Convolutional Neural Networks and Image Processing

Jiří Materna

About me

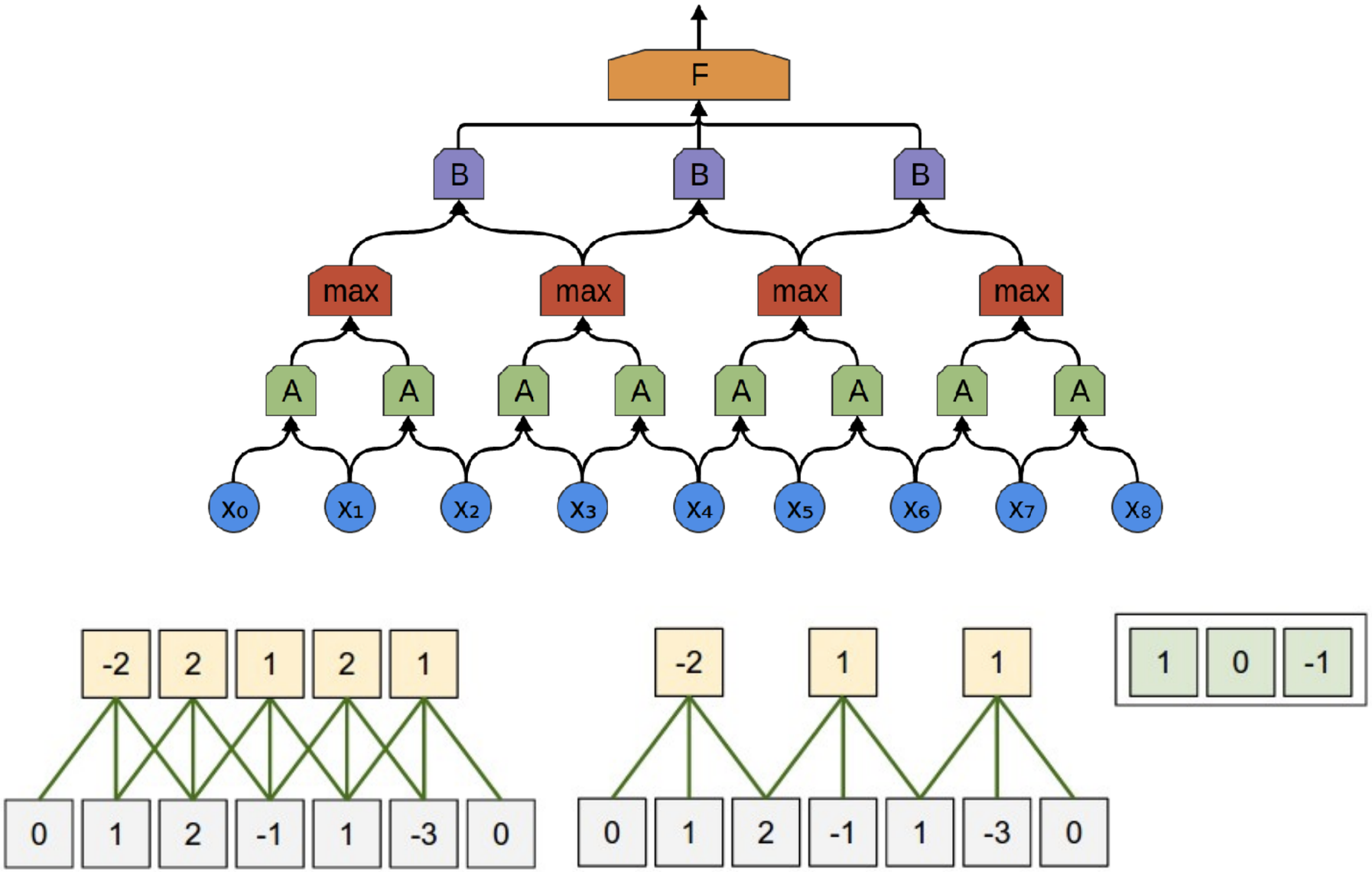
- Ph.D. in Natural Language Processing and Artificial Intelligence at Masaryk University
- 10 years at Seznam.cz (last 8 years as Head Of Research)
- Founder and lecturer at ML College
- Founder and co-organiser of ML Prague
- ML Freelance and consultant

www.mlguru.com **www.mlprague.com** **www.mlcollege.com**

Image processing

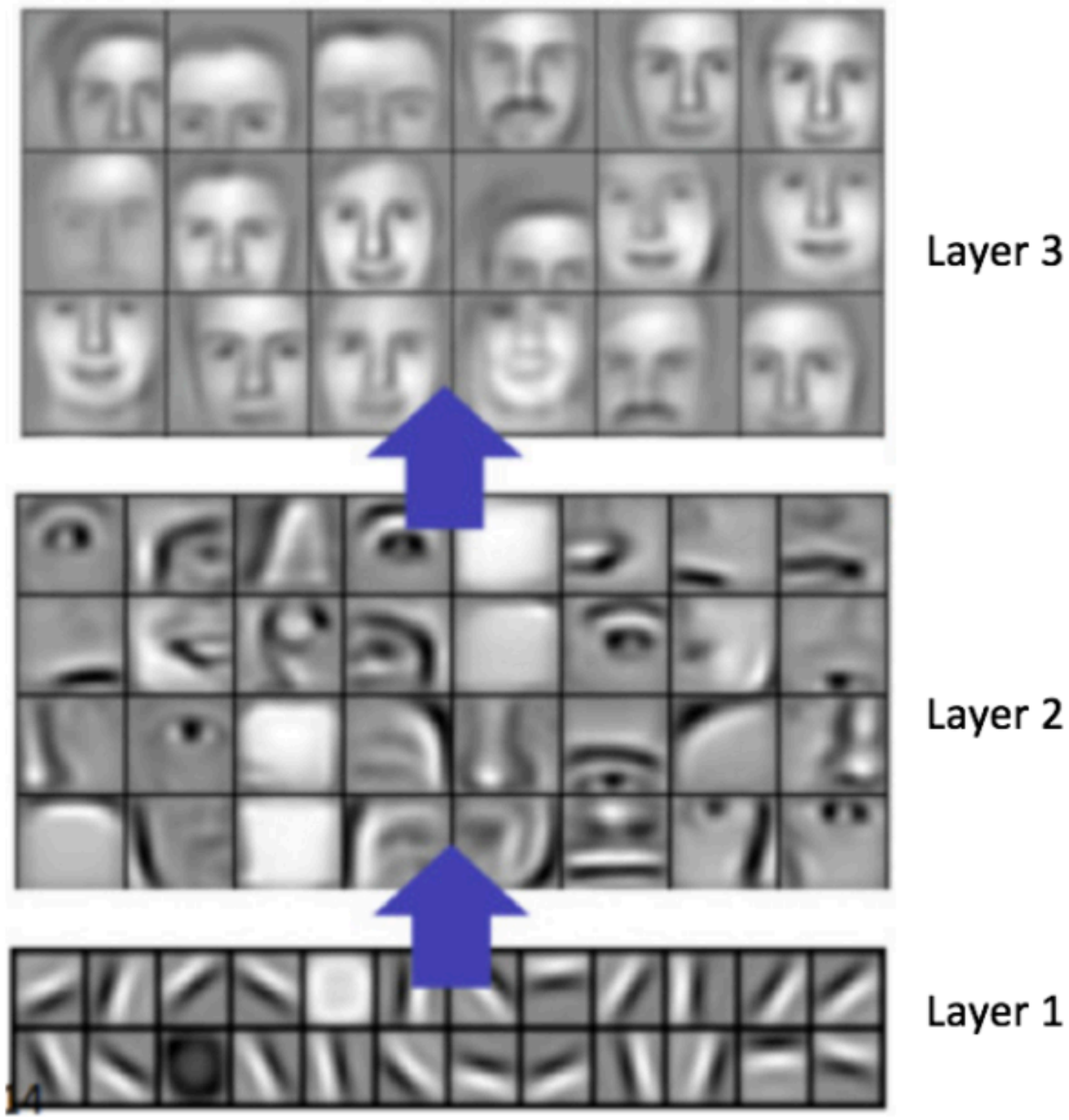
- Convolution
- VGG 16 and ResNet
- Transfer learning and fine-tuning
- Image classification
- Batch normalization and data augmentation
- U-net and Image segmentation
- GANs and superresolution
- Neural network explainability
- Adversarial patch

