

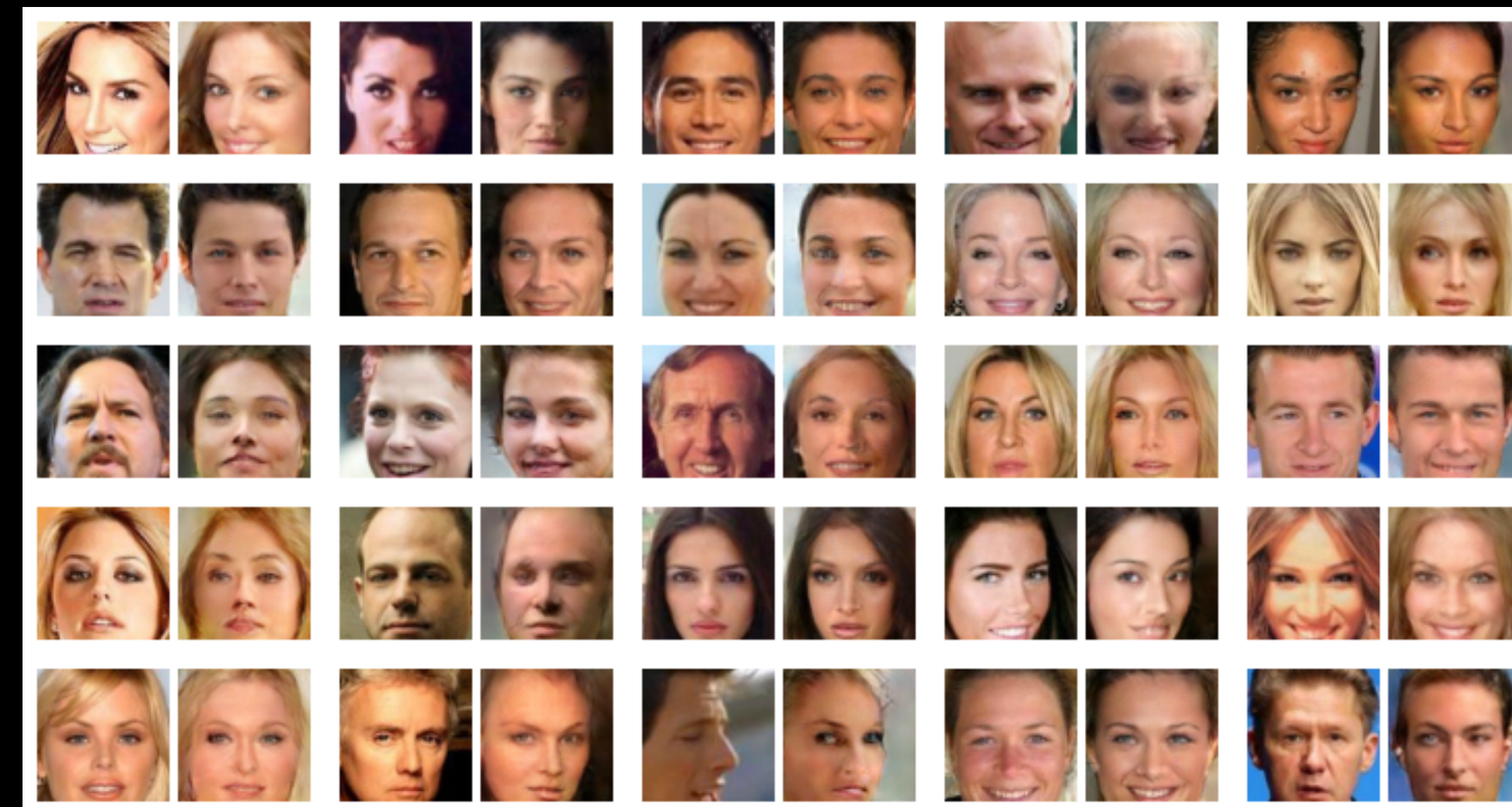
# DL Dev Course: Week 05

## Advanced CNNs

$$f(\text{ kitten image }) = \text{kitten}$$

Classification

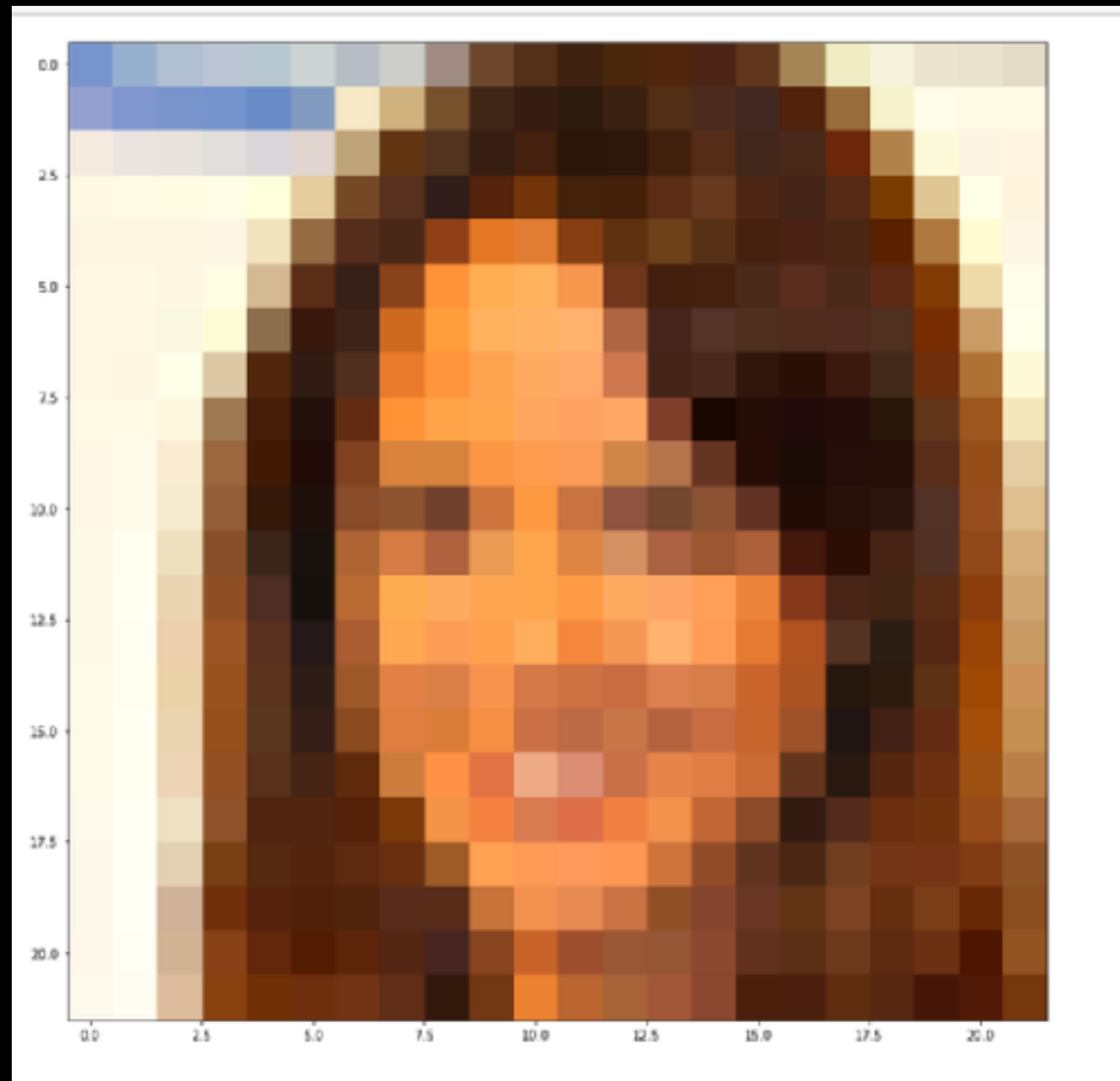
$$f(\text{ grid of 10 face images }) =$$



