# Deep Learning Applications for collider physics Lecture 2

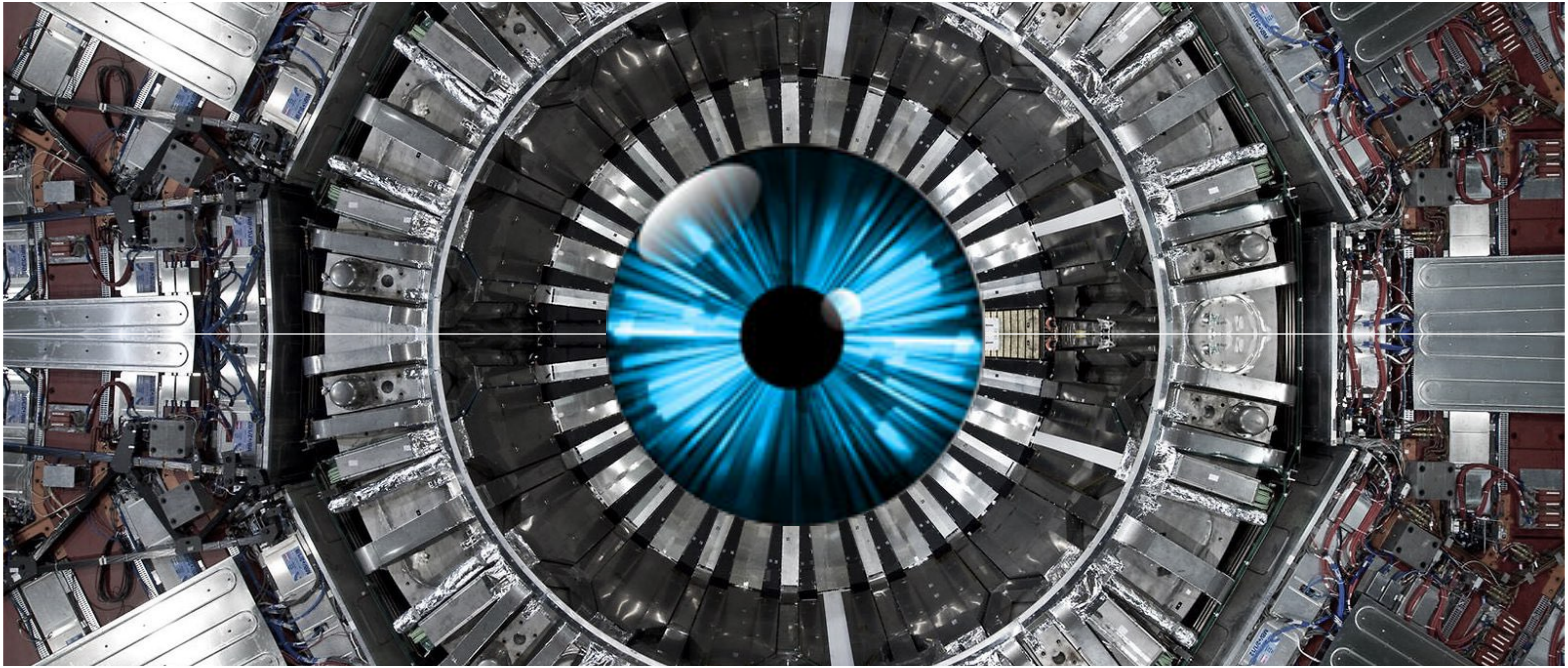
Maurizio Pierini

CERN

European Research Council

# Plan for this week

| | Day1 | Day2 | Day3 | Day4 | Day5 |
|---|---|---|---|---|---|
| **Lecture** | Introduction | ConvNN | RNNs | Graphs | Unsupervised Learning |
| **Tutorial** | Fully Connected Classifier | ConvNN Classifier | RNNs Classifier | Graphs Classifier | Anomaly Detection |

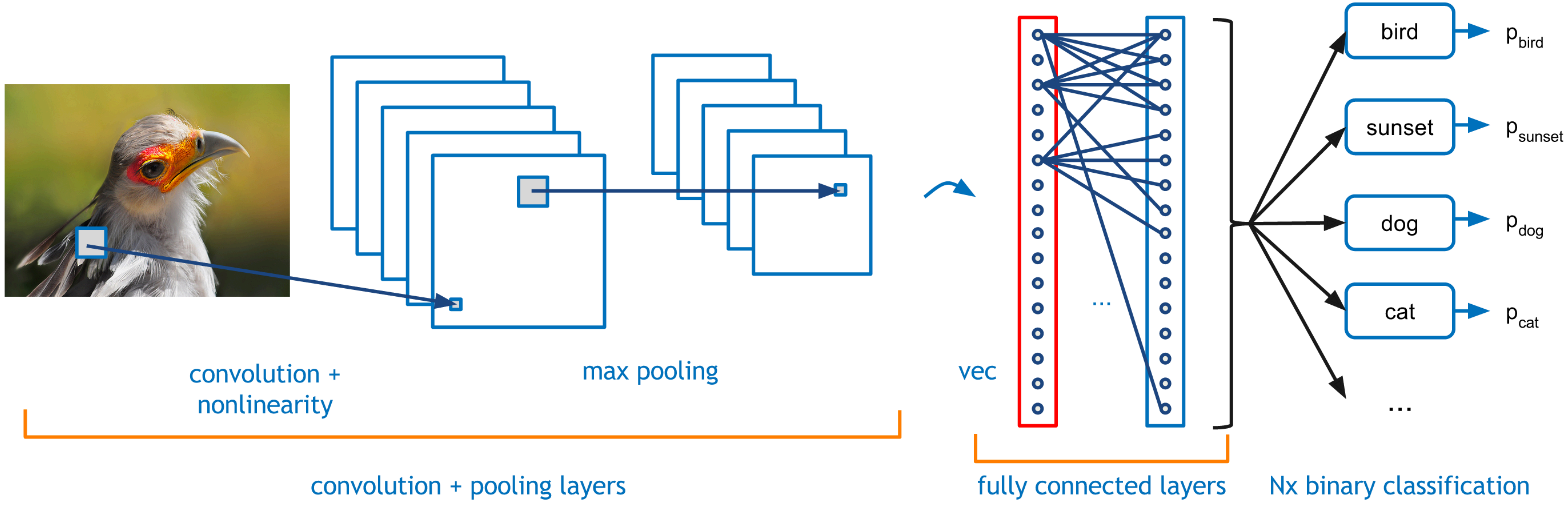


# Particle Reconstruction & Computer Vision

# Convolutional Layer

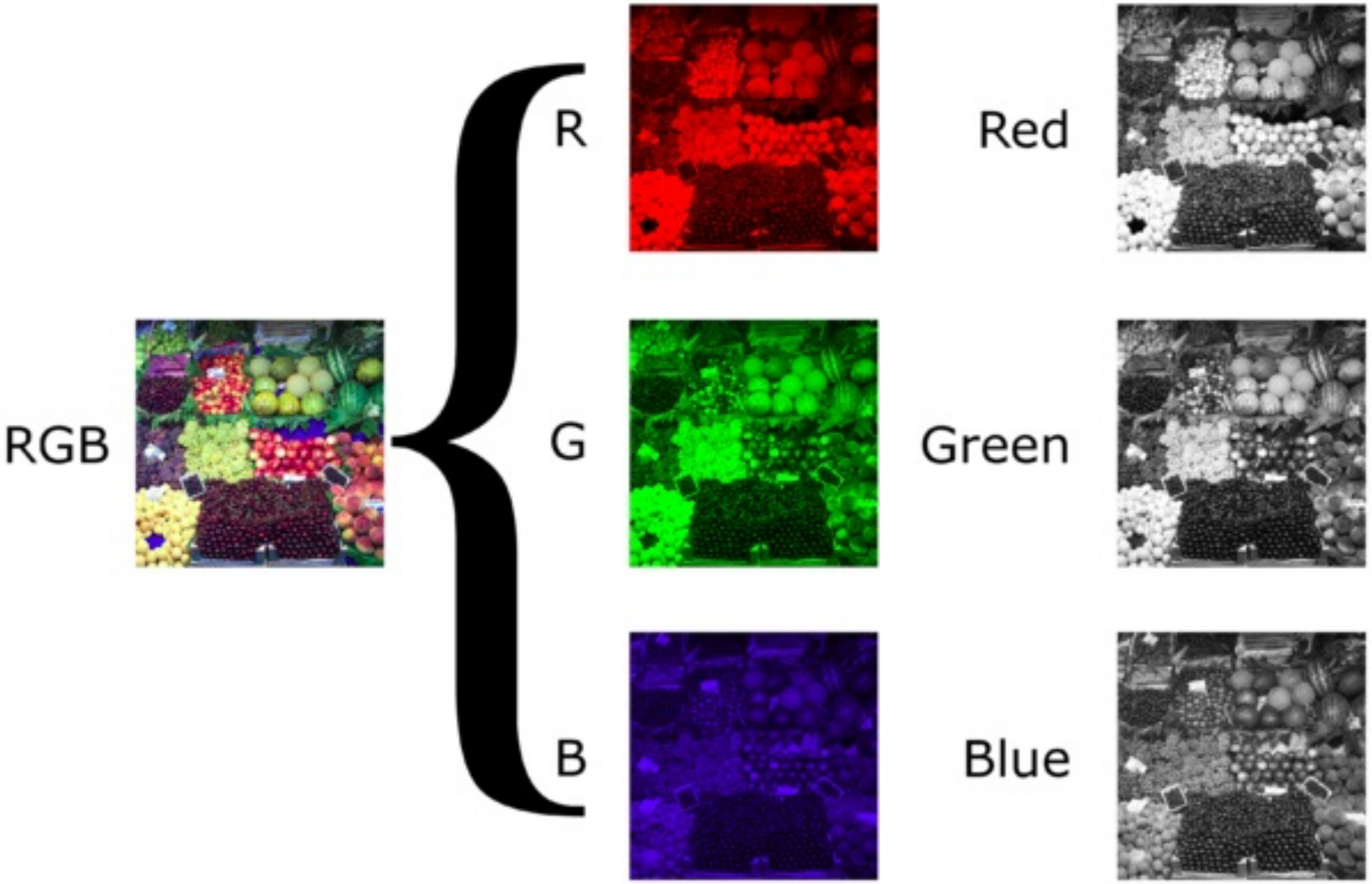
- *Special architectures read the raw information (e.g., images) and convert them into "smart variables" (high-level features) to accomplish the task*

- *Typical example: convolutional neural networks for image processing & computing vision*



# Digital images

- *Each image is a matrix of pixels*
- *Each pixel comes with a color*
- *In RGB scheme, these are three values i [0,1]*
- *Each image becomes a 3D tensor*
    - *3 channels of 2D pixelated images*




# Convolutional filter

- *The main ingredient of ConvNN is a filter, a k x k’ matrix of weights*
- *The filter scans the image and performs a scalar product of each image patch*
- *This results into a new matrix of values, with different dimensionality*

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

| | | |
|---|---|---|
| 4 | -1 | 4 |
| -2 | 2 | -5 |
| 3 | 1 | -6 |

**0x4 - 3x1 + 5x4 +**
**-7x2 + 4x2 - 7x5 +**
**9x3 + 1x1 - 2x6 = -8**

| | | | | |
|---|---|---|---|---|
| -8 | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |

# Filtro convolutional

- *The main ingredient of ConvNN is a filter, a k x k' matrix of weights*
- *The filter scans the image and performs a scalar product of each image patch*
- *The scan is done shifting the filter by a stride (of q, 2, … cells)*
- *This results into a new matrix of values, with different dimensionality*

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

| | | |
|---|---|---|
| 4 | -1 | 4 |
| -2 | 2 | -5 |
| 3 | 1 | -6 |

**3x4 - 5x1 + 6x4 +**
**-4x2 + 7x2 - 3x5 +**
**1x3 + 2x1 - 1x6 = 21**

| | | | | |
|---|---|---|---|---|
| -8 | 21 | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |

# Pooling

- *MaxPooling: Given an image and a filter of size k x k', scans the image and replaces each k x k' patch with its maximum*

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

| | | | | |
|---|---|---|---|---|
| 9 | 7 | 9 | 9 | 9 |
| 9 | 7 | 9 | 9 | 9 |
| 9 | 7 | 7 | 9 | 9 |
| 9 | 7 | 7 | 8 | 8 |
| 9 | 9 | 7 | 8 | 8 |

- *AveragePooling: Given an image and a filter of size k x k', scans the image and replaces each k x k' patch with its average*

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

| | | | | |
|---|---|---|---|---|
| 4.2 | | | | |
| | | | | |
| | | | | |
| | | | 5.0 | |
| 5.2 | | | | |

