{in}: Number of feature channels in current layer
  - C_{out}: Number of feature channels in next layer
  - $C_{in} = 1$ for first layer if input is a grayscale image
  - $C_{in} = 3$ for first layer if input is a color image
- $K \times K$: Convolutional filter **kernel size**

Network Layers with Spatial Dimension



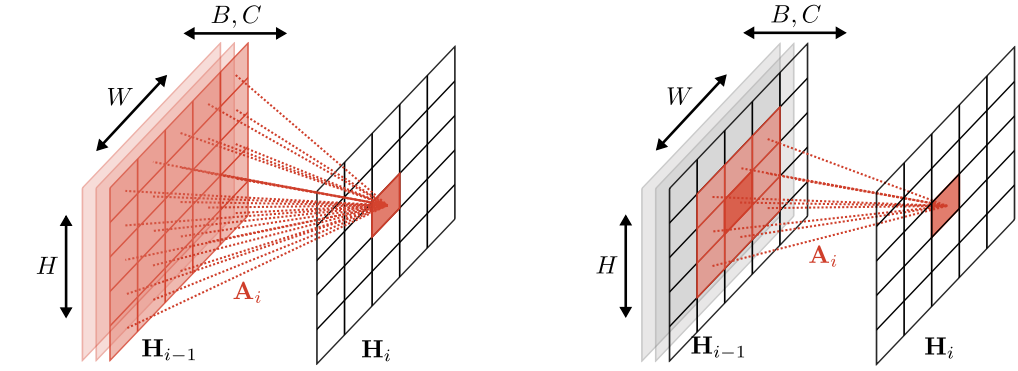
- In contrast to MLPs, ConvNet layers have a **spatial extent**

Fully Connected vs. Convolutional Layers



- **Fully connected layer:** #Weights $= W \times H \times C_{out} \times (W \times H \times C_{in} + 1)$
- **Convolutional layer:** #Weights $= C_{out} \times (K \times K \times C_{in} + 1)$ ("weight sharing")
- With C_{in} input and C_{out} output channels, layer size $W \times H$ and kernel size $K \times K$
- Convolution kernel is three-dimensional. Only 1 output channel shown for clarity.

Fully Connected vs. Convolutional Layers



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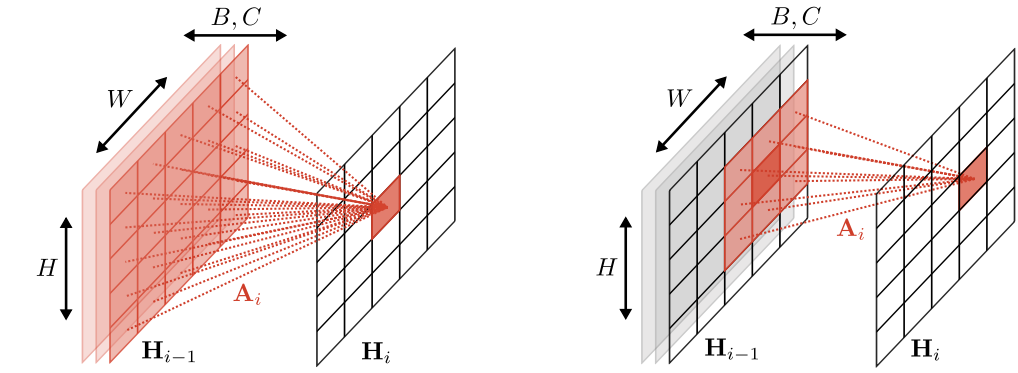

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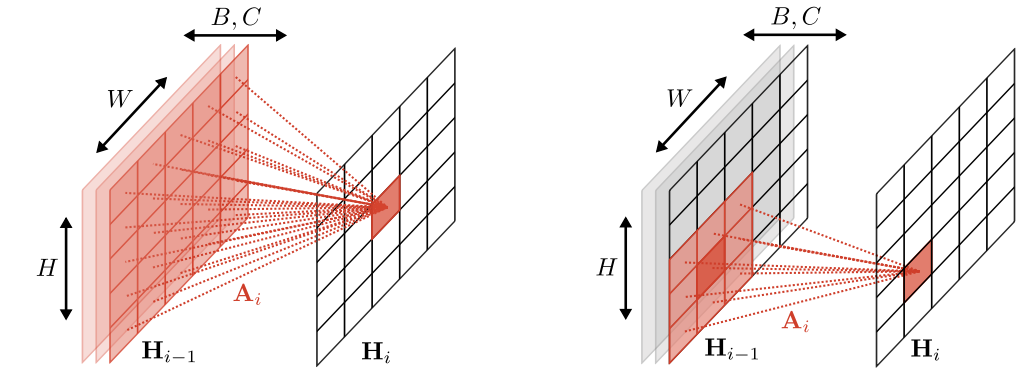

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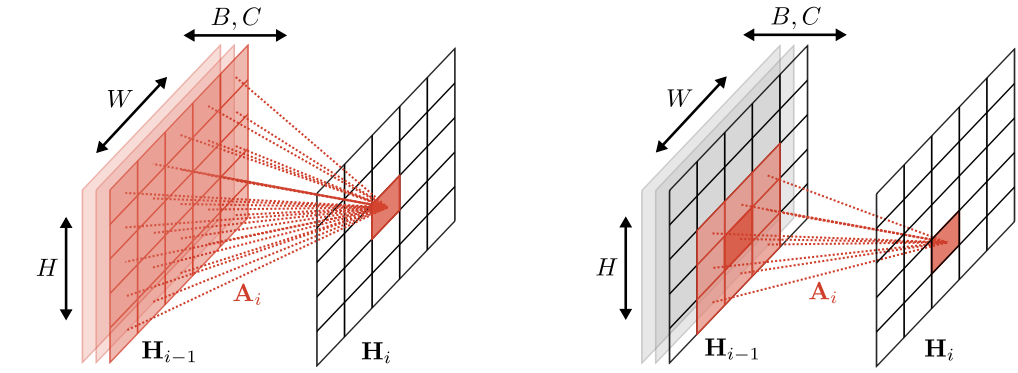

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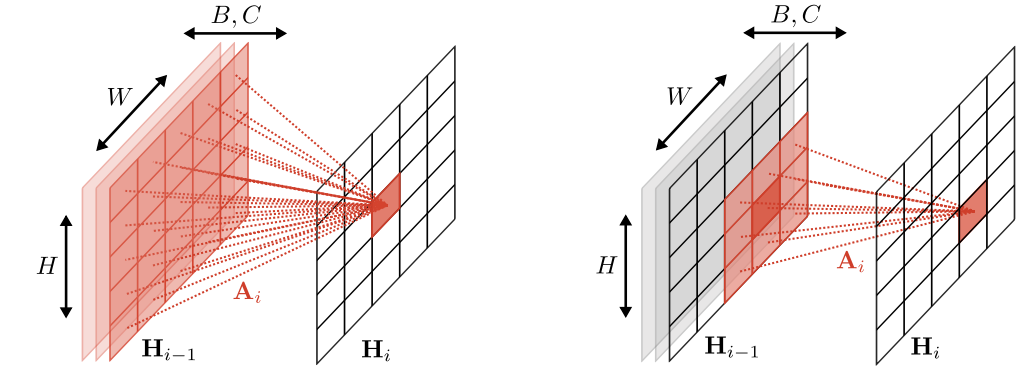

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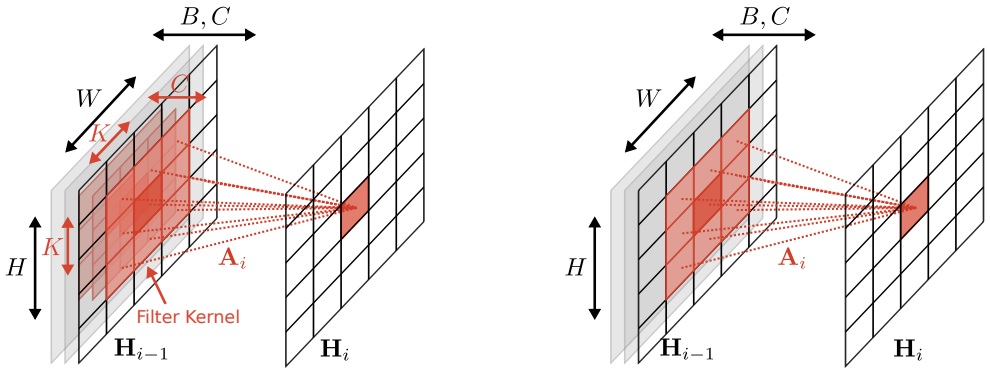
Remark on Illustration Conventions



- Convolution kernels are 3D, but in illustrations we drop the C dimension for clarity.
- Usually, multiple convolution kernels are convolved with the input, each producing a different output channel. In illustrations, we show a single convolution for clarity.
- We will use Einstein notation to make all operations formally clear and concise.

