UNDERSTANDING CNN

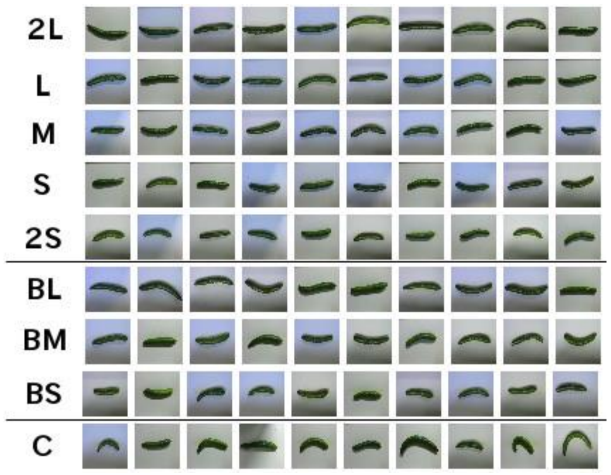
					Tasks					
					ADAS					
					Self Driving					
					Localization	Perception	Planning/ Control	Driver state	Vehicle Diagnosis	Smart factory
Methods	Traditional	Non-machine Learning			GPS, SLAM		Optimal control			
		Machine-Learning based method	Supervised	MLP		Pedestrian detection (HOG+SVM)				
	Deep-Learning based			CNN		Detection/ Segmentation/Classification	End-to-end Learning			
				RNN (LSTM)		Dry/wet road classification	End-to-end Learning			
				DNN						
			Reinforcement							
			Unsupervised							

TENSORFLOW-POWERED CUCUMBER SORTER

Cucumber sorting

- Each cucumber has different color, shape, quality and freshness.
- At Makoto's farm, they sort them into nine different classes, and his mother sorts them all herself — spending up to eight hours per day at peak harvesting times.

Makoto Koike, center, with his parents at the family cucumber farm



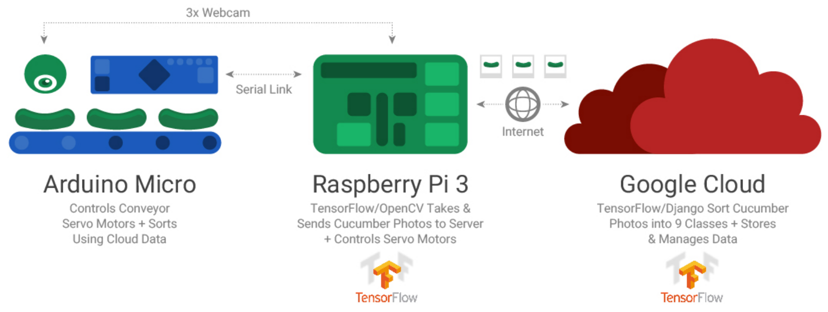
Cucumber sorting

- You have to look at not only the size and thickness, but also the color, texture, small scratches, whether or not they are crooked and whether they have prickles. It takes months to learn the system and **you can't just hire part-time workers during the busiest period**. I myself only recently learned to sort cucumbers well,” Makoto said.

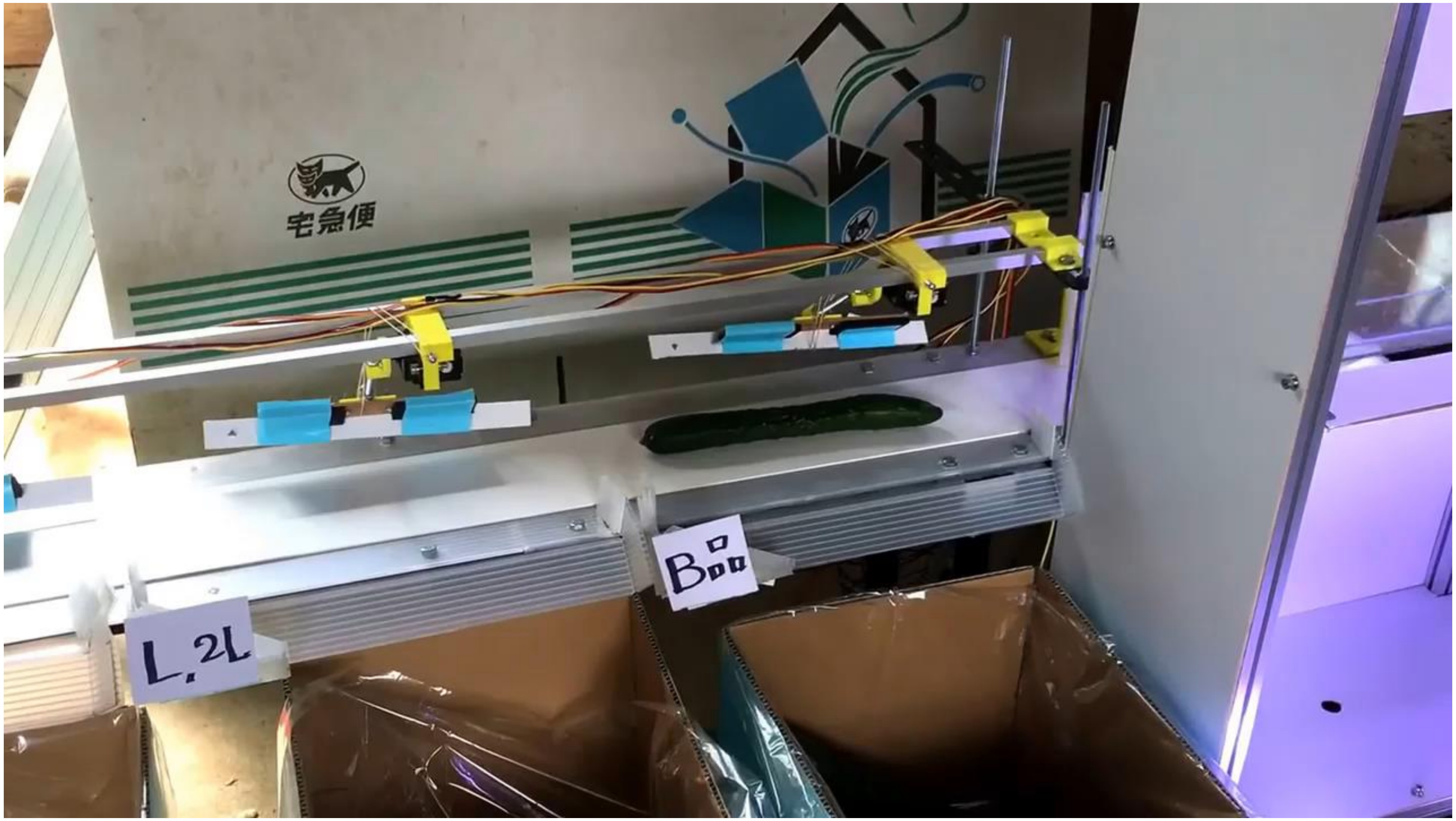
- Makoto doesn’t think sorting is an essential task for cucumber farmers. "**Farmers want to focus and spend their time on growing delicious vegetables**. I'd like to automate the sorting tasks before taking the farm business over from my parents.

Tensorflow-powered cucumber sorter

- Makoto used the sample TensorFlow code **Deep MNIST for Experts** with minor modifications to the convolution, pooling and last layers, changing the network design to adapt to the pixel format of cucumber images and the number of cucumber classes.


3x Webcam
Serial Link
Internet
Arduino Micro
Controls Conveyor Servo Motors + Sorts Using Cloud Data
Raspberry Pi 3
TensorFlow/OpenCV Takes & Sends Cucumber Photos to Server + Controls Servo Motors
TensorFlow
Google Cloud
TensorFlow/Django Sort Cucumber Photos into 9 Classes + Stores & Manages Data
TensorFlow

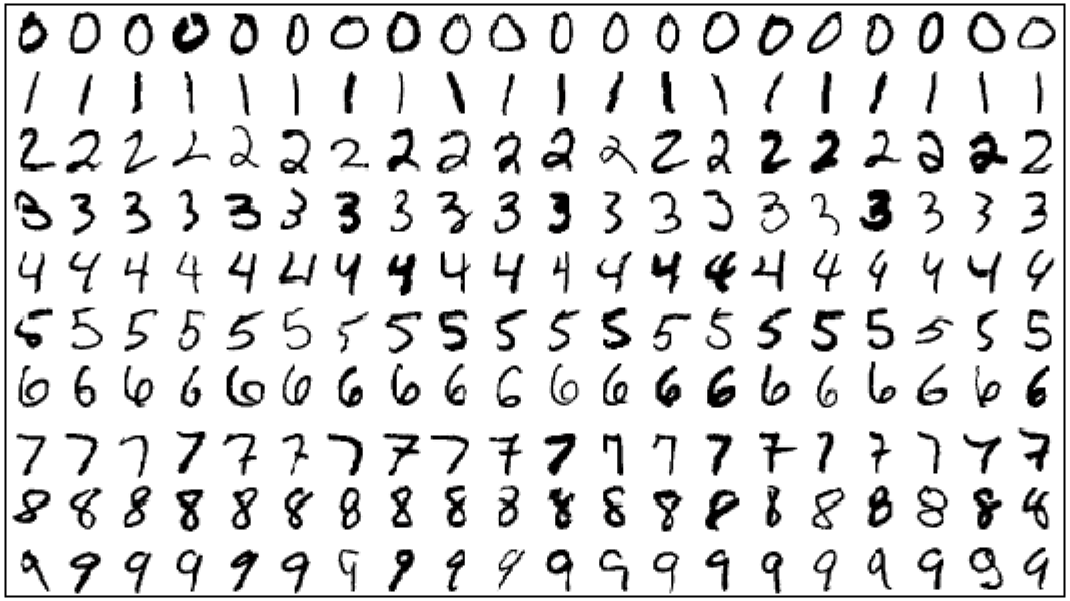
Cucumber sorter by Makoto Koike



MNIST & LENET

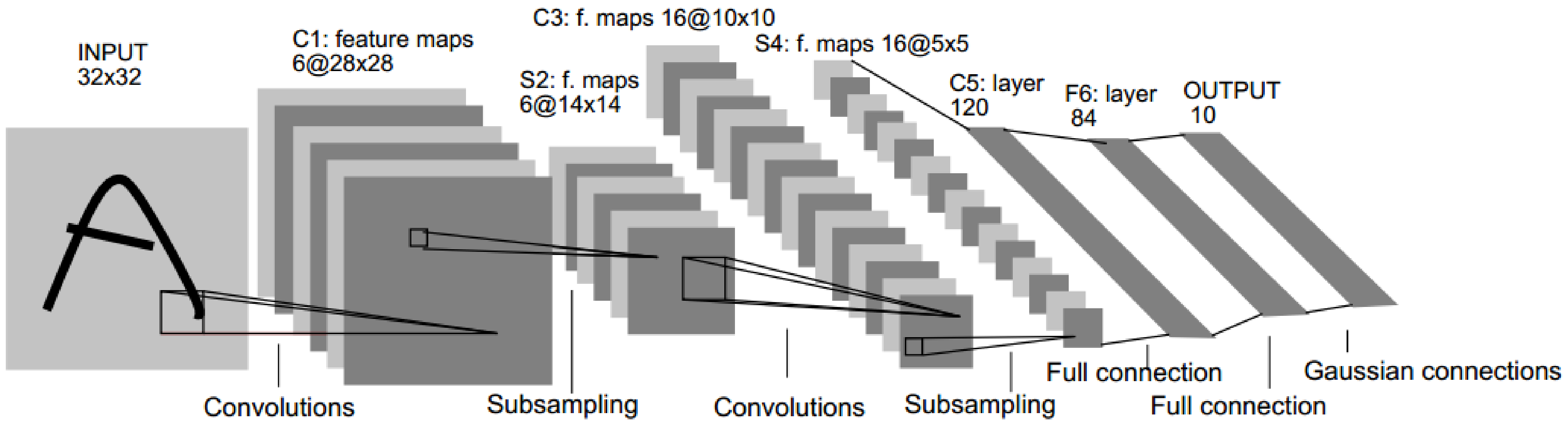
MNIST dataset

- handwritten digits
- a training set of 60,000 examples
- 28x28 images



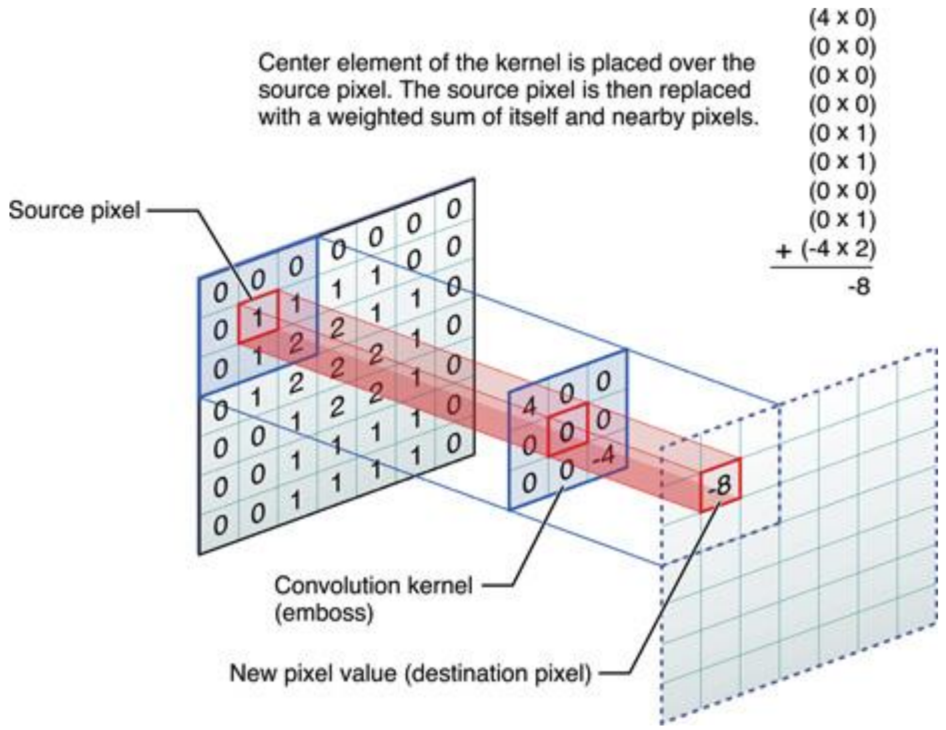
LeNet

- Yann LeCun and his collaborators developed a recognizer for handwritten digits by using back-propagation in a feed-forward net

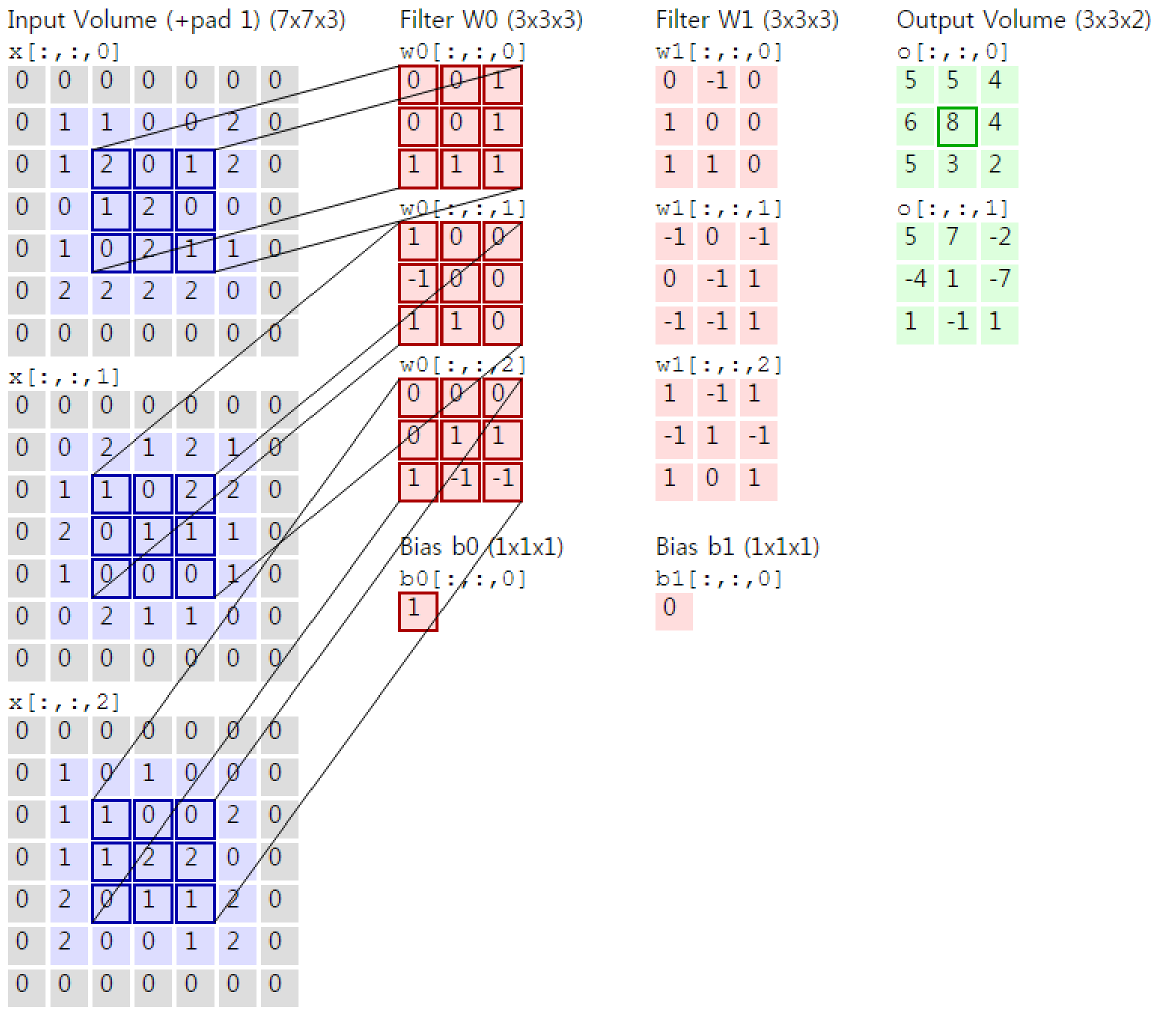


CNN BUILDING BLOCKS

Convolution


Center element of the kernel is placed over the source pixel. The source pixel is then replaced with a weighted sum of itself and nearby pixels.
(4 x 0)
(0 x 0)
(0 x 0)
(0 x 0)
(0 x 1)
(0 x 1)
(0 x 0)
(0 x 1)
+ (-4 x 2)
-8
Source pixel
Convolution kernel (emboss)
New pixel value (destination pixel)

Convolutions in CNNs



Input Volume (+pad 1) (7x7x3)

x[:,:,0]

0	0	0	0	0	0	0
0	1	1	0	0	2	0
0	1	2	0	1	2	0
0	0	1	2	0	0	0
0	1	0	2	1	1	0
0	2	2	2	2	0	0
0	0	0	0	0	0	0

x[:,:,1]

0	0	0	0	0	0	0
0	0	2	1	2	1	0
0	1	1	0	2	2	0
0	2	0	1	1	1	0
0	1	0	0	0	1	0
0	0	2	1	1	0	0
0	0	0	0	0	0	0

x[:,:,2]

0	0	0	0	0	0	0
0	1	0	1	0	0	0
0	1	1	0	0	2	0
0	1	1	2	2	0	0
0	2	0	1	1	2	0
0	2	0	0	1	2	0
0	0	0	0	0	0	0

Filter W0 (3x3x3)

w0[:,:,0]

0	0	1
0	0	1
1	1	1

w0[:,:,1]

1	0	0
-1	0	0
1	1	0

w0[:,:,2]

0	0	0
0	1	1
1	-1	-1

Bias b0 (1x1x1)

b0[:,:,0]

1

Filter W1 (3x3x3)

w1[:,:,0]

0	-1	0
1	0	0
1	1	0

w1[:,:,1]

-1	0	-1
0	-1	1
-1	-1	1

w1[:,:,2]

1	-1	1
-1	1	-1
1	0	1

Bias b1 (1x1x1)

b1[:,:,0]

0

Output Volume (3x3x2)

o[:,:,0]

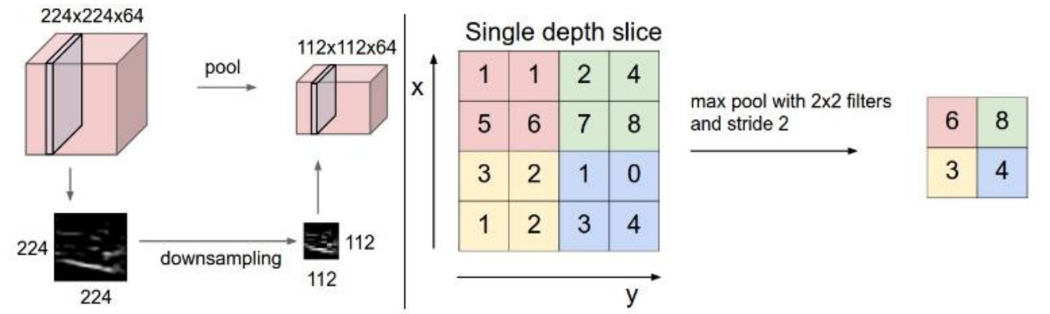
5	5	4
6	8	4
5	3	2

o[:,:,1]

5	7	-2
-4	1	-7
1	-1	1

Pooling

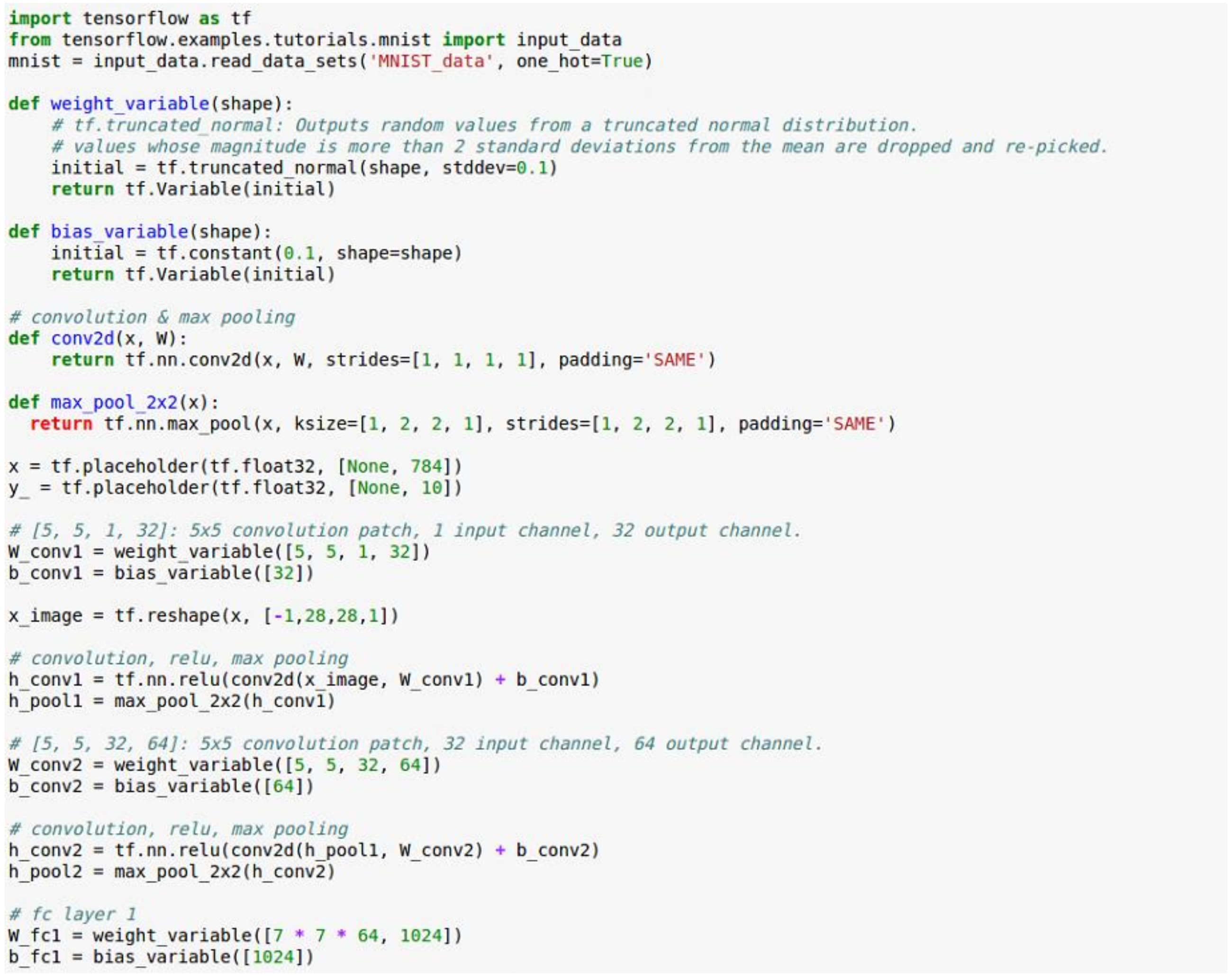
- Max vs Average pooling



Pooling layer downsamples the volume spatially, independently in each depth slice of the input volume. **Left:** In this example, the input volume of size [224x224x64] is pooled with filter size 2, stride 2 into output volume of size [112x112x64]. Notice that the volume depth is preserved. **Right:** The most common downsampling operation is max, giving rise to **max pooling**, here shown with a stride of 2. That is, each max is taken over 4 numbers (little 2x2 square).

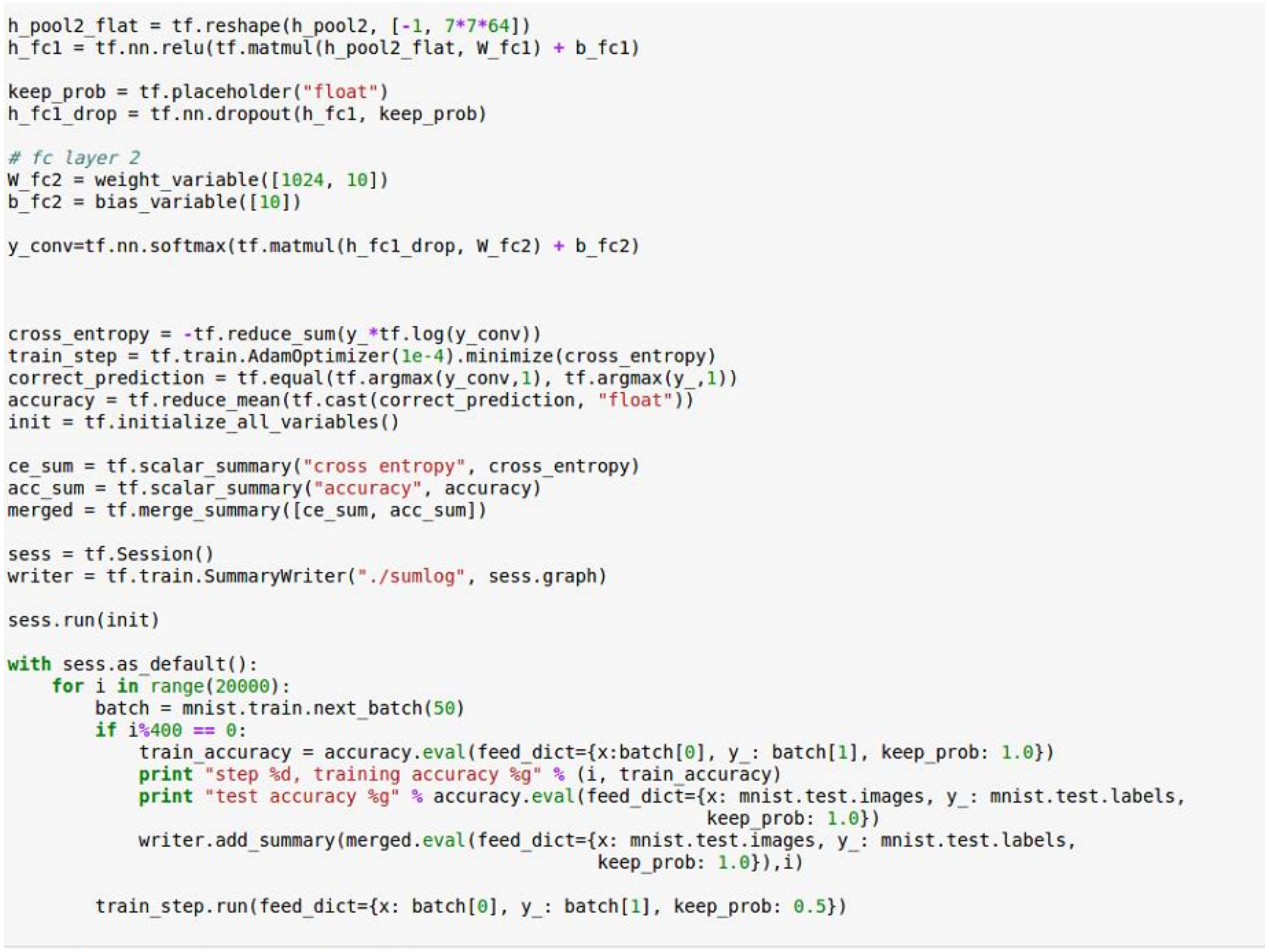
DEEP MNIST FOR EXPERTS

Deep MNIST for Experts



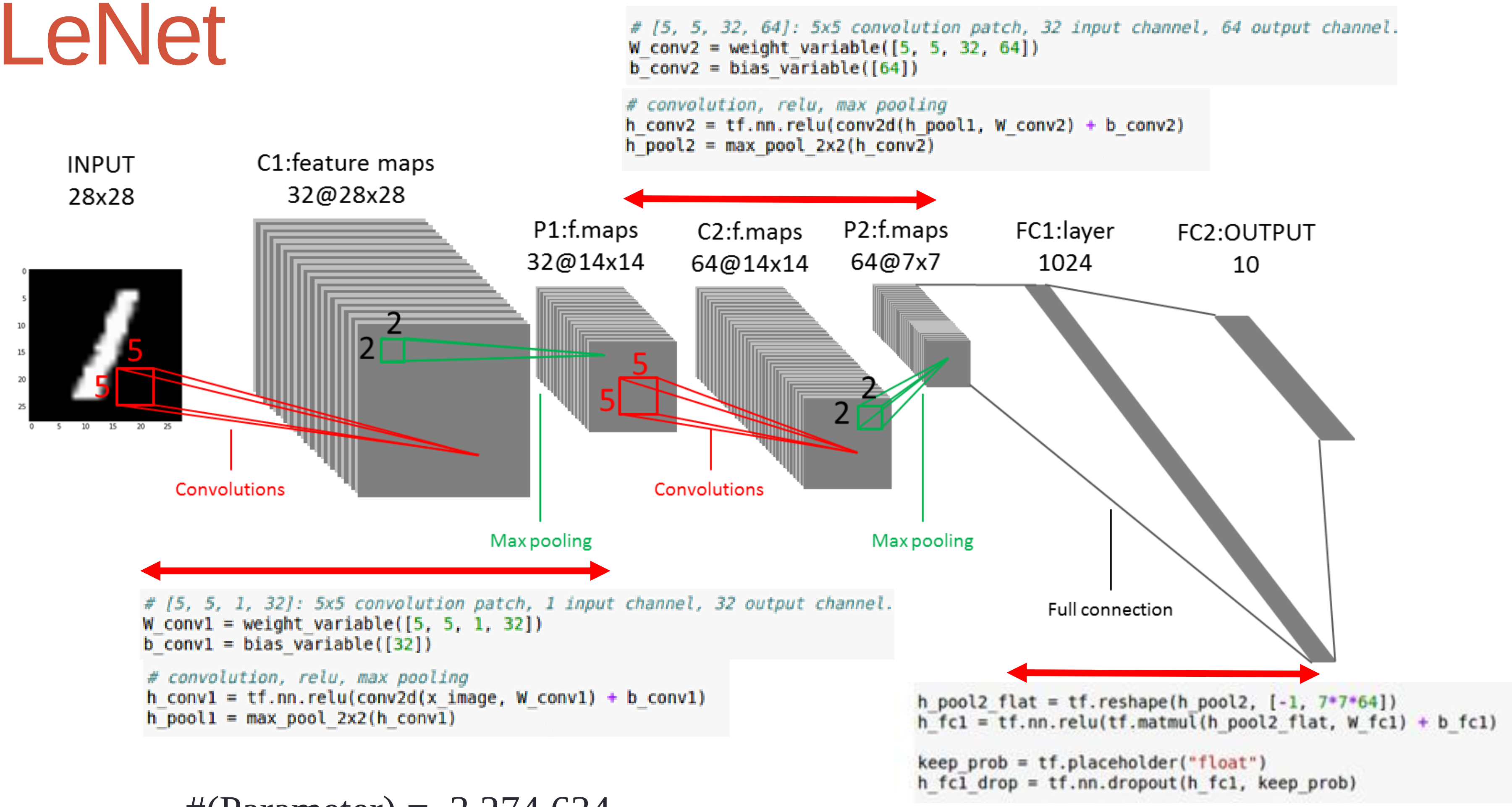
```python
import tensorflow as tf
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets('MNIST_data', one_hot=True)

def weight_variable(shape):
    # tf.truncated_normal: Outputs random values from a truncated normal distribution.
    # values whose magnitude is more than 2 standard deviations from the mean are dropped and re-picked.
    initial = tf.truncated_normal(shape, stddev=0.1)
    return tf.Variable(initial)

def bias_variable(shape):
    initial = tf.constant(0.1, shape=shape)
    return tf.Variable(initial)

# convolution & max pooling
def conv2d(x, W):
    return tf.nn.conv2d(x, W, strides=[1, 1, 1, 1], padding='SAME')

def max_pool_2x2(x):
  return tf.nn.max_pool(x, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')

x = tf.placeholder(tf.float32, [None, 784])
y_ = tf.placeholder(tf.float32, [None, 10])

# [5, 5, 1, 32]: 5x5 convolution patch, 1 input channel, 32 output channel.
W_conv1 = weight_variable([5, 5, 1, 32])
b_conv1 = bias_variable([32])

x_image = tf.reshape(x, [-1,28,28,1])

# convolution, relu, max pooling
h_conv1 = tf.nn.relu(conv2d(x_image, W_conv1) + b_conv1)
h_pool1 = max_pool_2x2(h_conv1)

# [5, 5, 32, 64]: 5x5 convolution patch, 32 input channel, 64 output channel.
W_conv2 = weight_variable([5, 5, 32, 64])
b_conv2 = bias_variable([64])

# convolution, relu, max pooling
h_conv2 = tf.nn.relu(conv2d(h_pool1, W_conv2) + b_conv2)
h_pool2 = max_pool_2x2(h_conv2)

# fc layer 1
W_fc1 = weight_variable([7 * 7 * 64, 1024])
b_fc1 = bias_variable([1024])
```