- …

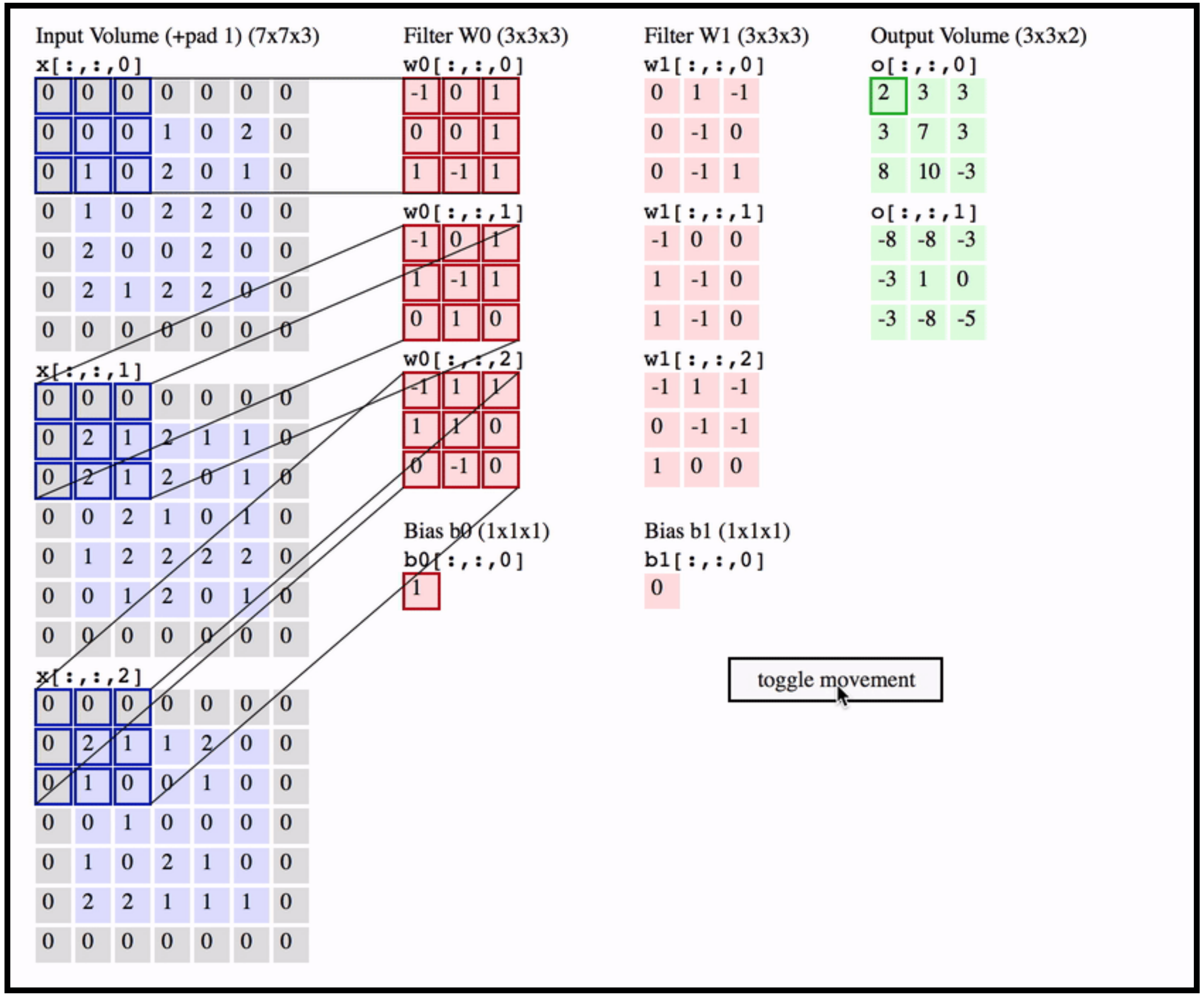
# Padding

- *When the filter arrived at the edge, it might exceeds it (if n/k is not an integer)*
- *In this case, a padding rule needs to be specified*
  - *Same: repeat the values at the boundary*
  - *Zero: fill the extra columns with zeros*

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

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

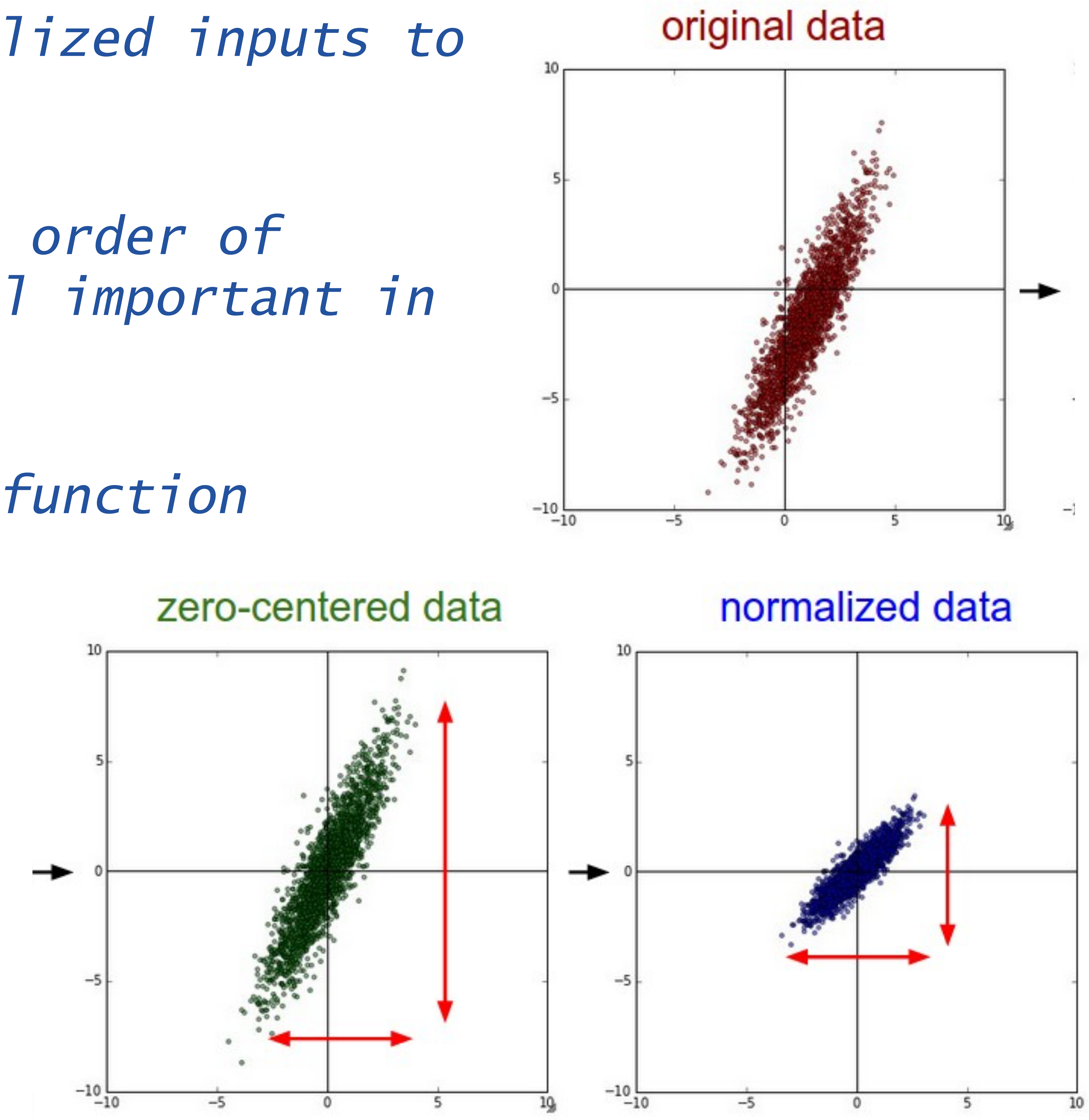
# Convolutional Layer



# BatchNormalization Layer

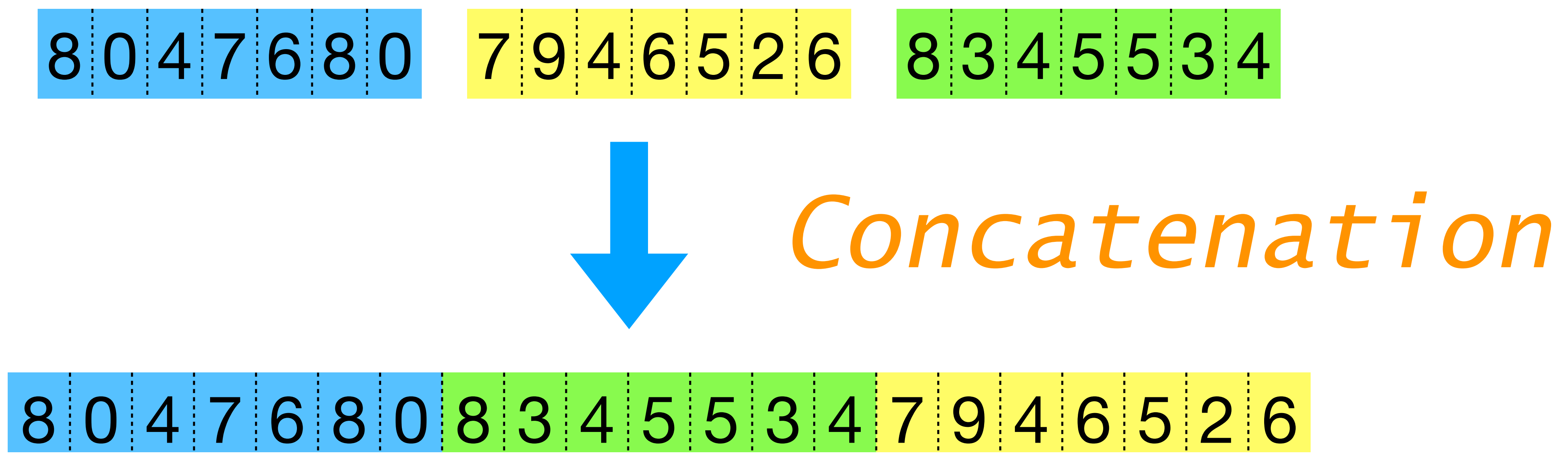
- *It is good practice to give normalized inputs to a layer*
  - *With all inputs having the same order of magnitude, all weights are equal important in the gradient*
  - *Prevents explosion of the loss function*

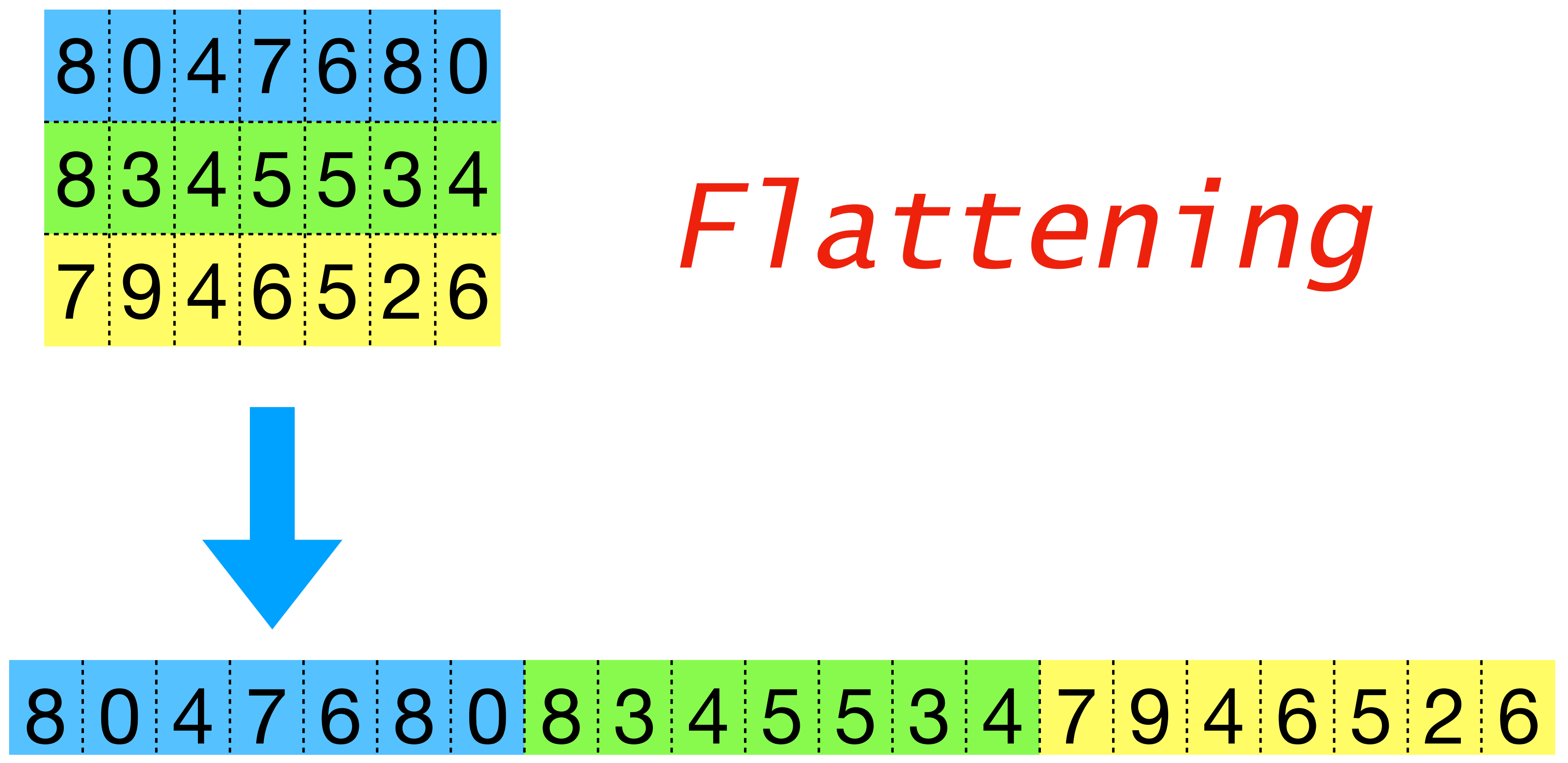
- *This can be done automatically with BatchNormalization*
  - *non-learnable shift and scale parameters, adjusted batch by batch*