Einstein Notation

Einstein Notation

We use a modified form of **Einstein Notation**
where **capital letters** are used to denote **slices of a tensor:**

- $A[i, j]$ denotes **one element** of the matrix A
- $A[i, J]$ denotes the **i'th row** of matrix A
- $A[I, j]$ denotes the **j'th column** of matrix A
- $A[I, J]$ denotes the **full matrix** A

- $H[i, j, k]$ denotes **one element** of the tensor H
- $\ldots$

Einstein Notation

Repeated capital letters in a product denote **summation** over those letters:

$$\begin{aligned} \mathbf{y} = \mathbf{A}\mathbf{x} \quad &\equiv \quad y[i] = \sum_j A[i,j]x[j] \\ &\equiv \quad y[i] = A[i,J]x[J] \end{aligned}$$

$$\begin{aligned} \mathbf{y} = \mathbf{x}^\top\mathbf{A} \quad &\equiv \quad y[j] = \sum_i A[i,j]x[i] \\ &\equiv \quad y[j] = A[I,j]x[I] \end{aligned}$$

Multiple capital letters denote summation over the **combination** of indices:

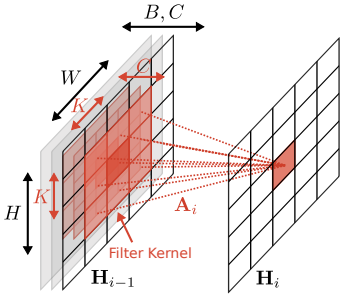
$$c = \sum_{i,j} A[i,j]B[i,j] = A[I,J]B[I,J]$$

Einstein Notation

- The indeces of tensors typically have **types** such as "batch index", "x coordinate", "y coordinate" or "channel index"
- Writing a tensor as $A[B, X, Y, C]$ with batch B, coordinates X, Y and feature channels C makes the type of the tensor elements and the order of the indeces **explicit.** It therefore also disambiguates $\mathbf{A}$ from $\mathbf{A}^\top$.
- We will therefore use Einstein notation to describe the (hidden) layers and filter weights in a CNN
- Einstein notation can also be used in **NumPy** (`numpy.einsum`)

Convolution Layer

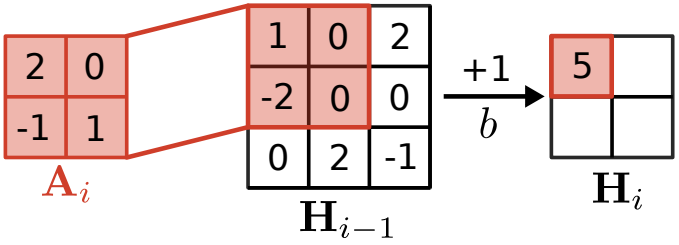
Convolution Layer



$$\underbrace{H_i[b, x, y, c_{out}]}_{\text{Current Layer}} = g\left(\underbrace{A_i[\Delta X, \Delta Y, C_{in}, c_{out}]}_{\text{Weights}} \underbrace{H_{i-1}[b, x + \Delta X, y + \Delta Y, C_{in}]}_{\text{Prev. Layer}} + \underbrace{b_i[c_{out}]}_{\text{Bias}}\right)$$

- b: Batch index x, y: Spatial locations c_{in}, c_{out}: Feature channels g: Act. func.
- $H_i[b, x, y, d]$ denotes feature d at image position x, y in layer i of batch b
- A_i and b_i depend on i as every layer has its own parameters
- Einstein summation considers all combinations over a range of indices $(\Delta X, \Delta Y)$

Convolution Example



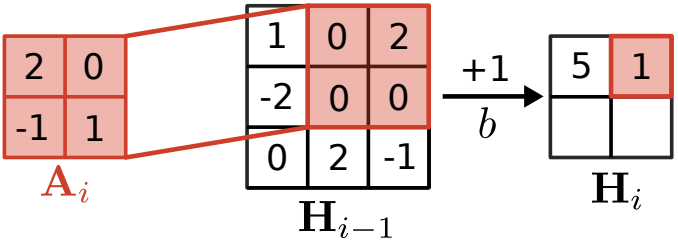
$$2 \cdot 1 + (-1) \cdot (-2) + 1 = 5$$

Remarks:

- Technically, ConvNets implement **correlation** (not convolution) operations
- Low-rank kernels can be implemented by efficient **separable convolutions**

https://towardsdatascience.com/a-basic-introduction-to-separable-convolutions-b99ec3102728

Convolution Example



$$0 + 1 = 1$$

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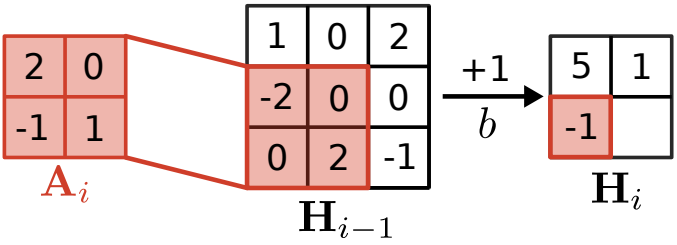
Convolution Example



$$2 \cdot (-2) + 1 \cdot 2 + 1 = -1$$

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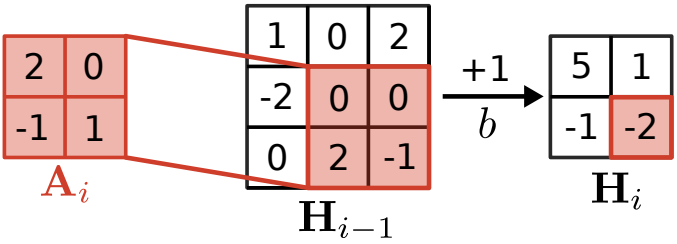
Convolution Example



$$(-1) \cdot 2 + 1 \cdot (-1) + 1 = -2$$

Remarks:

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Convolution Example

$*$

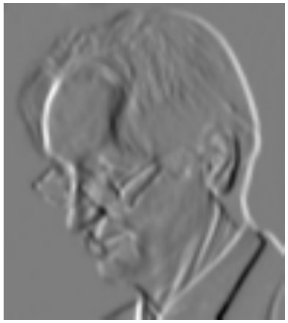
0	1	0
1	4	1
0	1	0

- Common filters. In deep learning our goal is to learn the filter kernels.

Convolution Example

$*$

1	0	-1
2	0	-2
1	0	-1



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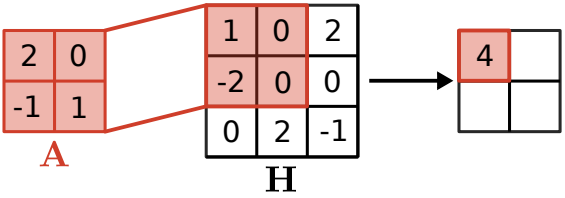
Convolution Operator

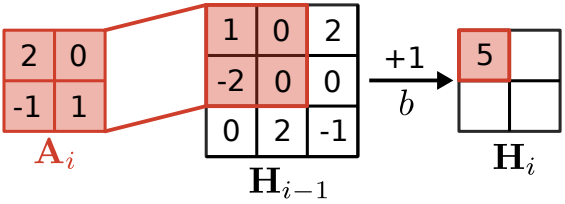


Definition of Convolution Operator:

$$[\mathbf{A} * \mathbf{H}](\mathbf{x}) = \sum_{\Delta\mathbf{x} \in \mathbb{Z}^2} \mathbf{A}(\Delta\mathbf{x})\, \mathbf{H}(\mathbf{x} + \Delta\mathbf{x})$$

- Convolution of feature map $\mathbf{H}$ with filter kernel $\mathbf{A}$
- Convolutions are **translation equivariant**

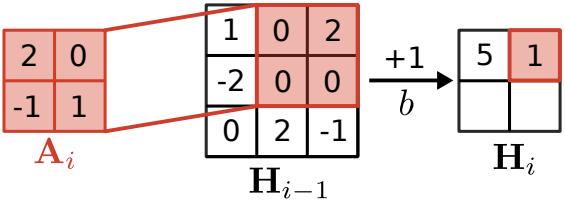
Convolution Example



Example (assuming 0-based indexing):

$$[\mathbf{A} * \mathbf{H}] \begin{pmatrix} 0 \\ 0 \end{pmatrix} = \mathbf{A} \begin{pmatrix} 0 \\ 0 \end{pmatrix} \mathbf{H} \begin{pmatrix} 0+0 \\ 0+0 \end{pmatrix} + \mathbf{A} \begin{pmatrix} 0 \\ 1 \end{pmatrix} \mathbf{H} \begin{pmatrix} 0+0 \\ 0+1 \end{pmatrix}$$
$$+ \mathbf{A} \begin{pmatrix} 1 \\ 0 \end{pmatrix} \mathbf{H} \begin{pmatrix} 0+1 \\ 0+0 \end{pmatrix} + \mathbf{A} \begin{pmatrix} 1 \\ 1 \end{pmatrix} \mathbf{H} \begin{pmatrix} 0+1 \\ 0+1 \end{pmatrix}$$

Convolution Example



Example (assuming 0-based indexing):

$$[\mathbf{A} * \mathbf{H}] \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \mathbf{A} \begin{pmatrix} 0 \\ 0 \end{pmatrix} \mathbf{H} \begin{pmatrix} 0+0 \\ 1+0 \end{pmatrix} + \mathbf{A} \begin{pmatrix} 0 \\ 1 \end{pmatrix} \mathbf{H} \begin{pmatrix} 0+0 \\ 1+1 \end{pmatrix}$$
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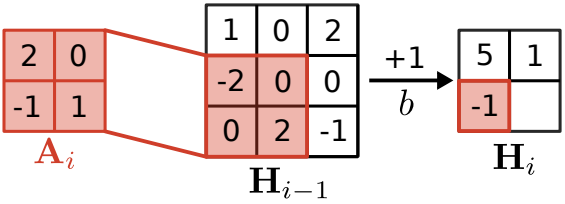
Convolution Example



