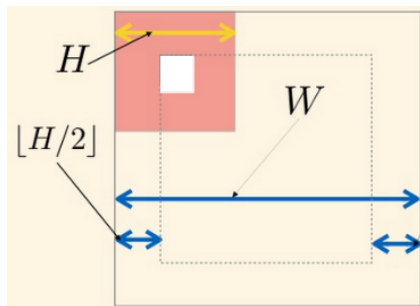


# Neural Networks and Deep Learning: Other Modern Deep Learning Components

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# Padding Modules

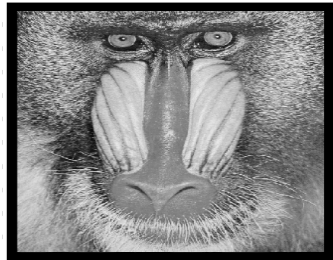
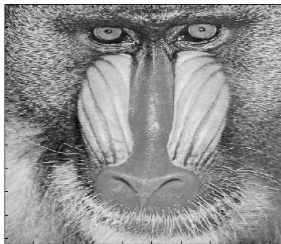
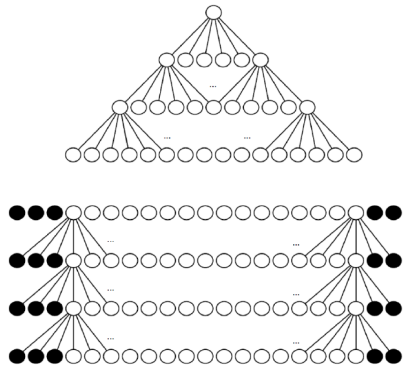


- ▶ Filter of size  $H$ : problem with the borders  $\lfloor \frac{H}{2} \rfloor$
- ▶ **Solution 1**: reduce processing to computable area  $\Rightarrow$  decreased output size
- ▶ **Solution 2**: padding, *i.e.* fill missing info with (arbitrary) values
  - ▶ Zero-padding, recopy, mirror, etc

|   |   |   |   |   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 1 | 1 | 2 | 5 | 6 | 3 | 6 | 7 | 3 | 0 | 0 |
| 0 | 0 | 2 | 3 | 4 | 6 | 7 | 5 | 1 | 8 | 4 | 0 | 0 |
| 0 | 0 | 8 | 7 | 6 | 5 | 7 | 6 | 3 | 3 | 4 | 0 | 0 |
| 0 | 0 | 2 | 3 | 5 | 6 | 7 | 8 | 2 | 7 | 3 | 0 | 0 |
| 0 | 0 | 4 | 5 | 3 | 2 | 1 | 6 | 8 | 7 | 2 | 0 | 0 |
| 0 | 0 | 1 | 4 | 5 | 3 | 2 | 6 | 7 | 8 | 1 | 0 | 0 |
| 0 | 0 | 2 | 3 | 4 | 5 | 6 | 8 | 9 | 2 | 1 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

|   |   |   |   |   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 2 | 2 | 3 | 4 | 6 | 7 | 5 | 1 | 8 | 4 | 4 | 4 |
| 1 | 1 | 1 | 1 | 2 | 5 | 6 | 3 | 6 | 7 | 3 | 3 | 3 |
| 1 | 1 | 1 | 1 | 2 | 5 | 6 | 3 | 6 | 7 | 3 | 3 | 7 |
| 3 | 2 | 2 | 3 | 4 | 6 | 7 | 5 | 1 | 8 | 4 | 4 | 8 |
| 7 | 8 | 8 | 7 | 6 | 5 | 7 | 6 | 3 | 3 | 4 | 4 | 3 |
| 3 | 2 | 2 | 3 | 5 | 6 | 7 | 8 | 2 | 7 | 3 | 3 | 7 |
| 5 | 4 | 4 | 5 | 3 | 2 | 1 | 6 | 8 | 7 | 2 | 2 | 7 |
| 4 | 1 | 1 | 4 | 5 | 3 | 2 | 6 | 7 | 8 | 1 | 1 | 8 |
| 3 | 2 | 2 | 3 | 4 | 5 | 6 | 8 | 9 | 2 | 1 | 1 | 2 |
| 3 | 2 | 2 | 3 | 4 | 5 | 6 | 8 | 9 | 2 | 1 | 1 | 2 |
| 3 | 1 | 1 | 4 | 5 | 3 | 2 | 6 | 7 | 8 | 1 | 1 | 2 |

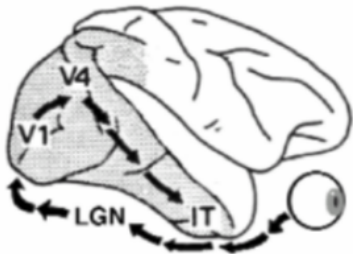
# Zero-Padding



- To avoid shrinking the spatial extent of the network rapidly

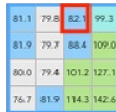
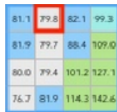
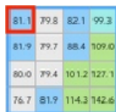
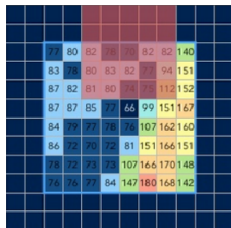
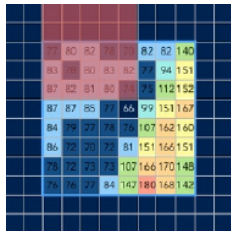
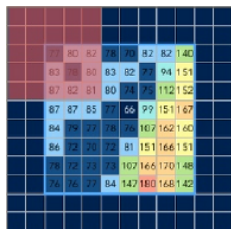
# Normalization: Local Feature Normalization

