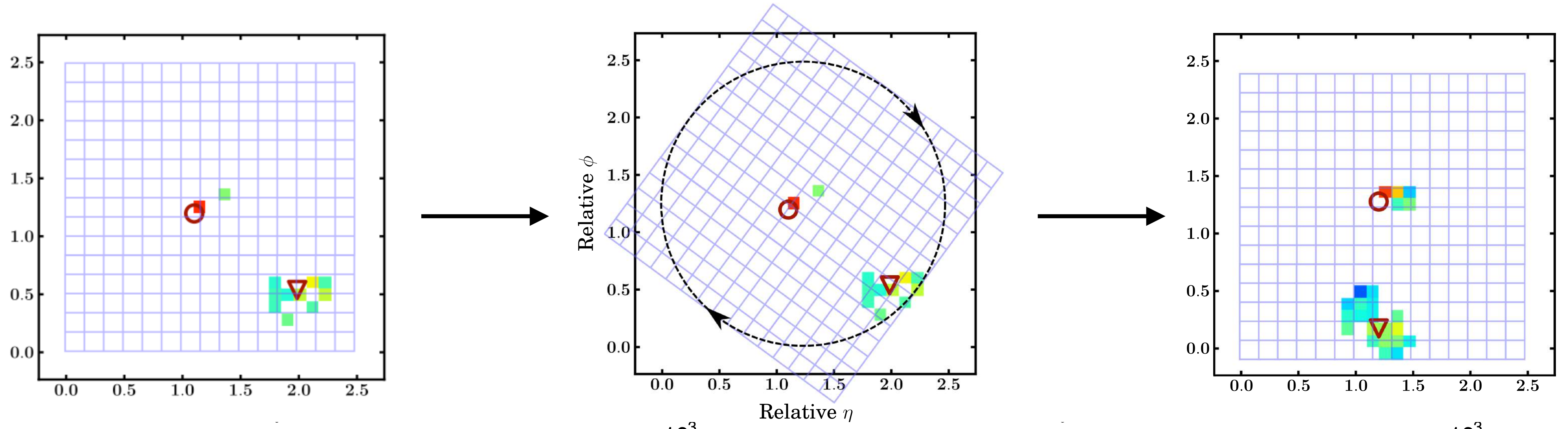
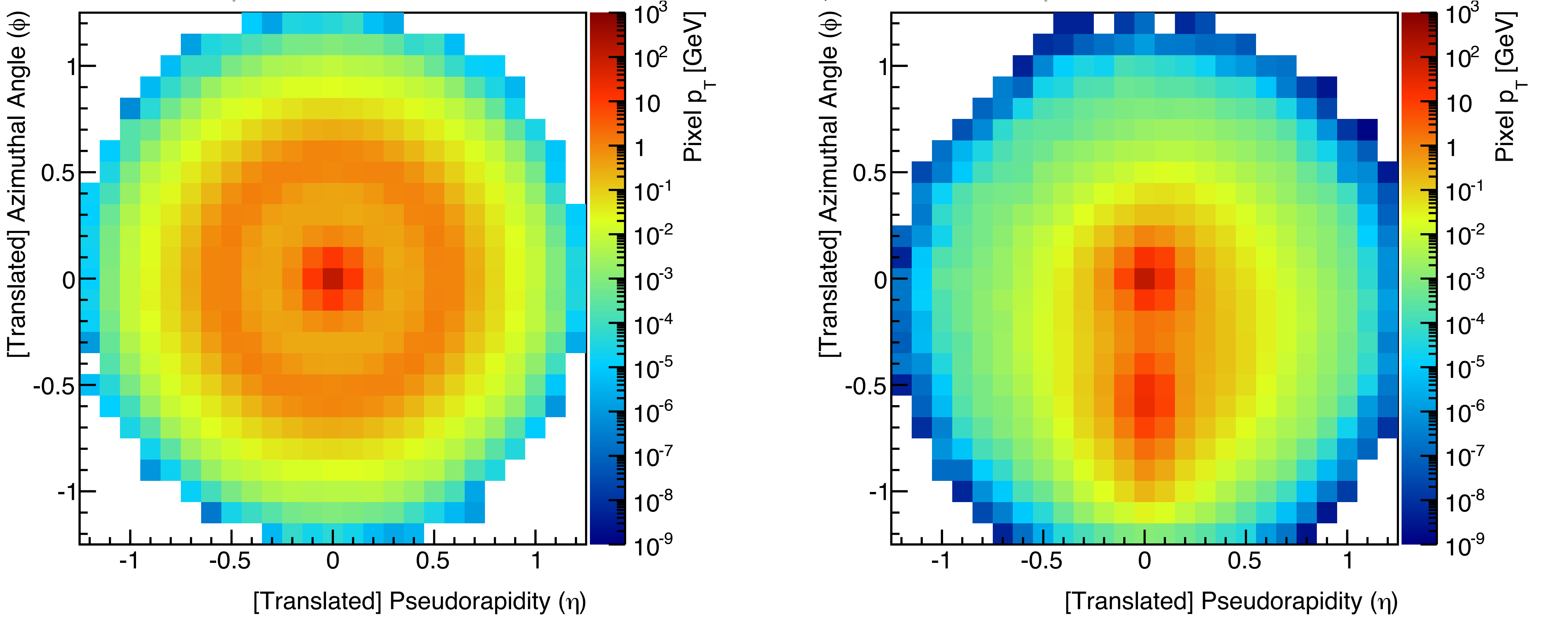
PHYS 139/239: Machine Learning in Physics