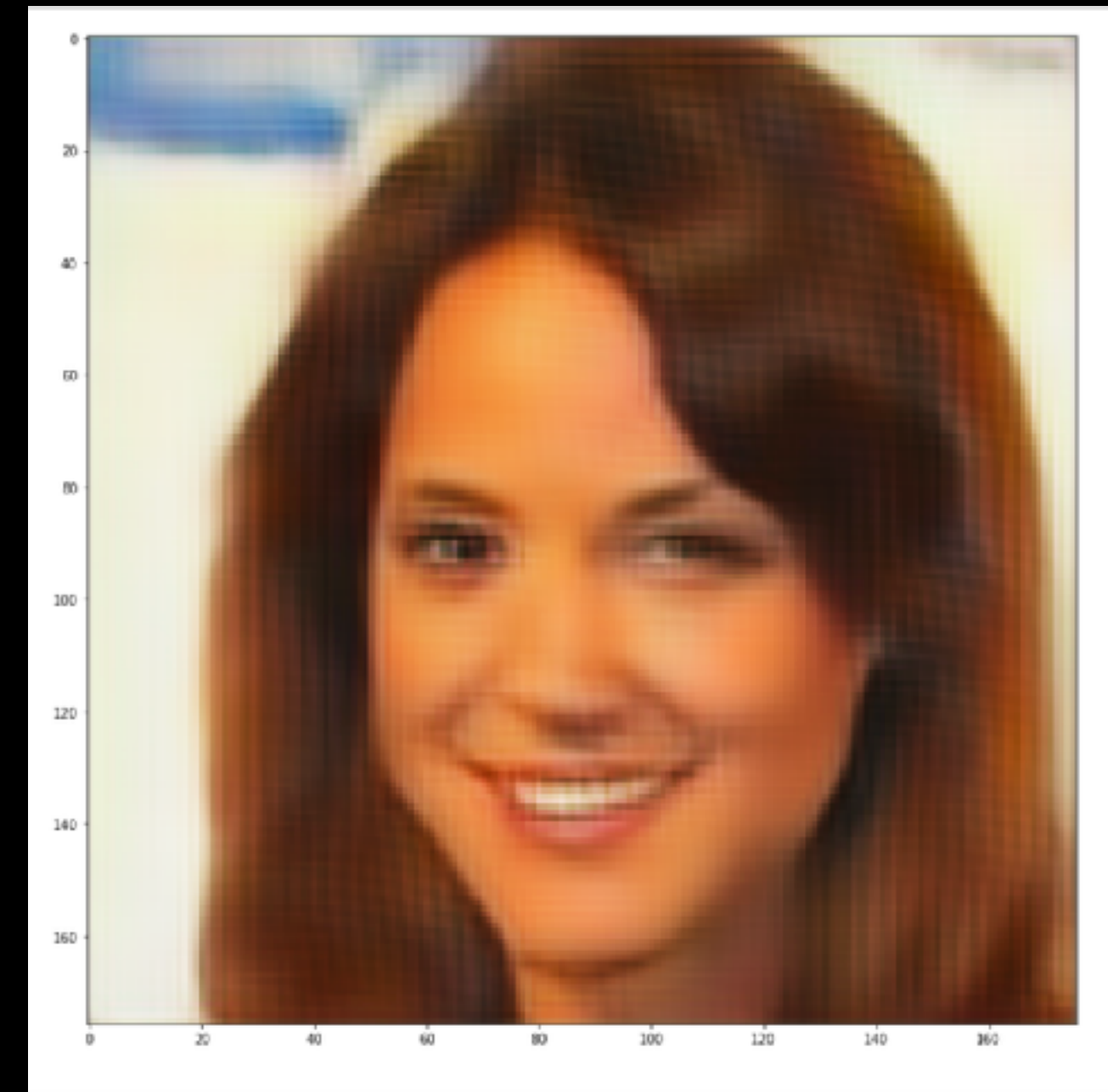
Generative

# 8x Super Resolution

**f(**

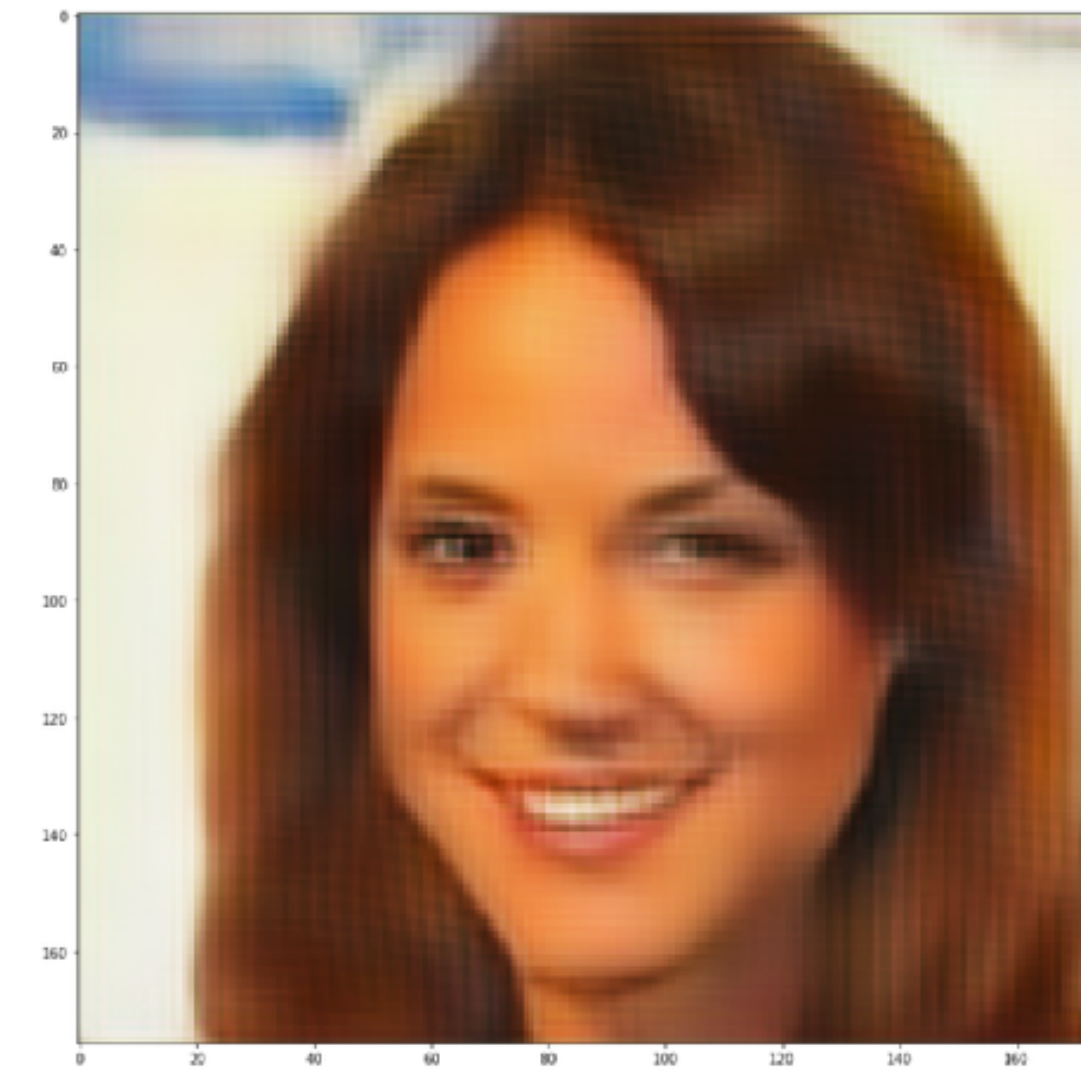
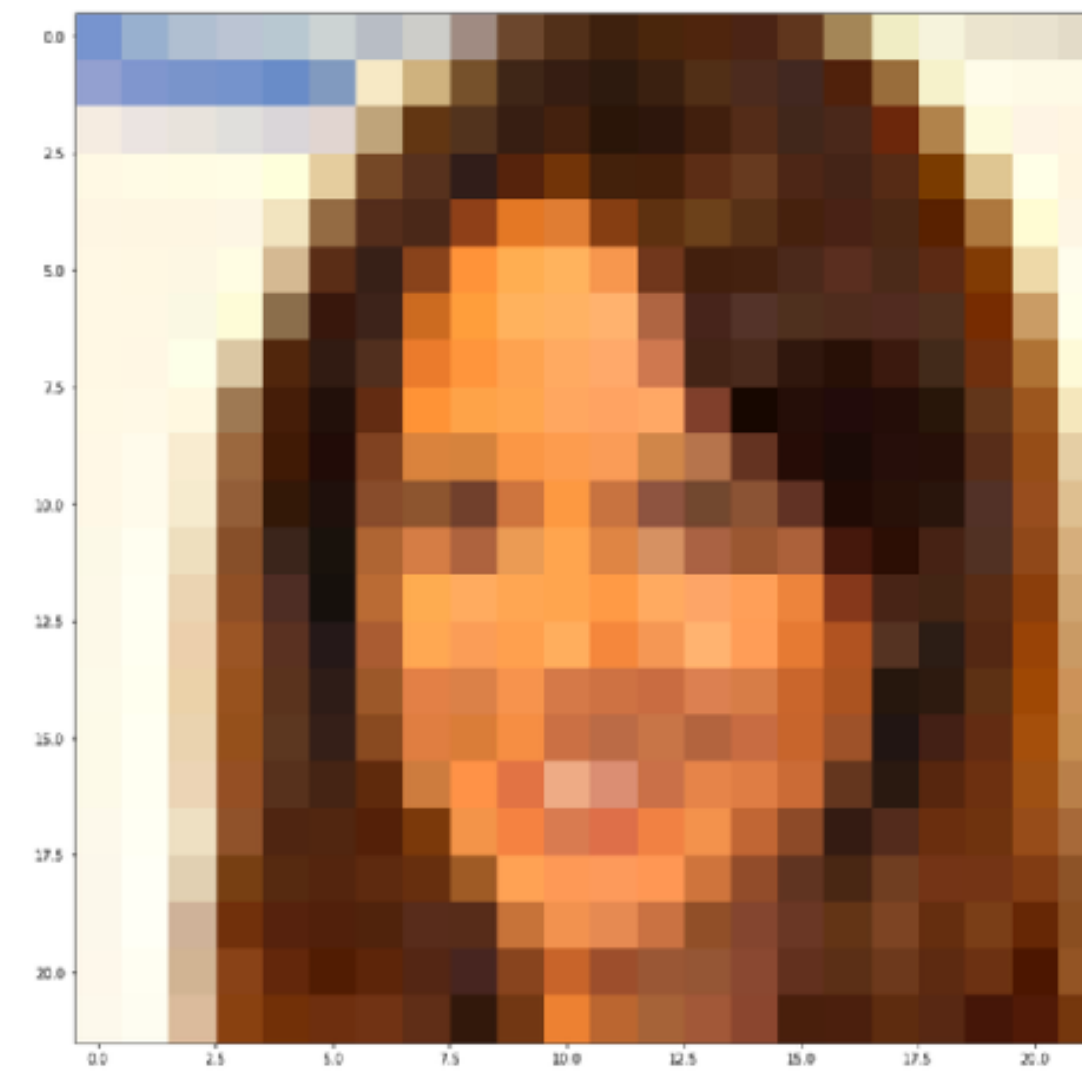


