



Universidad Veracruzana

Convolutional Neural Networks in Matlab

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Convolutional Neural Networks

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Convolutional Neural Network
3 things you need to know



What It Is



How It Works

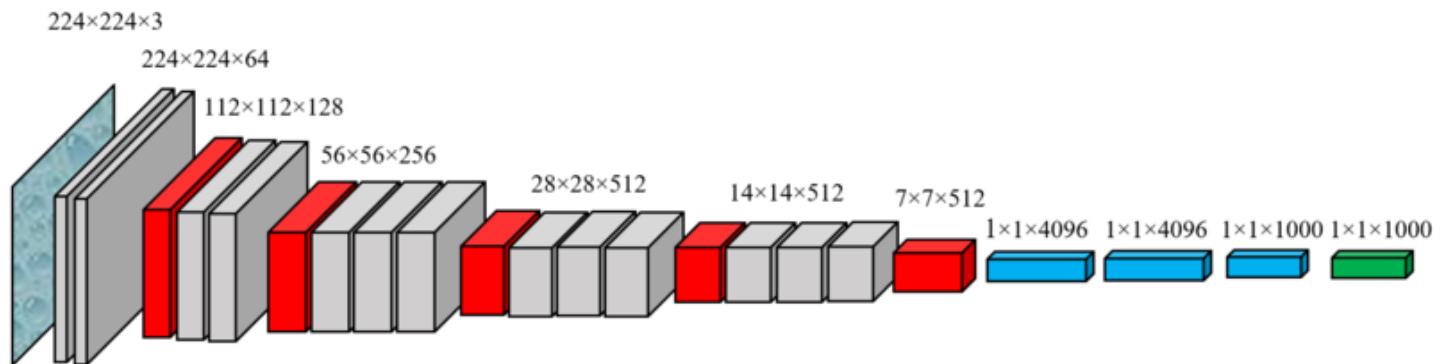
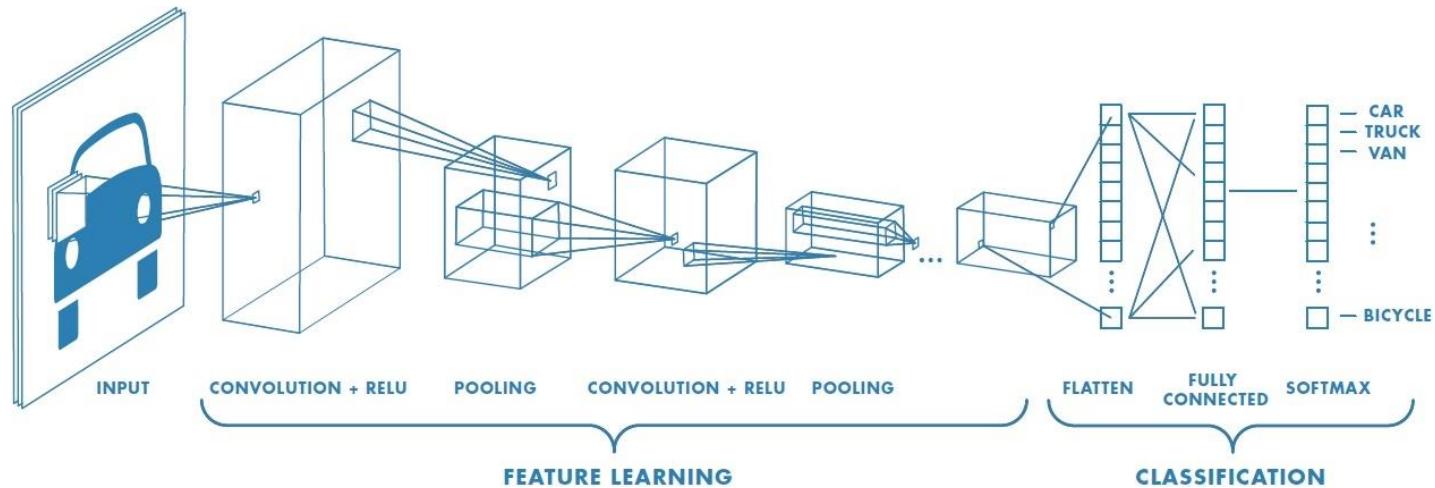


Using MATLAB
with a CNN

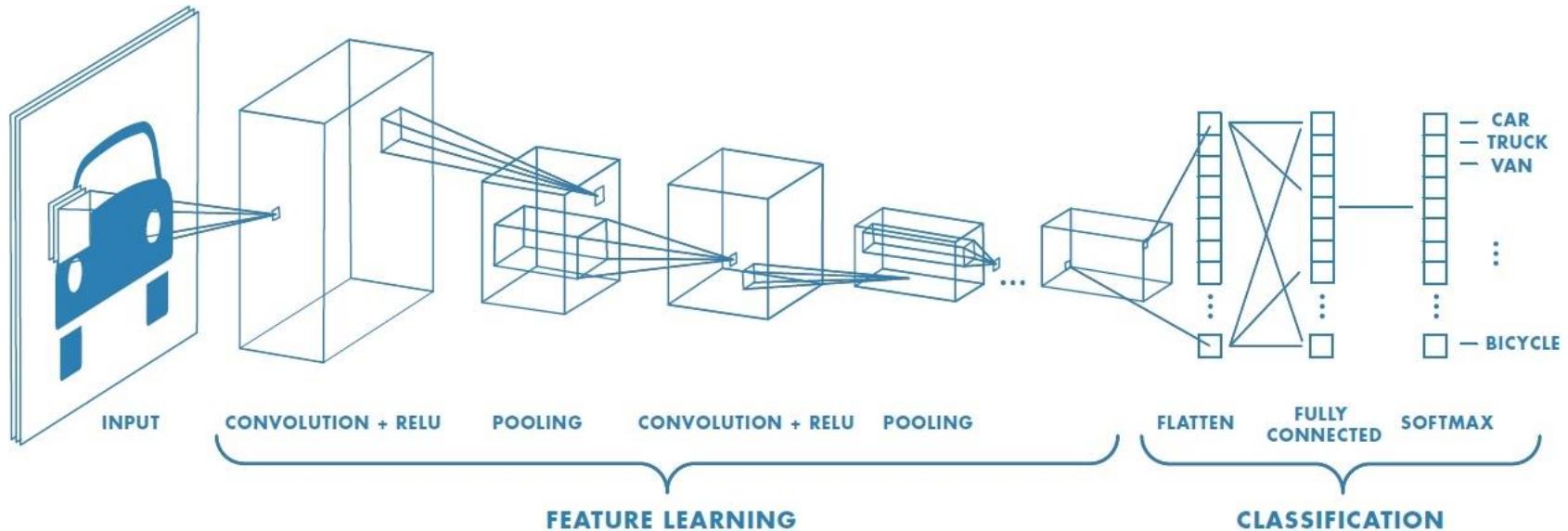
Material taken from MathWorks

<https://www.mathworks.com/solutions/deep-learning/convolutional-neural-network.html>

Convolutional Neural Networks



Convolutional Neural Networks



MATLAB Commands

```
>> newnet = trainNetwork data,layers,options)
```

MATLAB Variables

- layers**
- data**
- options**

Convolutional Neural Networks

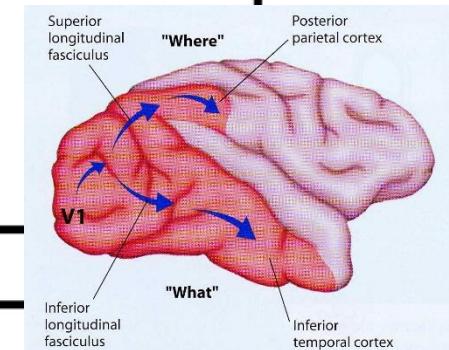
Classification

CNN - Deep Learning Toolbox™

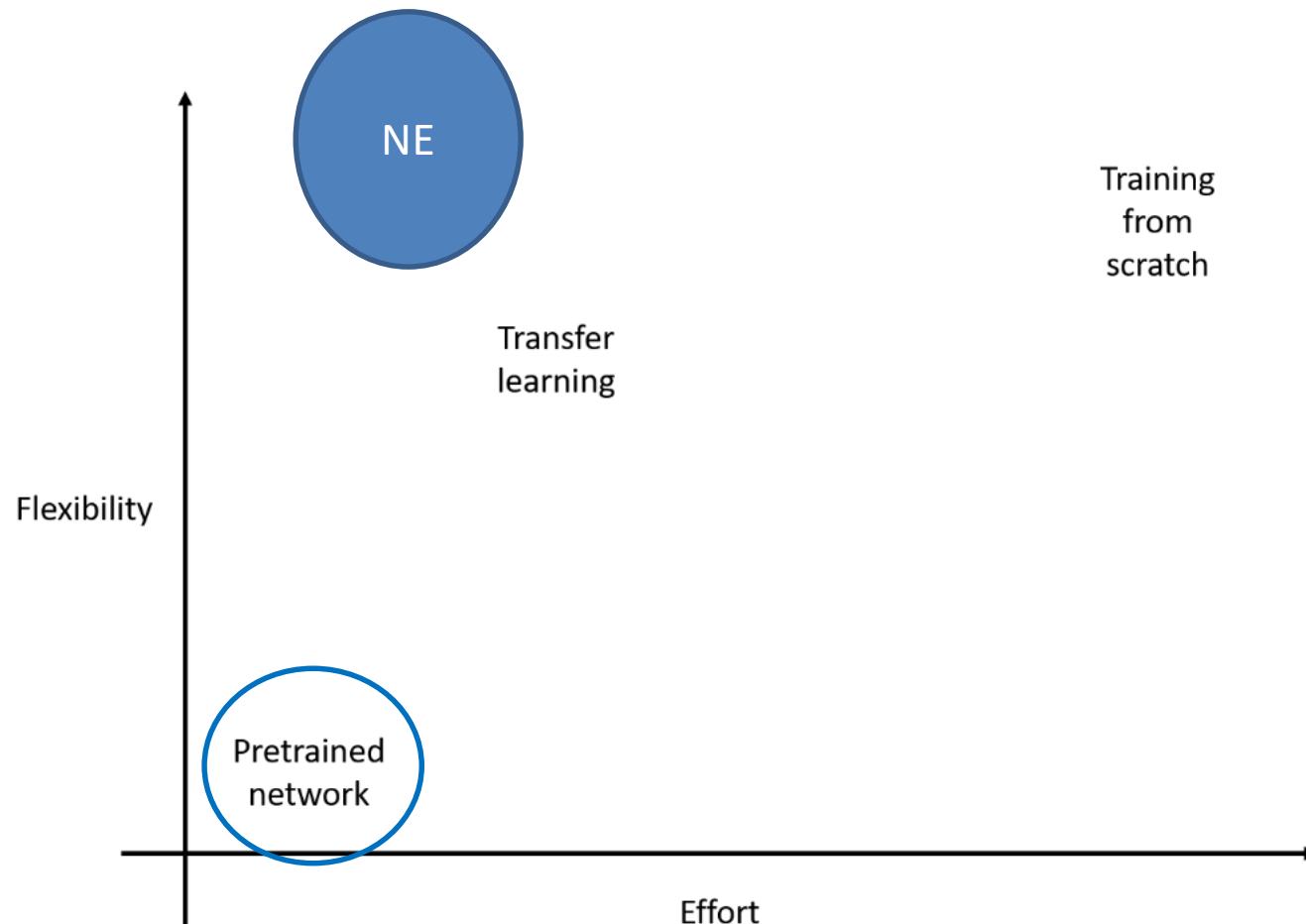
Regression

Object detection

R-CNN - Computer Vision Toolbox™

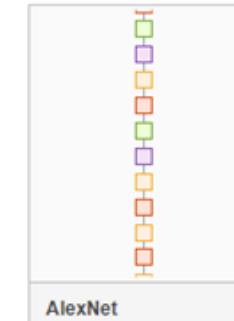
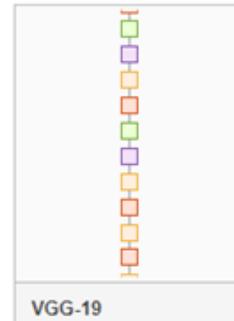
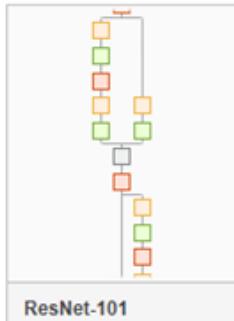
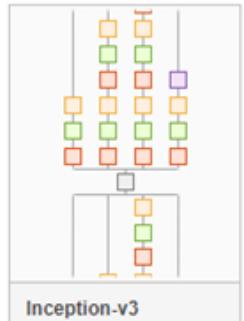
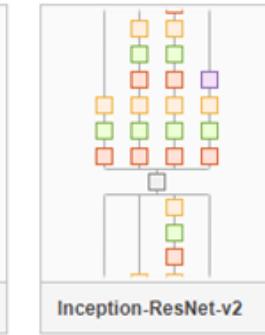
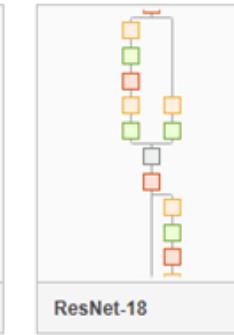
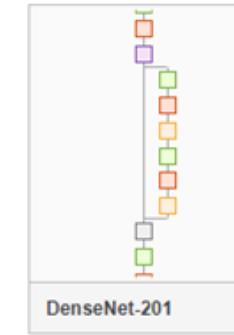
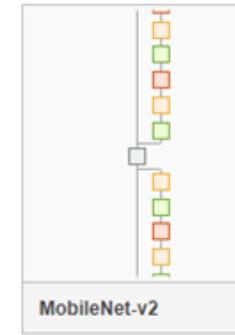
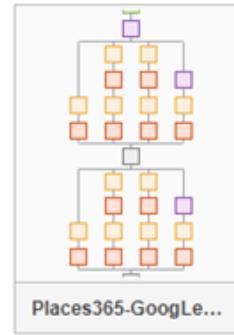
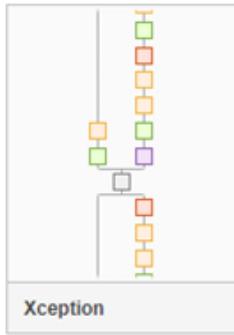
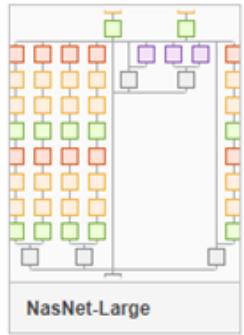
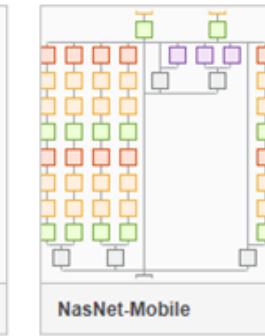
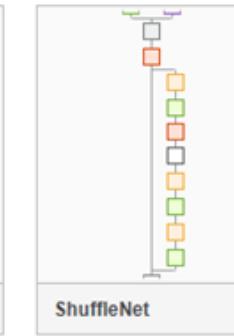
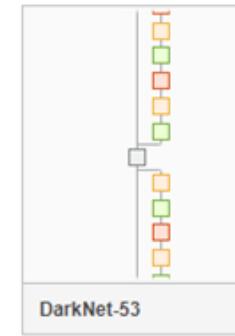
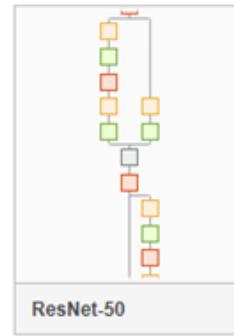
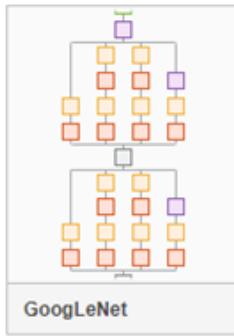
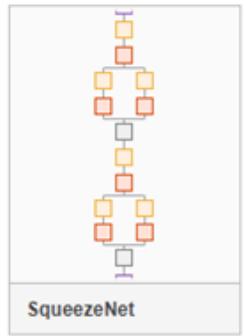


Convolutional Neural Networks



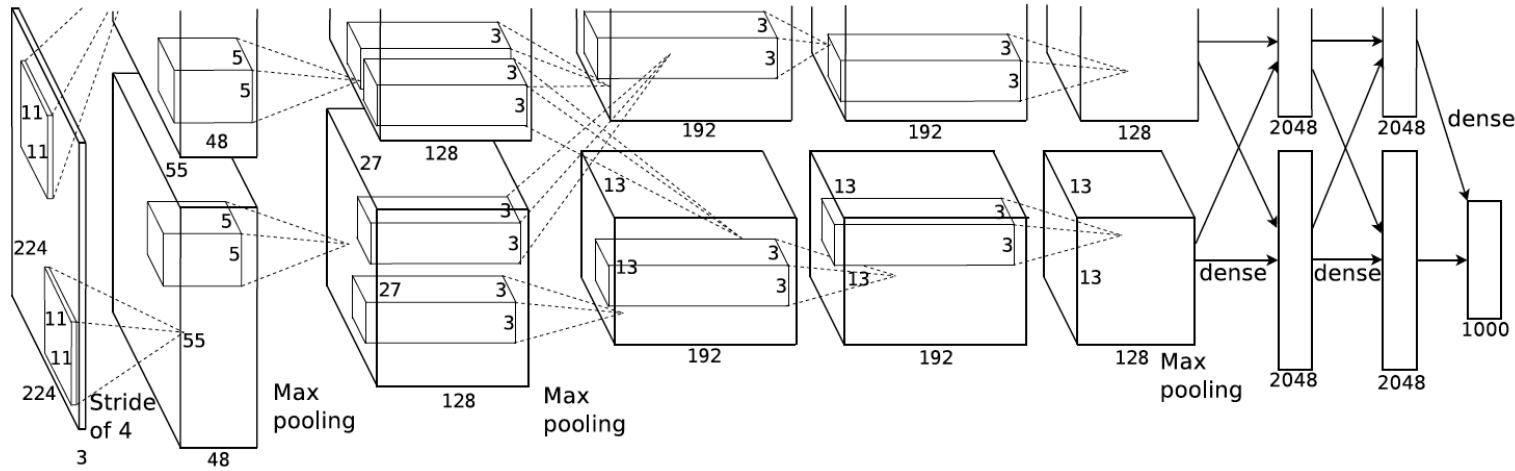
Networks

▼ Pretrained Networks



Alexnet

AlexNet is a pretrained Convolutional Neural Network (CNN) that has been trained on approximately 1.2 million images from the ImageNet Dataset (<http://image-net.org/index>). The model has 23 layers and can classify images into 1000 object categories (e.g. keyboard, mouse, coffee mug, pencil).



