

# CS5242 : Neural Networks and Deep Learning

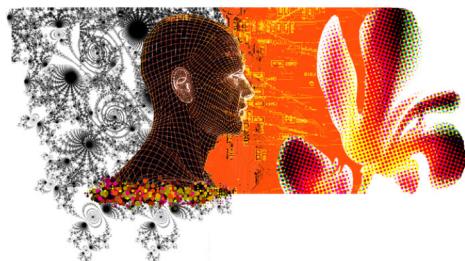
## Lecture Visualizing Convolutional Neural Networks

Semester 1 2021/22

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# Outline

- ConvNet features
- Domain of dependence of features
- Visualizing learned filters
- Hierarchical filters
- Improving ConvNets with visualization
- Conclusion

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# ConvNet features

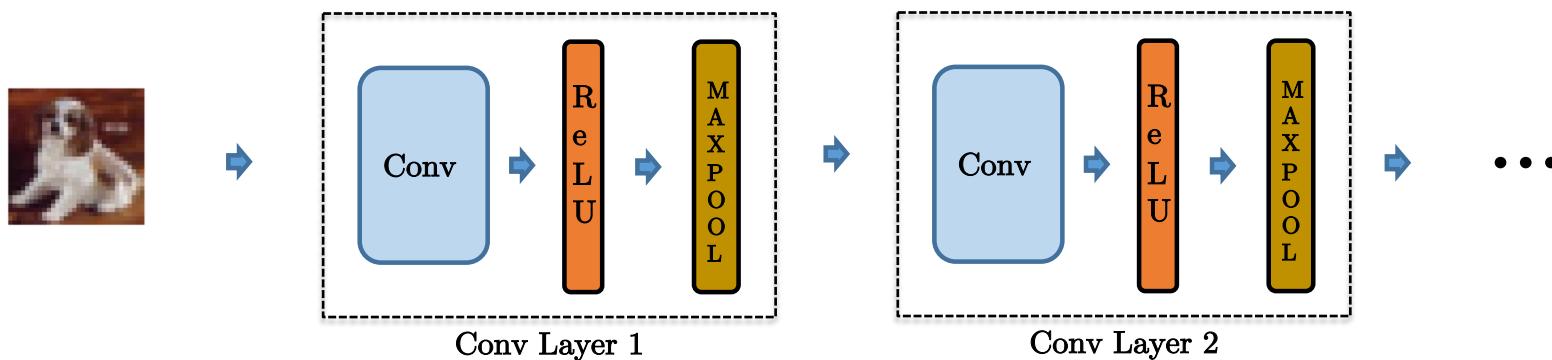
- ConvNets are extremely efficient at extracting compositional statistic patterns in large-scale and high-dimensional image datasets.
- Can we visualize the features/patterns learned that perform the classification task?
  - Some filters may have some human interpretations.
  - But most of them may not.
- However, visualizing some features can help to understand what ConvNet is doing.

# Outline

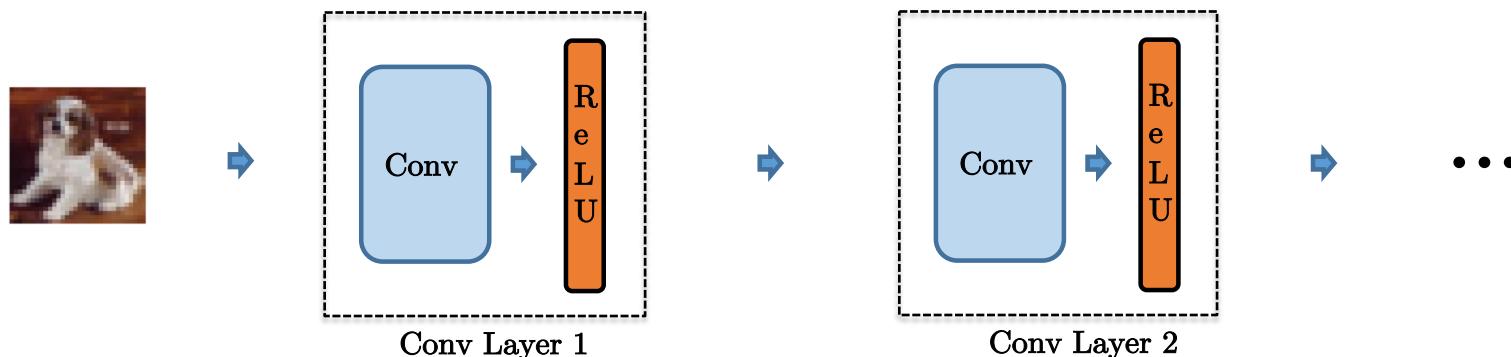
- ConvNet features
- **Domain of dependence of features**
- Visualizing learned filters
- Hierarchical filters
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## Domain of dependence

- Consider a L-layer ConvNet and  $3 \times 3$  filters :

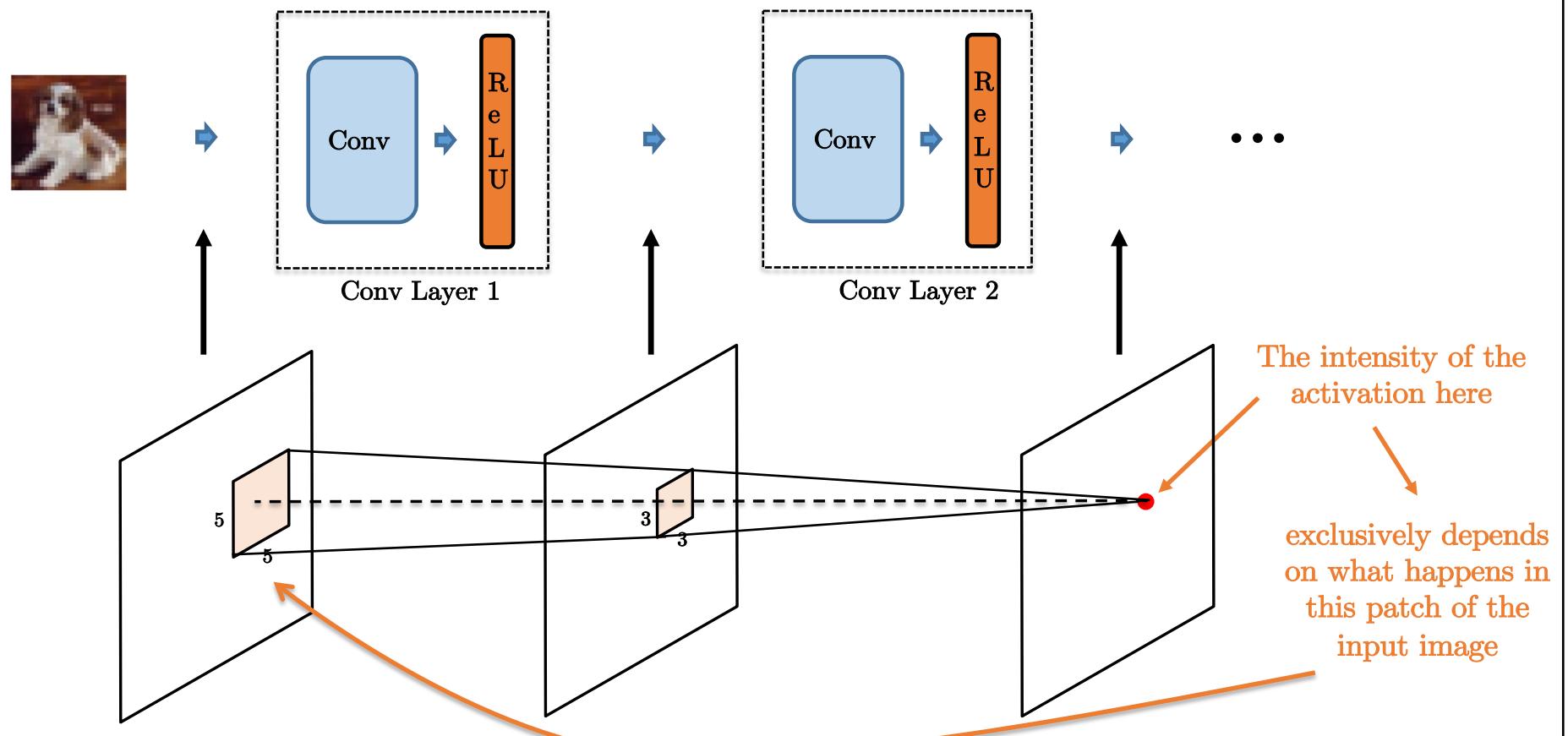


- For simplicity, suppose we do **not** use the Max Pooling layer :