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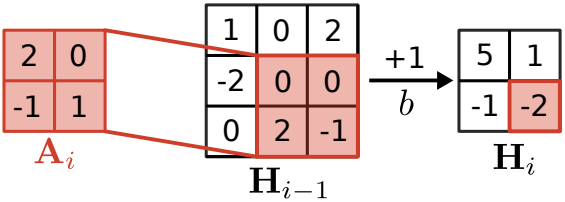
Convolution Example



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+ \mathbf{A} \begin{pmatrix} 1 \\ 0 \end{pmatrix} \mathbf{H} \begin{pmatrix} 1+1 \\ 1+0 \end{pmatrix} + \mathbf{A} \begin{pmatrix} 1 \\ 1 \end{pmatrix} \mathbf{H} \begin{pmatrix} 1+1 \\ 1+1 \end{pmatrix}
\end{aligned}
$$

Equivariance

Invariance vs. Equivariance

Invariance:

$$f(\mathbf{H}) = f(\mathcal{T}_\theta[\mathbf{H}])$$

Equivariance:

$$\mathcal{T}_\theta[f](\mathbf{H}) = f(\mathcal{T}_\theta[\mathbf{H}])$$

- With feature map $\mathbf{H}$, operation $f(\cdot)$ and transformation $\mathcal{T}_\theta$
- An operation is **invariant** if it returns the same result for any transformed input
- An operation is **equivariant** if its output transforms as its input for some specific transformation type (in the case of ConvNets: translation)

Translation Equivariance of Convolution

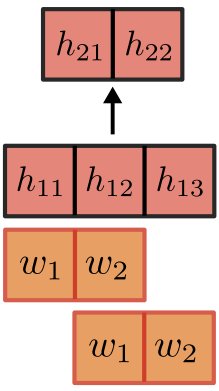
Proof:

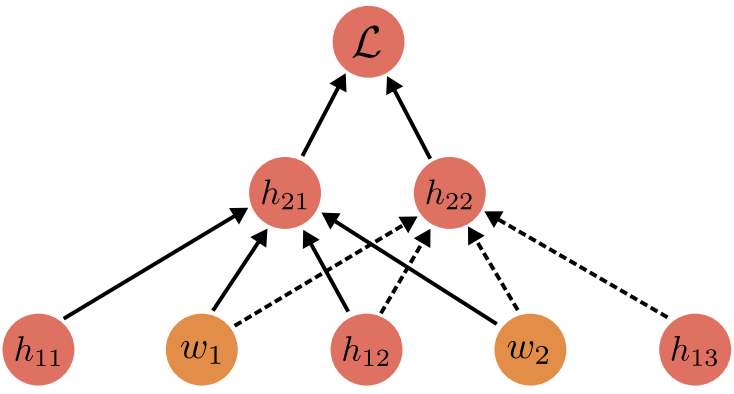
$$
\begin{aligned}
[\mathbf{A} * \mathcal{T}_{\mathbf{t}}[\mathbf{H}]](\mathbf{x}) &= \sum_{\Delta\mathbf{x}\in\mathbb{Z}^2} \mathbf{A}(\Delta\mathbf{x})\, \mathcal{T}_{\mathbf{t}}[\mathbf{H}](\mathbf{x}+\Delta\mathbf{x}) && \text{definition of convolution} \\
&= \sum_{\Delta\mathbf{x}\in\mathbb{Z}^2} \mathbf{A}(\Delta\mathbf{x})\, \mathbf{H}(\mathbf{x}+\Delta\mathbf{x}-\mathbf{t}) && \text{expanding translation operator} \\
&= \sum_{\Delta\mathbf{x}\in\mathbb{Z}^2} \mathbf{A}(\Delta\mathbf{x})\, \mathbf{H}((\mathbf{x}-\mathbf{t})+\Delta\mathbf{x}) && \text{rearranging} \\
&= [\mathbf{A} * \mathbf{H}](\mathbf{x}-\mathbf{t}) = \mathcal{T}_{\mathbf{t}}[\mathbf{A} * \mathbf{H}](\mathbf{x}) && \text{definition of convolution}
\end{aligned}
$$

- Convolutions are **translation equivariant** but not translation invariant
- Shifting the input, results in a **shifted output** (exception: image boundaries)
- Interpretation as **inductive bias** built into ConvNet architecture

Implementation as Computation Graph

Computation Graph

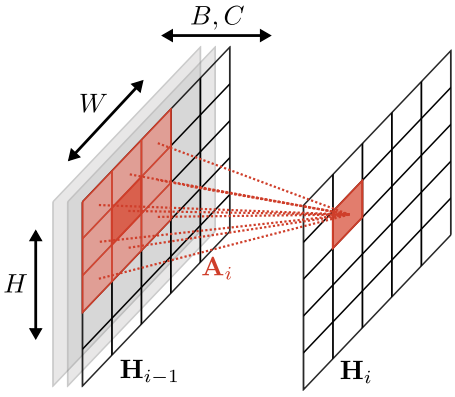




- Gradients get **accumulated** (summed up) across locations due to **weight sharing**

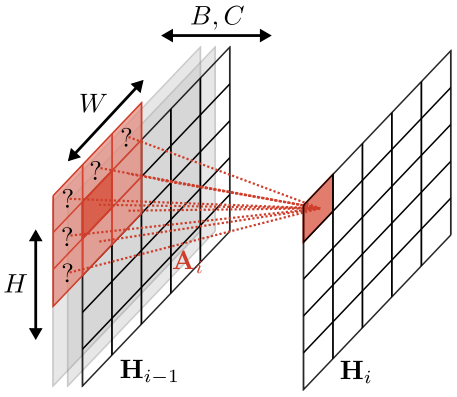
Padding

Padding



- Convolutions can only be executed if kernel lies entirely **within input domain**
- Often undesirable and **inconvenient** as it couples architecture and input size

Padding



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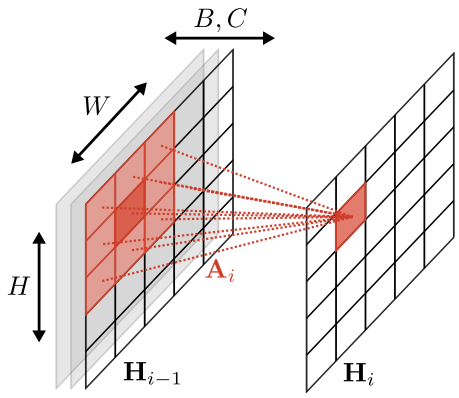
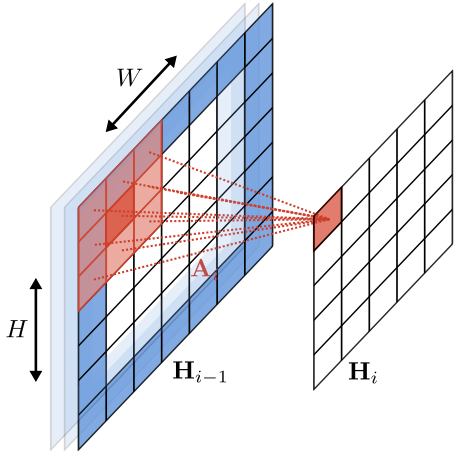
- Often undesirable and **inconvenient** as it couples architecture and input size

Padding





Idea of Padding:

- Add boundary of appropriate size with zeros (blue) around input tensor

Padding

- Let $H'[\cdot]$ denote a padded version of the tensor $H[\cdot]$
- In NumPy, this can be achieved as follows (with P the padding size):

```
H_pad = np.zeros(H+2P,W+2P)
H_pad[P:H+P,P:W+P] = H
```

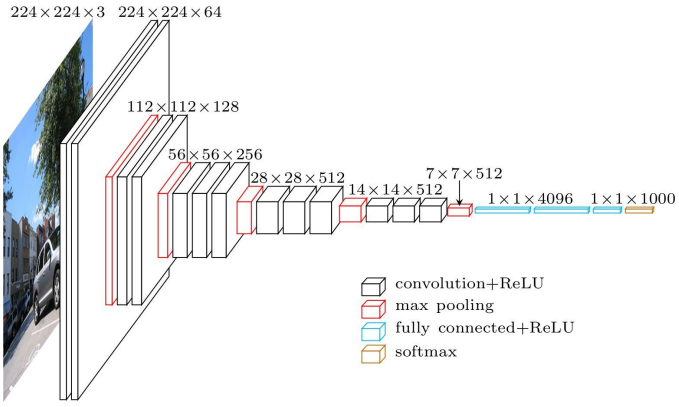
- The output of the **padded convolution** is given by:

$$\underbrace{H_i[b, x, y, c_{out}]}_{\text{Current Layer}} = g\left(\underbrace{A_i[\Delta X, \Delta Y, C_{in}, c_{out}]}_{\text{Weights}}\ \underbrace{H'_{i-1}[b, x+\Delta X, y+\Delta Y, C_{in}]}_{\text{Prev. Layer}} + \underbrace{b_i[c_{out}]}_{\text{Bias}}\right)$$

- Note: if the input is padded, then Δx and Δy are non-negative

7.2
Downsampling

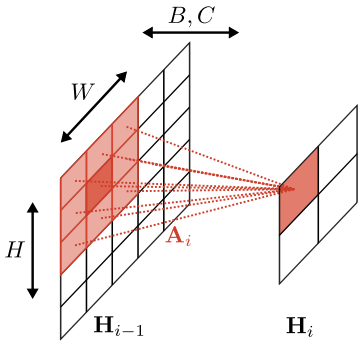
Downsampling



- Downsampling **reduces the spatial resolution** (e.g., for image level predictions)
- Downsampling **increases the receptive field** (which pixels influence a neuron)

Simonyan and Zisserman: Very Deep Convolutional Networks for Large-Scale Image Recognition. ICLR, 2015.

