

AI for Good Workshop

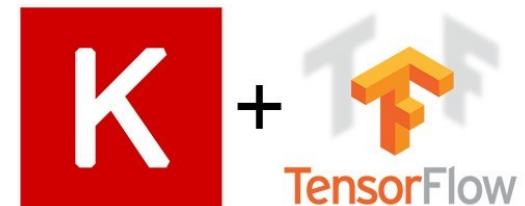
March 2019

Session 6

# Artificial Intelligence for everyone

Practical Deep Learning for  
Professional Context  
(Computer Vision)

<https://sites.google.com/view/AlforEveryone>



# Topics in this video

Jump start your practical solution development!

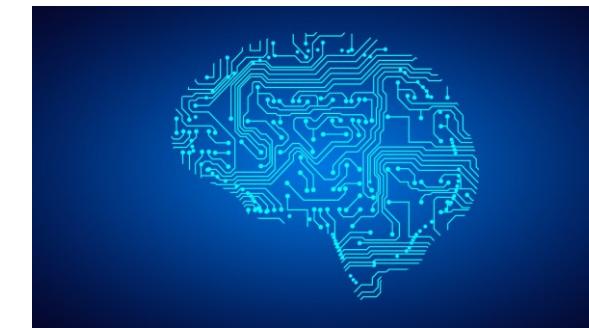
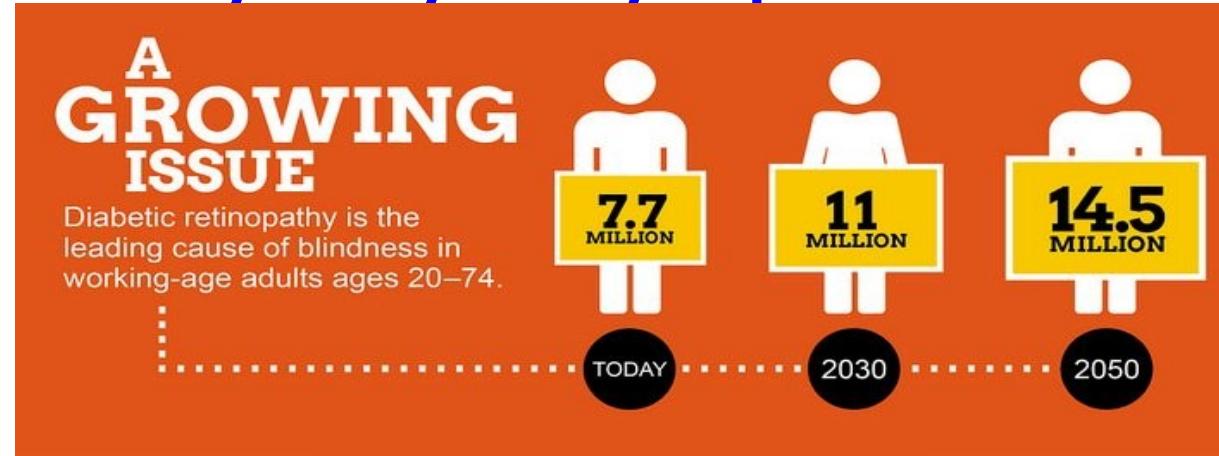
- 1. Deep Learning based Image Classification (Computer Vision)**
- 2. How to Create a professional solution ?**
- 3. Hands-on : Create your 1<sup>st</sup> Deep Learning based Image classification solution**