Convolution



Source: https://www.tensorflow.org

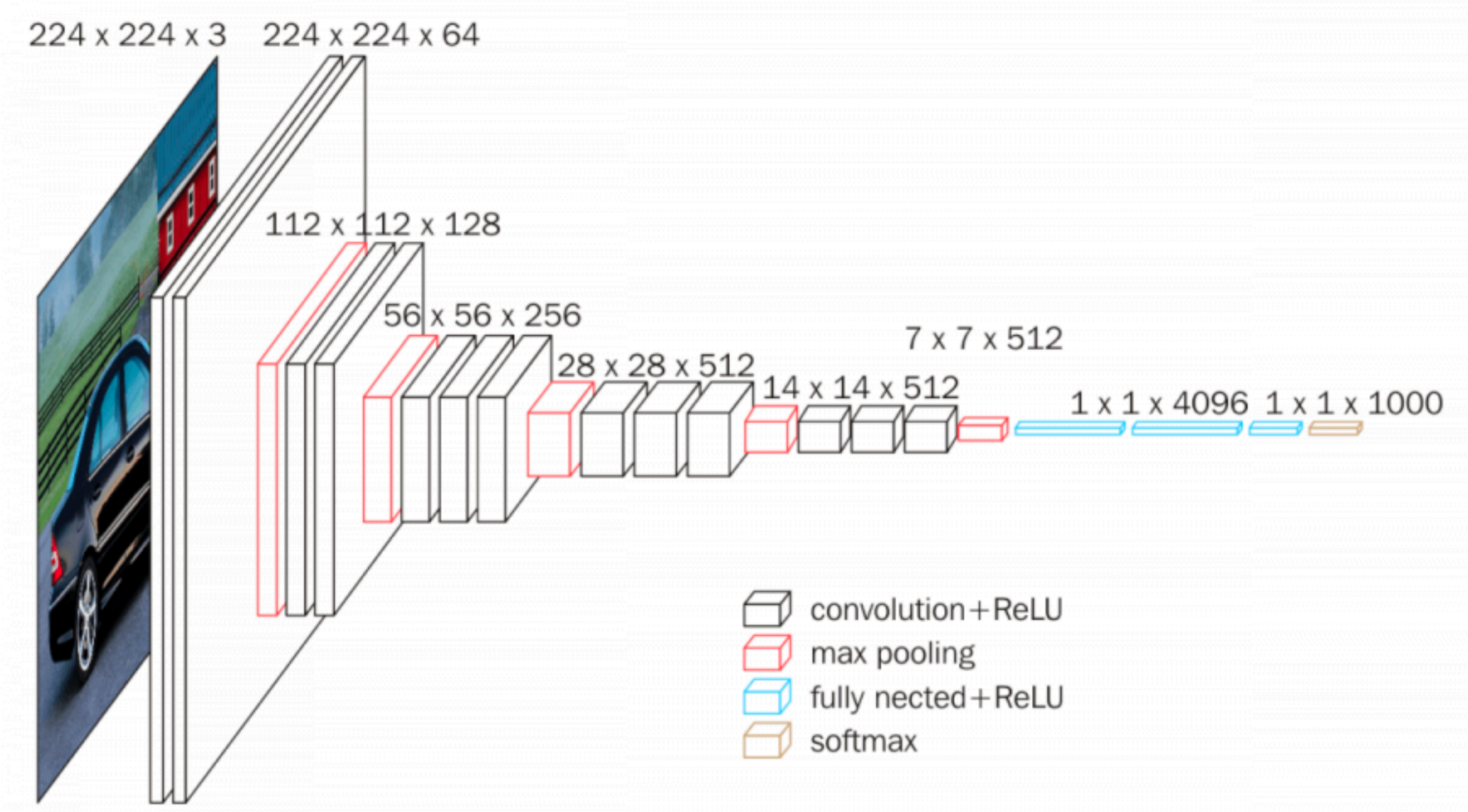
Weights visualization



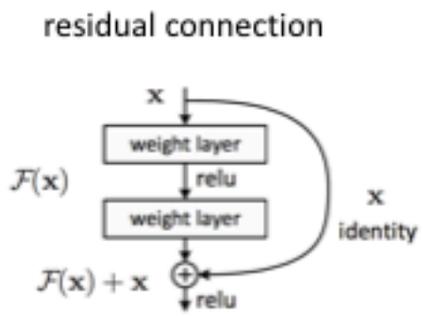
MNIST Classification

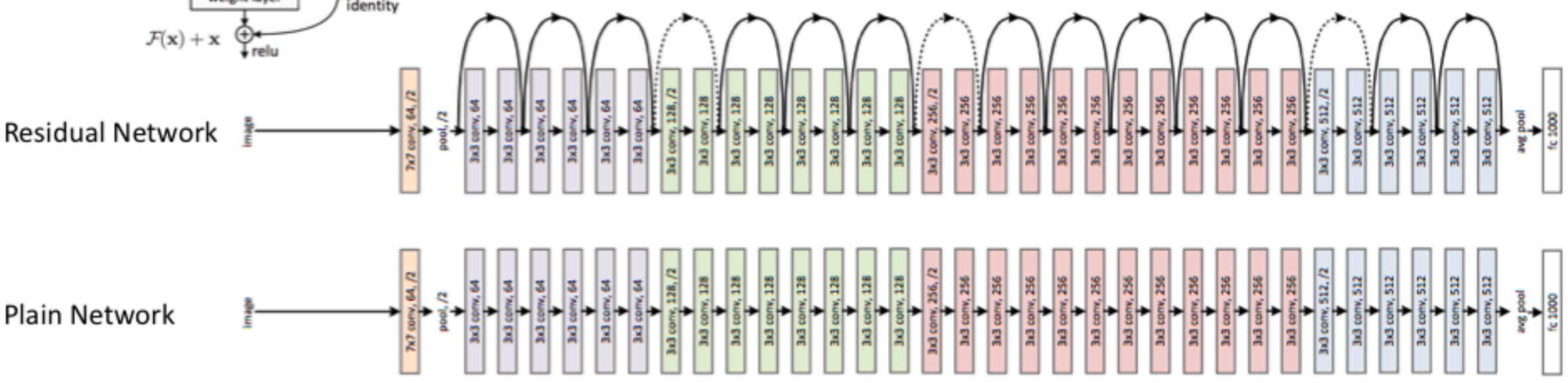
01-MNIST-classification.ipynb

VGG 16

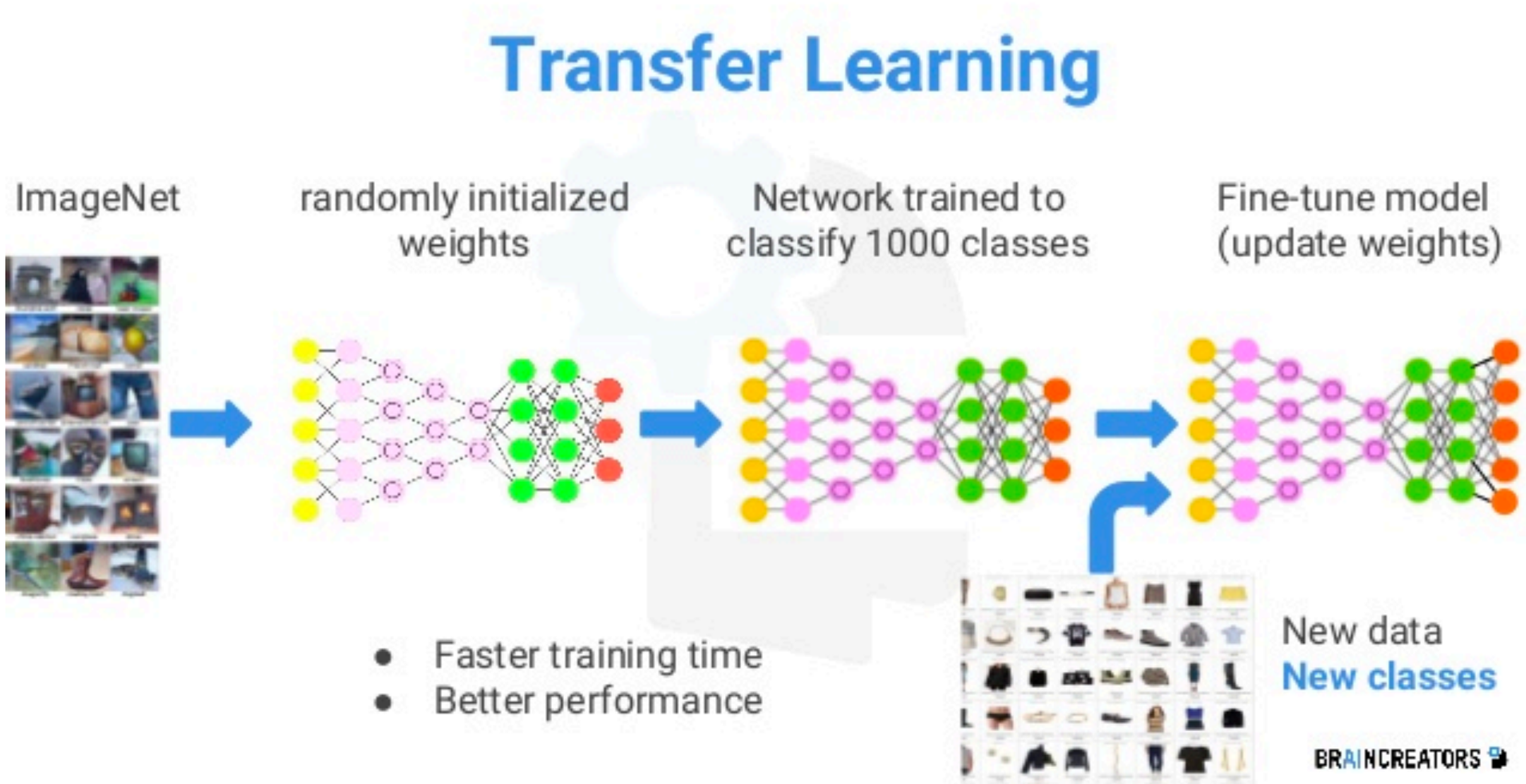

224 x 224 x 3
224 x 224 x 64
112 x 112 x 128
56 x 56 x 256
28 x 28 x 512
14 x 14 x 512
7 x 7 x 512
1 x 1 x 4096
1 x 1 x 1000
convolution+ReLU
max pooling
fully nected+ReLU
softmax

ResNet

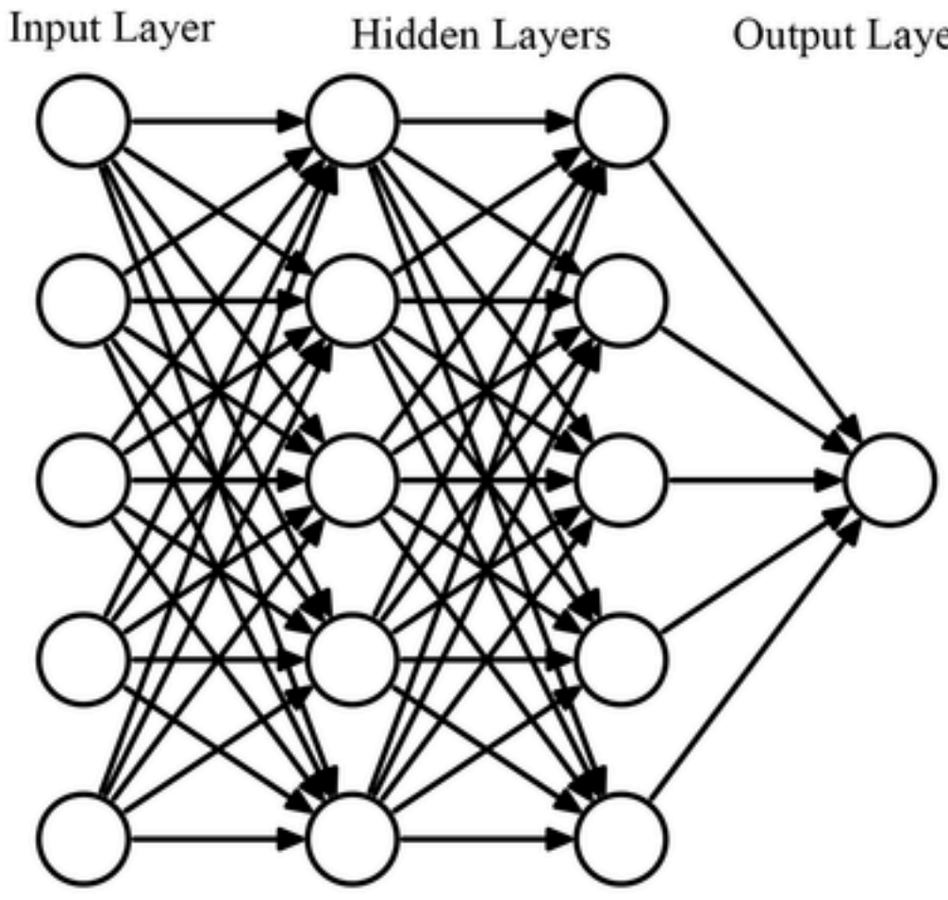

residual connection
x
weight layer
relu
weight layer
F(x)
x
identity
F(x) + x
relu


Residual Network
image
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 128
3x3 conv, 256, /2
3x3 conv, 256
3x3 conv, 512, /2
3x3 conv, 512
avg pool
fc 1000
Plain Network
image
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 128
3x3 conv, 256, /2
3x3 conv, 256
3x3 conv, 512, /2
3x3 conv, 512
avg pool
fc 1000