Lecture 8: Advanced convolutions neural networks

Javier Duarte — January 31, 2023

Caution: image preprocessing

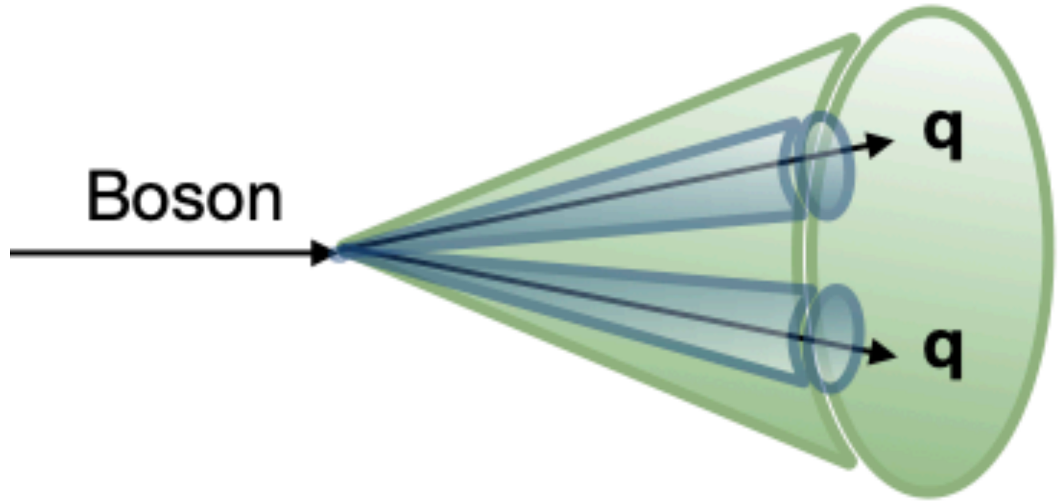




- Good practice to preprocess data, but beware of distortions to physically meaningful features

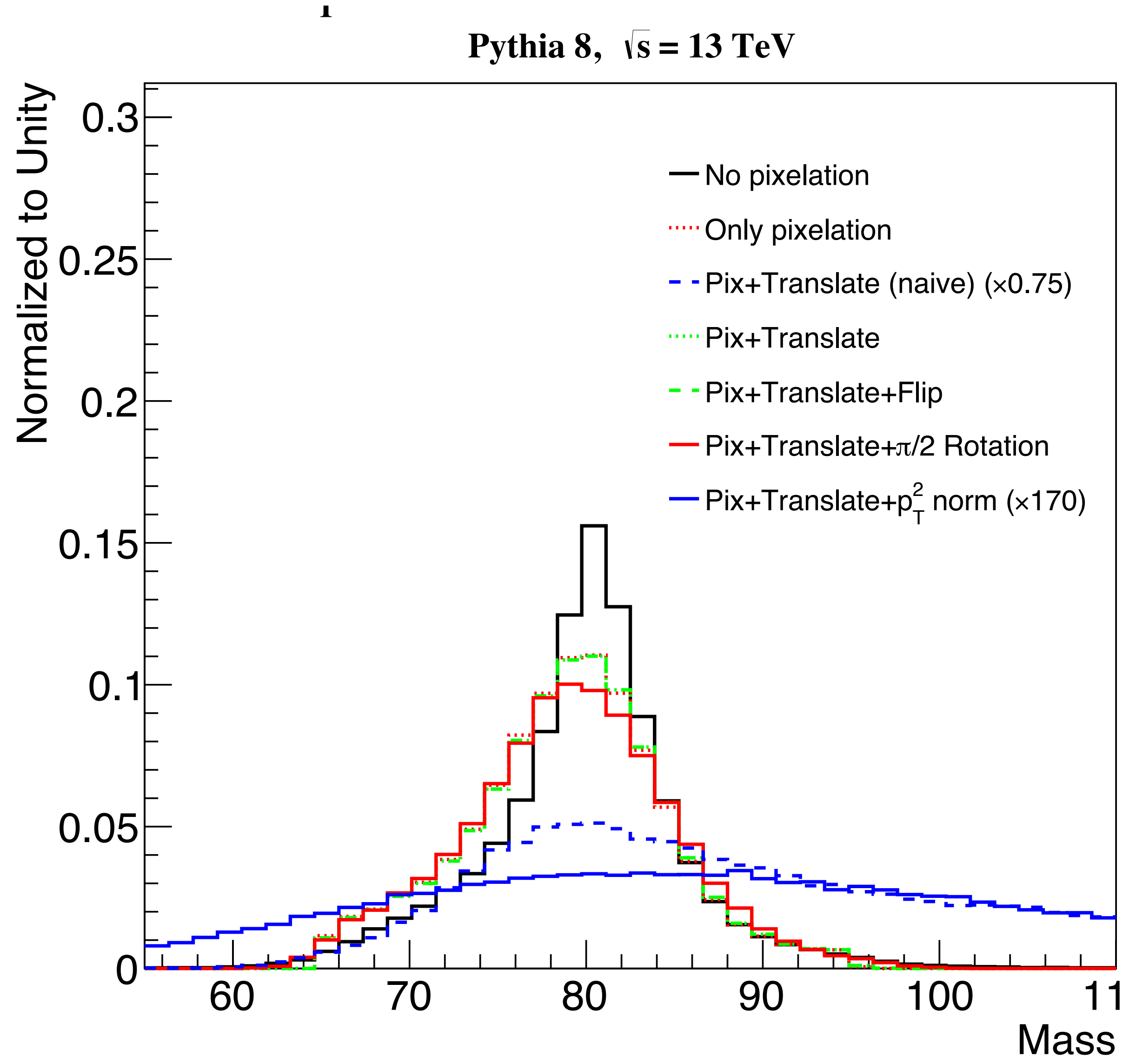
- Example: jet mass in $W(qq)$ jet images

$$m^2 = \sum_{i<j} \frac{p_{\mathrm{T},i} p_{\mathrm{T},j} (1 - \cos\theta_{ij})}{\cosh\eta_i \cosh\eta_j}$$