Deep MNIST for Experts



```
h_pool2_flat = tf.reshape(h_pool2, [-1, 7*7*64])
h_fc1 = tf.nn.relu(tf.matmul(h_pool2_flat, W_fc1) + b_fc1)

keep_prob = tf.placeholder("float")
h_fc1_drop = tf.nn.dropout(h_fc1, keep_prob)

# fc layer 2
W_fc2 = weight_variable([1024, 10])
b_fc2 = bias_variable([10])

y_conv=tf.nn.softmax(tf.matmul(h_fc1_drop, W_fc2) + b_fc2)



cross_entropy = -tf.reduce_sum(y_*tf.log(y_conv))
train_step = tf.train.AdamOptimizer(1e-4).minimize(cross_entropy)
correct_prediction = tf.equal(tf.argmax(y_conv,1), tf.argmax(y_,1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
init = tf.initialize_all_variables()

ce_sum = tf.scalar_summary("cross entropy", cross_entropy)
acc_sum = tf.scalar_summary("accuracy", accuracy)
merged = tf.merge_summary([ce_sum, acc_sum])

sess = tf.Session()
writer = tf.train.SummaryWriter("./sumlog", sess.graph)

sess.run(init)

with sess.as_default():
    for i in range(20000):
        batch = mnist.train.next_batch(50)
        if i%400 == 0:
            train_accuracy = accuracy.eval(feed_dict={x:batch[0], y_: batch[1], keep_prob: 1.0})
            print "step %d, training accuracy %g" % (i, train_accuracy)
            print "test accuracy %g" % accuracy.eval(feed_dict={x: mnist.test.images, y_: mnist.test.labels,
                                                                 keep_prob: 1.0})
            writer.add_summary(merged.eval(feed_dict={x: mnist.test.images, y_: mnist.test.labels,
                                                      keep_prob: 1.0}),i)

        train_step.run(feed_dict={x: batch[0], y_: batch[1], keep_prob: 0.5})
```

LeNet



```
# [5, 5, 32, 64]: 5x5 convolution patch, 32 input channel, 64 output channel.
W_conv2 = weight_variable([5, 5, 32, 64])
b_conv2 = bias_variable([64])
```

```
# convolution, relu, max pooling
h_conv2 = tf.nn.relu(conv2d(h_pool1, W_conv2) + b_conv2)
h_pool2 = max_pool_2x2(h_conv2)
```

```
# [5, 5, 1, 32]: 5x5 convolution patch, 1 input channel, 32 output channel.
W_conv1 = weight_variable([5, 5, 1, 32])
b_conv1 = bias_variable([32])
```

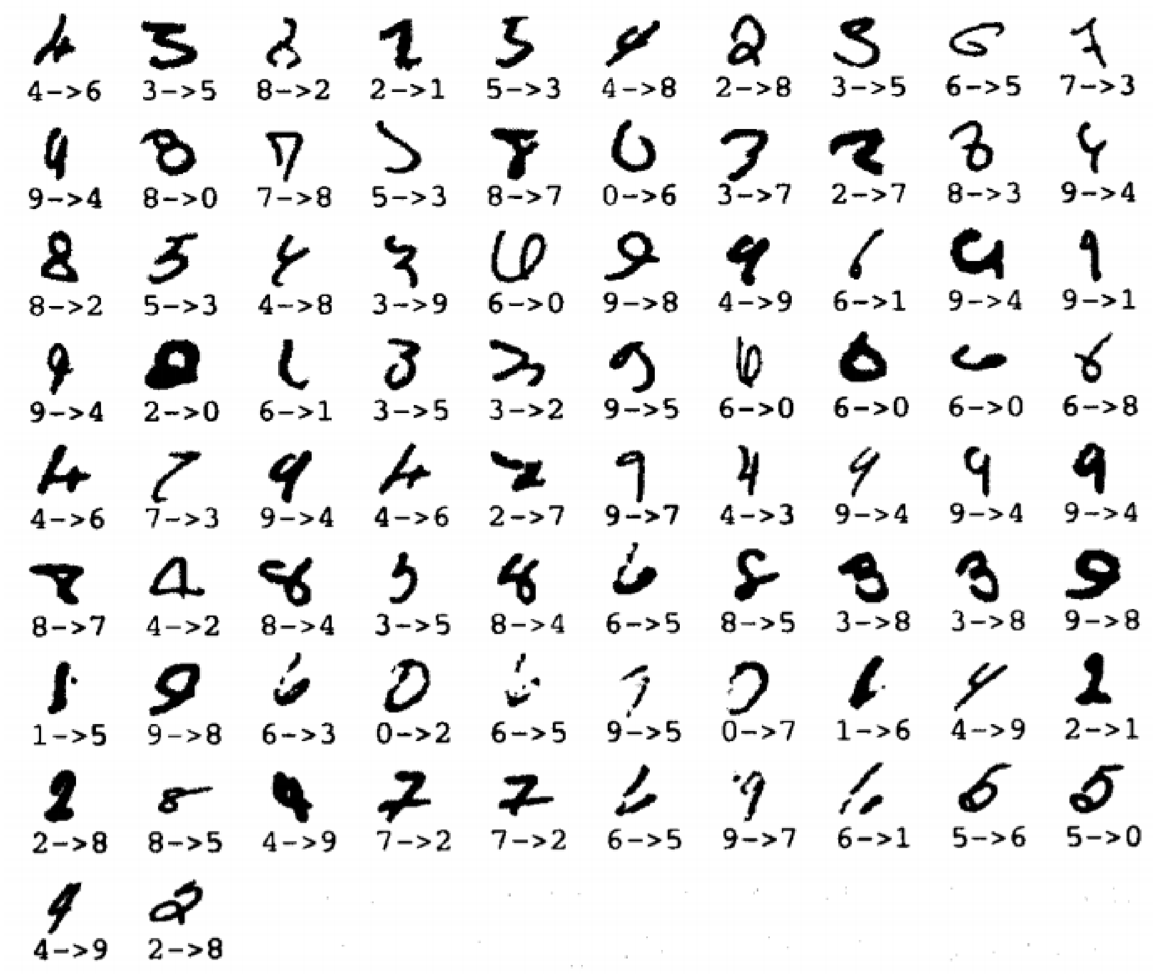
```
# convolution, relu, max pooling
h_conv1 = tf.nn.relu(conv2d(x_image, W_conv1) + b_conv1)
h_pool1 = max_pool_2x2(h_conv1)
```

```
h_pool2_flat = tf.reshape(h_pool2, [-1, 7*7*64])
h_fc1 = tf.nn.relu(tf.matmul(h_pool2_flat, W_fc1) + b_fc1)

keep_prob = tf.placeholder("float")
h_fc1_drop = tf.nn.dropout(h_fc1, keep_prob)
```

#(Parameter) = 3,274,634

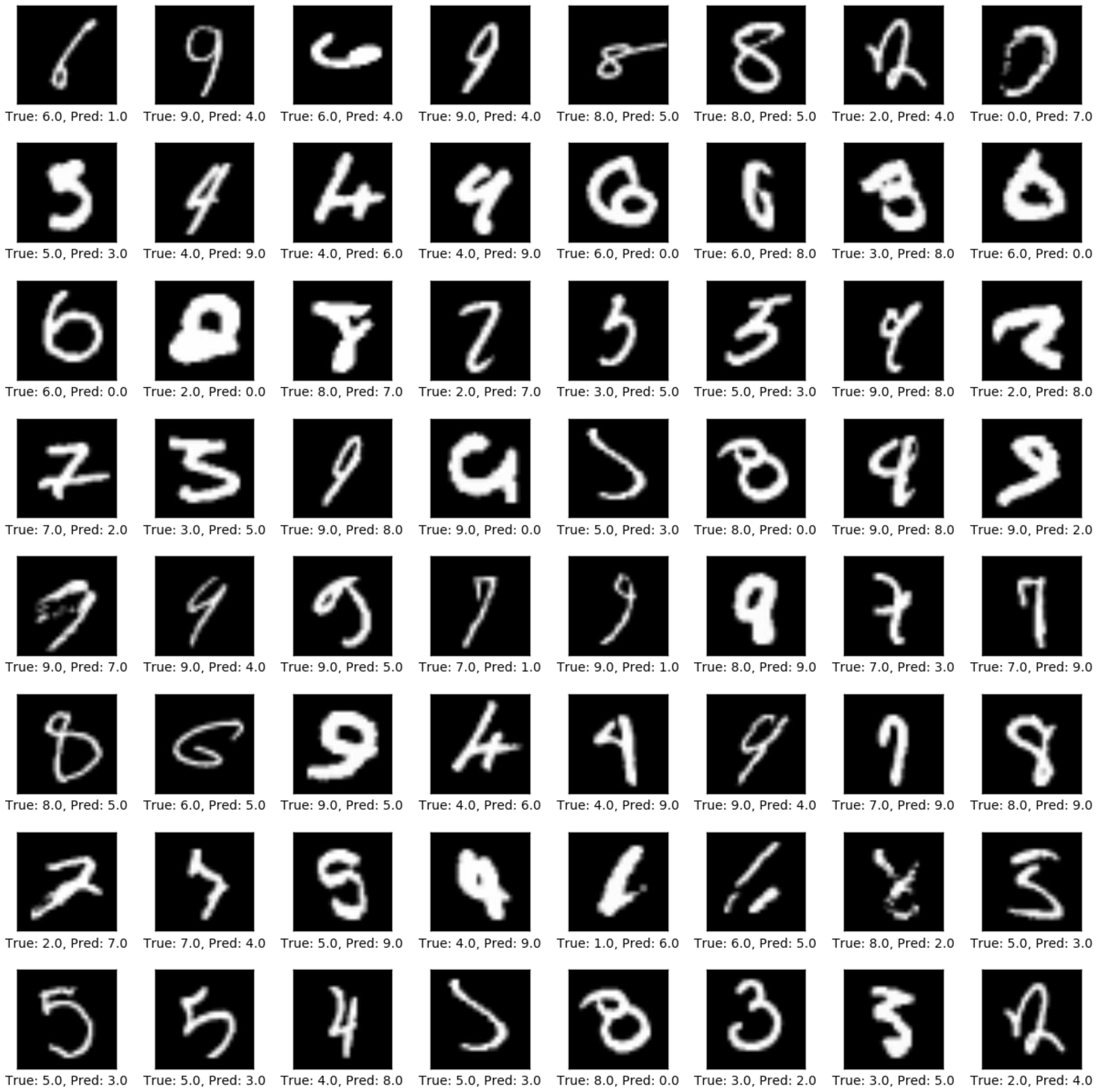
Layer	C1	C2	FC1	FC2
Weight	800	51,200	3,211,264	10,240
Bias	32	64	1,024	10

The 82 errors by LeNet5

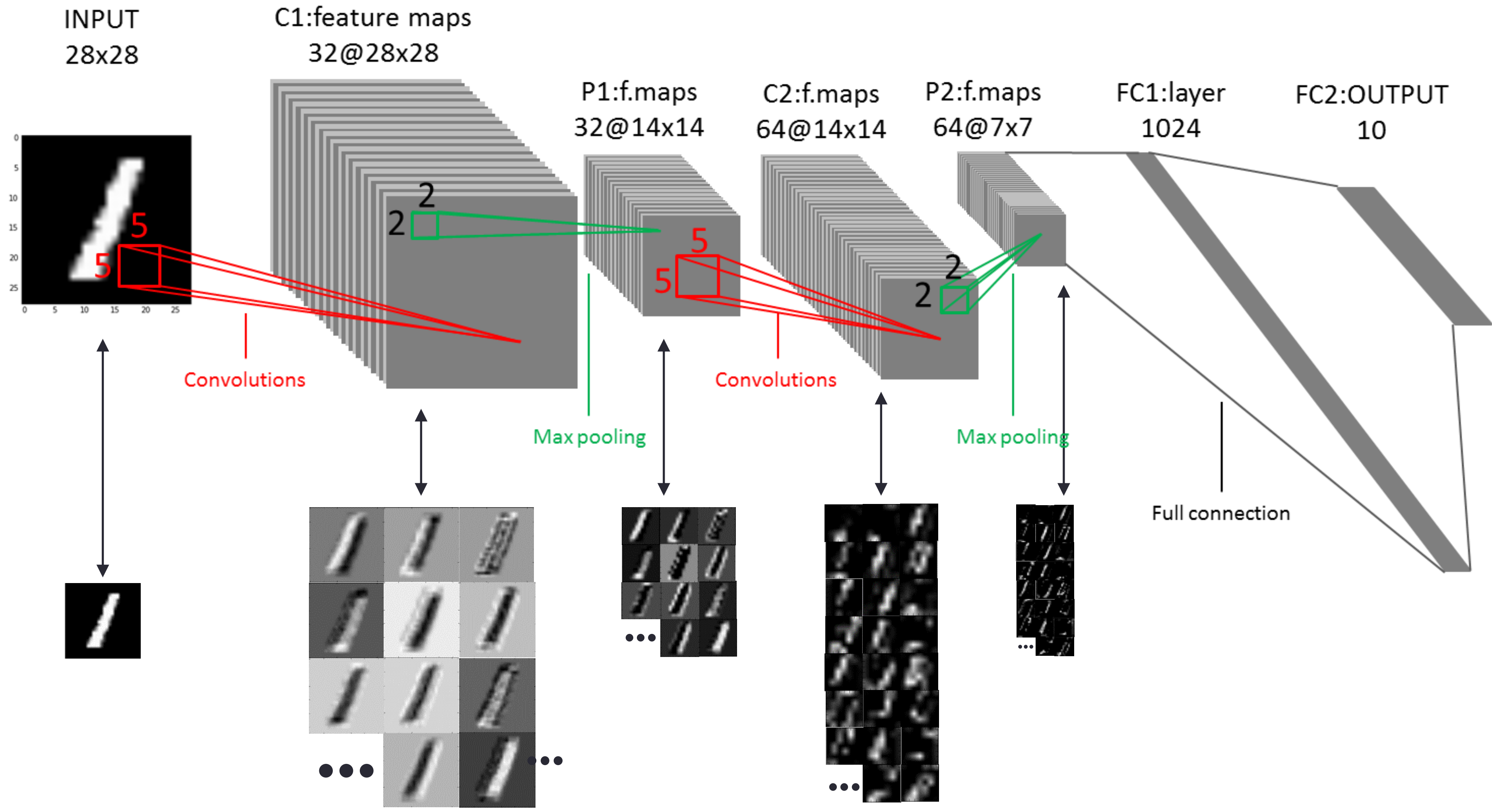


Notice that most of the errors are cases that people find quite easy.

The human error rate is probably 20 to 30 errors but nobody has had the patience to measure it.

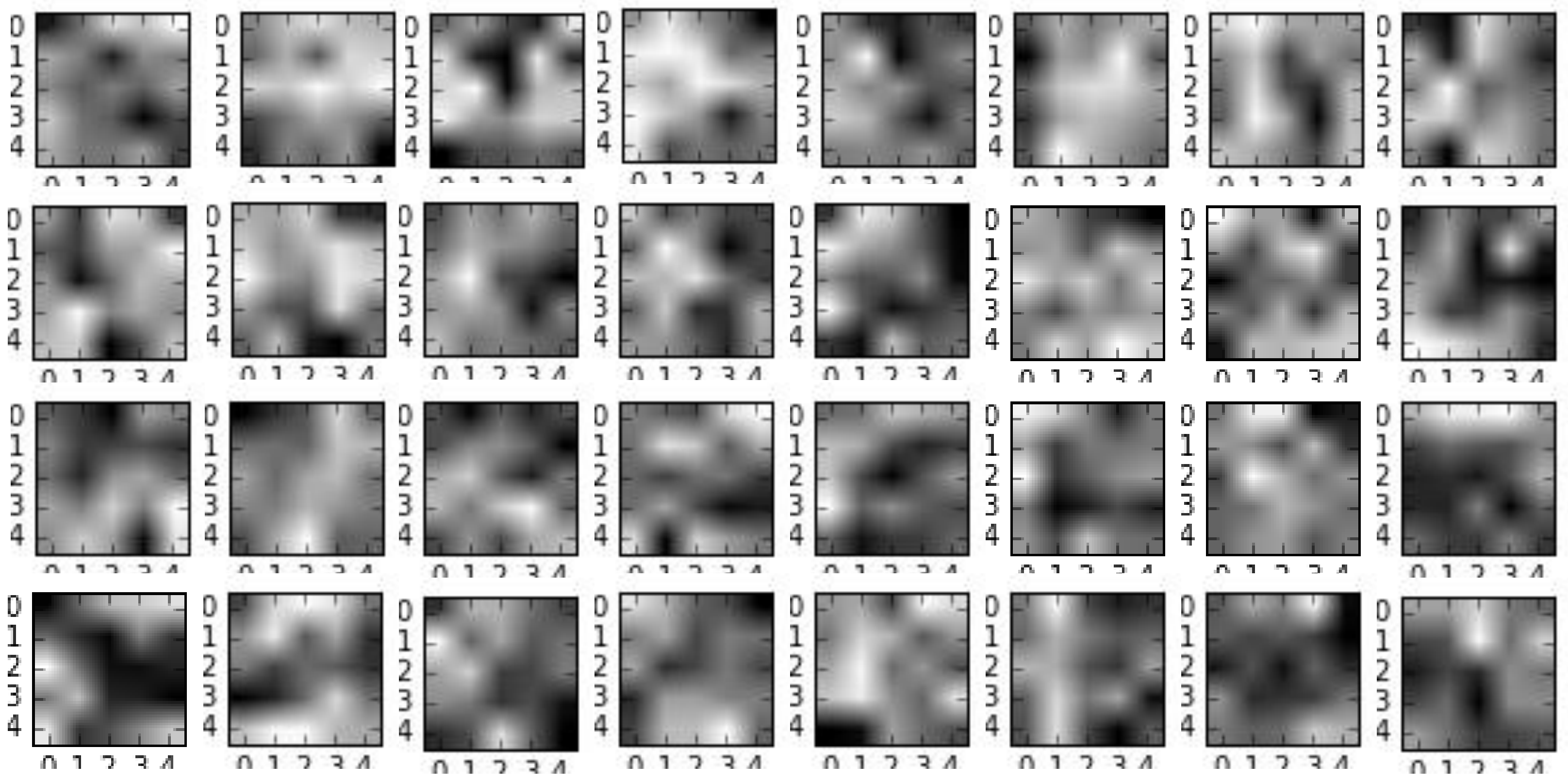

True: 6.0, Pred: 1.0
True: 9.0, Pred: 4.0
True: 6.0, Pred: 4.0
True: 9.0, Pred: 4.0
True: 8.0, Pred: 5.0
True: 8.0, Pred: 5.0
True: 2.0, Pred: 4.0
True: 0.0, Pred: 7.0
True: 5.0, Pred: 3.0
True: 4.0, Pred: 9.0
True: 4.0, Pred: 6.0
True: 4.0, Pred: 9.0
True: 6.0, Pred: 0.0
True: 6.0, Pred: 8.0
True: 3.0, Pred: 8.0
True: 6.0, Pred: 0.0
True: 6.0, Pred: 0.0
True: 2.0, Pred: 0.0
True: 8.0, Pred: 7.0
True: 2.0, Pred: 7.0
True: 3.0, Pred: 5.0
True: 5.0, Pred: 3.0
True: 9.0, Pred: 8.0
True: 2.0, Pred: 8.0
True: 7.0, Pred: 2.0
True: 3.0, Pred: 5.0
True: 9.0, Pred: 8.0
True: 9.0, Pred: 0.0
True: 5.0, Pred: 3.0
True: 8.0, Pred: 0.0
True: 9.0, Pred: 8.0
True: 9.0, Pred: 2.0
True: 9.0, Pred: 7.0
True: 9.0, Pred: 4.0
True: 9.0, Pred: 5.0
True: 7.0, Pred: 1.0
True: 9.0, Pred: 1.0
True: 8.0, Pred: 9.0
True: 7.0, Pred: 3.0
True: 7.0, Pred: 9.0
True: 8.0, Pred: 5.0
True: 6.0, Pred: 5.0
True: 9.0, Pred: 5.0
True: 4.0, Pred: 6.0
True: 4.0, Pred: 9.0
True: 9.0, Pred: 4.0
True: 7.0, Pred: 9.0
True: 8.0, Pred: 9.0
True: 2.0, Pred: 7.0
True: 7.0, Pred: 4.0
True: 5.0, Pred: 9.0
True: 4.0, Pred: 9.0
True: 1.0, Pred: 6.0
True: 6.0, Pred: 5.0
True: 8.0, Pred: 2.0
True: 5.0, Pred: 3.0
True: 5.0, Pred: 3.0
True: 5.0, Pred: 3.0
True: 4.0, Pred: 8.0
True: 5.0, Pred: 3.0
True: 8.0, Pred: 0.0
True: 3.0, Pred: 2.0
True: 3.0, Pred: 5.0
True: 2.0, Pred: 4.0

Feature map results

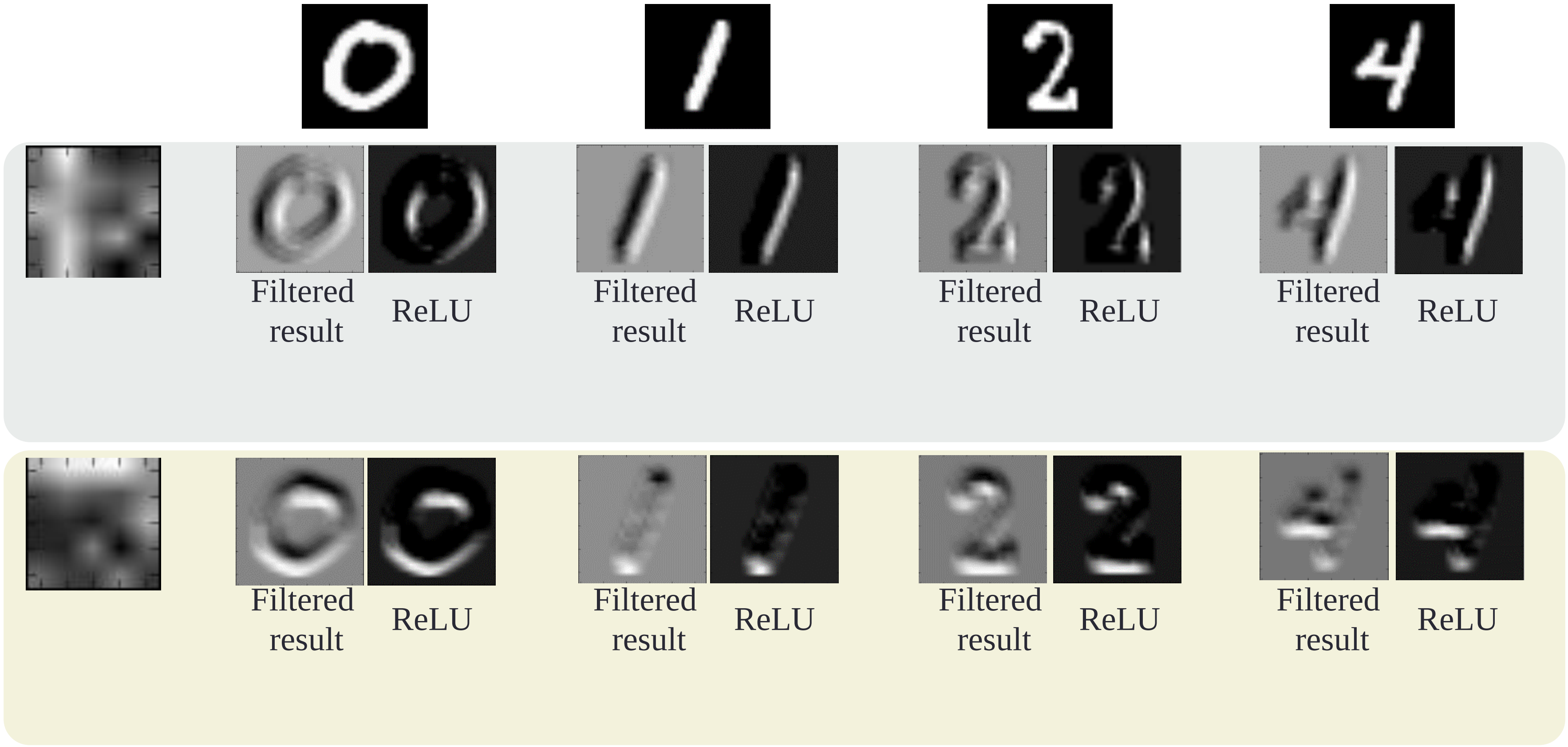


Learned Filters

Trained 32 filters on C1 layer



Learned Filters



TensorFlow codes

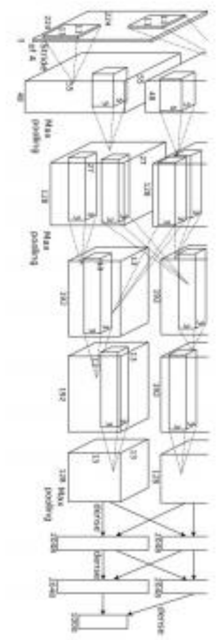
- LeNet tensorflow codes

IMAGE CLASSIFICATION

Image Classification (ImageNet)

Year 2012

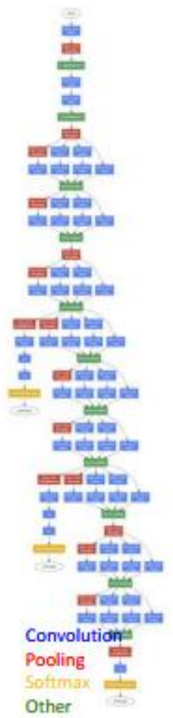
SuperVision



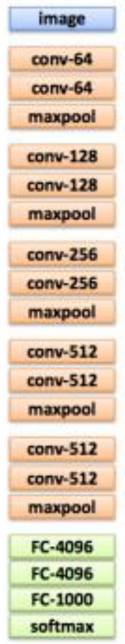
[Krizhevsky NIPS 2012]

Year 2014

GoogLeNet



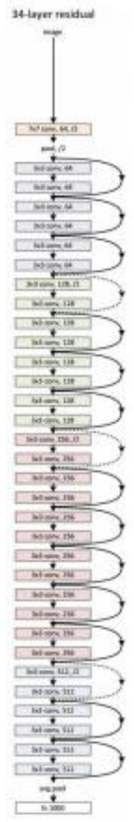
VGG



[Szegedy arxiv 2014] [Simonyan arxiv 2014]

Year 2015

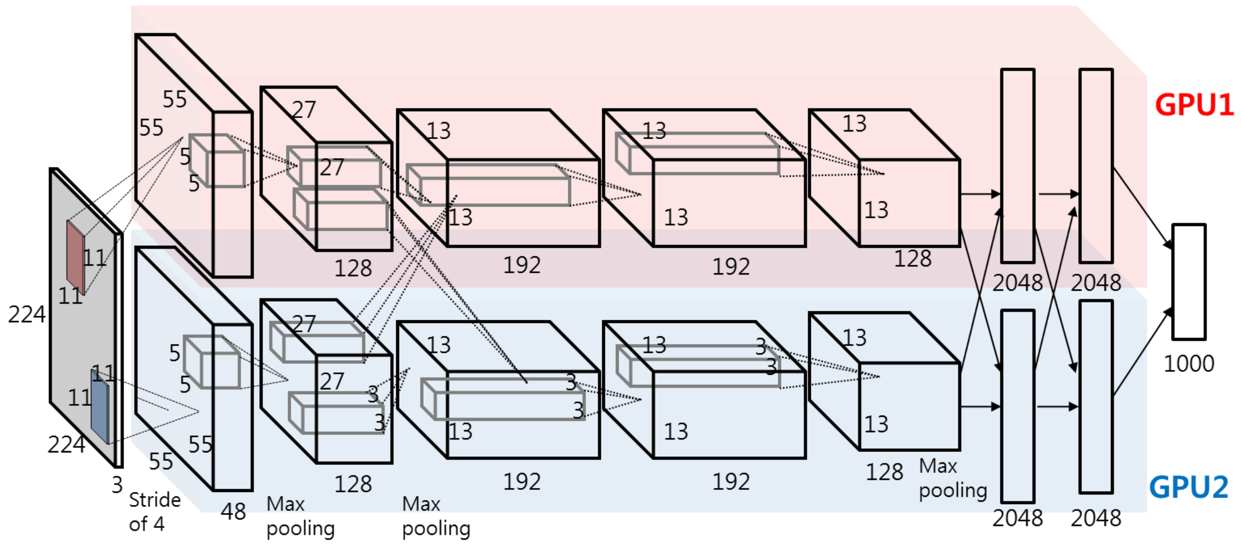
MSRA



ALEXNET

AlexNet

- AlexNet: won the 2012 ImageNet competition by making 40% less error than the next best competitor
  - It is composed of 5 convolutional layers
  - The input is a color RGB image
  - Computation is divided over 2 GPU architectures