# More complex structures

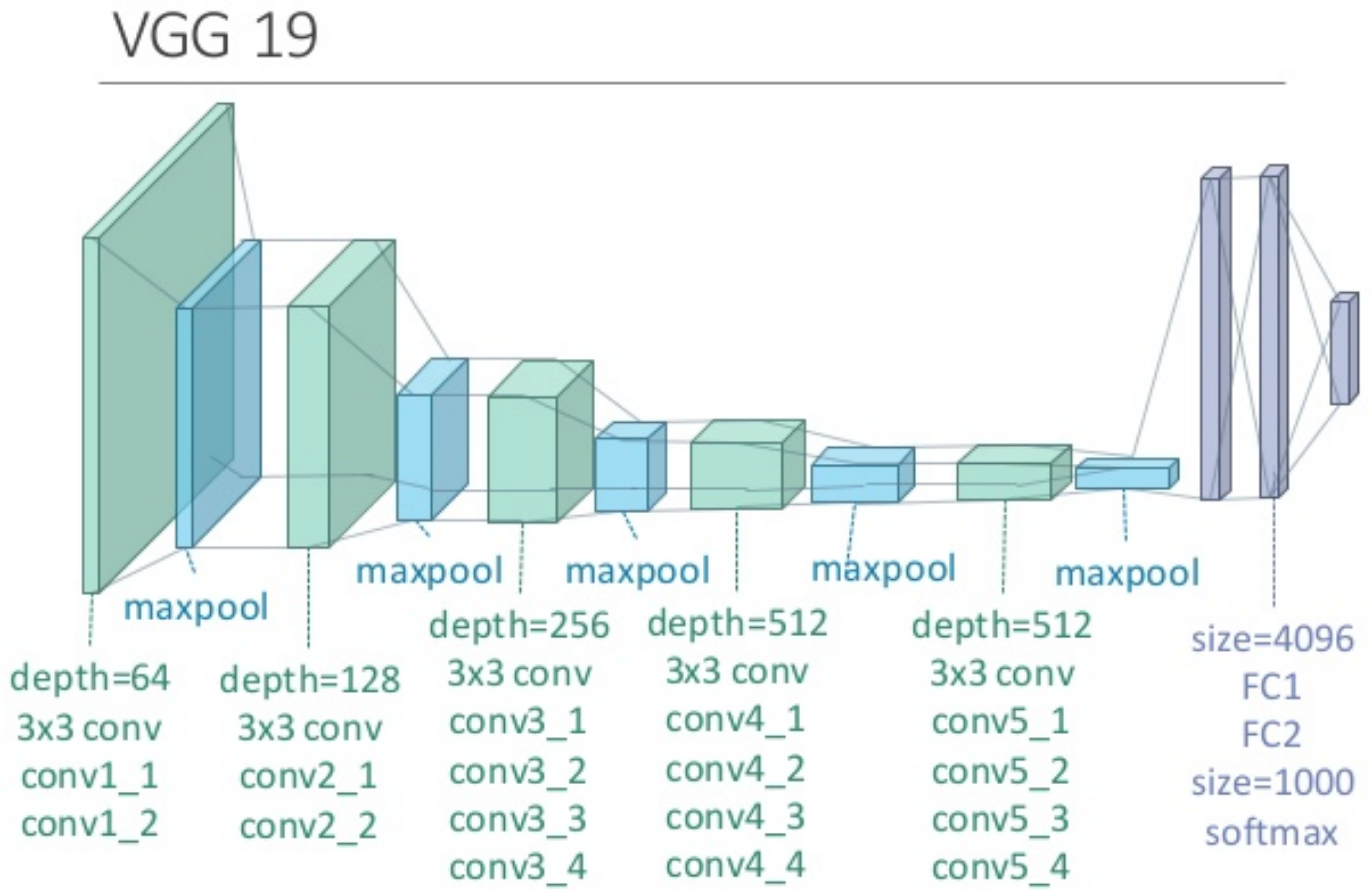
- Dense NN architectures can be made more complex
  - Multiple inputs
  - Multiple outputs
  - Different networks branches
- This is possible thanks to layer-manipulation layers
  - Add, Subtract, etc.
  - Concatenation
  - Flattening
- All these operations are usually provided with NN training libraries



# The full network

- *A full ConvNN is a sequence of Con2D+Pooling (+BatchNormalization+ Dropout) layers*
- *The Conv+Pooling layer reduces the 2D image representation*
- *The use of multiple filters on the image make the output grow on a third dimension*
- *Eventually, flattening occurs and the result is given to a dense layer*



# What does a ConvNN learn?

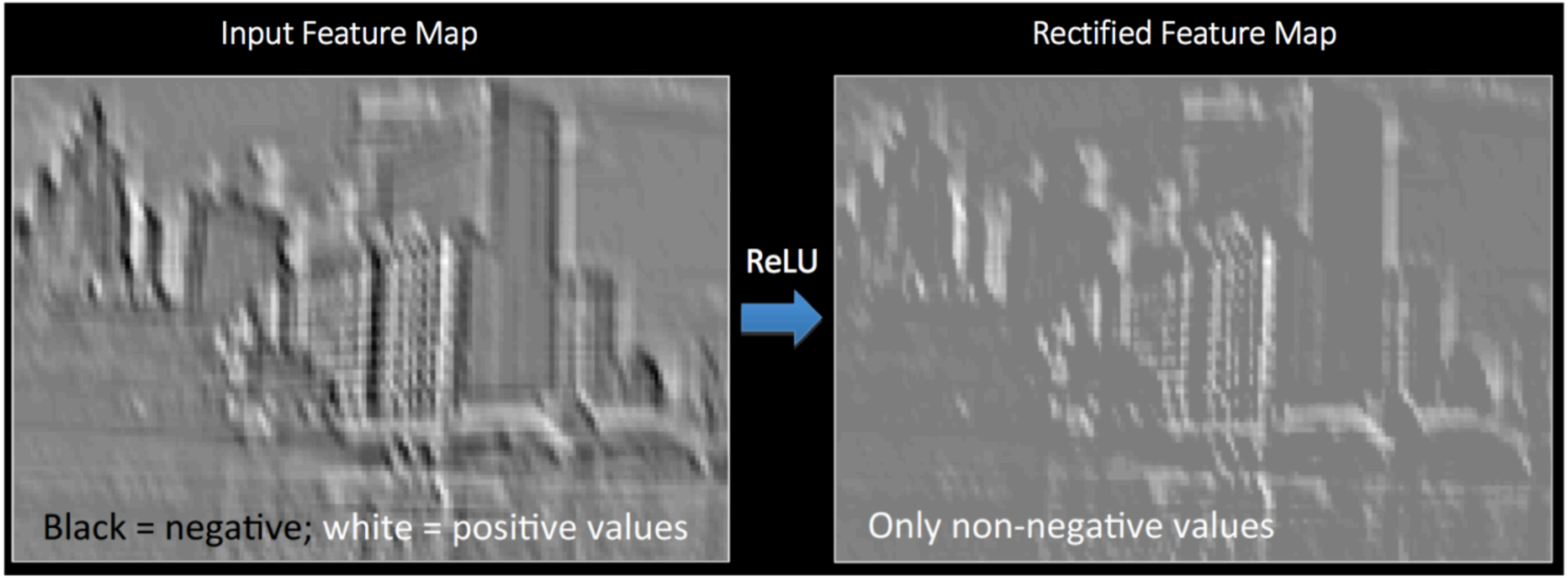
- *Each filter alters the image in a different way, picking up different aspects of the image*
  - *edges oriented in various ways*
  - *enhancing / blur of certain features*
- *It is interesting to check what each filter is doing (and to produce [DeepDreams](#))*

| Operation | Filter | Convolved Image |
|---|---|---|
| Identity | $\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$ |  |
| Edge detection | $\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$ |  |
| | $\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$ |  |
| | $\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$ |  |
| Sharpen | $\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$ |  |
| Box blur (normalized) | $\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$ |  |
| Gaussian blur (approximation) | $\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$ |  |

[Check this blog entry on ConvNNs](#)

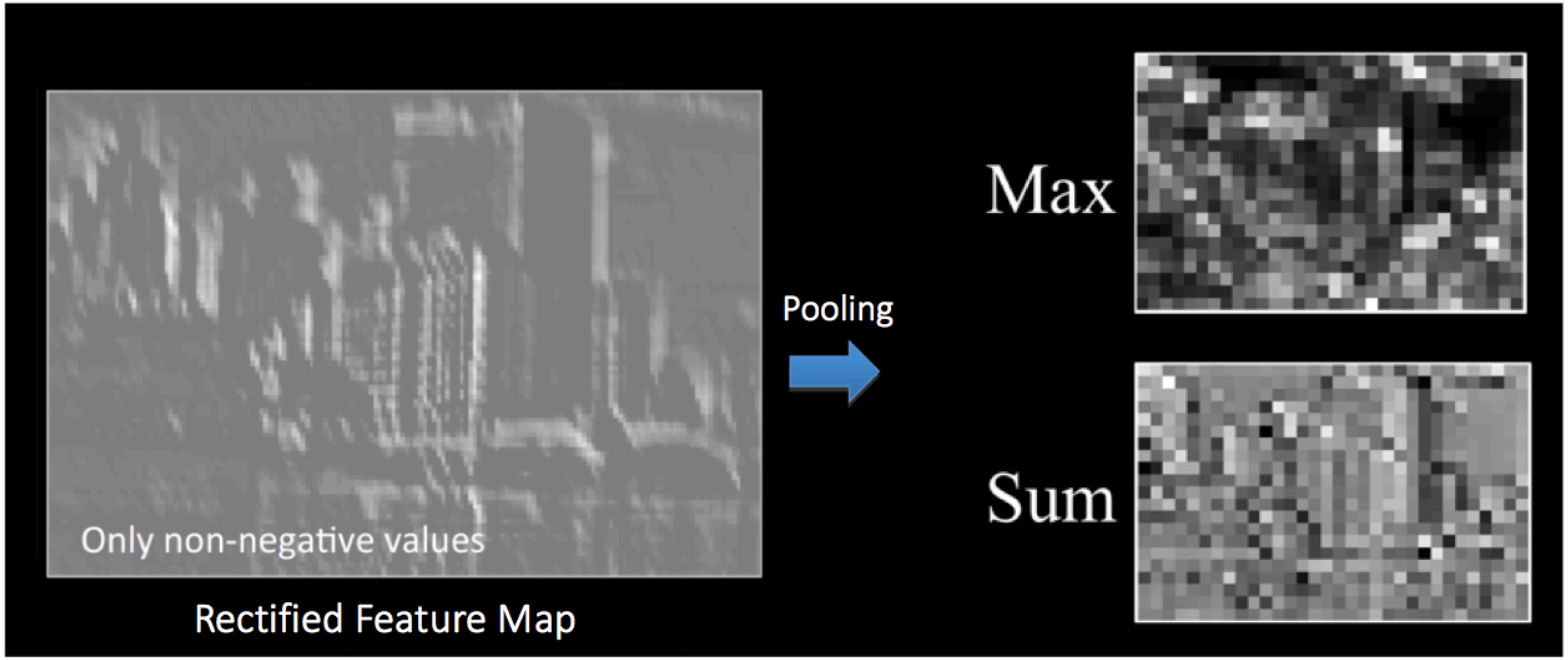
# What does a ConvNN learn?

- *The use on non-linear activation functions plays a special role in enhancing features*



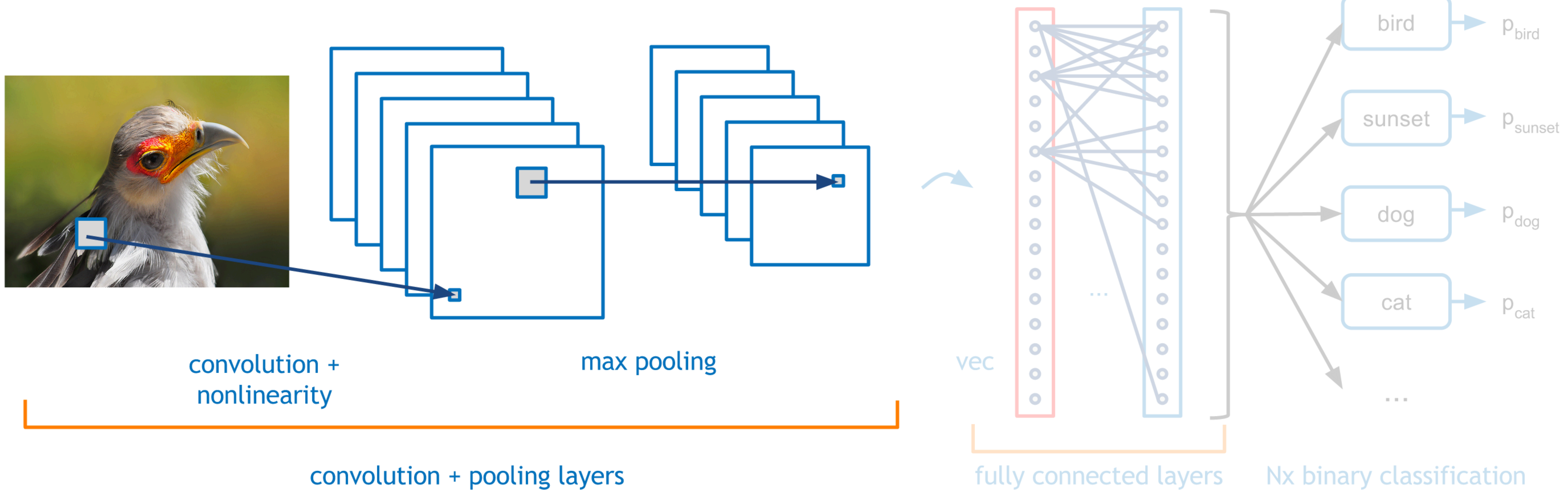
# What does a ConvNN learn?