  - Preprocessing: pixelization, rotation, flip, normalization

  - Preprocessing distorts distribution of the jet mass

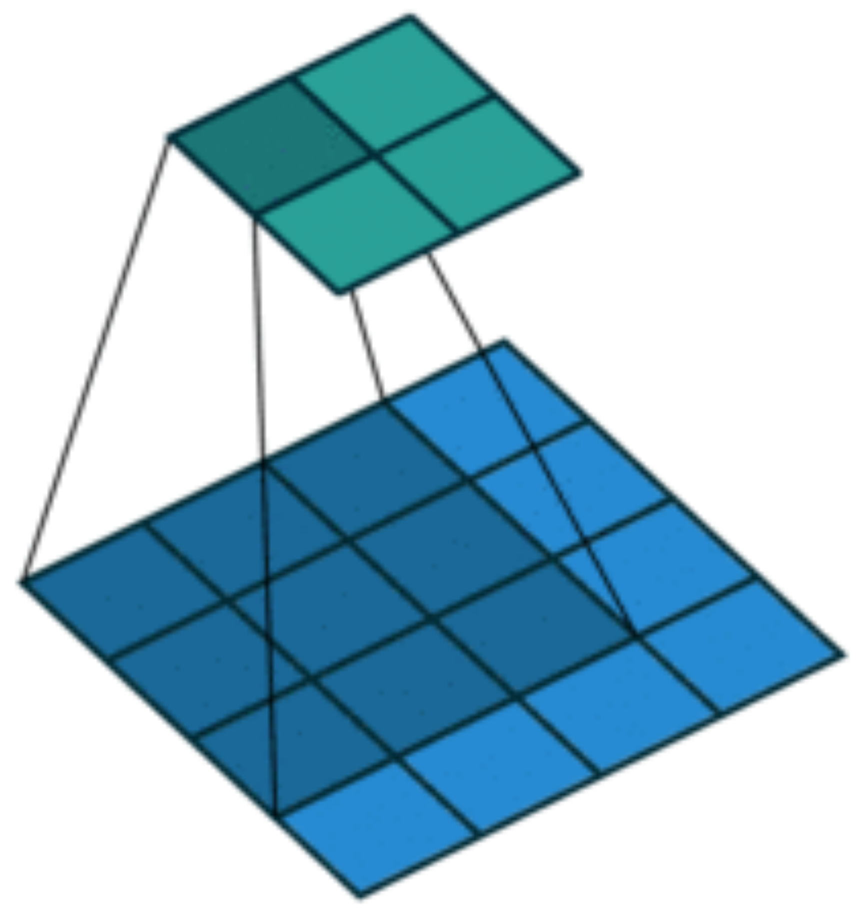


- Can choose (Lorentz-invariant) preprocessing that preserves jet mass

2D convolution hyperparameters

- 4×4 input
- 3×3 filter
- 1×1 stride
- No zero padding

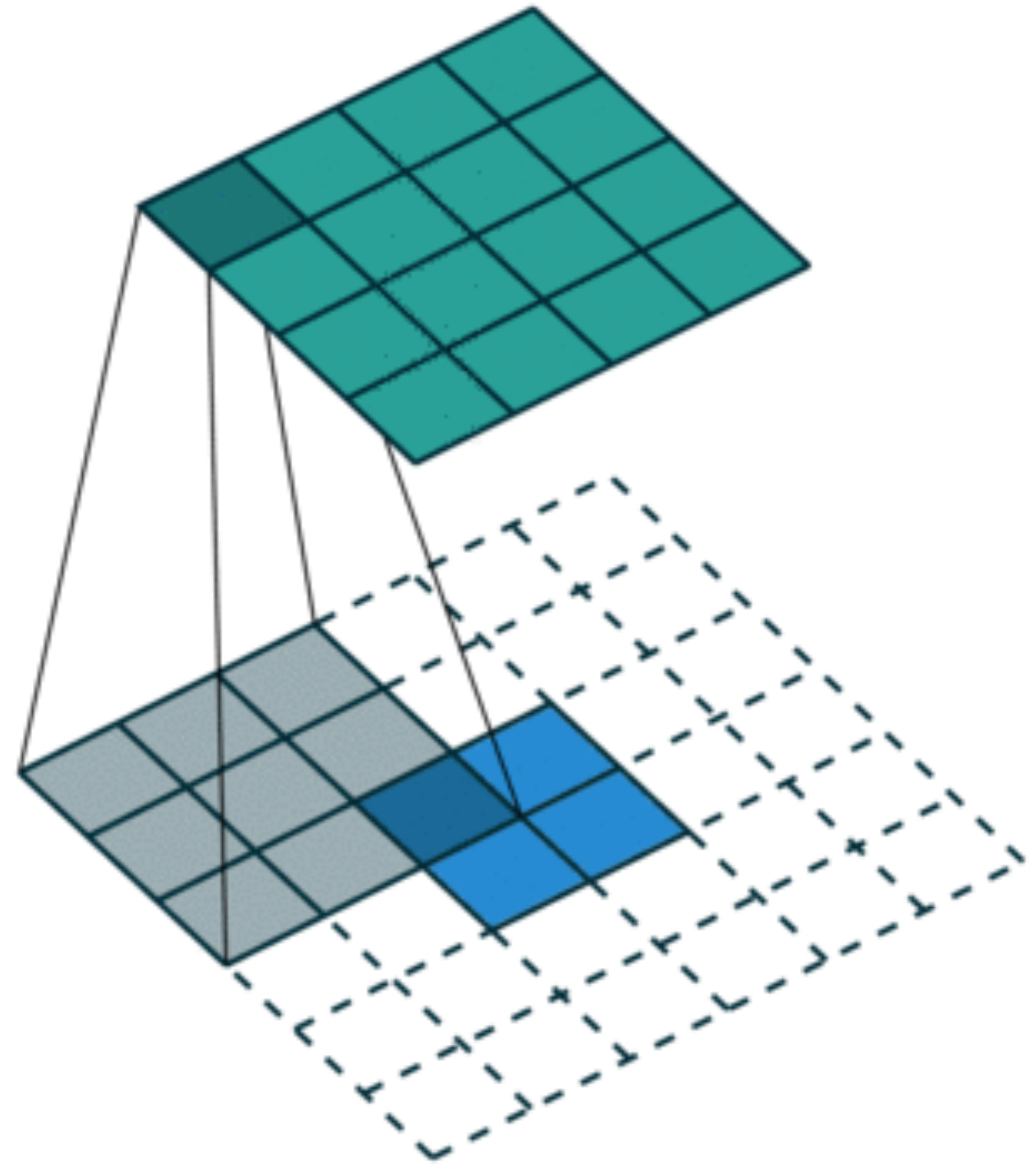
➡ 2×2 output



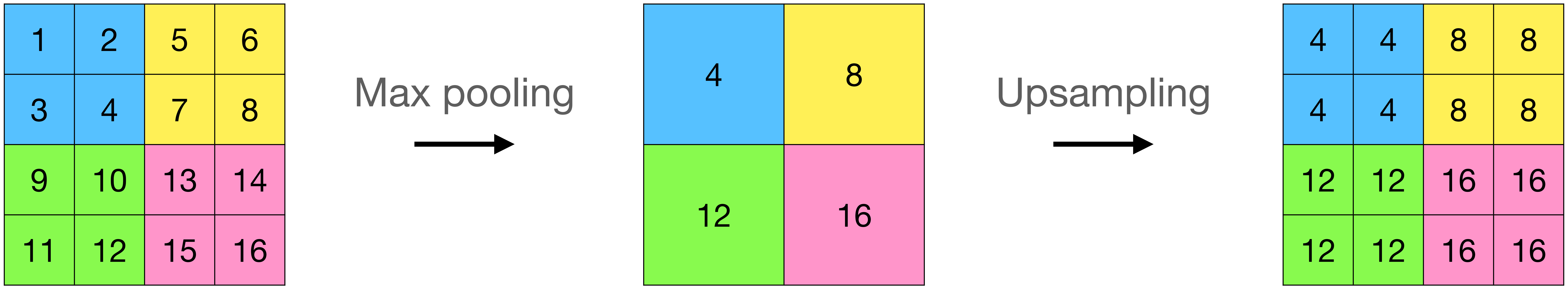
In reverse: transposed convolution

- 2×2 input
- 3×3 filter
- 1×1 stride
- 2×2 zero padding

➡ 4×4 output

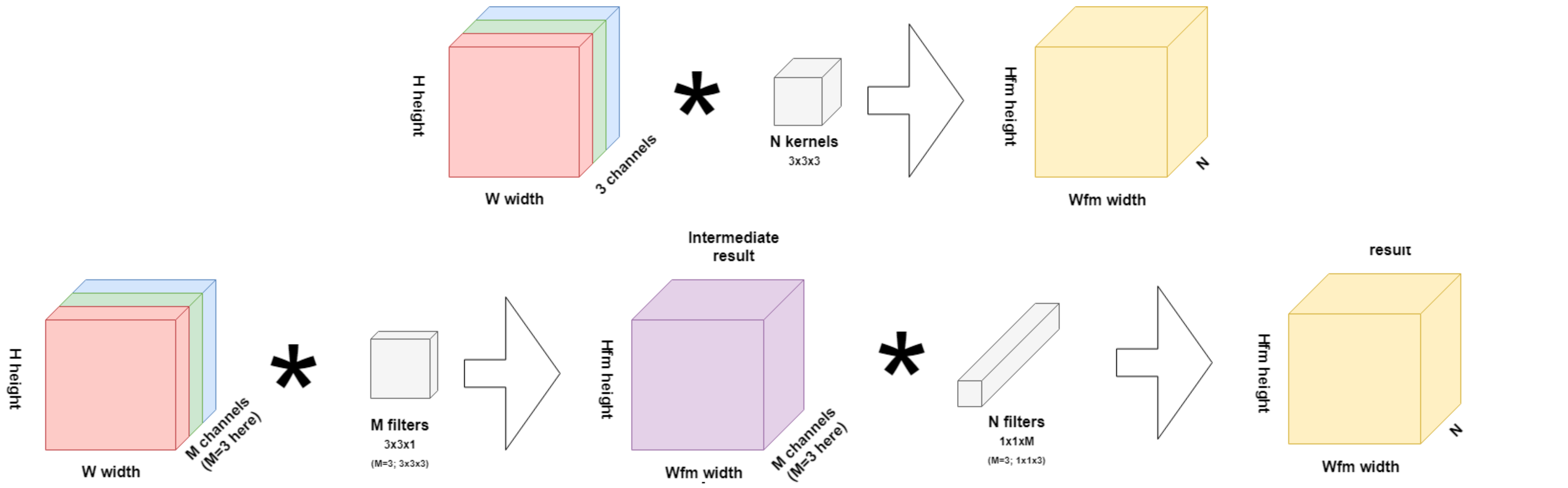


In reverse: upsampling



- Upsampling can be used to change the image size

More efficient: depthwise separable convolution



- Standard convolution requires many operations, e.g. for a $15 \times 15 \times 3$ image, 10 3×3 filters, no zero-padding, stride 1: $45{,}630$ multiplications
- Depthwise separable convolution factorizes into two separate operations
  - For the same settings: $9{,}633$ multiplications

Reconstruction tasks

- Classification: output class of image as a whole
- Regression: output a real number for the image as a whole
- Object detection & localization: find a “bounding box” for a given object
    - Can also be done for multiple objects
- Semantic segmentation: pixel-wise classification

A - Image classification

B - Object detection and localization

C - Multi-object detection and localization

D - Semantic segmentation

Reconstruction tasks

- Semantic segmentation: pixel-wise classification
- Instance segmentation: classify pixels based on “instances”
    - Panoptic segmentation: generalization to multiple classes