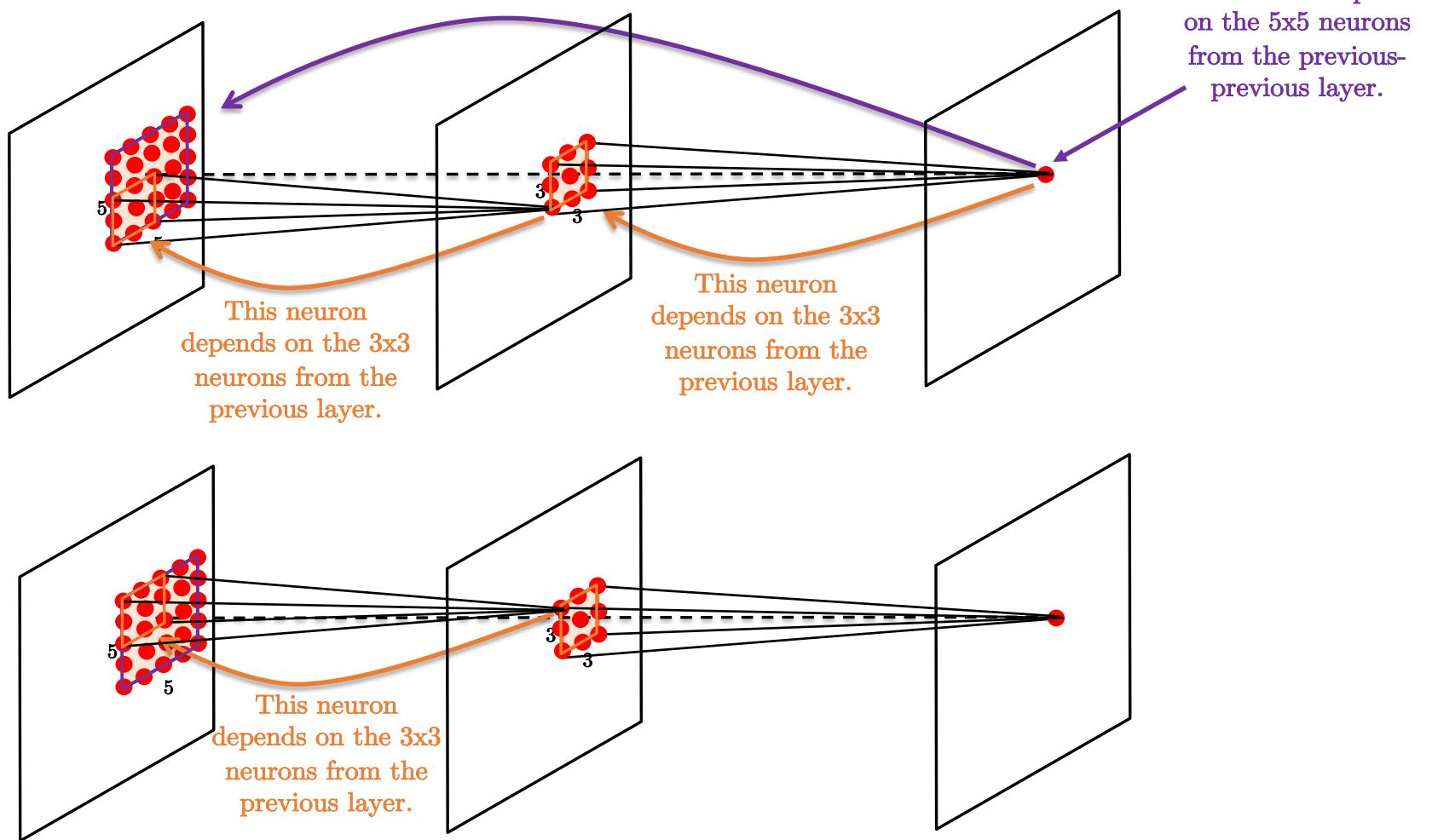


# Domain of dependence

- Consider a L-layer ConvNet and  $3 \times 3$  filters :



# Domain of dependence



# Domain of dependence

- When considering **3x3 convolutional filters** :
  - A neuron from the **1<sup>st</sup> layer** has access to **3 x 3** patches of the input image.
  - A neuron from the **2<sup>nd</sup> layer** has access to **5 x 5** patches of the input image.
  - A neuron from the **3<sup>rd</sup> layer** has access to **7 x 7** patches of the input image.
  - ...

# Outline

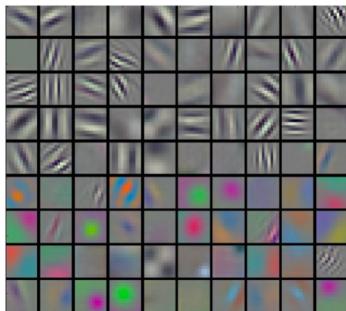
- ConvNet features
- Domain of dependence of features
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# Visualizing filters learned with ConvNets

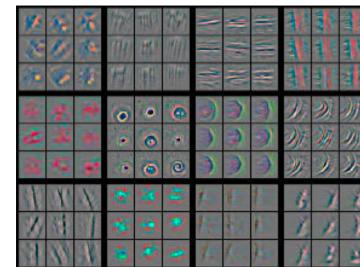
- Can we visualize the filters/patterns learned in the 1<sup>st</sup> layer, 2<sup>nd</sup> layer, 3<sup>rd</sup> layer, etc ?
- Intuition: **Hierarchical** filters/features learned in the layers :
  - **First** layers learn **low-level features** like edges, corners, small textures.
  - **Intermediate** layers learn **medium-level features** like eyes, noise, etc.
  - **Deep** layers learn **high-level features** like faces, cars, cats, etc.
- Can we check this intuition?

# DeConvNets

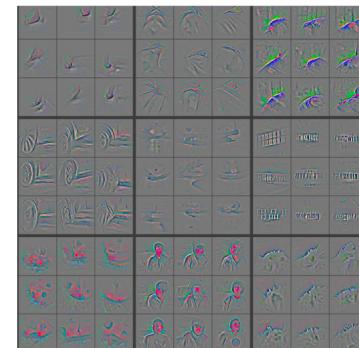
- Deconvolutional neural networks introduced by Zeiler and Fergus, 2013 :
  - Technique to map activations from deep layers back to input.
  - DeConvNets are like ConvNets, but in reverse order.
  - Can be used for visualizing filters learned with ConvNets.
  - It is **not** a learning technique.