**) =**

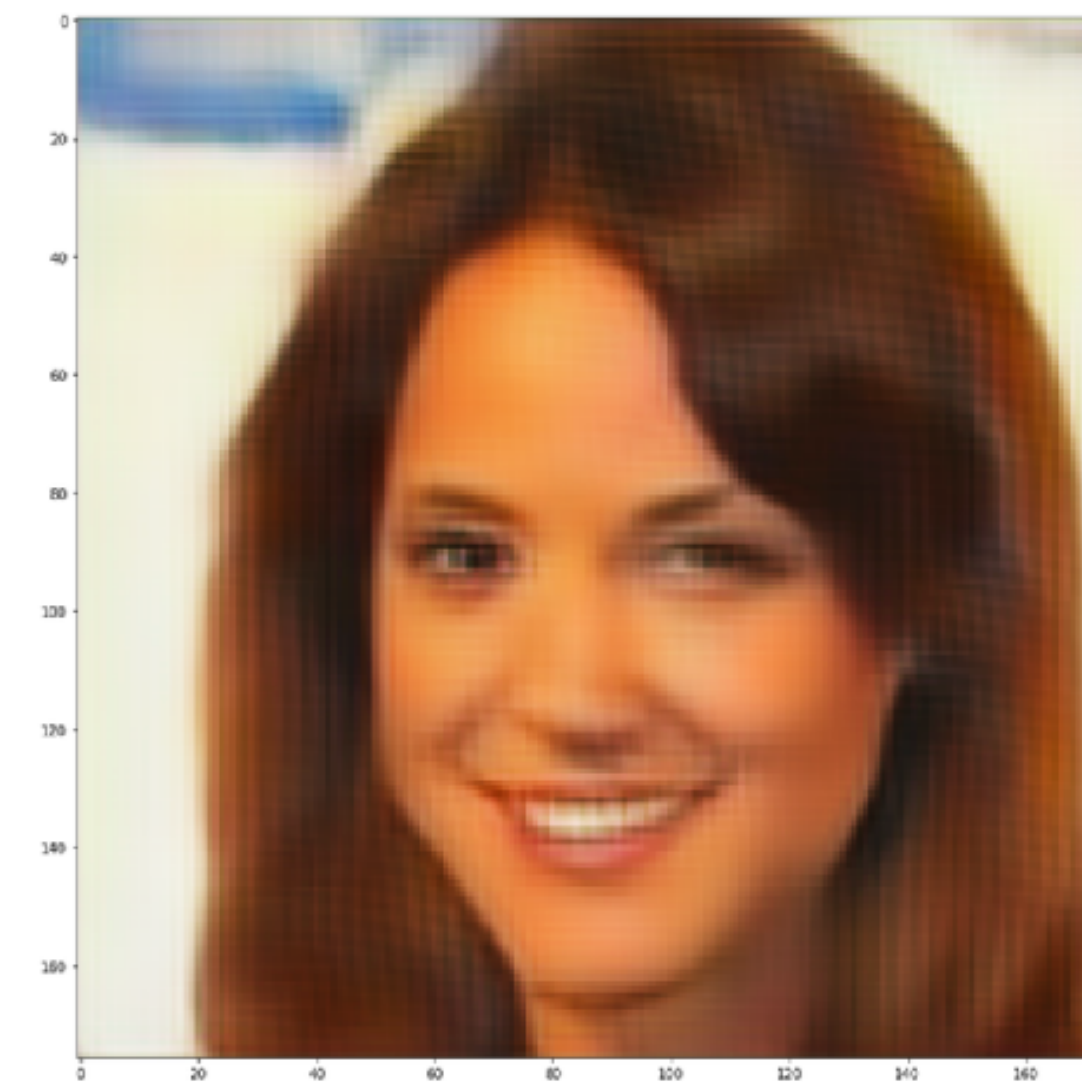




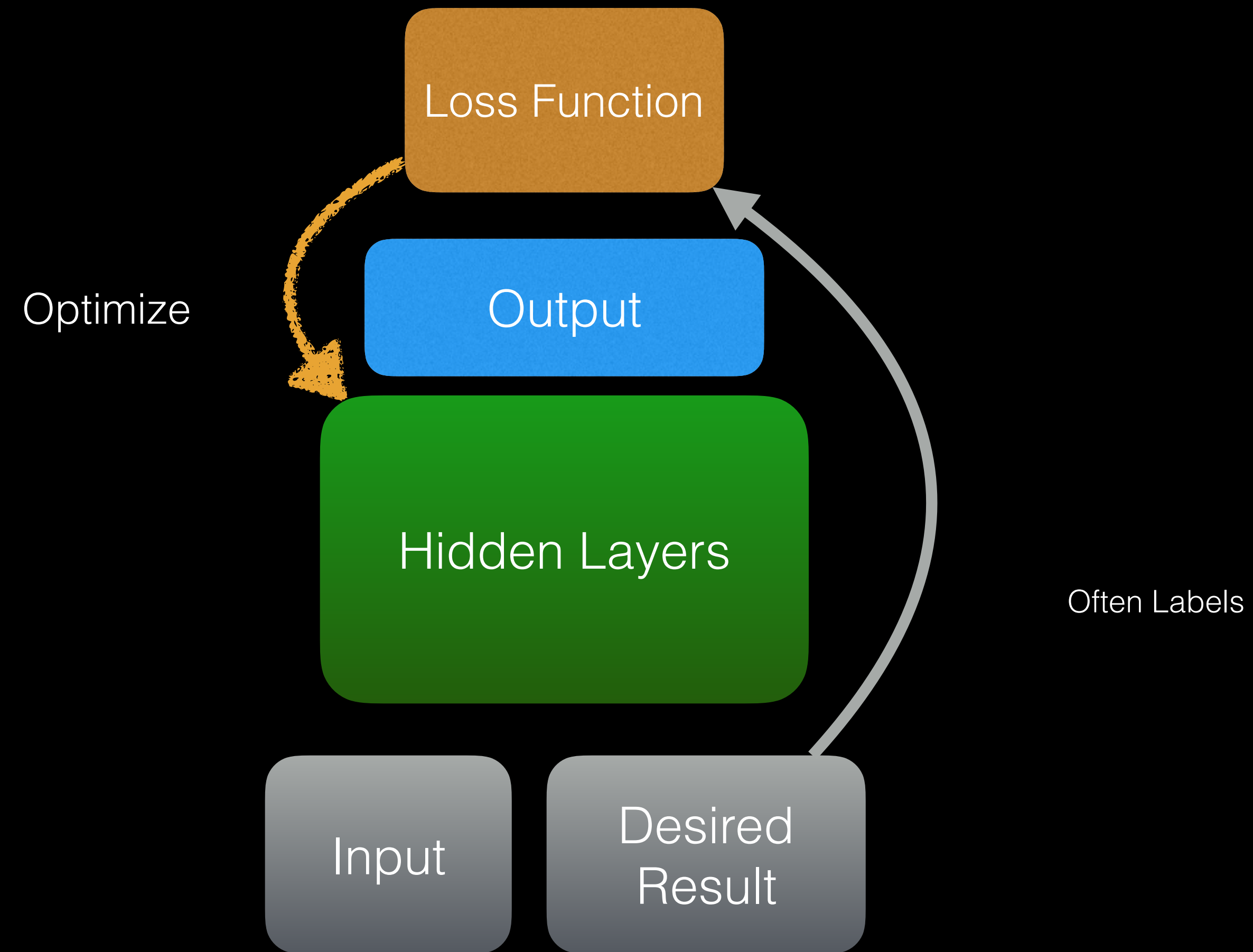
```
In [35]: compare_pics(arr_test_elr[24].astype('uint8'),p[24].astype('uint8'))
```



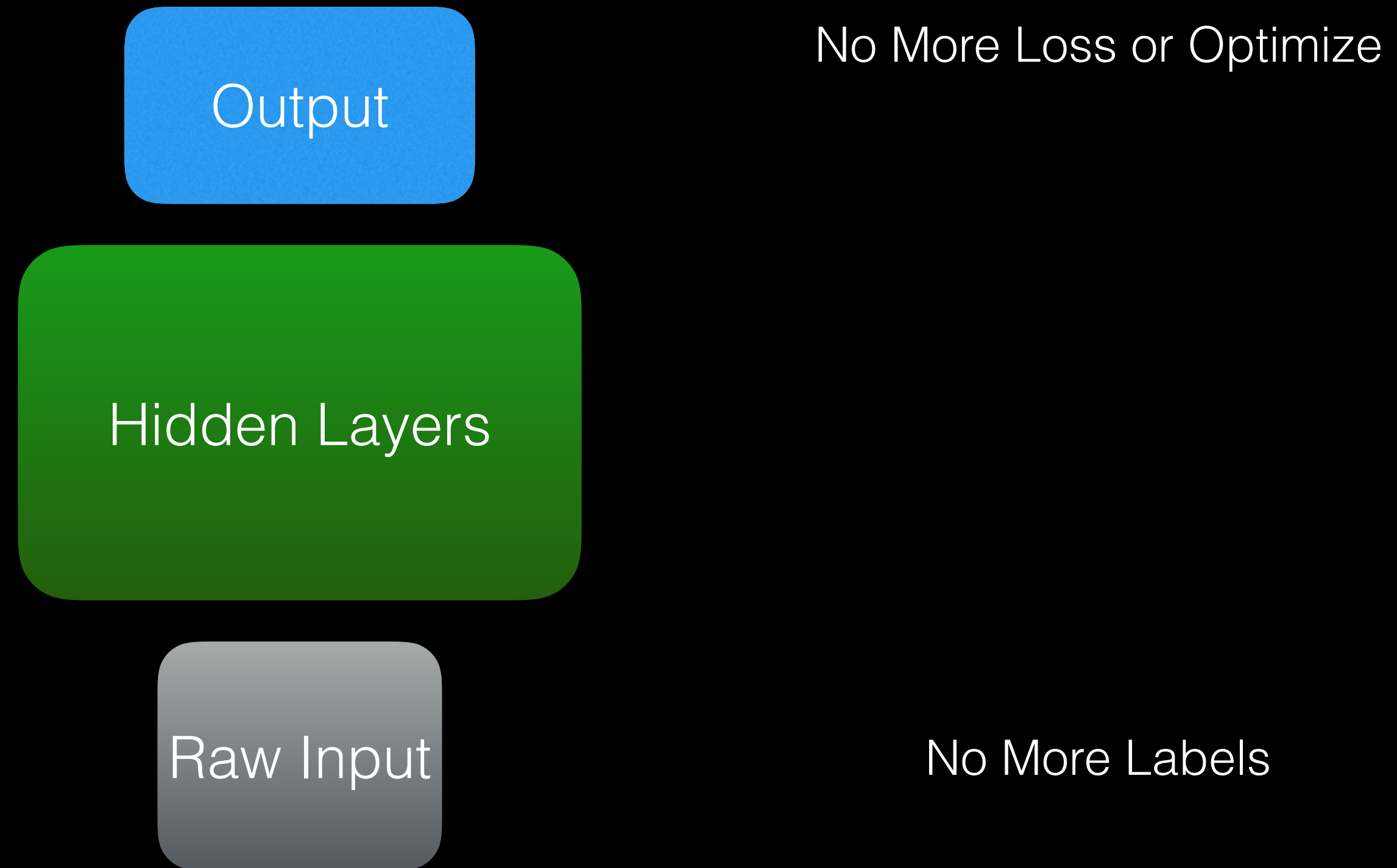
```
In [45]: compare_pics(arr_test_hr[24].astype('uint8'),p[24].astype('uint8'))
```



# Neural Network



# Neural Network Inference



# Classification CNN



Conv Blocks(Conv+Pooling) Relu

Reduction of HxW  
increased number of filters(K)