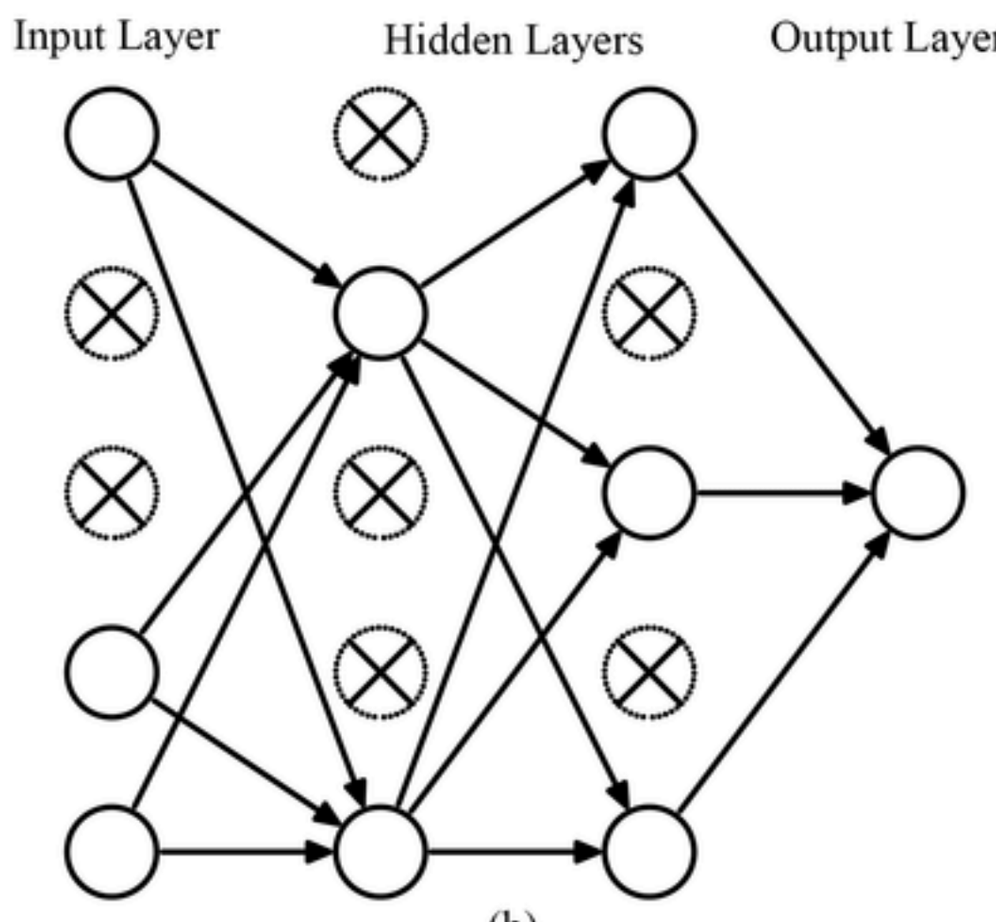
Finetuning


Transfer Learning
ImageNet
randomly initialized weights
Network trained to classify 1000 classes
Fine-tune model (update weights)
Faster training time
Better performance
New data
New classes
BRAINCREATORS

Dropout


Input Layer
Hidden Layers
Output Layer

(a)

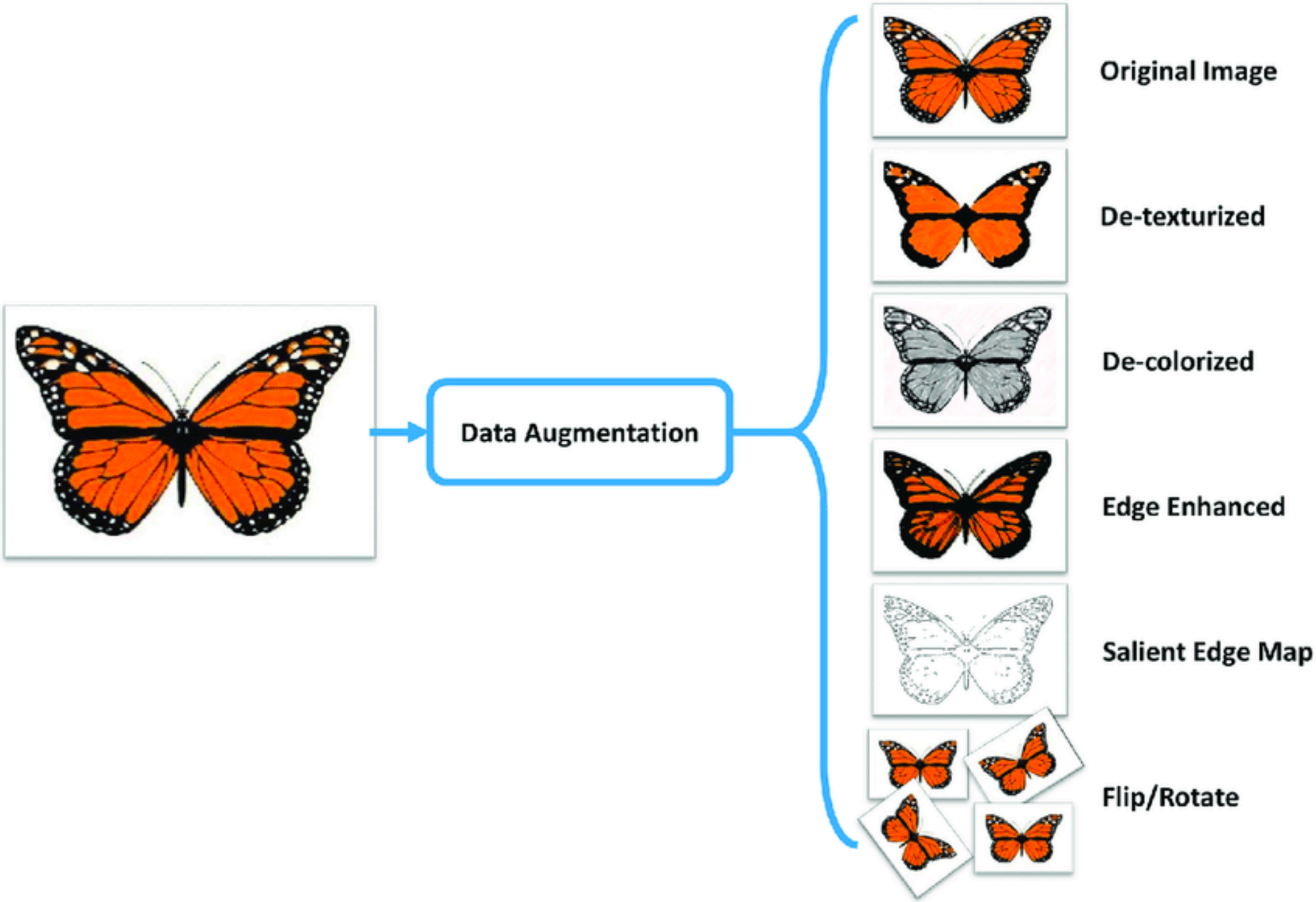

Input Layer
Hidden Layers
Output Layer

(b)