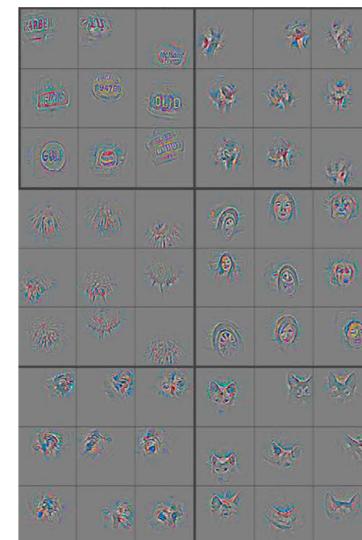
Filters learned 1<sup>st</sup> layer



Filters learned 2<sup>nd</sup> layer



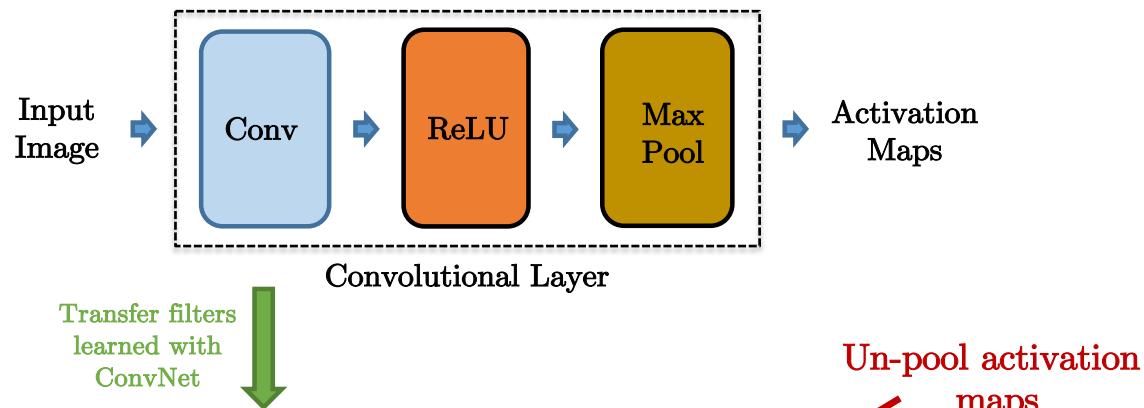
Filters learned 3<sup>rd</sup> layer



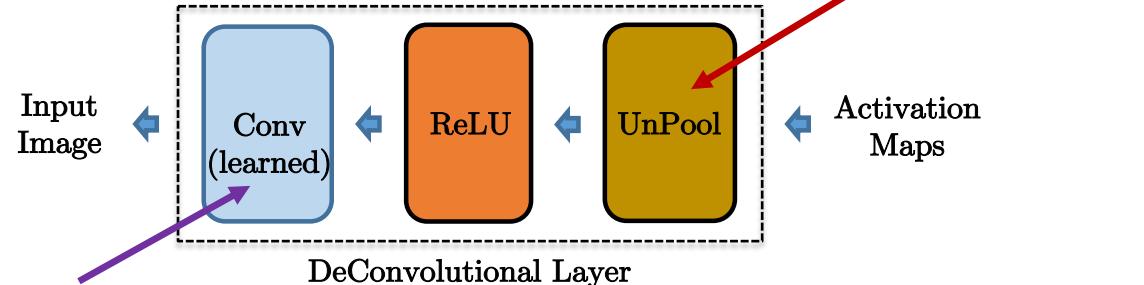
Filters learned 4<sup>th</sup> layer

# ConvNets vs DeConvNets

- ConvNets



- DeConvNets

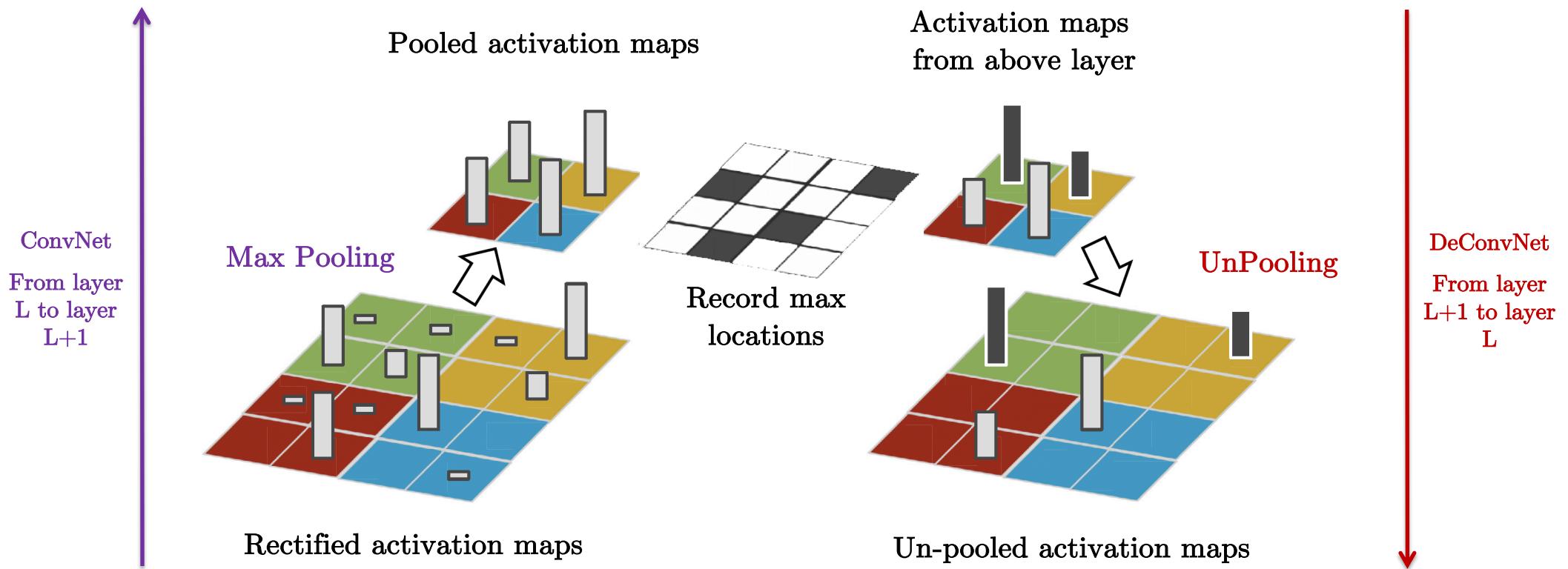


Convolve rectified un-pooled activation maps with filters learned from ConvNets

DeConvNets have no learning stage !

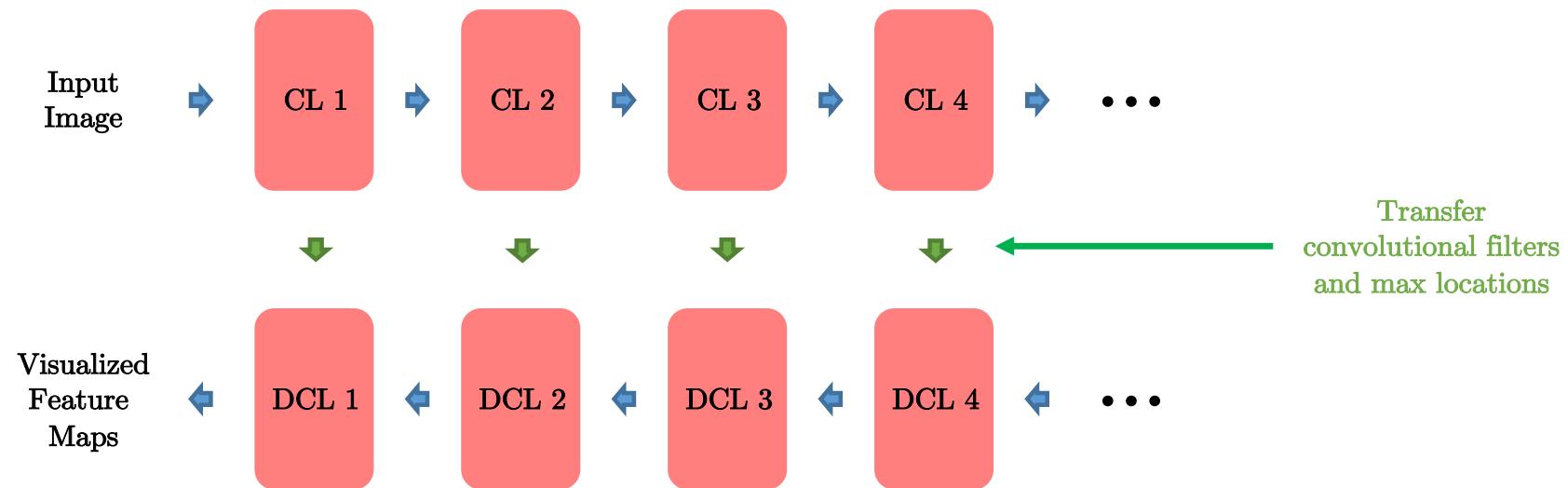
# Un-pooling

- Reverse Max Pooling:



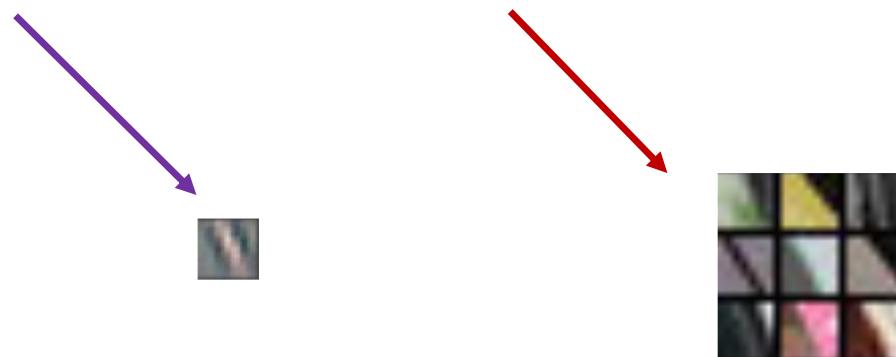
# Visualization architecture

- Visualization architecture couples ConvNets and DeConvNets together.
  - Visualization of ConvNet features is done *after training*.



# Visualization process

- It works as follows:
  - For the 1<sup>st</sup> layer, extract all 7x7 patches in the image and feed them to ConvNet.
  - Suppose we have 100 7x7 convolutional filters in the 1<sup>st</sup> layer.
    - Select 1 filter, find the top-9 7x7 patches with the maximum activation maps.

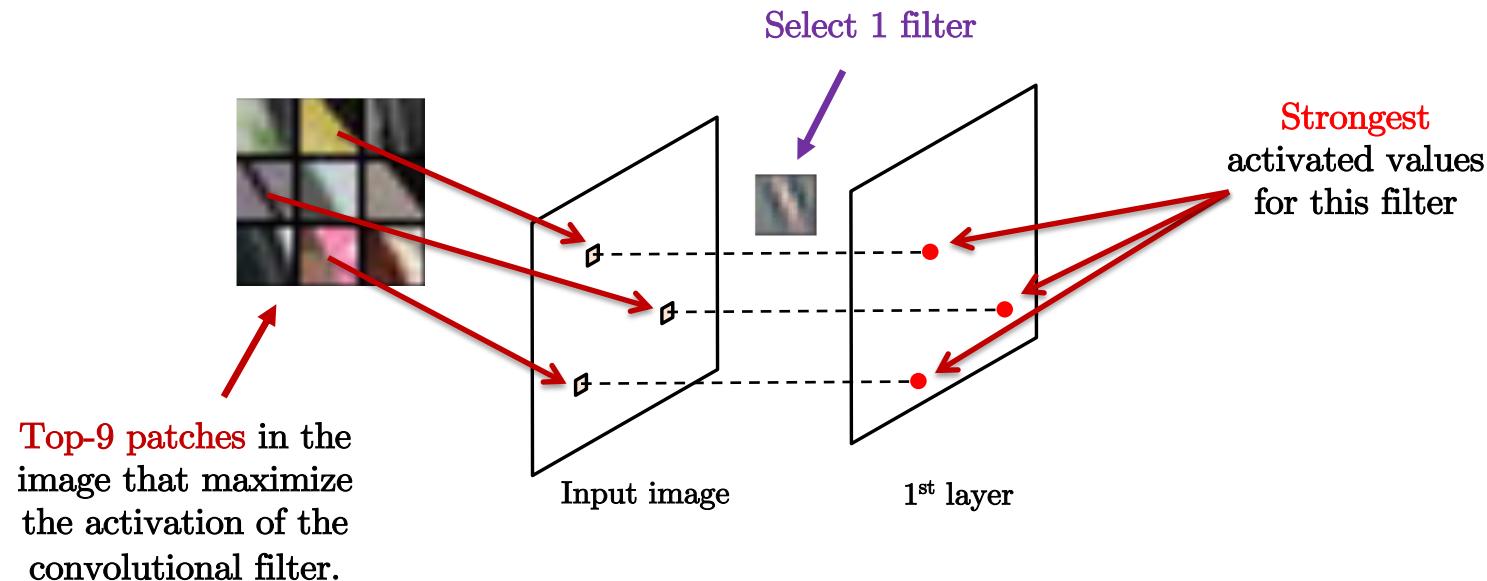


One convolutional filter

Top-9 patches  
that maximize the  
activation of the  
convolutional filter.

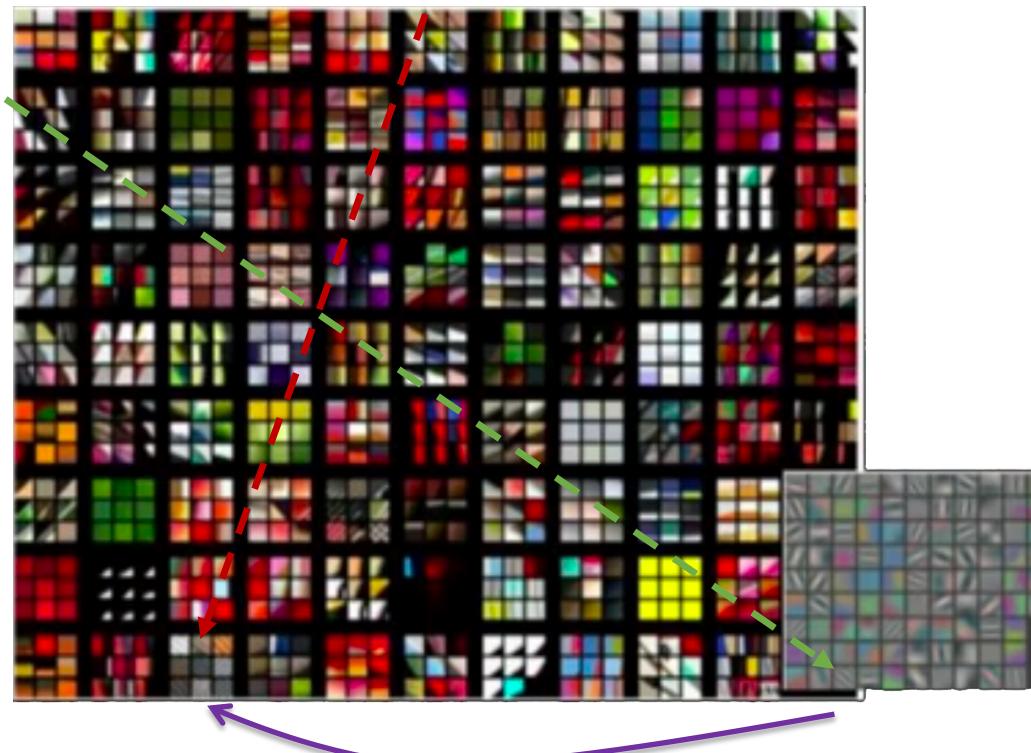
# Visualization process

- For the 1<sup>st</sup> layer, the 7x7 filters learned by ConvNet can be directly visualized.
  - There is no need to use for DeConvNet.



## Visualization process

- For the 1<sup>st</sup> layer :
  - Filters are simply visualized with ConvNet.
  - For each filter, also visualize the associated top-9 7x7 patches.