FCN layers

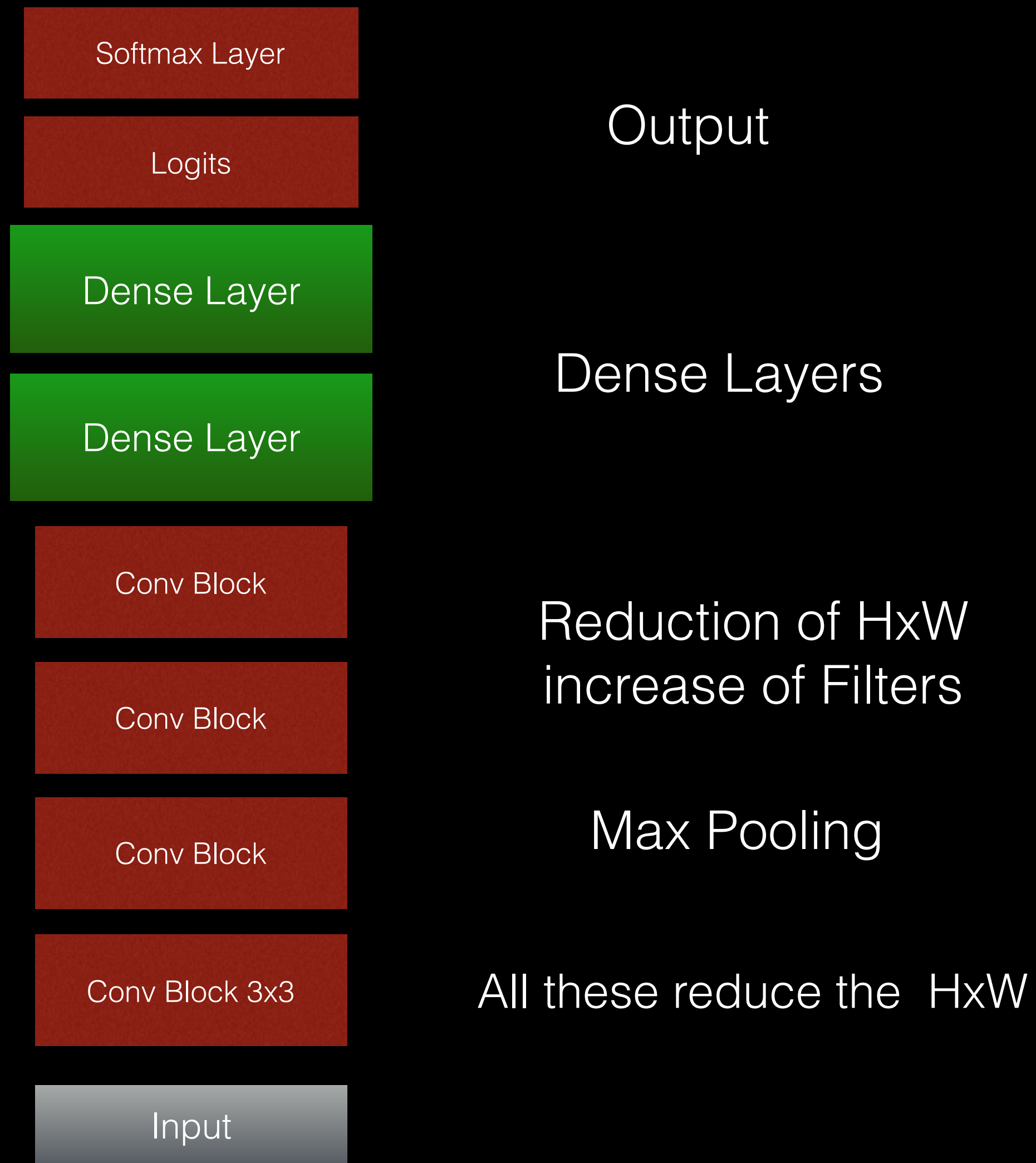
Prediction

# The Magic of CNNs

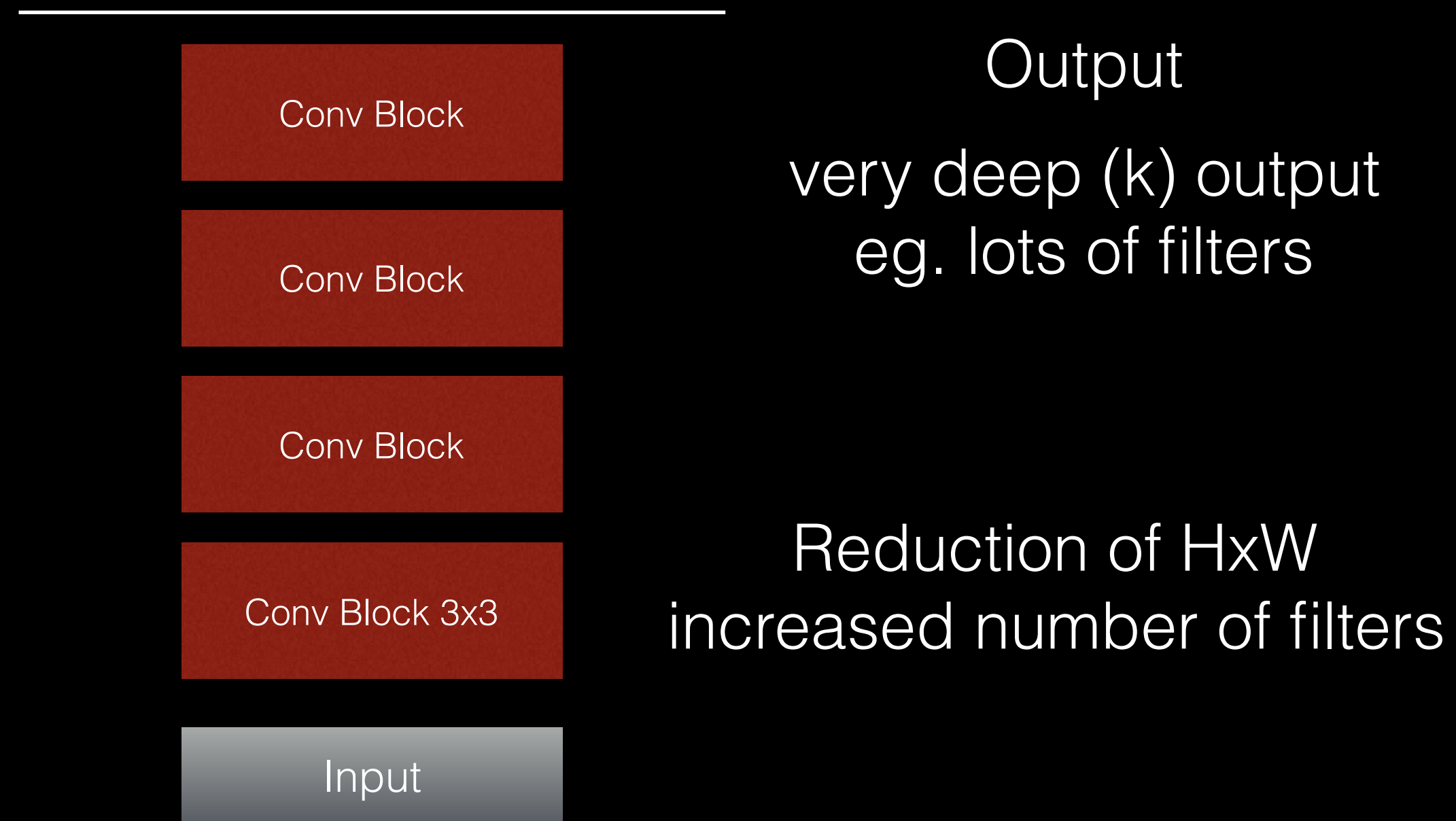
- CNNs are not just for classification
- Don't fall into the trap of thinking CNNs are just a precursor to a set of dense layers, logits and classes
- CNNs give us rich feature representations of what we put into them, if we cut off the dense layers and we use convolution blocks as our outputs



# Old Style CNN



# Modified CNN



# The paper

v1 [cs.CV] 27 Mar 2016

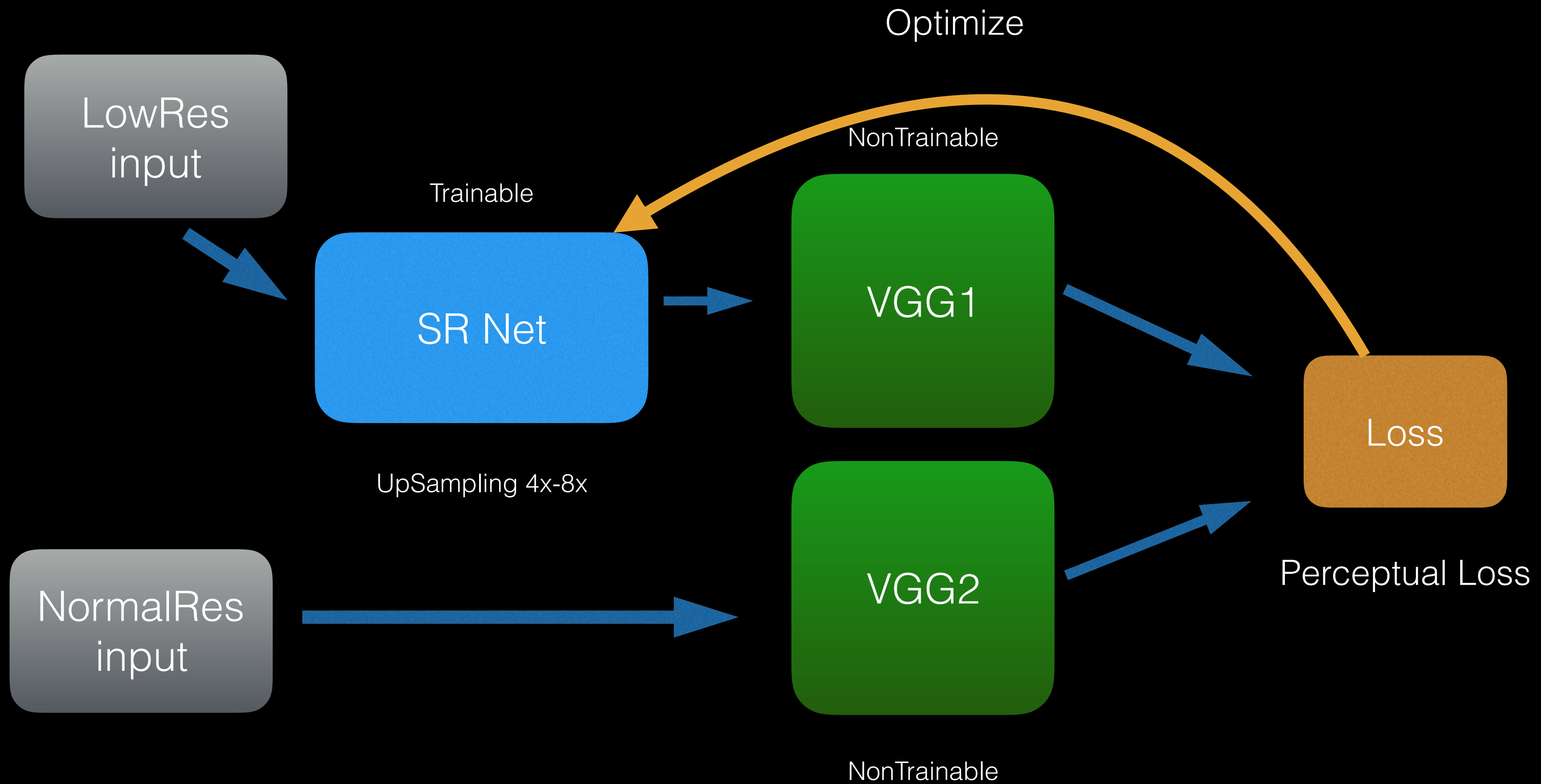
## Perceptual Losses for Real-Time Style Transfer and Super-Resolution

Justin Johnson, Alexandre Alahi, Li Fei-Fei  
{jcjohns, alahi, feifeili}@cs.stanford.edu

Department of Computer Science, Stanford University

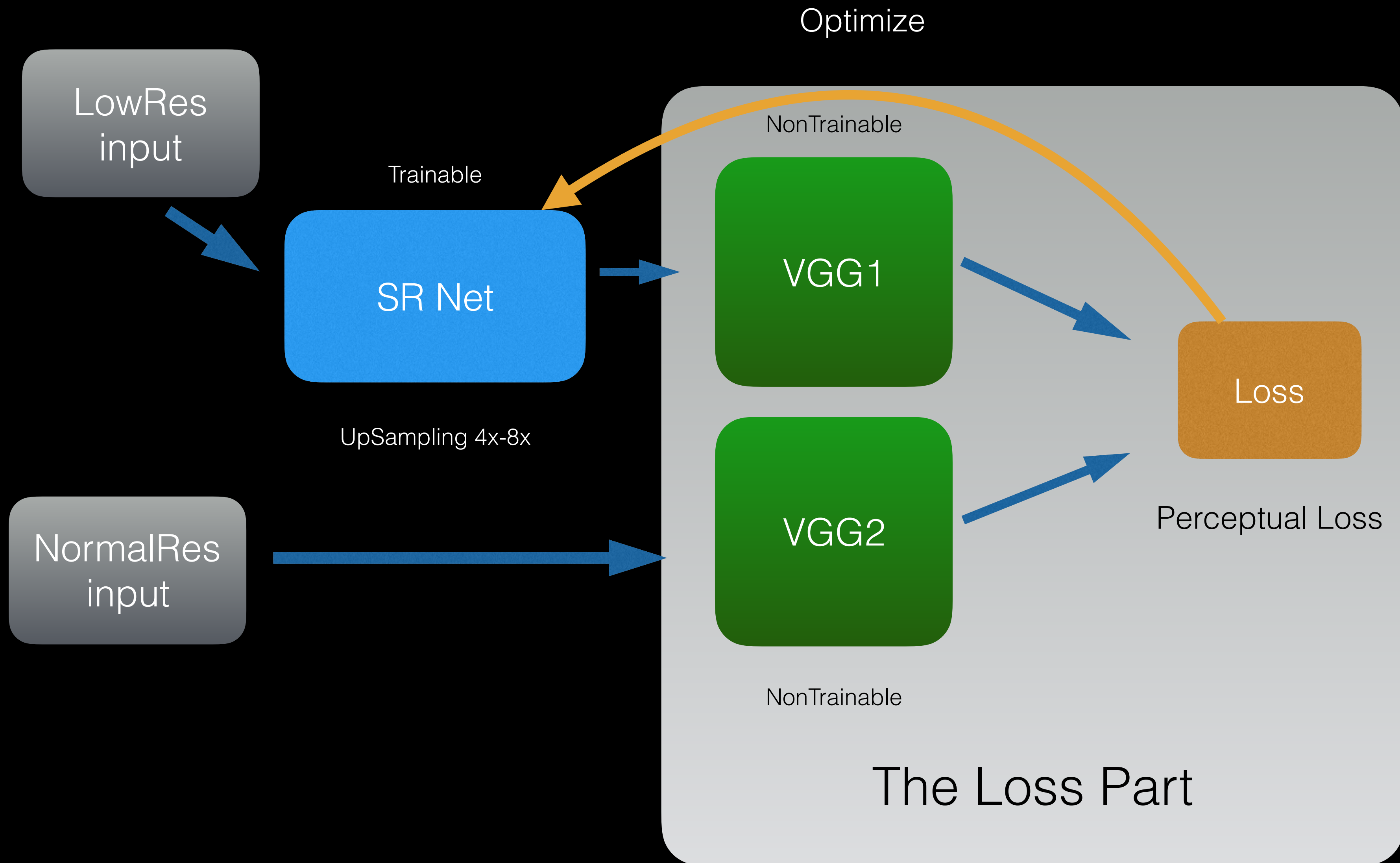
**Abstract.** We consider image transformation problems, where an input image is transformed into an output image. Recent methods for such problems typically train feed-forward convolutional neural networks using a *per-pixel* loss between the output and ground-truth images. Parallel work has shown that high-quality images can be generated by defining and optimizing *perceptual* loss functions based on high-level features extracted from pretrained networks. We combine the benefits of both ap-