Transfer learning example

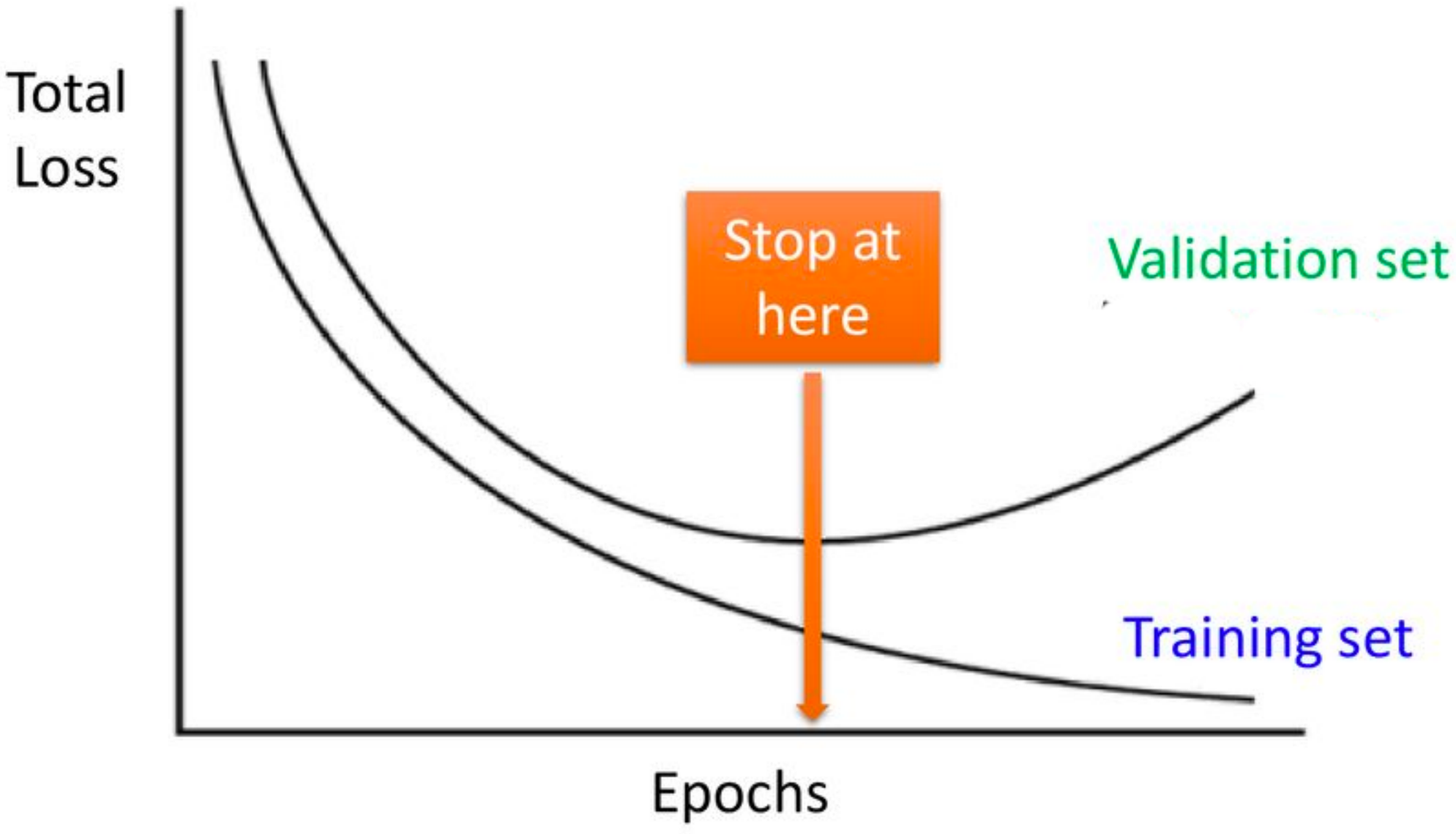
02-Transfer_learning.ipynb

Data augmentation



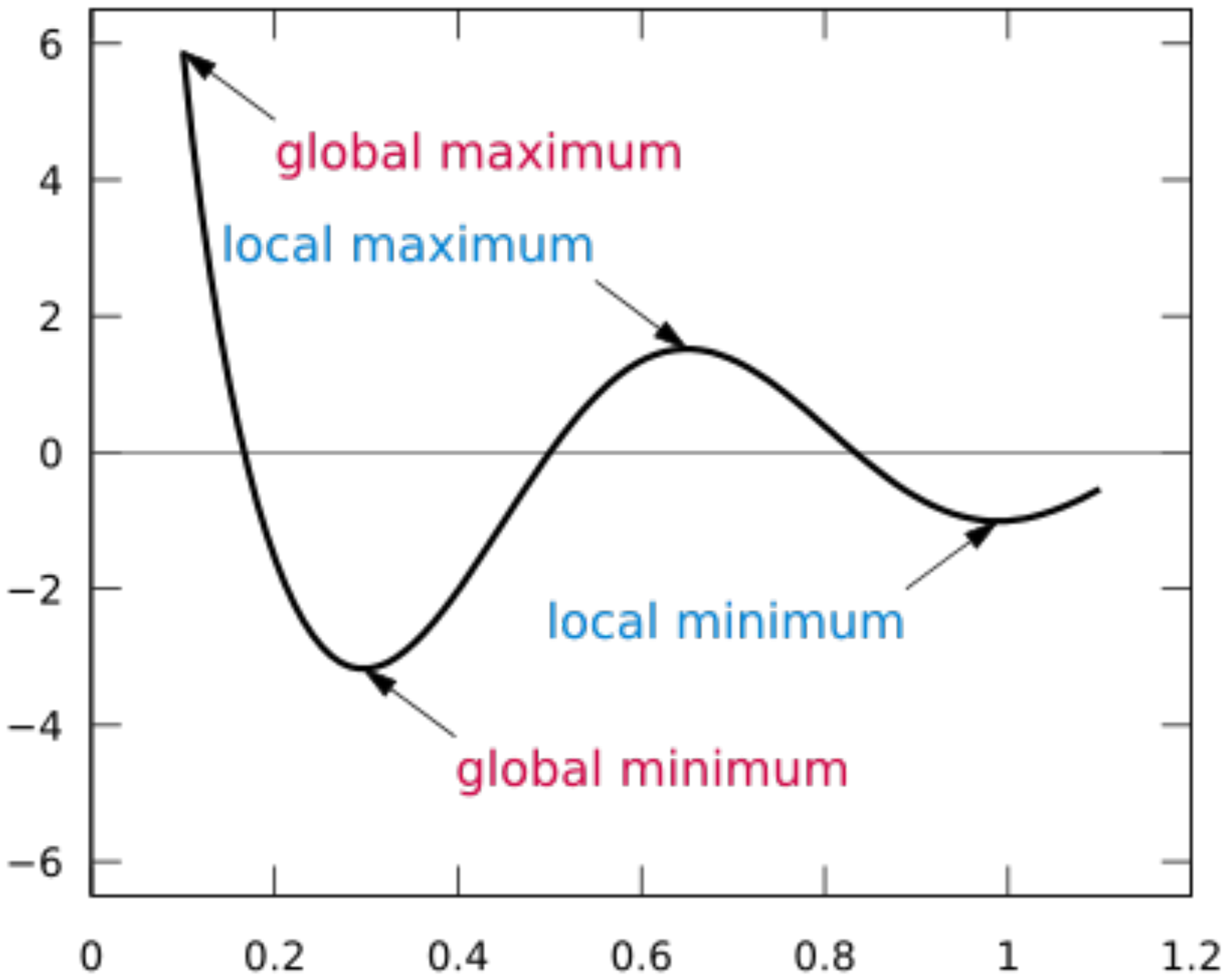
https://medium.com/secure-and-private-ai-writing-challenge/data-augmentation-increases-accuracy-of-your-model-but-how-aa1913468722

Early stopping



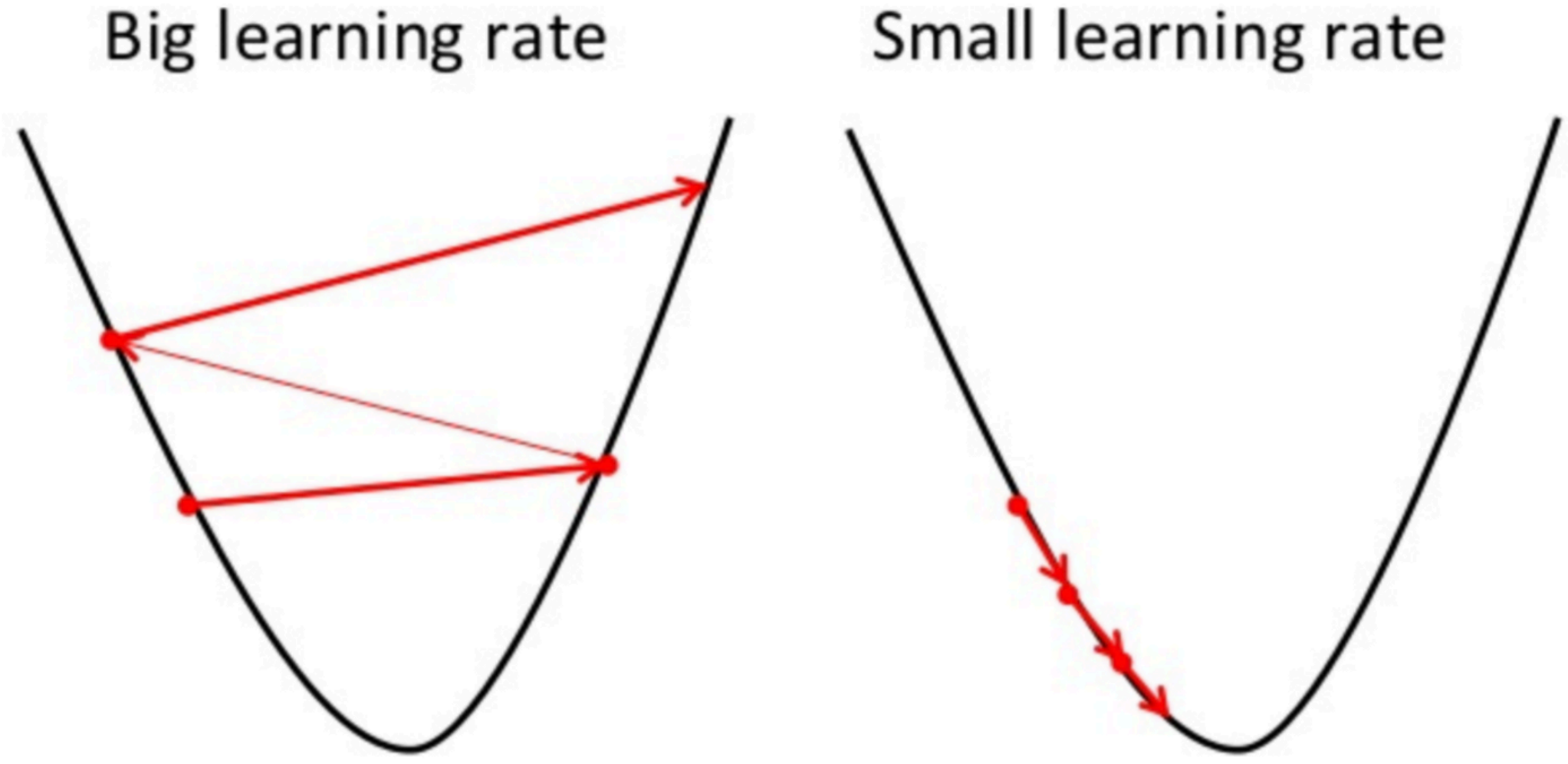
https://keras.io/getting_started/intro_to_keras_for_engineers/

Parameter optimization strategies

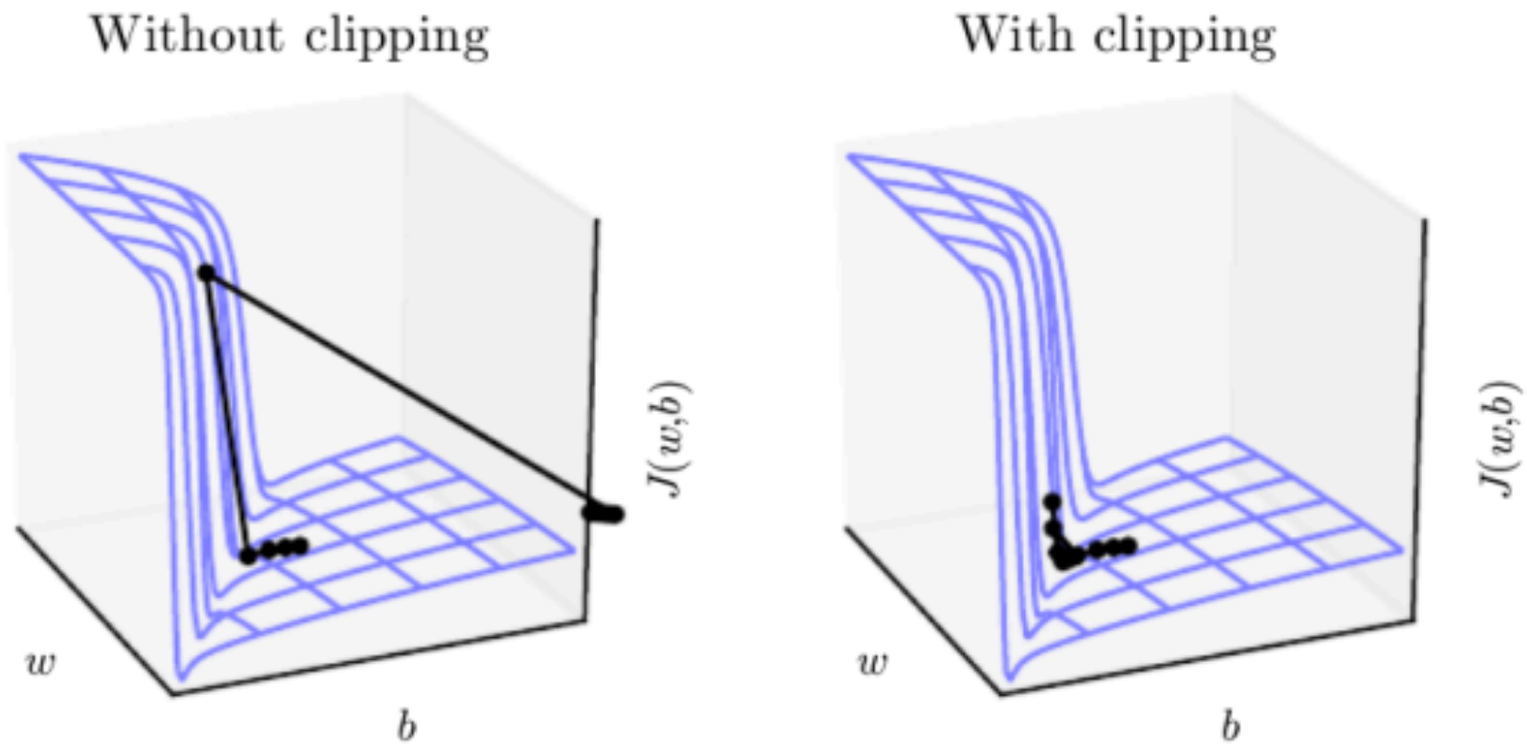


https://heartbeat.fritz.ai/an-empirical-comparison-of-optimizers-for-machine-learning-models-b86f29957050

Learning rate tuning



Gradient clipping



https://neptune.ai/blog/understanding-gradient-clipping-and-how-it-can-fix-exploding-gradients-problem