# Visualization process

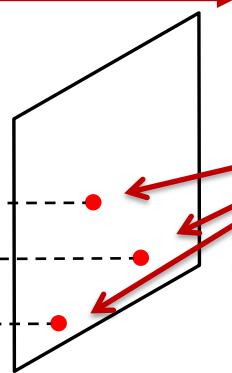
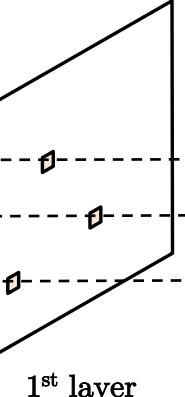
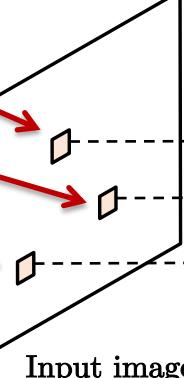
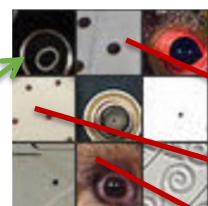
- For the 2<sup>nd</sup> layer :
  - We **cannot** directly visualize the filters learned with ConvNets.
  - We proceed as follows:
    - Extract all 11x11 patches in the image and feed them to (learned) ConvNet.
    - Suppose we have 100 7x7 convolutional filters in the 2<sup>nd</sup> layer.
      - Select 1 filter, find the top-9 11x11 patches with the maximum activation maps.
      - Use DeConvNet to visualize the filters associated with these top-9 patches.

# Visualization process

Select 1 filter at  
Layer 2 :

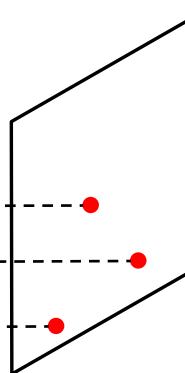
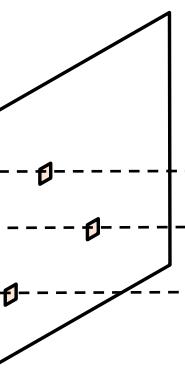
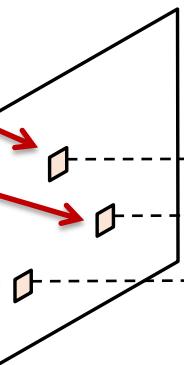
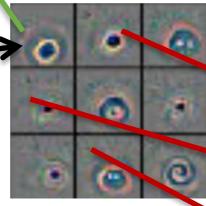
$W$   
It cannot be  
directly  
visualized!

ConvNet pass



Strongest  
activated values  
for filter  $W$  at  
Layer 2.

Filter  $W$   
at Layer 2  
associated to  
this image  
patch

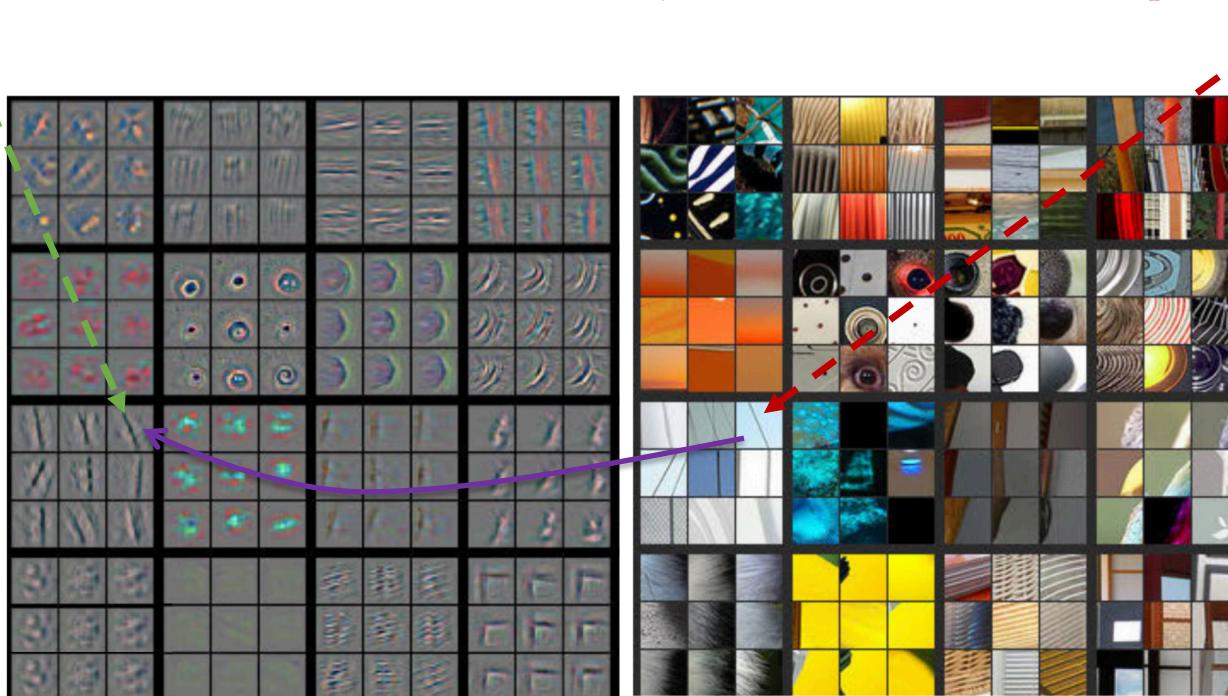


DeConvNet :  
Project back the  
activation to the  
input layer for  
visualizing filter  $W$   
at Layer 2.

DeConvNet pass

# Visualization process

- For the 2<sup>nd</sup> layer :
  - Filters are visualized with DeConvNet.
  - For each filter and each maximum activation, visualize the associated top-1 11x11 patch.



# Visualization process

- For the  $L^{\text{th}}$  layer :
  - Extract all  $21 \times 21$  patches in the image and feed them to (learned) ConvNet.
  - Suppose we have 100  $7 \times 7$  convolutional filters in the  $L^{\text{th}}$  layer.
    - Select 1 filter, find the top-9  $21 \times 21$  patches with the maximum activation maps.
    - Use DeConNet to visualize the filters associated with these top-9 patches.

# Visualization process

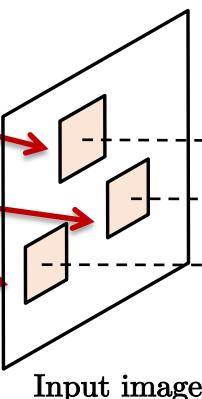
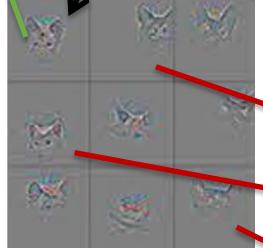
Select 1 filter at  
Layer L :

$W$

ConvNet pass

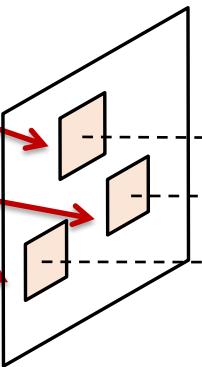


Filter  $W$   
at Layer L associated  
to this image patch.

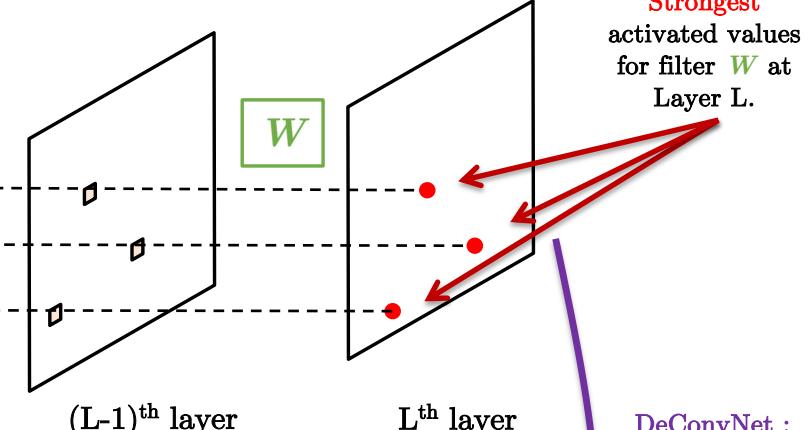


Input image

Filter associated  
to this image  
patch



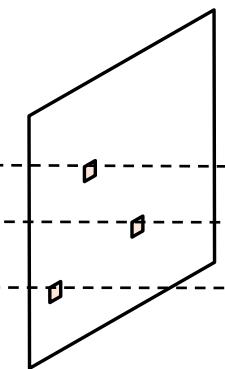
Input image



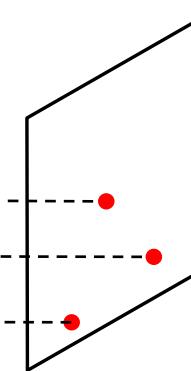
$(L-1)^{\text{th}}$  layer

$L^{\text{th}}$  layer

Strongest  
activated values  
for filter  $W$  at  
Layer L.