# App idea: Selfie that checks your eye health



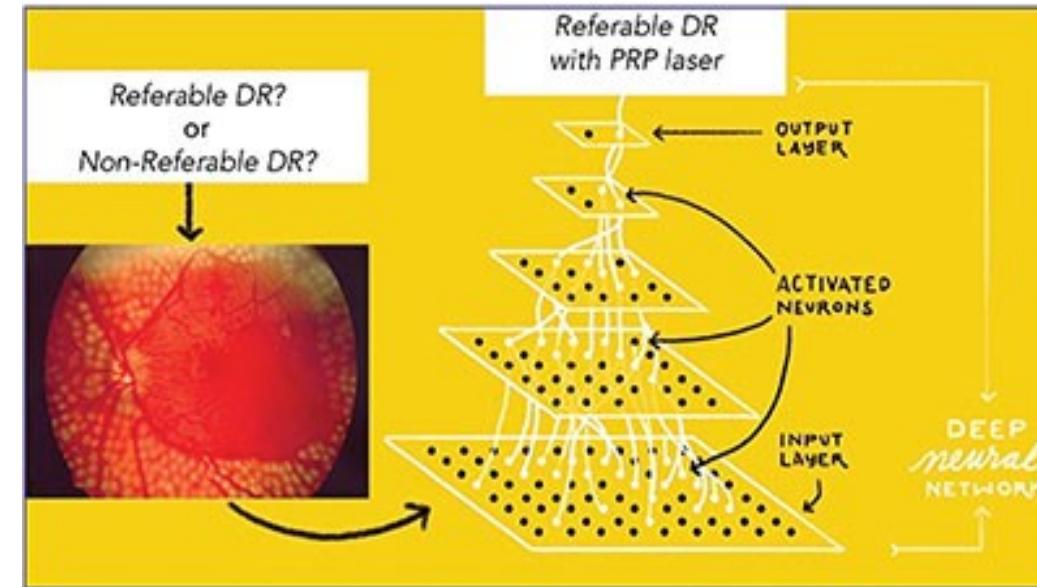
Idea: Check your eyes as you pose for a selfie !



Your Eye is healthy

Better, Go for a  
eye check-up

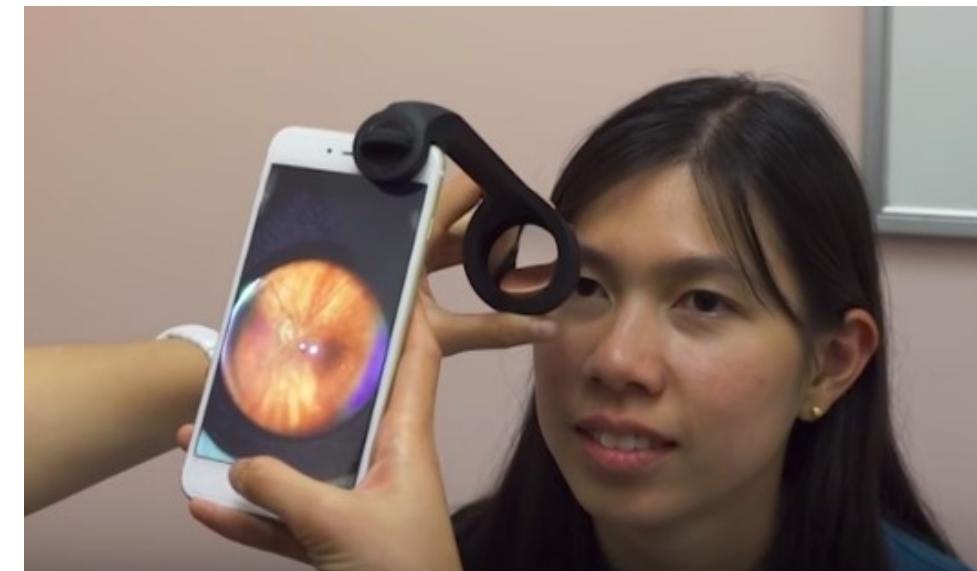
# App idea: App that Screens your eyes as you pose for a selfie