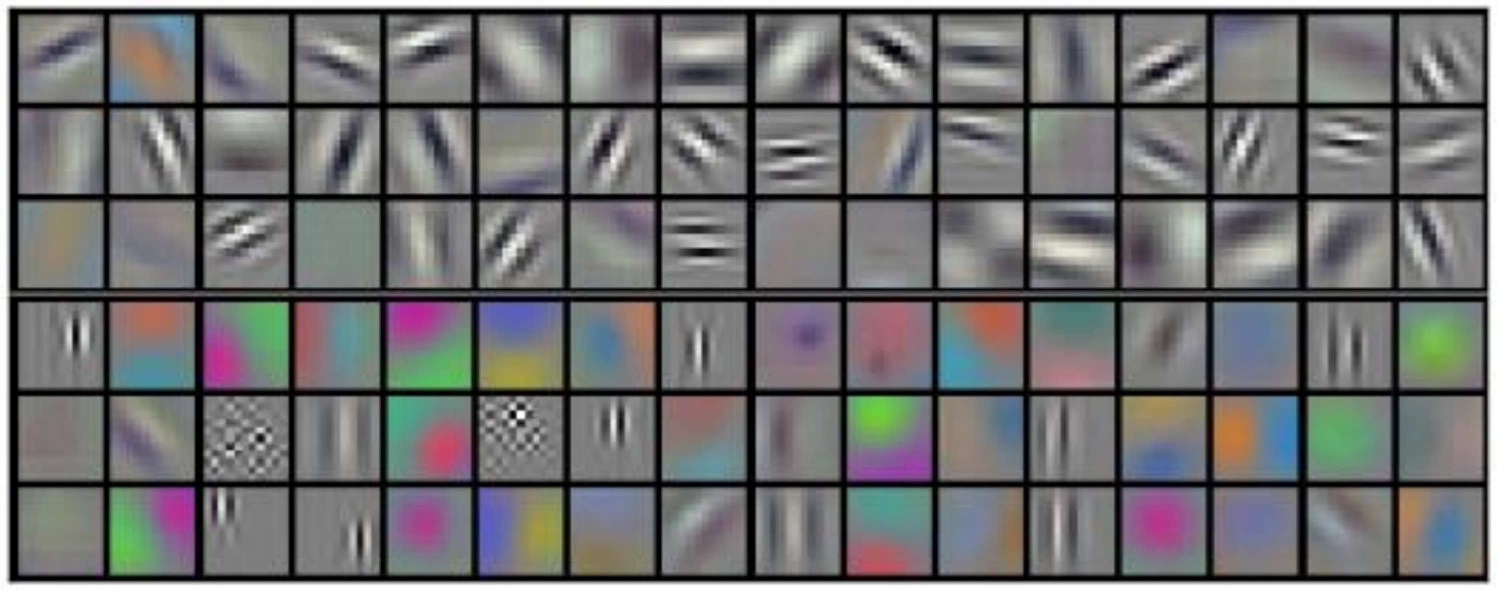


AlexNet results

- AlexNet TensorFlow codes and some results

AlexNet Visualization

- Filters learned by the first convolutional layer. The top half corresponds to the layer on one GPU, the bottom on the other. From Krizehvsky et al. (2012)
- Each of the 96 filters is of size [11x11x3]



VISUALIZATION

Motivation

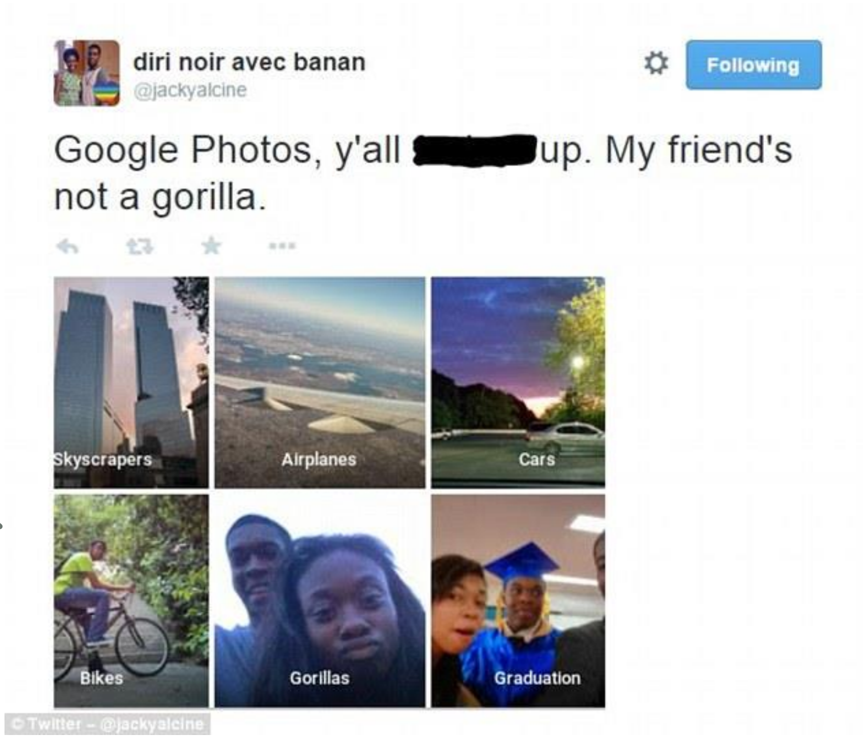
- It is well known that Artificial Neural Networks show **remarkable performance** in image classification
- However, **we actually understand little** of why certain models work and others don’t

- There have been some attempts to visualize at each layer in the neural network
  - to know “how neural networks work and what each layer has learned”

https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

Why is this important?

- There is a need of training networks with information we want to learn



diri noir avec banan
@jackyalcine

Google Photos, y'all [redacted] up. My friend's not a gorilla.

But this program couldn't ignore what we don't care about

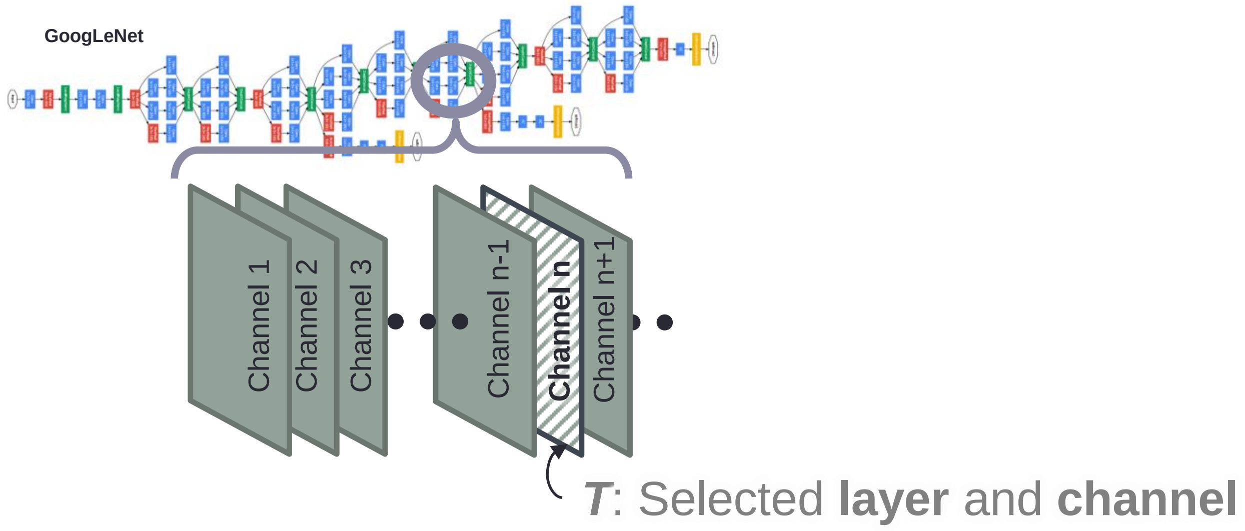
http://www.dailymail.co.uk/sciencetech/article-3145887/Google-apologises-Photos-app-tags-black-people-gorillas-Fault-image-recognition-software-mislabelled-picture.html

Visualization method

- Deconvolution
  - Matthew D. Zeiler and Rob Fergus, “Visualizing and Understanding Convolutional Networks,” ECCV 2014

- Input optimization
  - Naïve visualization
  - Low/High frequency normalization
    - With image prior
    - With Laplacian (pyramid gradient) normalization

Naïve visualization

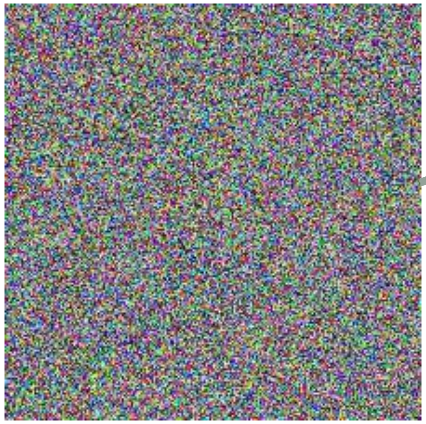


Objective function: L = mean(T)

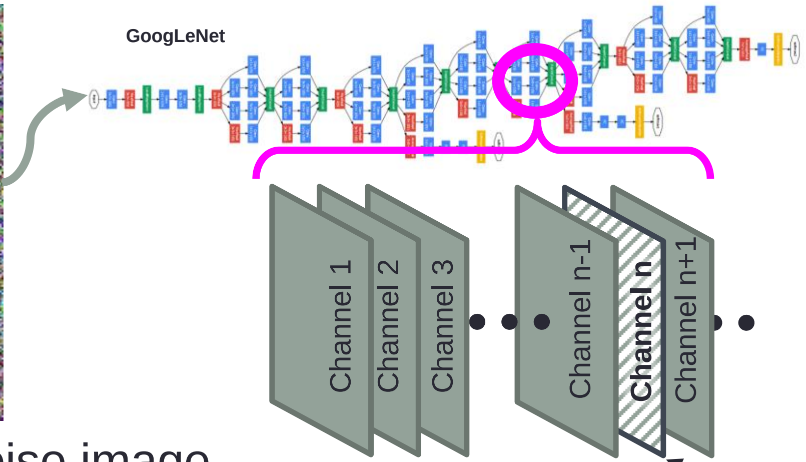
GRADIENT ASCENT:

$$img_{new} \leftarrow img_{old} + \alpha \times \frac{\partial(L)}{\partial(img)}\Big|_{img_{old}}$$

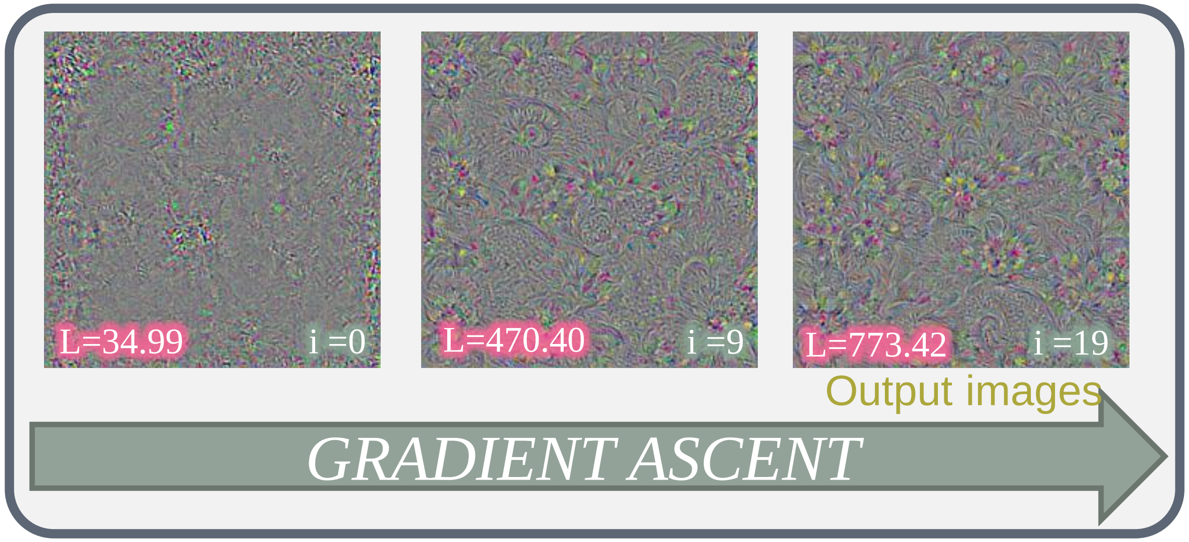
Naïve visualization



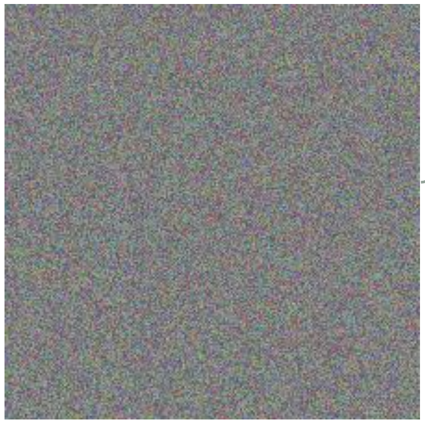
Initial input: an arbitrary noise image



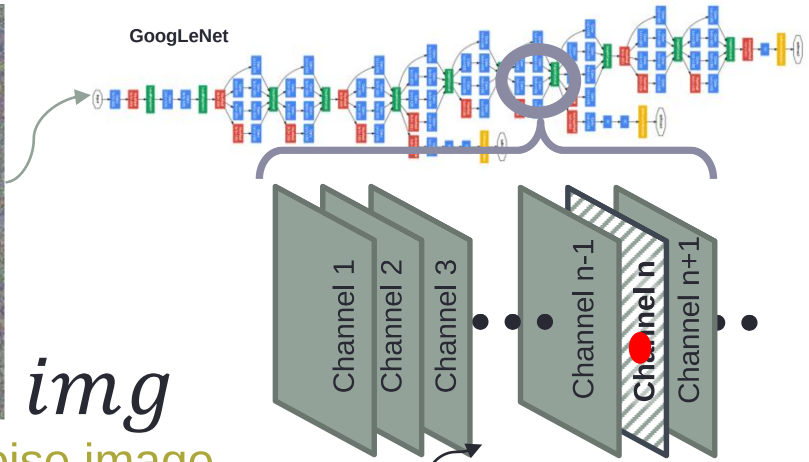
Selected (**layer**, **channel)**



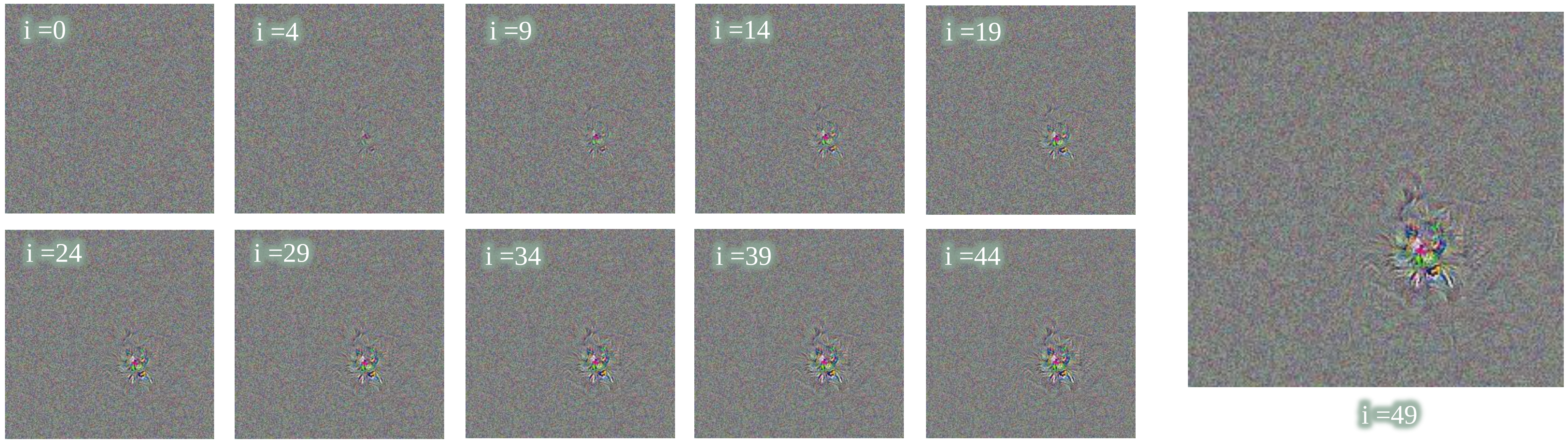
Single neuron activation



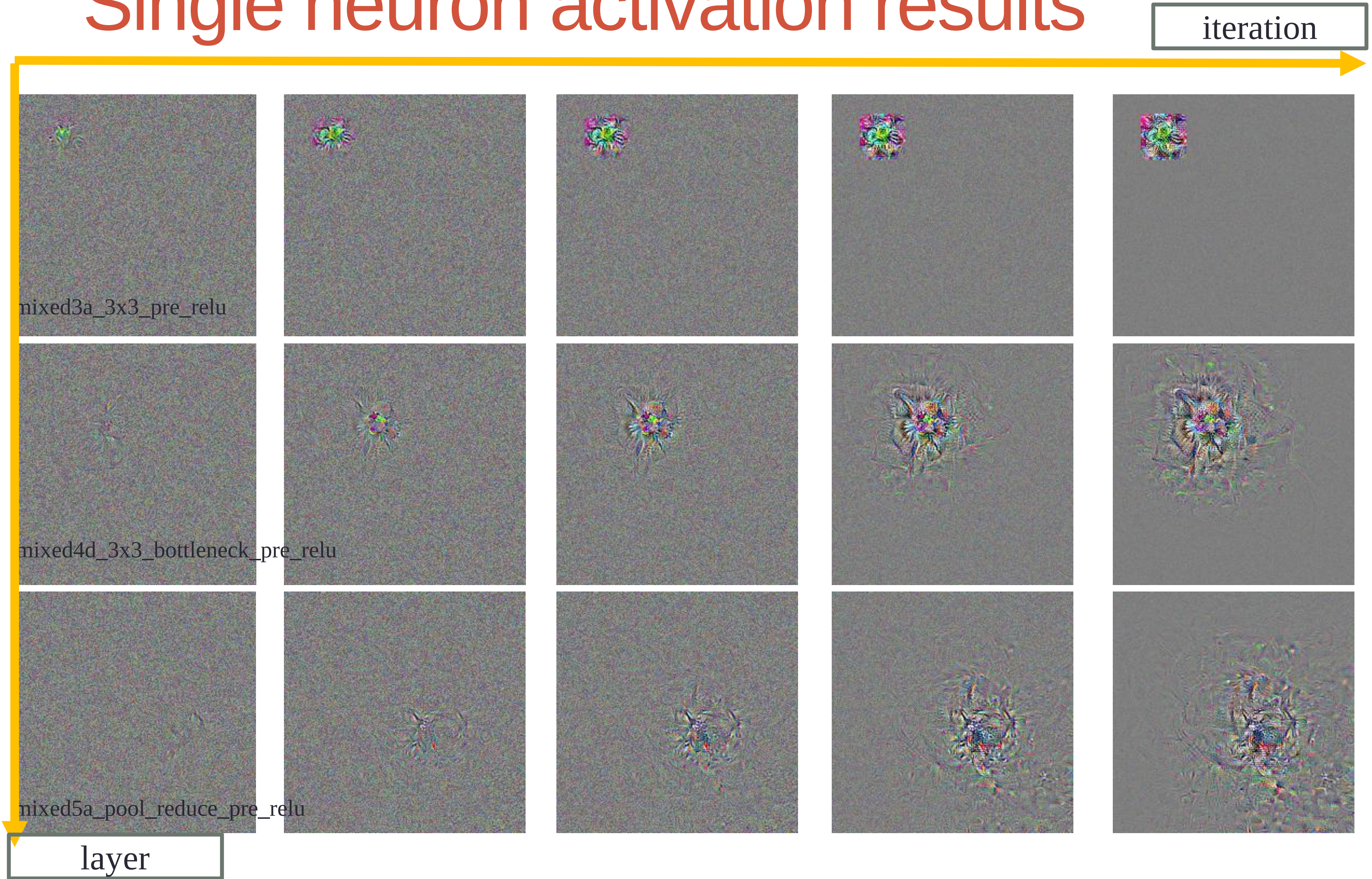
Initial input: an arbitrary noise image



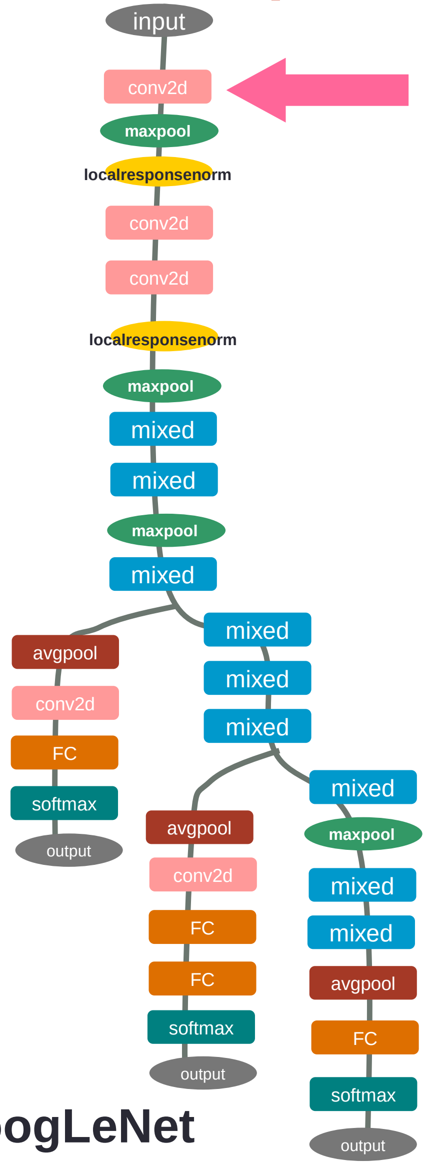
T: Selected (**layer**,**channel, position)**