$(L-1)^{\text{th}}$  layer



$L^{\text{th}}$  layer

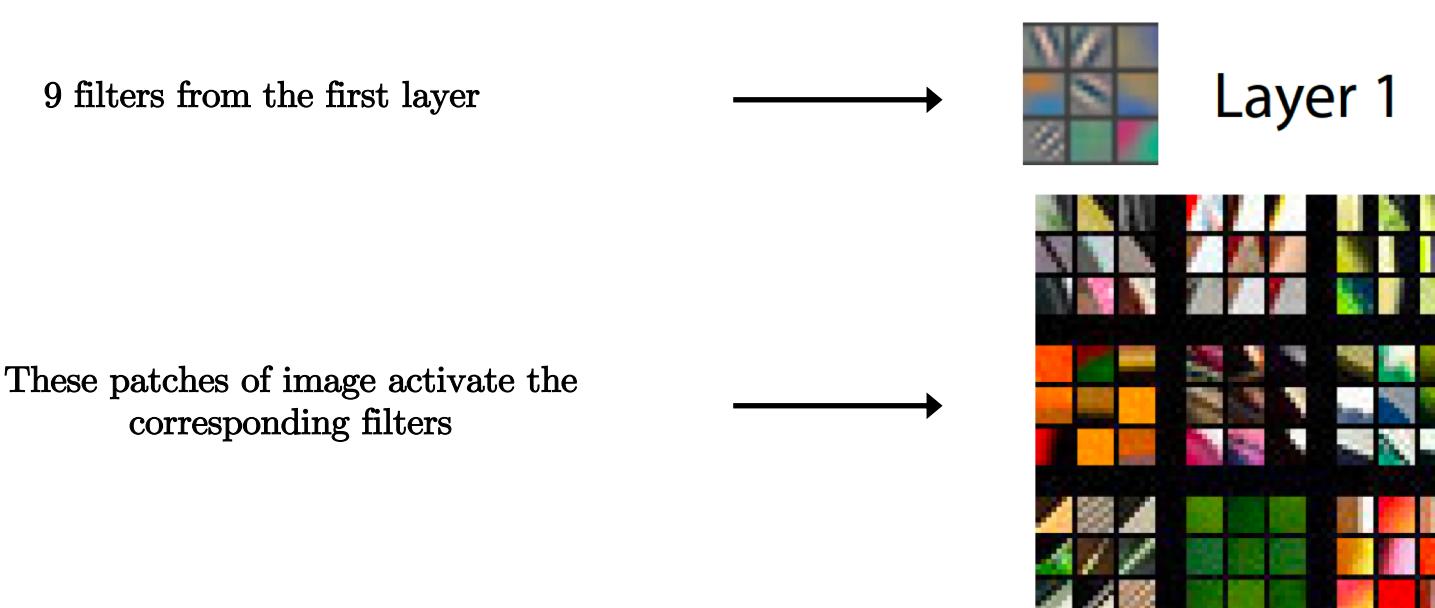
DeConvNet :  
Project back the  
activation to the  
input layer for  
visualizing filter  
 $W$  at Layer L.

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# Hierarchical filters

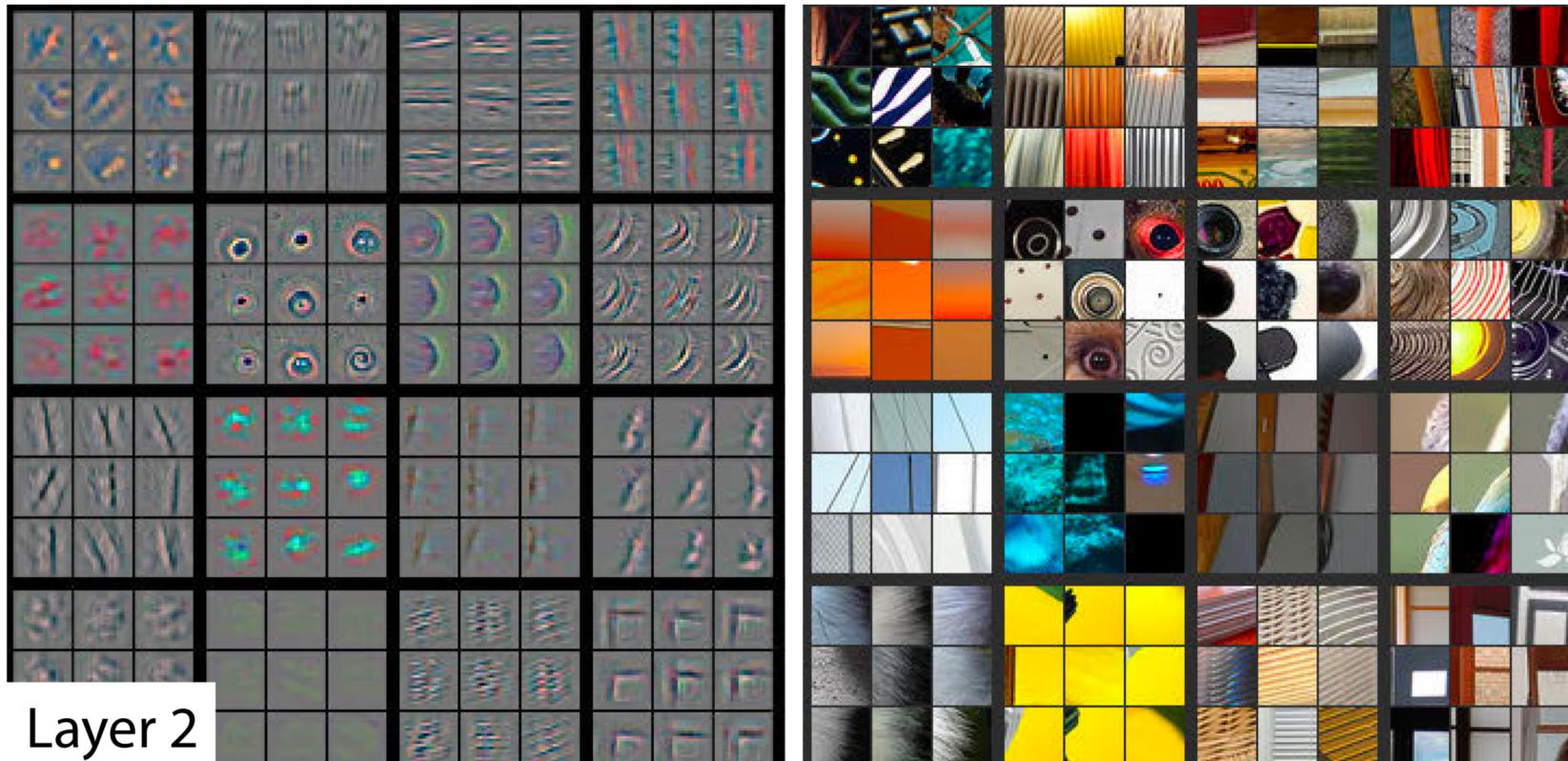
- Let us check if ConvNet learns **hierarchical filters**.
  - The neurons in the **1<sup>st</sup> layer** respond to **orientated edges and colors** :



For each filter, the top-9 patches are shown.