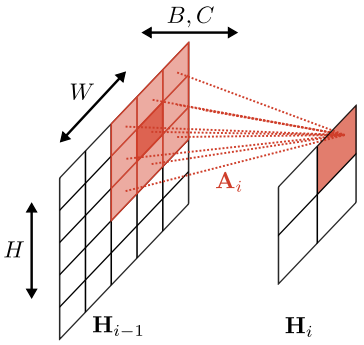
Pooling



$$\underbrace{H_i[b, x, y, c]}_{\text{Current Layer}} = \max_{\Delta x, \Delta y} \underbrace{H_{i-1}[b, s \cdot x + \Delta x, s \cdot y + \Delta y, c]}_{\text{Prev. Layer}}$$

- Typically, stride $s = 2$ and kernel size $2 \times 2 \Rightarrow$ **reduces spatial dimensions** by 2
- Pooling has **no parameters** (typical pooling operations: max, min, mean)
- Pooling is **applied to each channel separately** $\Rightarrow$ keeps number of channels

Pooling



$$\underbrace{H_i[b, x, y, c]}_{\text{Current Layer}} = \max_{\Delta x, \Delta y} \underbrace{H_{i-1}[b, s \cdot x + \Delta x, s \cdot y + \Delta y, c]}_{\text{Prev. Layer}}$$

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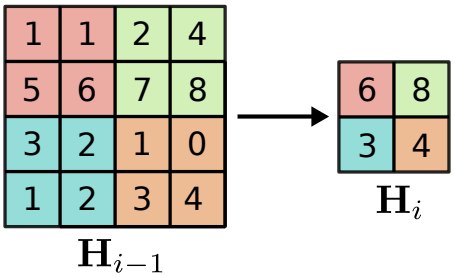
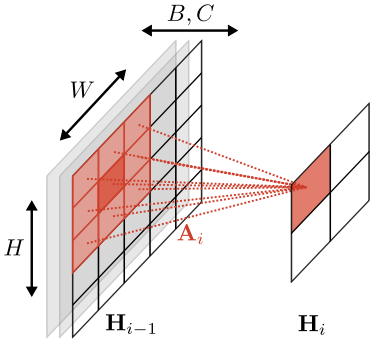
Pooling Example



$$\underbrace{H_i[b, x, y, c]}_{\text{Current Layer}} = \max_{\Delta x, \Delta y} \underbrace{H_{i-1}[b, s \cdot x + \Delta x, s \cdot y + \Delta y, c]}_{\text{Prev. Layer}}$$

- Max pooling with stride $s = 2$ and kernel size 2×2 reduces spatial dimension by 2
- Remark: Max pooling provides **invariance** to small translations of the input

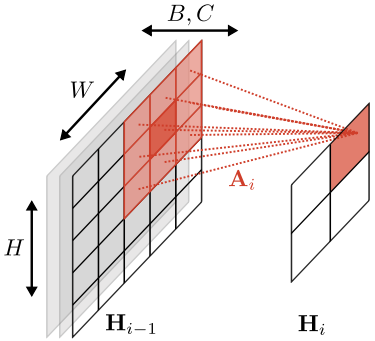
Strided Convolution



$$\underbrace{H_i[b, x, y, c_{out}]}_{\text{Current Layer}} = g\left(\underbrace{A_i[\Delta X, \Delta Y, C_{in}, c_{out}]}_{\text{Weights}} \underbrace{H_{i-1}[b, s \cdot x + \Delta X, s \cdot y + \Delta Y, C_{in}]}_{\text{Prev. Layer}} + \underbrace{b_i[c_{out}]}_{\text{Bias}}\right)$$

- **Move convolution filter** (with parameters $\mathbf{A}$ and $\mathbf{b}$) by stride s
- **Learned downsampling.** Often replaces max pooling today (e.g., in ResNet)

Strided Convolution



$$\underbrace{H_i[b, x, y, c_{out}]}_{\text{Current Layer}} = g\left(\underbrace{A_i[\Delta X, \Delta Y, C_{in}, c_{out}]}_{\text{Weights}} \underbrace{H_{i-1}[b, s \cdot x + \Delta X, s \cdot y + \Delta Y, C_{in}]}_{\text{Prev. Layer}} + \underbrace{b_i[c_{out}]}_{\text{Bias}}\right)$$

- **Move convolution filter** (with parameters $\mathbf{A}$ and $\mathbf{b}$) by stride s
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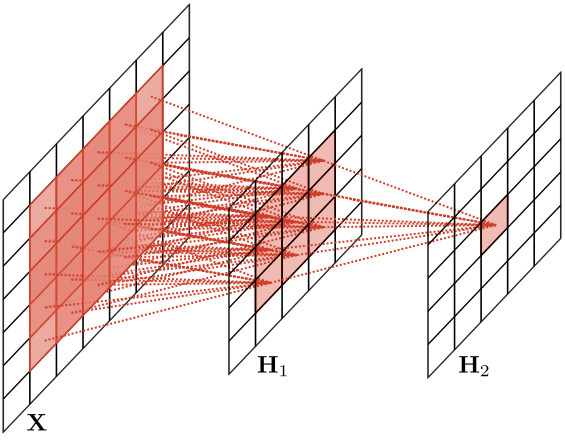
Receptive Field and Arithmetics

Receptive Field

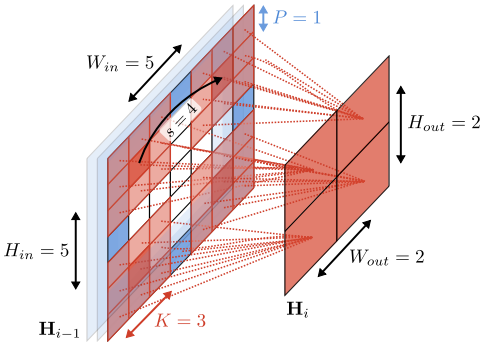


- **Receptive field** of a neuron is defined as all pixels in the input $\mathbf{X}$ which influence it

Arithmetics

Assuming:

- Input: $W_{in} \times H_{in}$
- Filter: $K \times K$
- Padding: P
- Stride: s

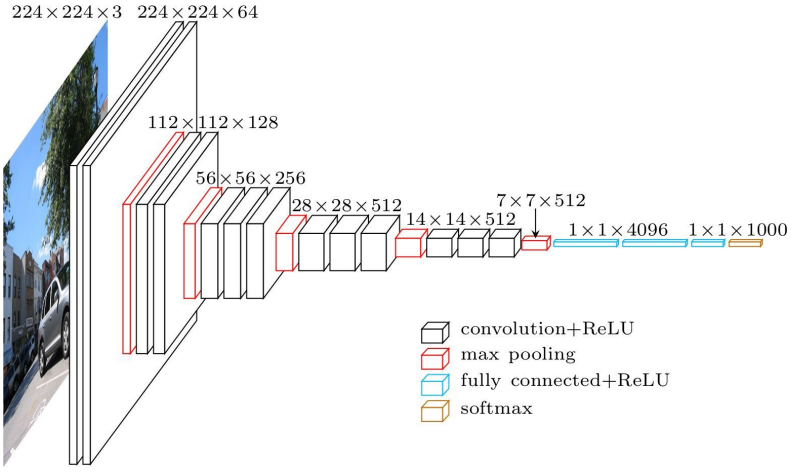


Then, the output has size:

$$\underbrace{\left(\left\lfloor \frac{W_{in} + 2P - K}{s} \right\rfloor + 1\right)}_{W_{out}} \times \underbrace{\left(\left\lfloor \frac{H_{in} + 2P - K}{s} \right\rfloor + 1\right)}_{H_{out}}$$

Fully Connected Layers

Fully Connected Layers

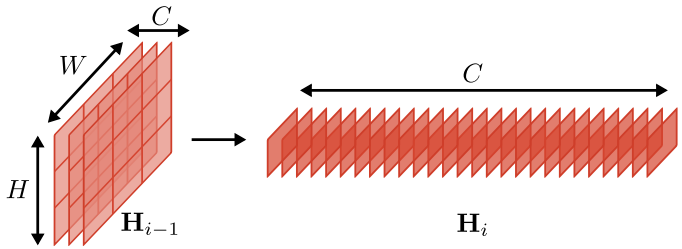


- Fully connected layers are most **memory intensive** part of VGG architecture

Simonyan and Zisserman: Very Deep Convolutional Networks for Large-Scale Image Recognition. ICLR, 2015.