- Pooling is important in smoothing out the image
    - reduce parameters downstream (and prevent overfitting)
    - makes processing independent to local features (distortion, translation)
    - yields a scale invariant representation of the image (which could be good or bad)



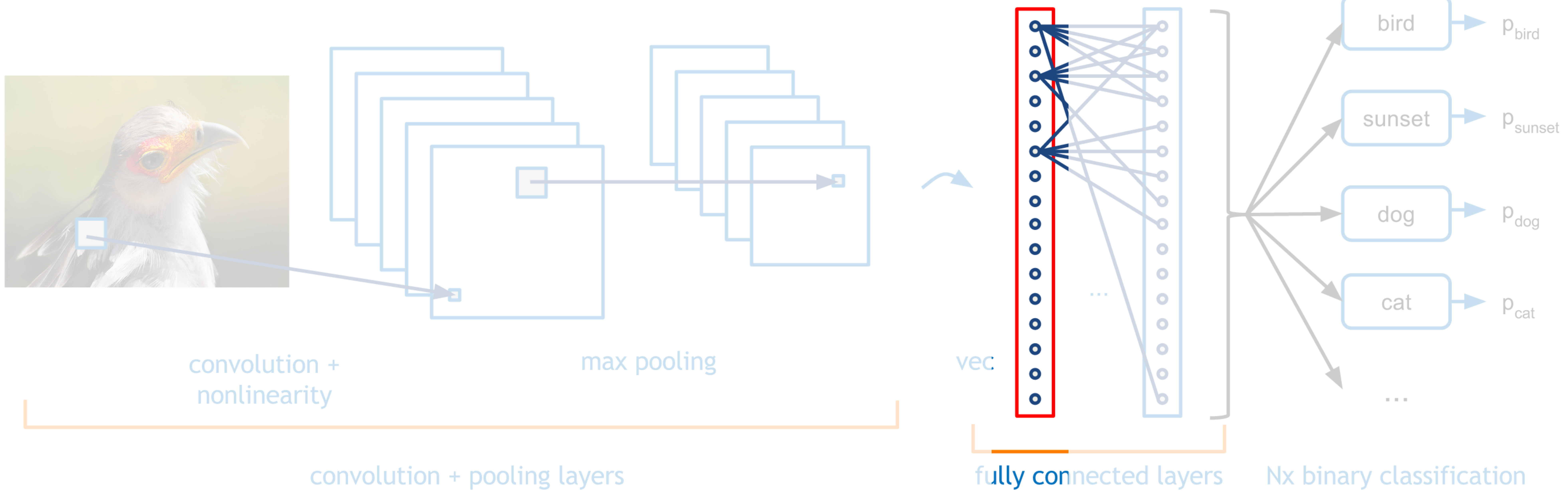
# Two tasks in one network

- ***The Conv layer stars from RAW data and defines interesting quantities (high level features)***
- *The HLFs replace the physics-motivated inputs of a DNN*
- *The DNN at the end exploits the engineered features to accomplish the task*



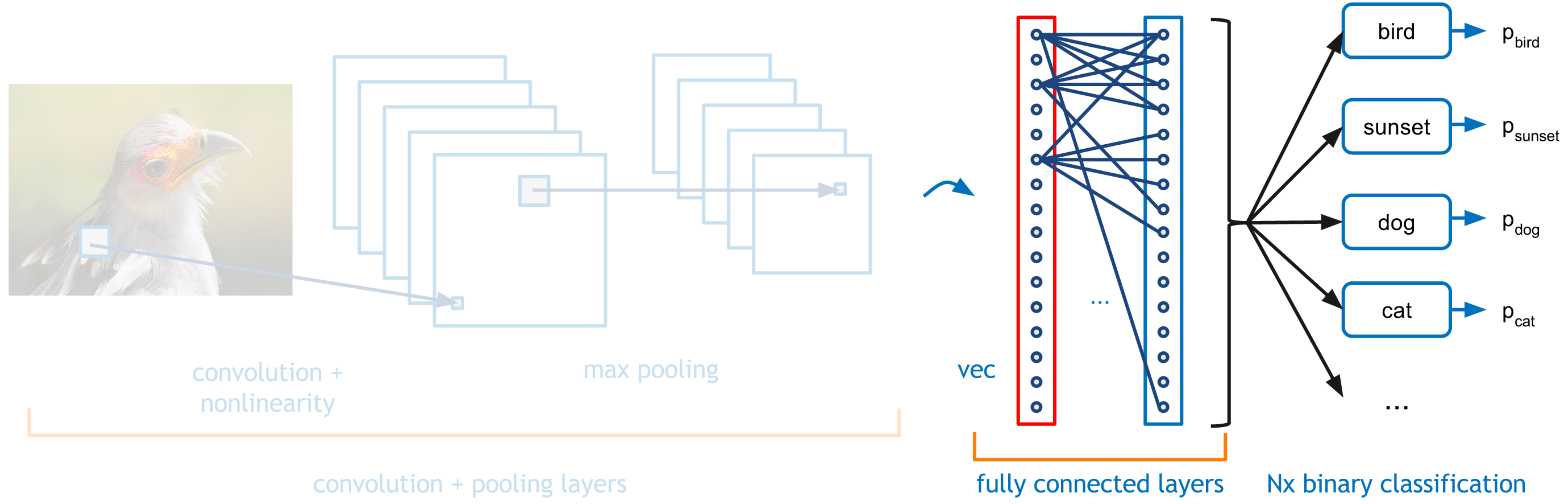
# Two tasks in one network

- *The Conv layer stars from RAW data and defines interesting quantities (high level features)*
- ***The HLFs replace the physics-motivated inputs of a DNN***
- *The DNN at the end exploits the engineered features to accomplish the task*



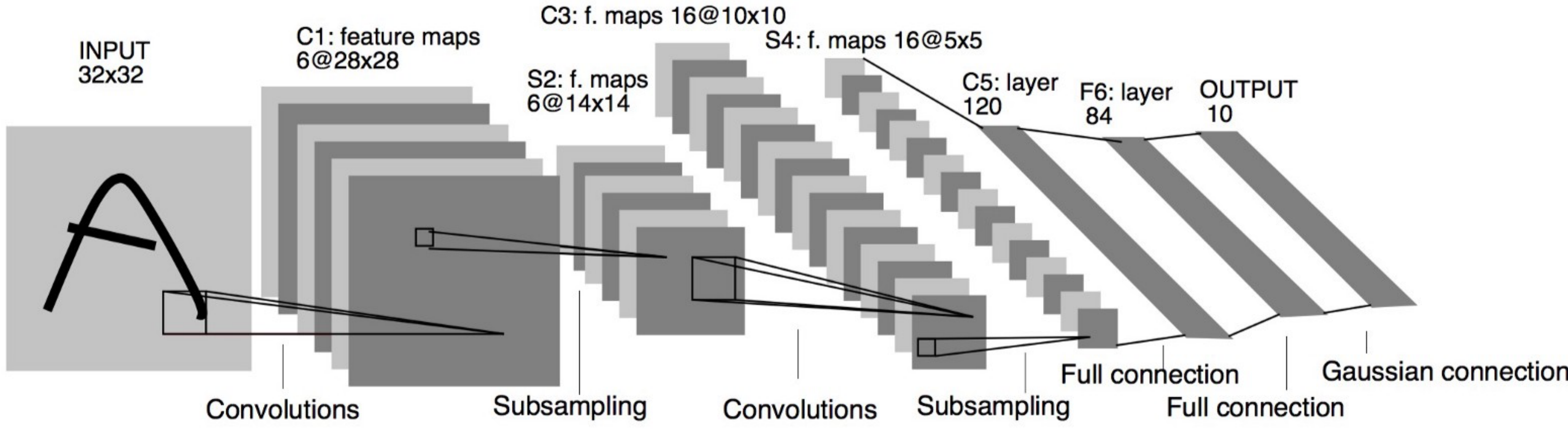
# Two tasks in one network

- *The Conv layer stars from RAW data and defines interesting quantities (high level features)*
- *The HLFs replace the physics-motivated inputs of a DNN*
- ***The DNN at the end exploits the engineered features to accomplish the task***

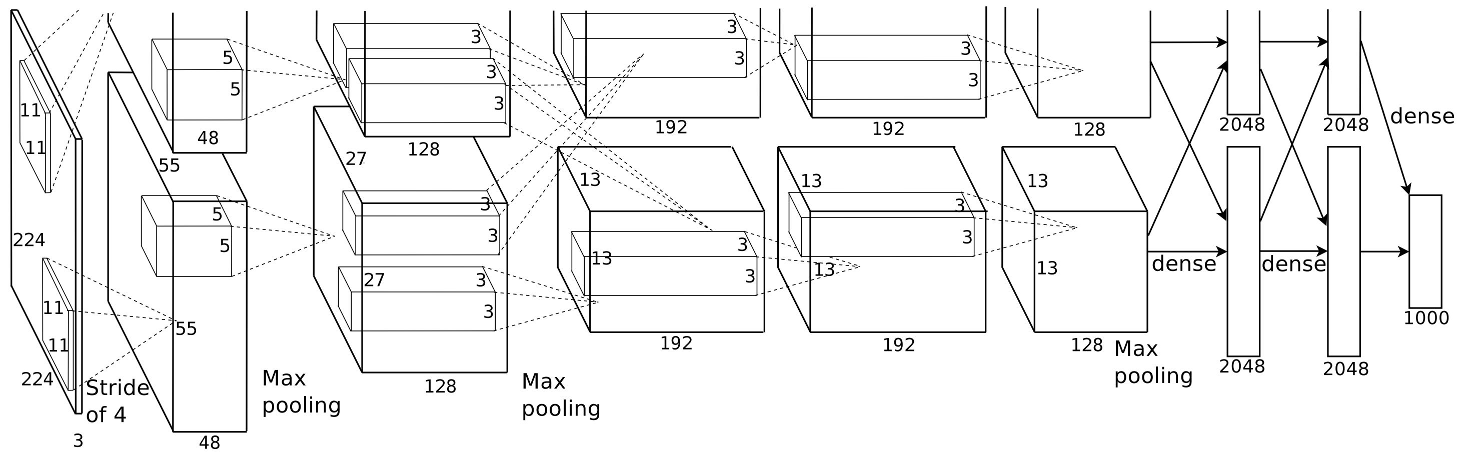


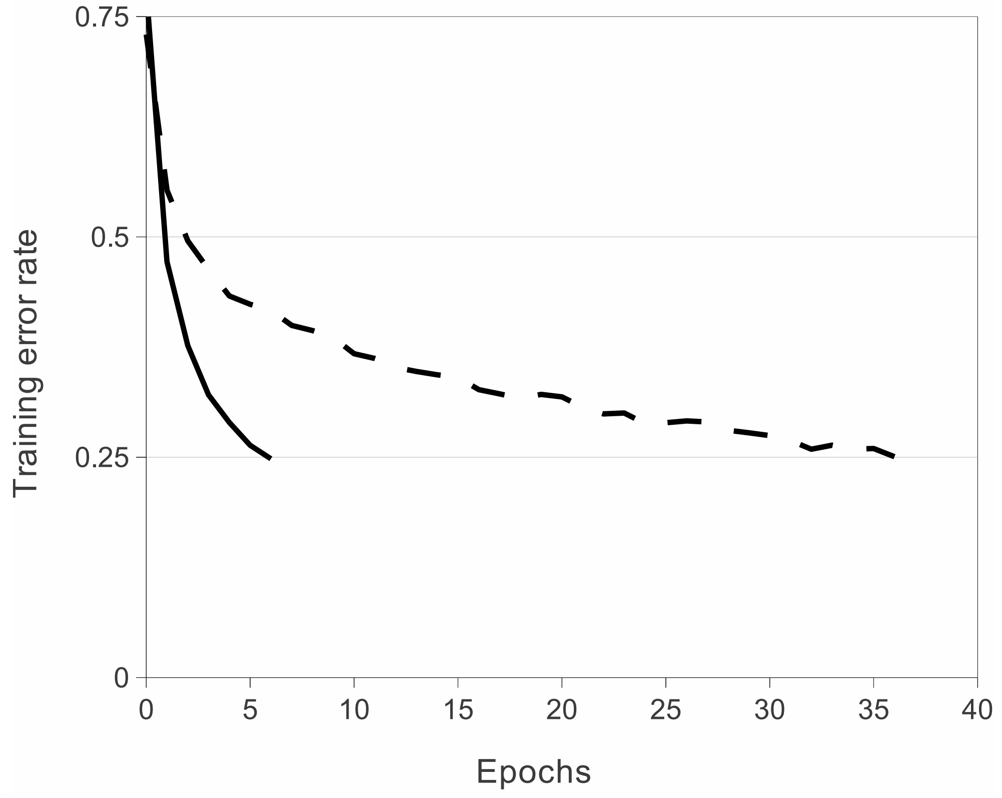
# A history of ConvNNs

- [Neocognitron (1980):]() translation-invariant image processing with NNs

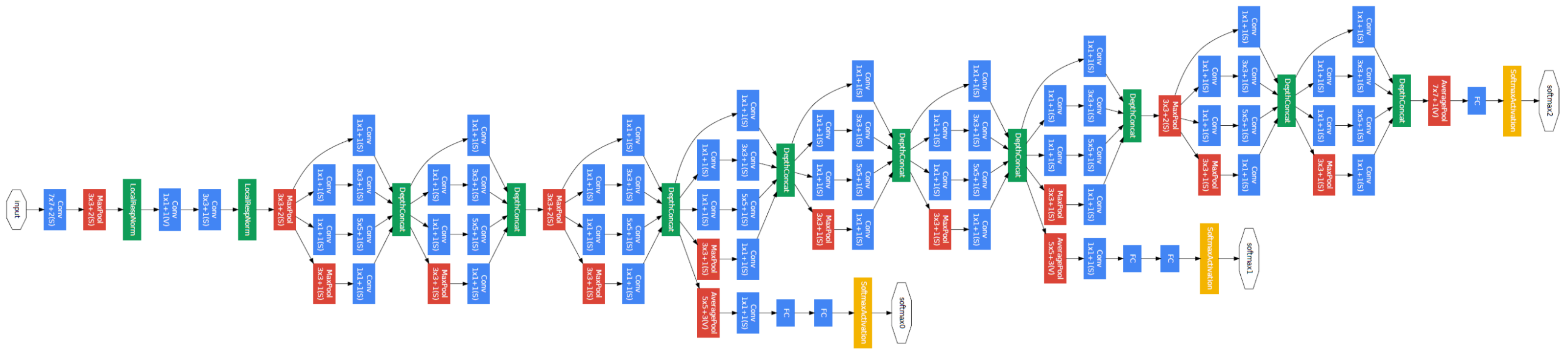



- LeNet (1989): considered the very first ConvNN, designer for digit recognition (ZIP codes)