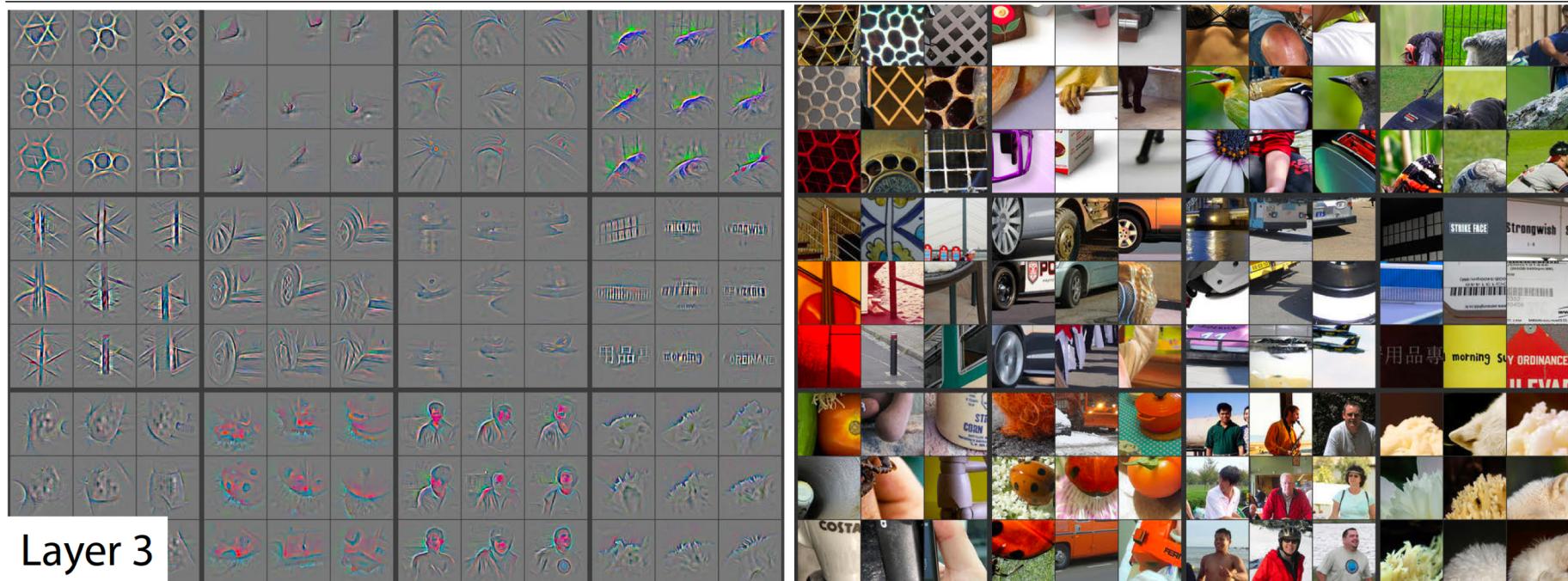
# Hierarchical filters

- The 2<sup>nd</sup> layer responds to corners and other edge/color conjunctions :



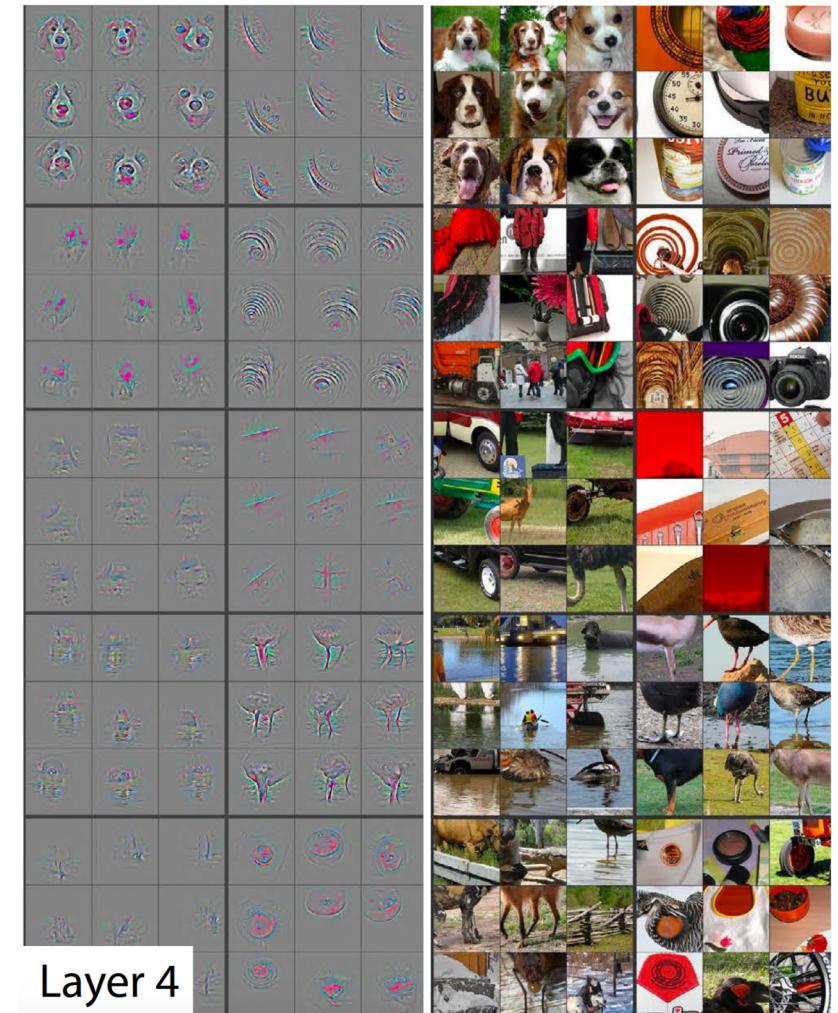
# Hierarchical filters

- The 3<sup>rd</sup> layer responds to more complex patterns: mesh, wheel, text, etc...



# Hierarchical filters

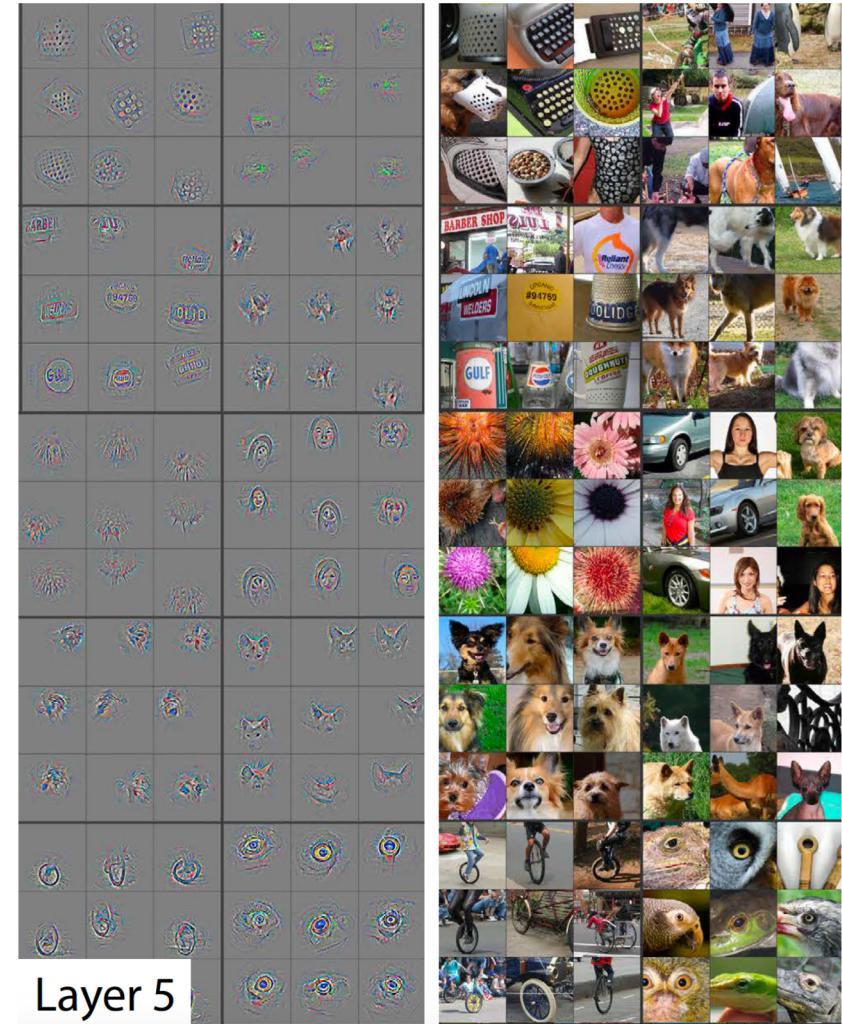
- The 4<sup>th</sup> layer gets even more complex : Dog faces, birds' legs, ...