Fully Connected Layers

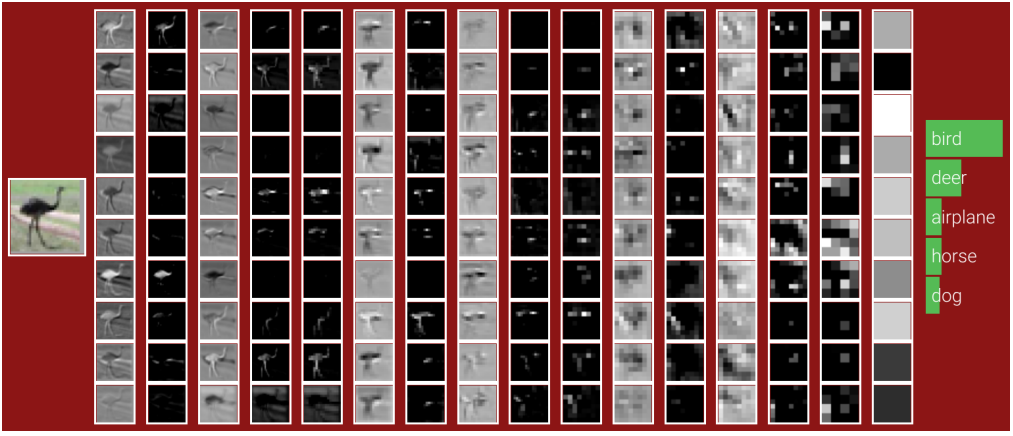
- Reshape $H_{i-1}[B, X, Y, C]$ into $H_i[B, C]$



- Now X and Y are **reshaped** into the feature channel dimension C
- A fully connected layer in **Einstein notation** can be written as:

$$\underbrace{H_i[b, c_{out}]}_{\text{Current Layer}} = g\left(\underbrace{A_i[c_{out}, C_{in}]}_{\text{Weights}} \underbrace{H_{i-1}[b, C_{in}]}_{\text{Prev. Layer}} + \underbrace{b_i[c_{out}]}_{\text{Bias}}\right)$$

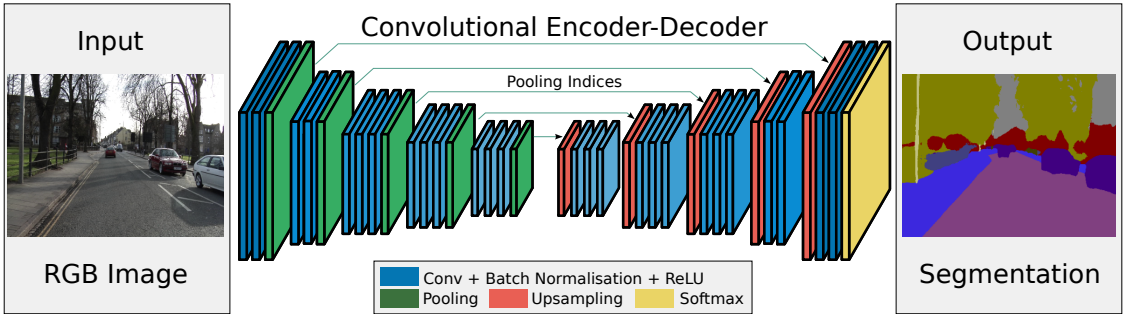
Convolution Network Example



http://cs231n.stanford.edu/2017/index.html

7.3
Upsampling

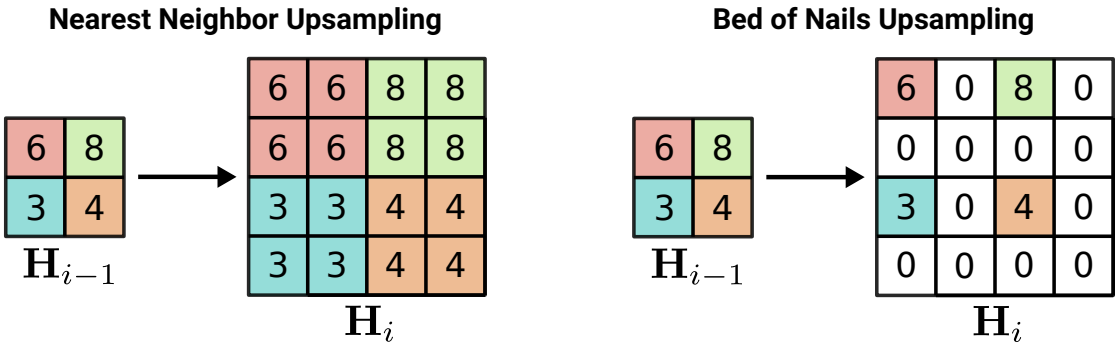
Upsampling



- If **pixel-level outputs** are desired, we have to **upsample** the features again
- Downsampling provides strong features with large receptive field
- Upsampling yields output at the same resolution as input

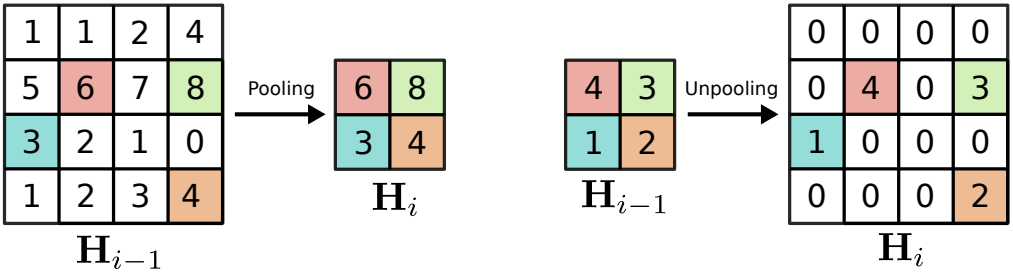
Badrinarayanan, Kendall and Cipolla: SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. TPAMI, 2017.

Upsampling



- **Nearest neighbor:** scale each channel using nearest neighbor interpolation
- **Bilinear:** scale each channel using bilinear neighbor interpolation
- **Bed of nails:** insert elements at sparse location (followed by convolution)

Max Unpooling



- For unpooling, **remember** which element was **maximum** during pooling
- Requires corresponding pairs of downsampling and upsampling layers
- This approach has been used in SegNet

Badrinarayanan, Kendall and Cipolla: SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. TPAMI, 2017.

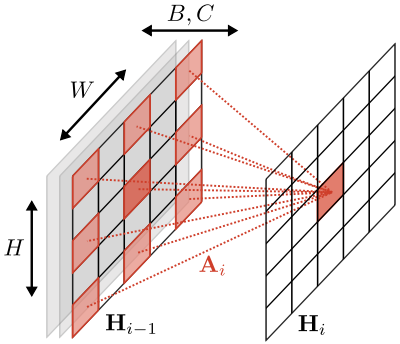
Dilated Convolution

Dilated Convolution

- Dilated convolutions are an alternative to combining downsampling and upsampling opterations in order to reach a large receptive field size quickly
- Dilated convolutions increase the receptive field of standard convolutions without increasing the number of parameters
- Thus, a network with dilated convolutions is able to perform image-level predictions (e.g., semantic segmentation) without upsampling and downsampling
- Without dilated convolutions, a very large number of layers of standard convolutions would be required to reach the same receptive field size without using upsampling and downsampling (as in a U-Net)
- Remark: Dilated convolutions are not upsampling operations

Yu and Koltun: Multi-Scale Context Aggregation by Dilated Convolutions. ICLR, 2016.

Dilated Convolution

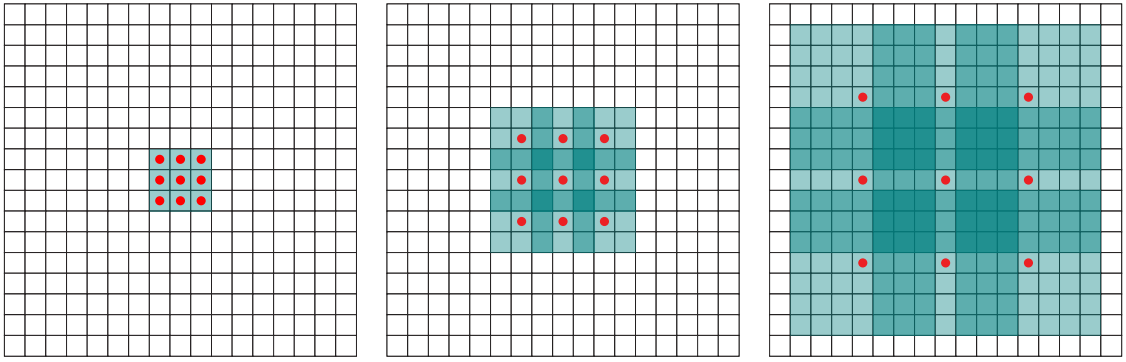


$$\underbrace{H_i[b, x, y, c_{out}]}_{\text{Current Layer}} = g\left(\underbrace{A_i[\Delta X, \Delta Y, C_{in}, c_{out}]}_{\text{Weights}} \underbrace{H_{i-1}[b, x + d \cdot \Delta X, y + d \cdot \Delta Y, C_{in}]}_{\text{Prev. Layer}} + \underbrace{b_i[c_{out}]}_{\text{Bias}}\right)$$

- Dilation factor d (here $d = 2$) leads to more "distributed" sampling of the input
- **Increases receptive field** without increasing parameters or reducing spatial dim.

Yu and Koltun: Multi-Scale Context Aggregation by Dilated Convolutions. ICLR, 2016.