# The SR Network

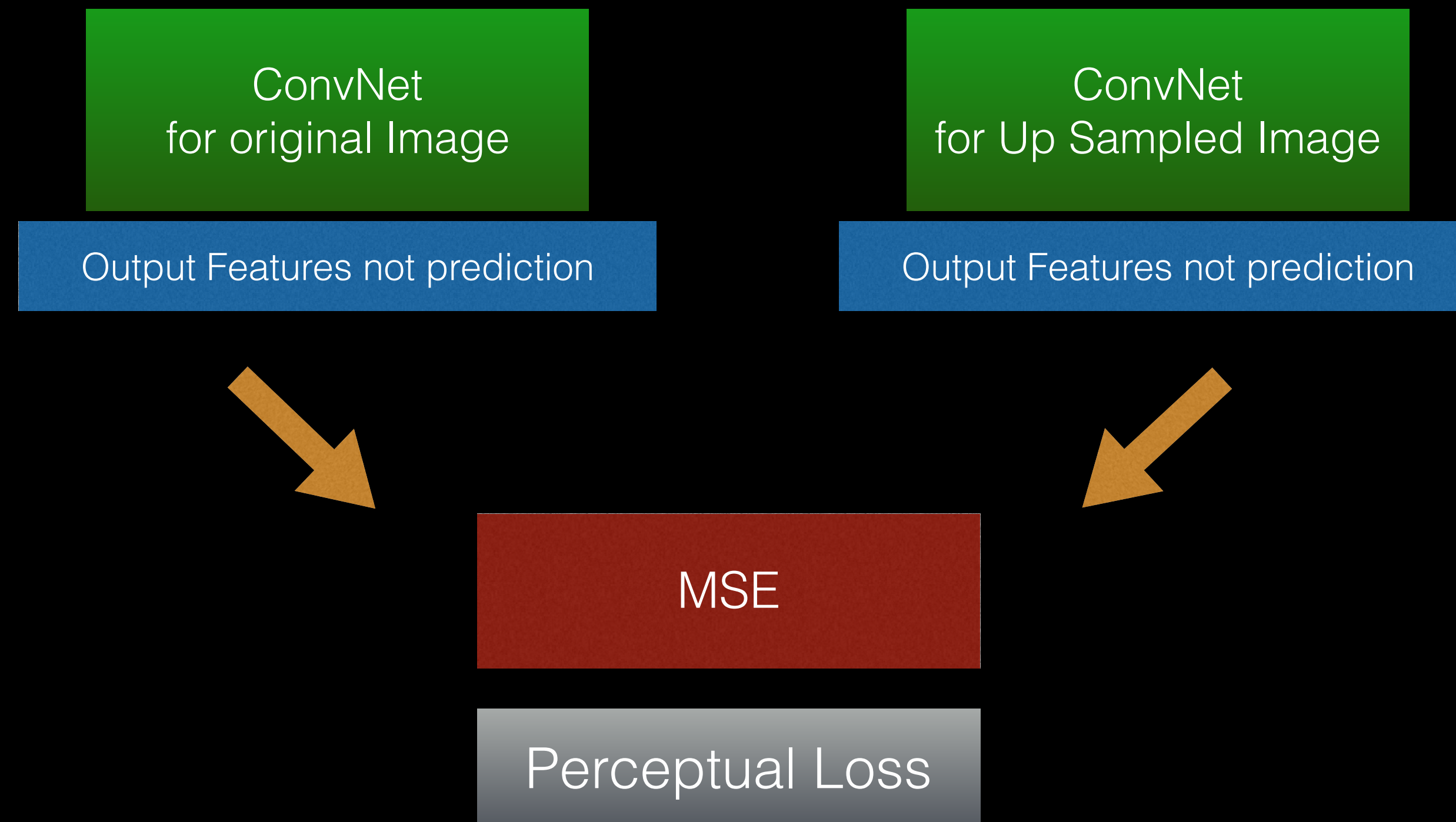




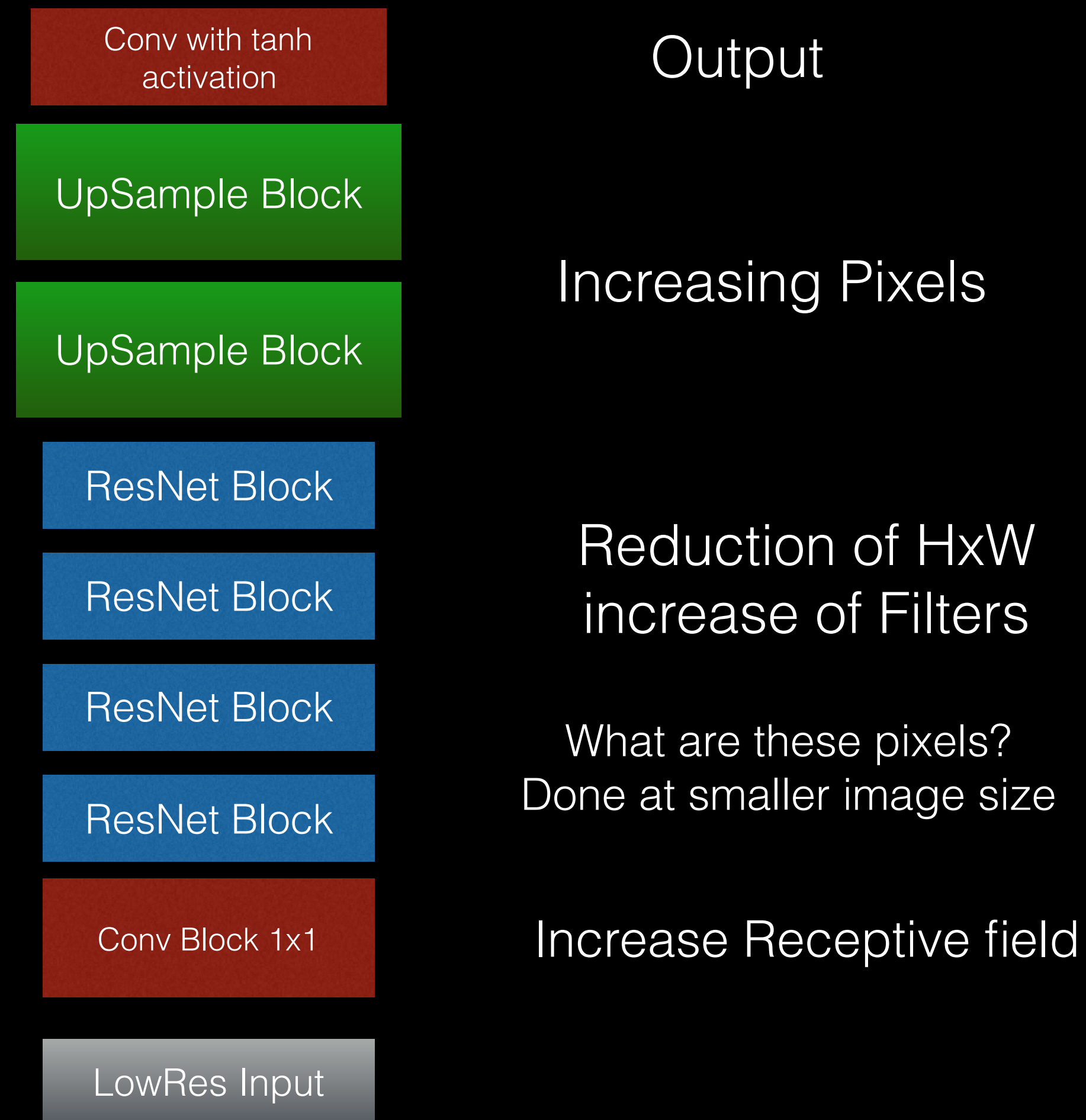
# The SR Network



# Perceptual Loss

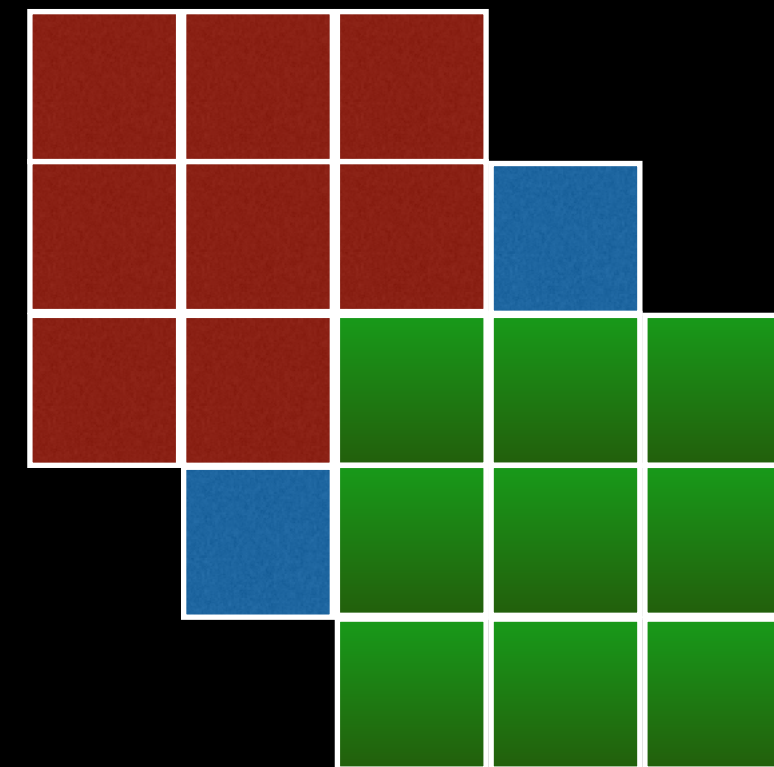
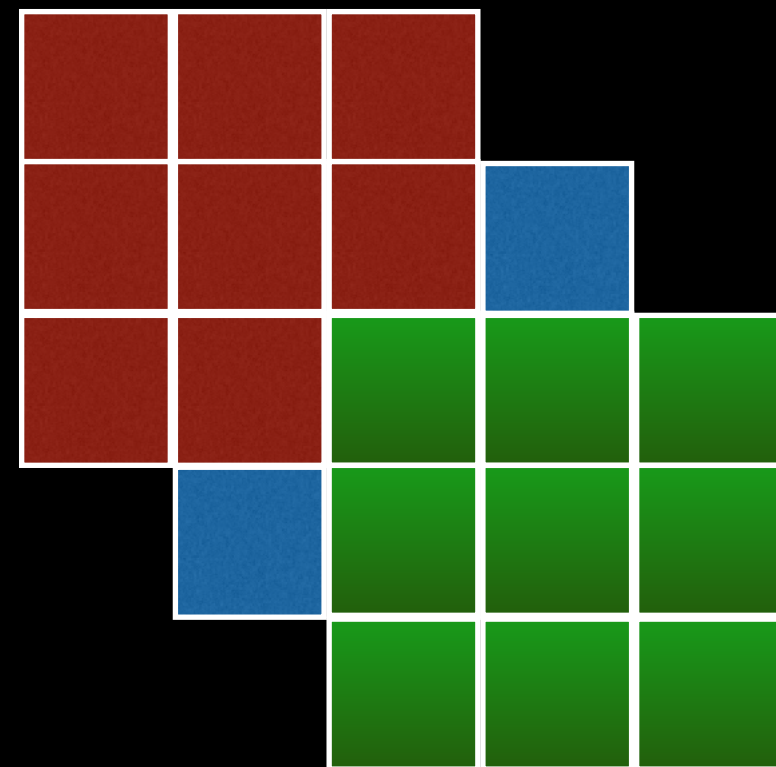
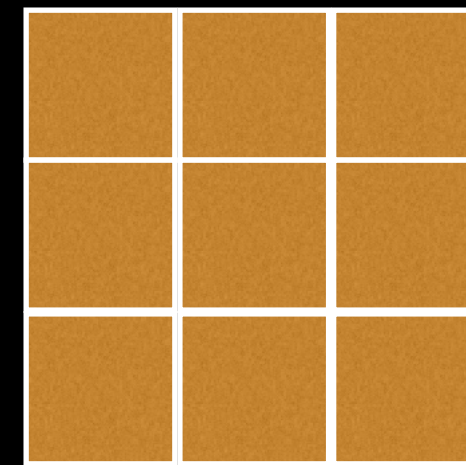
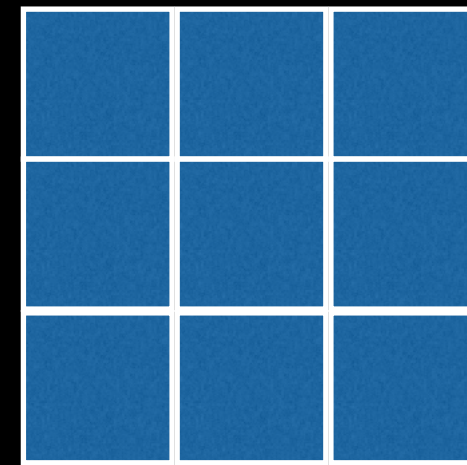