E - Non-instance segmentation

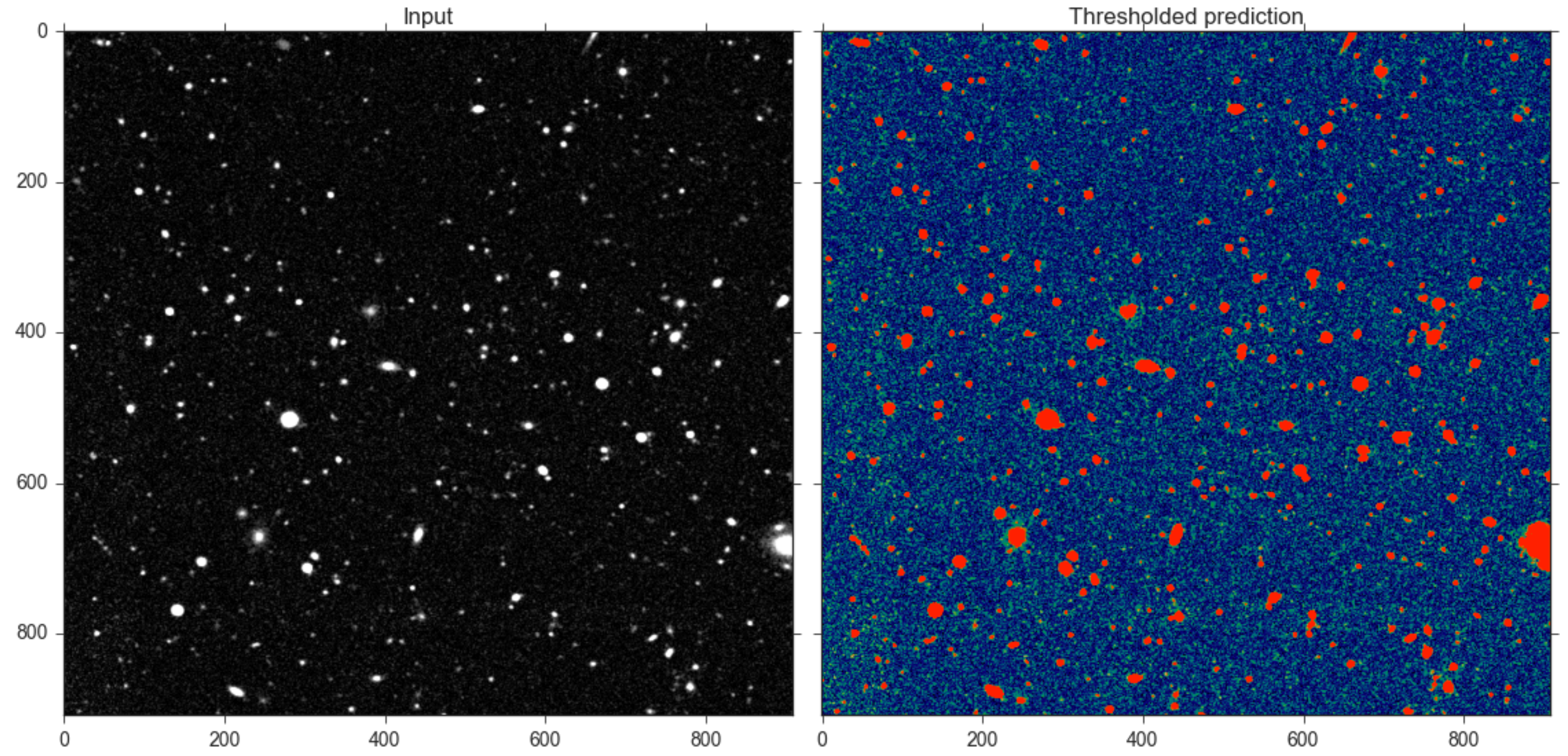
F - Instance segmentation

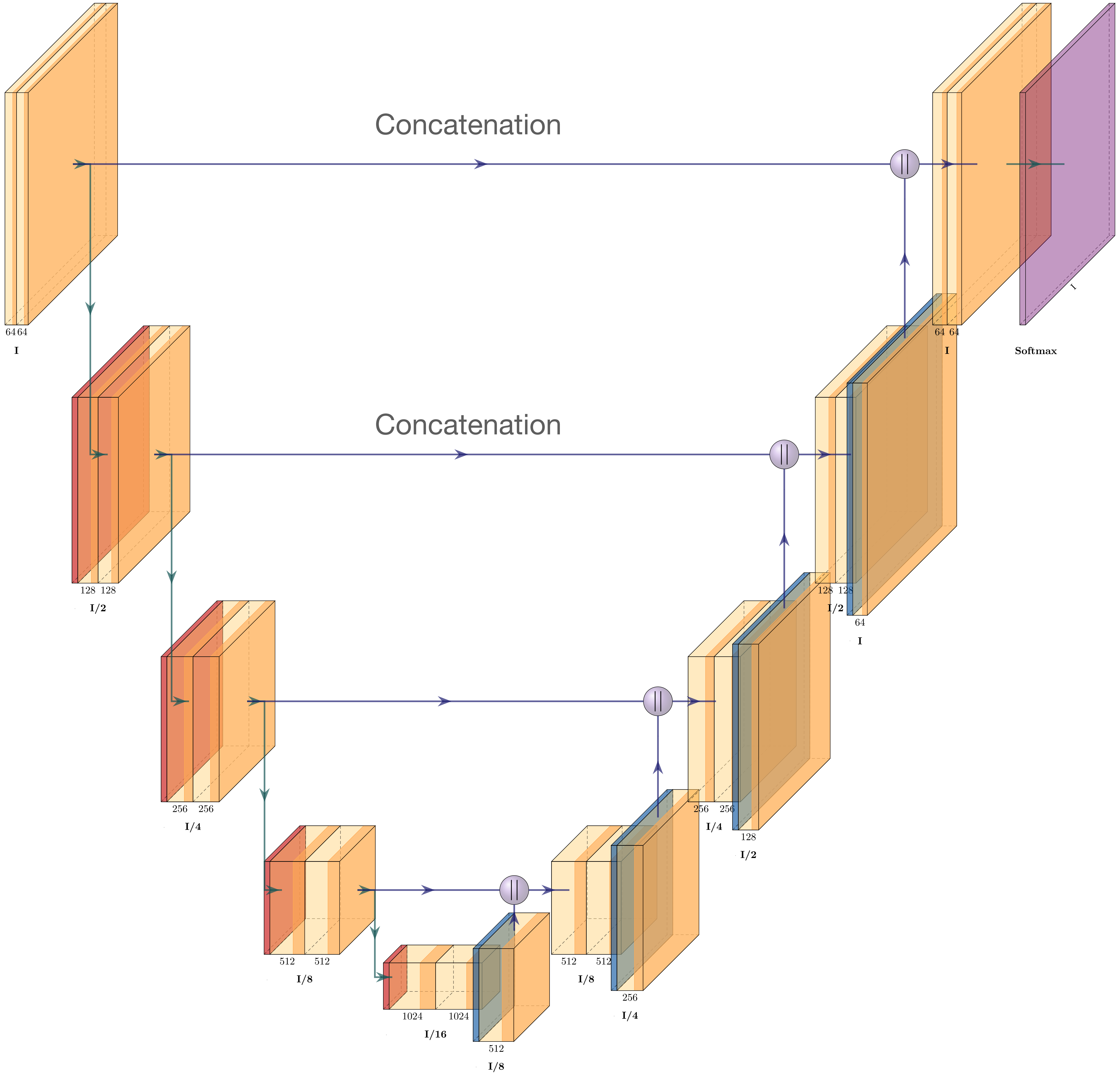
U-Net

arXiv:1505.04597

- U-Net first proposed for semantic segmentation in biomedical imaging

- Also used for detection of neutrinos [arXiv:1903.05663], galaxies, RF interference [arXiv:1609.09077], …