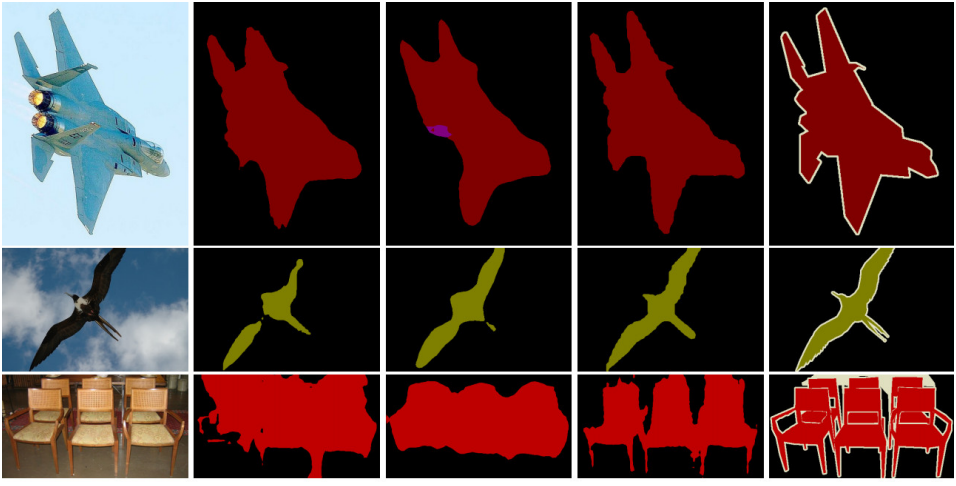
Dilated Convolution



- **No pooling** required to increase the receptive field
- Can produce predictions at the **same resolution** as the inputs
- Examples: semantic segmentation, depth, optical flow, …

Yu and Koltun: Multi-Scale Context Aggregation by Dilated Convolutions. ICLR, 2016.

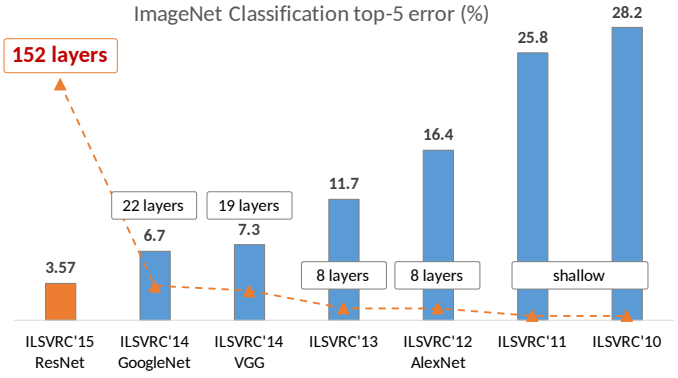
Dilated Convolution



Yu and Koltun: Multi-Scale Context Aggregation by Dilated Convolutions. ICLR, 2016.

7.4
Architectures

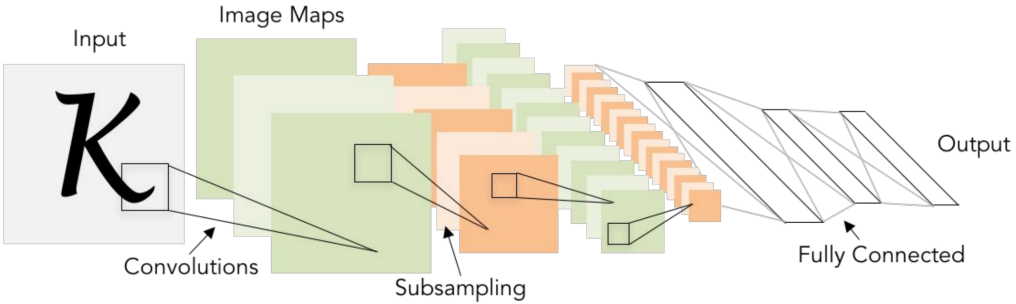
ImageNet Large Scale Visual Recognition Challenge



- Deeper networks are better (provided enough training data and compute)
- Nearly all state-of-the-art networks for image applications use convolution layers

Russakovsky et al.: ImageNet Large Scale Visual Recognition Challenge. IJCV, 2015.

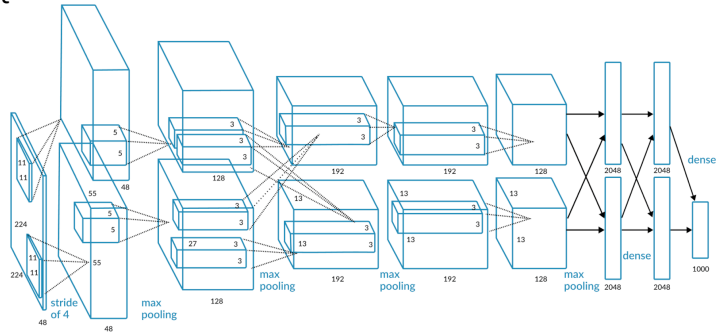
1998: LeNet-5



- 2 convolution layers (5×5), 2 pooling layers (2×2), 2 fully connected layers
- Achieved state-of-the-art accuracy on MNIST (prior to ImageNet)

LeCun et al. Gradient-based learning applied to document recognition. IEEE, 1998.

2012: AlexNet

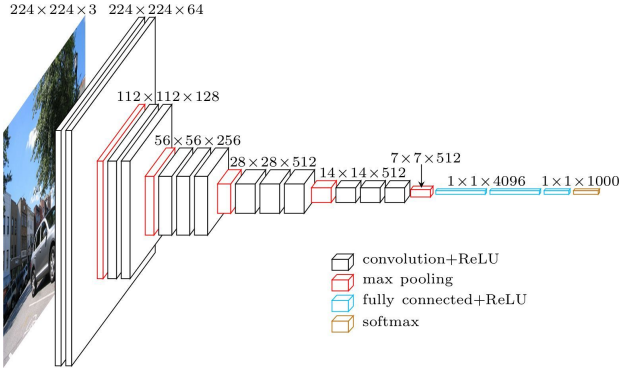


AlexNet:

- 8 layers, ReLUs, dropout, data augmentation, trained on 2 GTX 580 GPUs
- Number of feature channels increase with depth, spatial resolution decreases
- Triggered deep learning revolution, showed that CNNs work well in practice

Krizhevsky, Sutskever and Hinton: ImageNet Classification with Deep Convolutional Neural Networks. NIPS, 2012.

2015: VGG

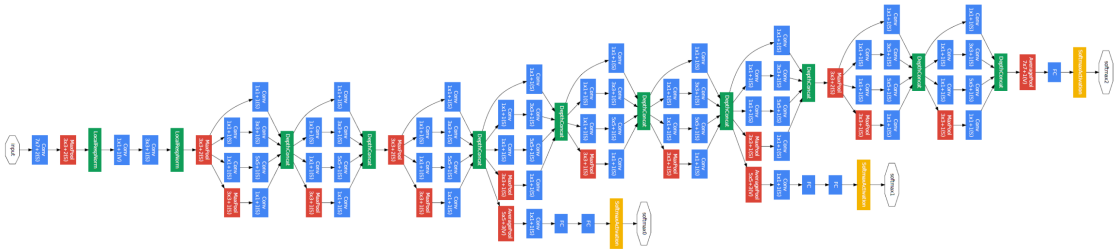


VGG:

- Uses 3×3 convolutions everywhere (same expressiveness, fewer parameters)
- Three 3×3 layers: same receptive field as one 7×7 layer, but less parameters
- 2 Variants: 16 and 19 Layers. Showed that deeper networks are better.

Simonyan and Zisserman: Very Deep Convolutional Networks for Large-Scale Image Recognition. ICLR, 2015.

2015: Inception / GoogLeNet

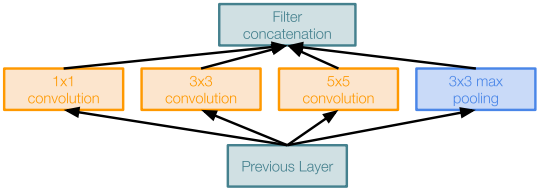


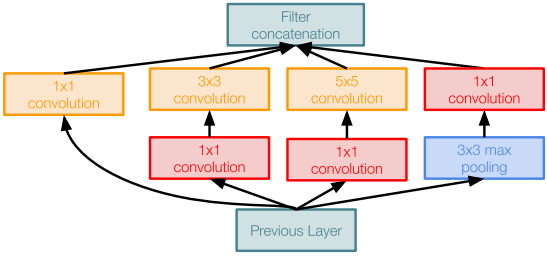
Inception:

- 22 layers. Inception modules utilize conv/pool operations with varying filter size
- Multiple intermediate classification heads to improve gradient flow
- Global avarage pooling (no FC layers), 27x less parameters (5 million) than VGG-16
- Uses 1×1 convolutions to reduce number of features $\Rightarrow$ higher efficiency

Szegedy et al.: Going deeper with convolutions. CVPR, 2015.

2015: Inception / GoogLeNet





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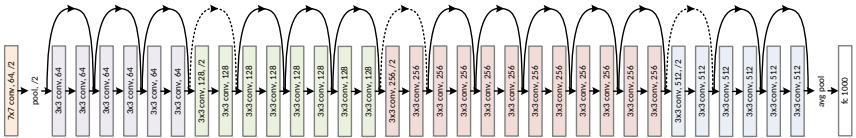
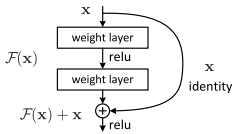
Szegedy et al.: Going deeper with convolutions. CVPR, 2015.