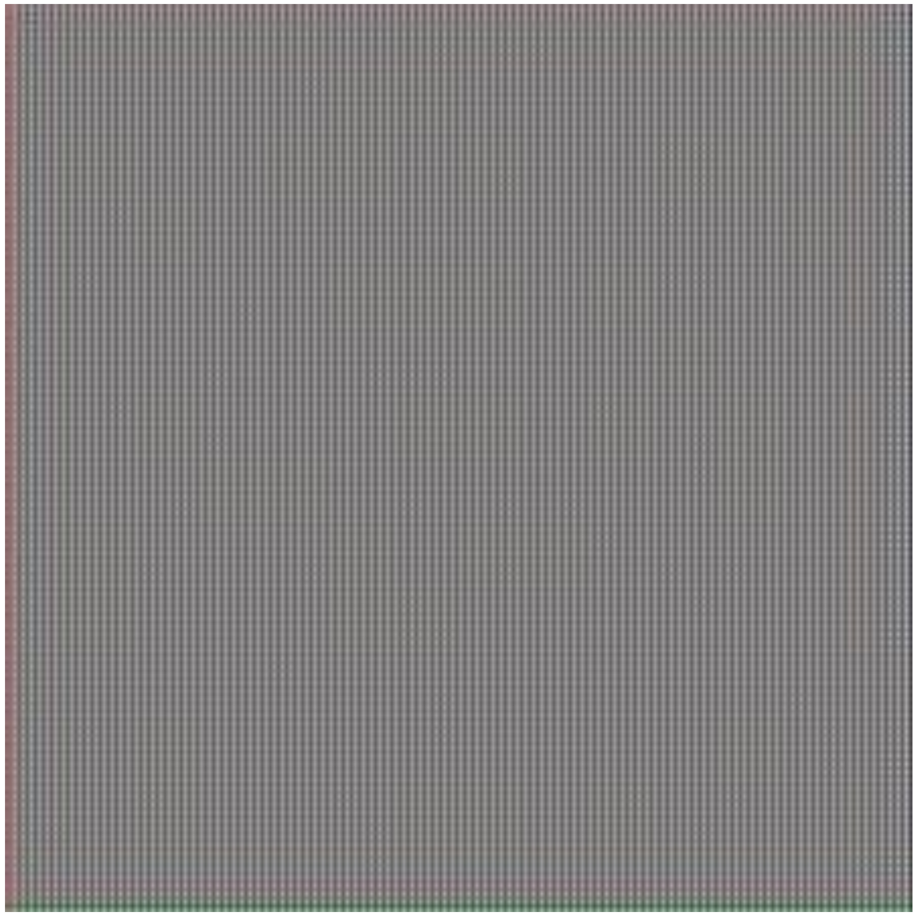


Single neuron activation results



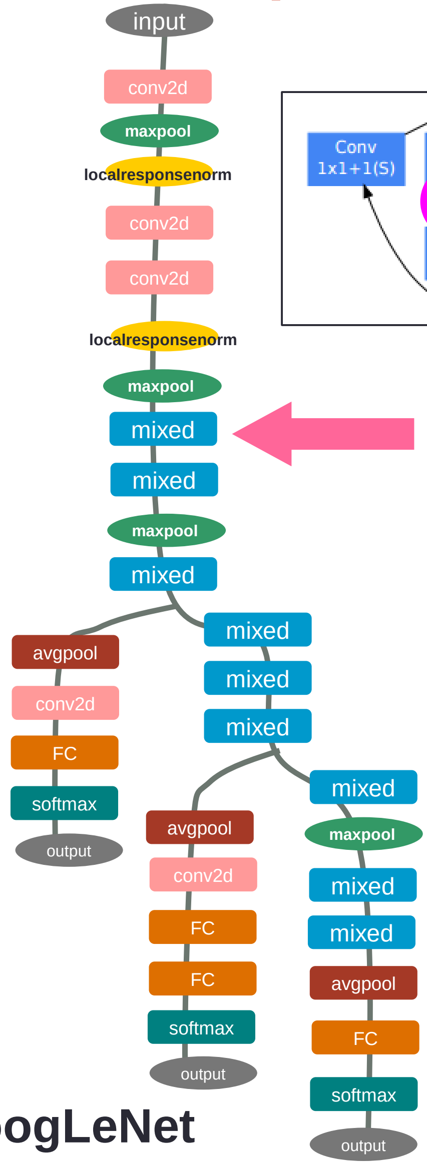
Examples of naïve feature visualization

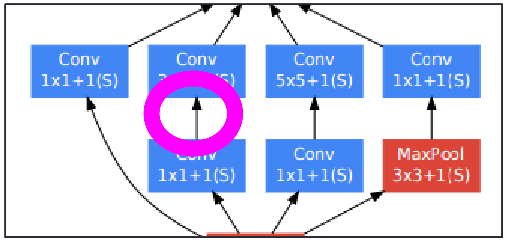


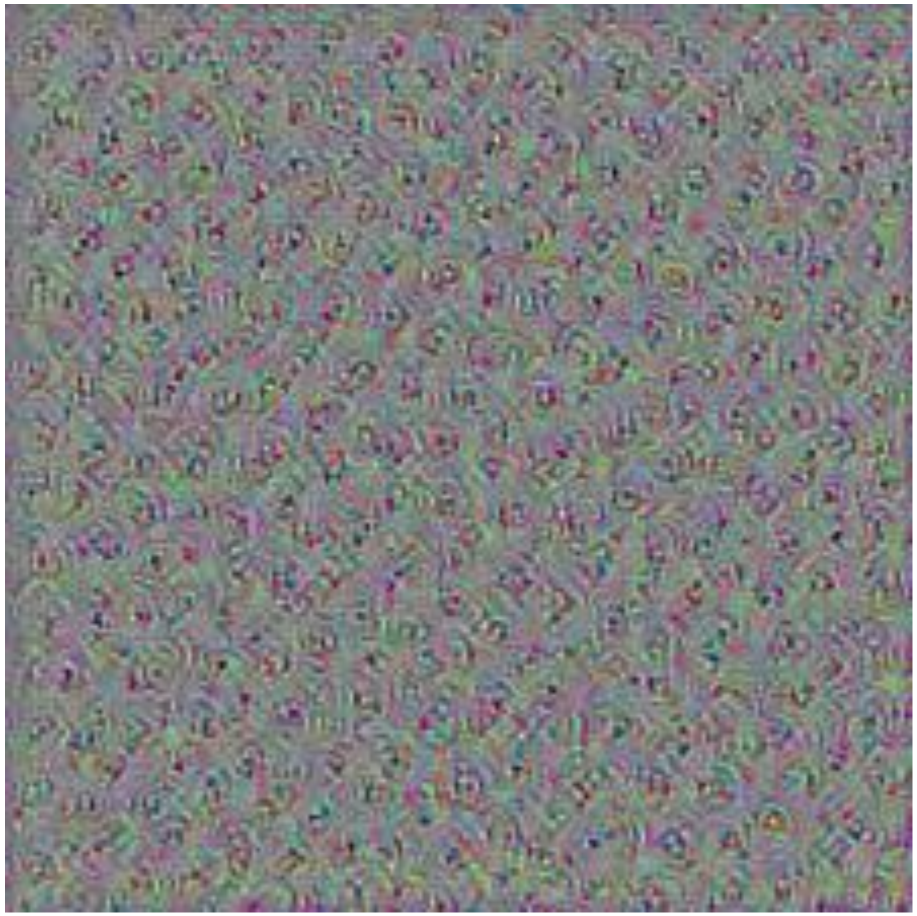


GoogLeNet

Examples of naïve feature visualization

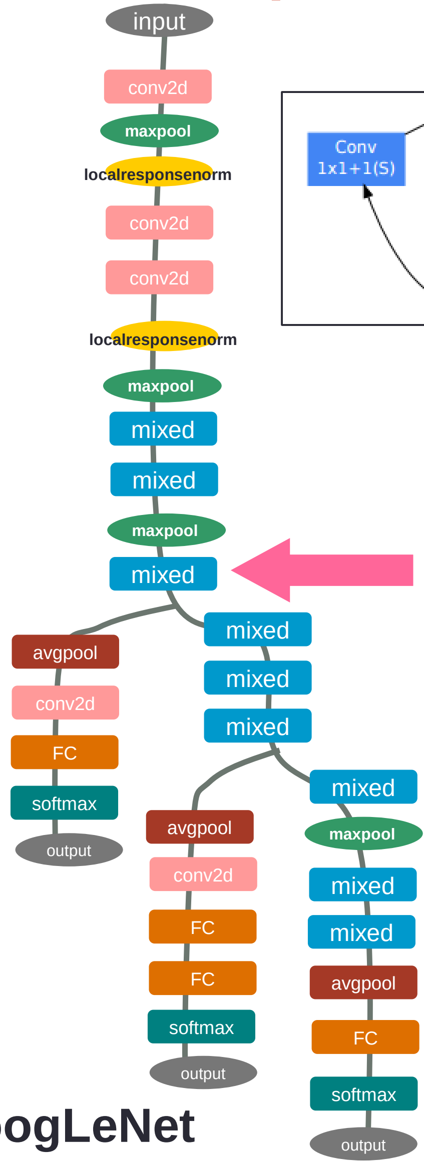


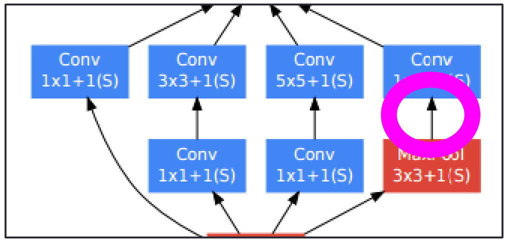


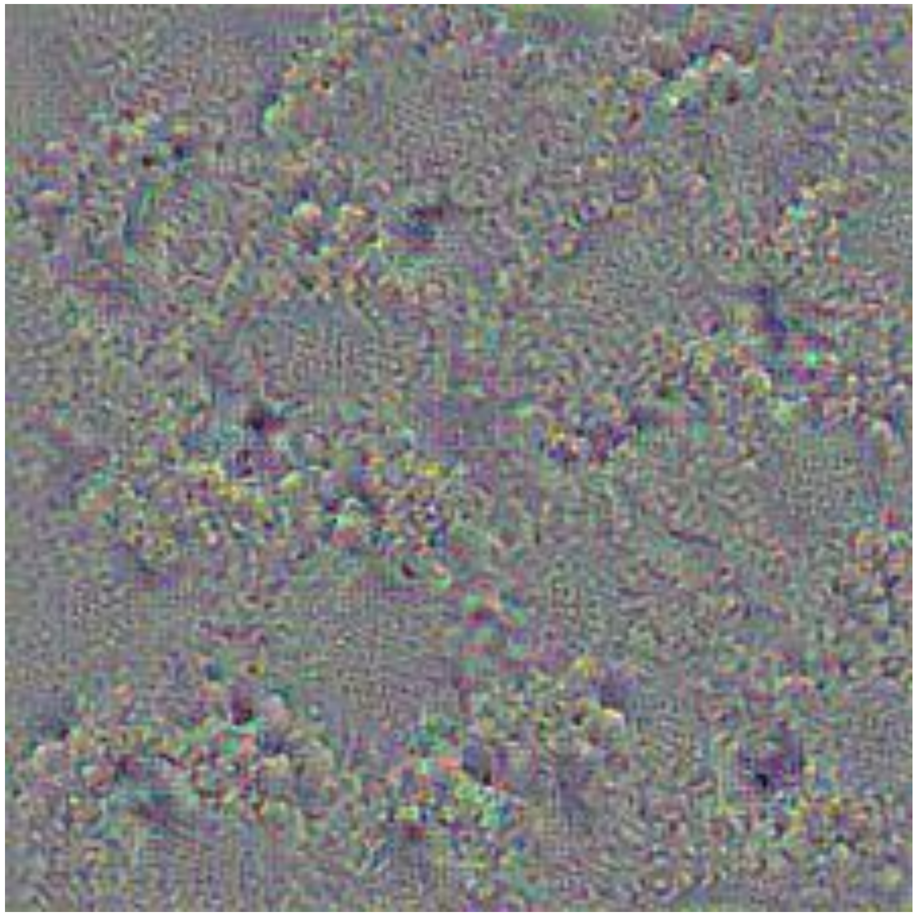


GoogLeNet

Examples of naïve feature visualization

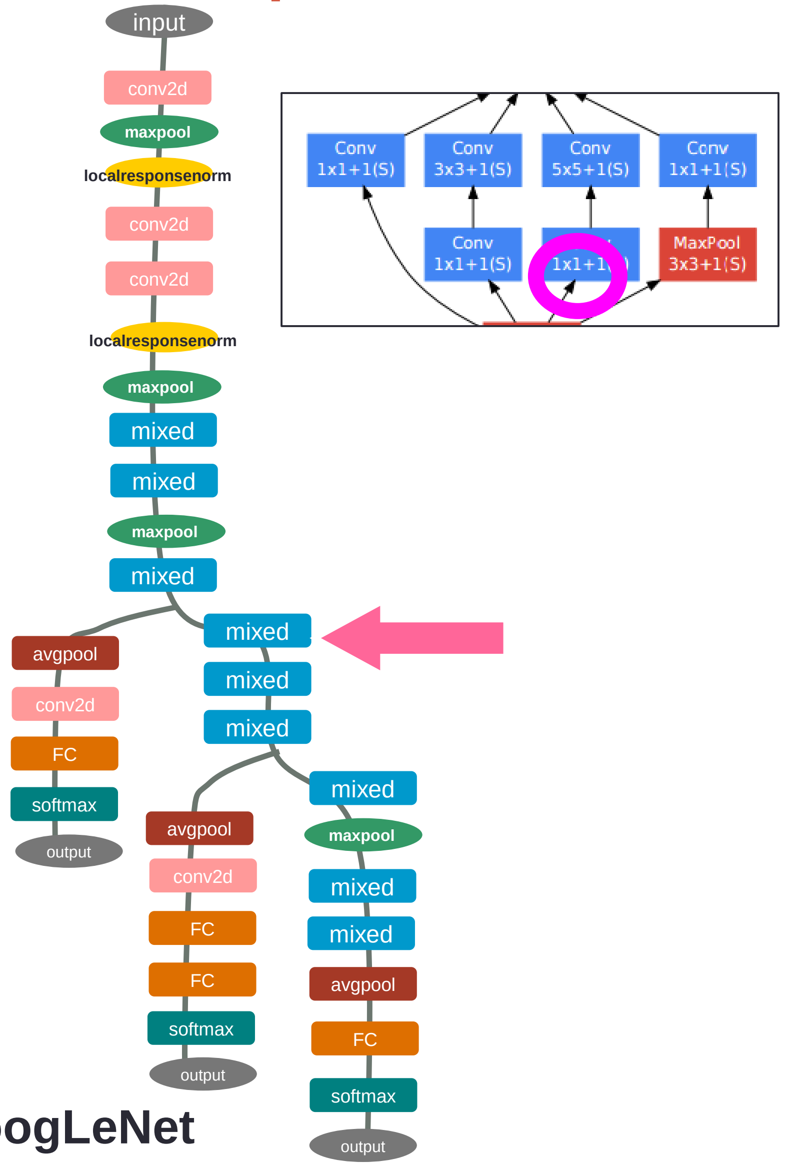


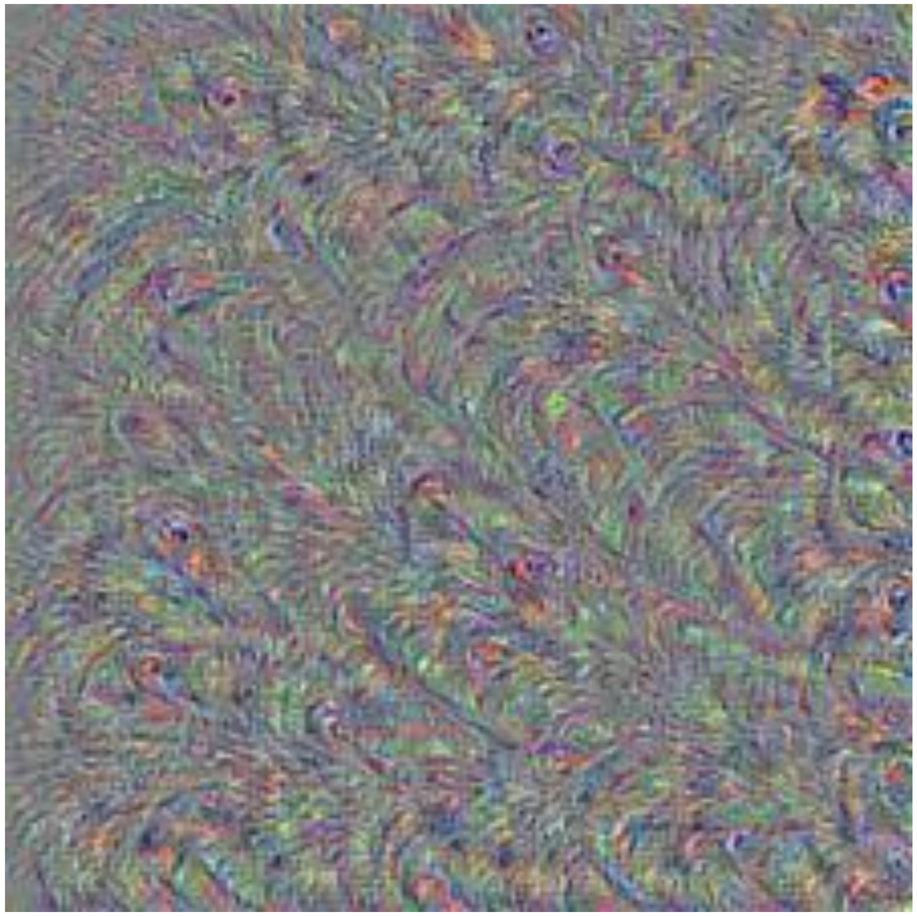




GoogLeNet

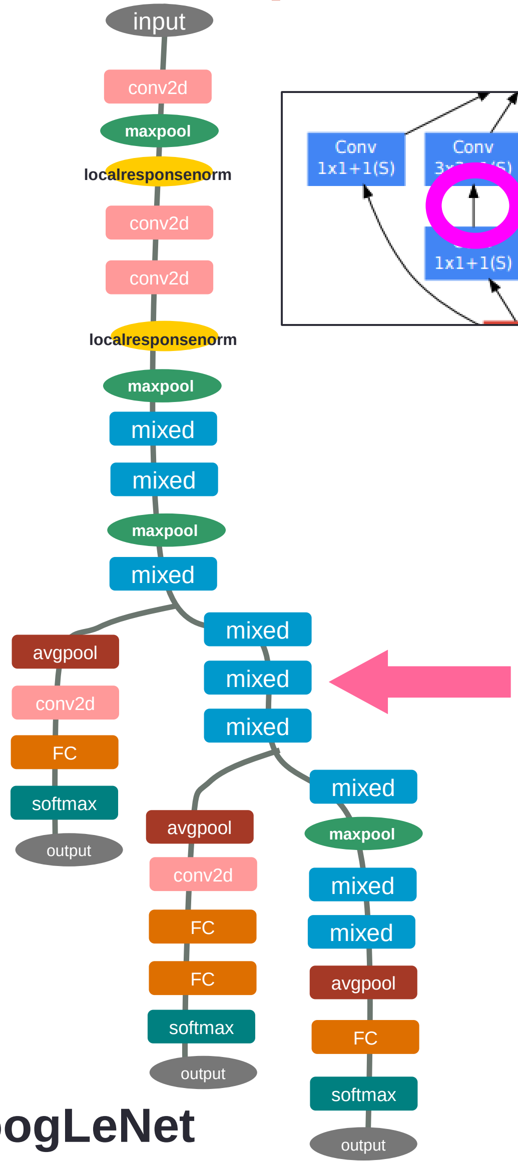
Examples of naïve feature visualization

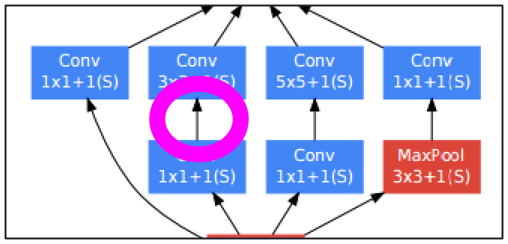


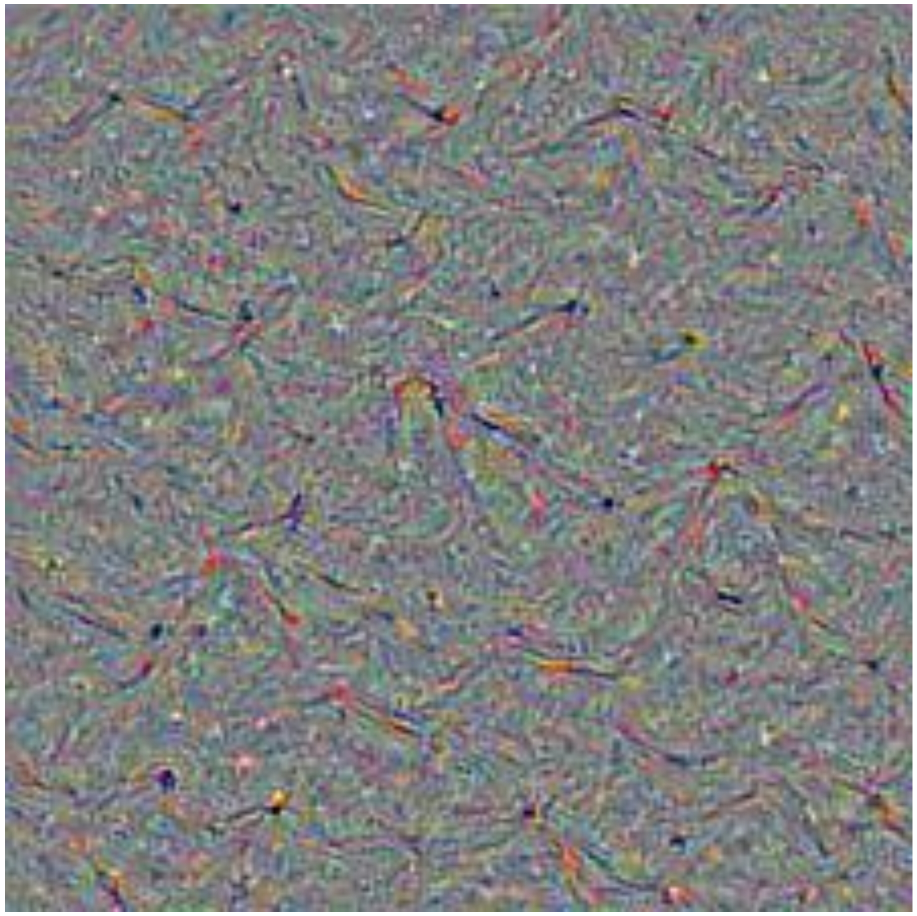


GoogLeNet

Examples of naïve feature visualization

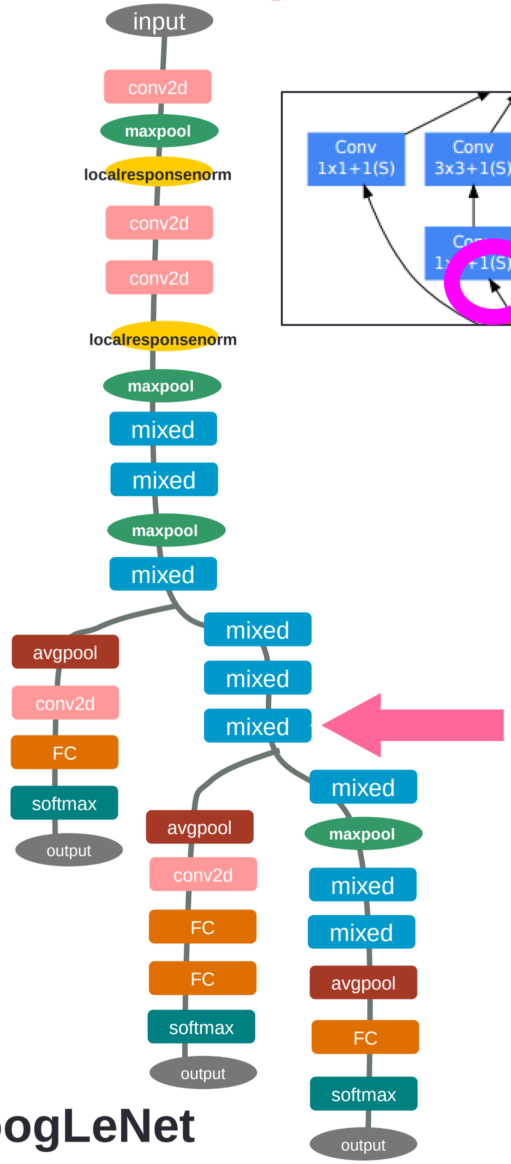


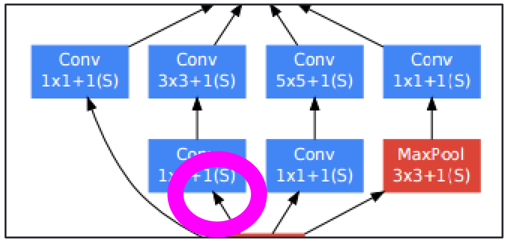


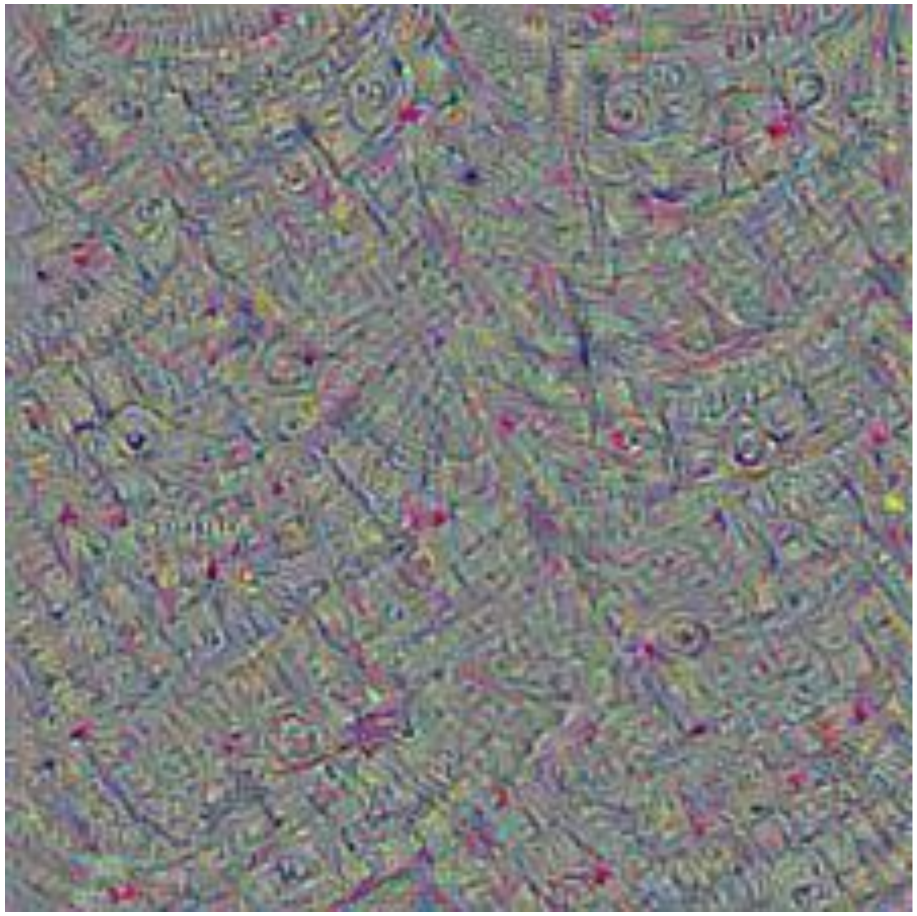


GoogLeNet

Examples of naïve feature visualization

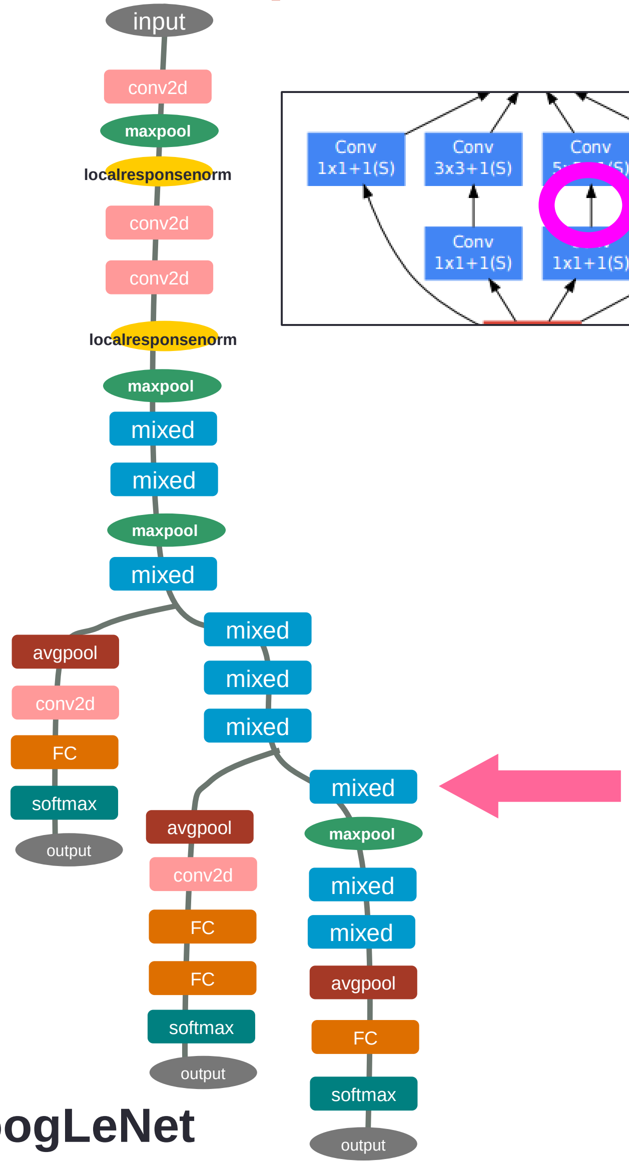


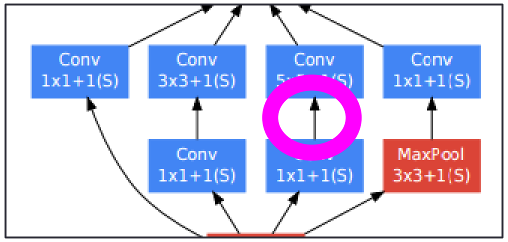


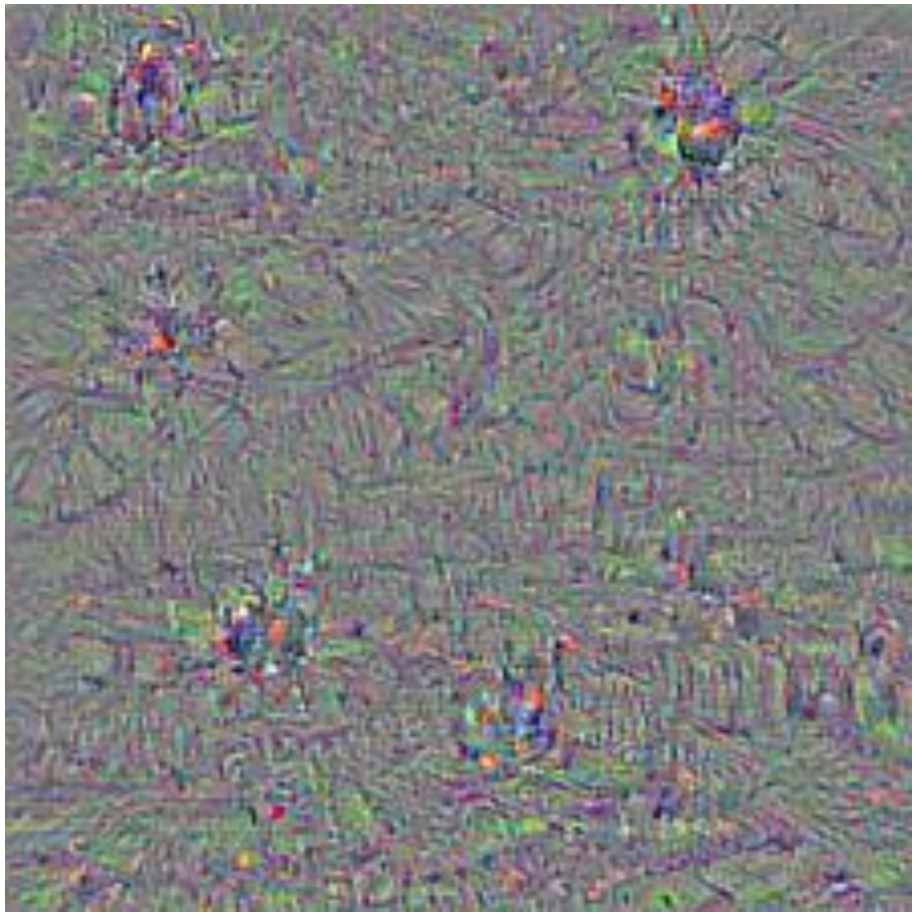


GoogLeNet

Examples of naïve feature visualization

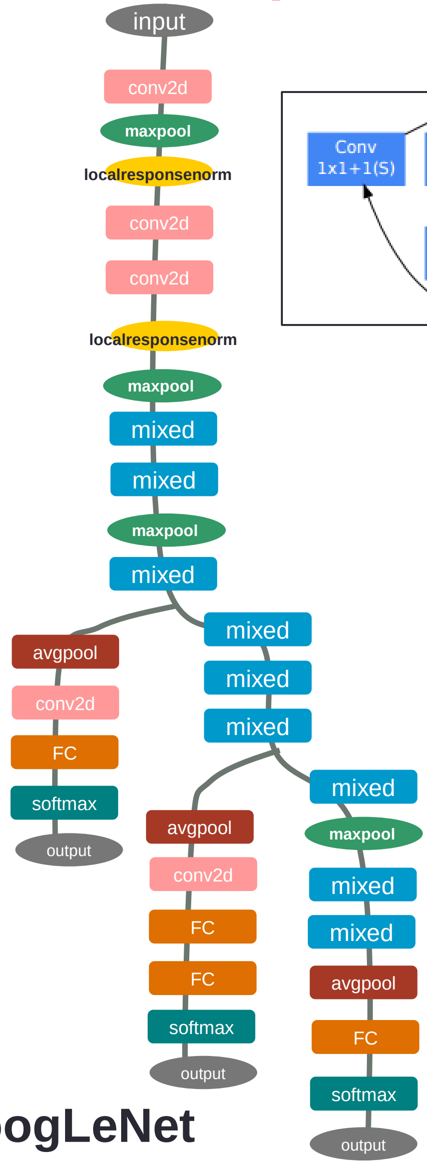


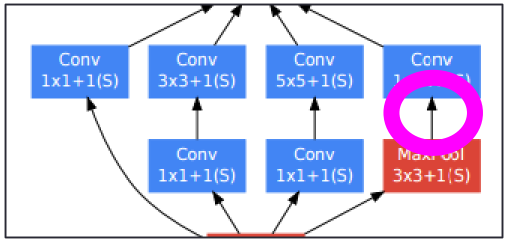


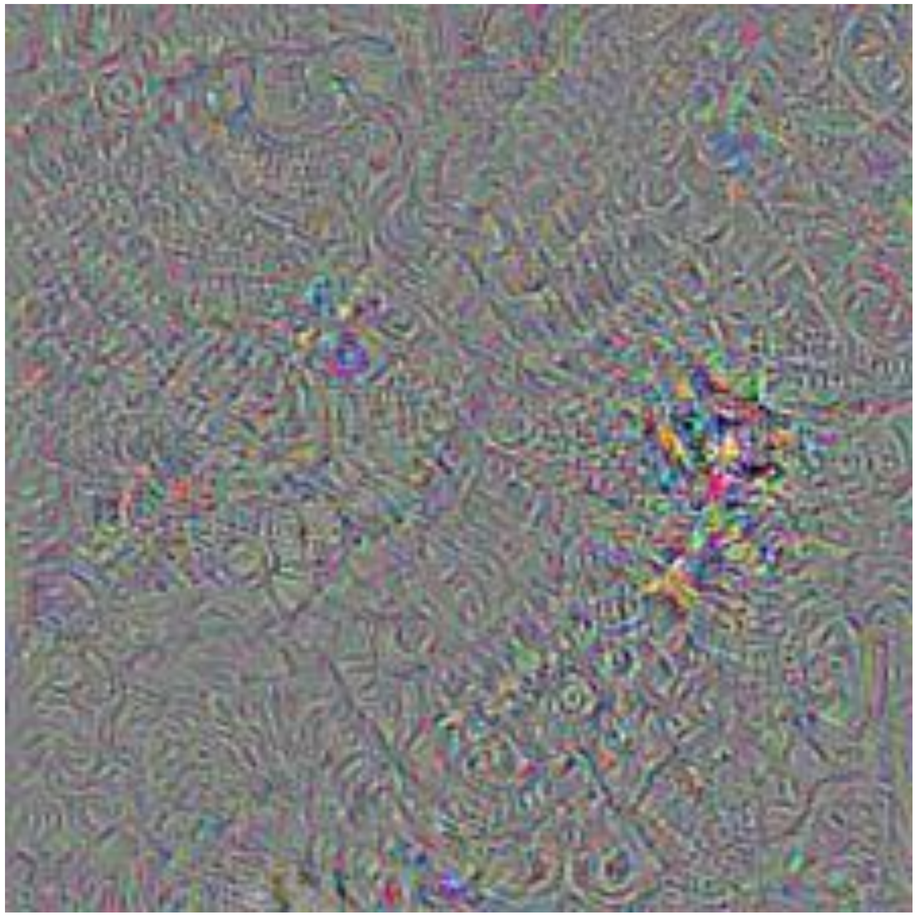


GoogLeNet

Examples of naïve feature visualization

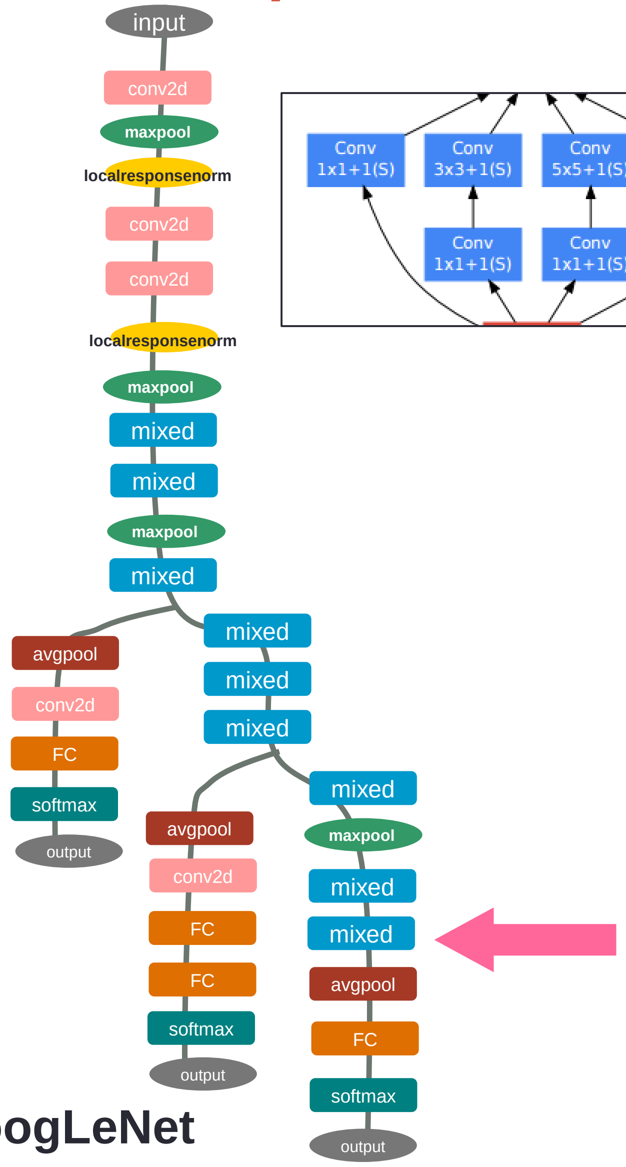


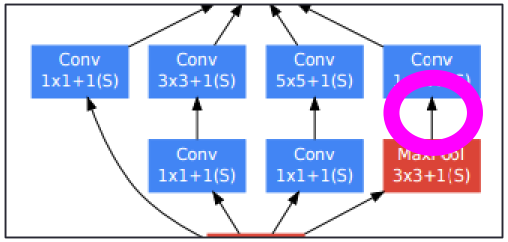


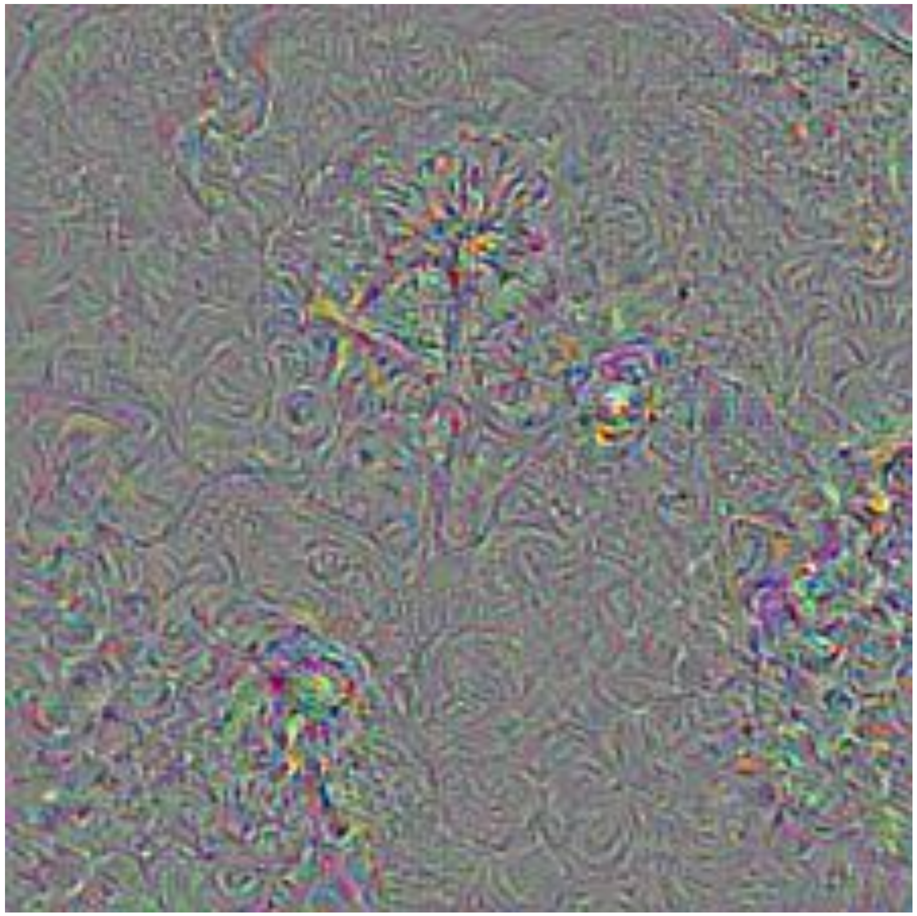


GoogLeNet

Examples of naïve feature visualization.