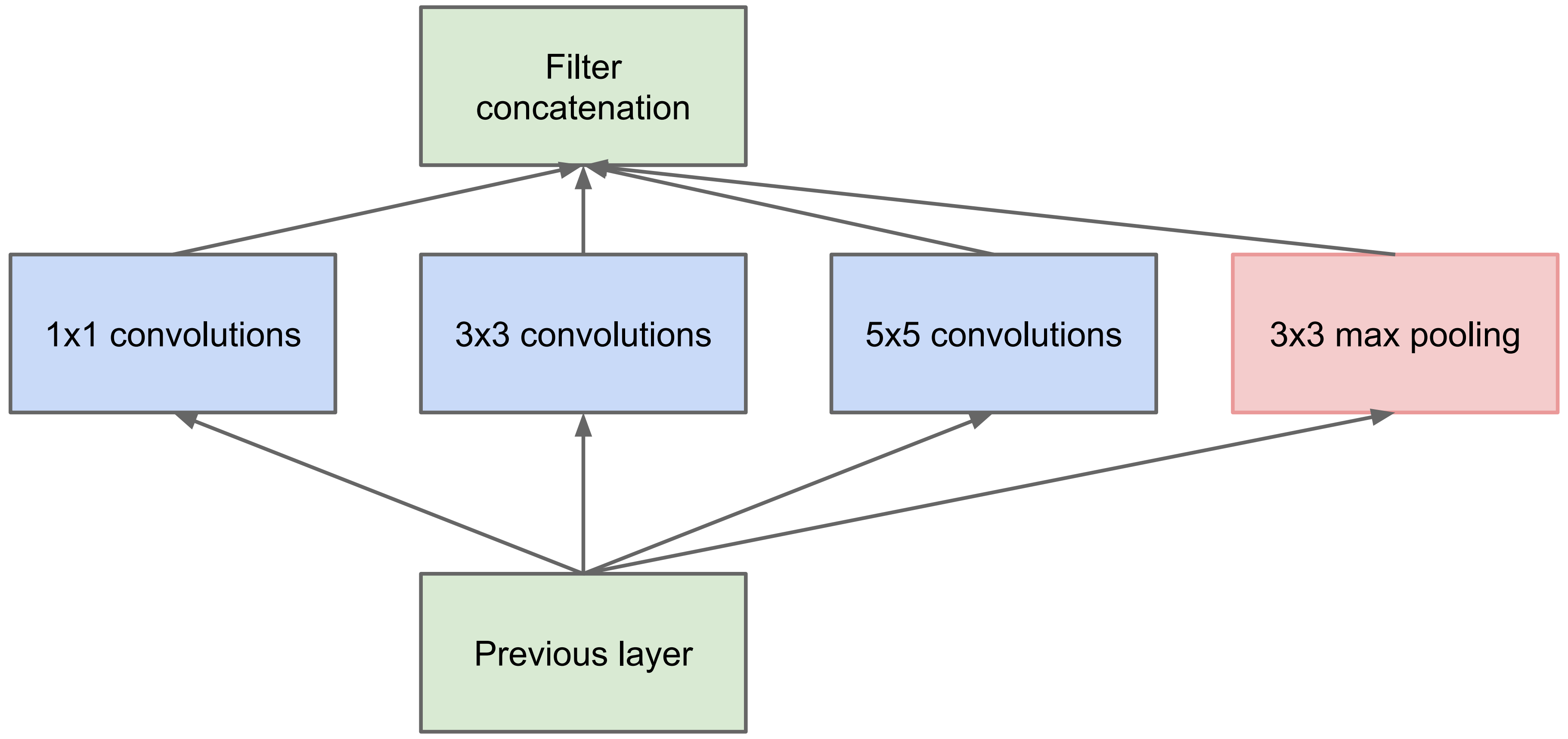

- AlexNet (2012): the first big ConvNN (60M parameters, 650K neurtons), setting the state of the art: trained on GPUs, using ReLU and Dropout



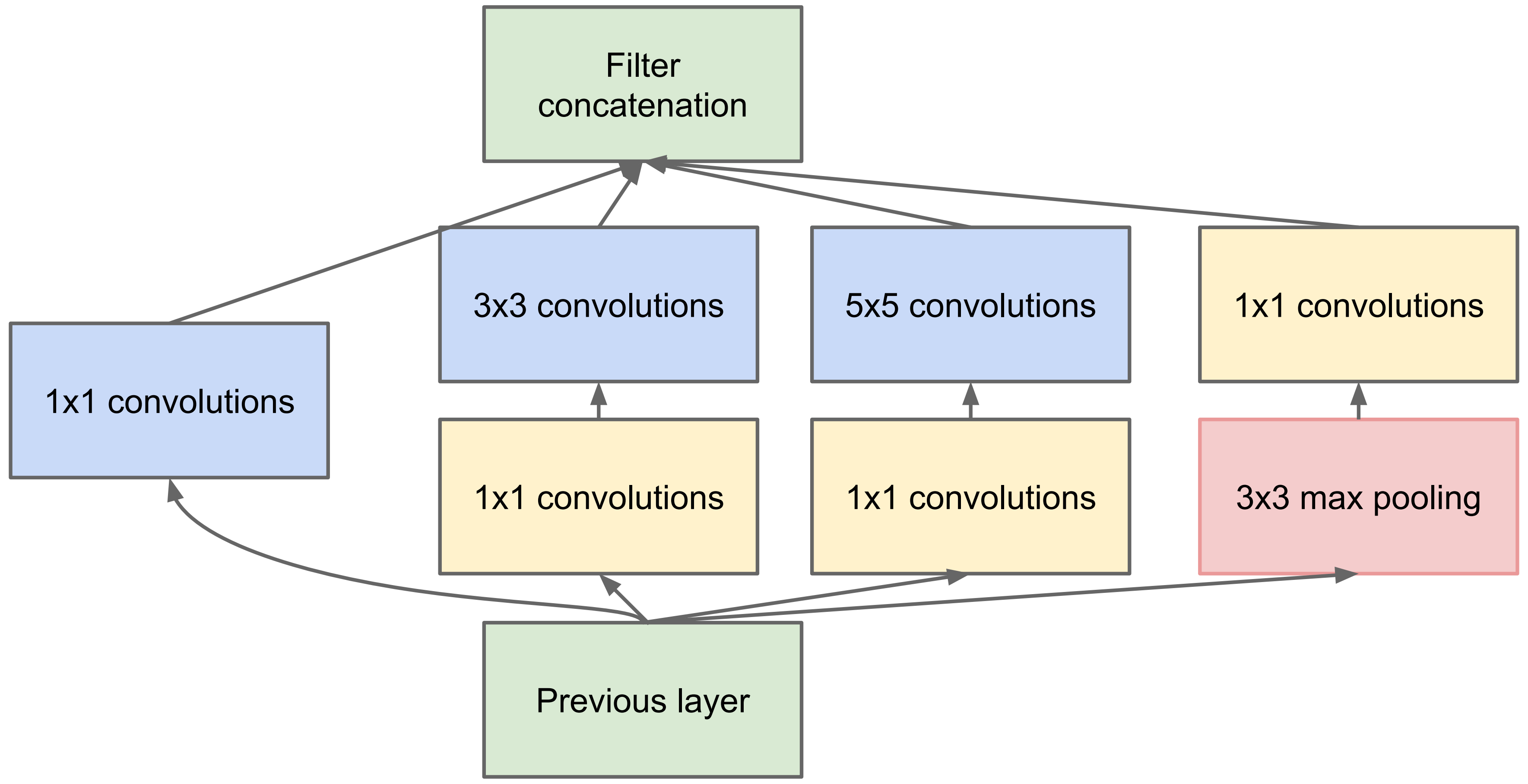
- GoogleNet (2014): built on AlexNet, introduced an inception model to reduce e the number of parameters

# Inception Module

- Rather than going deeper and deeper, inception architecture go wider
- Several conv layers, with different filter size, process the same inputs
- This way, more features can be detected from the same image
- The outcome of this parallel processing is then recombined through a concatenation step ass channels of an image




(a) Inception module, naïve version



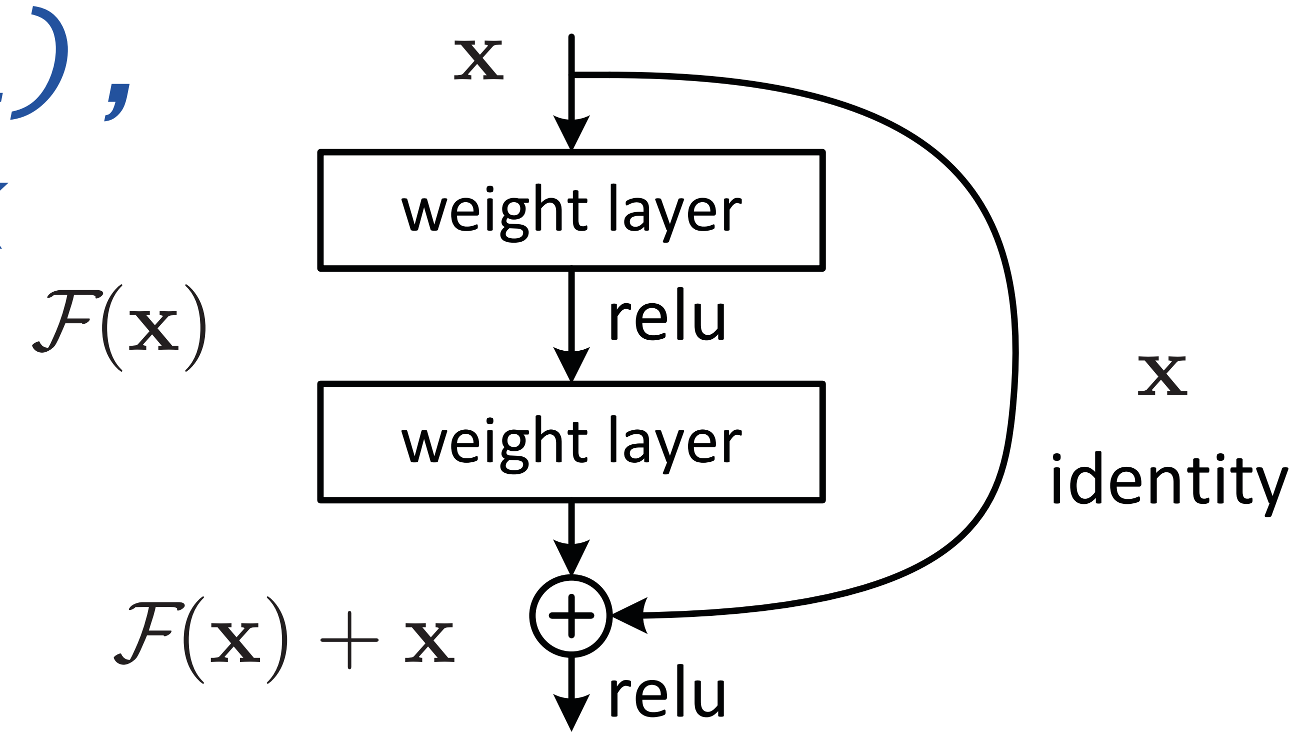

(b) Inception module with dimension reductions



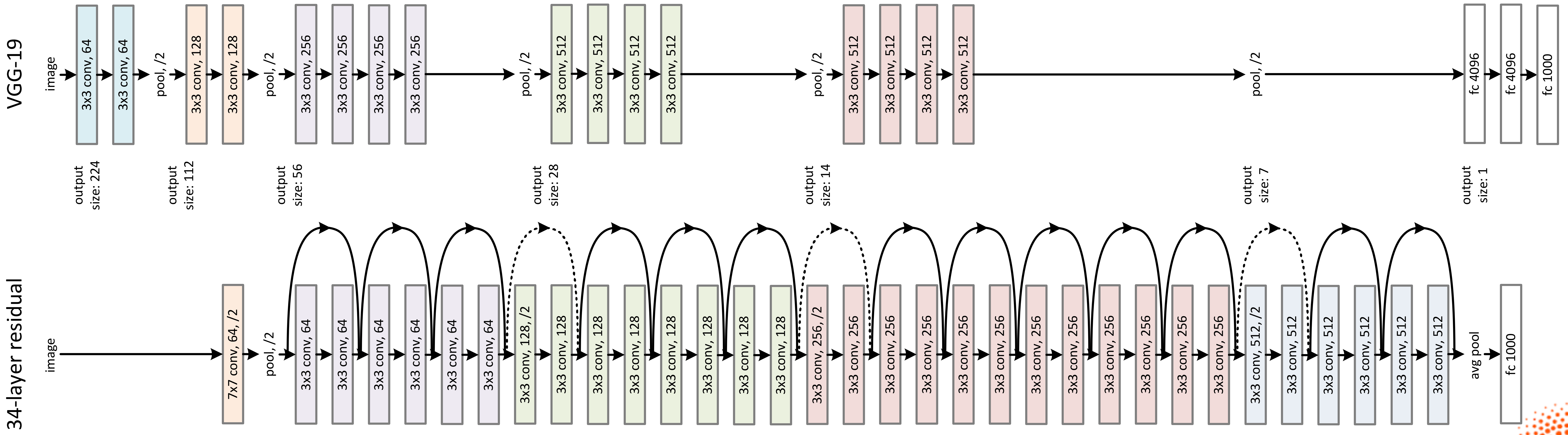
European Research Council

# A history of ConvNNs

- *[VGGNet(2014)](#):exploit small filters (3x3, 1x1), previously considered not optimal in a stack of Conv layers (rather than 1Conv+1Pooling)*