2016: ResNet



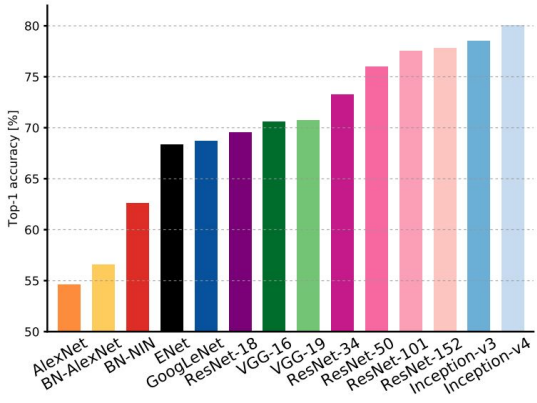


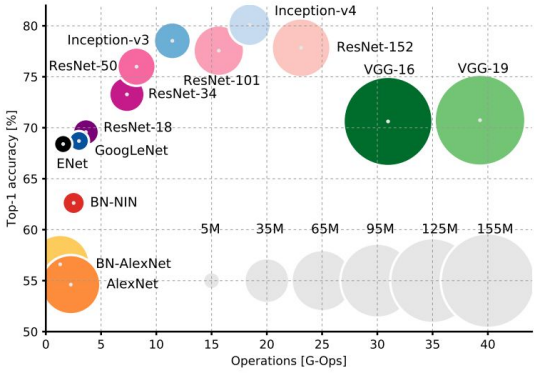
ResNet:

- Residual connections allow for training deeper networks (up to 152 layers)
- Very simple and regular network structure with 3×3 convolutions
- Uses strided convolutions for downsampling
- ResNet and ResNet-like architectures are dominating today

He, Zhang, Ren and Sun: Deep Residual Learning for Image Recognition. CVPR, 2016.

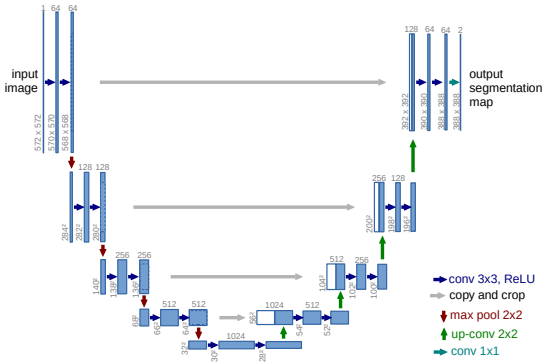
Complexity





- VGG has most parameters and is slowest
- ResNet/Inception/GoogLeNet are faster and have fewer parameters

U-Net



U-Net:

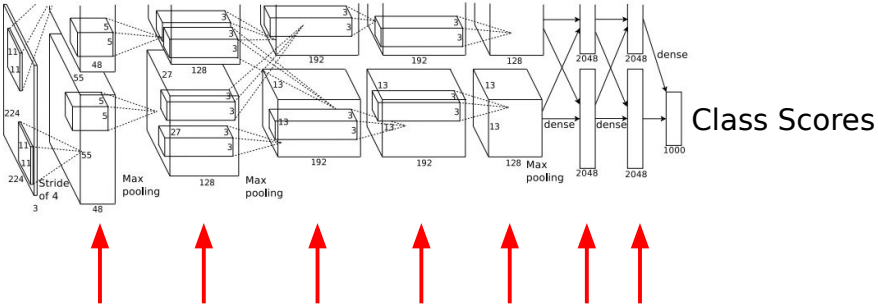
- Max-pooling, up-convolutions and skip-connections
- Defacto standard for many tasks with image output (e.g., depth, segmentation)

Ronneberger, Fischer and Brox: U-Net: Convolutional Networks for Biomedical Image Segmentation. MICCAI, 2015.

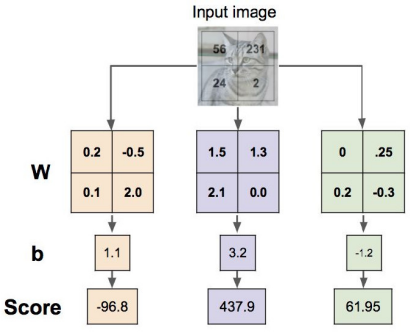
7.5
Visualization

Visualization

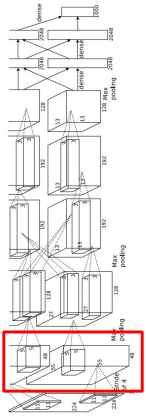
Input Image

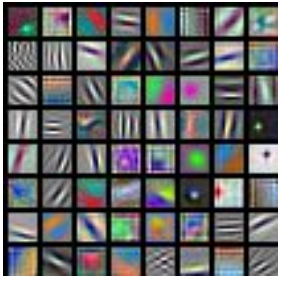


Visualizing a Linear Classifier



First Layers: Visualization of Features





AlexNet:
64 x 3 x 11 x 11

ResNet-18:
64 x 3 x 7 x 7

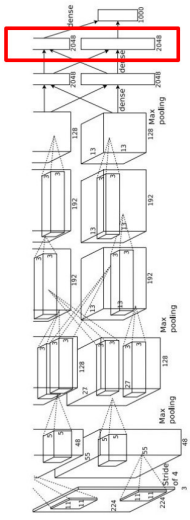
ResNet-101:
64 x 3 x 7 x 7

DenseNet-121:
64 x 3 x 7 x 7

- First layer learns **simple gradient/Gabor filters** ⇒ connection to V1 cells in brain
- Visualization less useful for later layers

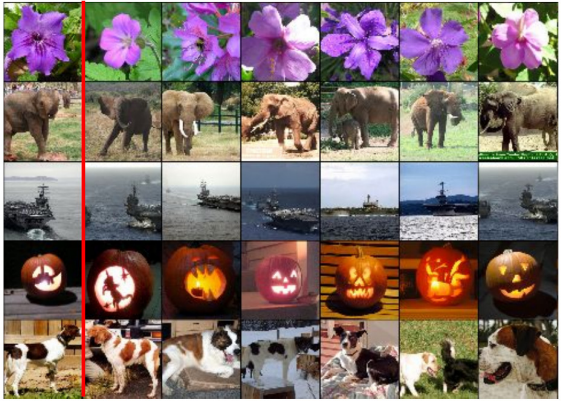
Last Layer: Nearest Neighbors

4096-dim vector

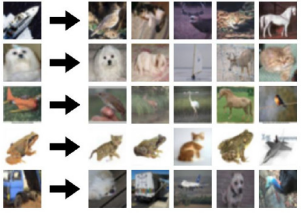


Test image

L2 Nearest neighbors in feature space



Recall: Nearest neighbors in pixel space



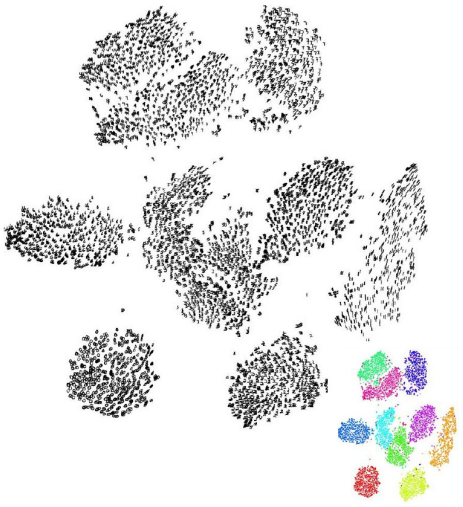
Krizhevsky et al.: ImageNet Classification with Deep Convolutional Neural Networks. NIPS, 2012.

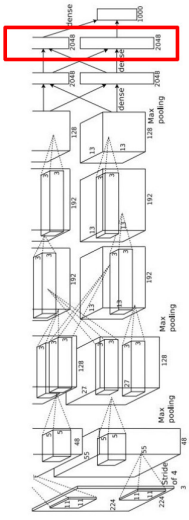
Last Layer: Dimensionality Reduction

Visualize the “space” of FC7 feature vectors by reducing dimensionality of vectors from 4096 to 2 dimensions

Simple algorithm: Principal Component Analysis (PCA)

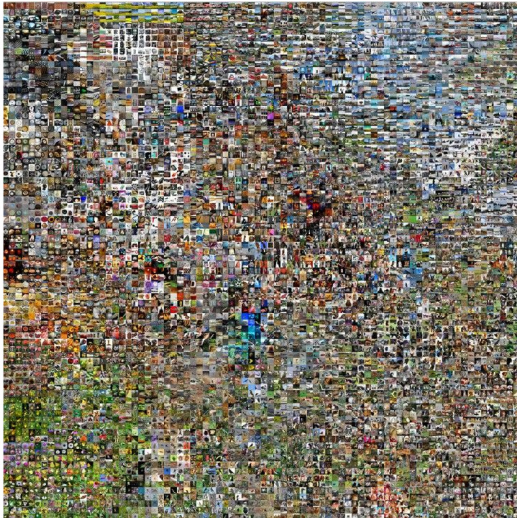
More complex: **t-SNE**





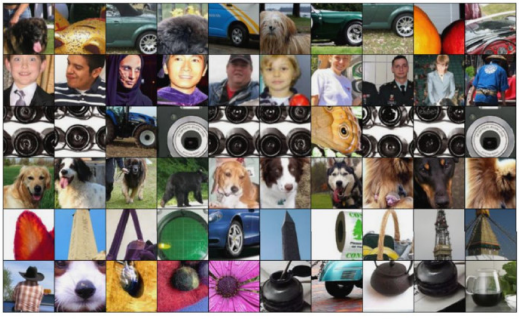
Van der Maaten and Hinton: Visualizing Data using t-SNE. JMLR, 2008.

Last Layer: Dimensionality Reduction



Van der Maaten and Hinton: Visualizing Data using t-SNE. JMLR, 2008.