Generalizations: Data augmentations

Rotation-invariant convolutional neural networks for galaxy morphology prediction

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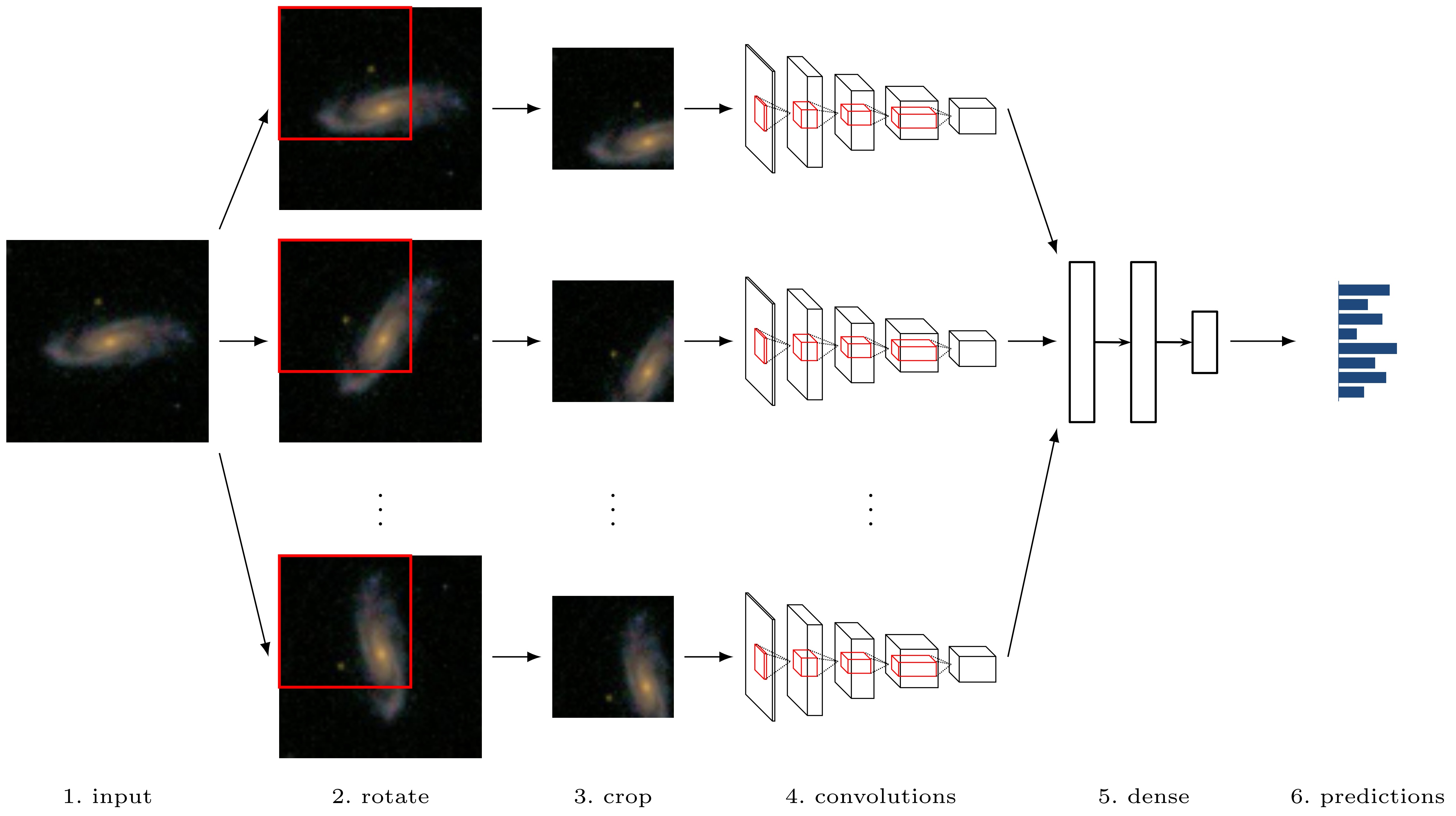
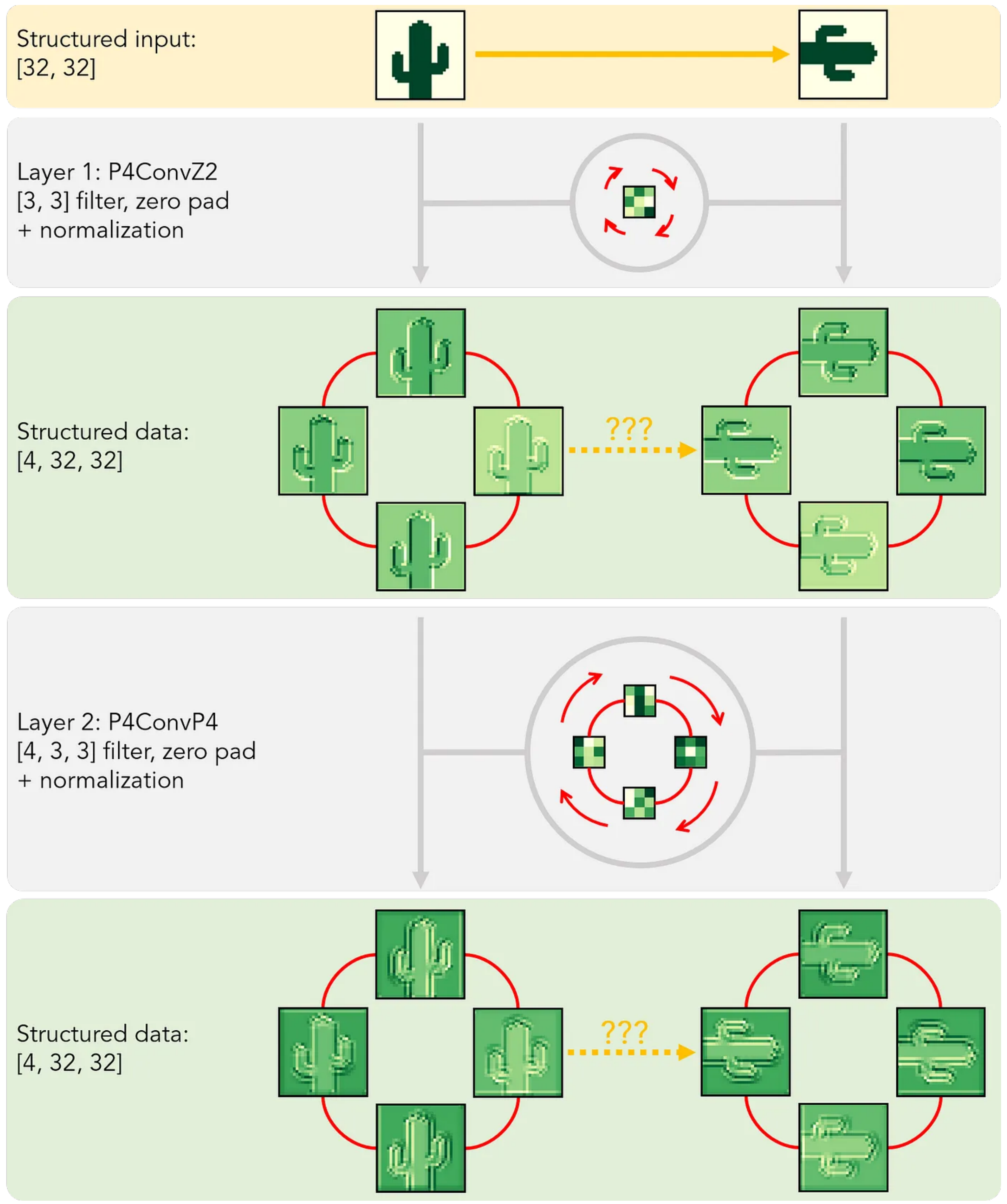
- One way to generalize CNNs to rotation-invariant operations:
    - Use data augmentations, concatenate feature maps, and apply dense layers