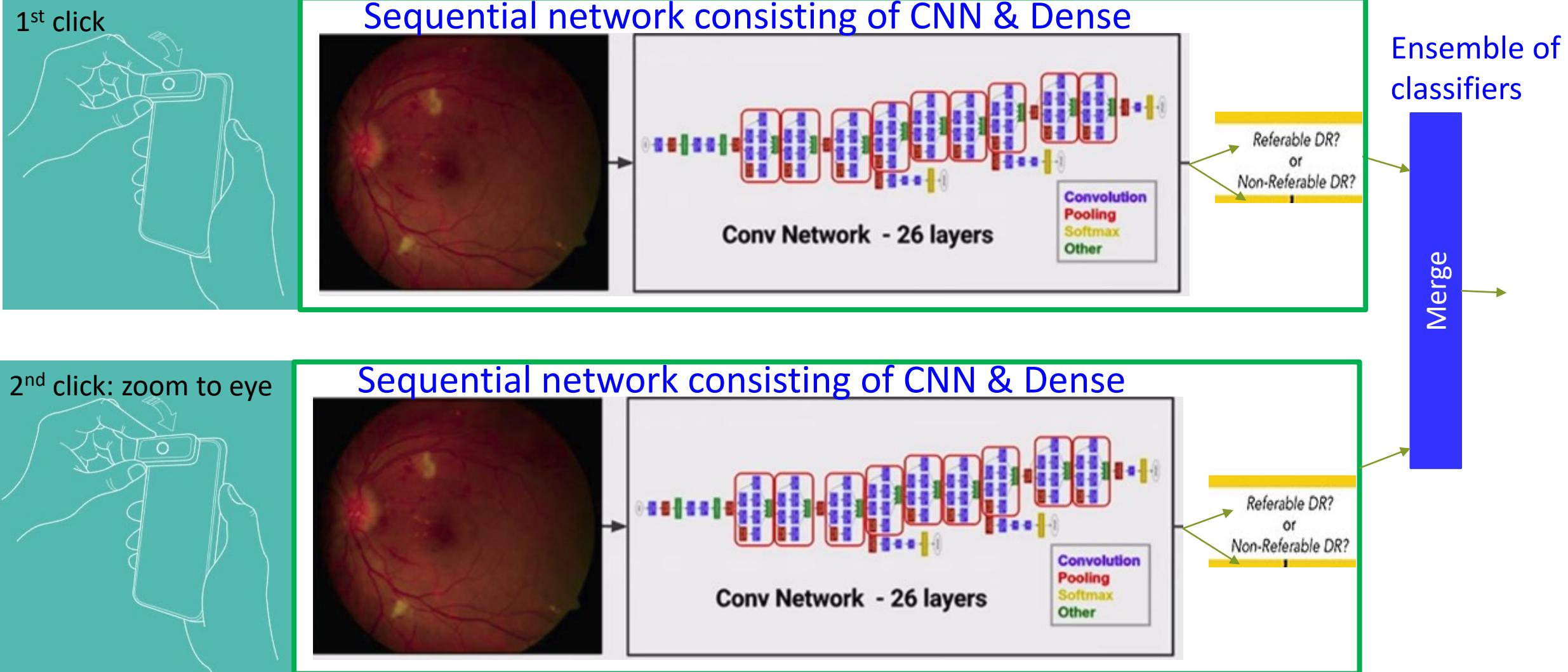
## Screening Protocol

- Patients who need urgent referral
- Patients who need routine referral
- Patients who need regular screening and follow up annual