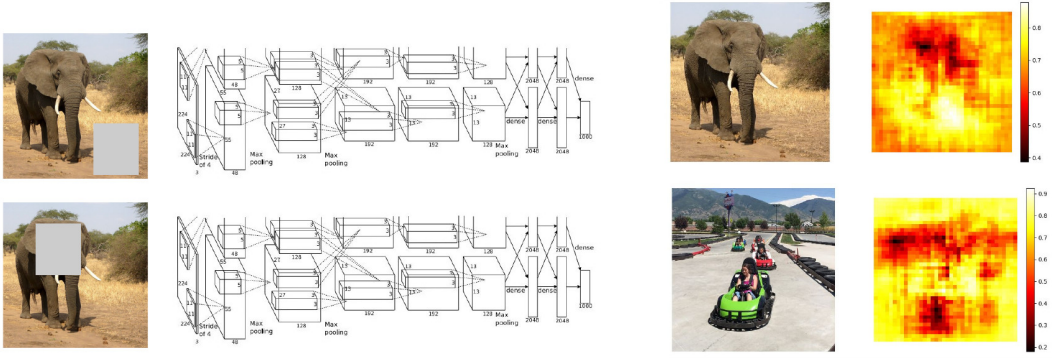
Maximally Activating Patches



- Run many images through network
- Record which images/patches maximally **activate a specific neuron**
- Here: each row corresponds to one neuron in the last convolutional layer

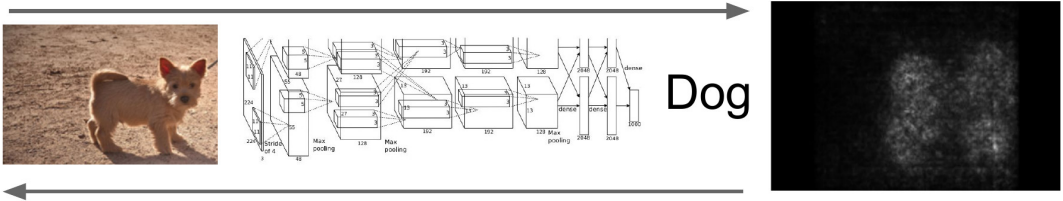
Springenberg et al.: Striving for Simplicity: The All Convolutional Net. ICLR Workshop, 2015.

Saliency via Masking



- **Mask image partially** before feeding to CNN (try many image locations)
- How much do the predicted probabilities for the correct class change?
- Results in **saliency map**

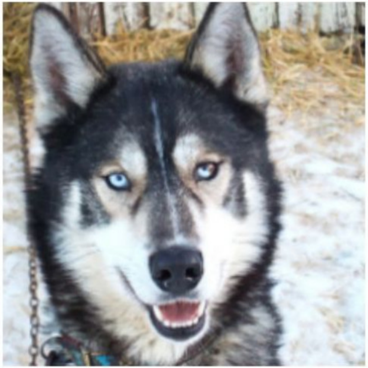
Saliency via Backpropagation



- Compute gradient of class score with respect to image pixels
- Changing which pixels of the input affects class score most strongly?
- Threshold to obtain **saliency map**

Simonyan, Vedaldi and Zisserman: Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps. ICLR Workshop, 2014.

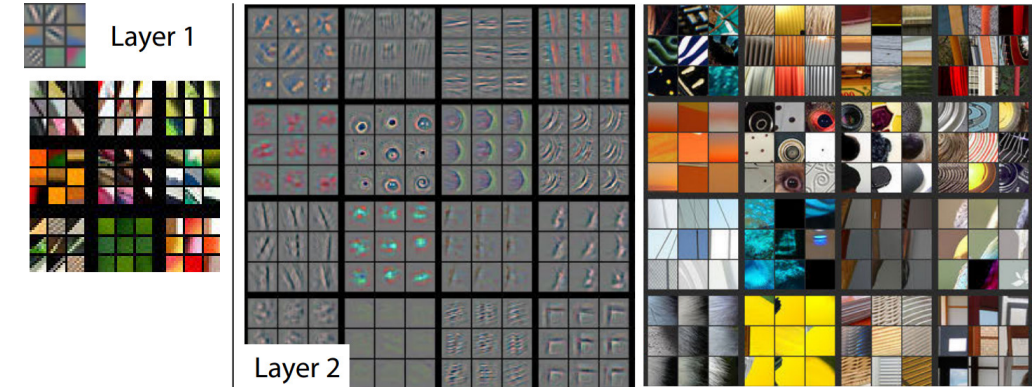
Saliency via Backpropagation



- Saliency maps can also **uncover unwanted biases** in the data/model
- In this case, the classifier detects snow to wrongly classify dog as wolf

Simonyan, Vedaldi and Zisserman: Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps. ICLR Workshop, 2014.

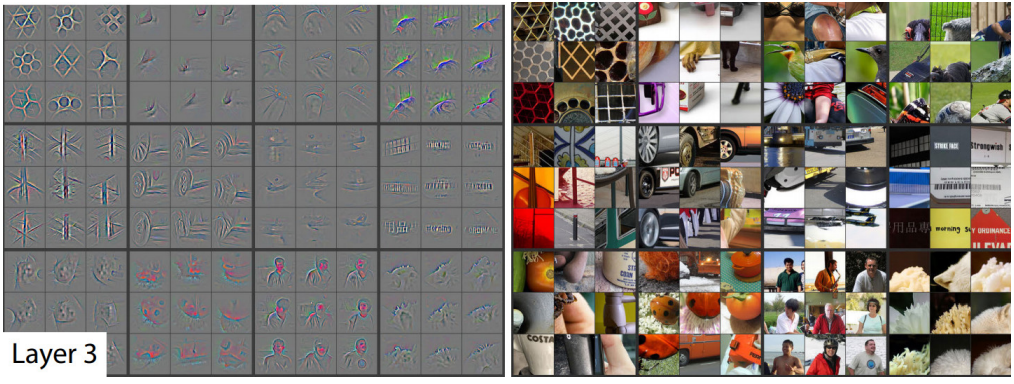
Deconvolution



- **DeConvNet** constructs a ConvNet in reverse order, starting from one neuron
- Remembers index of maximal activations during pooling for backward pass

Zeiler and Fergus: Visualizing and Understanding Convolutional Networks. ECCV, 2014.

Deconvolution



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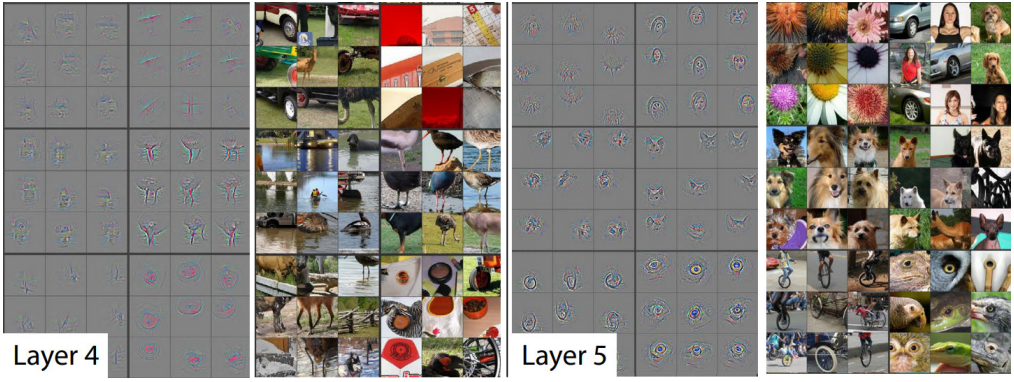
Deconvolution



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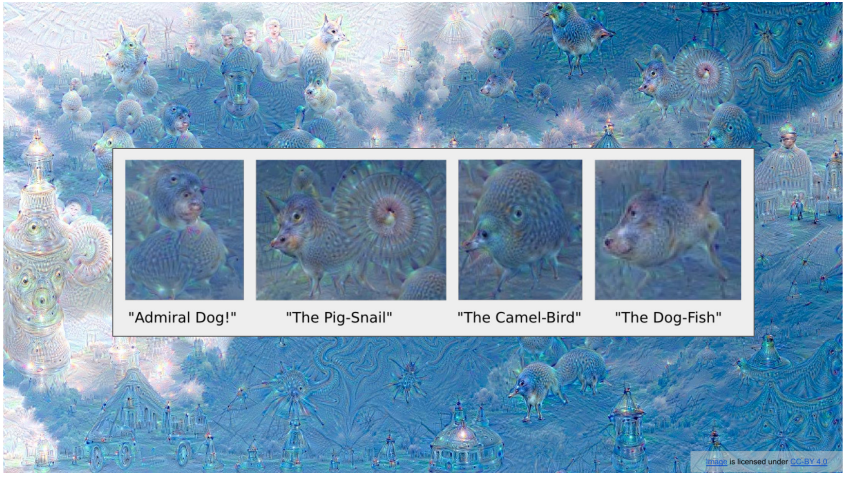
Zeiler and Fergus: Visualizing and Understanding Convolutional Networks. ECCV, 2014.

DeepDream

- **Amplify activation** of chosen layer wrt. a given image (gradient = activation)

Mordvintsev, Olah and Tyka: Inceptionism: Going Deeper into Neural Networks. Google Research Blog.

DeepDream



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Mordvintsev, Olah and Tyka: Inceptionism: Going Deeper into Neural Networks. Google Research Blog.