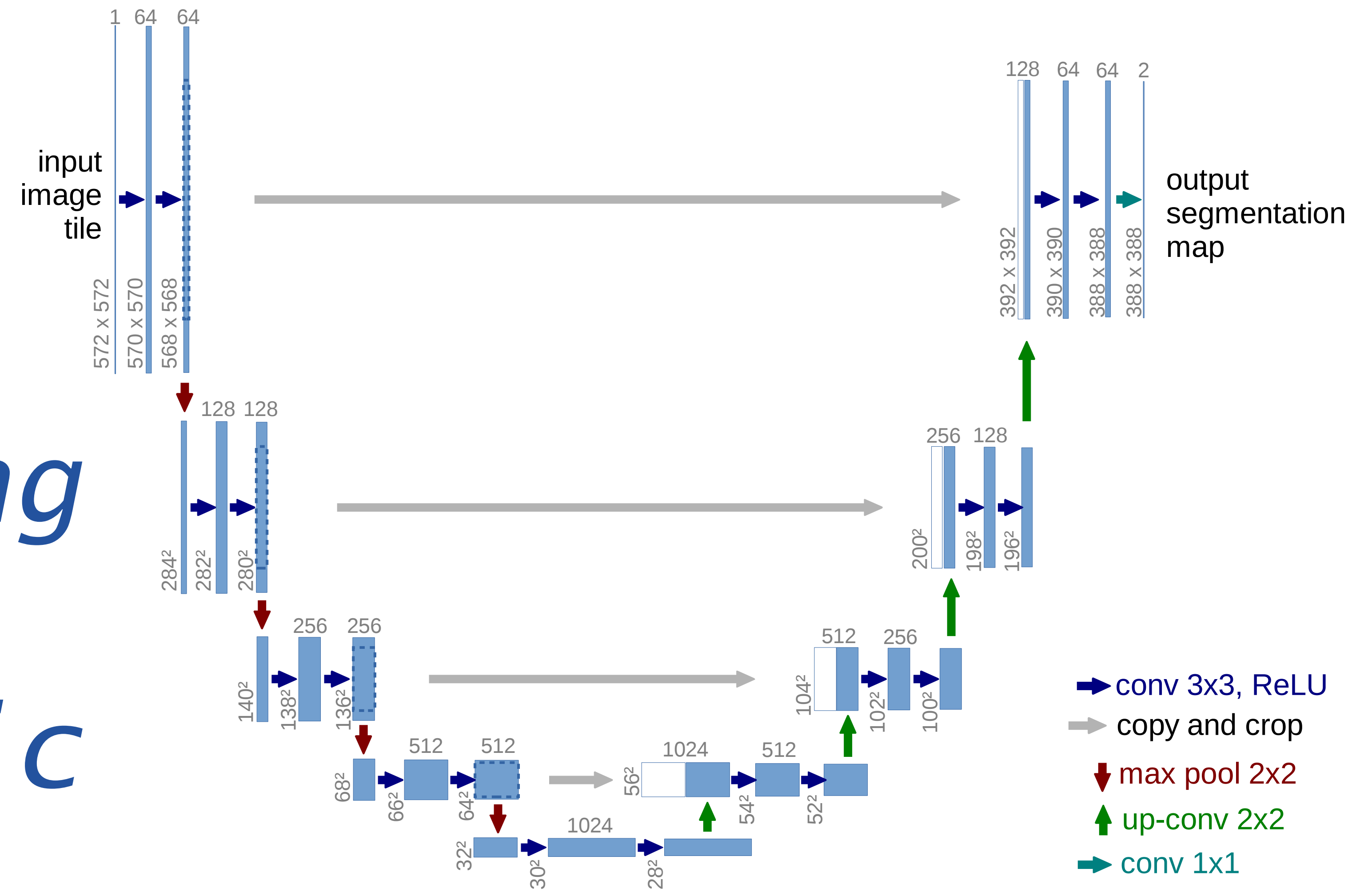

- *[ResNet (2015)](#):implemented skip connections, which were proven to boost performances*

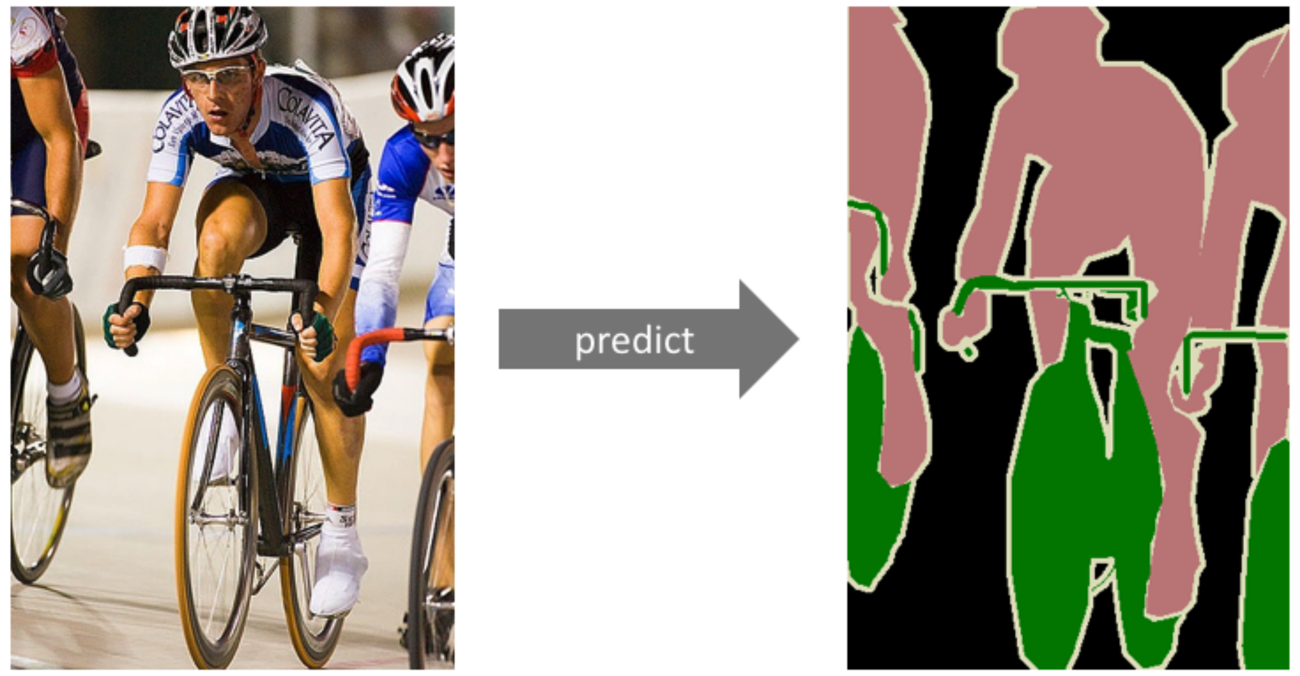



[Check this blog entry on ConvNNs](#)

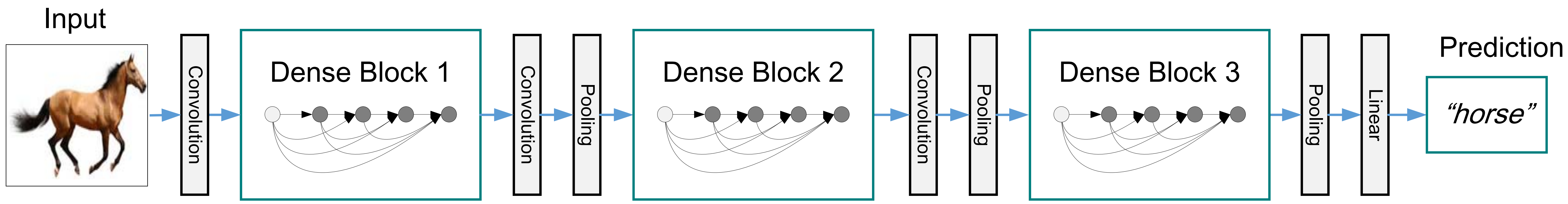
# A history of ConvNNs

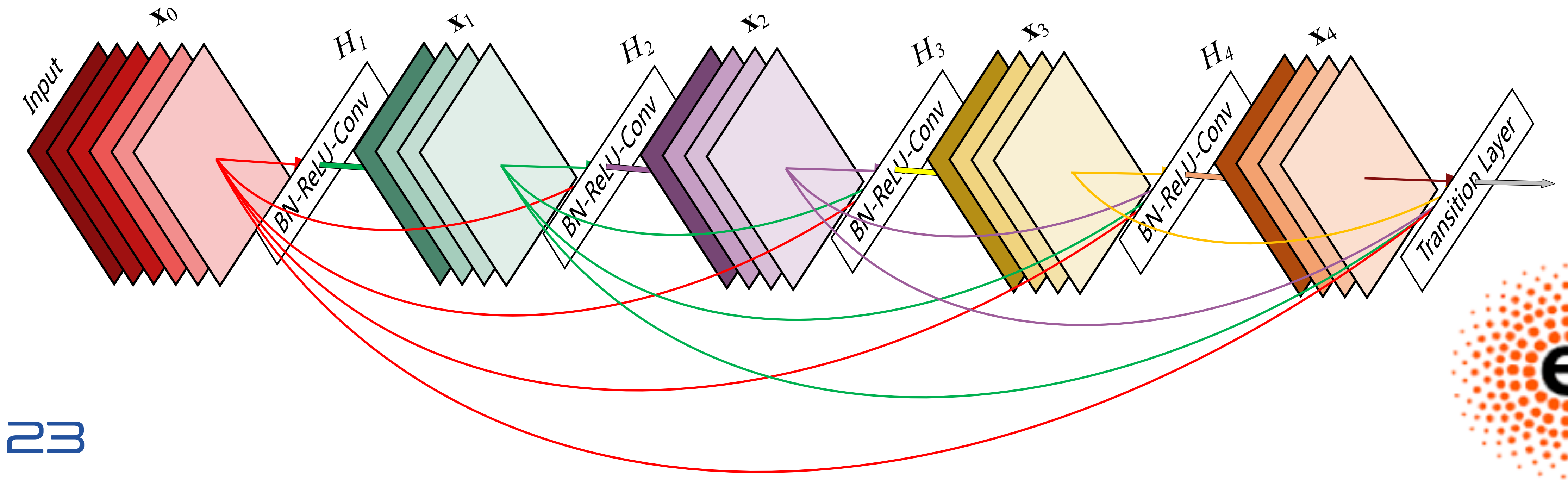
- [U-net (2015)](): conv layers with skip connections, in a downsampling+upsampling U-shaped sequence. Introduced for semantic segmentation




- [DenseNet (2016)](): uses skip connections between a given layer and all the layers downstream in a dense block, with Conv layers in between