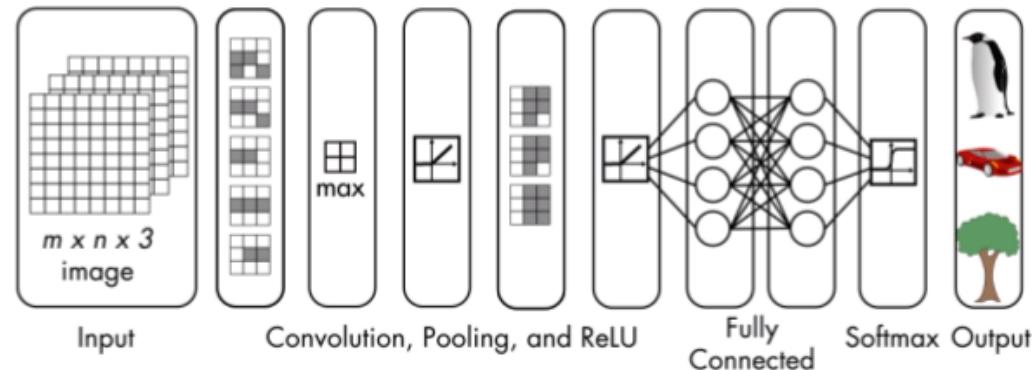
Alexnet in Matlab

Install: Deep Learning Toolbox Model for AlexNet
Network support package for the pretrained weights.

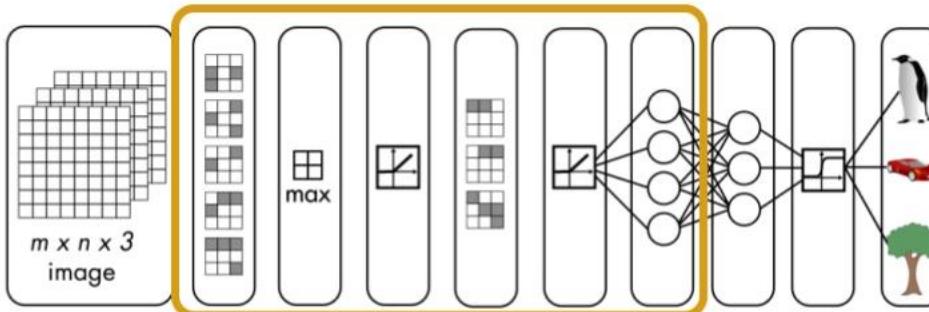
```
%Get AlexNet
```

```
net = alexnet;
```

```
layers = net.Layers:
```

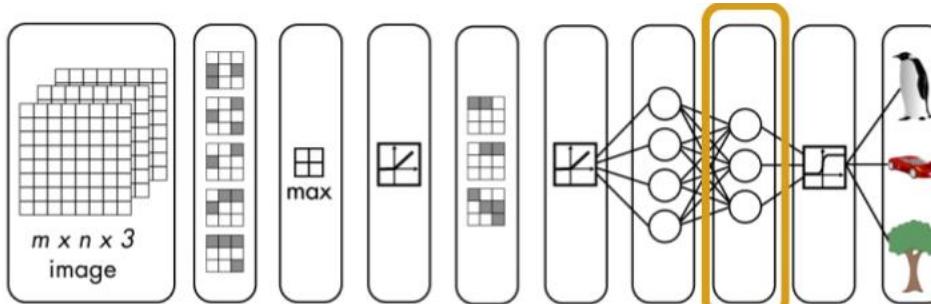


Structure



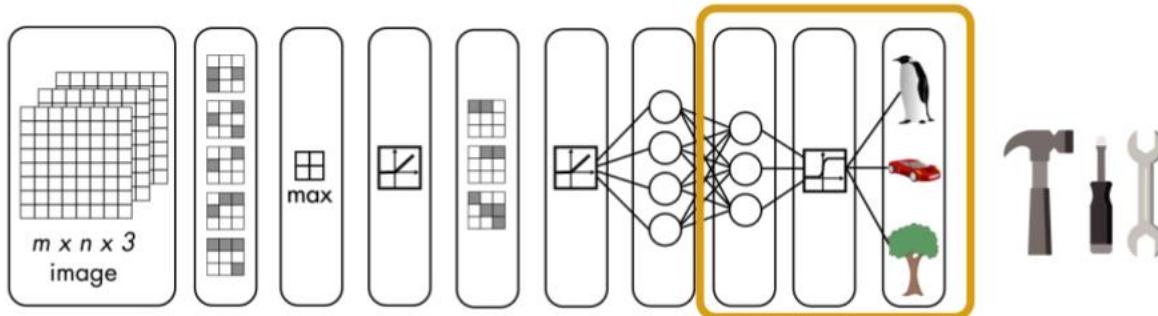
```
1  'data'          Image Input           227x227x3 images with 'zerocenter' normalization
2  'conv1'         Convolution        96 11x11x3 convolutions with stride [4 4] and padding [0 0 0 0]
3  'relu1'         ReLU
4  'norm1'         Cross Channel Normalization
5  'pool1'         Max Pooling      cross channel normalization with 5 channels per element
6  'conv2'         Convolution        3x3 max pooling with stride [2 2] and padding [0 0 0 0]
7  'relu2'         ReLU             256 5x5x48 convolutions with stride [1 1] and padding [2 2 2 2]
8  'norm2'         Cross Channel Normalization
9  'pool2'         Max Pooling      cross channel normalization with 5 channels per element
10 'conv3'         Convolution        3x3 max pooling with stride [2 2] and padding [0 0 0 0]
11 'relu3'         ReLU             384 3x3x256 convolutions with stride [1 1] and padding [1 1 1 1]
12 'conv4'         Convolution        ReLU
13 'relu4'         ReLU             384 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
14 'conv5'         Convolution        ReLU
15 'relu5'         ReLU             256 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
16 'pool5'         Max Pooling      ReLU
17 'fc6'          Fully Connected   3x3 max pooling with stride [2 2] and padding [0 0 0 0]
18 'relu6'         ReLU             4096 fully connected layer
19 'drop6'         Dropout          ReLU
20 'fc7'          Fully Connected   50% dropout
21 'relu7'         ReLU             4096 fully connected layer
22 'drop7'         Dropout          ReLU
23 'fc8'          Fully Connected   50% dropout
24 'prob'          Softmax          1000 fully connected layer
25 'output'        Classification Output softmax
                                crossentropyex with 'tench', 'goldfish', and 998 other classes
```

Structure



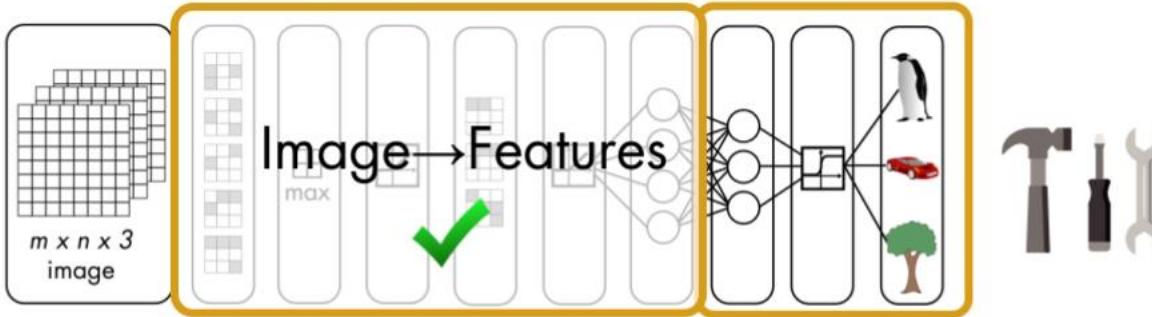
```
1  'data'      Image Input           227x227x3 images with 'zerocenter' normalization
2  'conv1'     Convolution          96 11x11x3 convolutions with stride [4 4] and padding [0 0 0 0]
3  'relu1'     ReLU
4  'norm1'    Cross Channel Normalization cross channel normalization with 5 channels per element
5  'pool1'     Max Pooling         3x3 max pooling with stride [2 2] and padding [0 0 0 0]
6  'conv2'     Convolution          256 5x5x48 convolutions with stride [1 1] and padding [2 2 2 2]
7  'relu2'     ReLU
8  'norm2'    Cross Channel Normalization cross channel normalization with 5 channels per element
9  'pool2'     Max Pooling         3x3 max pooling with stride [2 2] and padding [0 0 0 0]
10 'conv3'    Convolution          384 3x3x256 convolutions with stride [1 1] and padding [1 1 1 1]
11 'relu3'     ReLU
12 'conv4'    Convolution          384 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
13 'relu4'     ReLU
14 'conv5'    Convolution          256 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
15 'relu5'     ReLU
16 'pool3'     Max Pooling         3x3 max pooling with stride [2 2] and padding [0 0 0 0]
17 'fc6'      Fully Connected      4096 fully connected layer
18 'relu6'     ReLU
19 'drop6'    Dropout             50% dropout
20 'fc7'      Fully Connected      4096 fully connected layer
21 'relu7'     ReLU
22 'drop7'    Dropout             50% dropout
23 'fc8'      Fully Connected      1000 fully connected layer
24 'prob'     SOFTMAX
25 'output'   Classification Output SOFTMAX
                                         crossentropyex with 'tench', 'goldfish', and 998 other classes
```

Structure



```
1  'data'      Image Input           227x227x3 images with 'zerocenter' normalization
2  'conv1'     Convolution          96 11x11x3 convolutions with stride [4 4] and padding [0 0 0 0]
3  'relu1'    ReLU
4  'norm1'   Cross Channel Normalization cross channel normalization with 5 channels per element
5  'pool1'   Max Pooling          3x3 max pooling with stride [2 2] and padding [0 0 0 0]
6  'conv2'   Convolution          256 5x5x48 convolutions with stride [1 1] and padding [2 2 2 2]
7  'relu2'   ReLU
8  'norm2'   Cross Channel Normalization cross channel normalization with 5 channels per element
9  'pool2'   Max Pooling          3x3 max pooling with stride [2 2] and padding [0 0 0 0]
10 'conv3'   Convolution          384 3x3x256 convolutions with stride [1 1] and padding [1 1 1 1]
11 'relu3'   ReLU
12 'conv4'   Convolution          384 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
13 'relu4'   ReLU
14 'conv5'   Convolution          256 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
15 'relu5'   ReLU
16 'pool5'   Max Pooling          3x3 max pooling with stride [2 2] and padding [0 0 0 0]
17 'fc6'    Fully Connected      4096 fully connected layer
18 'relu6'   ReLU
19 'drop6'   Dropout             50% dropout
20 'fc7'    Fully Connected      4096 fully connected layer
21 'relu7'   ReLU
22 'drop7'   Dropout             50% dropout
23 'fc8'    Fully Connected      1000 fully connected layer
24 'prob'   Softmax
25 'output' Classification Output softmax
                                         crossentropyex with 'tench', 'goldfish', and 998 other classes
```

Structure



```
1  'data'      Image Input          227x227x3 images with 'zerocenter' normalization
2  'conv1'     Convolution         96 11x11x3 convolutions with stride [4 4] and padding [0 0 0 0]
3  'relu1'    ReLU
4  'norm1'   Cross Channel Normalization cross channel normalization with 5 channels per element
5  'pool1'   Max Pooling        3x3 max pooling with stride [2 2] and padding [0 0 0 0]
6  'conv2'   Convolution         256 5x5x48 convolutions with stride [1 1] and padding [2 2 2 2]
7  'relu2'   ReLU
8  'norm2'   Cross Channel Normalization cross channel normalization with 5 channels per element
9  'pool2'   Max Pooling        3x3 max pooling with stride [2 2] and padding [0 0 0 0]
10 'conv3'  Convolution         384 3x3x256 convolutions with stride [1 1] and padding [1 1 1 1]
11 'relu3'  ReLU
12 'conv4'  Convolution         384 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
13 'relu4'  ReLU
14 'conv5'  Convolution         256 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
15 'relu5'  ReLU
16 'pool5'  Max Pooling        3x3 max pooling with stride [2 2] and padding [0 0 0 0]
17 'fc6'    Fully Connected    4096 fully connected layer
18 'relu6'  ReLU
19 'drop6'  Dropout            50% dropout
20 'fc7'    Fully Connected    4096 fully connected layer
21 'relu7'  ReLU
22 'drop7'  Dropout            50% dropout
23 'fc8'    Fully Connected    1000 fully connected layer
24 'prob'   Softmax
25 'output' Classification Output crossentropyex with 'tench', 'goldfish', and 998 other classes
```

Pretrained Network

```
% CNN in 10 lines
camera=webcam;

nnet=alexnet;

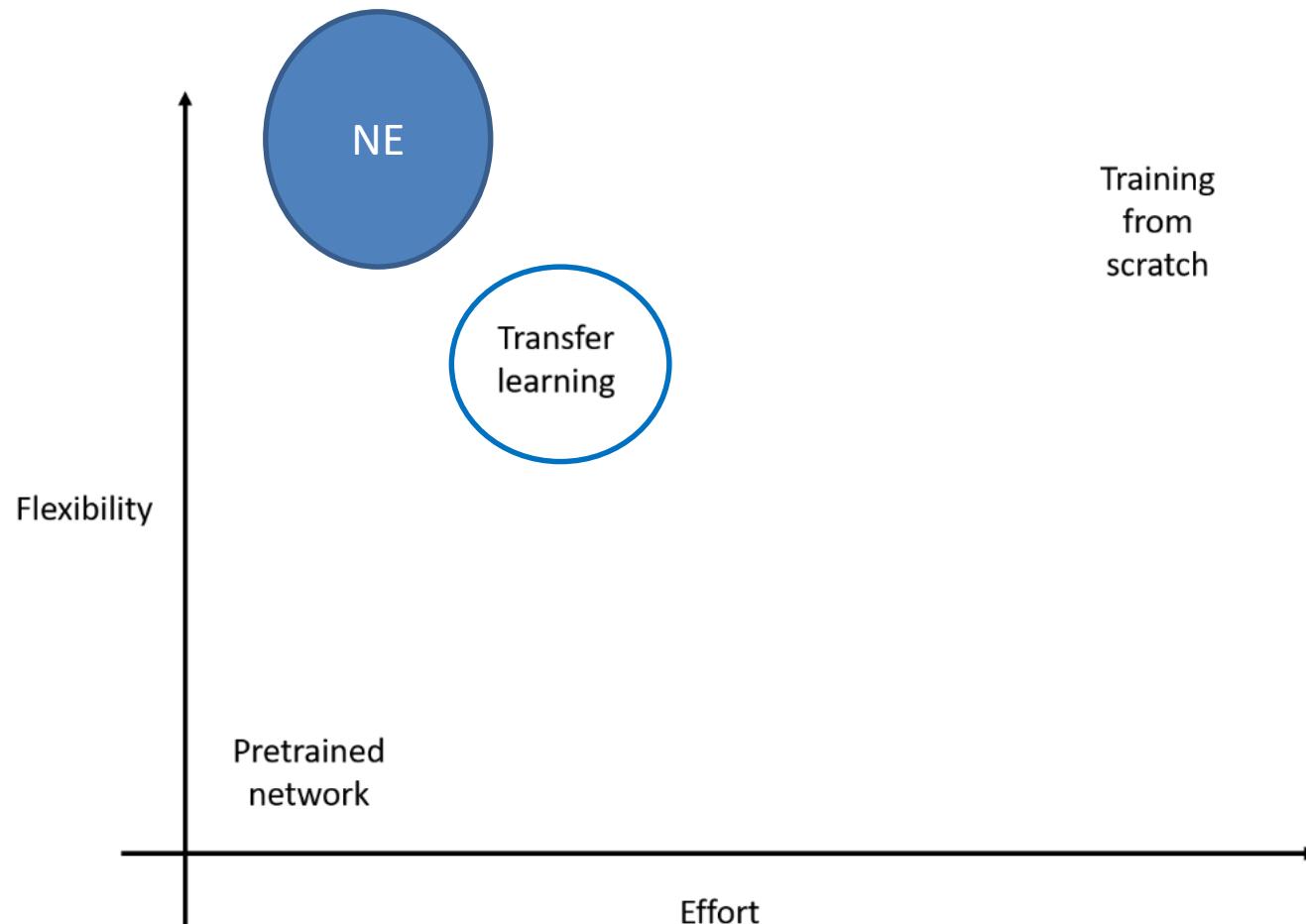
while true
    picture=camera.snapshot;
    picture=imresize(picture,[227,227]);

    label=classify(nnet,picture);

    image(picture)
    title(char(label))
    drawnow;

end
```

Transfer learning



Transfer learning

This example shows how to fine-tune a pretrained AlexNet convolutional neural network to perform classification on a new collection of images.