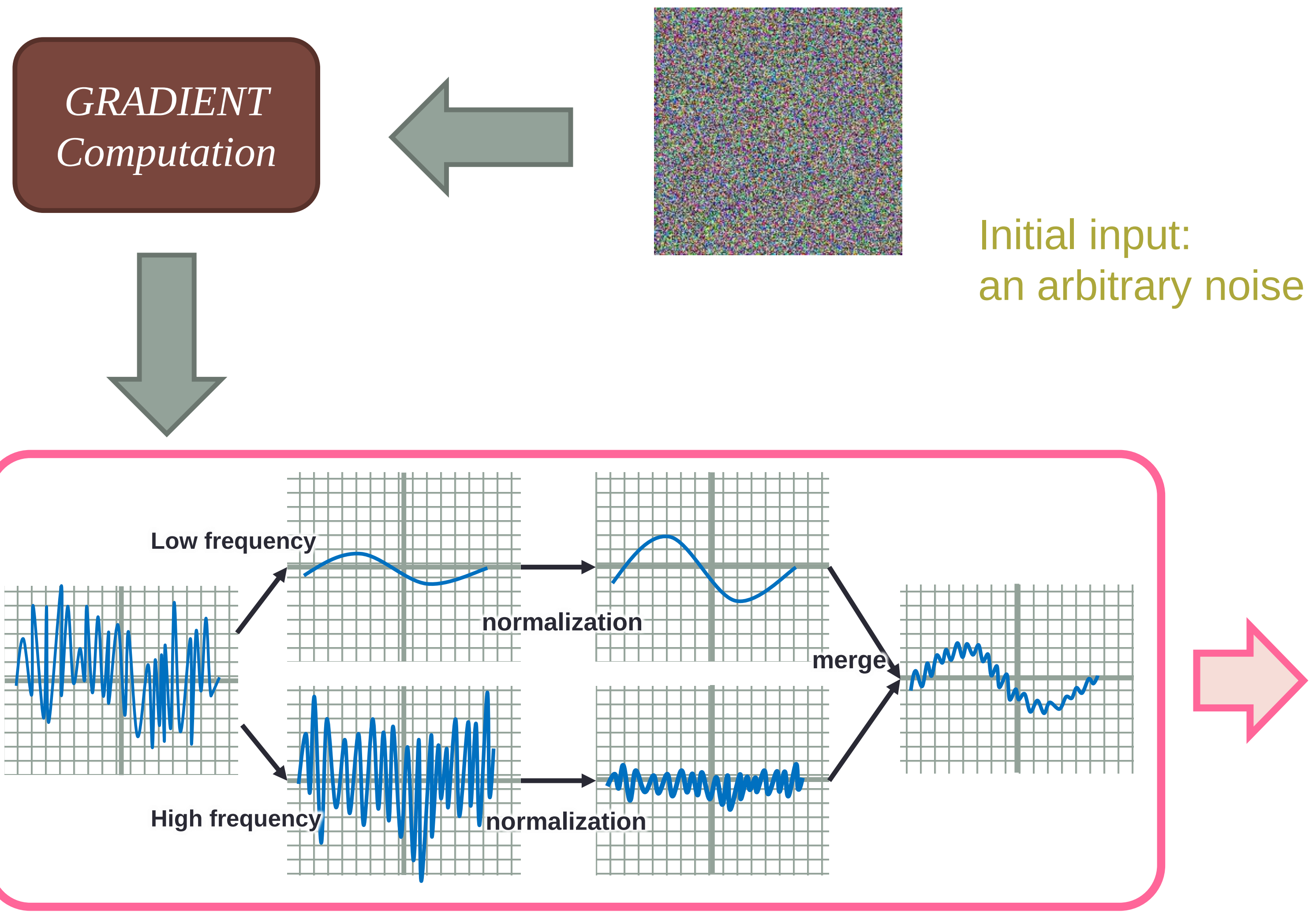




GoogLeNet

LOW/HIGH FREQUENCY NORMALIZATION

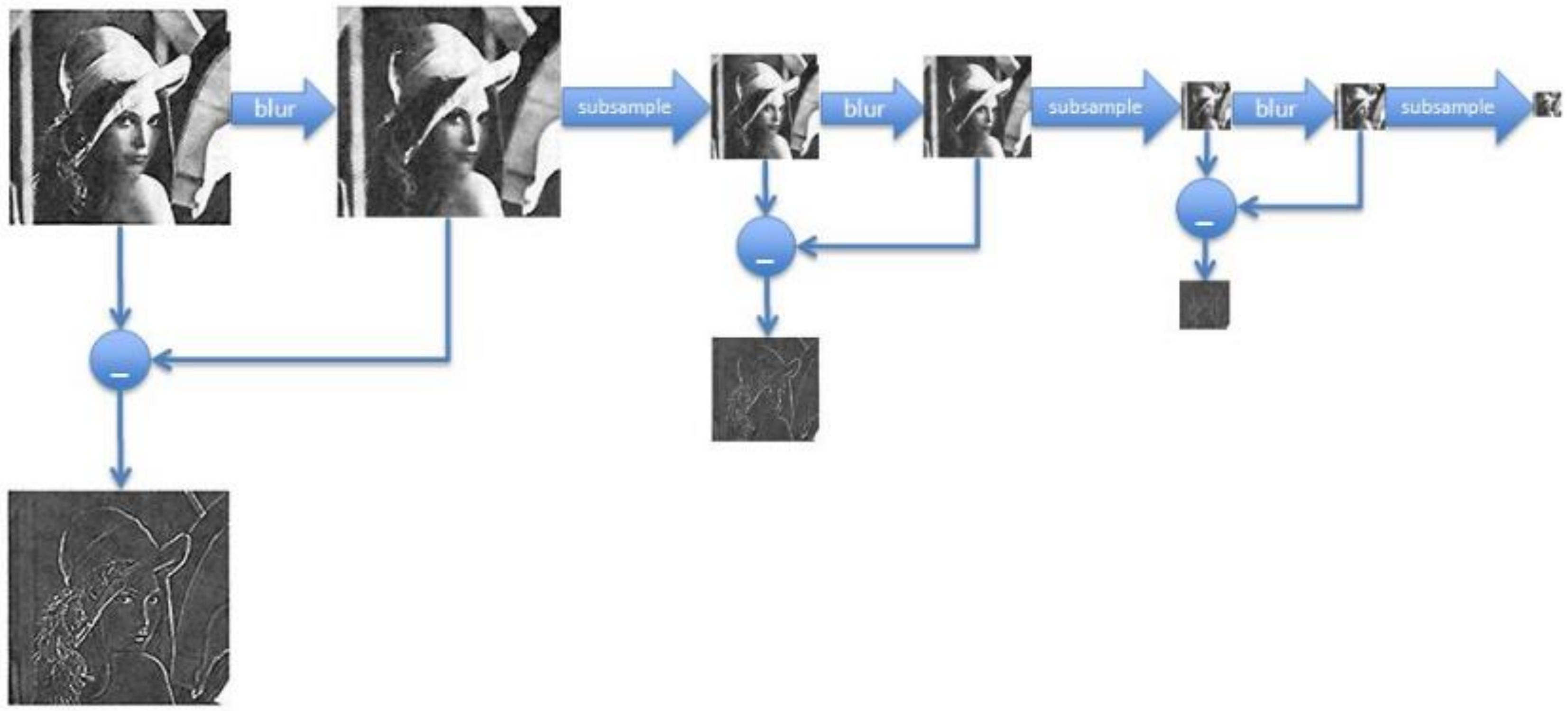
Gradient normalization



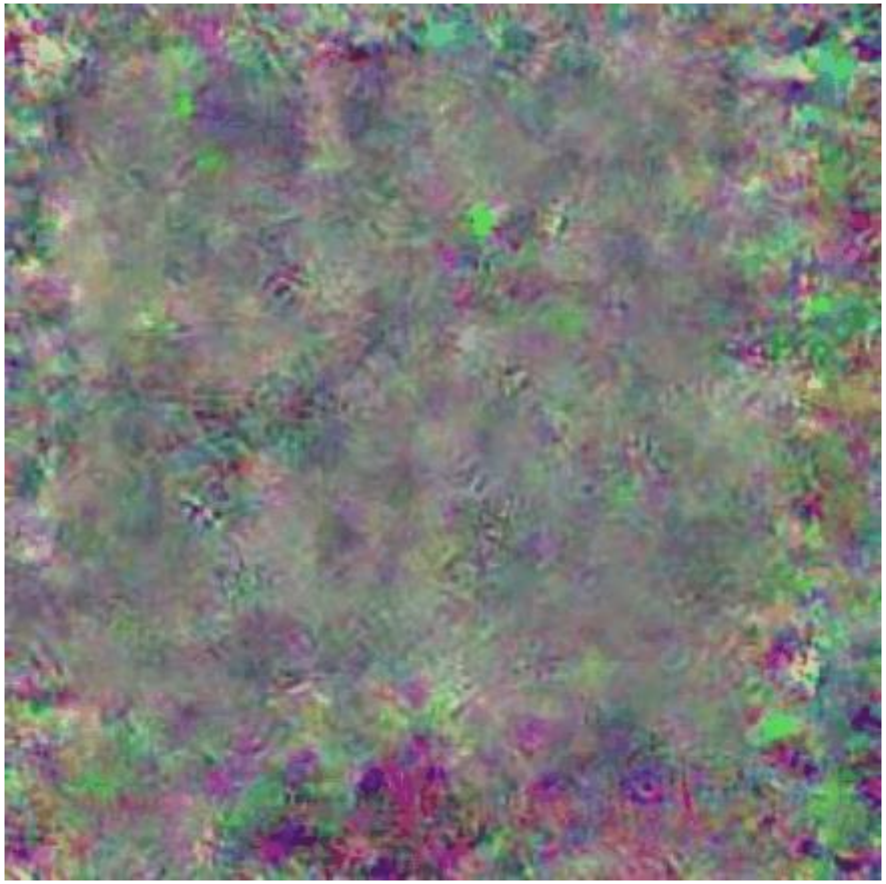
Initial input:
an arbitrary noise image

Normalized gradient

Laplacian pyramid

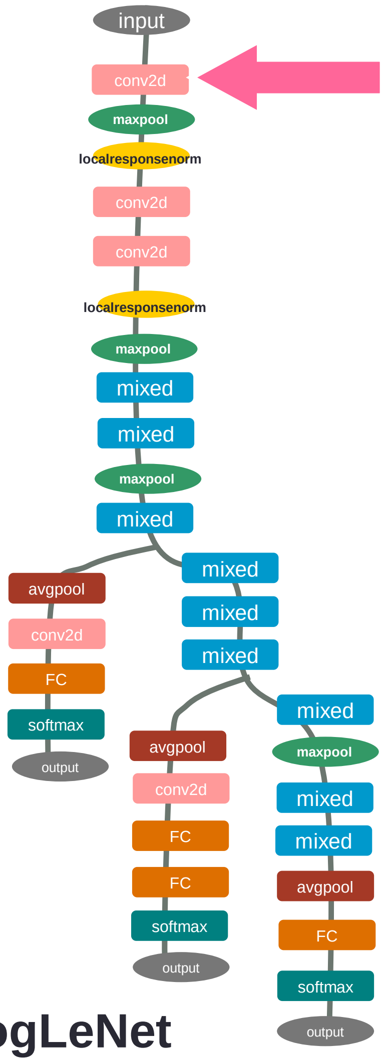


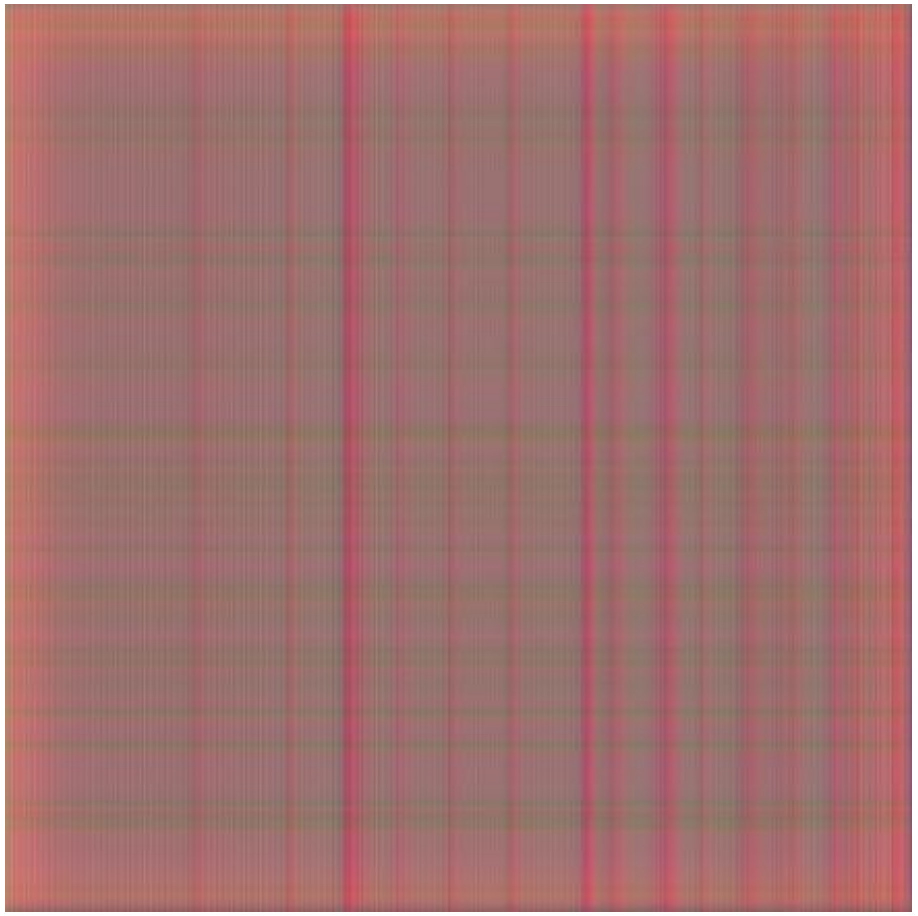
Convergence example



L=102.42

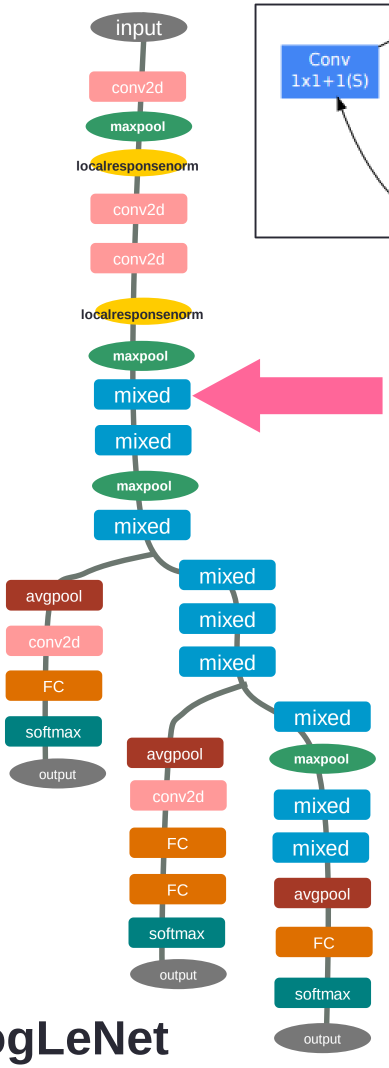
Result of Laplacian pyramid method

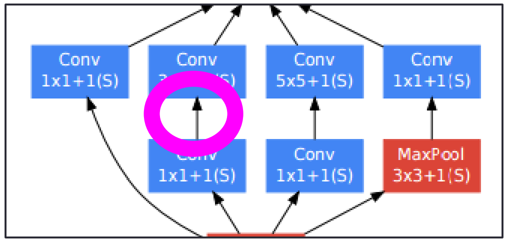


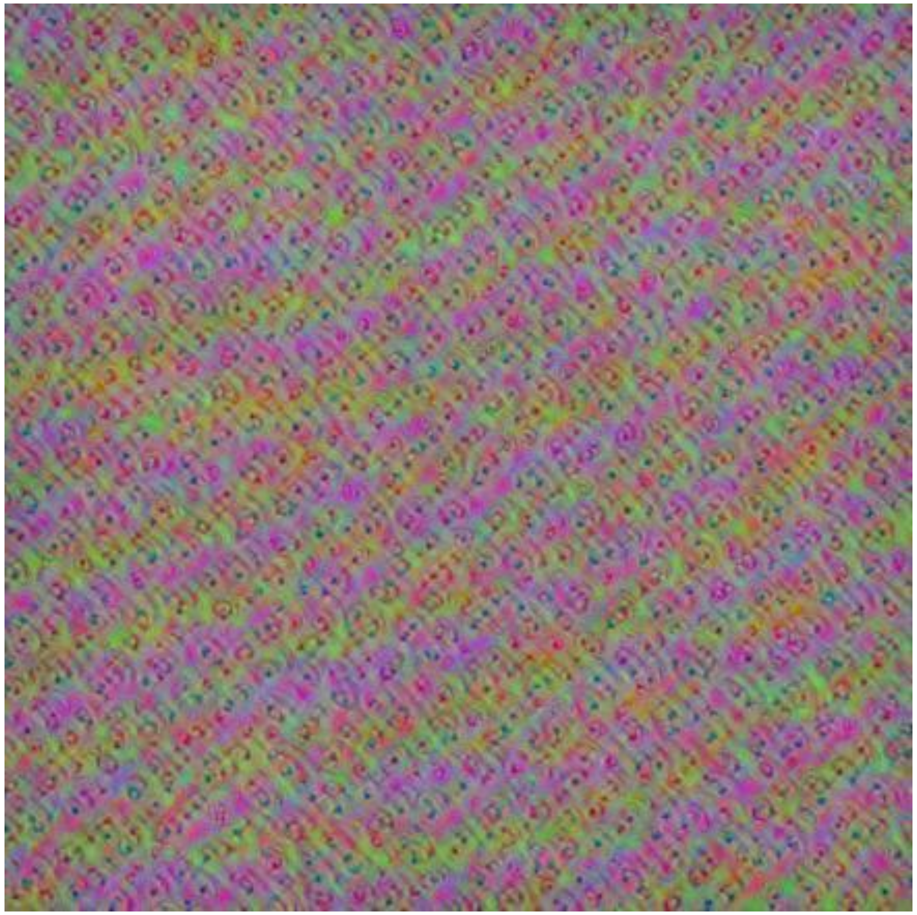


GoogLeNet

Result of Laplacian pyramid method

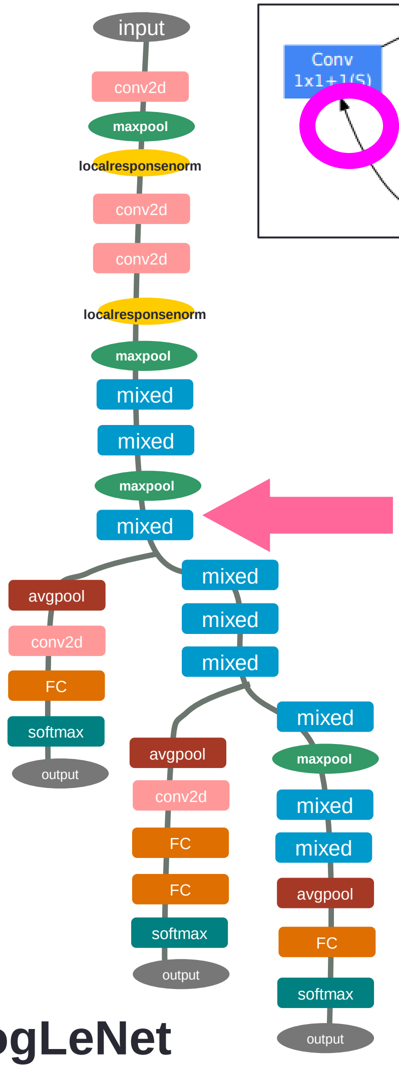


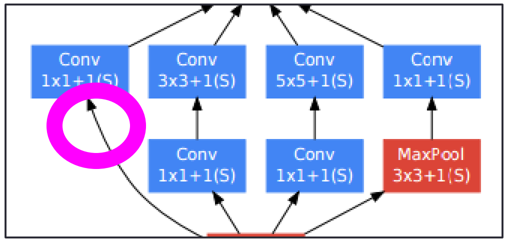


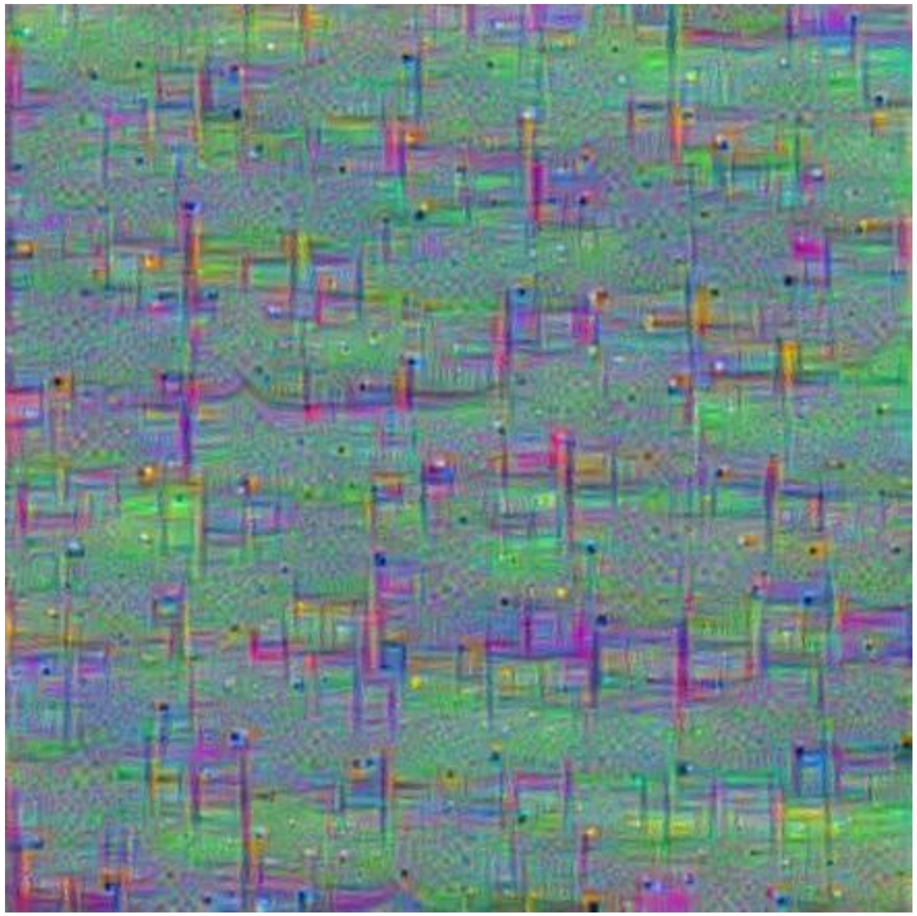


GoogLeNet

Result of Laplacian pyramid method

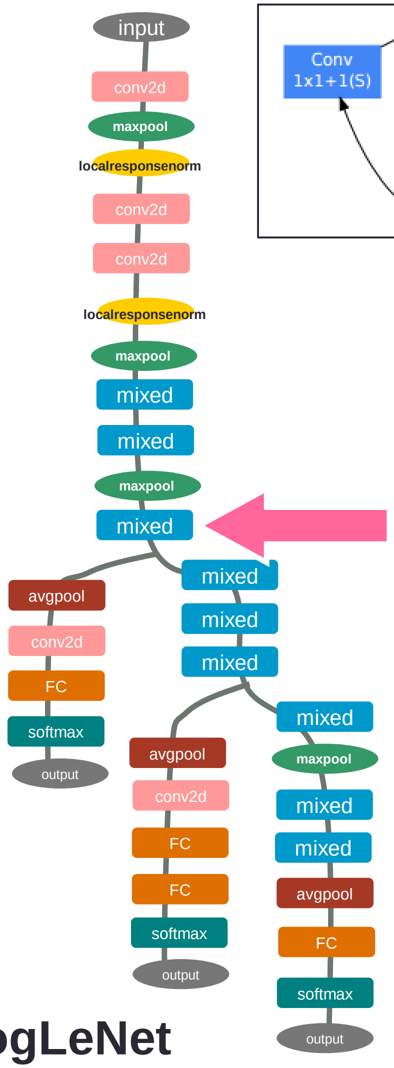


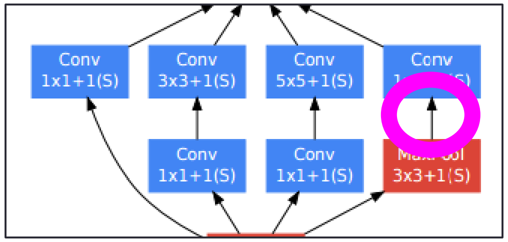


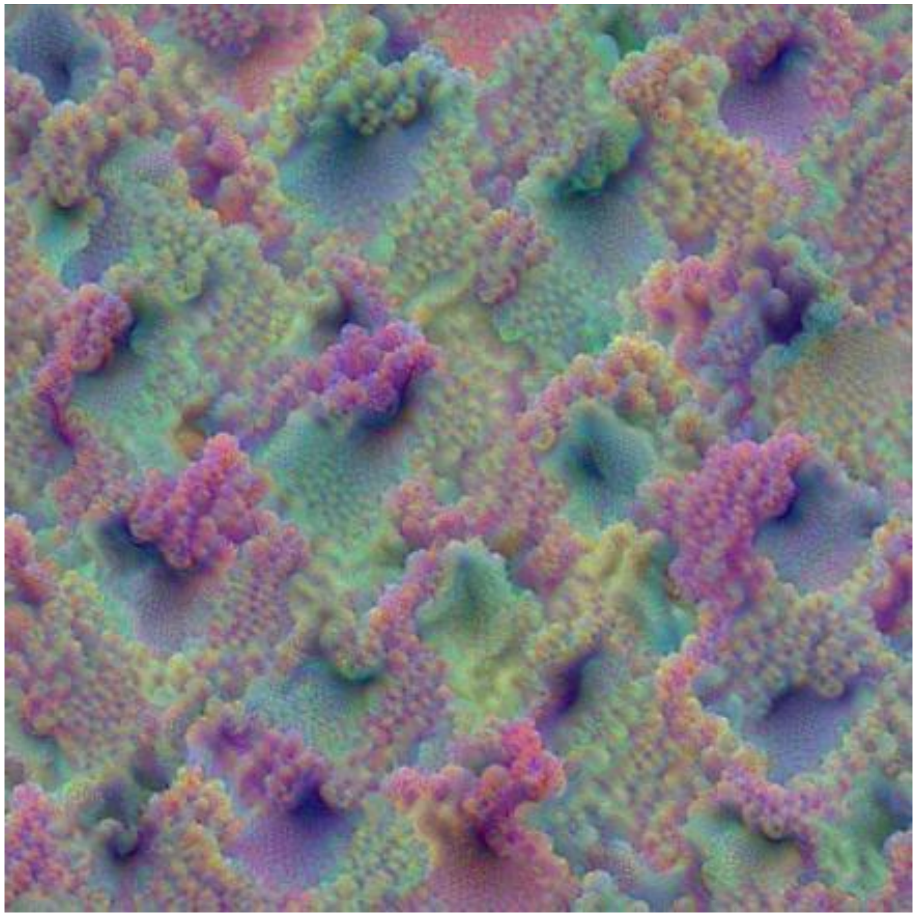


GoogLeNet

Result of Laplacian pyramid method

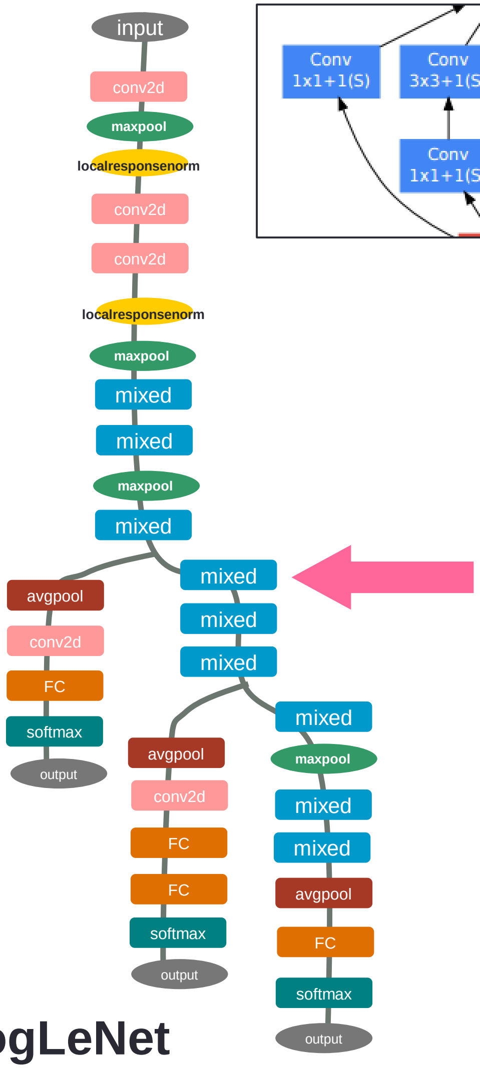