# Up Sampling CNN



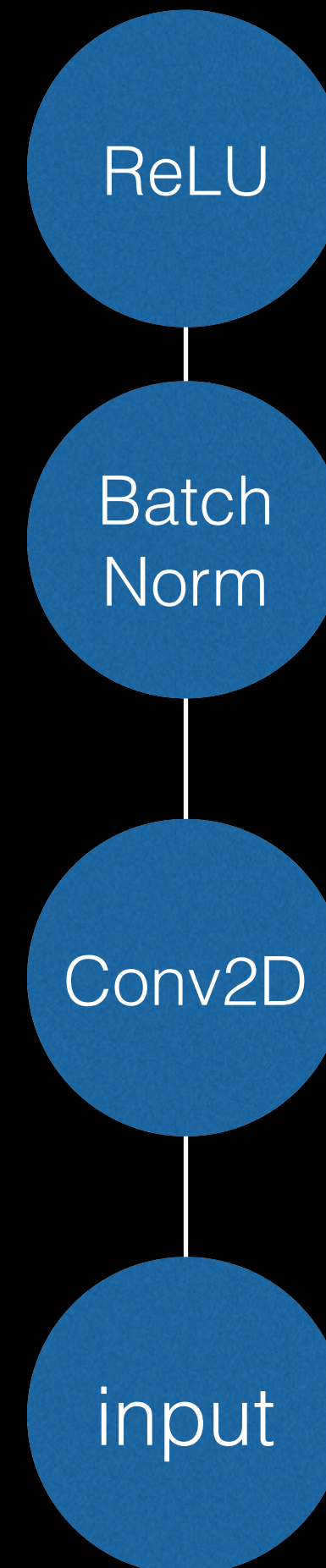
# Receptive Field

3x3 filter on 3x3 input give 5x5 receptive field

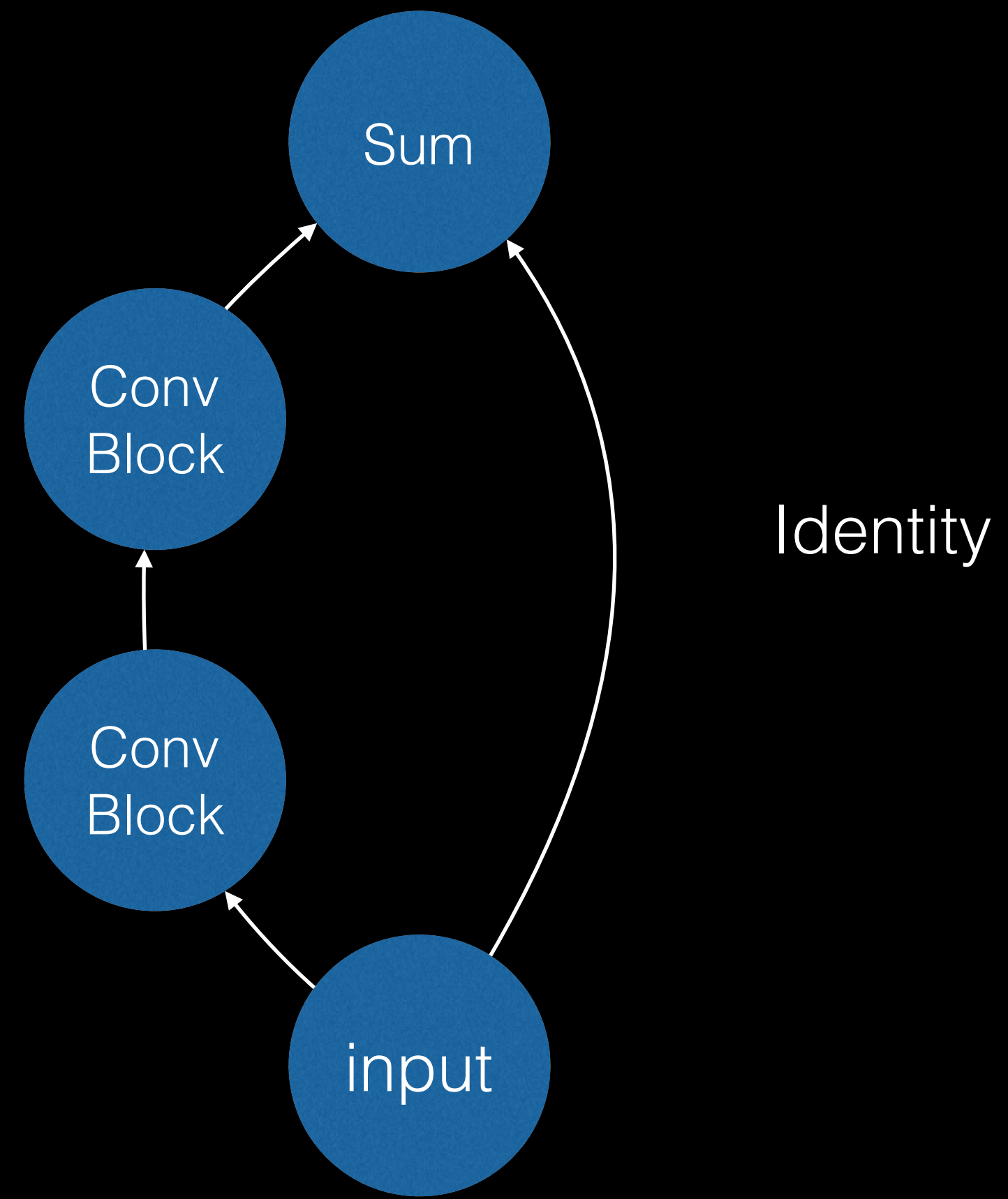




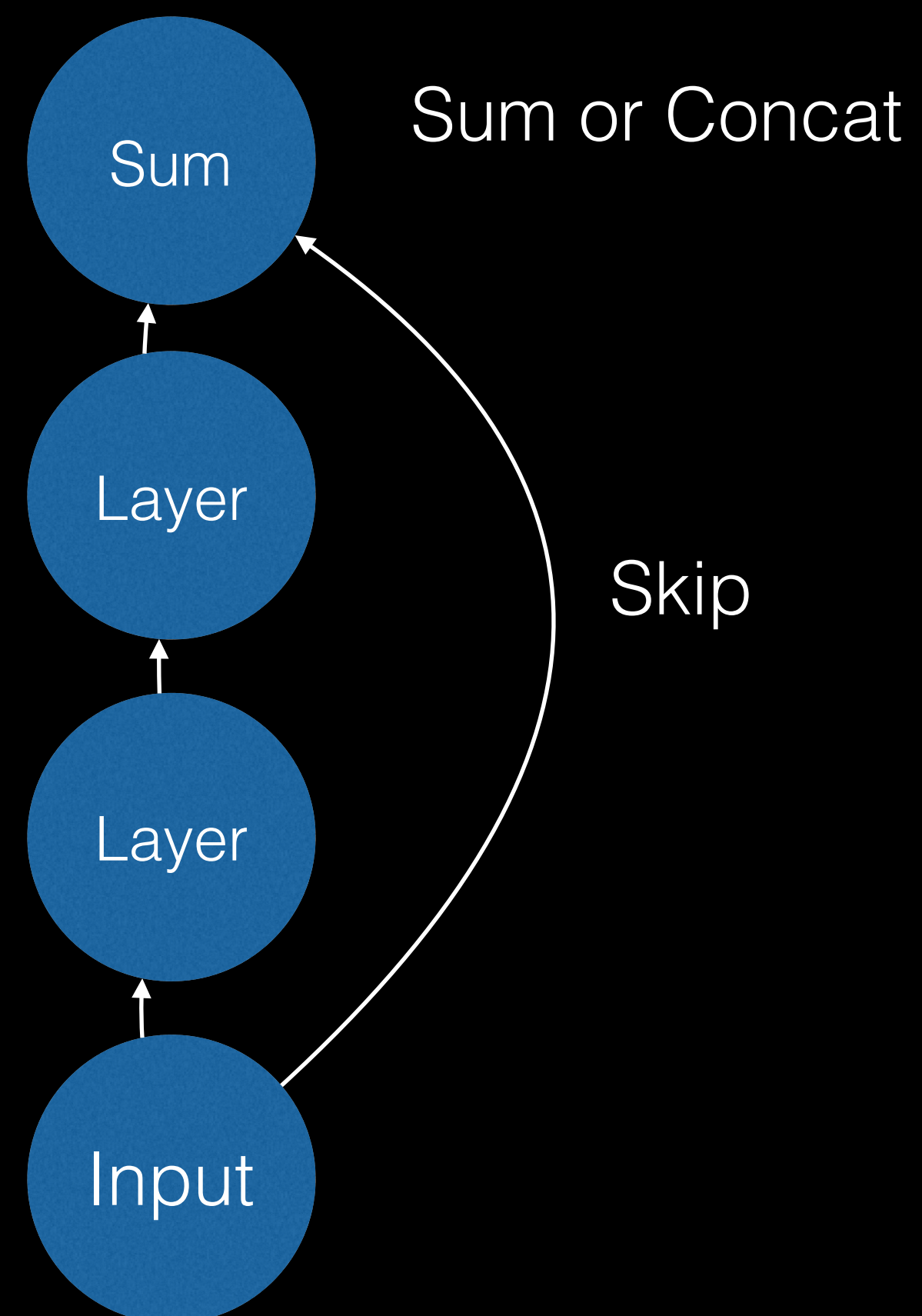
# Conv Block



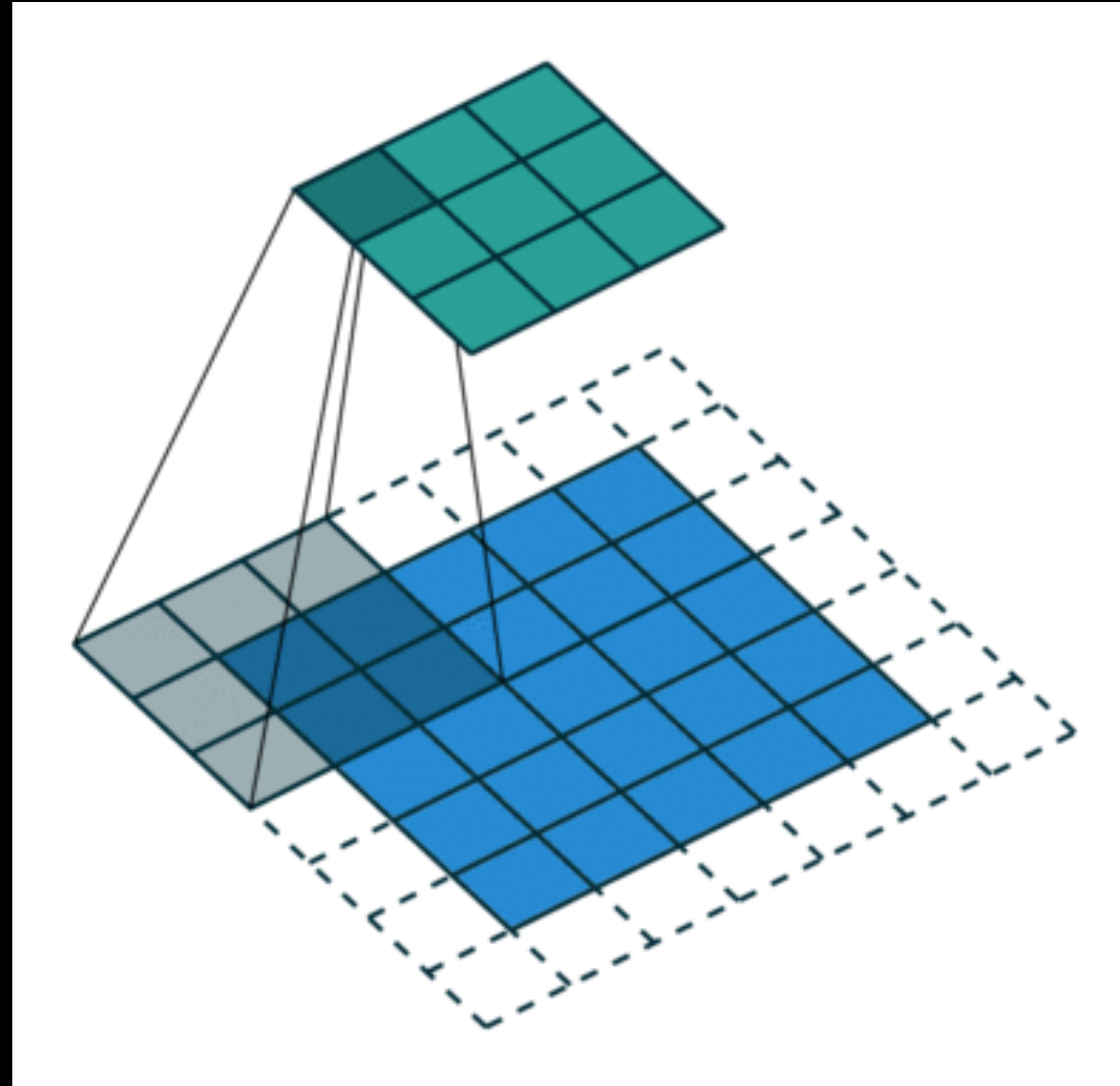
# ResNet Block



# Skip Connections

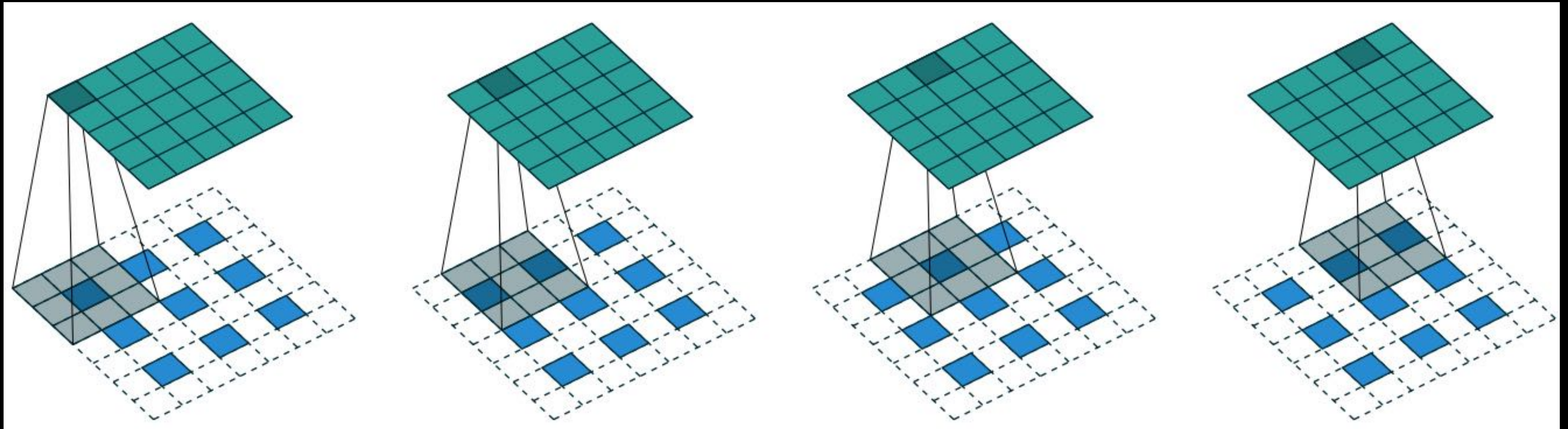


# Normal Convolutions

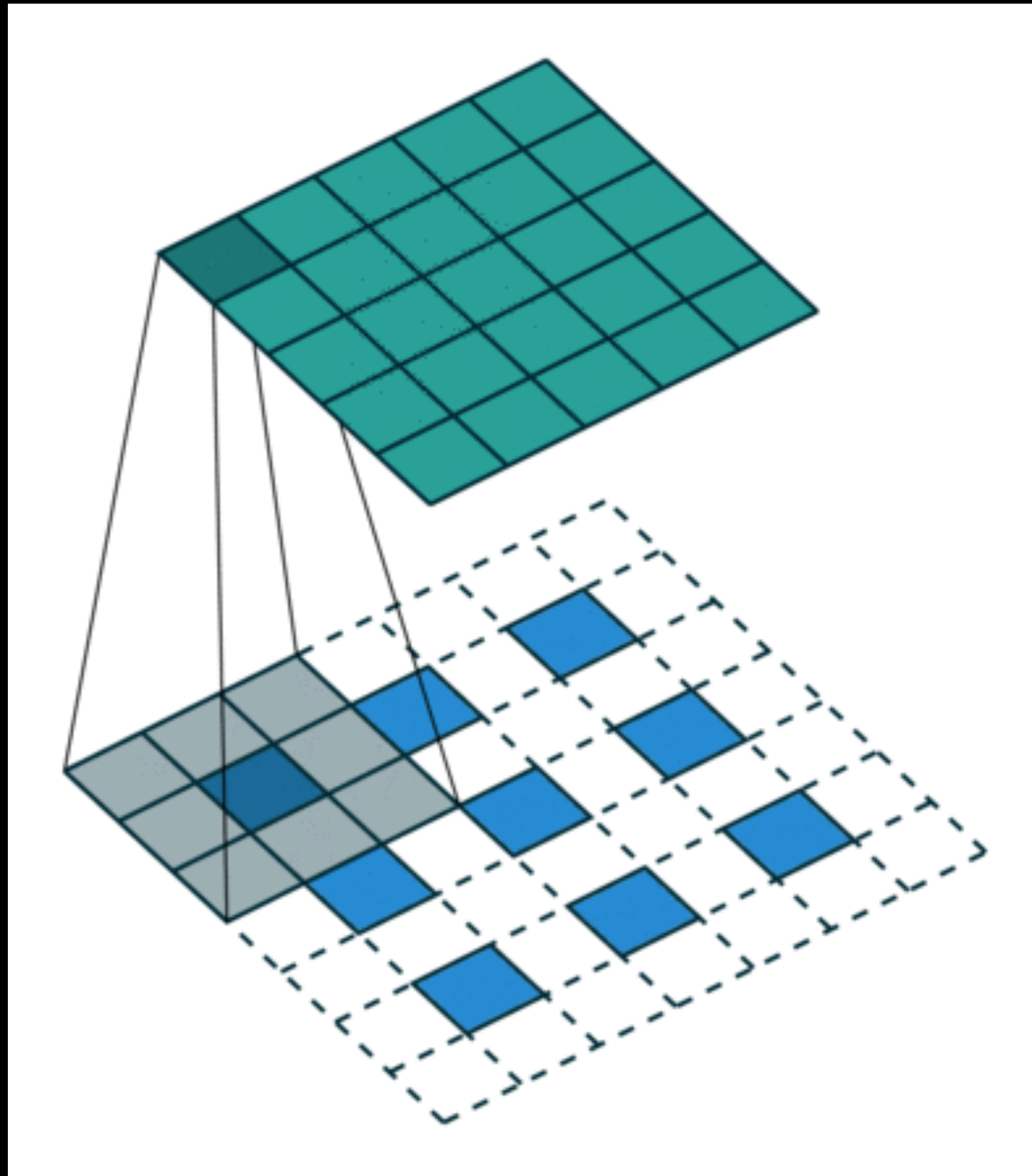




# Transposed Convolutions



# Transposed Convolutions



# Transposed Convolutions

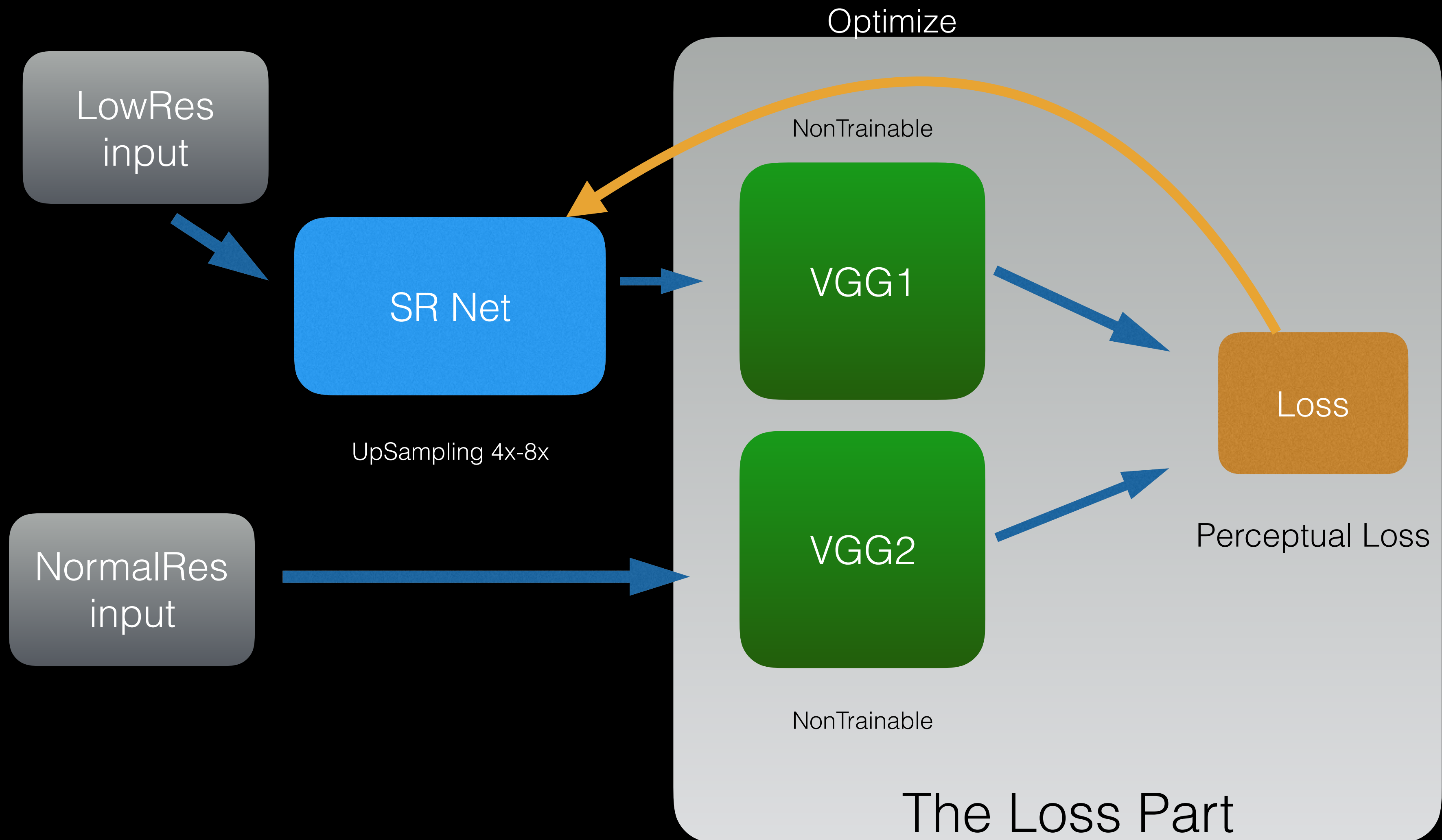