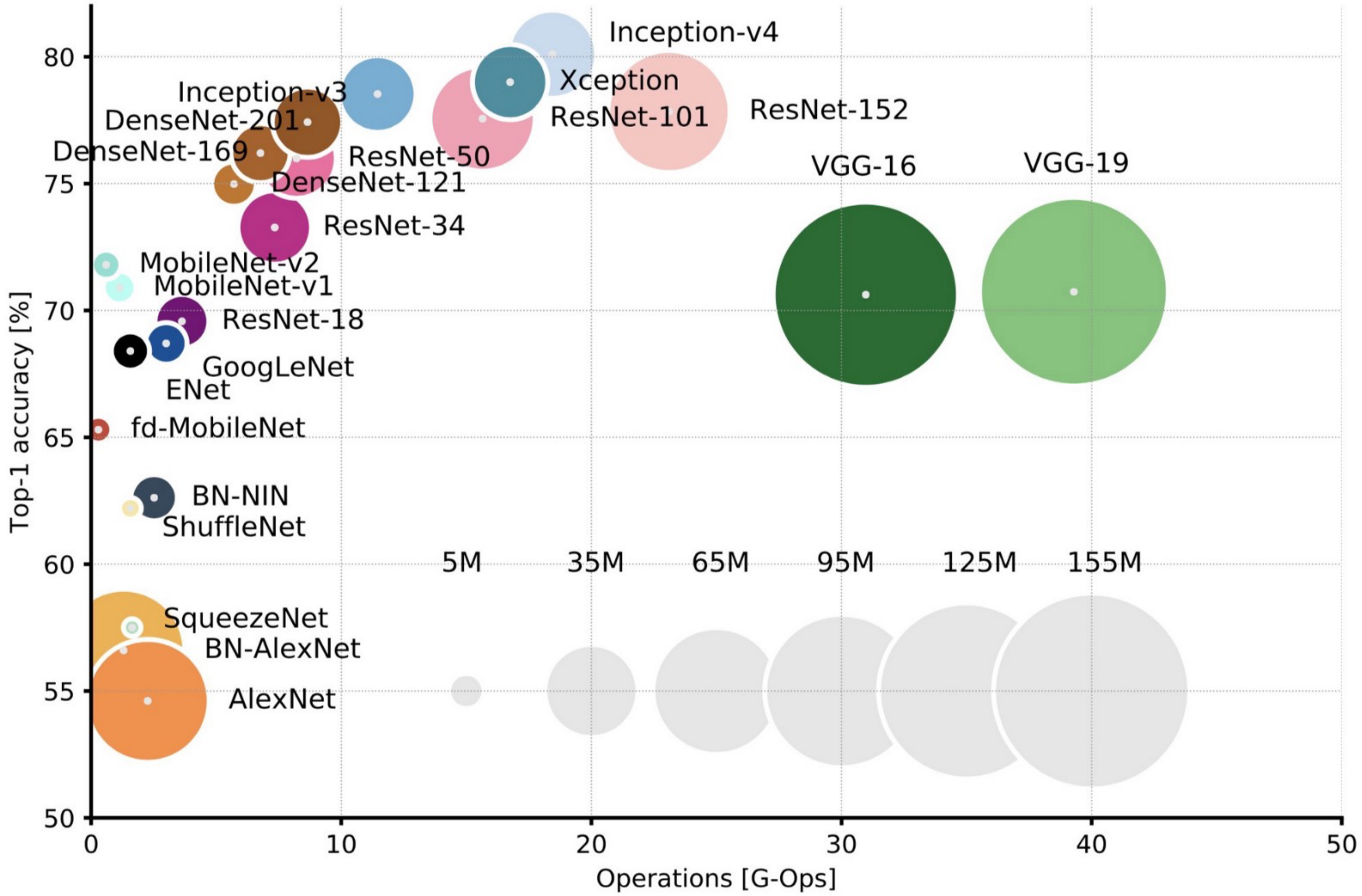


# The computational cost

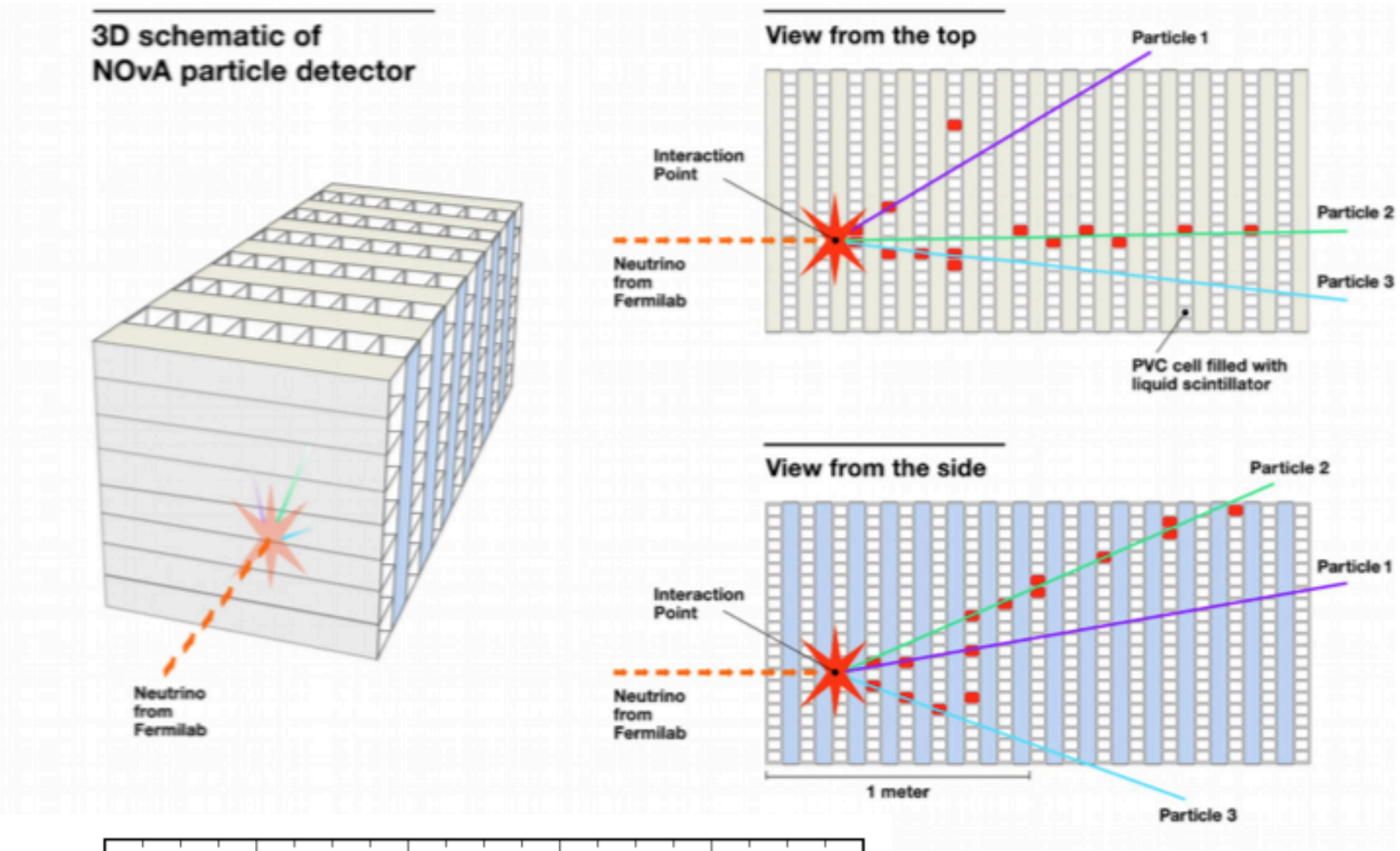
- *In this evolution, computing-vision networks drastically improved in performance*
- *This came at a big cost in complexity (number of parameters and operations)*
- *The inference with this network became particularly slow*
  - *big interest in optimize these networks on dedicated resources, e.g. FPGAs*
- *Many cloud providers provide optimized versions of these networks:*
  - *you can just use them (re-training if needed), rather than inventing your own one*

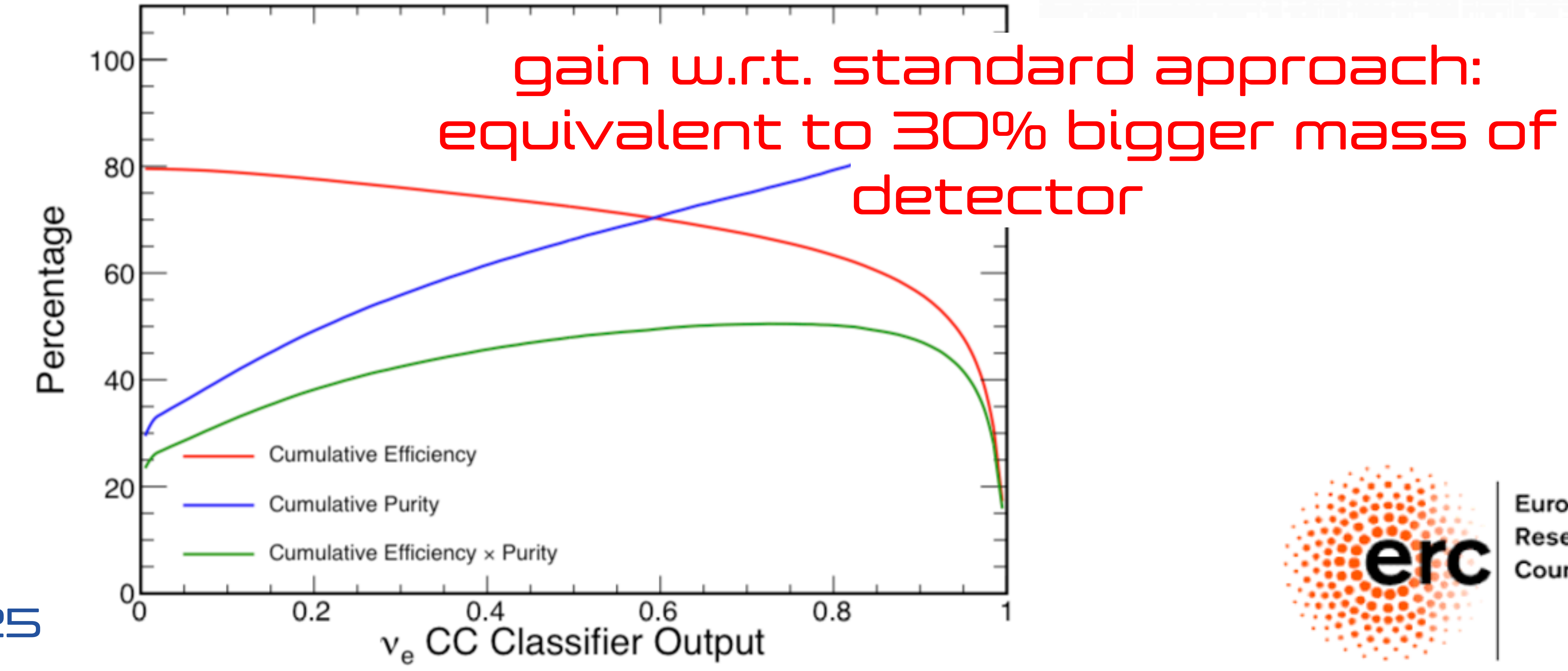
https://towardsdatascience.com/neural-network-architectures-156e5bad51ba



# Example: PID for ν experiments

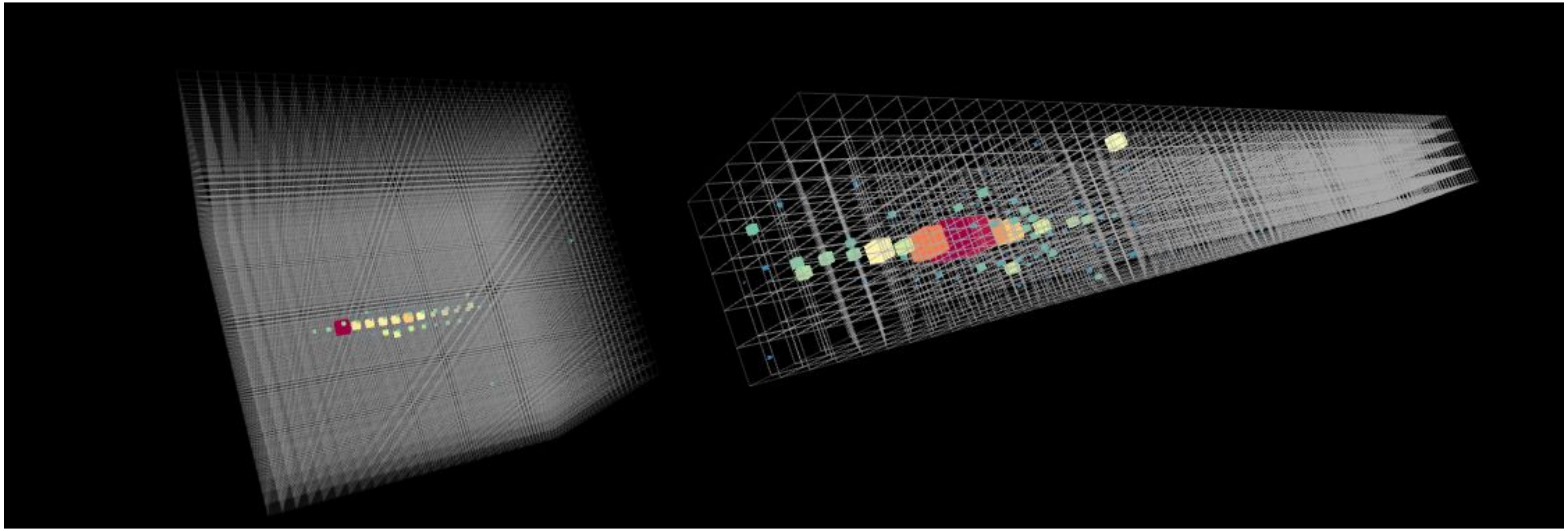
- Many HEP detectors (particularly underground) more and more structured as regular arrays of sensors
- Modern computer-vision techniques work with images as arrays of pixel sensor (in 1D, 2D, and 3D)
- These techniques were applied by Nova on electron and muon ID
- Impressive gain over traditional techniques (comparable to +30% detector == $$$ saved)