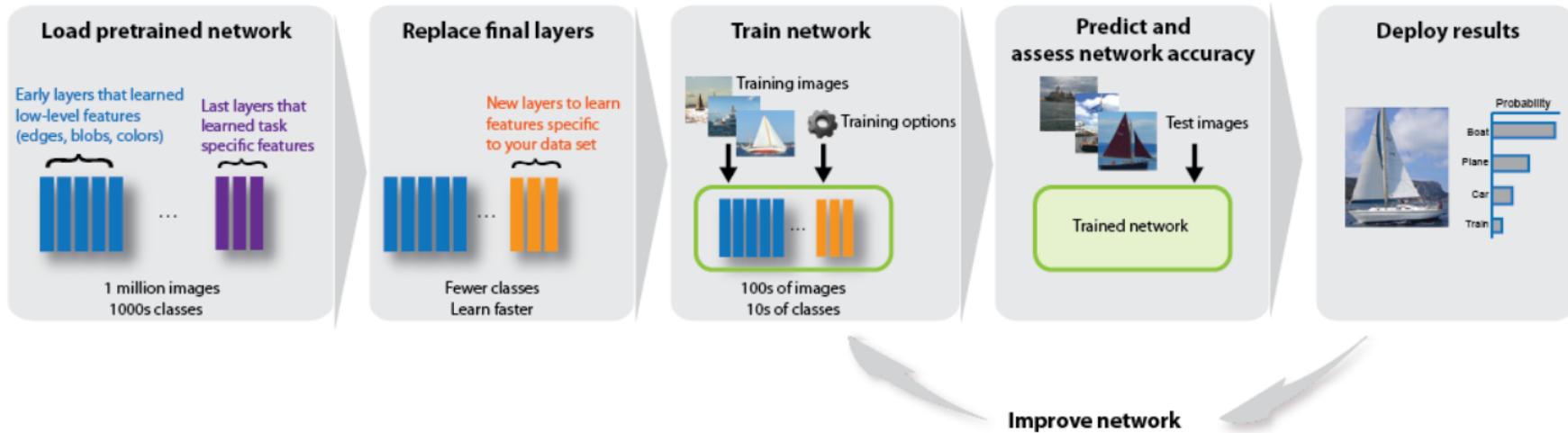
AlexNet has been trained on over a million images and can classify images into 1000 object categories (such as keyboard, coffee mug, pencil, and many animals). The network has learned rich feature representations for a wide range of images. The network takes an image as input and outputs a label for the object in the image together with the probabilities for each of the object categories.

Transfer learning is commonly used in deep learning applications. You can take a pretrained network and use it as a starting point to learn a new task. Fine-tuning a network with transfer learning is usually much faster and easier than training a network with randomly initialized weights from scratch. You can quickly transfer learned features to a new task using a smaller number of training images.

This example uses:
[Deep Learning Toolbox](#)
[Deep Learning Toolbox Model for AlexNet Network](#)

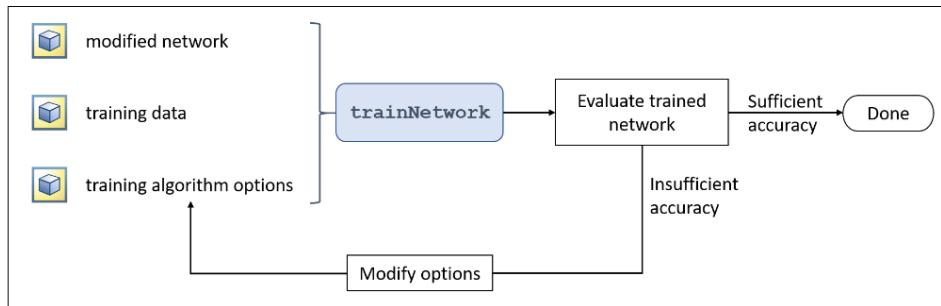
[View MATLAB Command](#)

Reuse Pretrained Network



Transfer learning

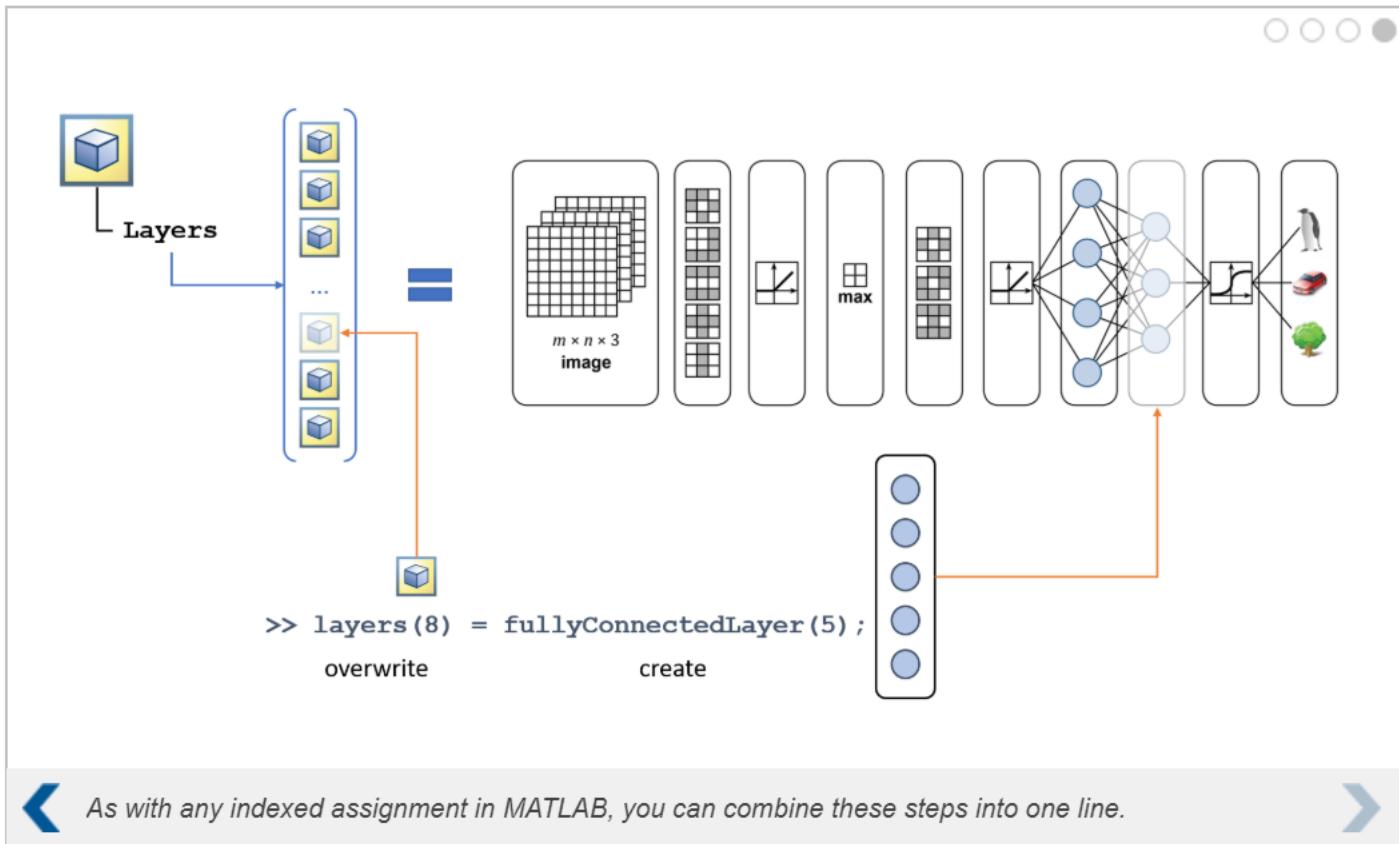
Typical workflow for transfer learning



To perform transfer learning, you need to create three components:

1. An array of layers representing the network architecture. For transfer learning, this is created by modifying a preexisting network such as AlexNet.
2. Images with known labels to be used as training data. This is typically provided as a datastore.

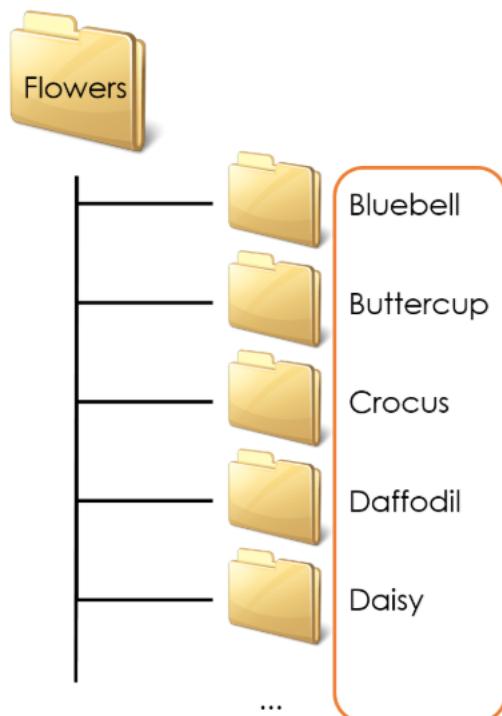
Transfer learning



Data

Labeling training images

When training a network, you need to provide known labels for the training images. The `Flowers` folder contains 12 subfolders, each of which contains 80 images of one type of flower. The name of the folder can therefore be used to provide the labels needed for training.



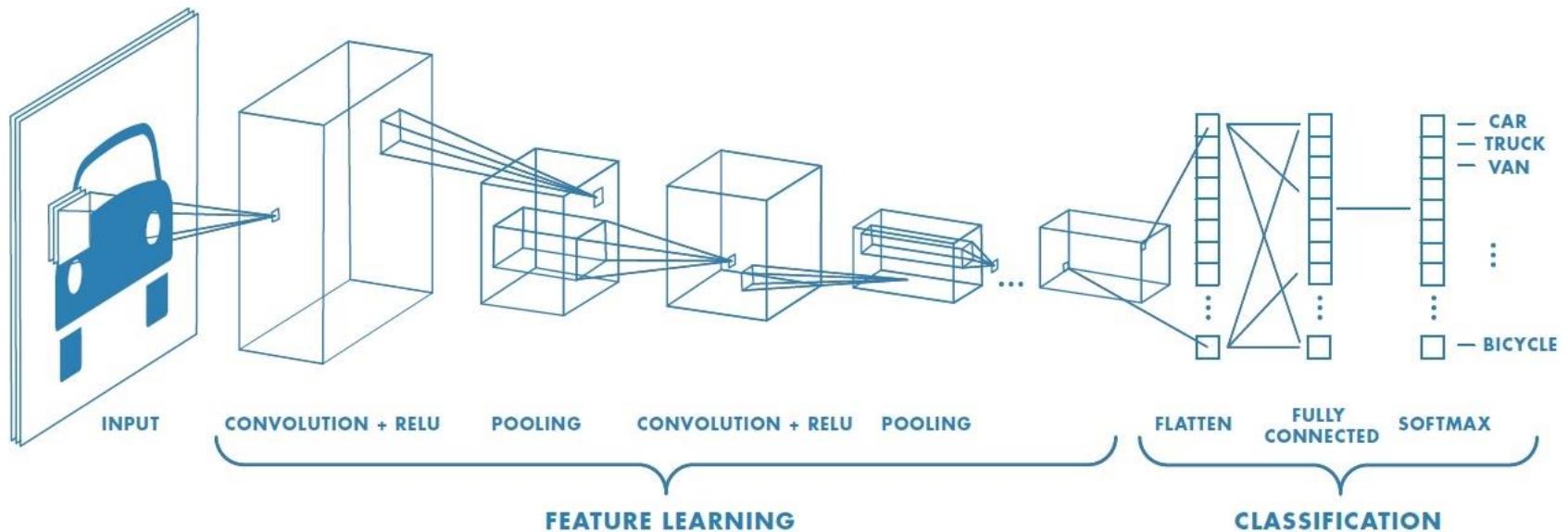
GPU device check

```
% Get GPU device information
deviceInfo = gpuDevice
% Check the GPU compute capability
computeCapability = str2double(deviceInfo.ComputeCapability);
```

CUDADevice with properties:

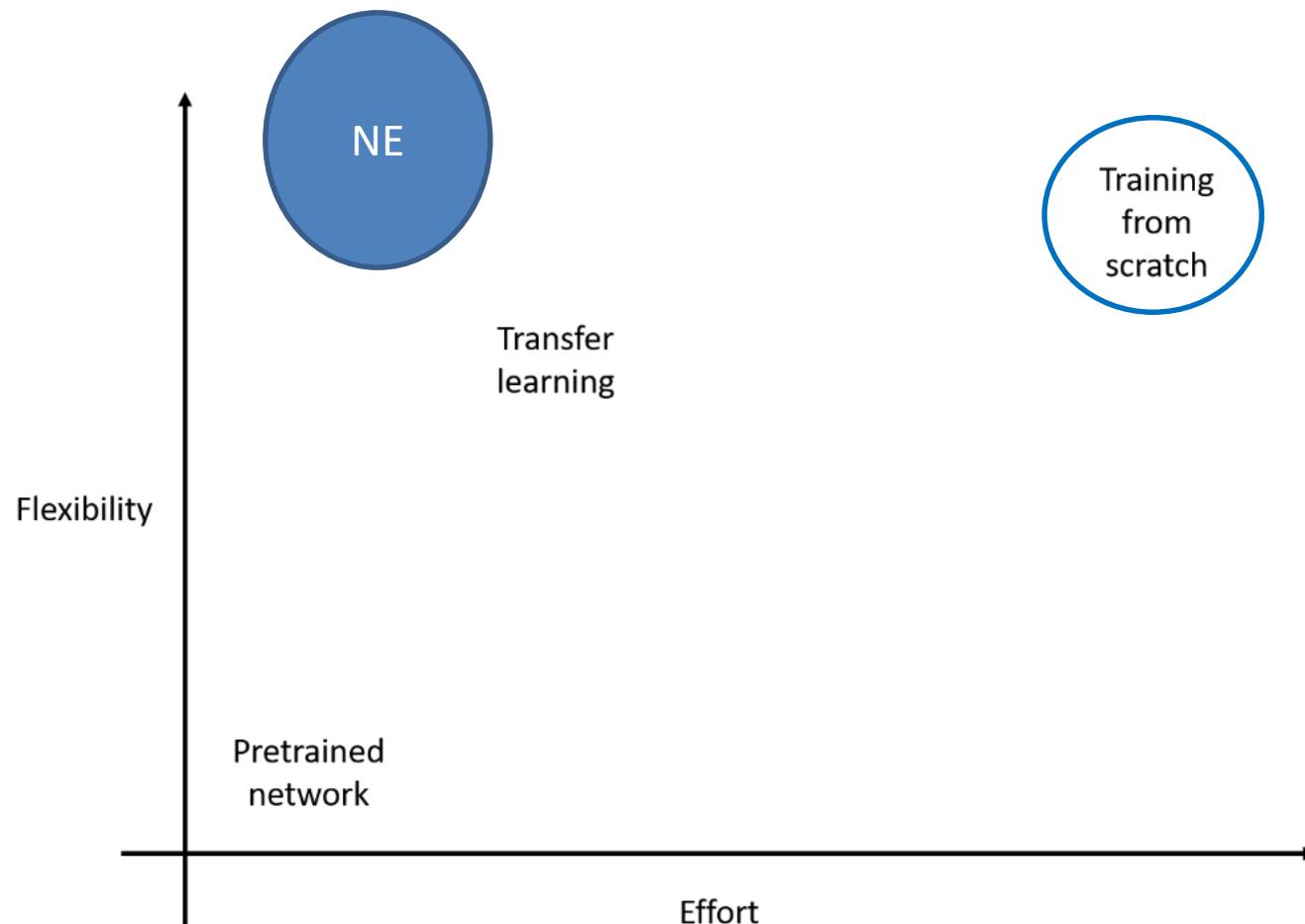
```
Name: 'Quadro P1000'
Index: 1
ComputeCapability: '6.1'
SupportsDouble: 1
DriverVersion: 11.2000
ToolkitVersion: 11.2000
MaxThreadsPerBlock: 1024
MaxShmemPerBlock: 49152 (49.15 KB)
MaxThreadBlockSize: [1024 1024 64]
    MaxGridSize: [2.1475e+09 65535 65535]
    SIMDWidth: 32
    TotalMemory: 4294967296 (4.29 GB)
    AvailableMemory: 3432408679 (3.43 GB)
MultiprocessorCount: 5
ClockRateKHz: 1480500
ComputeMode: 'Default'
GPUOverlapsTransfers: 1
KernelExecutionTimeout: 1
CanMapHostMemory: 1
DeviceSupported: 1
DeviceAvailable: 1
DeviceSelected: 1
```

Transfer learning



See code: [TransfL_Alexnet1.m](#) (Flowers)

Training from scratch

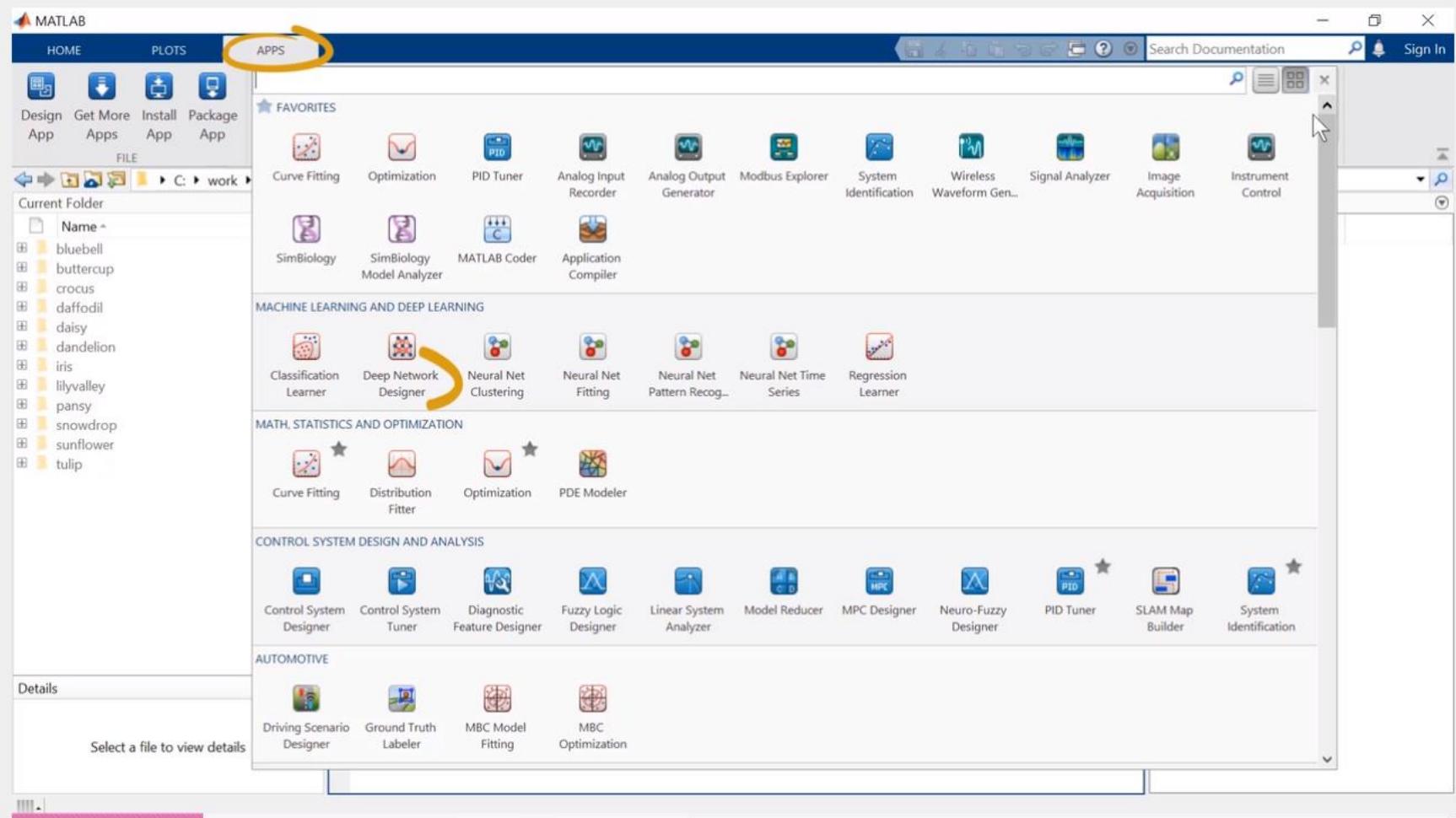


Training from scratch (Layers)

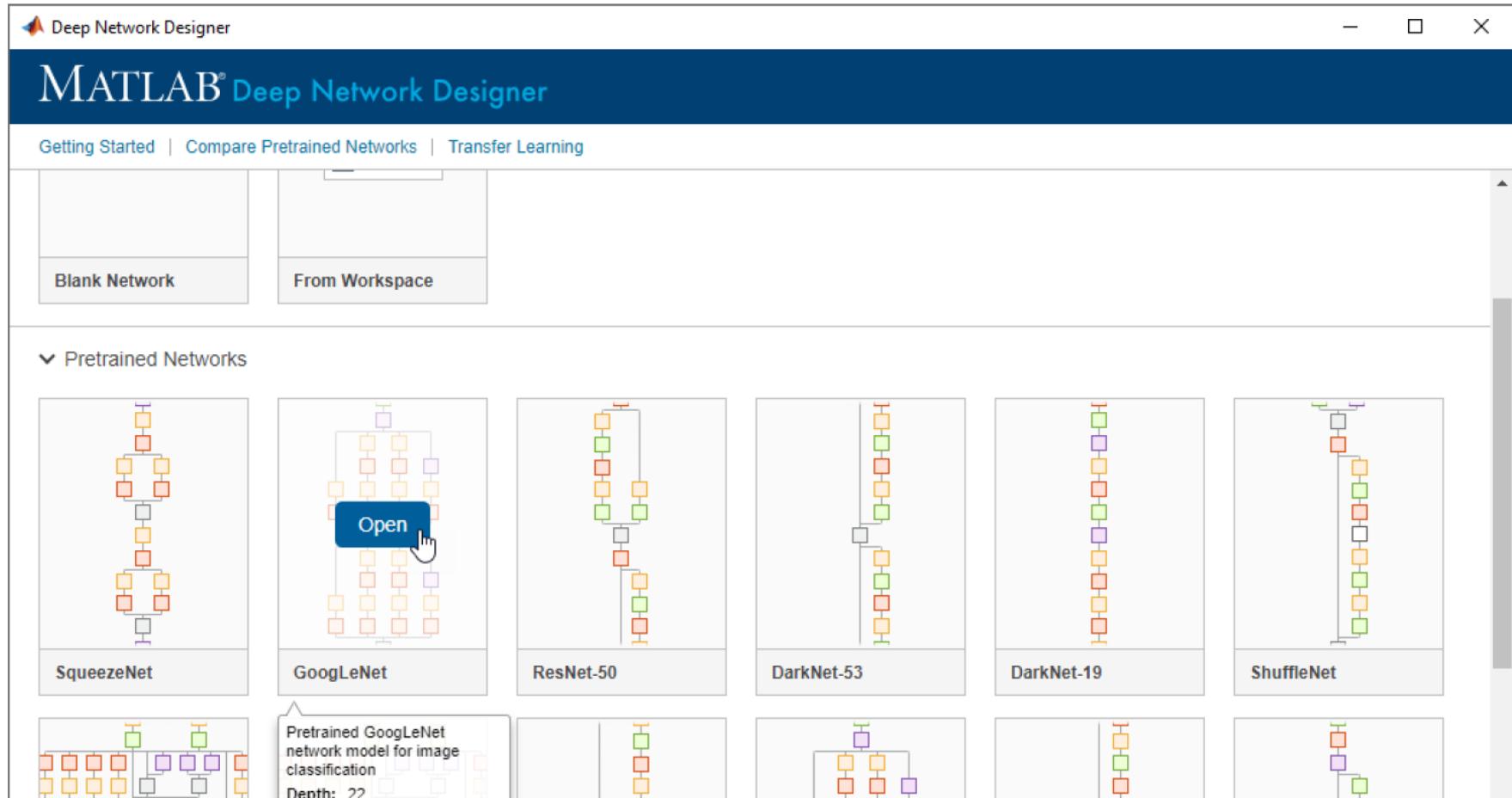
Example 1: Scratch_Digits.m

analyzeNetwork(net)