Generalizations: Other symmetry groups

- By employing weight sharing across group actions, we can generalize to other symmetry groups



Group Equivariant Convolutional Networks

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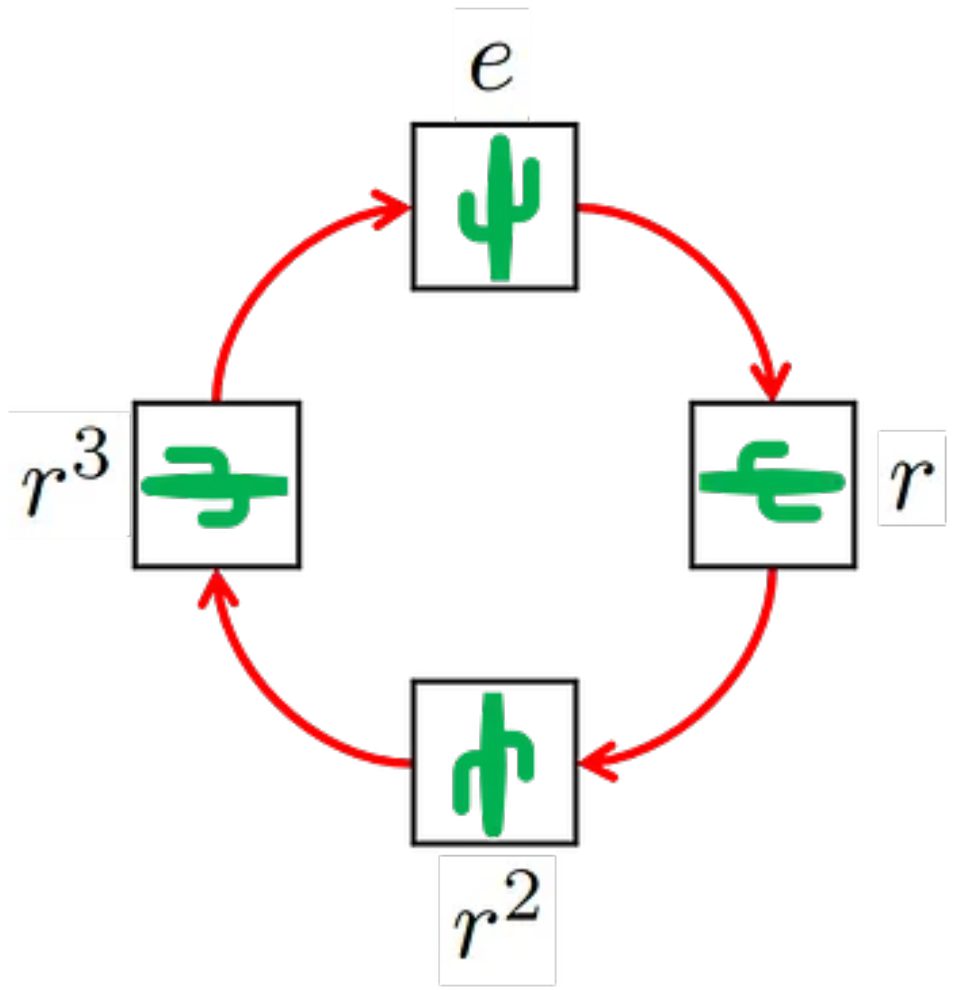
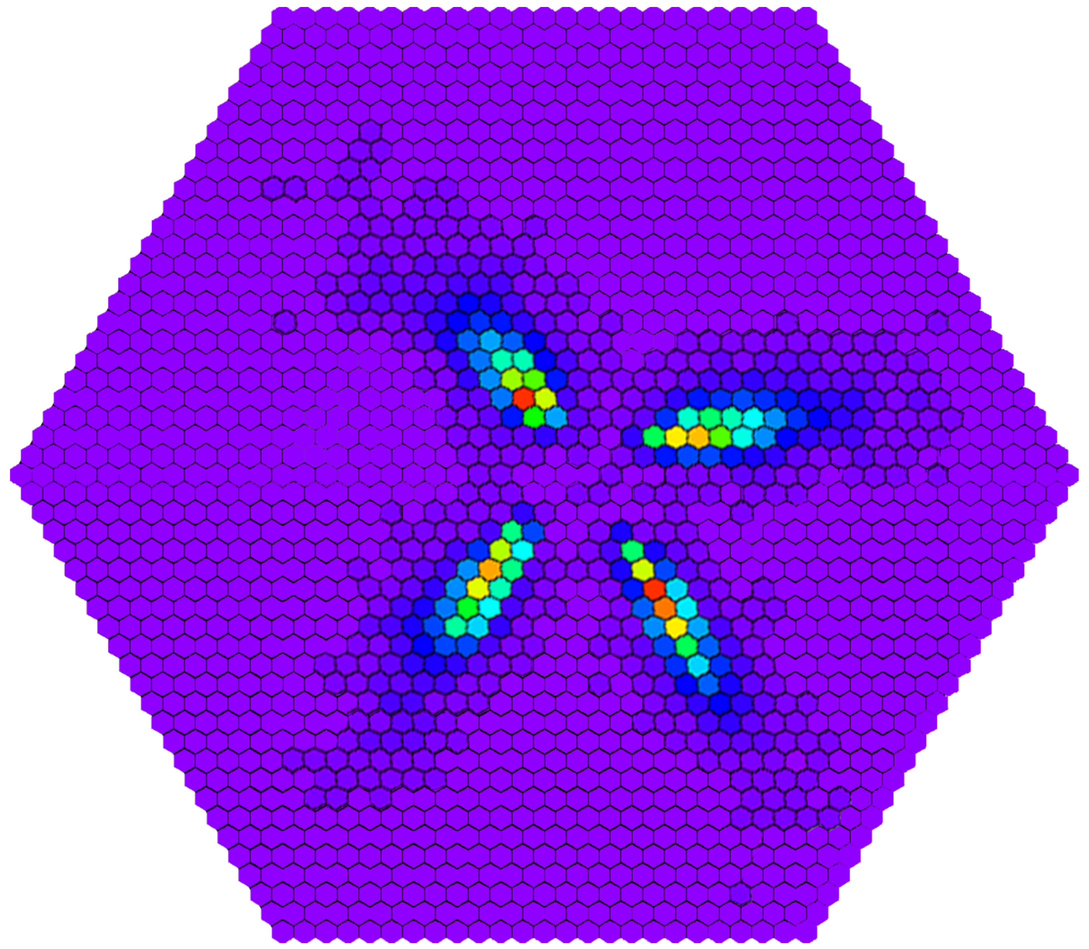