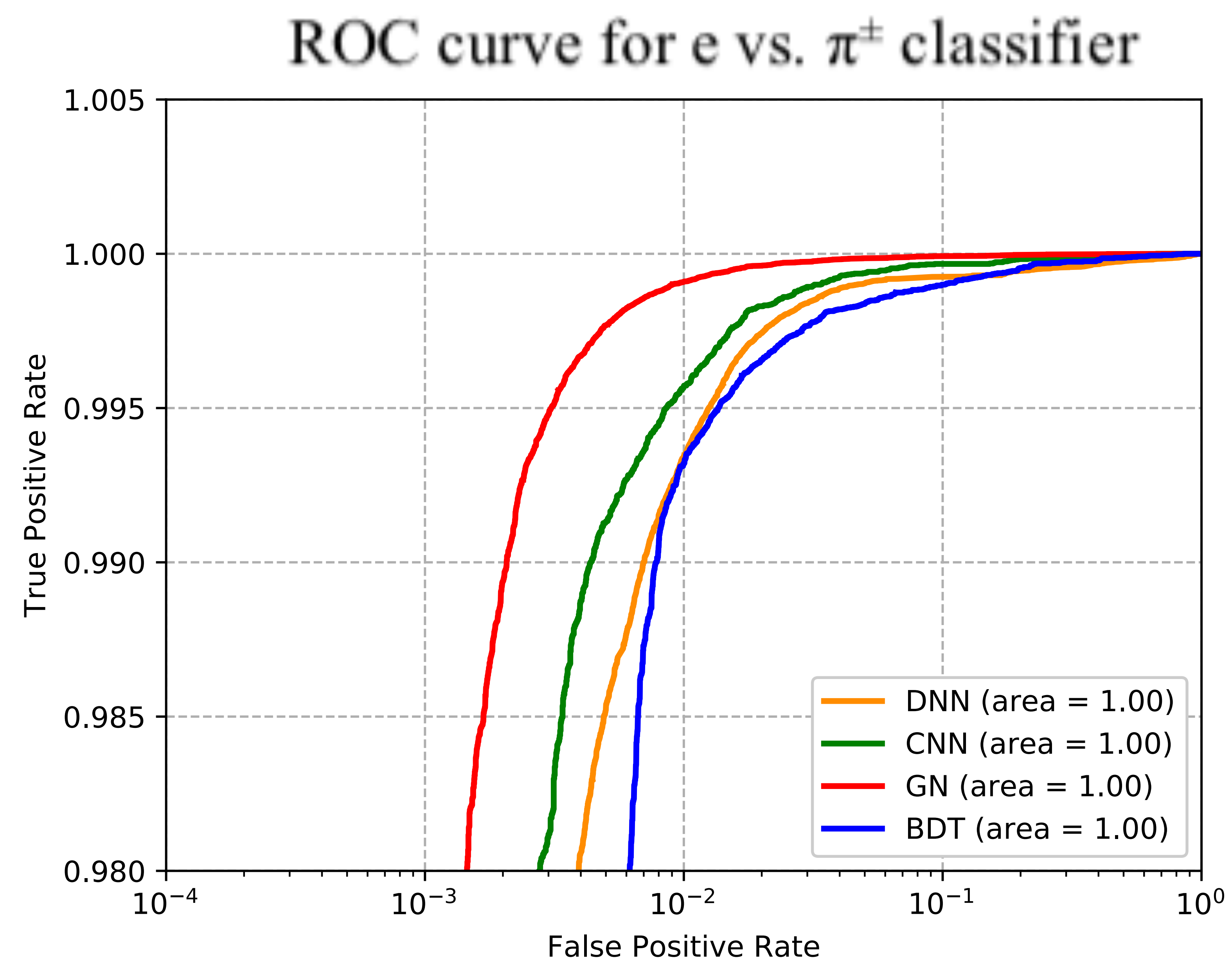
# Calorimetry & Computer Vision

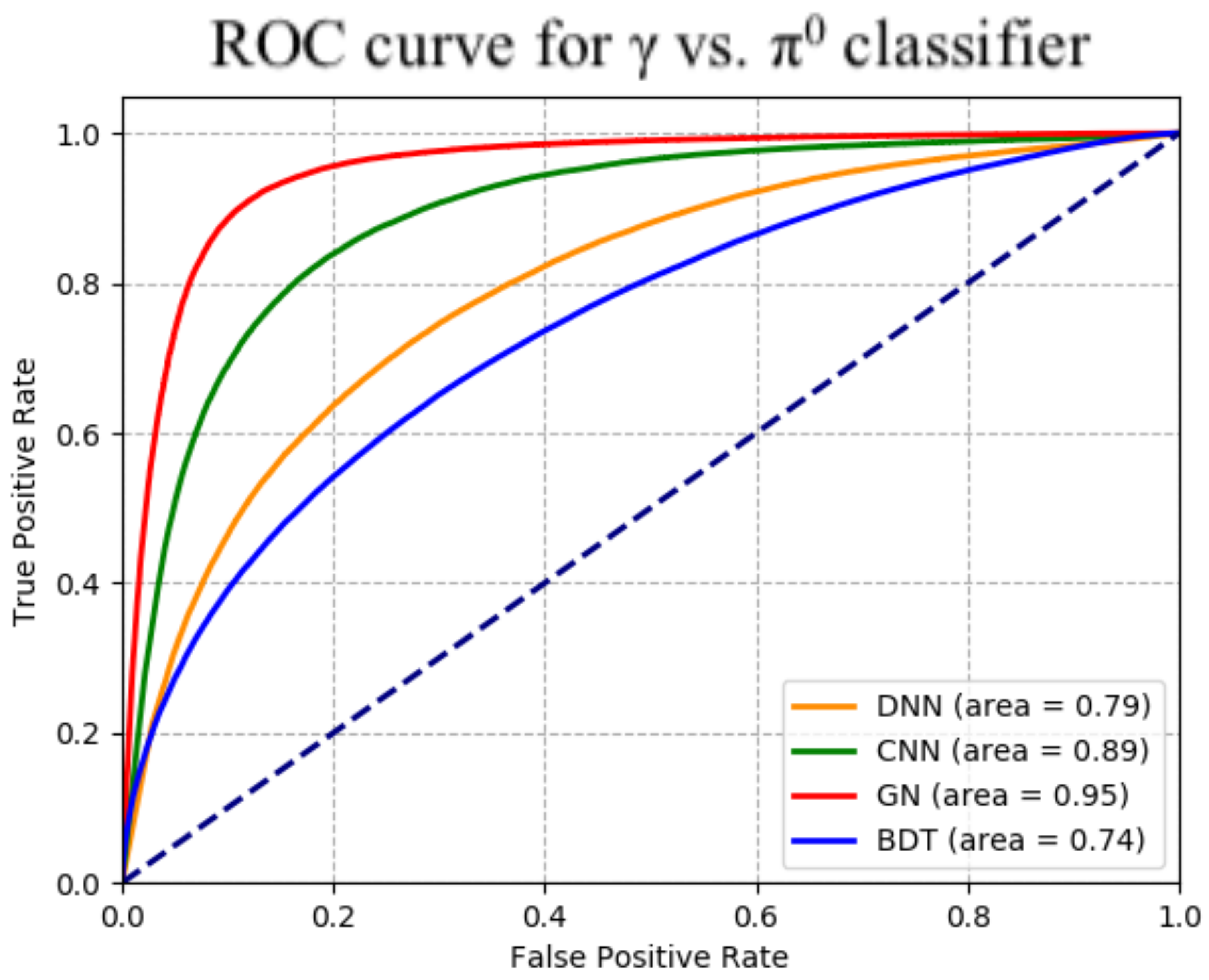
- *(next generation) digital calorimeters: 3D arrays of sensors with more regular geometry*
- *Ideal configuration to apply Convolutional Neural Network*
  - *speed up reconstruction at similar performances*
  - *and possibly improve performances*



# Example: Particle ID

- We tried particle ID on a sample of simulated events
  - one particle/event (e, γ, $\pi^0$, π)
- Different event representations
  - high-level features related to event shape (moments of X,Y, and Z projections, etc)
  - raw data (energy recorded in each cell)
- Pre-filtered pion events to select the nasty ones and make the problem harder

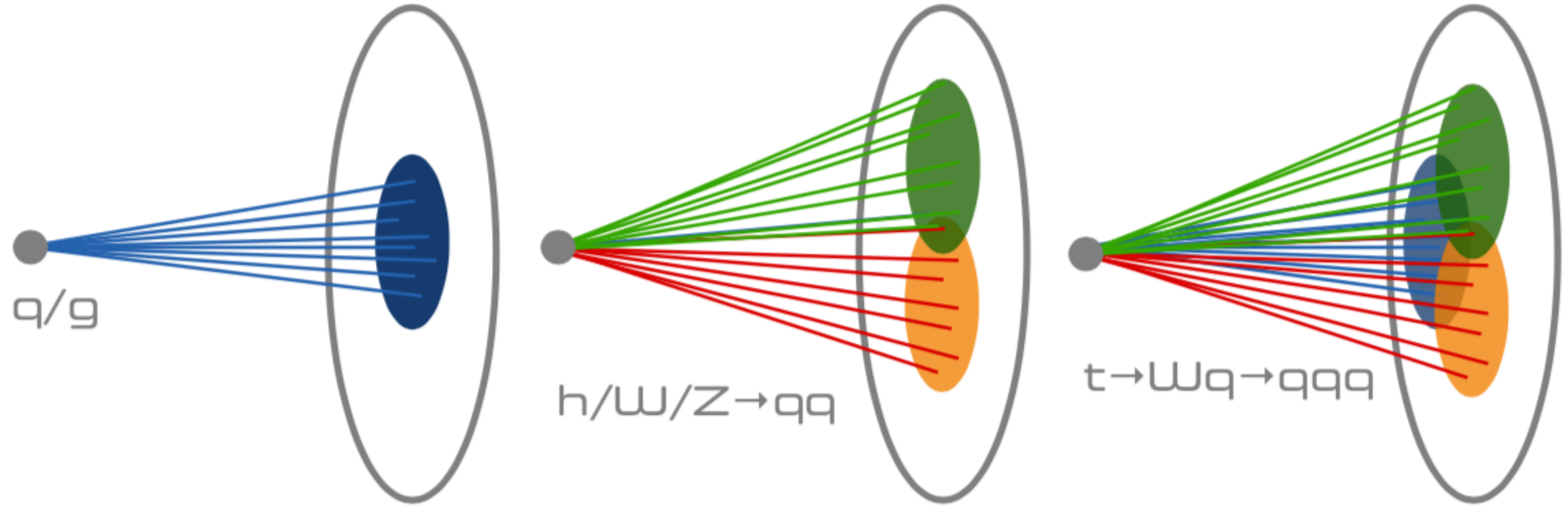


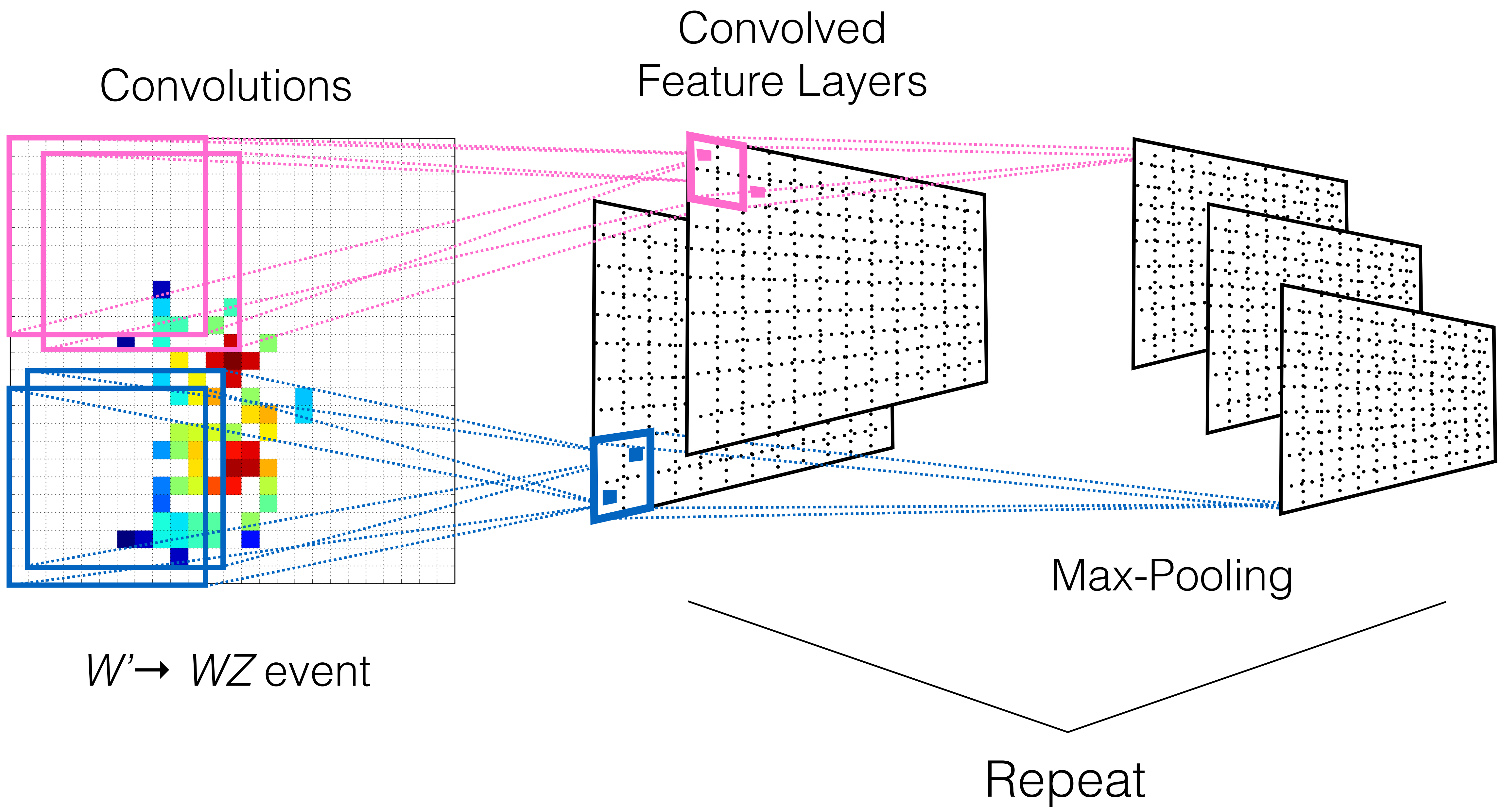




European Research Council

# Jet as images (for ConvNN)

- One can pixelate the surface crossed by the jet and create an image with the momentum deposited in each cell
- Such an image can then be processed with computing-vision techniques
- Pros: can benefit of the progresses made in optimizing computing vision
- Cons: underlying assumption on detector geometry (regular array of pixels) made sacrificing information of the actual detector

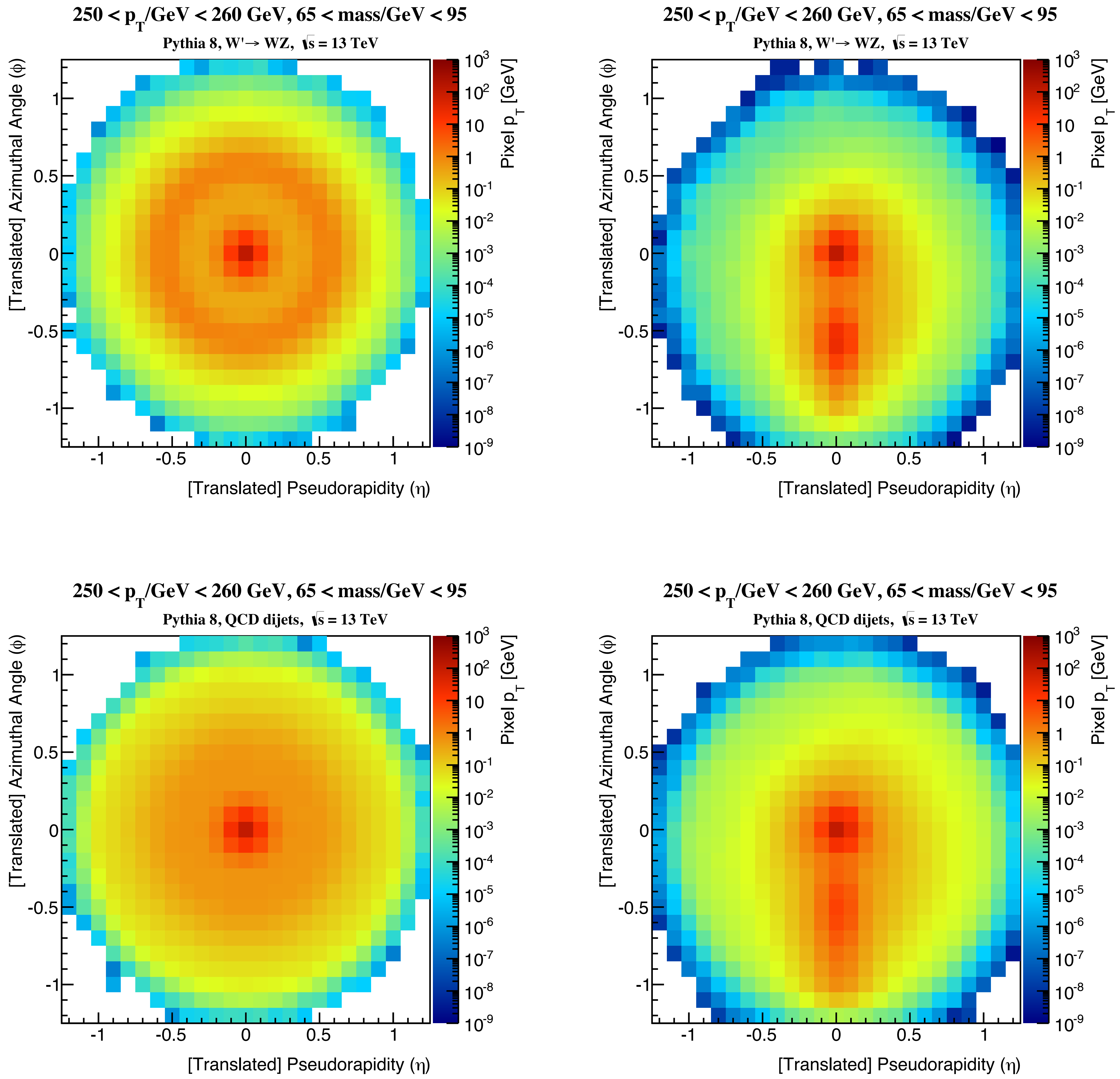



https://arxiv.org/abs/1511.05190

# Jet as images (for ConvNN)

- One can pixelate the surface crossed by the jet and create an image with the momentum deposited in each cell
- Such an image can then be processed with computing-vision techniques
- Pros: can benefit of the progresses made in optimizing computing vision
- Cons: underlying assumption on detector geometry (regular array of pixels) made sacrificing information of the actual detector




https://arxiv.org/abs/1511.05190

# Summary

- *Conv Networks are the most striking example of the success of Deep Learning*
  - *A story of improvement from the 90s to now*
  - *Very effective as a fast tool for particle reconstruction*
  - *Same geometry can be used for image generation with adversarial training*
  - *Can speed up one of the heaviest tasks in particle physics*