- ▶ **Normalize value wrt neighbors in different feature maps**
- ▶ Operates at each spatial position independently
- ▶ Feature groups: subset of maps (sliding window)
- ▶ ~ Lateral inhibition



# Pooling Modules

Overlapping Pooling - Ex: pooling size: 5, stride s=2



Credit: K. Matsui

# Pooling Modules

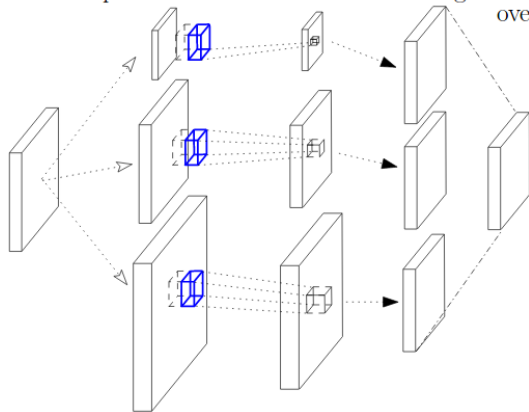
## Pooling across feature maps

- ▶ Aggregation for a given spatial position, between different tensor maps
- ▶ Tensor maps (filter output) associated to a given transformation  $\Rightarrow$  invariance with max pooling

# Pooling across feature maps

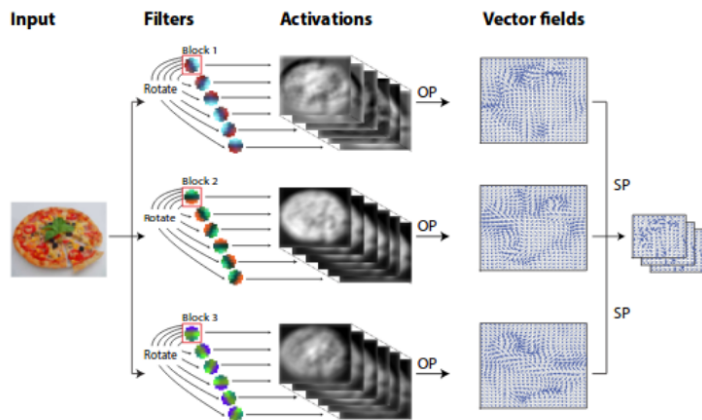
- ▶ Ex: scaling [Kanazawa et al., 2014]

1. Scale input 2. Convolution 3. Undo scaling 4. Max-Pool over Scales



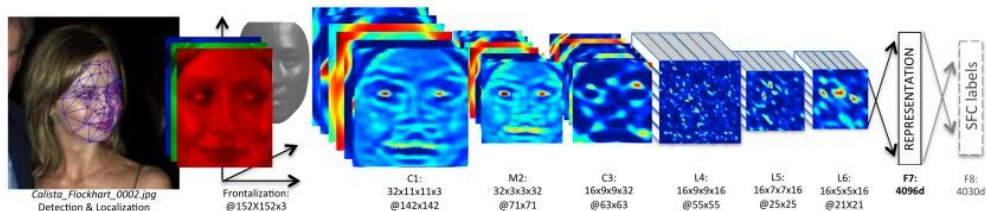
# Pooling across feature maps

- ▶ Ex: rotation [Marcos et al., 2017]

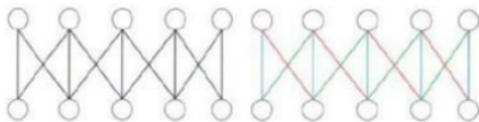




# Locally Connected vs Convolution Layers

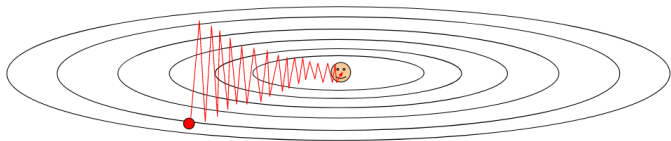


- ▶ Locally connected: different features detected across image positions
- ▶ Successful in specific context, e.g. DeepFace [Taigman et al., 2014]



# Other Modern ConvNet Modules: Conclusion

- ▶ **Spatial resolution:** padding, overlapping pooling
- ▶ **Specificity and invariance:** normalization, locally connected layers, pooling across maps
- ▶ **Optimization issues?**  
⇒ following!



# References I



Kanazawa, A., Sharma, A., and Jacobs, D. W. (2014).  
Locally scale-invariant convolutional neural networks.  
*In Deep Learning and Representation Learning Workshop: NIPS 2014.*



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