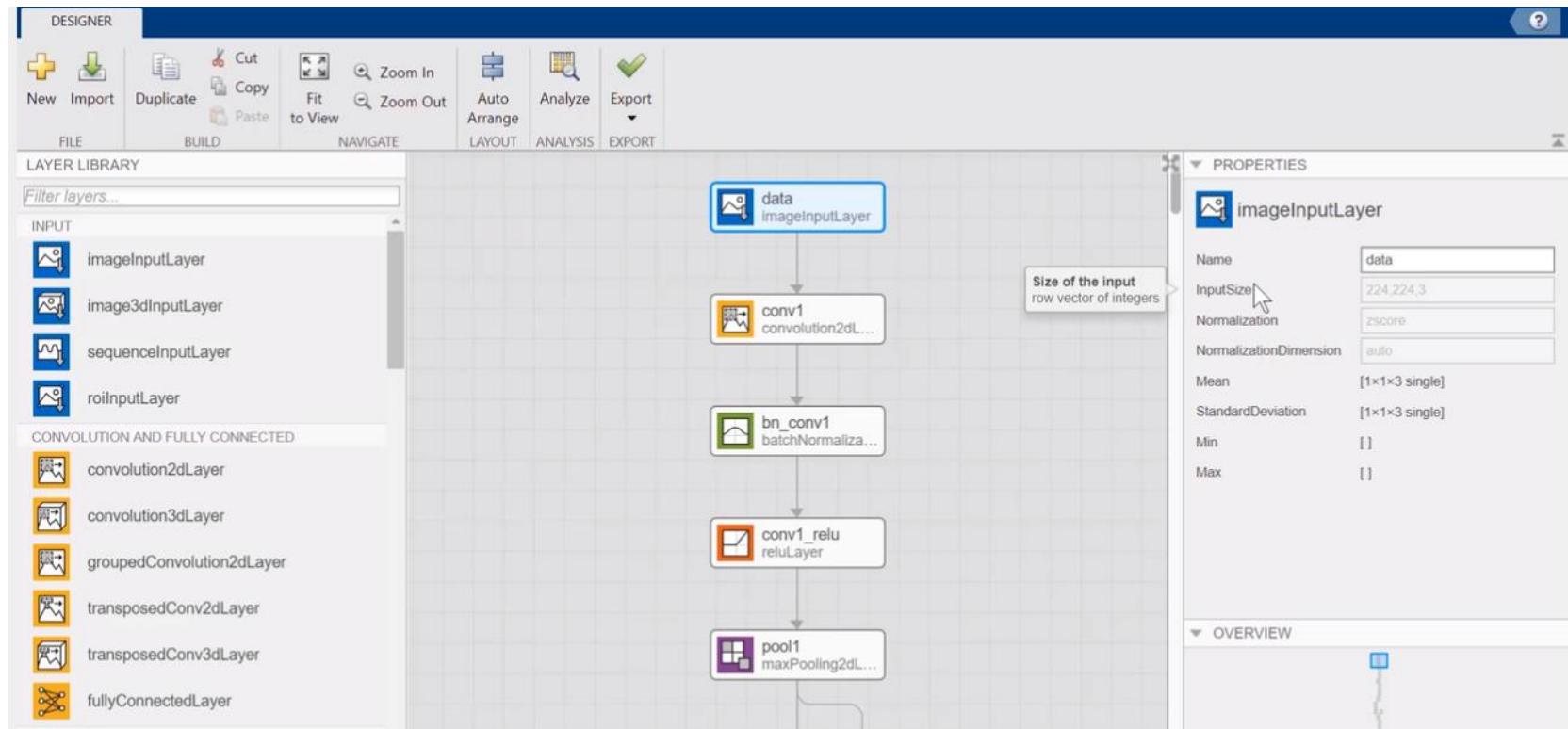
Deep Network Designer



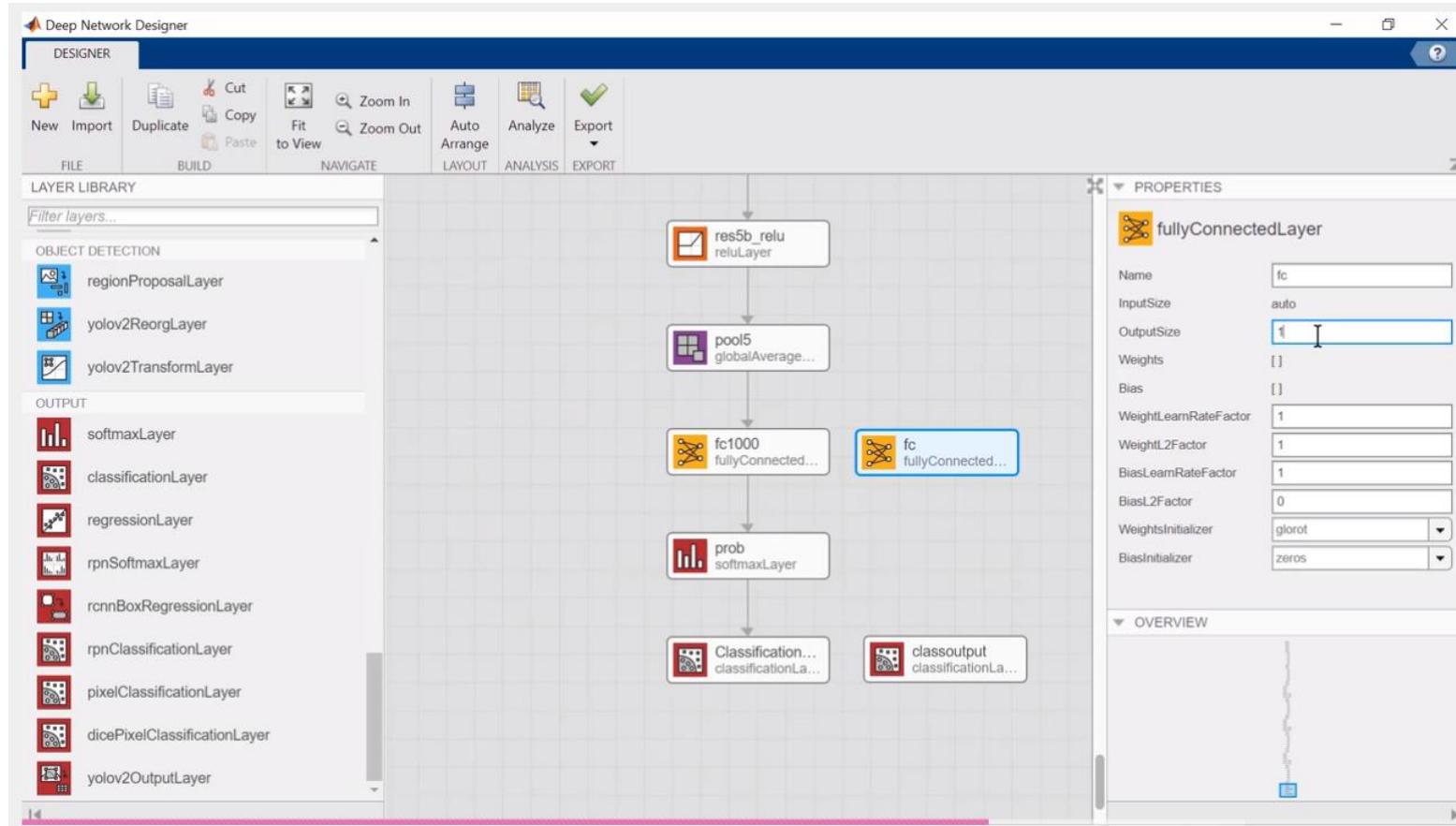
Deep Network Designer



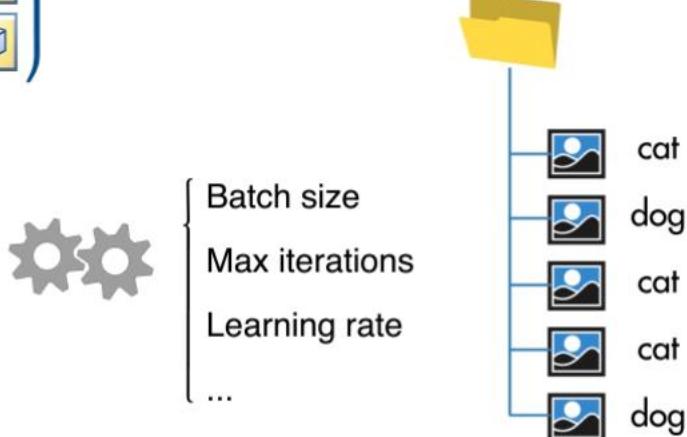
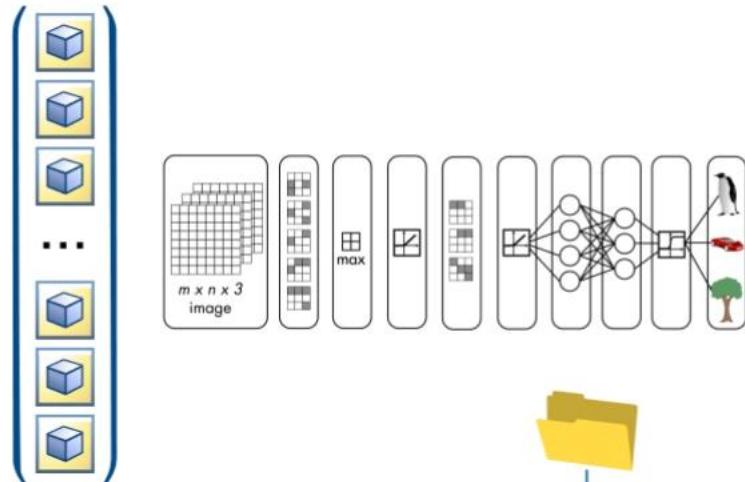
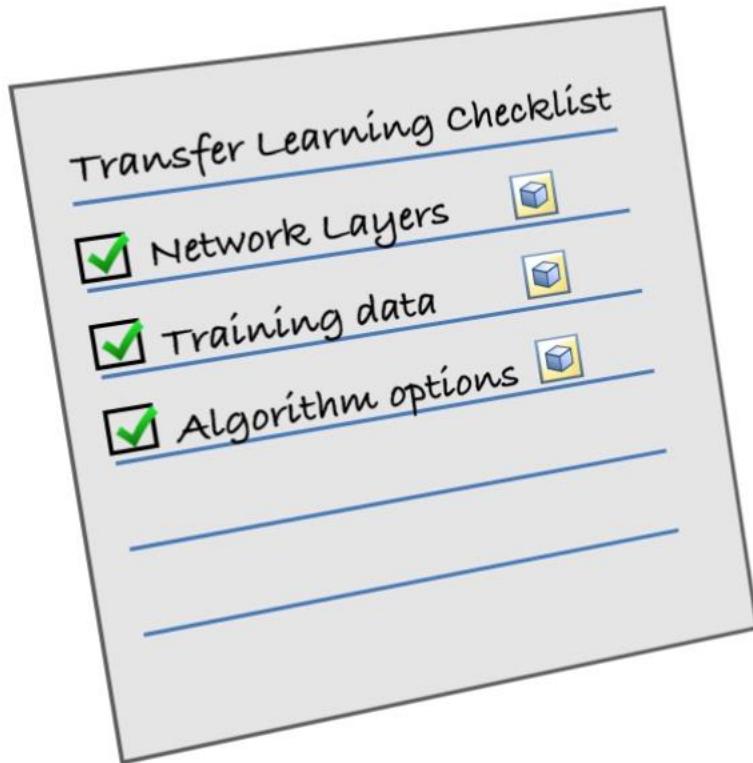
Deep Network Designer



Deep Network Designer

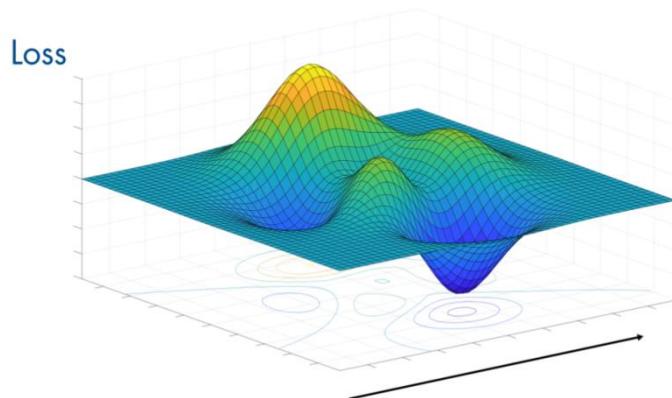


Training



Optimization parameters

See options code.



Training

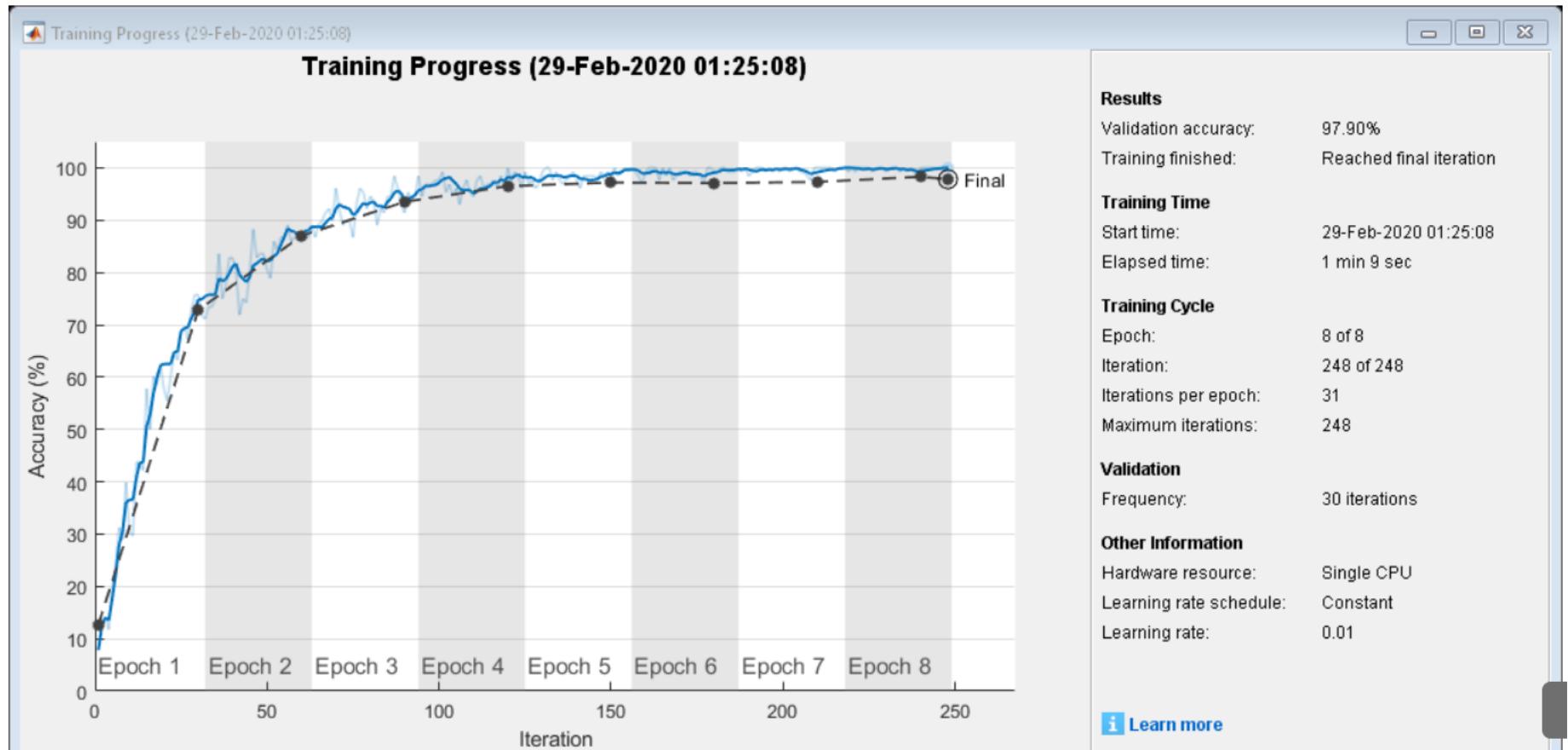
```
>> newnet = trainNetwork(data,layers,options)
```



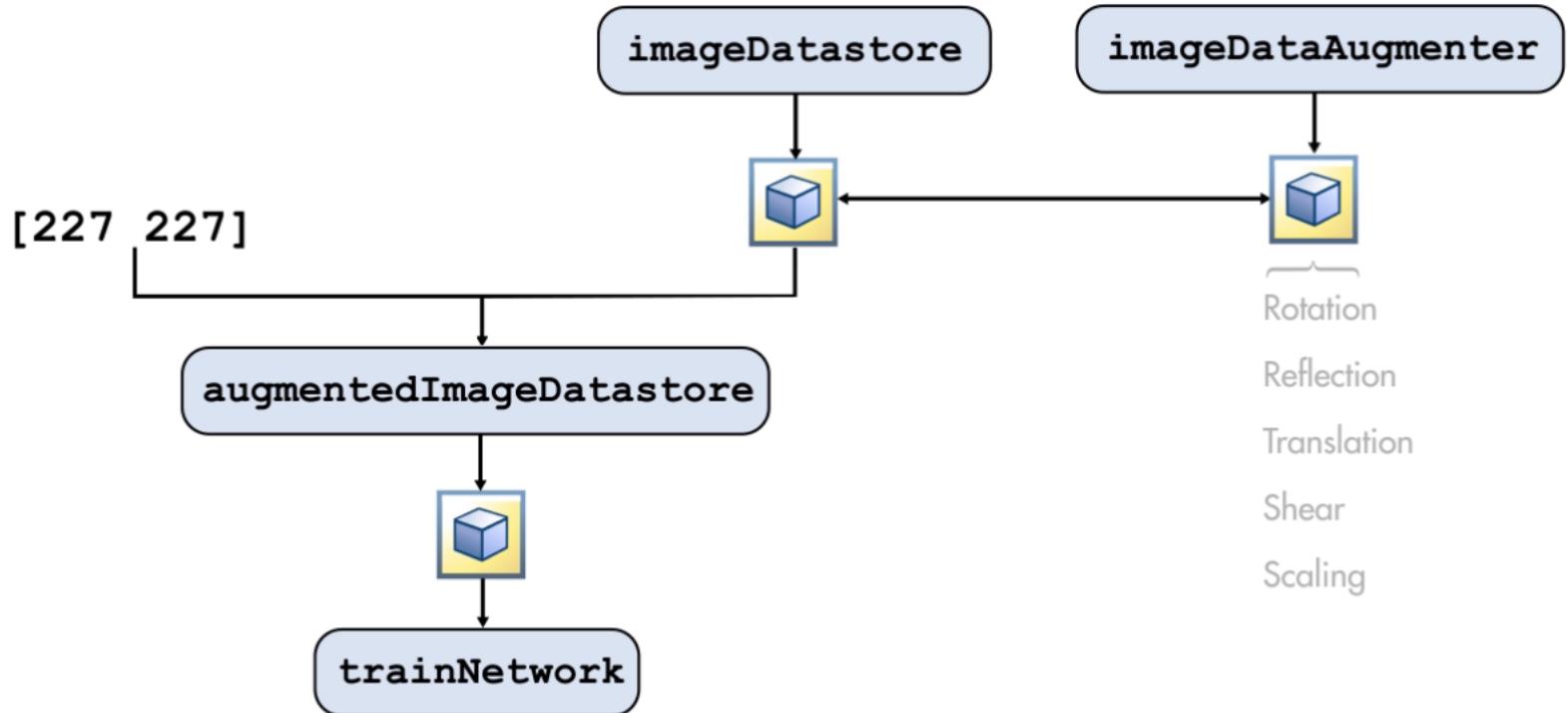
Training on single GPU.
Initializing image normalization.

Epoch	Iteration	Time Elapsed (seconds)	Mini-batch Loss	Mini-batch Accuracy	Base Learning Rate
1	1	0.47	3.5061	7.81%	0.0010
3	10	10.31	0.7686	75.00%	0.0010
5	20	18.96	0.2371	92.19%	0.0010
8	30	27.43	0.0770	97.66%	0.0010
10	40	35.31	0.0336	99.22%	0.0010
13	50	43.17	0.0289	99.22%	0.0010
15	60	50.15	0.0104	100.00%	0.0010
18	70	56.84	0.0072	100.00%	0.0010
20	80	63.00	0.0210	99.22%	0.0010
23	90	69.37	0.0035	100.00%	0.0010

Training



Data



Data augmentation in Matlab

imageDataAugmenter

Description

An image data augmenter configures a set of preprocessing options for image augmentation, such as resizing, rotation, and reflection. The imageDataAugmenter is used by an [augmentedImageDatastore](#) to generate batches of augmented images. For more information, see [Augment Images for Training](#).