Batch normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

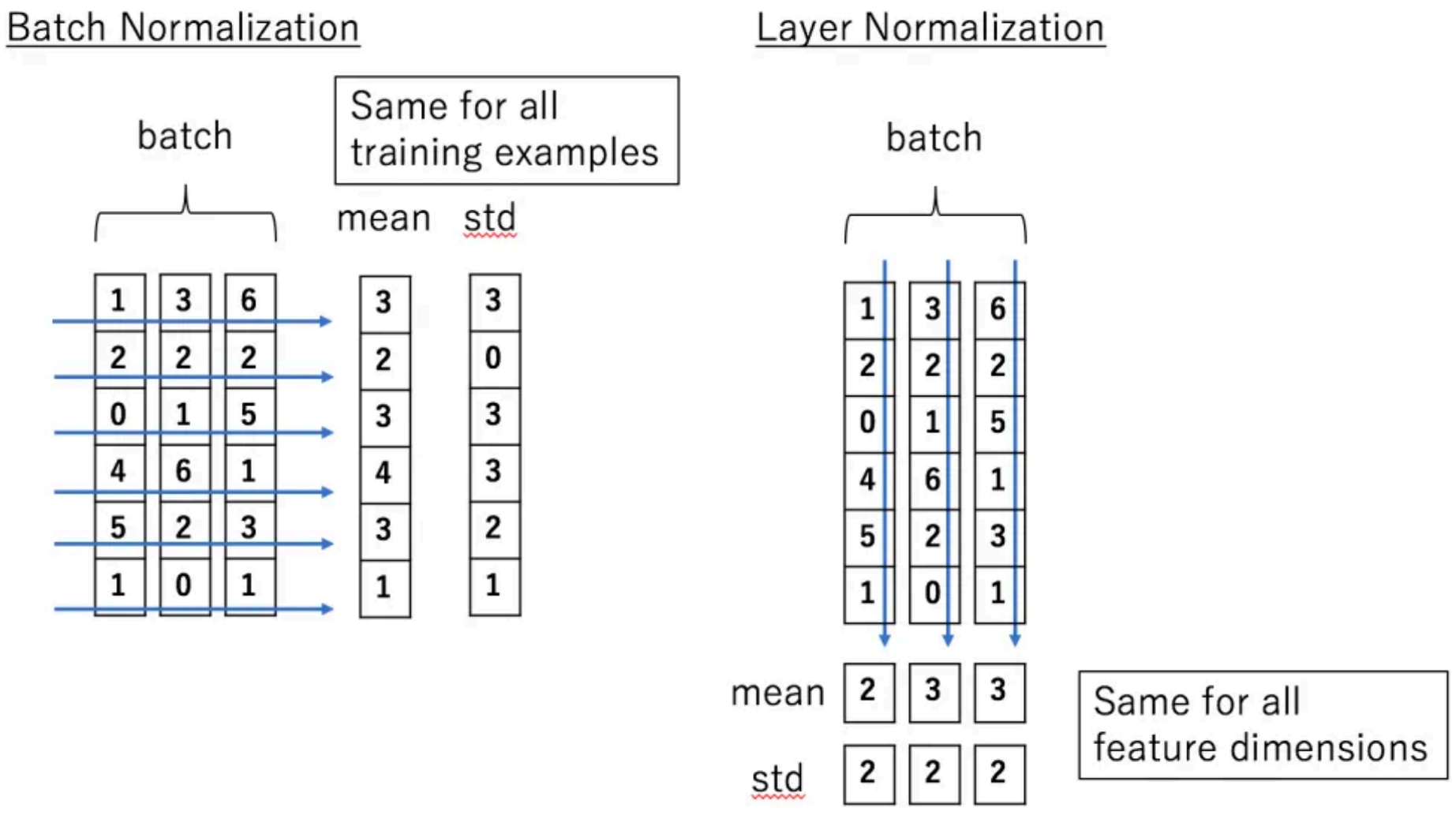
$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

https://arxiv.org/abs/1502.03167

Layer normalization



https://mlexplained.com/2018/01/13/weight-normalization-and-layer-normalization-explained-normalization-in-deep-learning-part-2/

Functional API in Keras

```
# Sequential model
from keras.models import Sequential
from keras.layers import Dense

model = Sequential()
model.add(10, input_shape=(10,),activation='relu')
model.add(Dense(20, activation='relu')
model.add(Dense(10, activation='relu')
model.add(Dense(1, activation='sigmoid')
```

```
# Functional model
from keras.models import Model
from keras.layers import Input, Dense

visible = Input(shape=(10,))
hidden1 = Dense(10, activation='relu')(visible)
hidden2 = Dense(20, activation='relu')(hidden1)
hidden3 = Dense(10, activation='relu')(hidden2)
output = Dense(1, activation='sigmoid')(hidden3)
model = Model(inputs=visible, outputs=output)
```

Shared Input

```
# Shared Input Layer
from keras.utils import plot_model
from keras.models import Model
from keras.layers import Input, Dense, Flatten
from keras.layers.convolutional import Conv2D
from keras.layers.pooling import MaxPooling2D
from keras.layers.merge import concatenate
# input layer
visible = Input(shape=(64,64,1))
# first feature extractor
conv1 = Conv2D(32, kernel_size=4, activation='relu')(visible)
pool1 = MaxPooling2D(pool_size=(2, 2))(conv1)
flat1 = Flatten()(pool1)
# second feature extractor
conv2 = Conv2D(16, kernel_size=8, activation='relu')(visible)
pool2 = MaxPooling2D(pool_size=(2, 2))(conv2)
flat2 = Flatten()(pool2)
# merge feature extractors
merge = concatenate([flat1, flat2])
# interpretation layer
hidden1 = Dense(10, activation='relu')(merge)
# prediction output
output = Dense(1, activation='sigmoid')(hidden1)
model = Model(inputs=visible, outputs=output)
```

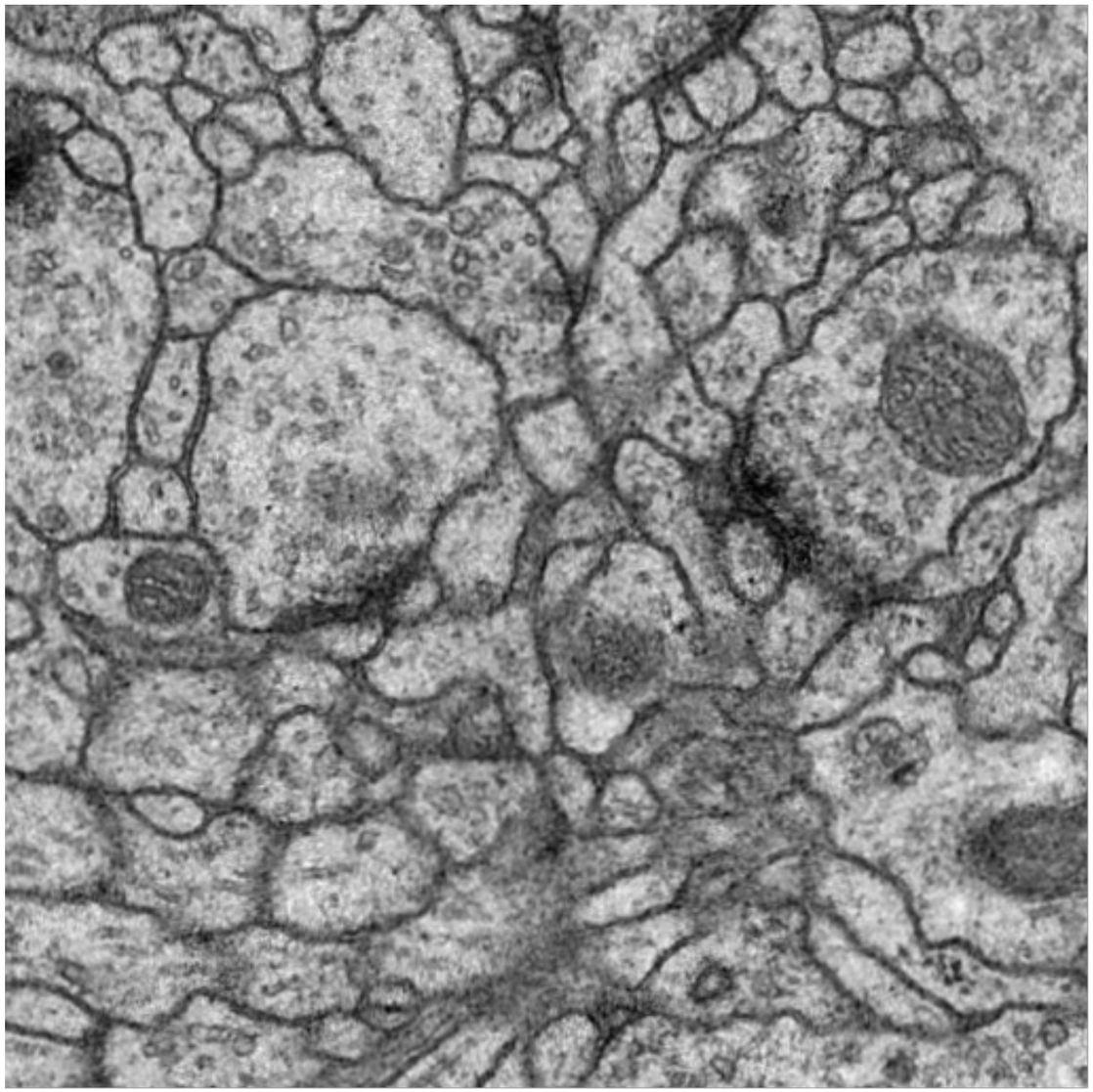
Multiple inputs (outputs)

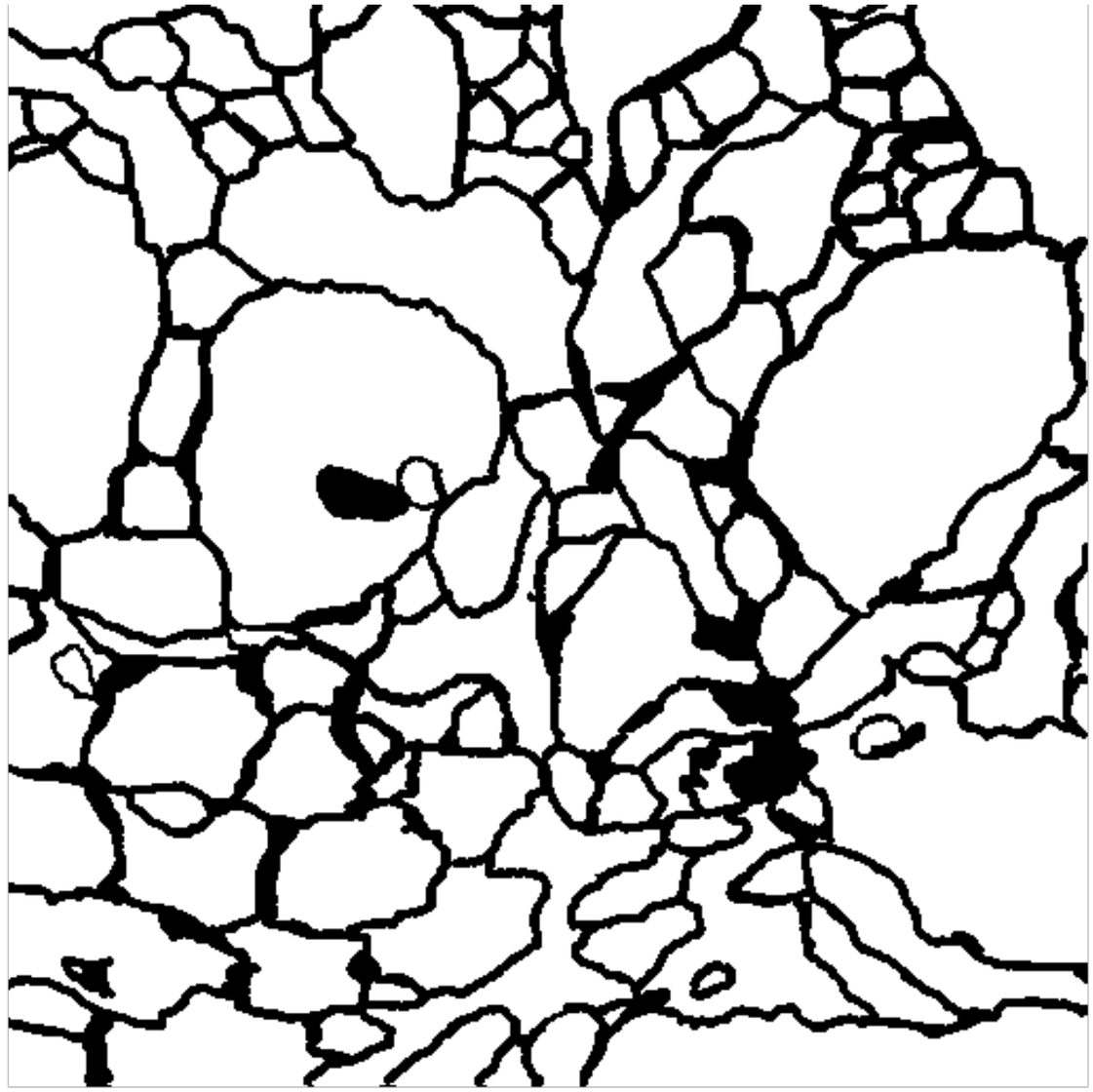
```python
# Multiple Inputs
from keras.utils import plot_model
from keras.models import Model
from keras.layers import Input
from keras.layers import Dense
from keras.layers import Flatten
from keras.layers.convolutional import Conv2D
from keras.layers.pooling import MaxPooling2D
from keras.layers.merge import concatenate
# first input model
visible1 = Input(shape=(64,64,1))
conv11 = Conv2D(32, kernel_size=4, activation='relu')(visible1)
pool11 = MaxPooling2D(pool_size=(2, 2))(conv11)
conv12 = Conv2D(16, kernel_size=4, activation='relu')(pool11)
pool12 = MaxPooling2D(pool_size=(2, 2))(conv12)
flat1 = Flatten()(pool12)
# second input model
visible2 = Input(shape=(32,32,3))
conv21 = Conv2D(32, kernel_size=4, activation='relu')(visible2)
pool21 = MaxPooling2D(pool_size=(2, 2))(conv21)
conv22 = Conv2D(16, kernel_size=4, activation='relu')(pool21)
pool22 = MaxPooling2D(pool_size=(2, 2))(conv22)
flat2 = Flatten()(pool22)
# merge input models
merge = concatenate([flat1, flat2])
# interpretation model
hidden1 = Dense(10, activation='relu')(merge)
hidden2 = Dense(10, activation='relu')(hidden1)
output = Dense(1, activation='sigmoid')(hidden2)
model = Model(inputs=[visible1, visible2], outputs=output)
```