**Deconvolutions (not correct)**

**Transposed Convolutions**

**Fractional Strided Convolutions**



# The SR Network



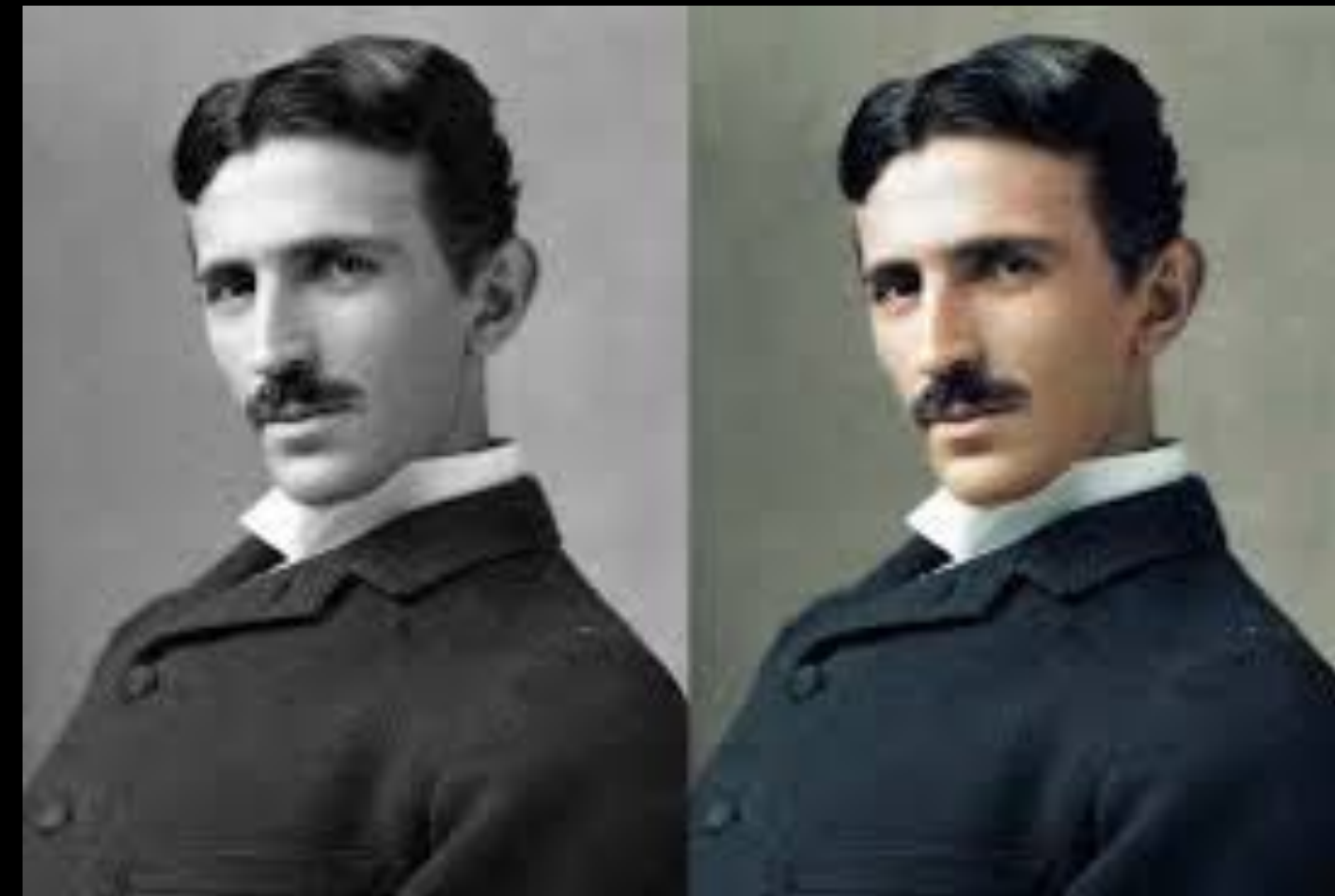
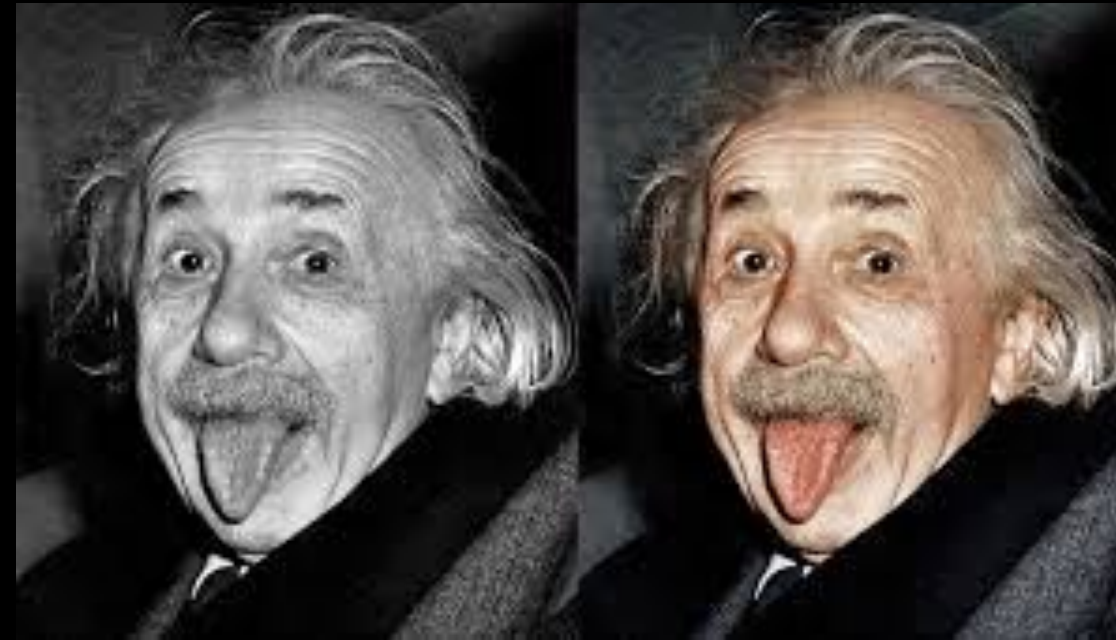


# Code Walk through

# CNN between anything?

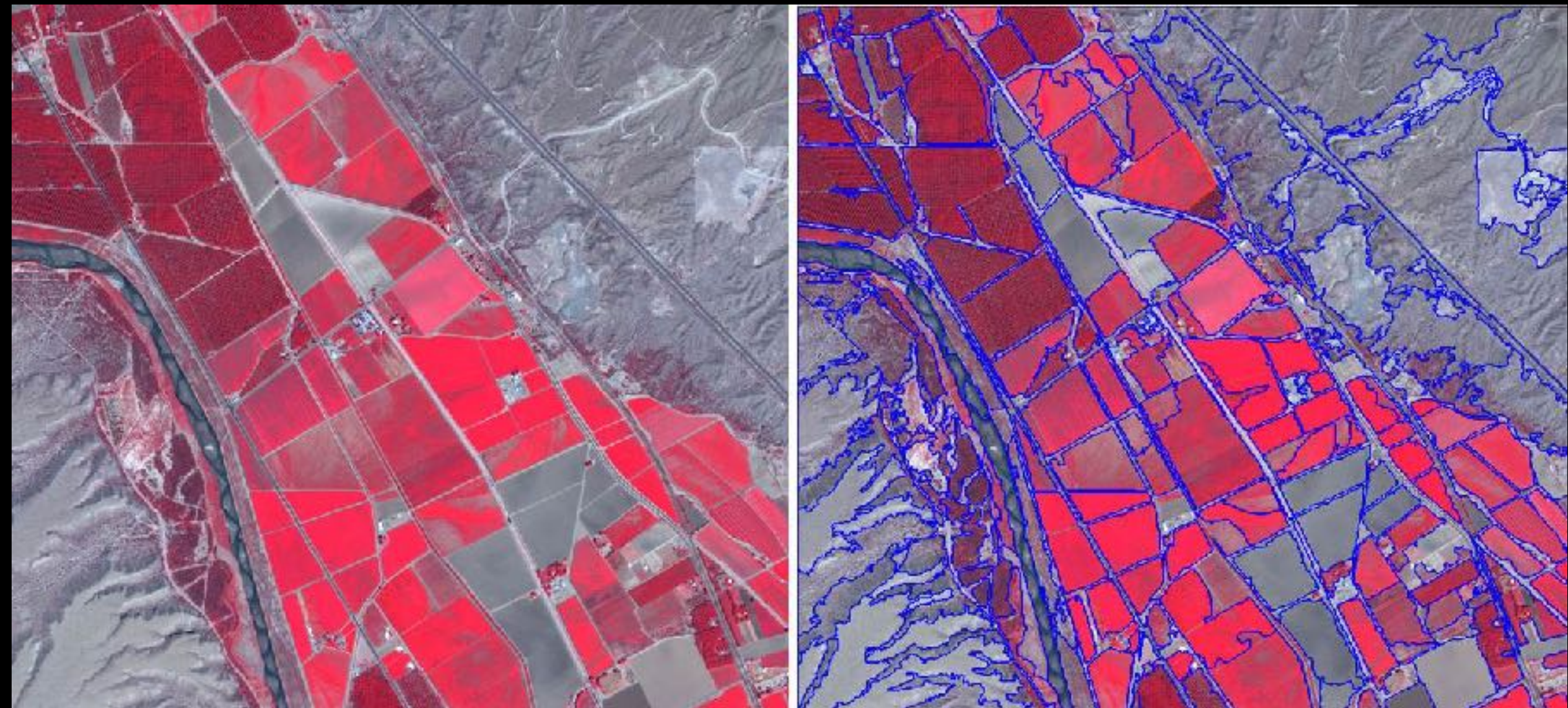
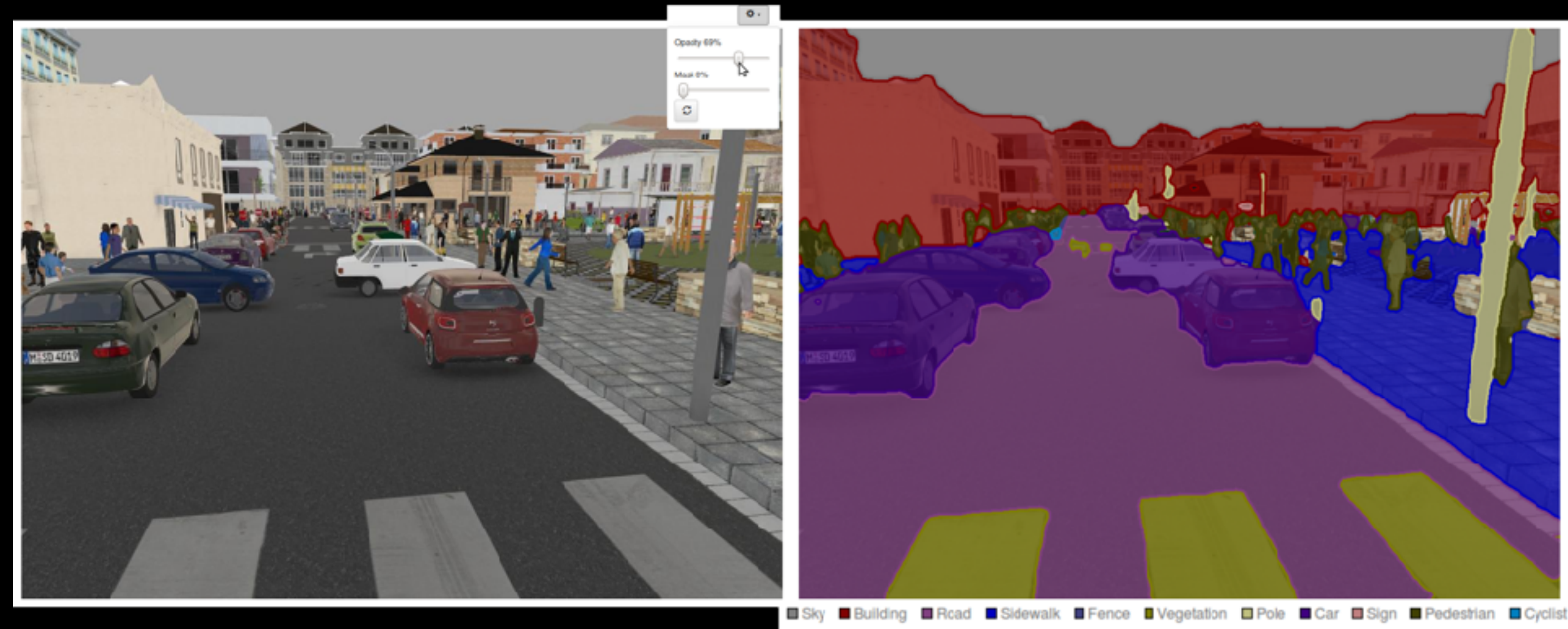


# Colorization





# Segmentation





# CNN between anything?





# Others

- Depth Perception
- De-noising
- Visual Filters
- Audio Clarity
- Audio Filters

# Summary

- Generative models go far beyond just artist models
- The power of CNN beyond classification
- Perceptual Loss from comparing 2 CNNs
- Generative = image in -> image out
- Try putting a CNN between some data to manipulate it to get what you want

# Links

- <https://buptldy.github.io/2016/10/29/2016-10-29-deconv/>
- <https://datascience.stackexchange.com/questions/6107/what-are-deconvolutional-layers>
- [http://deeplearning.net/software/theano/tutorial/conv\\_arithmetic.html](http://deeplearning.net/software/theano/tutorial/conv_arithmetic.html)