Syntax

```
aug = imageDataAugmenter  
aug = imageDataAugmenter(Name,Value)
```

Data augmentation

```
% Create an imageDataAugmenter object that specifies  
preprocessing options for image augmentation
```

```
[XTrain,YTrain] = digitTrain4DArrayData;
```

```
imageAugmenter = imageDataAugmenter( ...  
    'RandRotation',[-20,20], ...  
    'RandXTranslation',[-3 3], ...  
    'RandYTranslation',[-3 3])
```

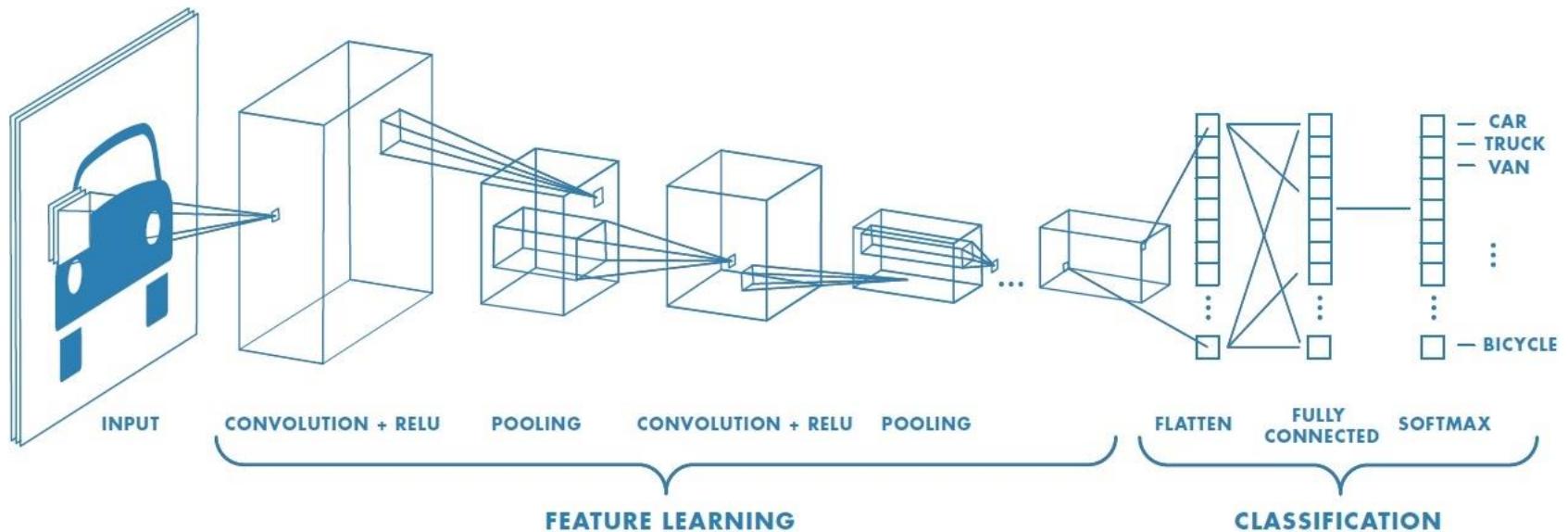
```
imageSize = [28 28 1];
```

```
augimds =  
augmentedImageDatastore(imageSize,XTrain,YTrain,'DataAug  
mentation',imageAugmenter);
```

Training from scratch (Layers)

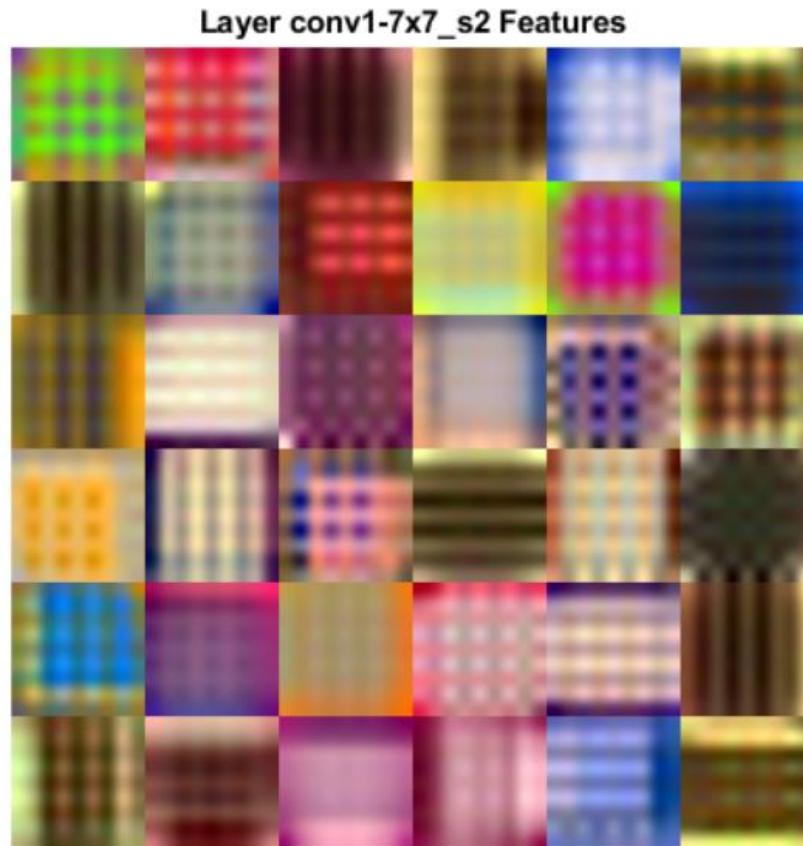
Example 2: Scratch_Digits_Augment.m

Feature extraction



See: [Demo_FeatureExtraction.m](#) (cfar10)

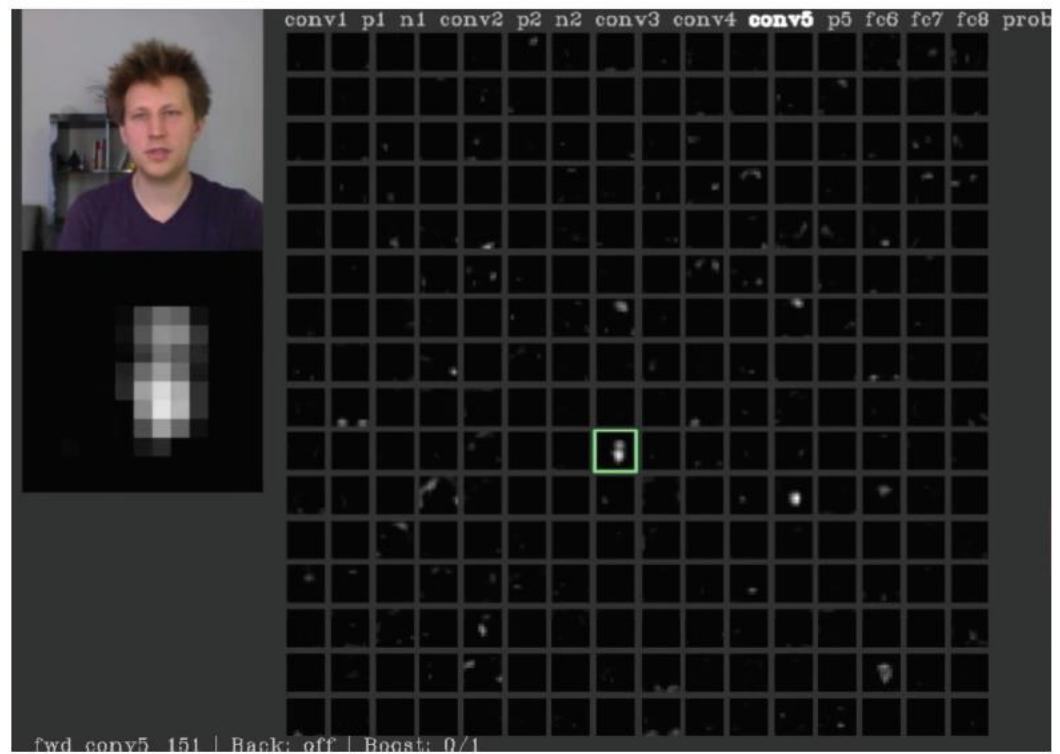
Visualize Features of a CNN



<https://www.mathworks.com/help/deeplearning/ug/visualize-features-of-a-convolutional-neural-network.html>

Visualize Features of a CNN

conv5 feature map is
128x13x13; visualize
as 128 13x13
grayscale images



Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.
Figure copyright Jason Yosinski, 2014. Reproduced with permission.

<https://www.youtube.com/watch?v=AgkfIQ4IGaM>

Understanding CNN



MODELS

Models

The OpenAI Microscope is a collection of visualizations of every significant layer and neuron of 13 important vision models.

[LEARN MORE ▶](#)

AlexNet

A landmark in computer vision, this 2012 winner of ImageNet has over 50,000 citations.



AlexNet (Places)

The same architecture as the classic AlexNet model, but trained on the Places365 dataset.



Inception v1

Also known as GoogLeNet, this network set the state of the art in ImageNet classification in 2014.



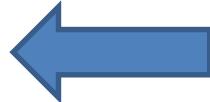
<https://microscope.openai.com/models>

Convolutional Neural Networks

Classification

CNN - Deep Learning Toolbox™

Regression



Object detection

R-CNN - Computer Vision Toolbox™

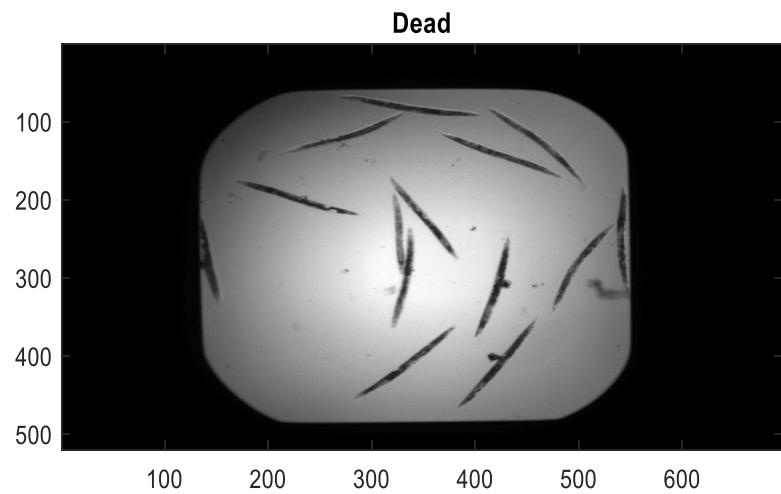
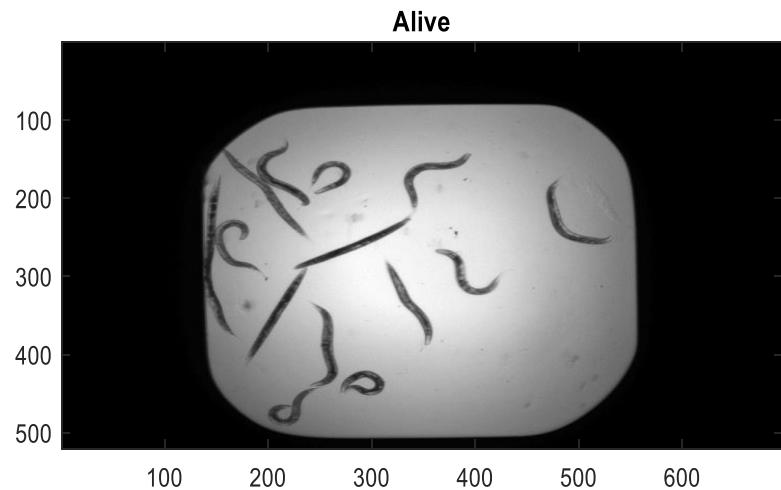
CNN for regression

Original	Corrected
4 0 7 3 1 1 3	4 0 1 3 1 1 3
4 7 1 8 3 4 1	4 7 1 8 3 4 1
1 6 2 6 1 3 2	7 6 2 6 1 3 2
8 7 7 1 0 6 2	8 7 7 7 0 6 2
5 5 2 0 0 3 2	5 5 2 0 0 3 2
2 4 0 3 4 2 0	2 4 0 3 4 2 0
0 3 3 3 8 8 8	0 3 3 3 8 8 8

See: [Scratch_Digits_Regress.m](#)

Homework 12: Worm classification

- Propose and implement a methodology using CNN to perform a binary classification of the worm database.
- A minimum accuracy of 90% is expected.

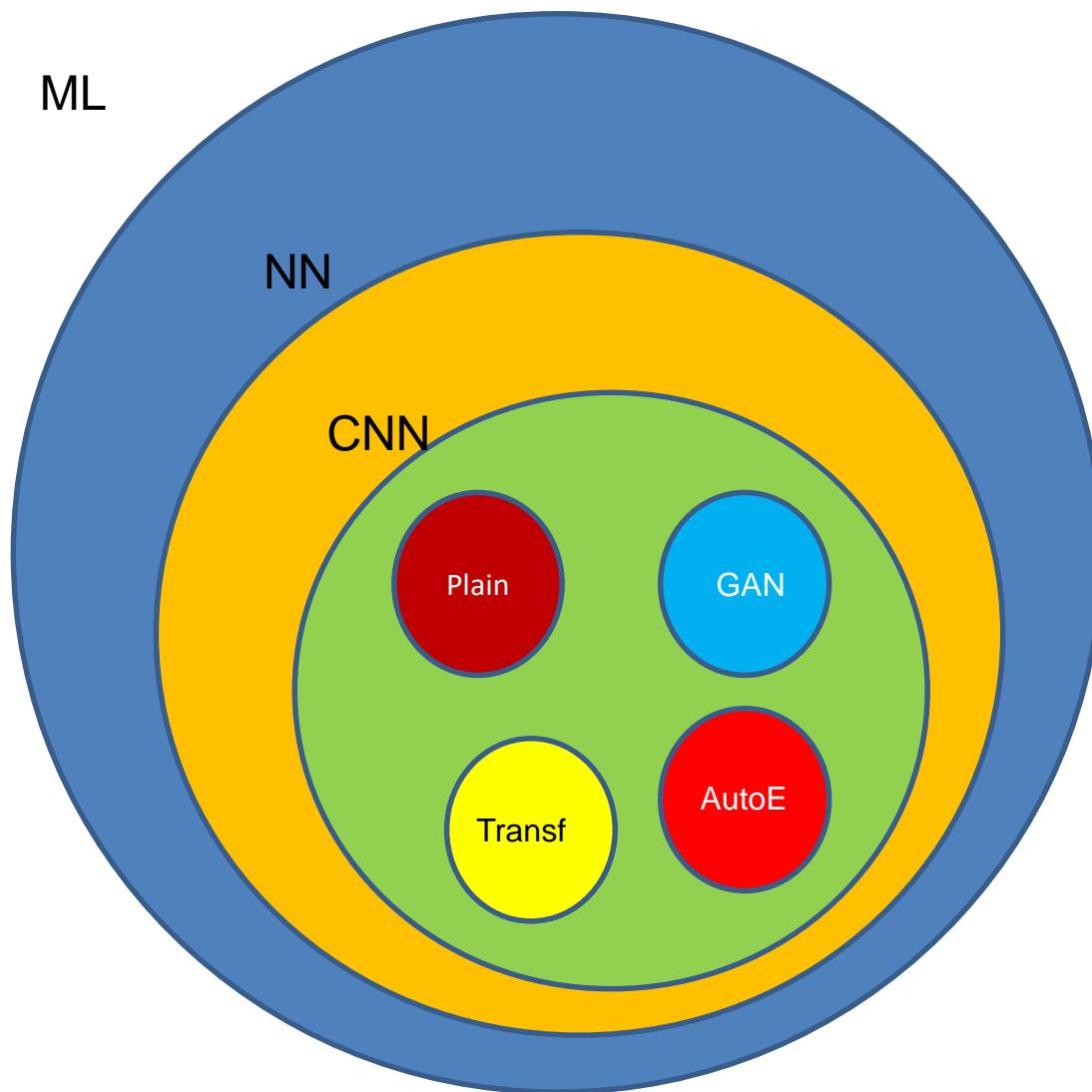


Nota: Las etiquetas de clase están en el archivo .csv este lo pueden leer desde matlab con la instrucción: `labels= readtable('WormData.csv');`

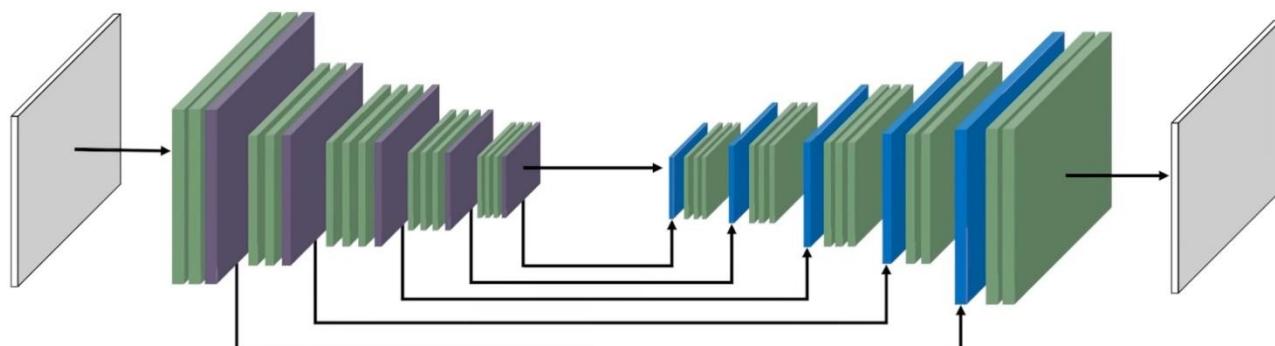
Convolutional Neural Networks

- CNN
 - Classification (Alexnet).
 - Regression (?).
- R-CNN
 - Localization (YOLO).
 - Segmentation (U-Net).
- Adversial
 - DCGAN.
 - cDCGAN.