https://medium.com/swlh/geometric-deep-learning-group-equivariant-convolutional-networks-ec687c7a7b41

Generalizations: Other geometries

- Can generalize to other geometries like hexagonal data



HexCNN: A Framework for Native Hexagonal Convolutional Neural Networks

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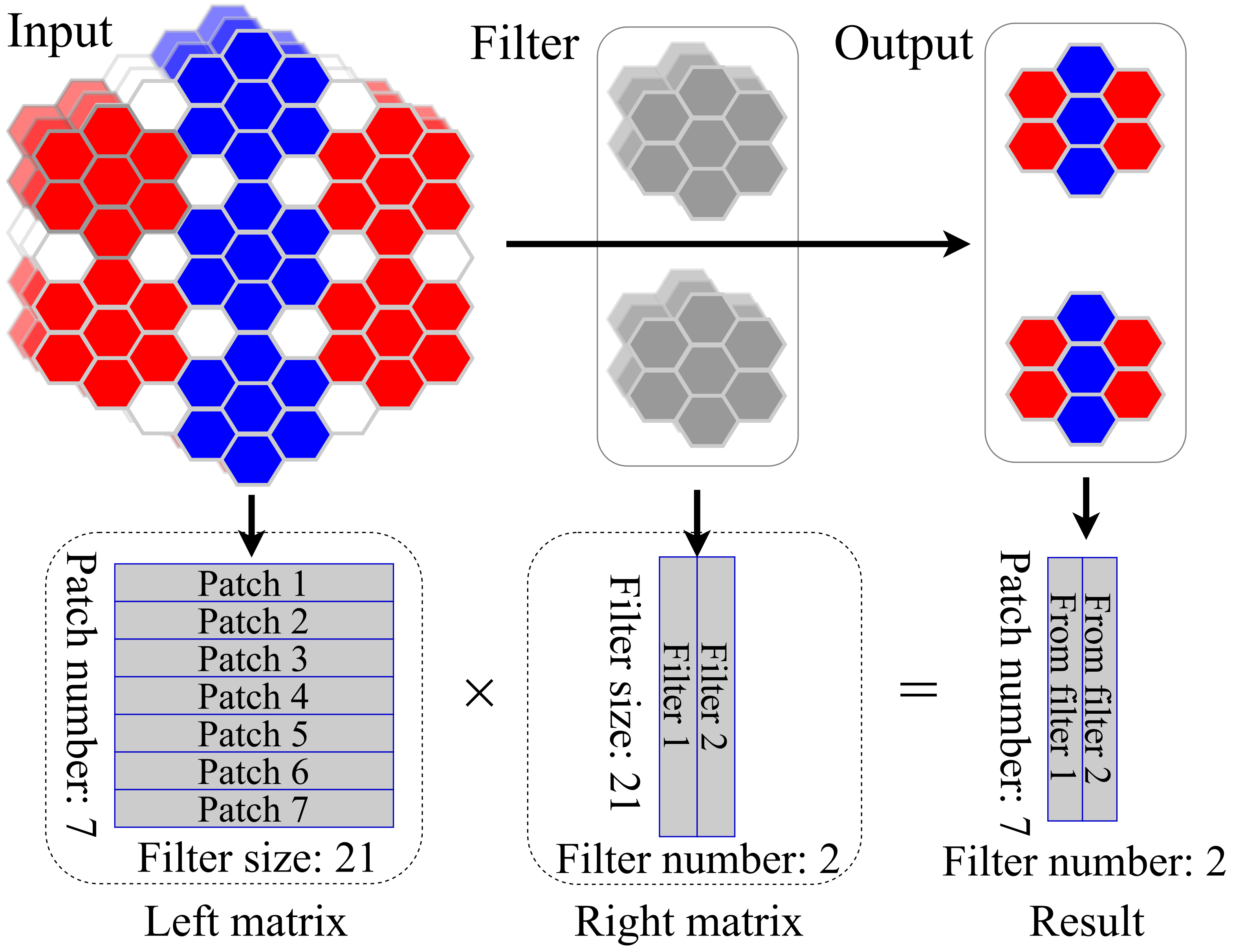

Next time

- Time series and recurrent neural networks