Practical example on regularization and normalization

03-Normalization-and-regularization-assignment.ipynb

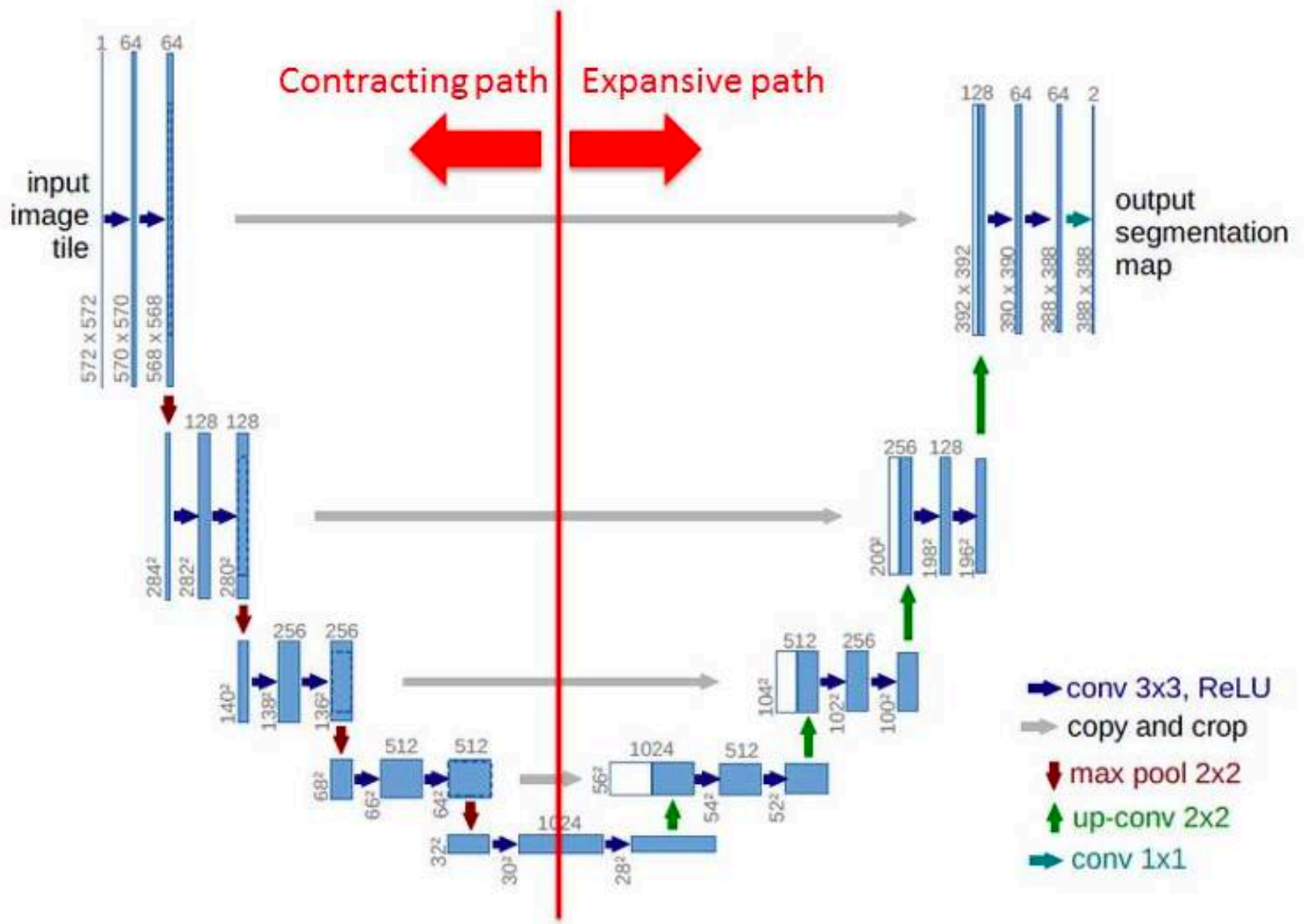
Image segmentation





U-Net

Network Architecture



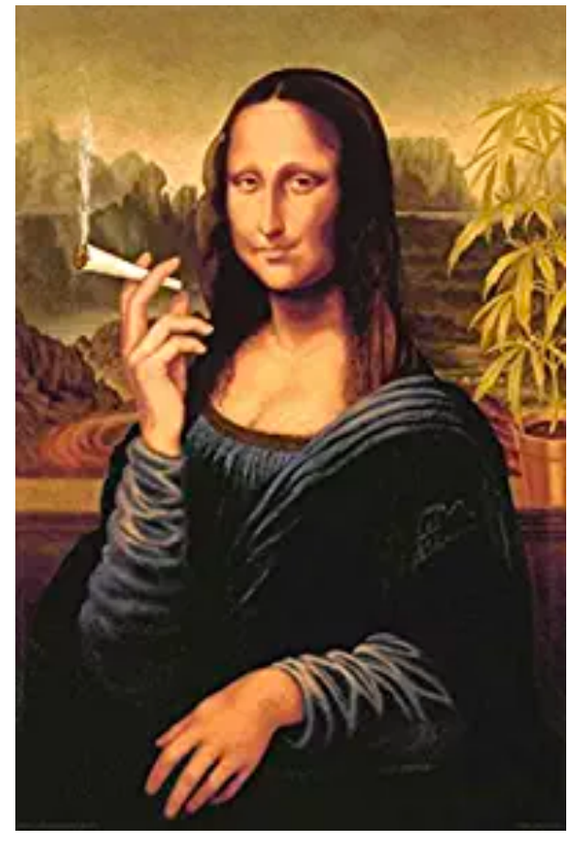
U-Net segmentation example

04-Segmentation.ipynb

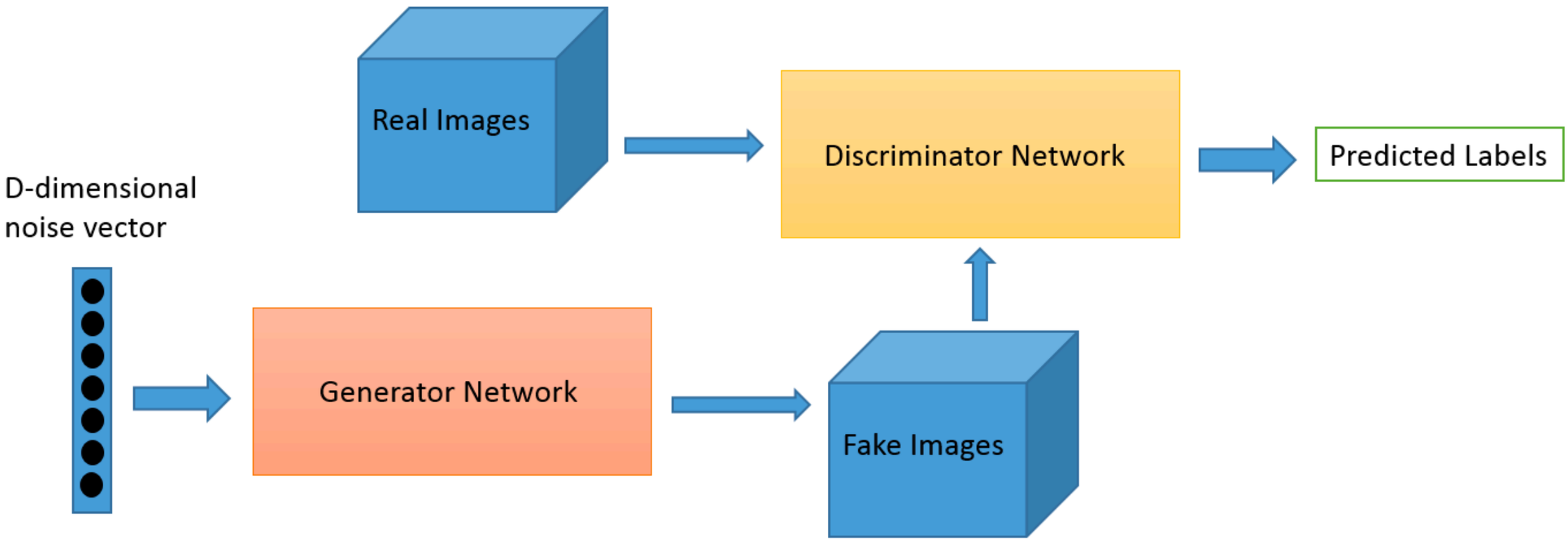
Generative models with neural networks

Random noice

Artificial Neural network



Generative Adversarial Networks



Superresolution

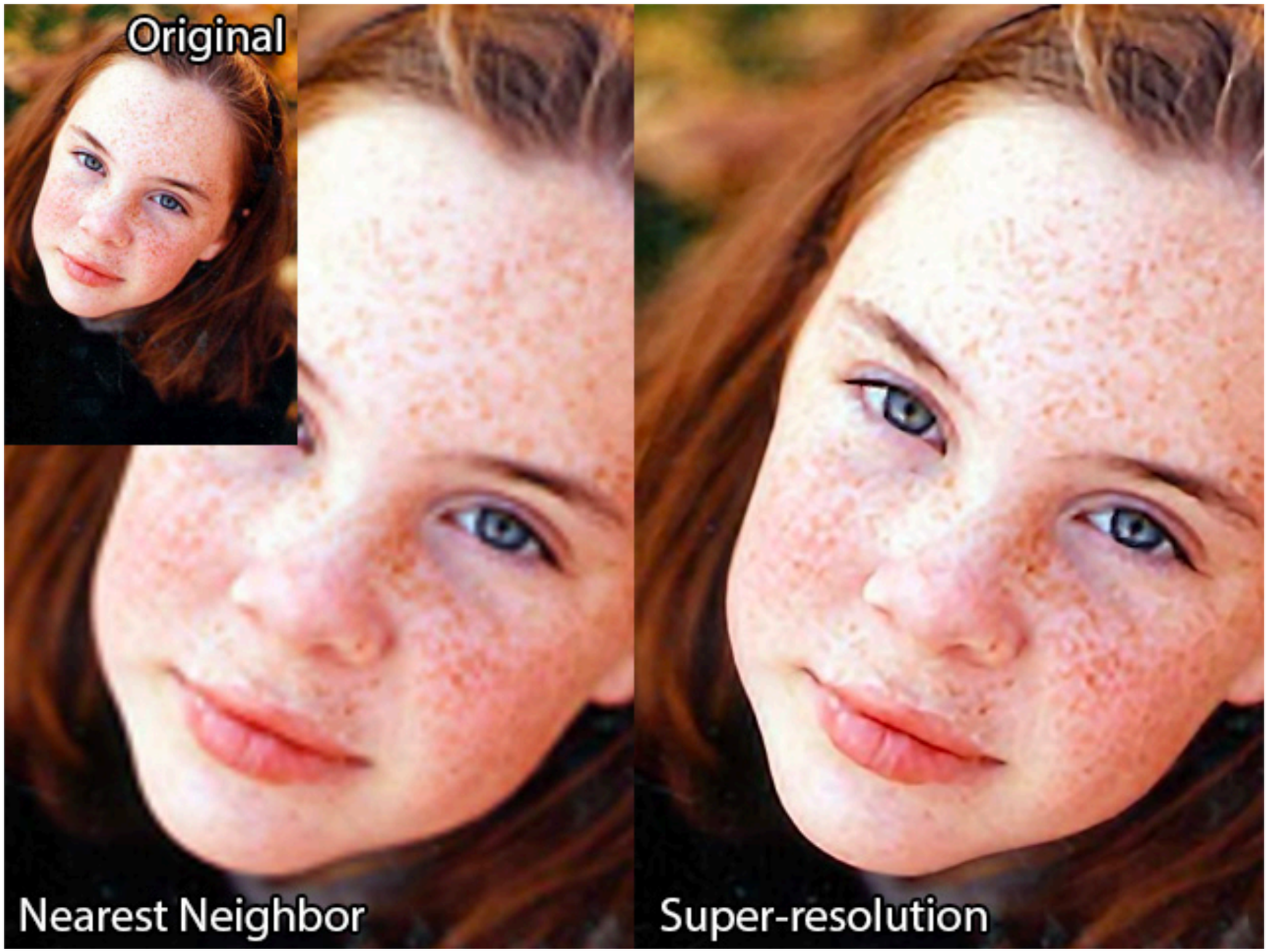