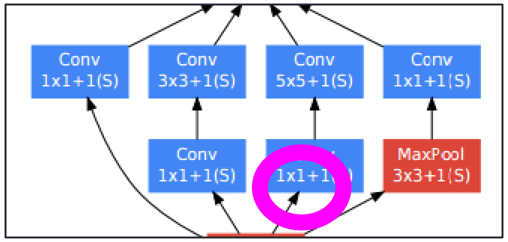


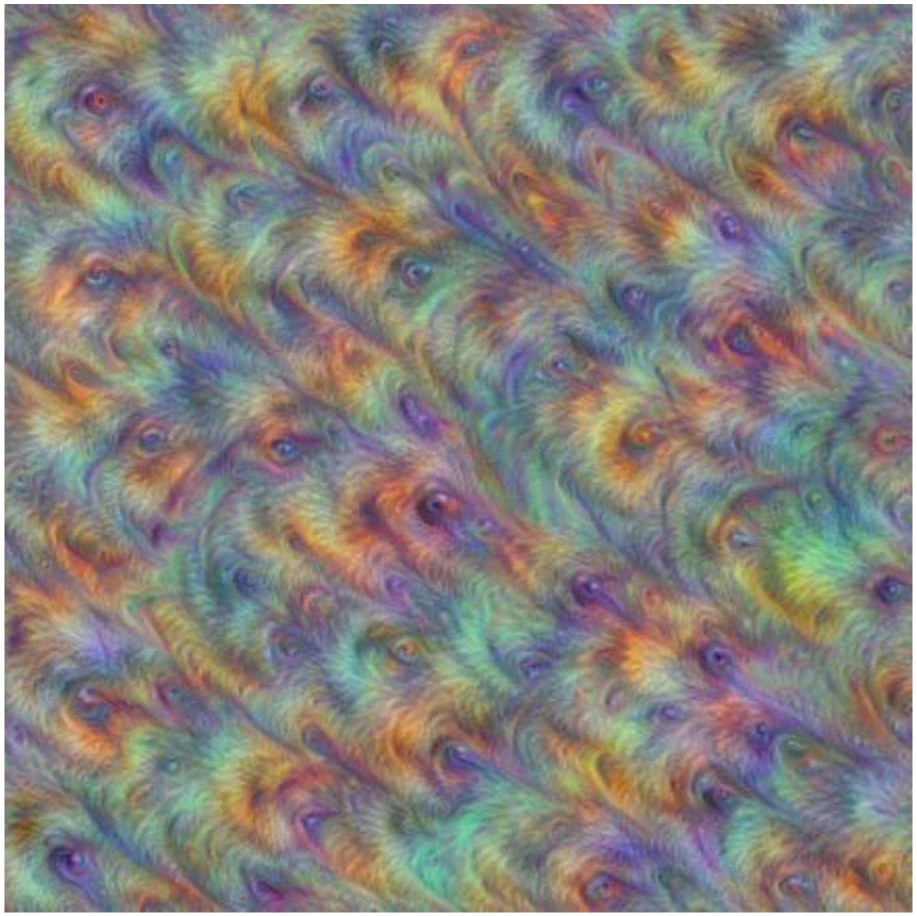


GoogLeNet

Result of Laplacian pyramid method

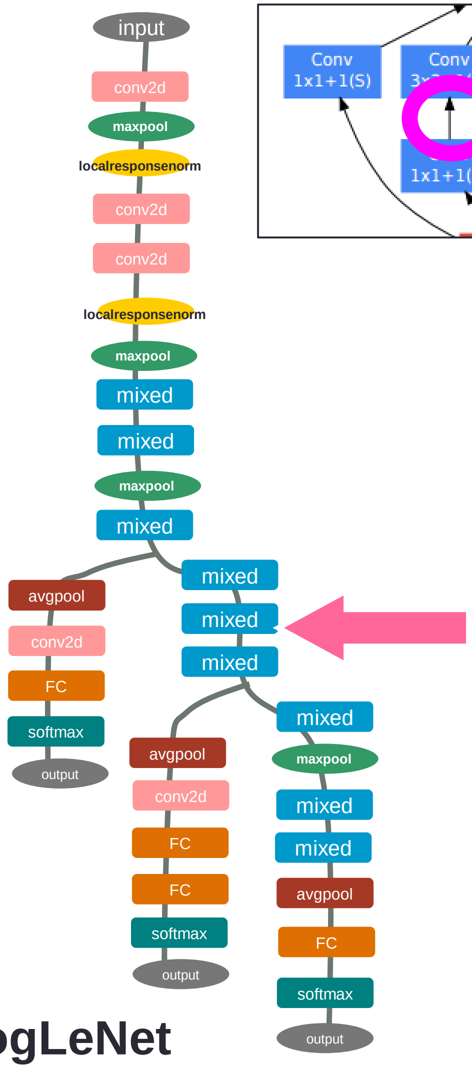


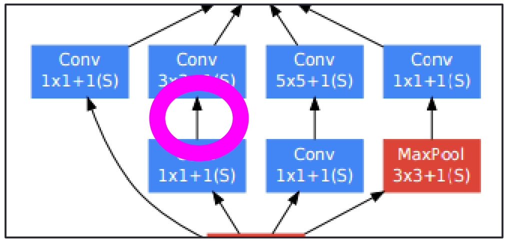


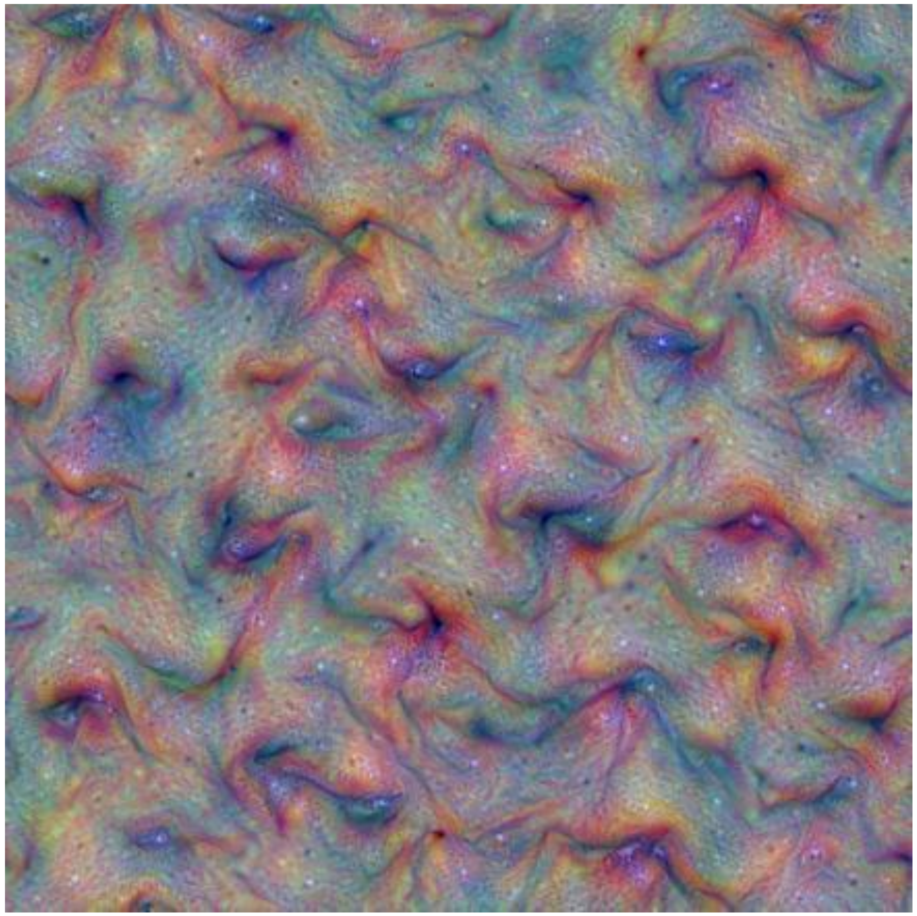


GoogLeNet

Result of Laplacian pyramid method

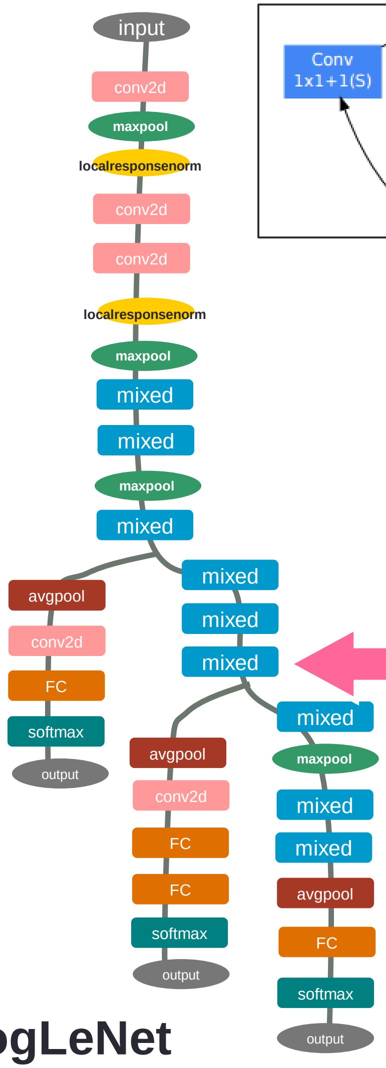


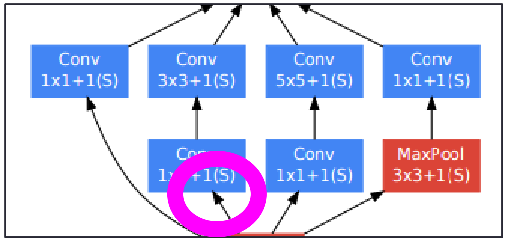


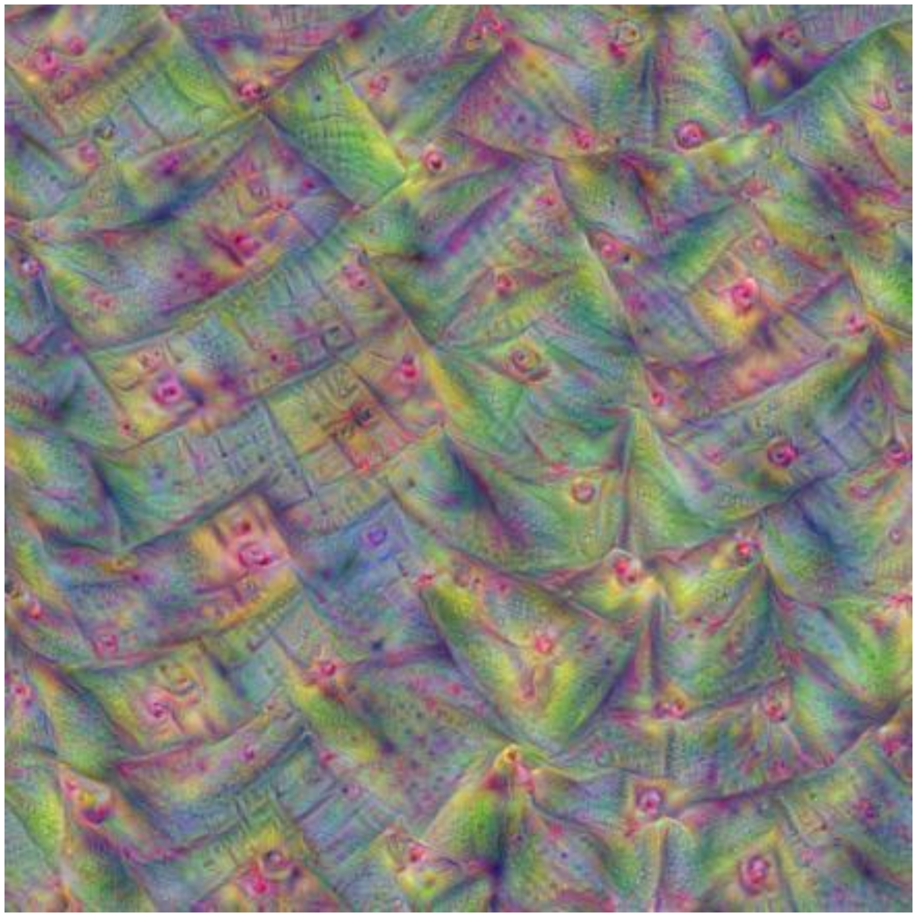


GoogLeNet

Result of Laplacian pyramid method

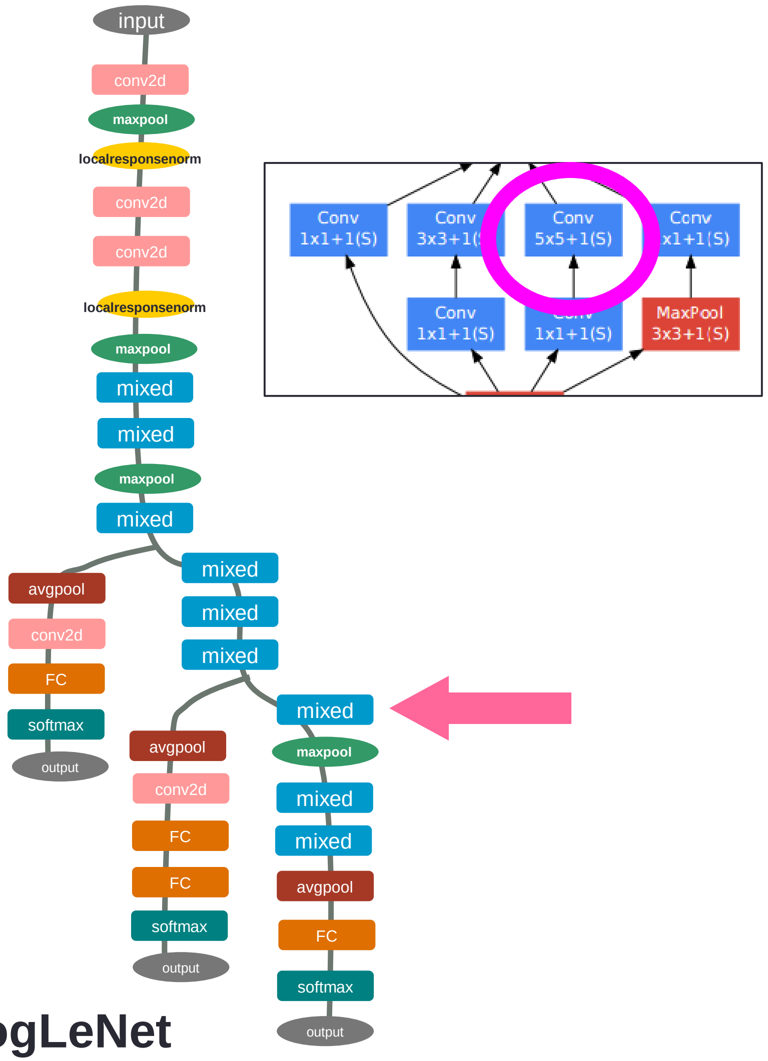


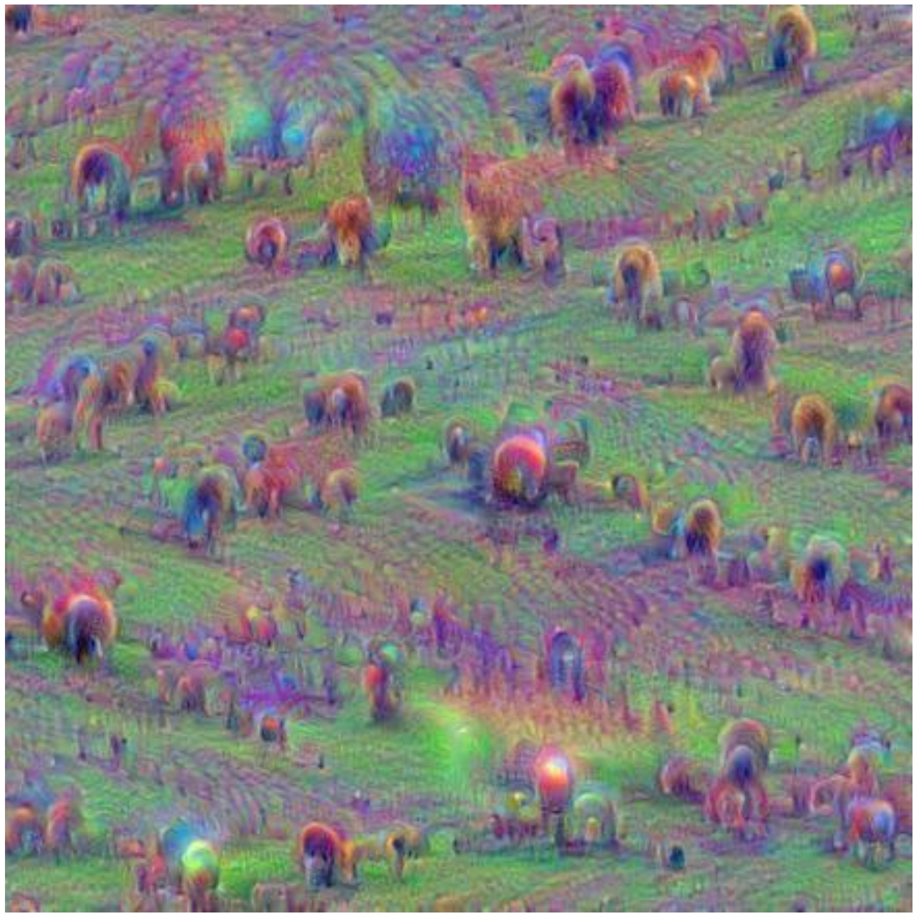




GoogLeNet

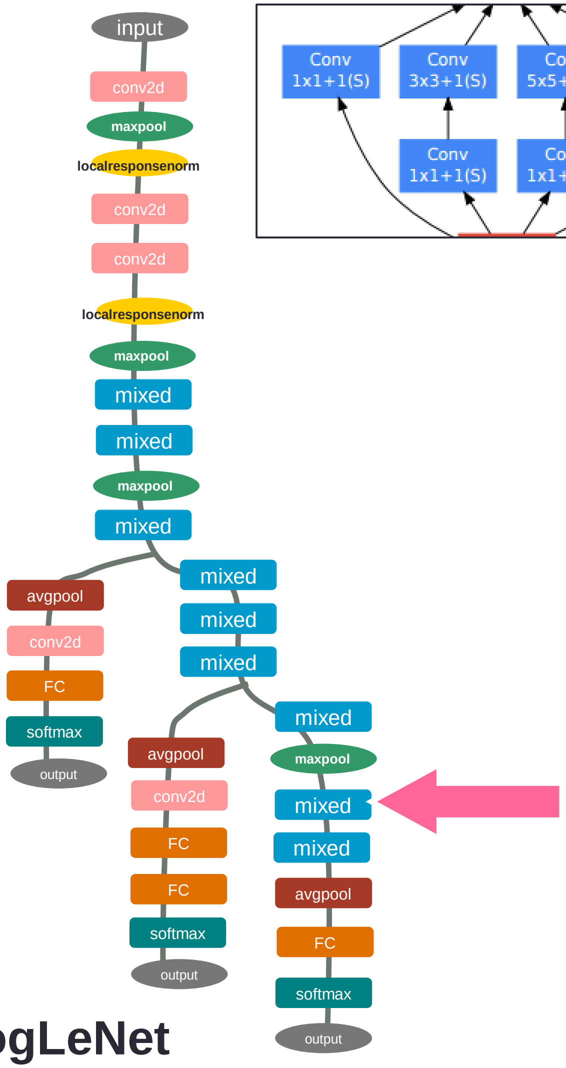
Result of Laplacian pyramid method

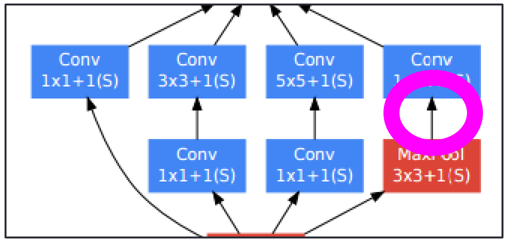


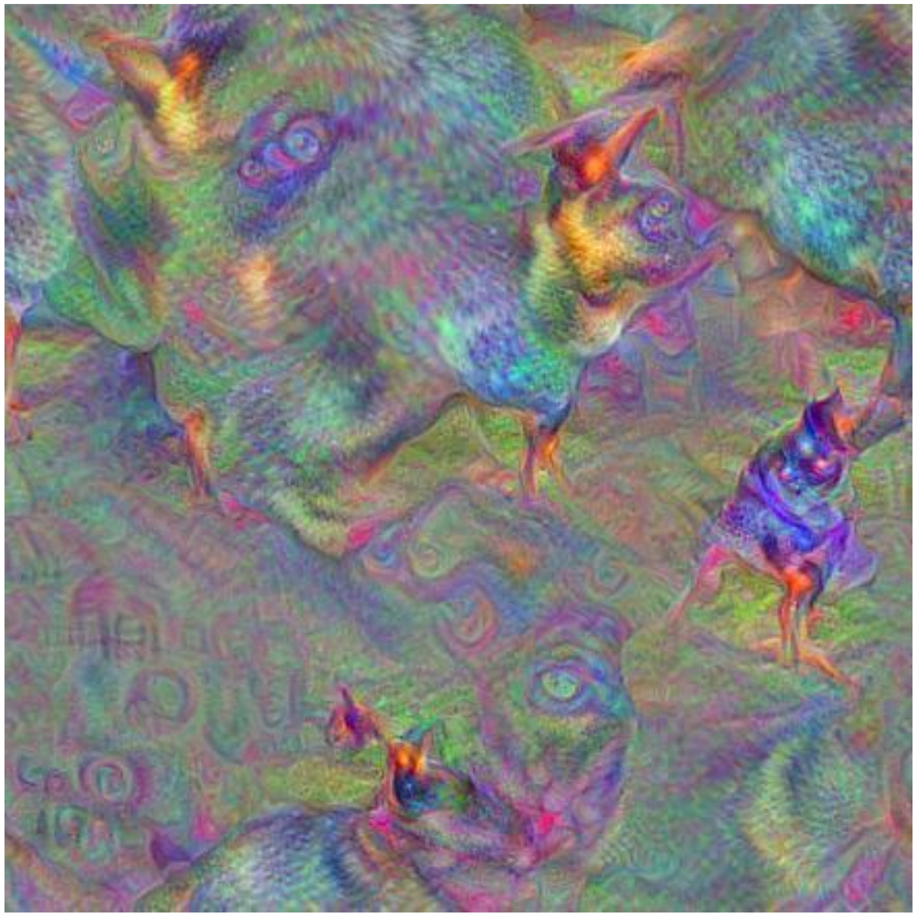


GoogLeNet

Result of Laplacian pyramid method

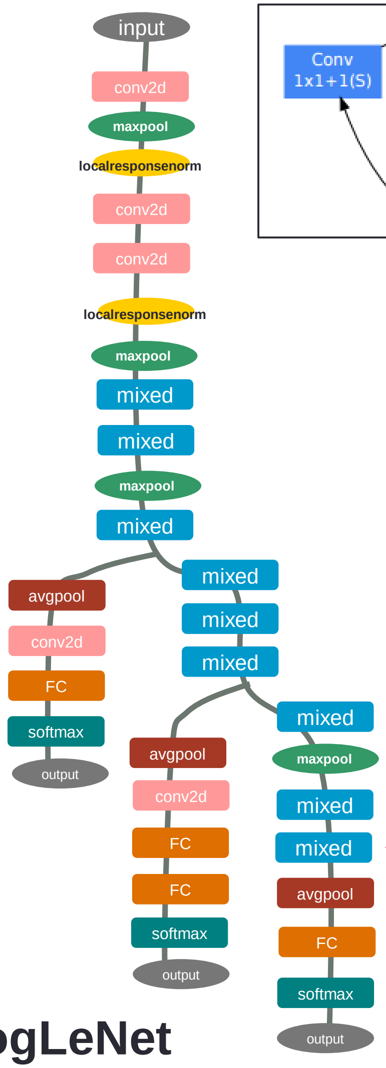


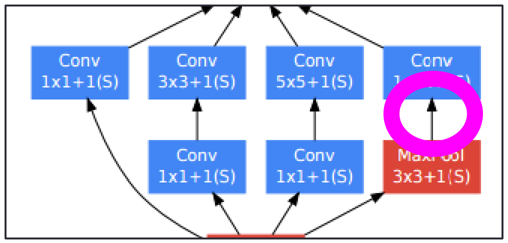


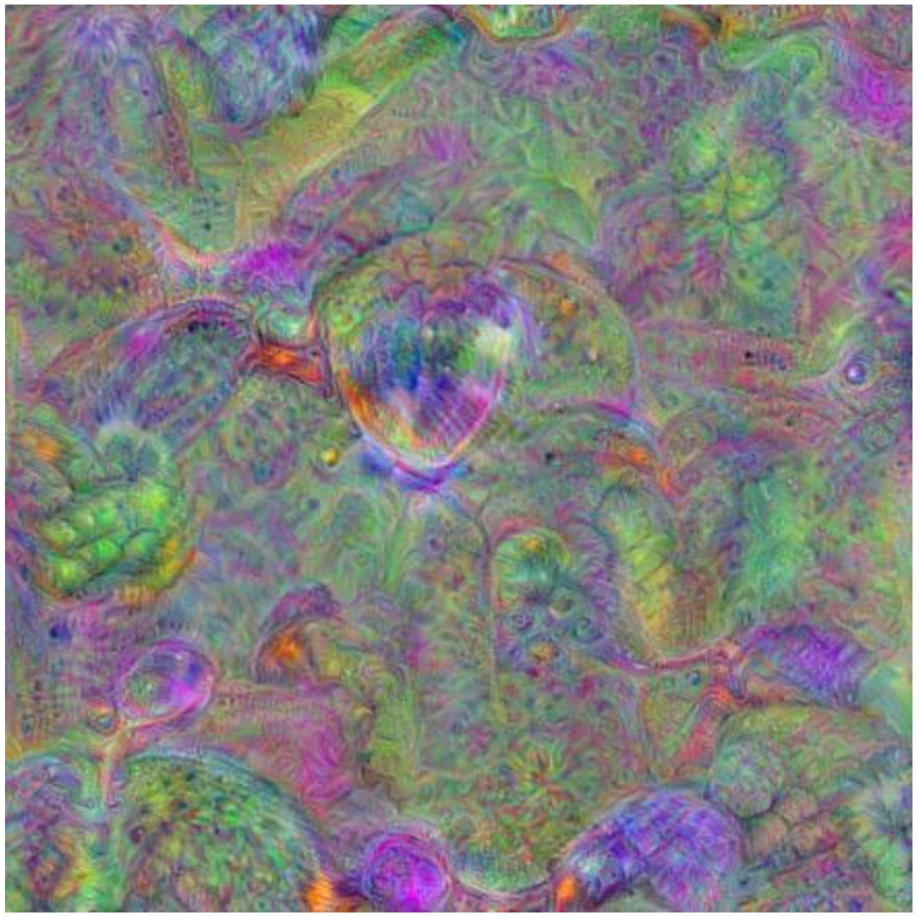


GoogLeNet

Result of Laplacian pyramid method.