# Fighting blindness with your Deep Learning smartphone app

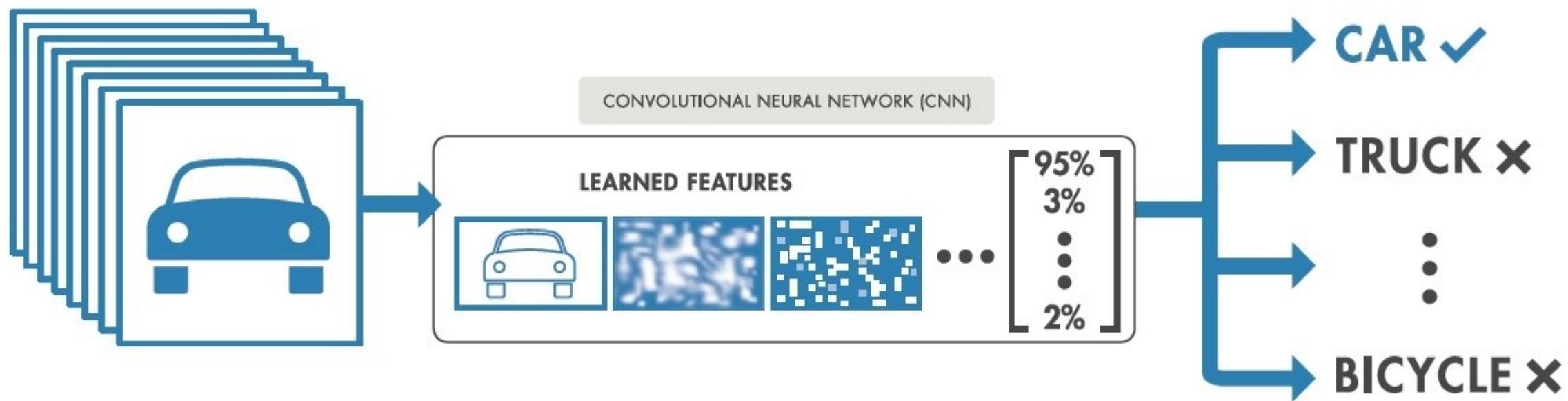


# Fighting blindness with your Deep Learning smartphone app



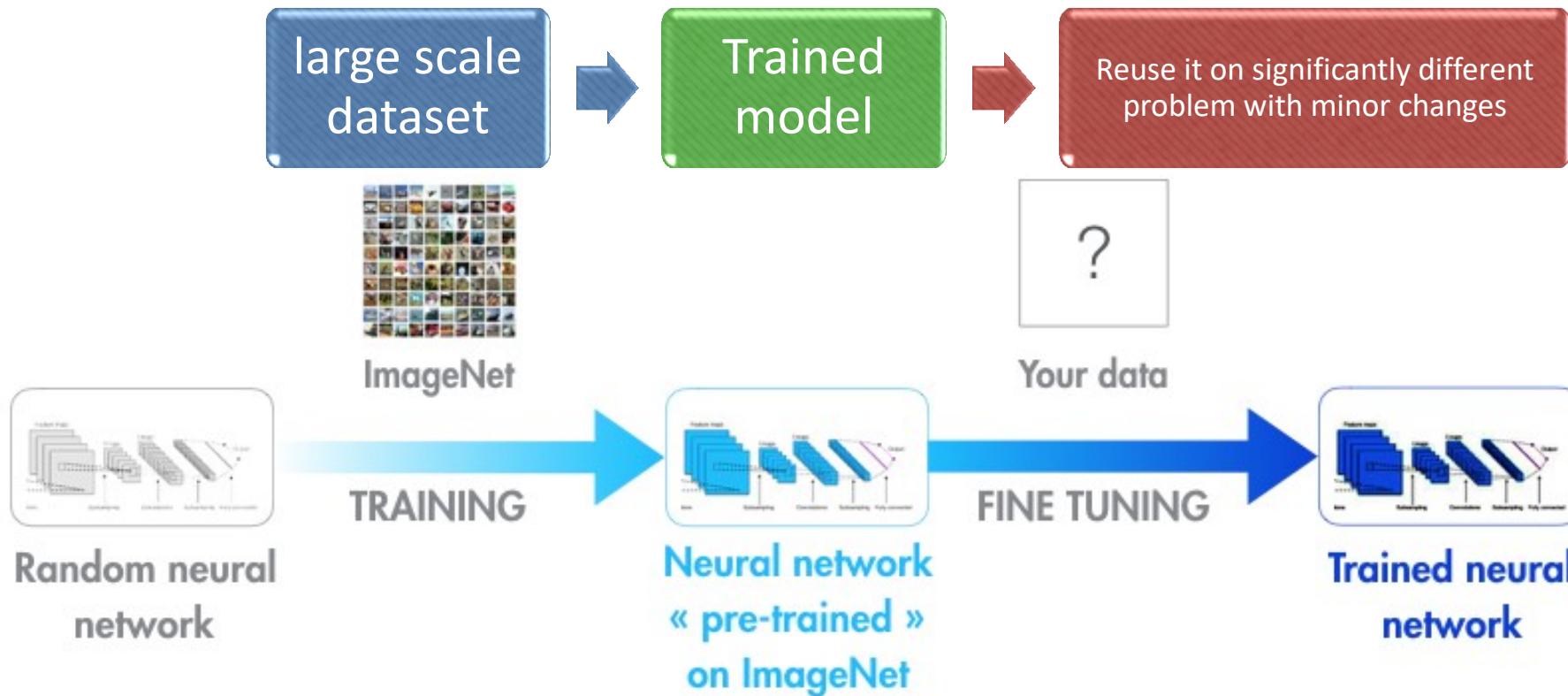
# What type of problem?