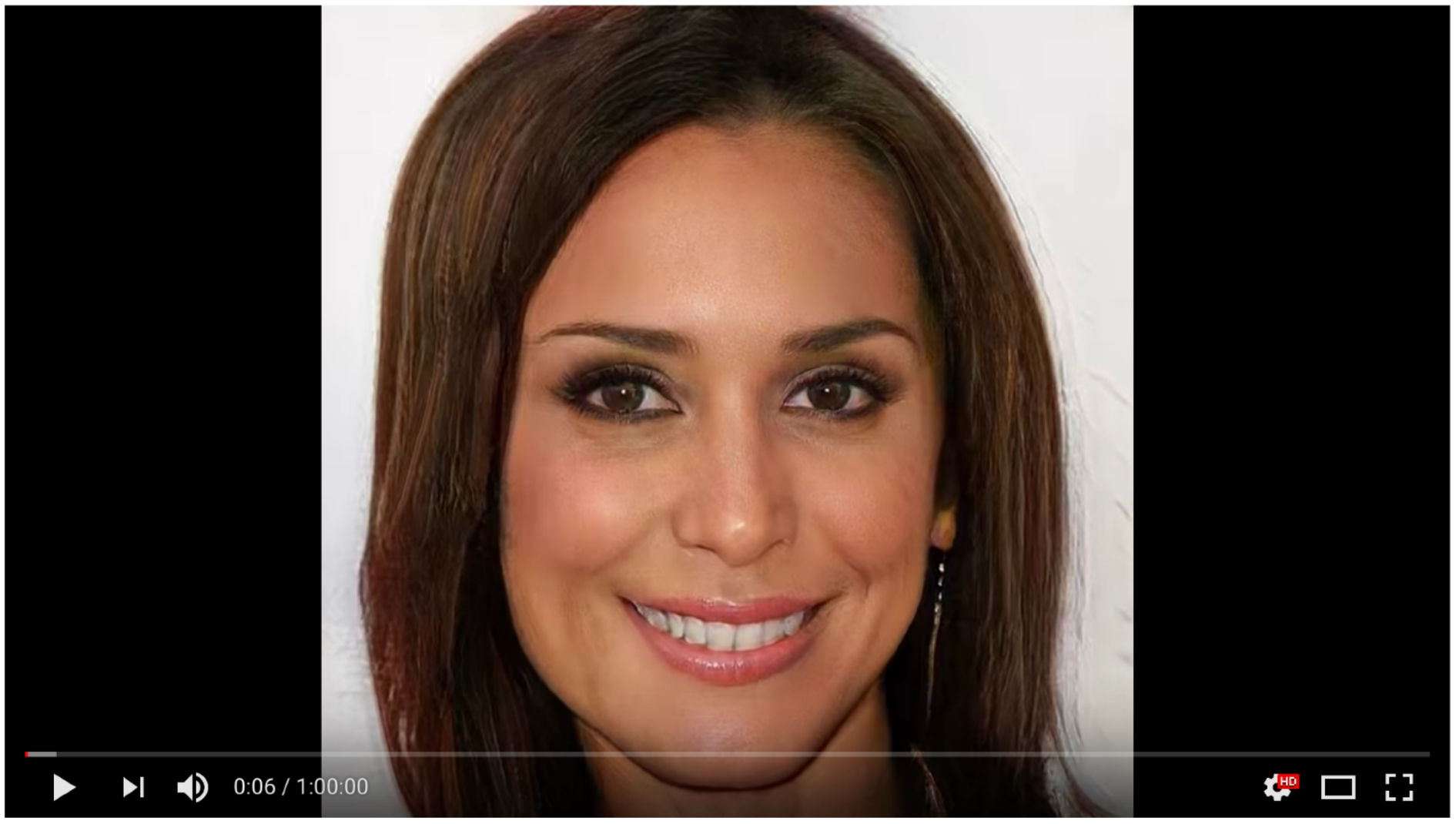


Image synthesis



One hour of imaginary celebrities

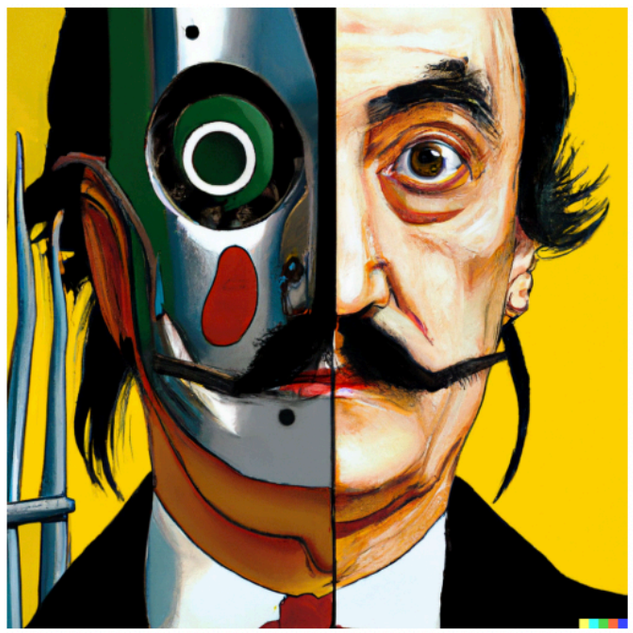
95 832 zhlédnutí

TO SE MI LÍBÍ NELÍBÍ SE SDÍLET

Which one is fake?

Image manipulation

Diffusion models



vibrant portrait painting of Salvador Dalí with a robotic half face

a shiba inu wearing a beret and black turtleneck

a close up of a handpalm with leaves growing from it

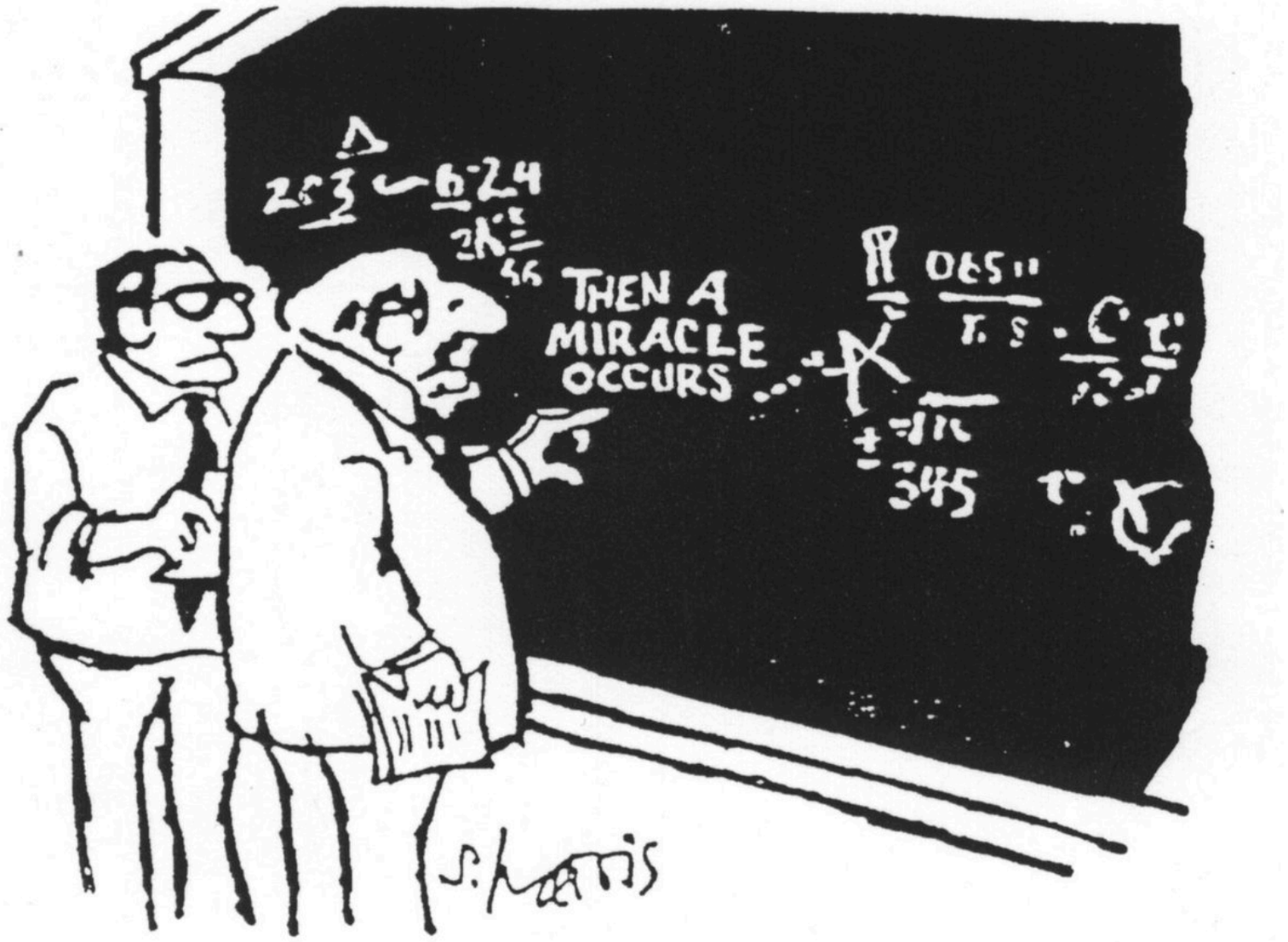
an espresso machine that makes coffee from human souls, artstation