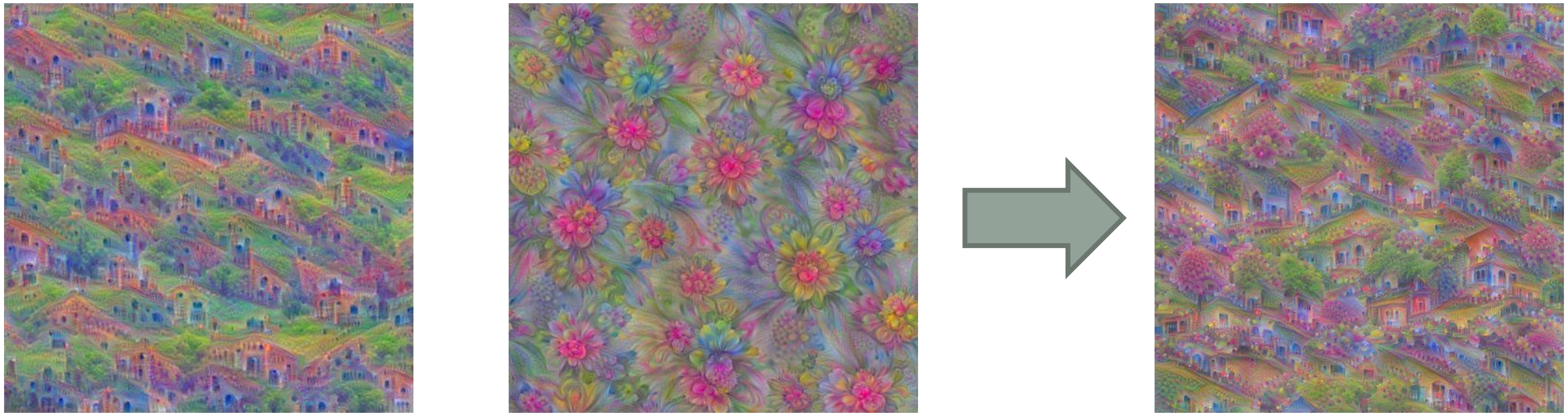


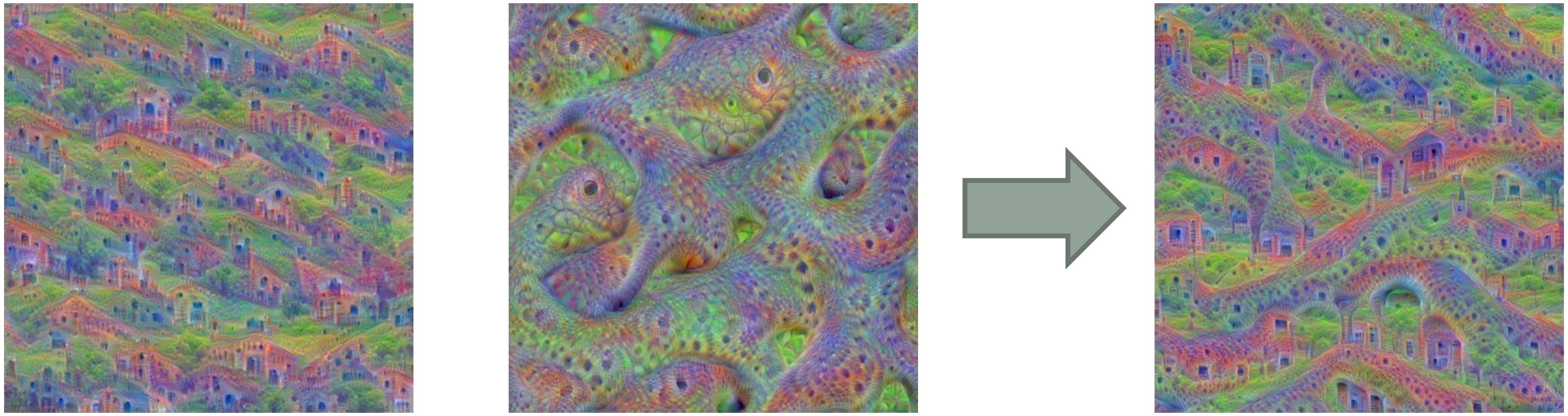




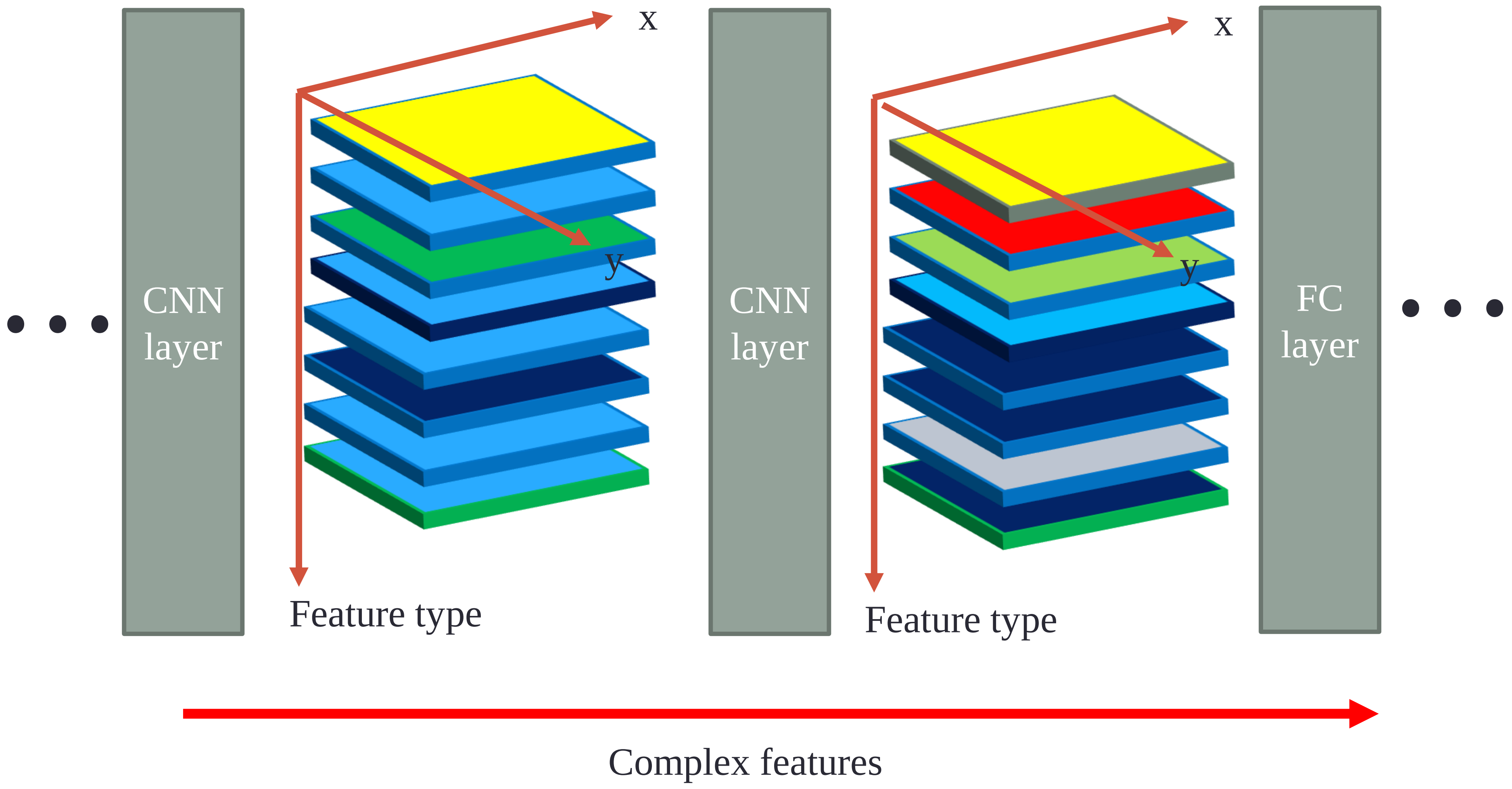
GoogLeNet

Results with two channels





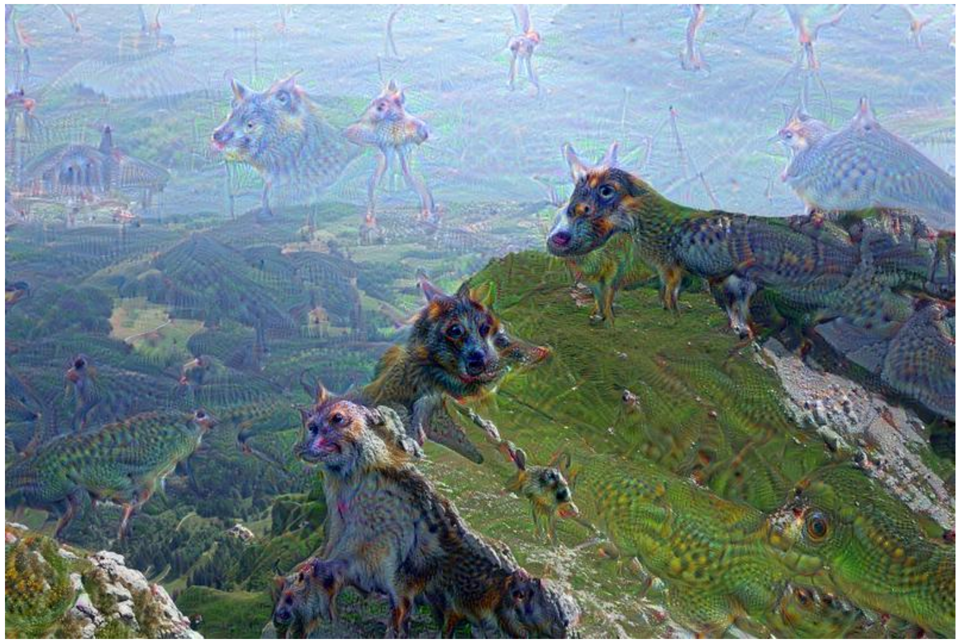
Summary


• • •
CNN layer
x
y
Feature type
CNN layer
x
y
Feature type
FC layer
• • •
Complex features

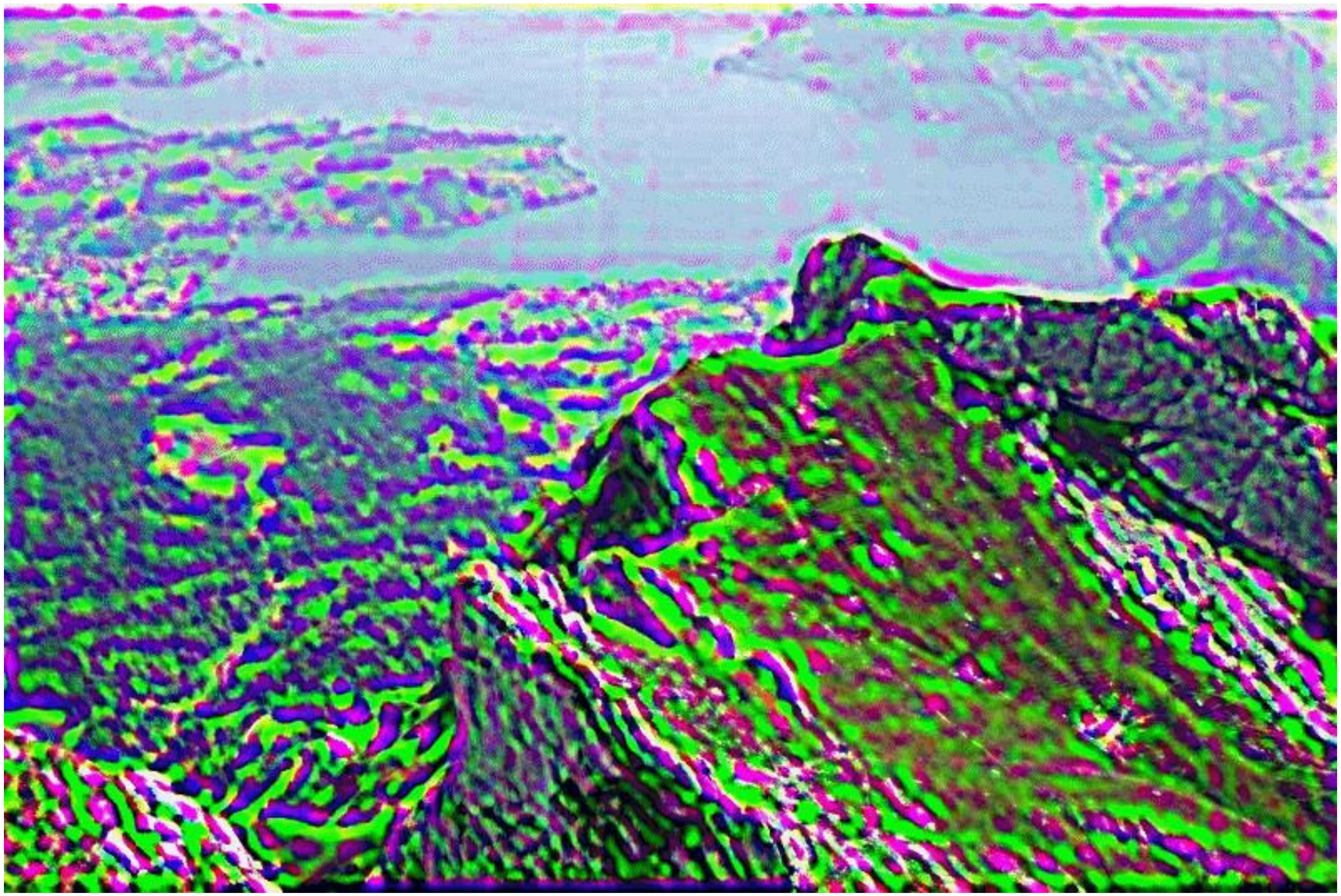
DEEPDREAM

DeepDream

- Square cost function
  - $(1+1)^2$ vs 1^2
  - $(100+1)^2$ vs 100^2



Examples (all feature maps in a layer)



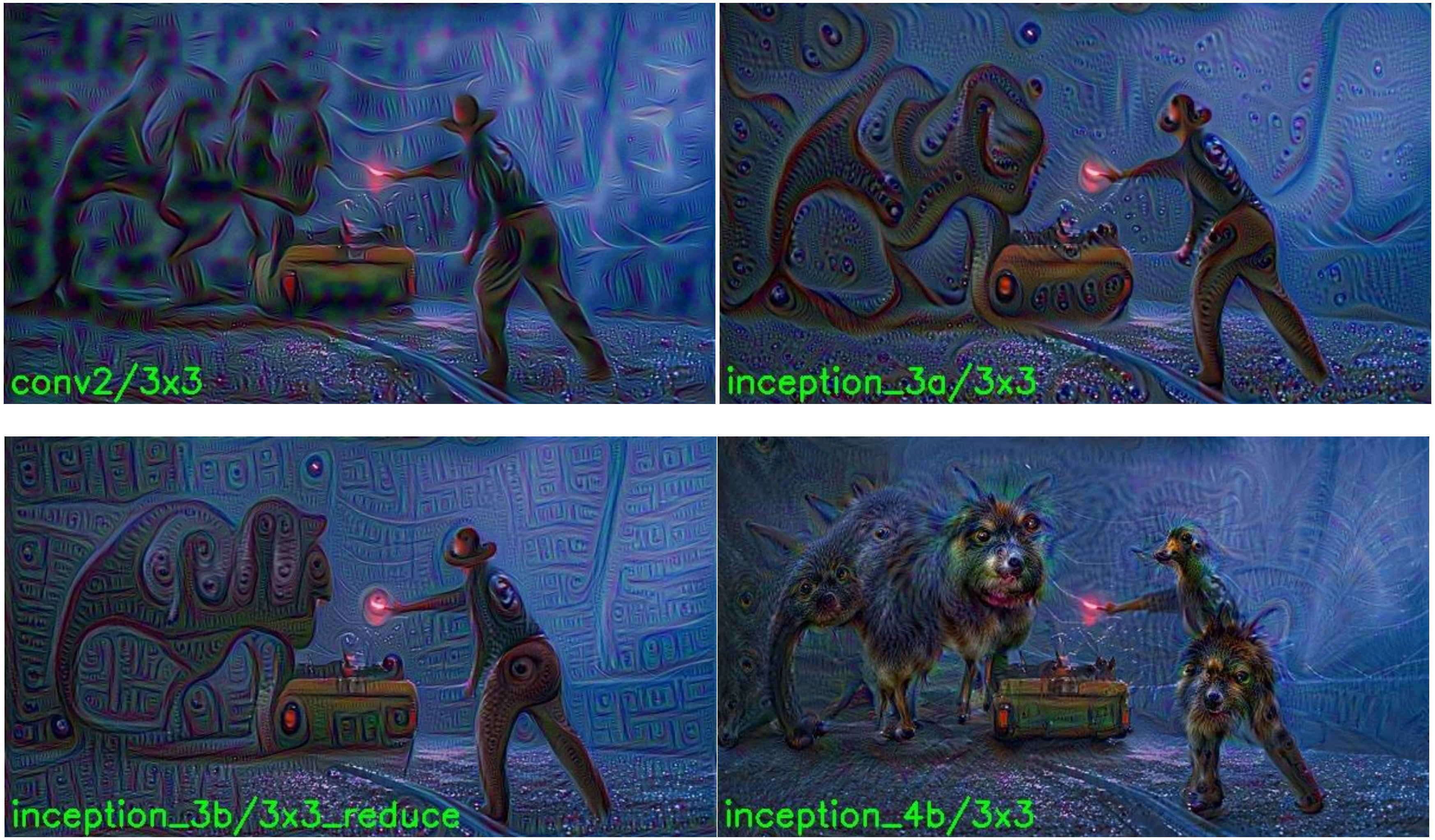
DeepDream example

http://www.pyimagesearch.com/2015/08/03/deep-dream-visualizing-every-layer-of-googlenet/

DeepDream example

conv1/7x7_s2

http://www.pyimagesearch.com/2015/08/03/deep-dream-visualizing-every-layer-of-googlenet/



http://www.pyimagesearch.com/2015/08/03/deep-dream-visualizing-every-layer-of-googlenet/

TOPICS IN CNN

COMPARISON

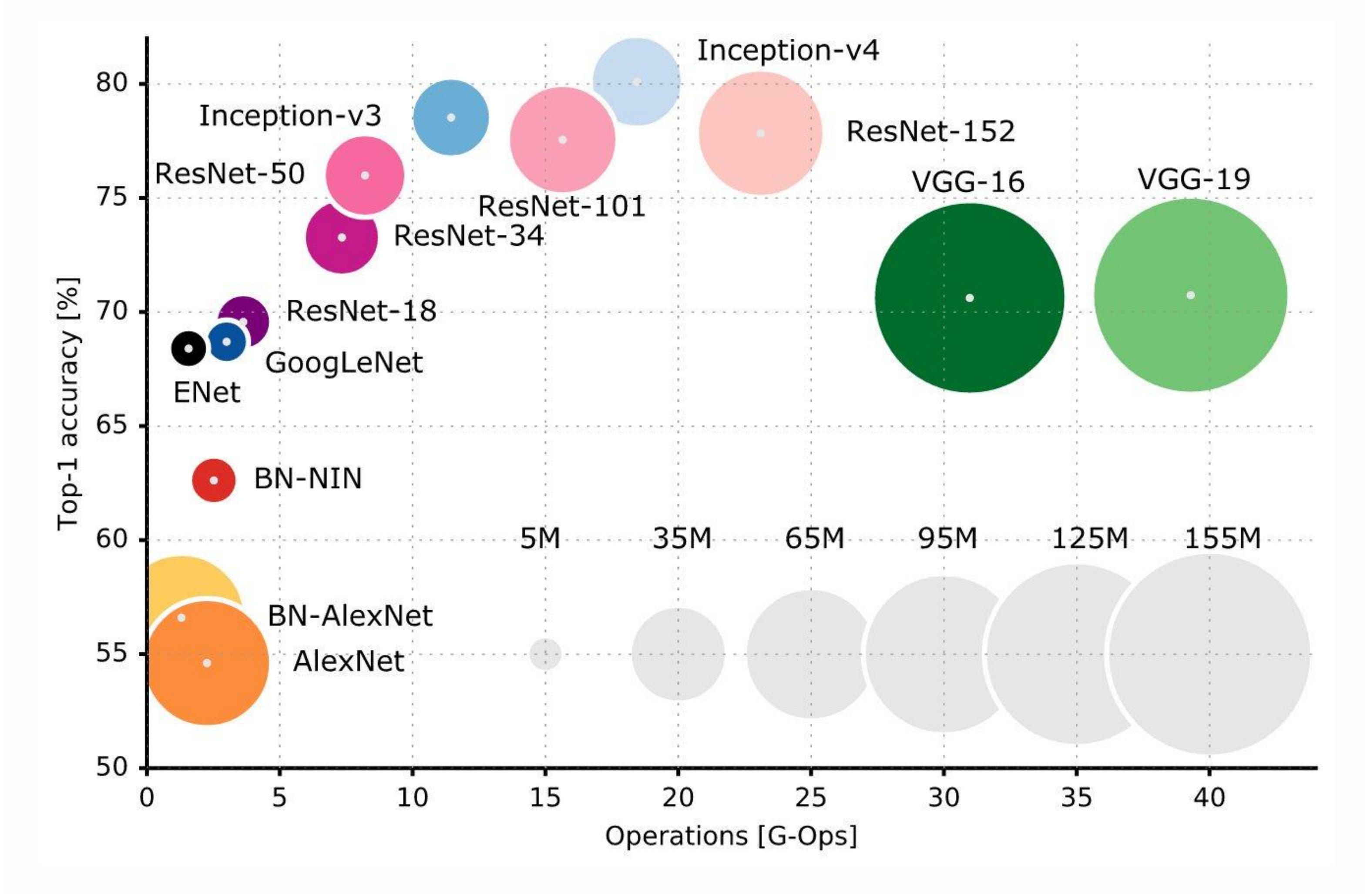
AlexNet VS VGG-19 VS GoogLeNet

	Parameters	Operations (MACs)	*Top-1 accuracy (%)	*Top-5 accuracy %
AlexNet	60 M	832 M	56.9	80.1
VGG-19	144 M	19,632 M	68.5	88.5
GoogLeNet	6.8 M	1,502 M	68.7	89.0

*Evaluated with ImageNet2012

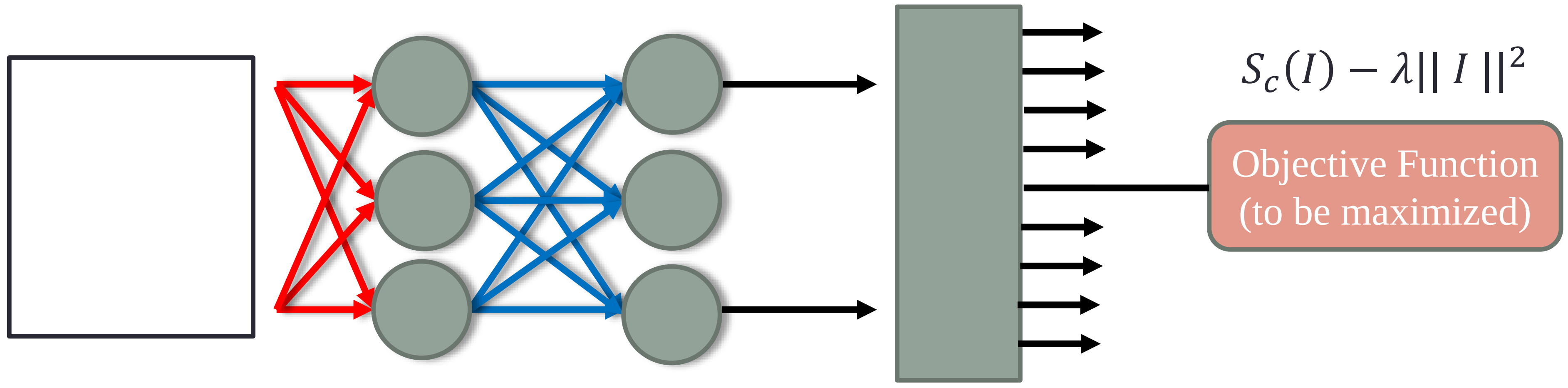
*https://github.com/BVLC/caffe/wiki/Models-accuracy-on-ImageNet-2012-val

Comparison


Top-1 accuracy [%]
Operations [G-Ops]
Inception-v4
Inception-v3
ResNet-152
ResNet-50
ResNet-101
ResNet-34
VGG-16
VGG-19
ResNet-18
GoogLeNet
ENet
BN-NIN
BN-AlexNet
AlexNet
5M
35M
65M
95M
125M
155M
80
75
70
65
60
55
50
0
5
10
15
20
25
30
35
40

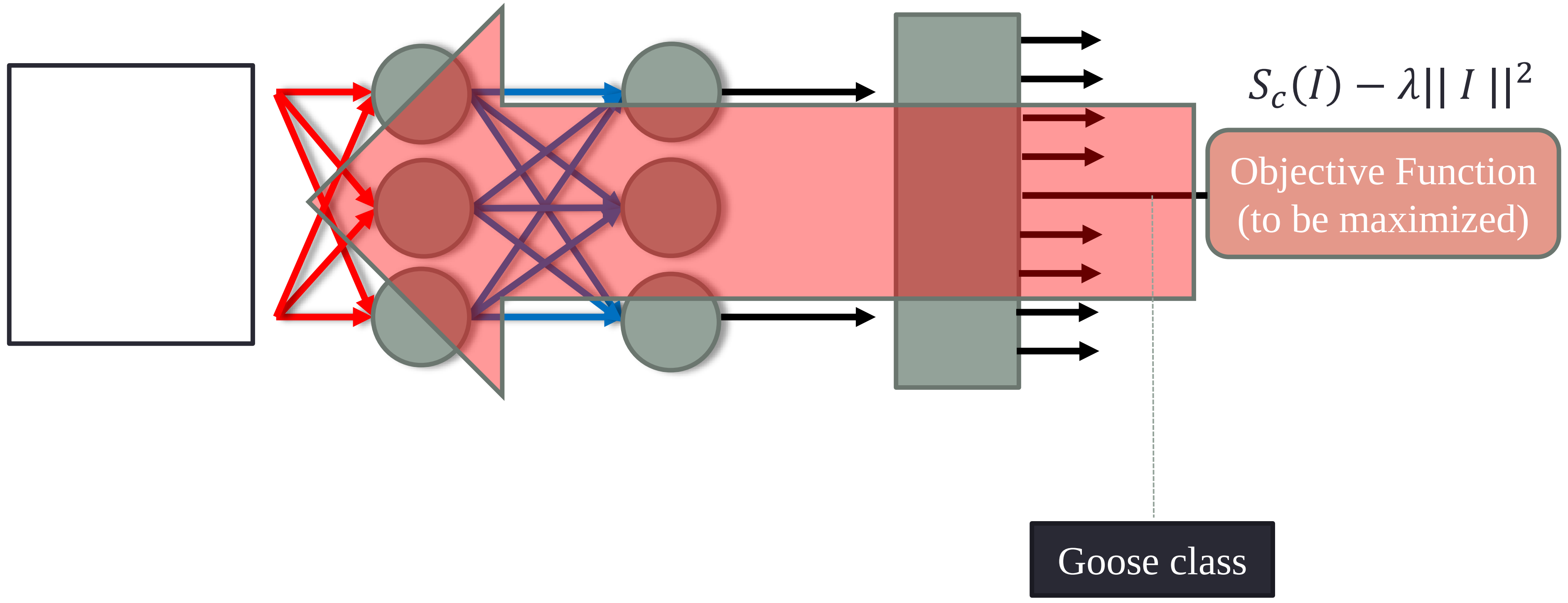
VISUALIZING IMAGE CLASSIFICATION MODEL

Inputs maximizing class score

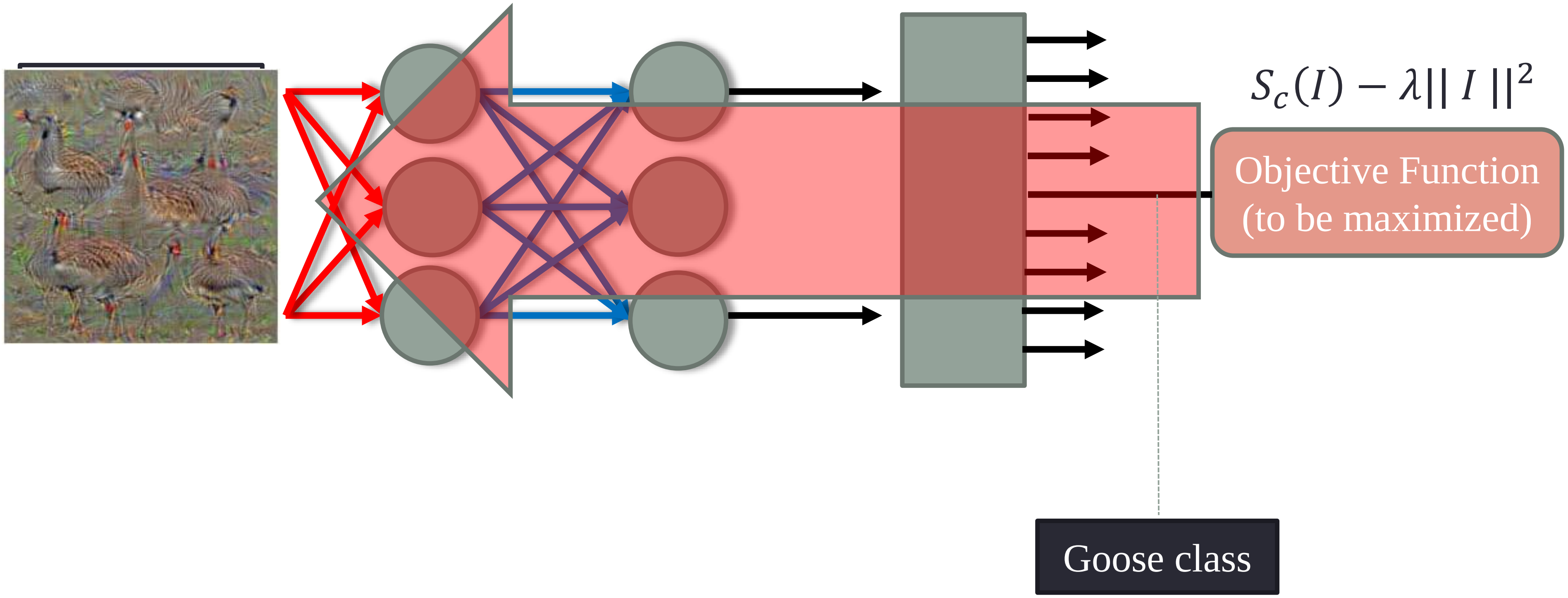

$S_c(I) - \lambda || I ||^2$

K. Simonyan, A. Vedaldi, A. Zisserman, "**Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps**", *ICLR Workshop 2014*

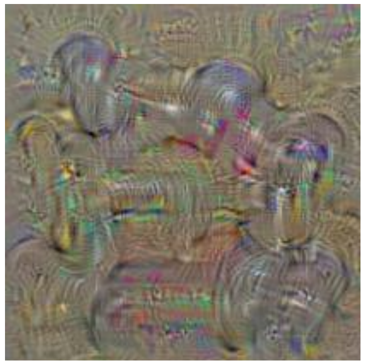
Inputs maximizing class score

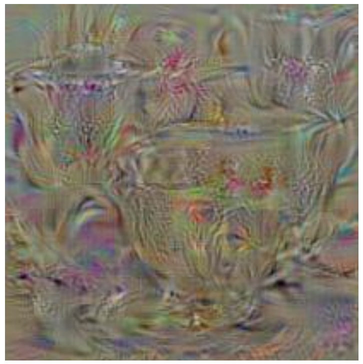

$S_c(I) - \lambda|| I ||^2$
Objective Function (to be maximized)
Goose class

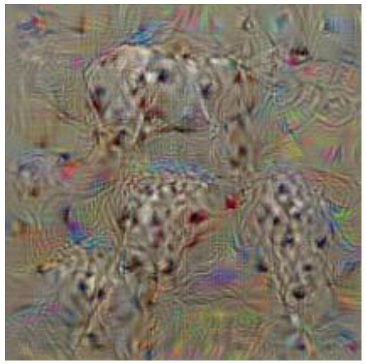
Maximizing class score

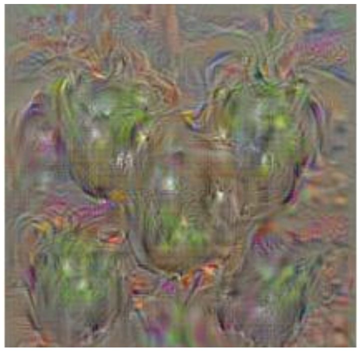

$S_c(I) - \lambda|| \, I \, ||^2$
Objective Function (to be maximized)
Goose class