Convolutional Neural Networks



Encoder-decoder structure



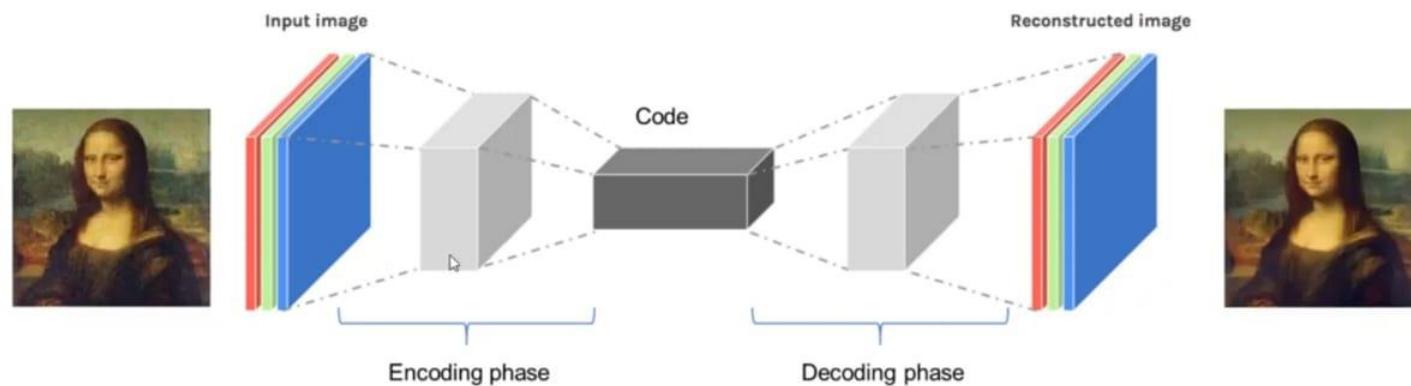
Encoder

Decoder

Autoencoder

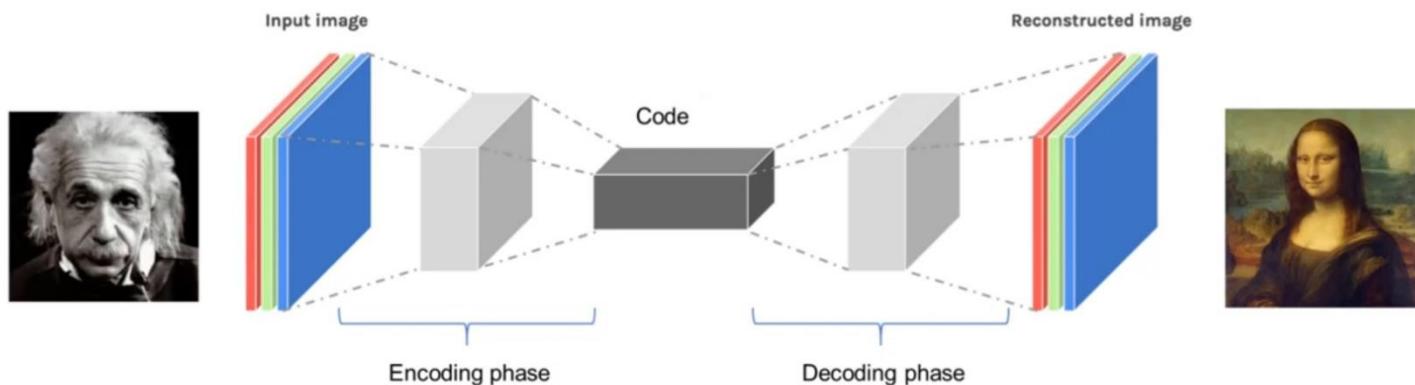
Autoencoder Applications

Noise Reduction



Pix2Pix

Autoencoder Applications Domain adaptation

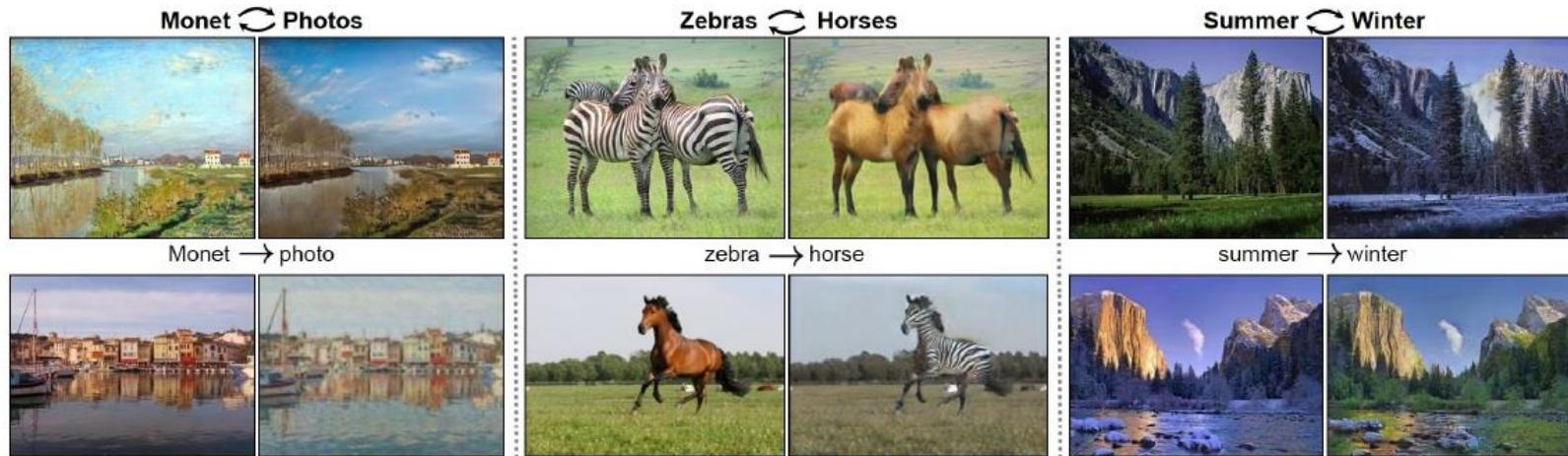


Animaciones sintéticas

- Deepfake.
- Transferencia de estilo.

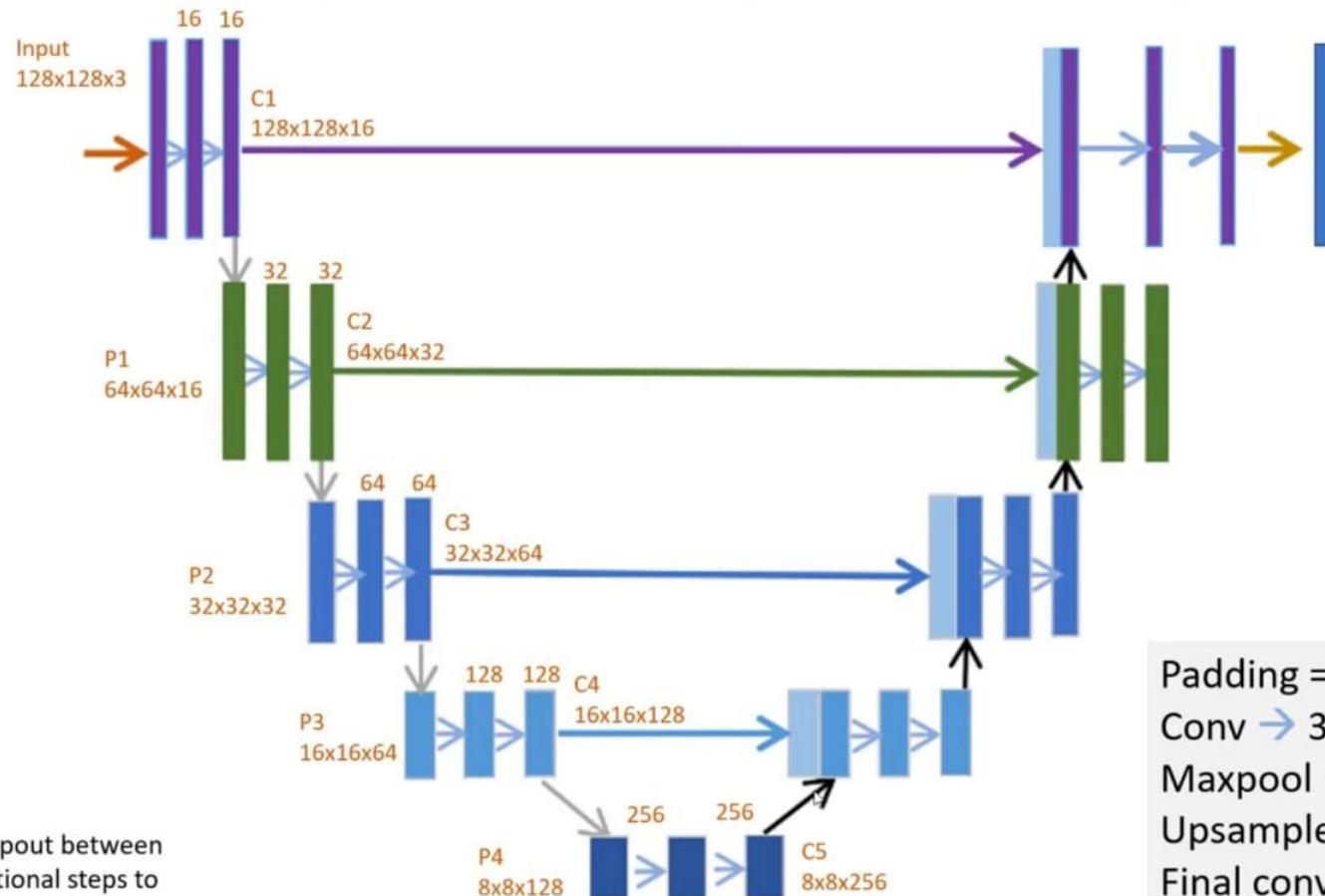


<https://commons.wikimedia.org/wiki/File:Sw-face-swap.png>



Jun-Yan Zhu*, Taesung Park*, Phillip Isola, and Alexei A. Efros. "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks", in IEEE International Conference on Computer Vision (ICCV), 2017.

U-Net



Padding = same
Conv \rightarrow 3x3 ReLU
Maxpool \rightarrow 2x2 (Stride=2)
Upsample \rightarrow 2x2
Final conv. \rightarrow 1x1

Segmentación de placenta

Tesis de maestría del Ing. José A. Fuentes Tomás.



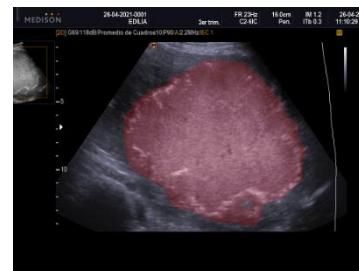
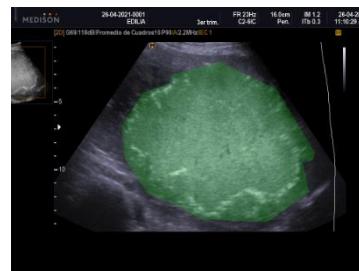
Original



Groundtruth

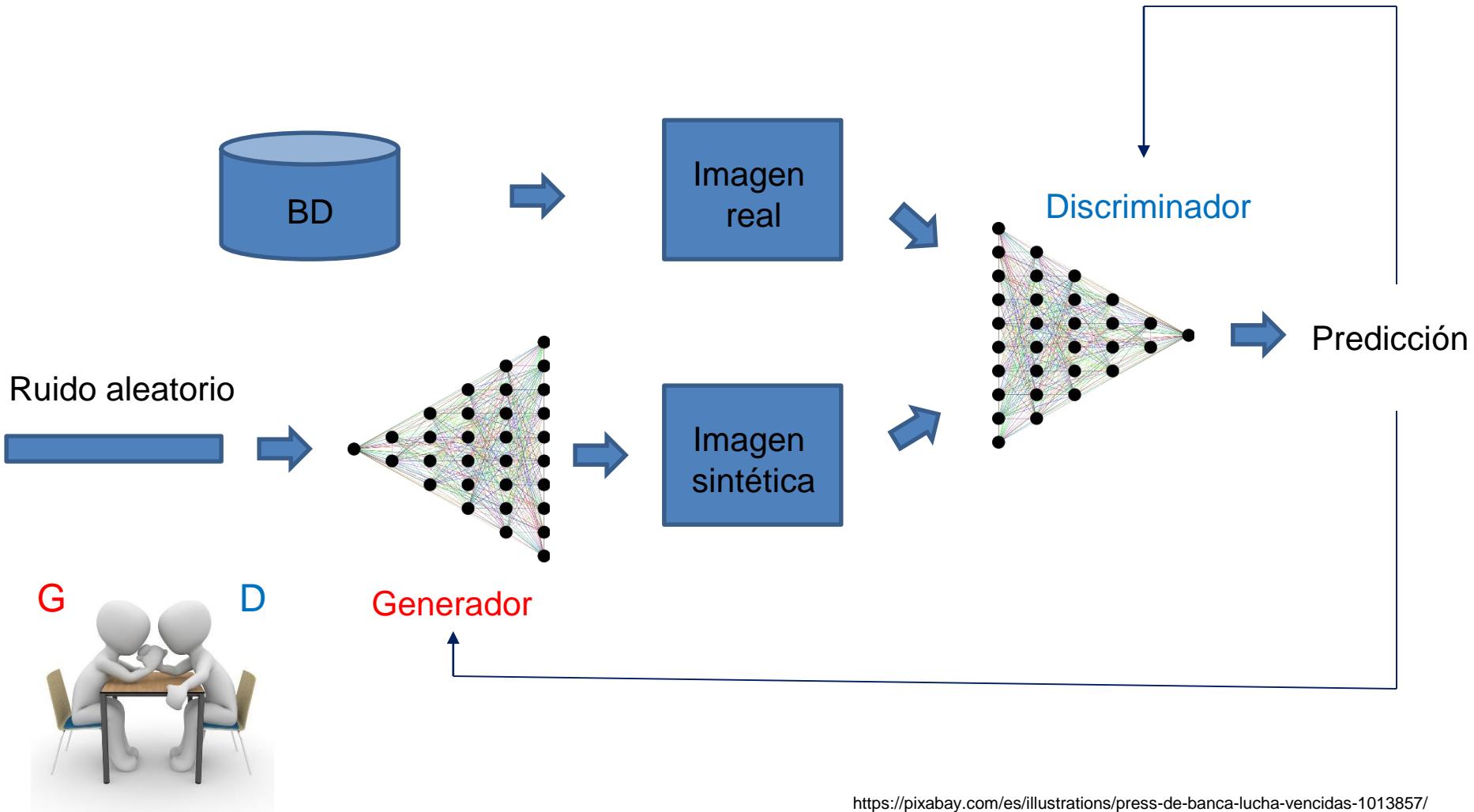


Predicted



Redes generativas adversarias (GANs)

- Goodfellow, 2014.



Aplicaciones

- Generación de imágenes sintéticas.

MyHeritage Árbol Fotos Investigación ADN Ayuda

Anime sus fotos familiares

Anime los rostros en sus fotos familiares con una tecnología asombrosa. ¡Experimente su historia familiar como nunca antes!

Cargue una foto

O ARRASTRE Y SUELTE ➔

Se requiere una inscripción gratuita. Las fotos que cargue sin haber completado la inscripción se eliminarán automáticamente para proteger su privacidad.

Licencia concedida a MyHeritage por parte de D



<https://www.myheritage.es/deep-nostalgia>



<https://thispersondoesnotexist.com/>

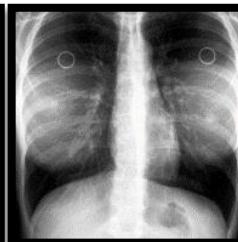
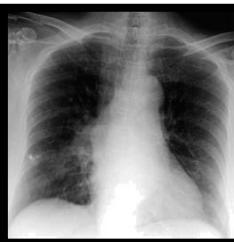
Síntesis de radiografías de torax

Tesis de maestría del Ing. Juan A. Rodríguez de la Cruz.