panda mad scientist mixing sparkling chemicals, artstation

a corgi's head depicted as an explosion of a nebula

Stable Diffusion: https://huggingface.co/spaces/stabilityai/stable-diffusion

Neural network explainability

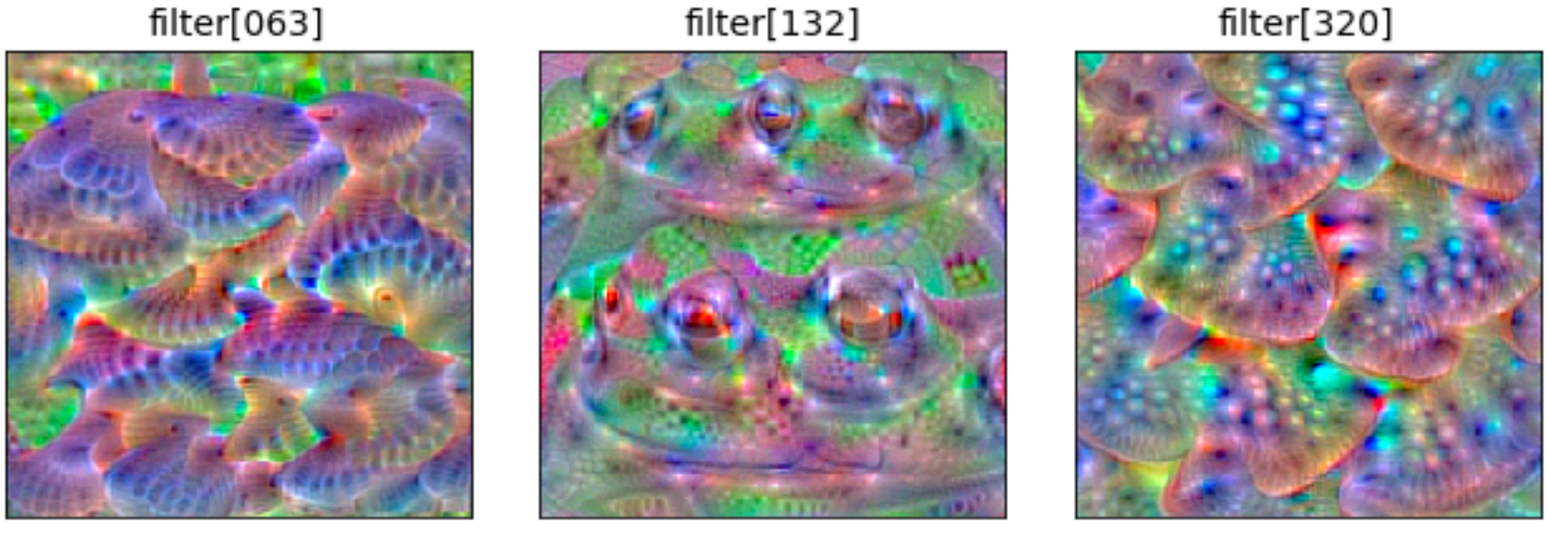


https://analyticsindiamag.com/deep-learning-is-not-so-much-a-black-box-anymore-and-thats-a-great-development/

Activation Maximization

Visualized output classification Layer

Visualized hidden convolutional layers

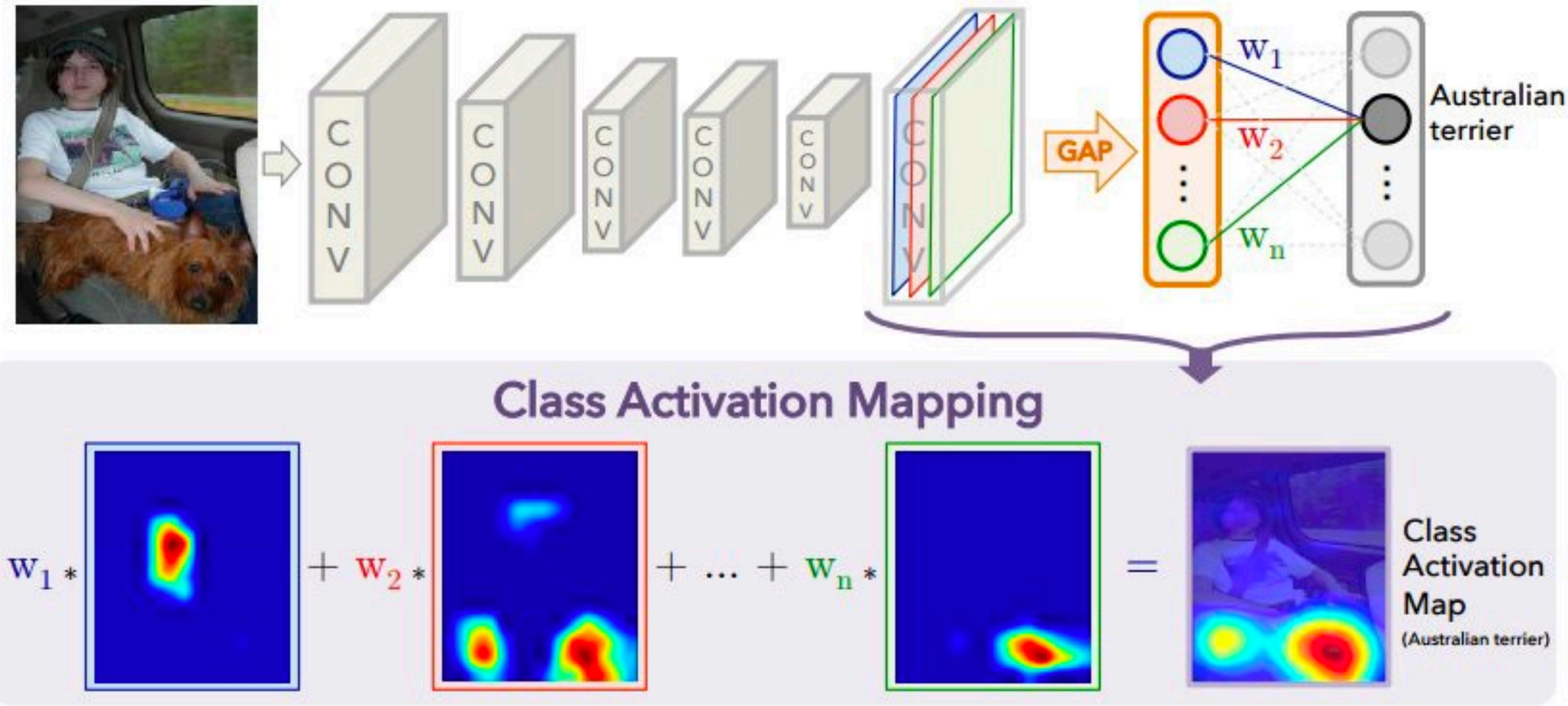


https://pypi.org/project/tf-keras-vis/

Grad-CAM heat maps

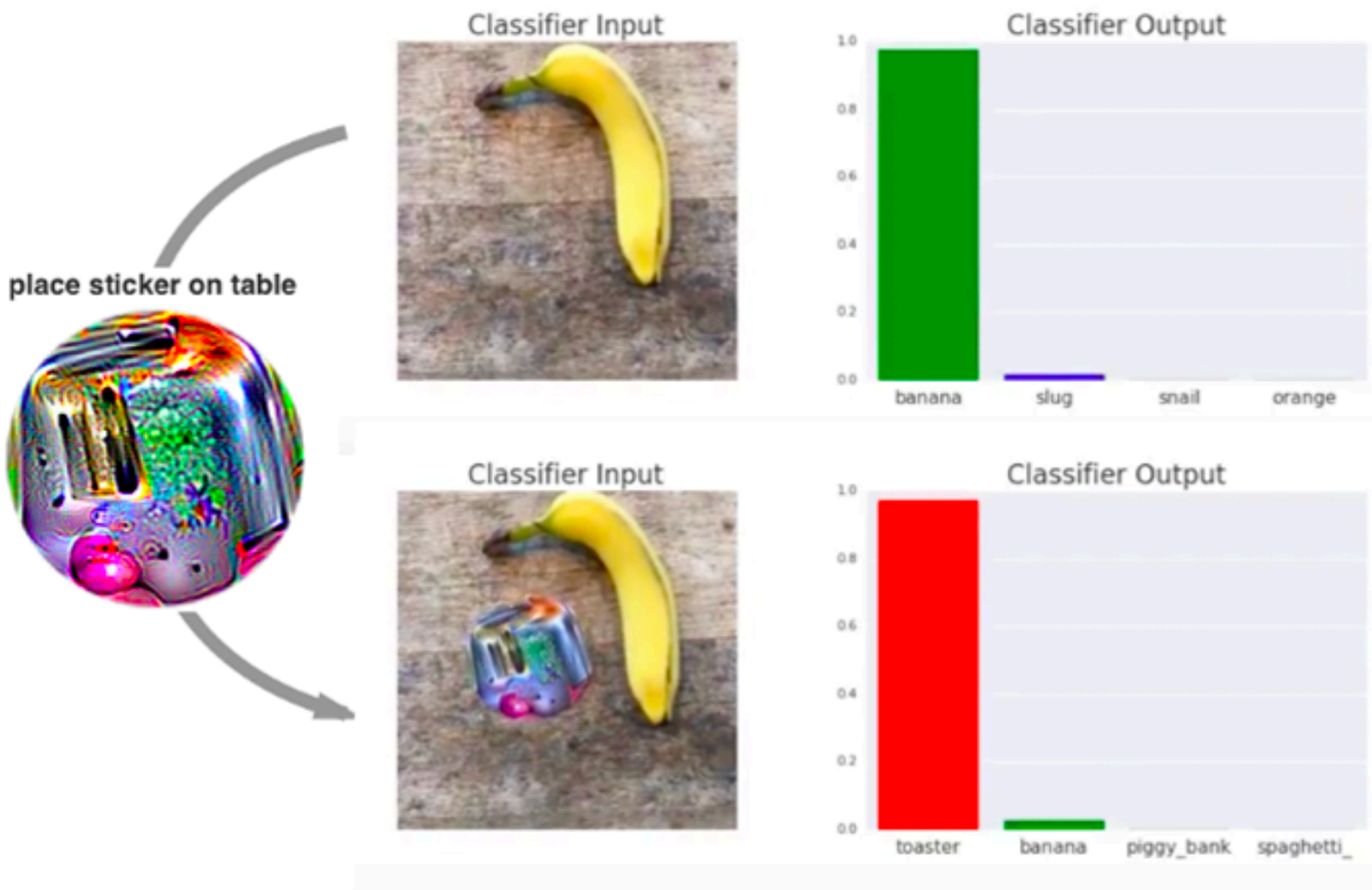
https://keras.io/examples/vision/grad_cam/

CAM heat maps



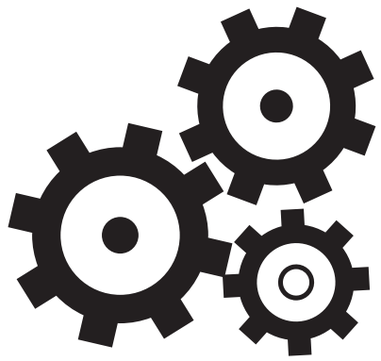
https://towardsdatascience.com/demystifying-convolutional-neural-networks-using-class-activation-maps-fe94eda4cef1

Adversarial Patch



What next?

https://www.mlcollege.com/en/#courses



Machine Learning Prague

MACHINE LEARNING
meetups

Thank you for your attention

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