# Hierarchical filters

- The 5<sup>th</sup> layer shows entire objects : Full dog, keyboard, ...

The deeper we go in the network, the more complex and abstract are the detected patterns !

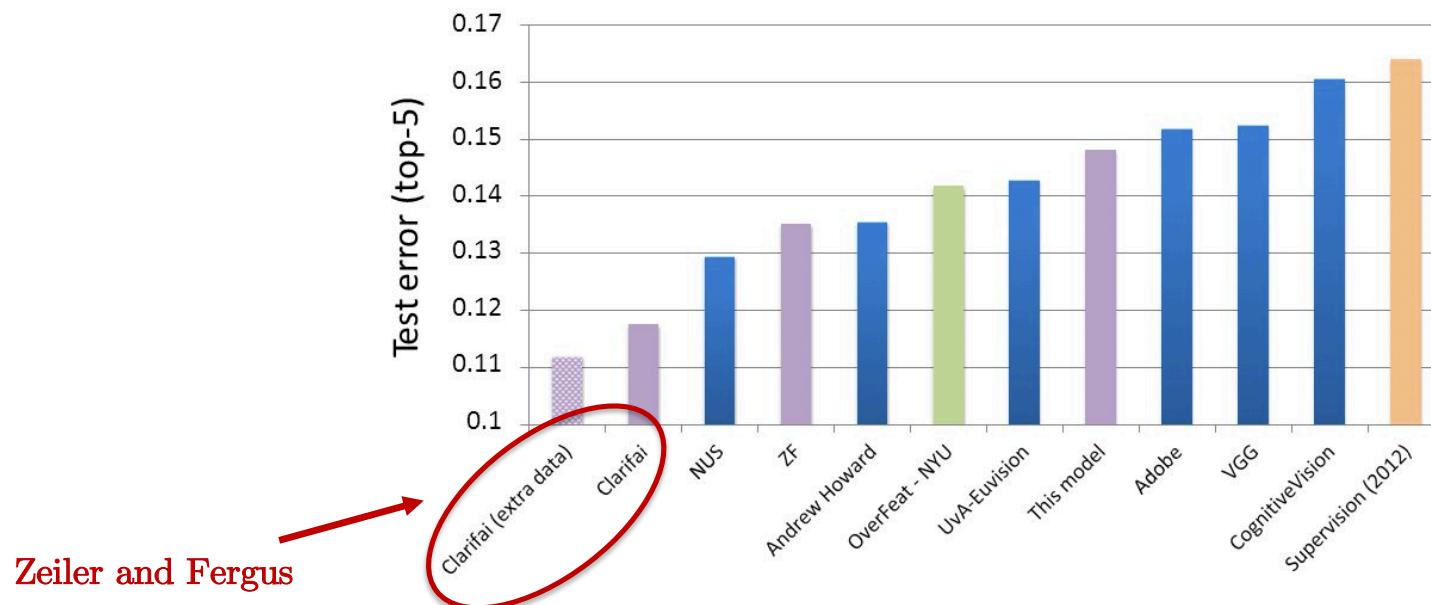


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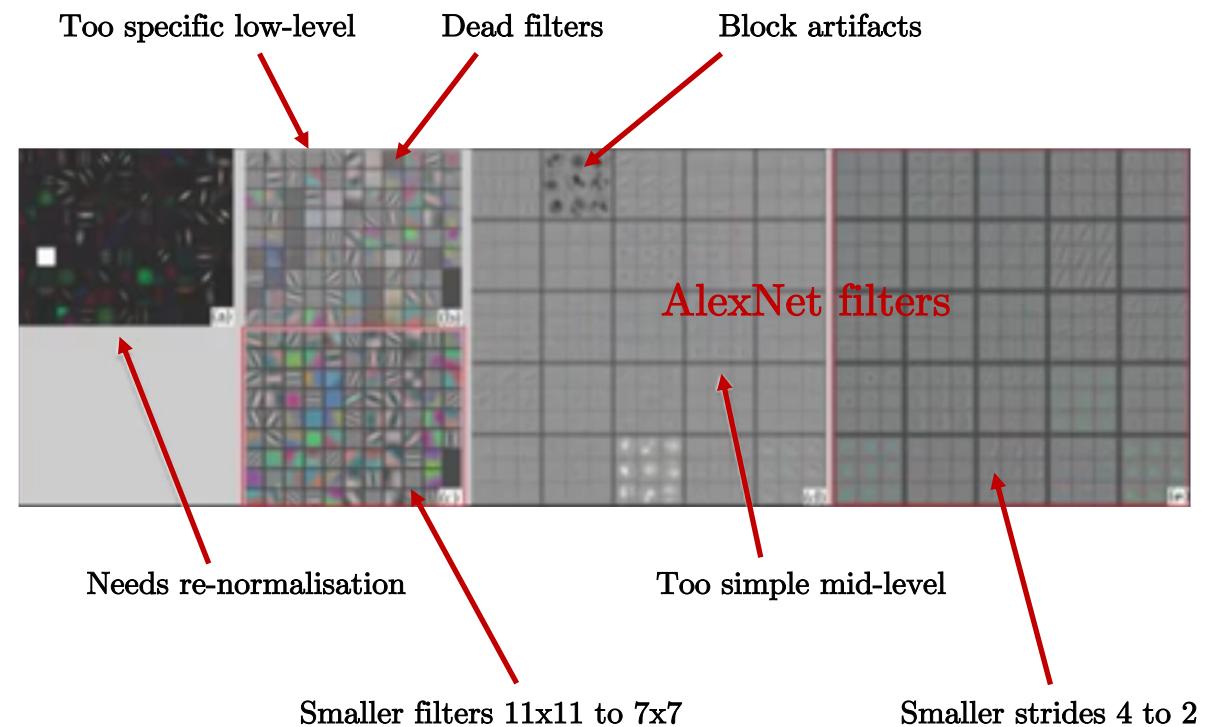
# ImageNet 2013 contest

- 1<sup>st</sup> rank in ImageNet 2013 :
  - Visualization helped to boost the performance on ImageNet classification by 2%, and won the 2013 contest !



# ImageNet 2013 contest

- Visualization helped to improve the 2012 winner architecture.
- AlexNet architecture have some limitations:
  - Filters in the 1<sup>st</sup> layer are not normalized ⇒ Re-normalization is needed.
  - Filters in the 1<sup>st</sup> layer are too large 11x11 and learn too specific low-level filters and some dead filters ⇒ Smaller 7x7 filters fix the issues.
  - There are some block artifacts in the 2<sup>nd</sup> layer and very simple mid-level filters ⇒ Smaller strides fix these problems.



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# Conclusion

- Why ConvNet works so well?
  - It learns **strong discriminative features** for visual tasks.
  - These features are **compositional** (from simple to abstract representations).
- Warning :
  - It may also be an **anthropomorphic** explanation of ConvNets.
- Mathematical reasons of **success** may be
  - Global and local translation invariance
  - Deep representation
  - SGD is the right tool to find these features.



Questions?