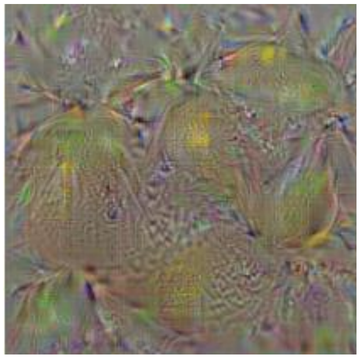
Inputs maximizing class score

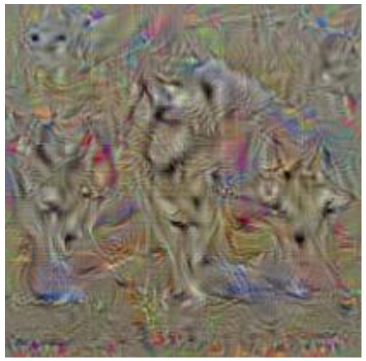

dumbbell


cup

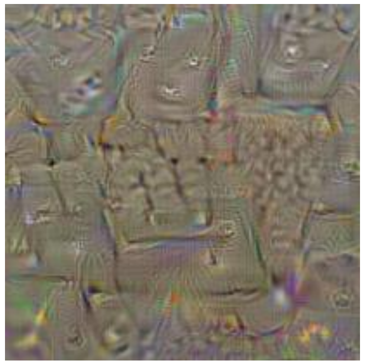

dalmatian

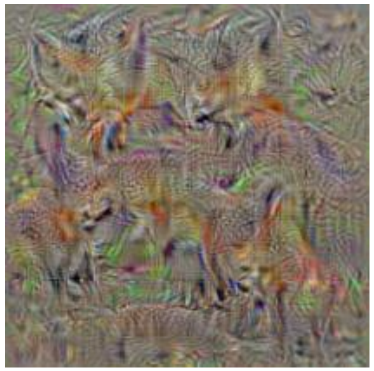

bell pepper

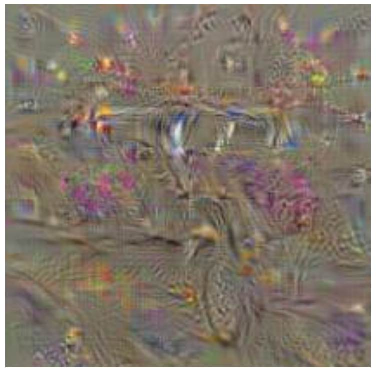

lemon

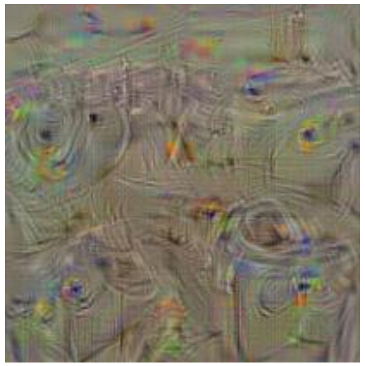

husky

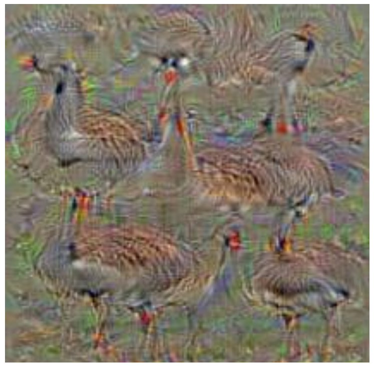
Inputs maximizing class score

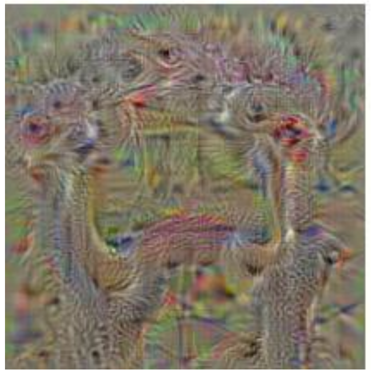

computer keyboard


kit fox


limousine


Washing machine


goose


ostrich

SALIENCY

Saliency visualization

- Linear score model for class c:

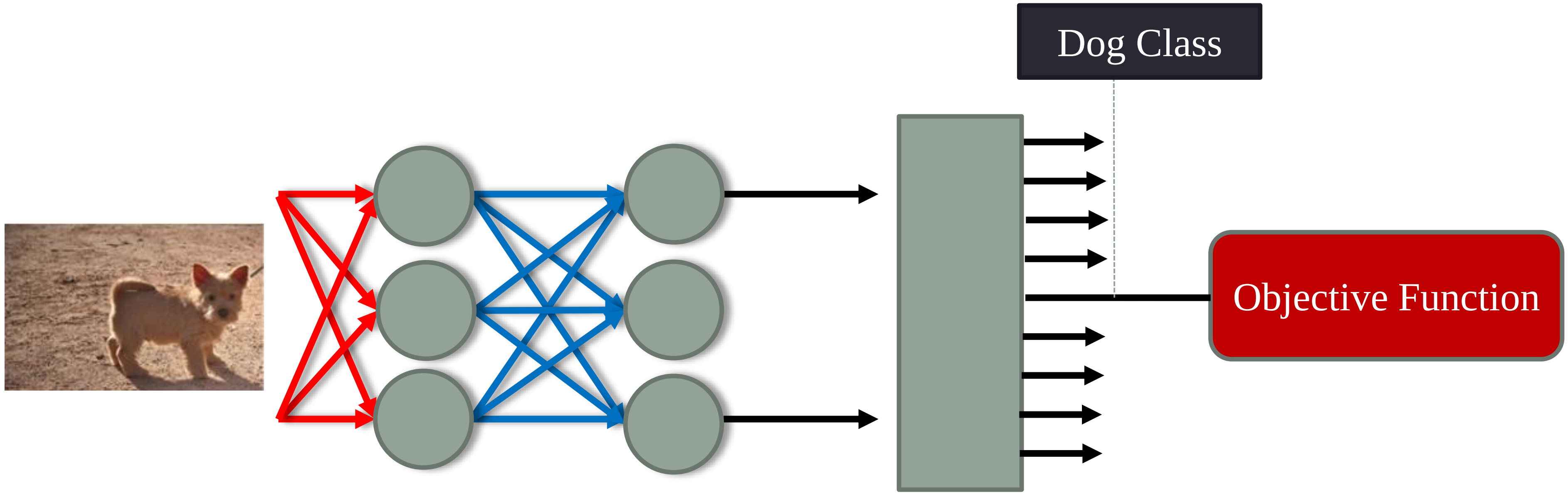
$$S_c(I) \approx wI + b$$

$$\Downarrow$$

$$w = \frac{\partial S_c}{\partial I}\bigg|_{I_0}$$

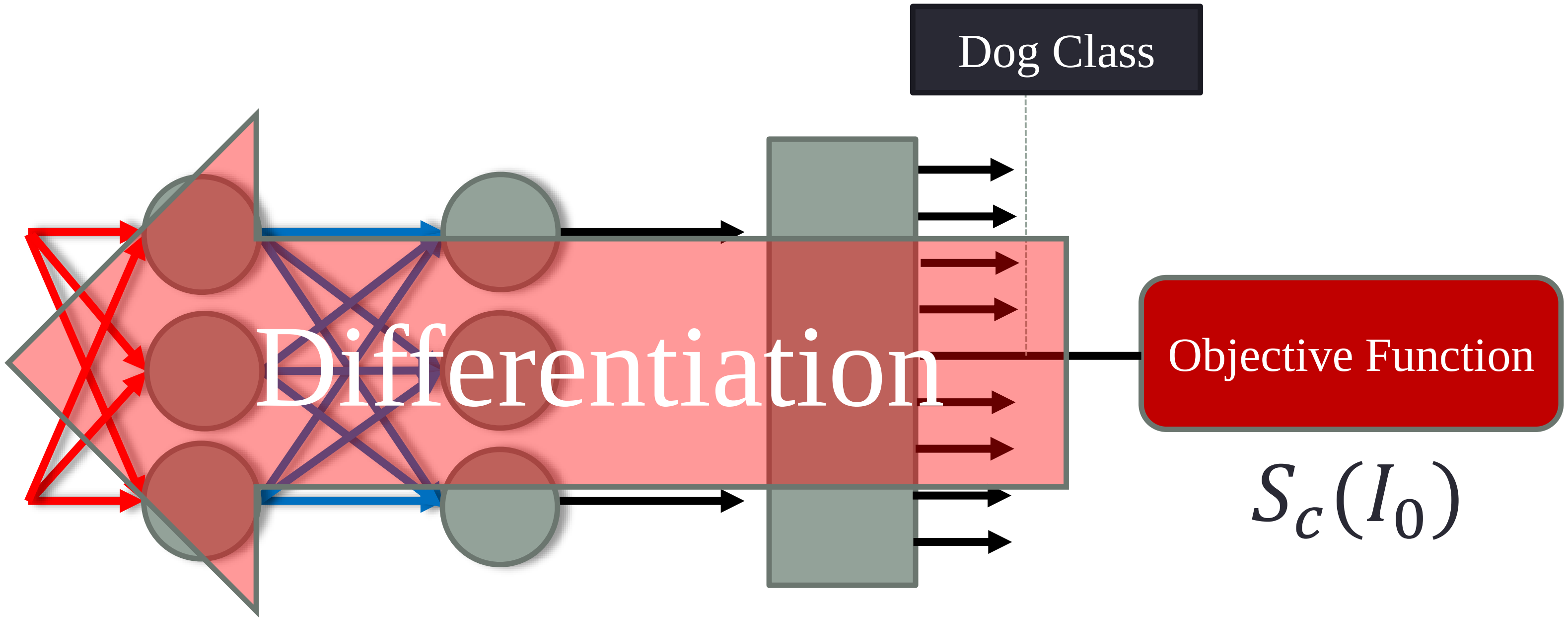
w : importance of corresponding pixels of I for class c

Saliency visualization



Saliency visualization

$$w = \frac{\partial S_c}{\partial I}\Big|_{I_0}$$



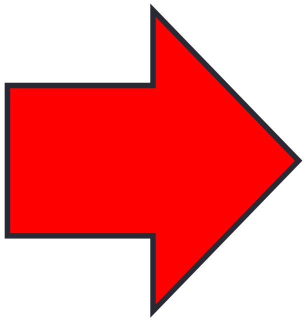
$S_c(I_0)$

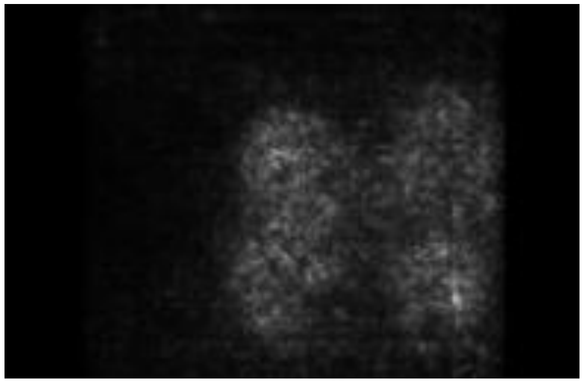
$I_0 =$

Saliency visualization

$I_0 =$

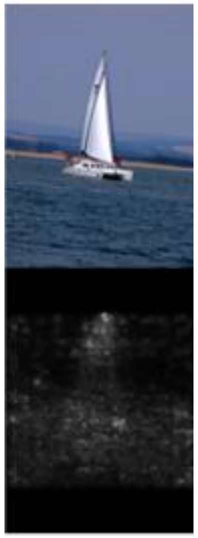
$$w = \frac{\partial S_c}{\partial I}\bigg|_{I_0}$$



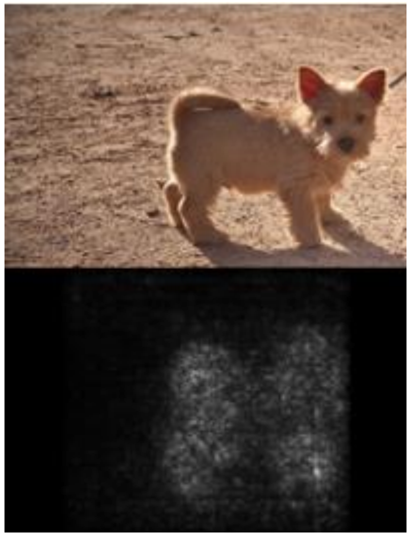


saliency map

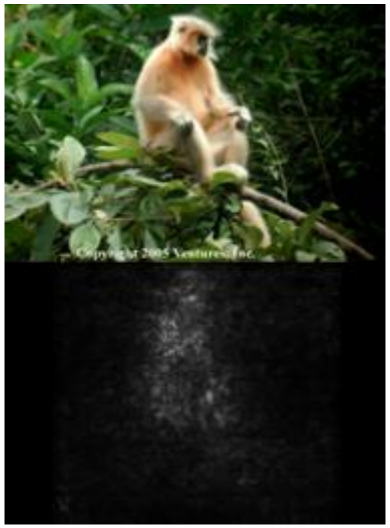
yacht



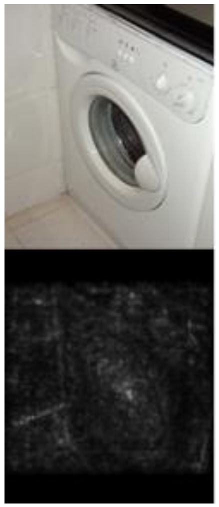
dog



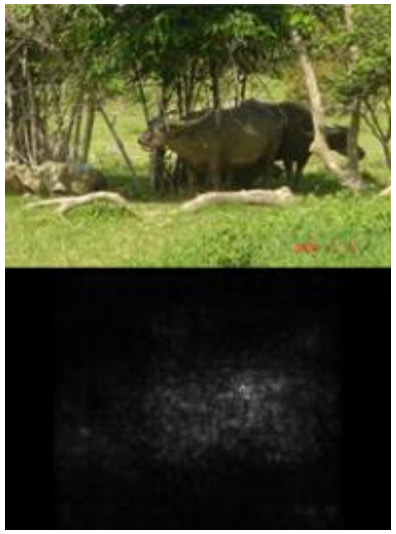
monkey



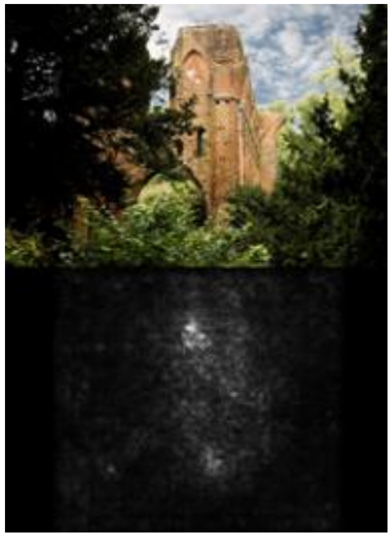
washing machine



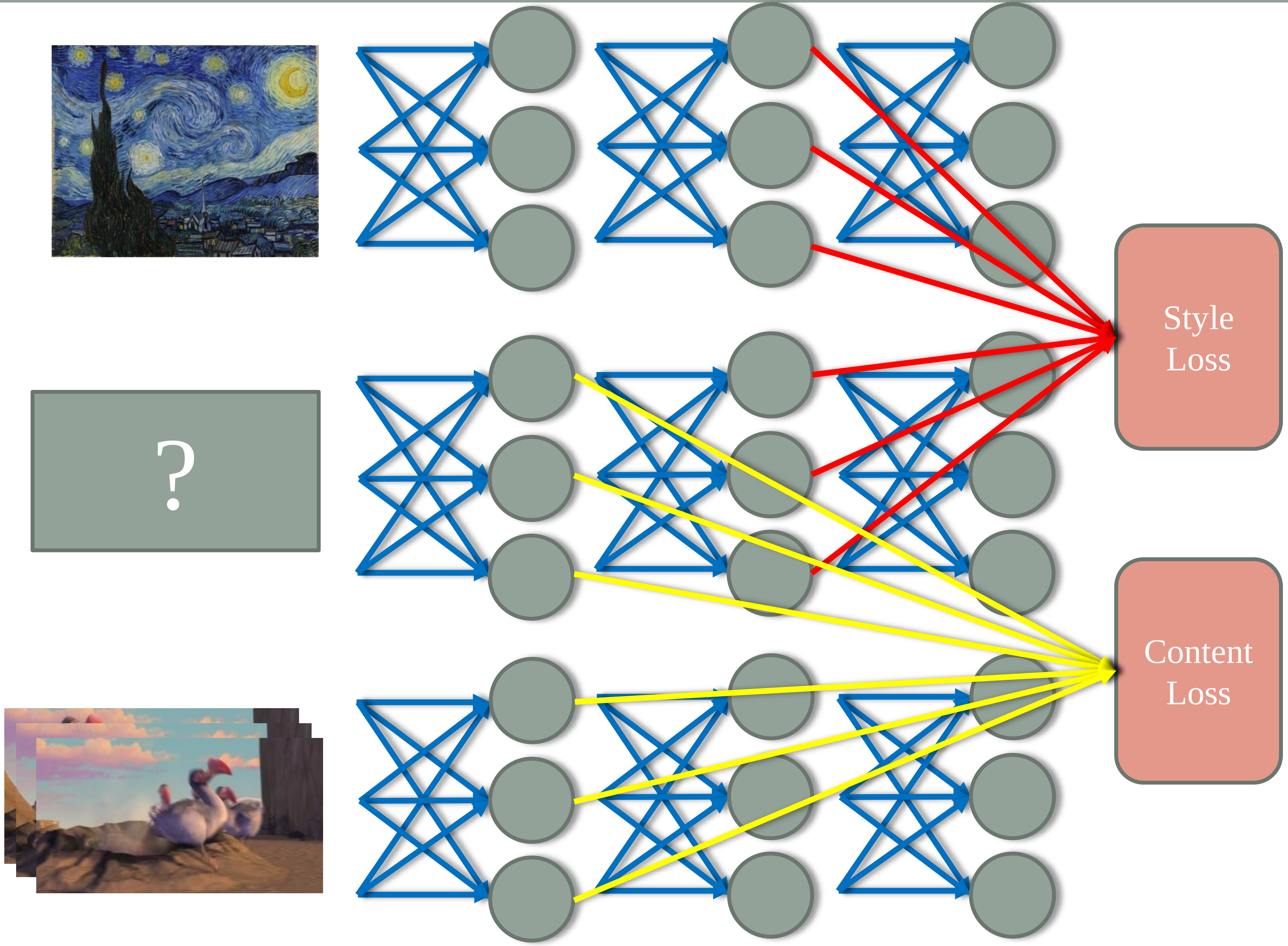
cow



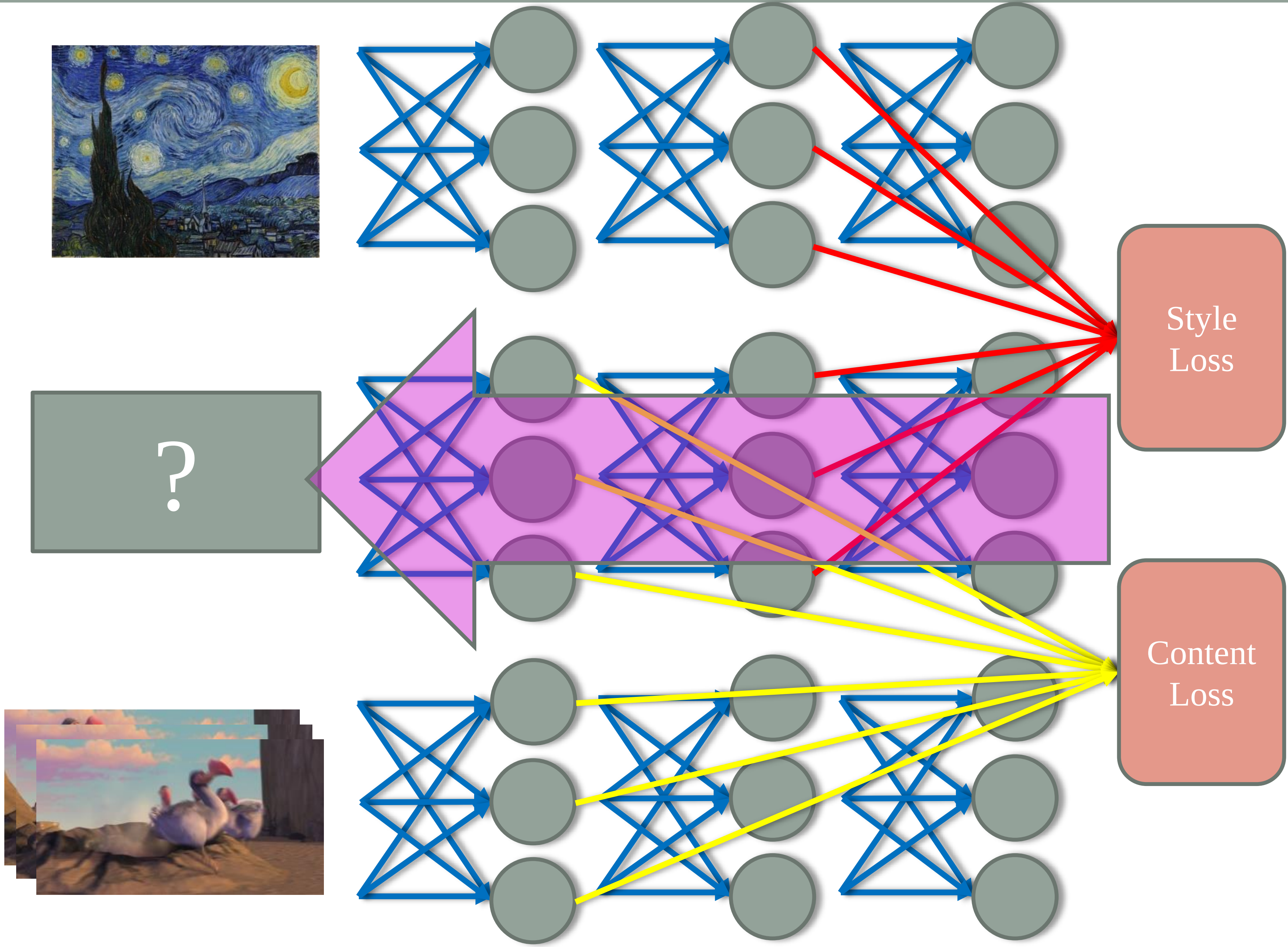
building



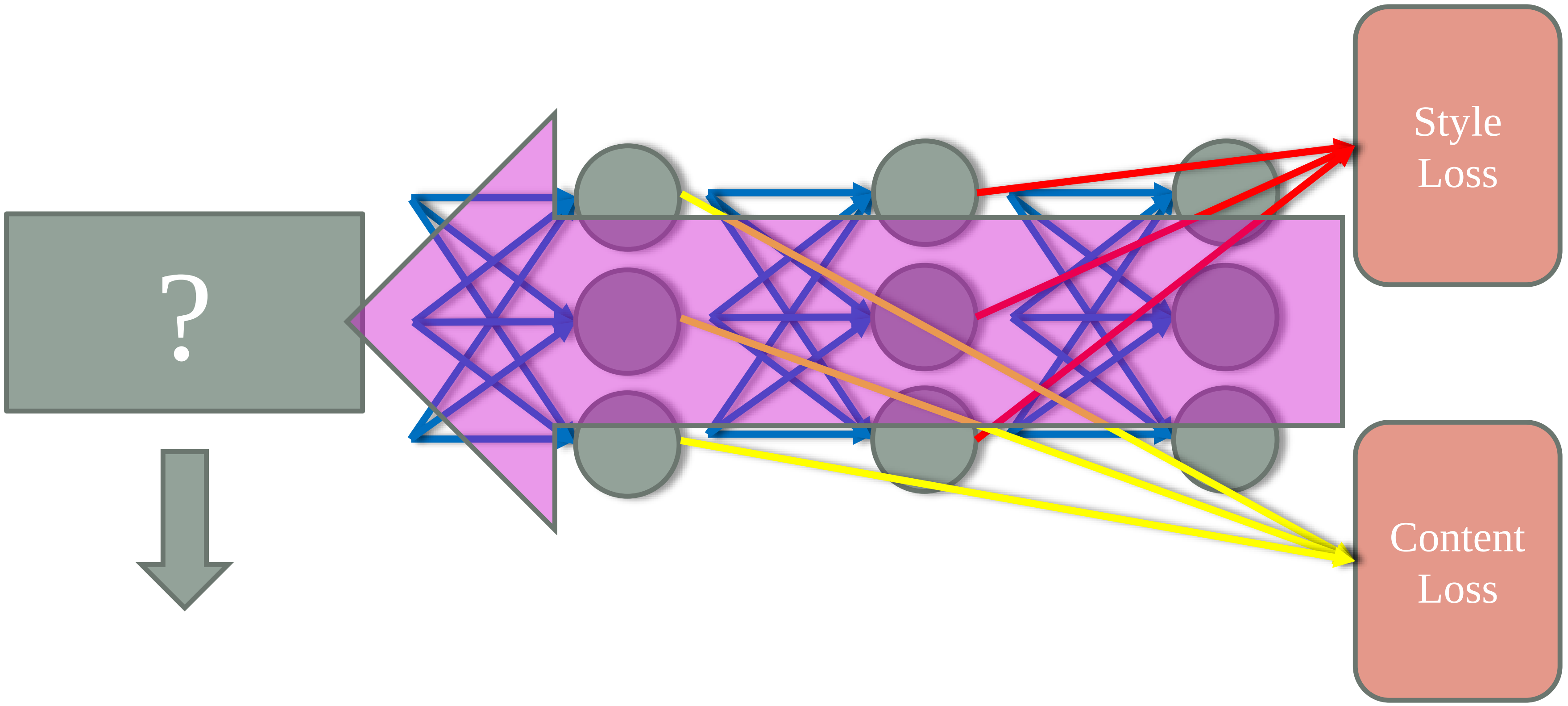
A NEURAL ALGORITHM OF ARTISTIC STYLE



Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. **"A neural algorithm of artistic style."** *arXiv preprint arXiv:1508.06576* (2015).

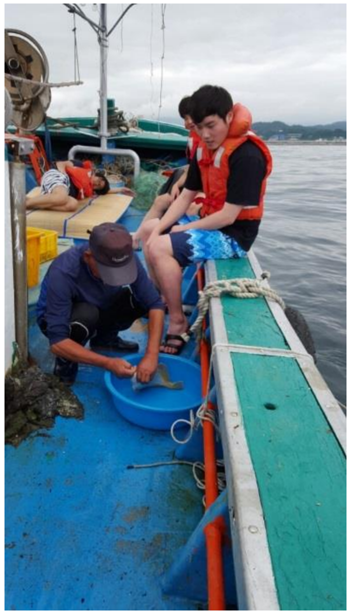


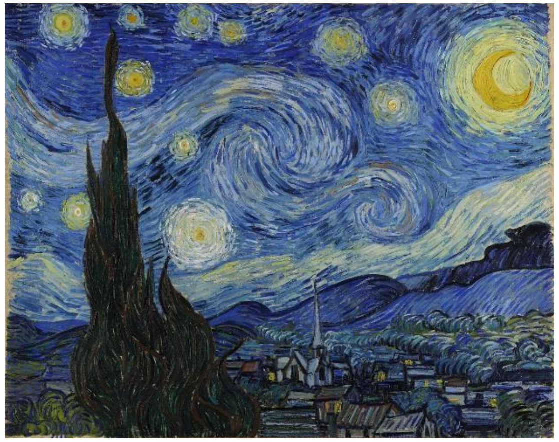
Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. **"A neural algorithm of artistic style."** *arXiv preprint arXiv:1508.06576* (2015).

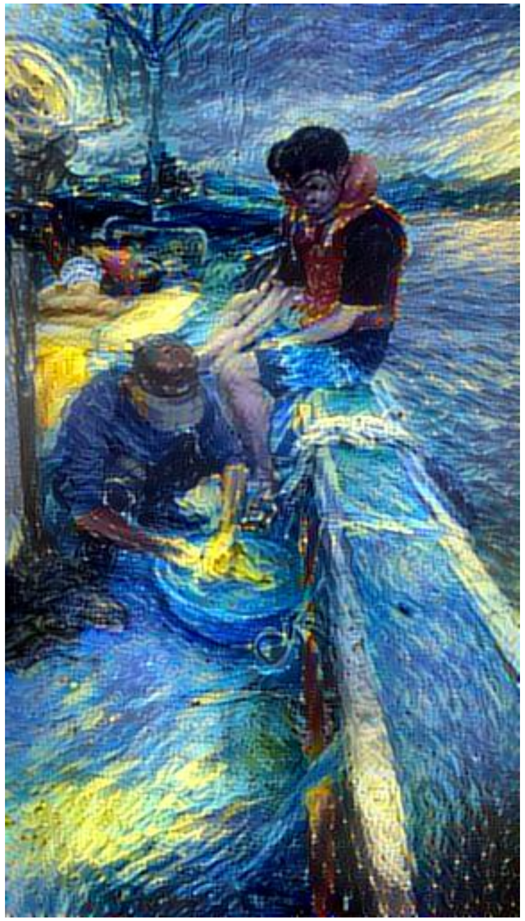


Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. **"A neural algorithm of artistic style."** *arXiv preprint arXiv:1508.06576* (2015).

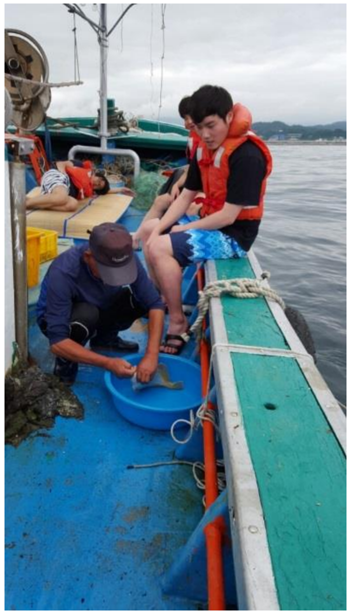
Artistic style

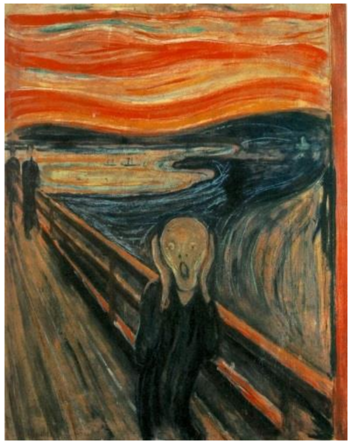


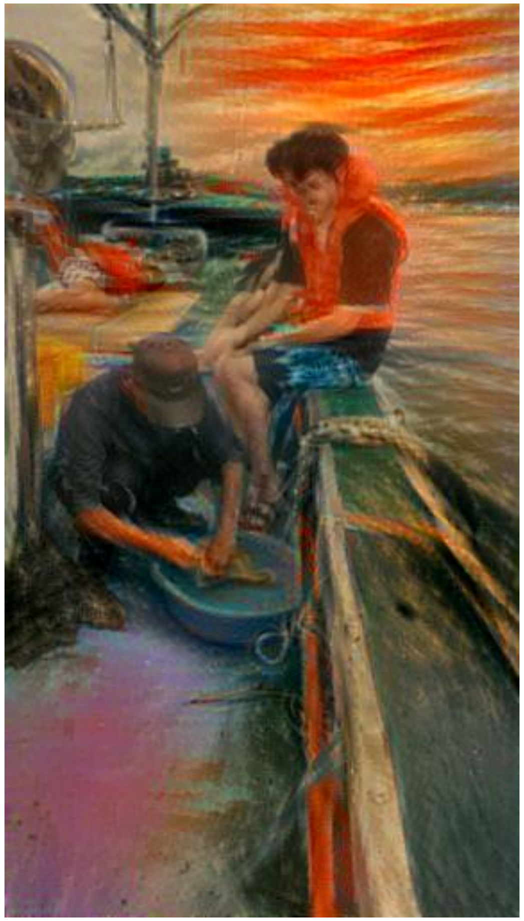




Artistic style







예제코드

- Tensorflow codes
- Tensorflow codes

ADVERSARIAL EXAMPLE

예제코드

- Codes