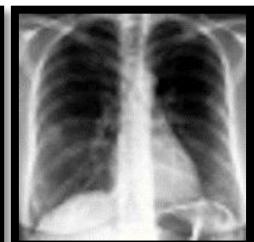
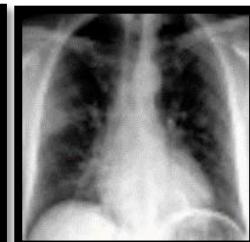
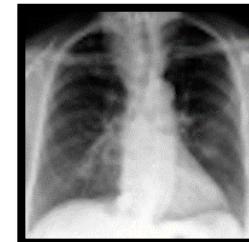


COVID-19

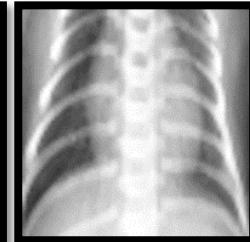
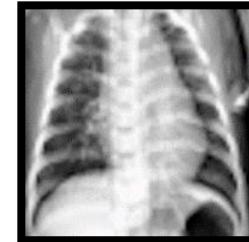
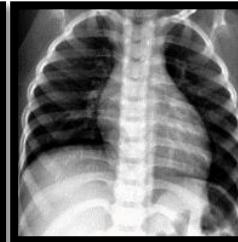
REAL



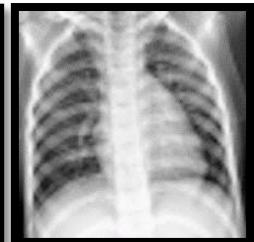
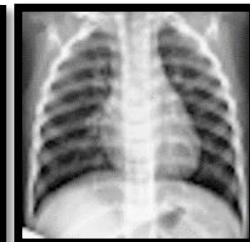
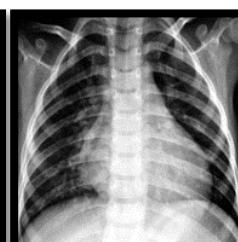
SINTÉTICAS



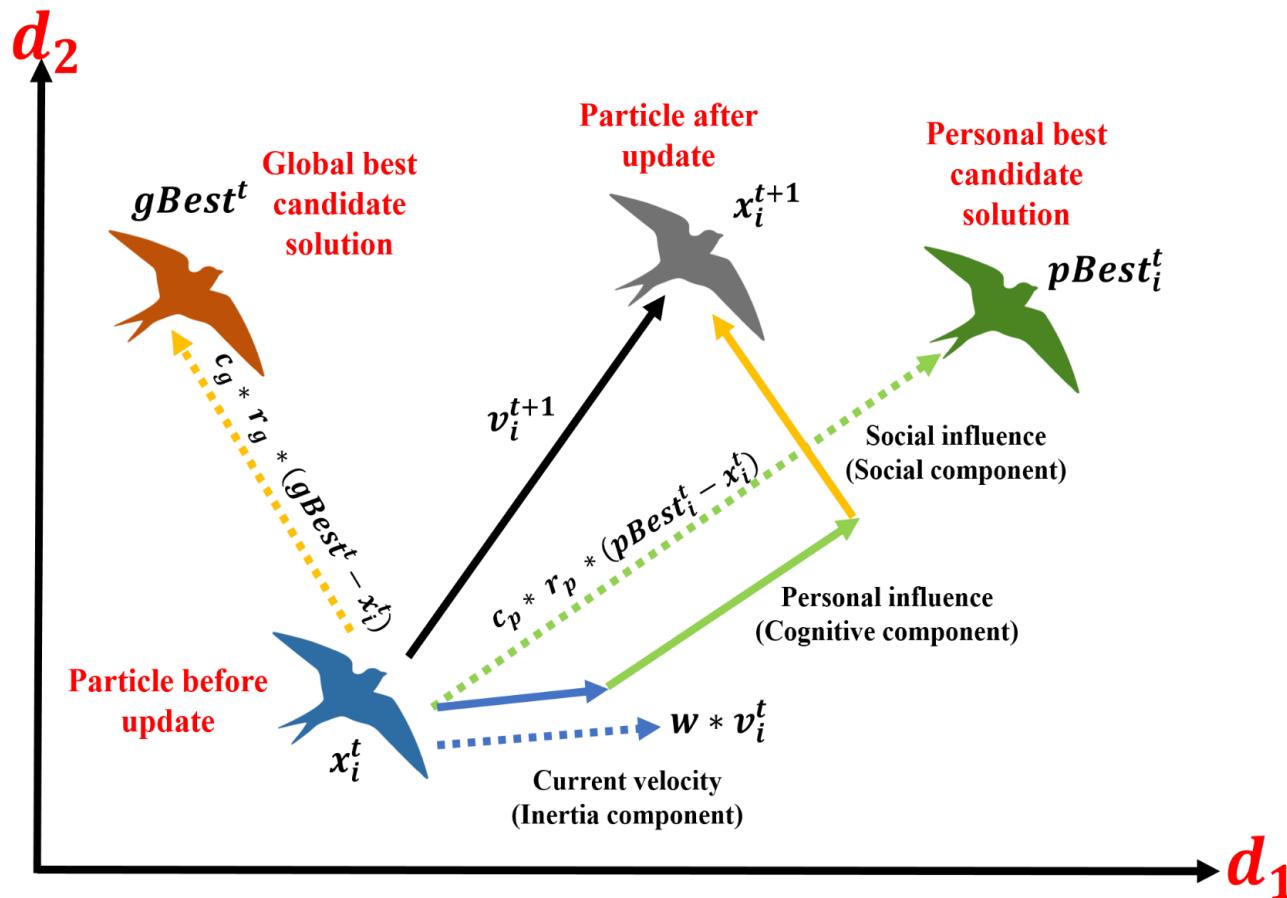
NEUMONIA



SANO



Optimización por enjambre de partículas



Síntesis de radiografías de torax

Mejora en la clasificación

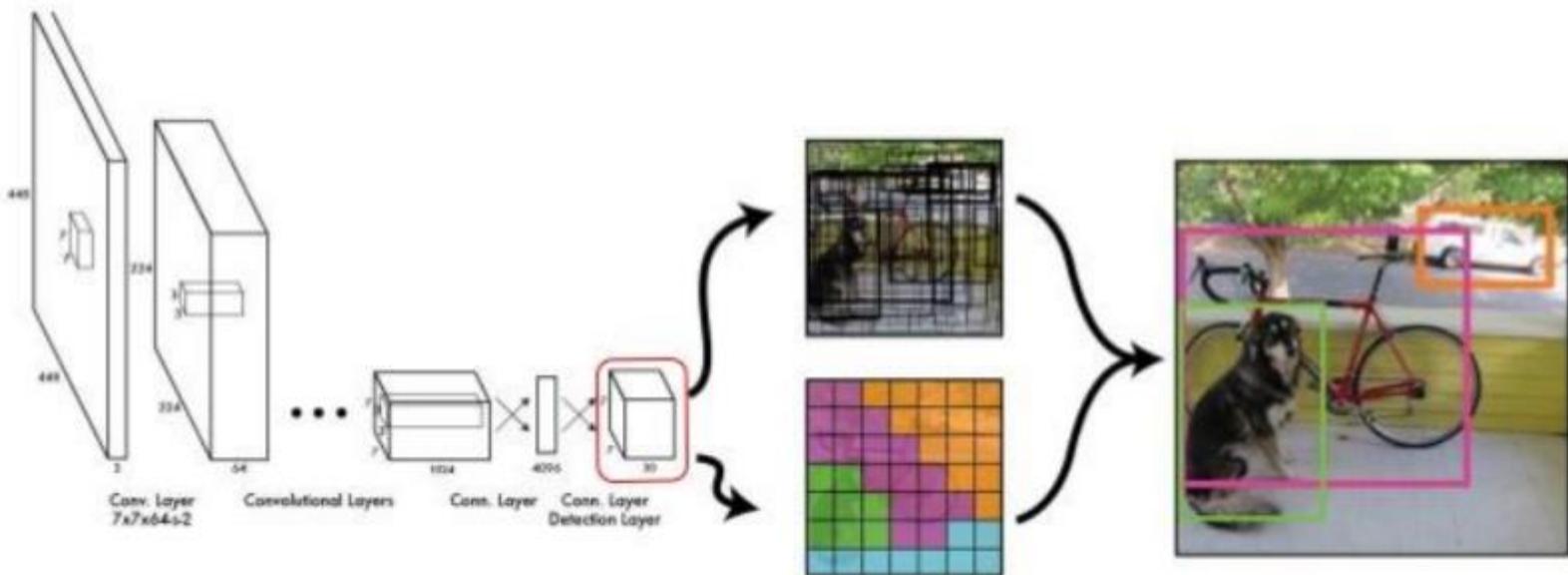
Datos	Classes	Nº images	Exactitud
Desbalanceados	COVID-19	600 reales	72.3 ± 4.3
	No-COVID-19	1200 reales	
Balanceados	COVID-19	600 reales + 600 sintéticas	80.4 ± 3.12
	No-COVID-19	1200 reales	

Juan-Antonio Rodríguez-de-la-Cruz, Héctor-Gabriel Acosta-Mesa and Efrén Mezura-Montes. Evolution of Generative Adversarial Networks using PSO for synthesis of COVID-19 Chest X-ray images. Accepted for publication in IEEE Congress on Evolutionary Computation (2021).

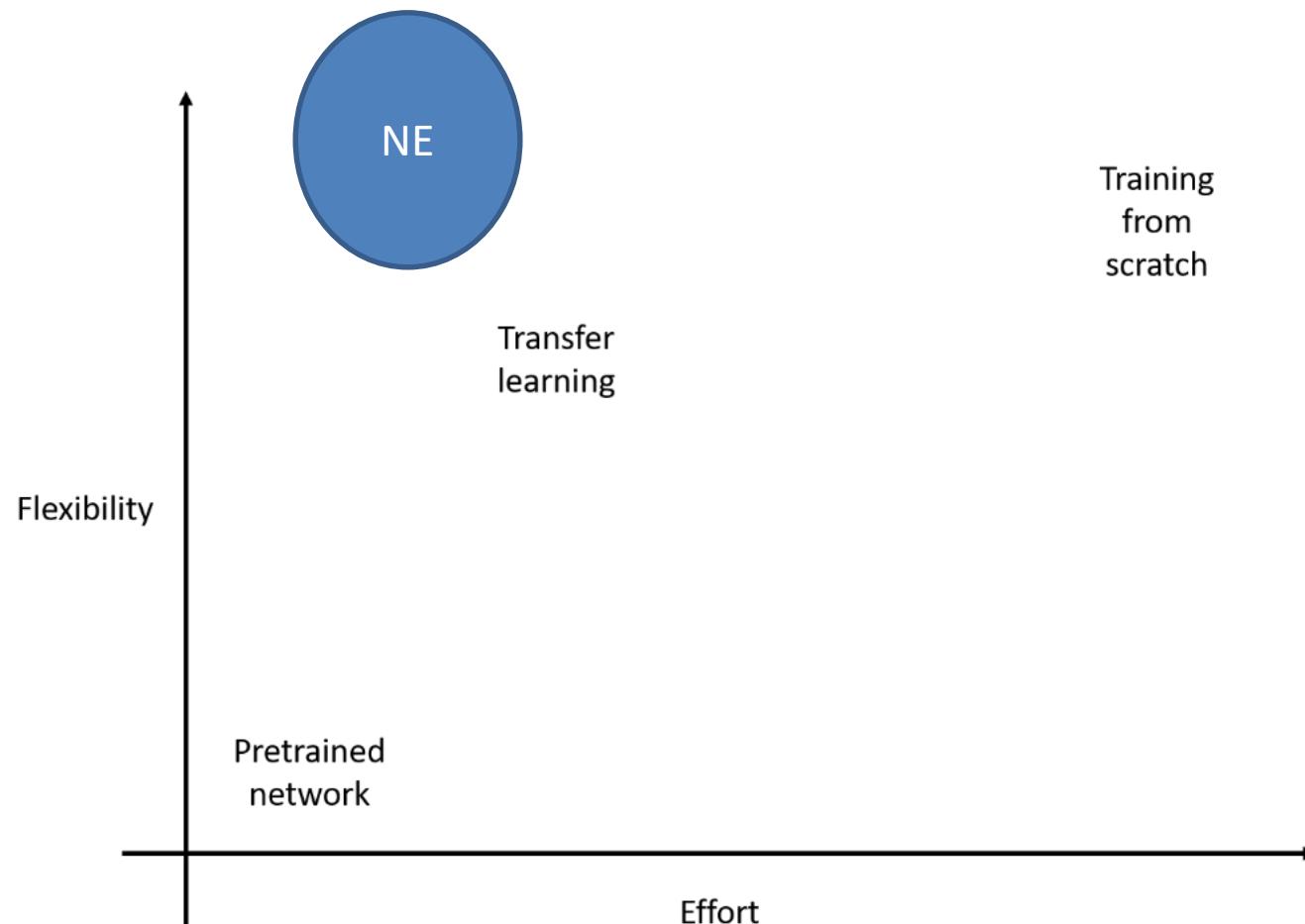
Juan-Antonio Rodríguez-de-la-Cruz, Héctor-Gabriel Acosta-Mesa, Efrén Mezura-Montes, Fernando Arámbula Cosío, Boris Escalante-Ramírez, and Jimena Olveres Montiel. Evolution of conditional-GANs for the synthesis of chest X-ray images. The 17th International Symposium on Medical Information Processing and Analysis (SIPAIM). 2021

YOLO

YOLO: You Only Look Once



Convolutional Neural Networks



Clasificación de radiografías de tórax

Tesis de maestría del Ing. Gustavo A. Vargas Hákim.



a)



COVID-19

b)



Pneumonia

c)

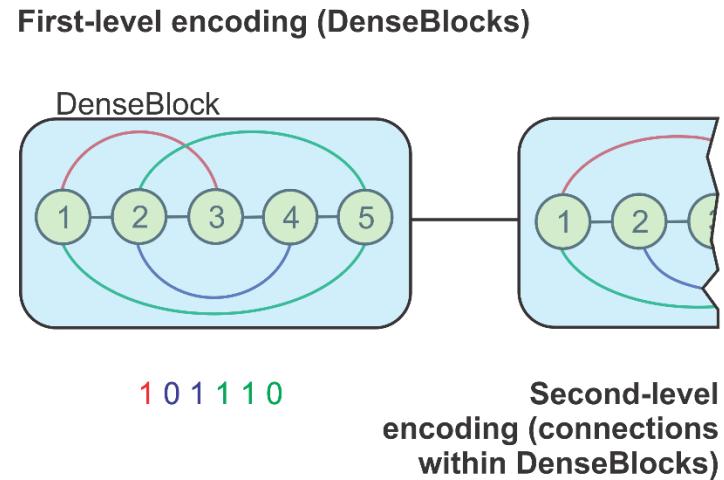
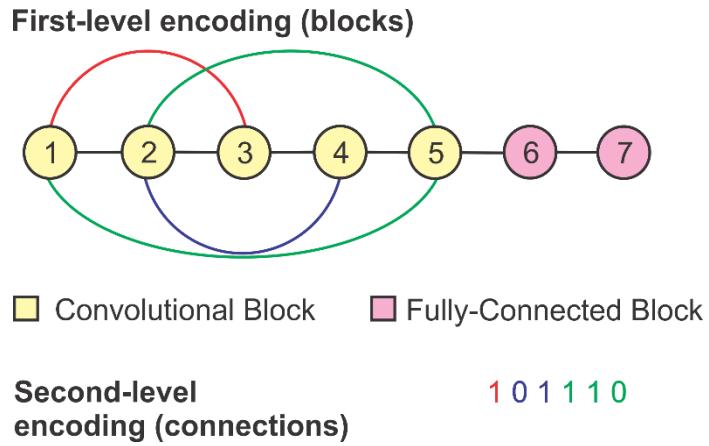


Healthy

Imágenes obtenidas de:

- Cohen, J. P. et al. (2020). "COVID-19 Image Data Collection: Prospective Predictions Are the Future". In: arXiv 2006-11988
- Mooney, P. (2017). *Chest X-Ray Images (Pneumonia)*. URL: <https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia>

Propuesta de codificación



Codificación propuesta*

Codificación de Wang**

* Gustavo-Adolfo Vargas-Hákim, Efrén Mezura-Montes, Héctor-Gabriel Acosta-Mesa. A Review on Convolutional Neural Networks. Encodings for Neuroevolution. IEEE Transactions on Evolutionary Computation. Factor de impacto 11.16

** Wang, Y. Sun, et al. (2017). "A Hybrid GA-PSO Method for Evolving Architecture and Short Connections of Deep Convolutional Neural Networks". In: *Proceedings of the Pacific Rim International Conference on Artificial Intelligence*. Springer, pp. 650-663
DOI:10.1007/978-3-030-29894-4_52.

Datos utilizados

Colección de imágenes



2754 imágenes

- 918 COVID-19
- 918 bacterial/viral pneumonia
- 918 healthy

Cohen, J. et al. (2020). "COVID-19 Image Data Collection: Prospective Predictions Are the Future". In: ArXiV 2006.11988, URL: <https://github.com/ieee8023/covidchestxray-dataset>

Wang, L., A. Wong, et al. (2020). *Actualmed COVID-19 Chest X-ray Dataset Initiatives*. URL: <https://github.com/agchung/Actualmed-COVID-chestxraydataset>

Mooney, P. (2017). *Chest X-Ray Images (Pneumonia)*. URL: <https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia>

Resultados

Comparación con CNNs diseñadas a mano