**Practical problems: Image classification for small datasets**

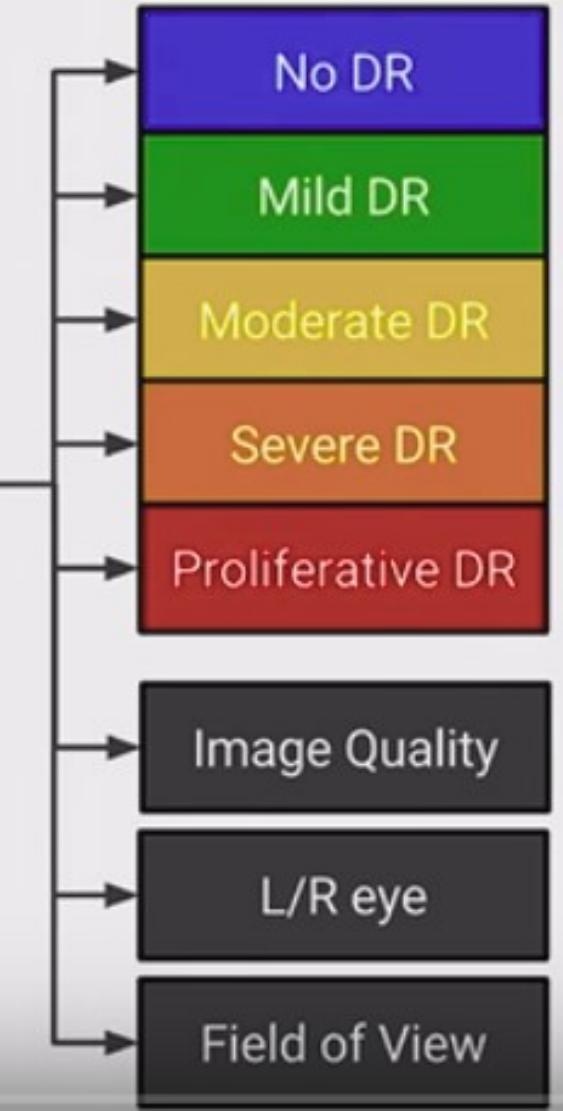
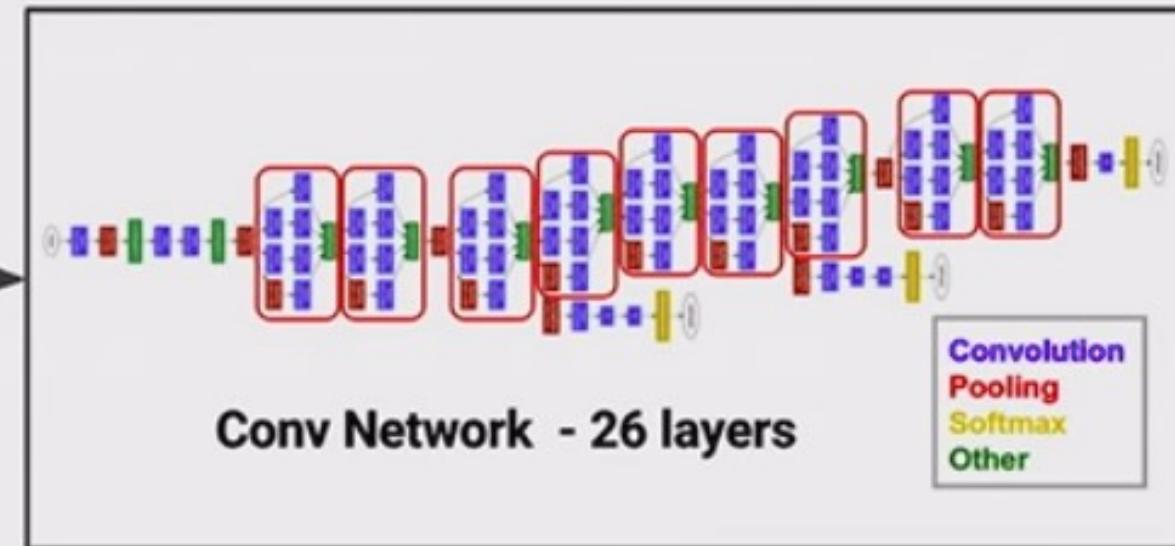


# Have only very little data for training? Deep learning models are re-purposable!

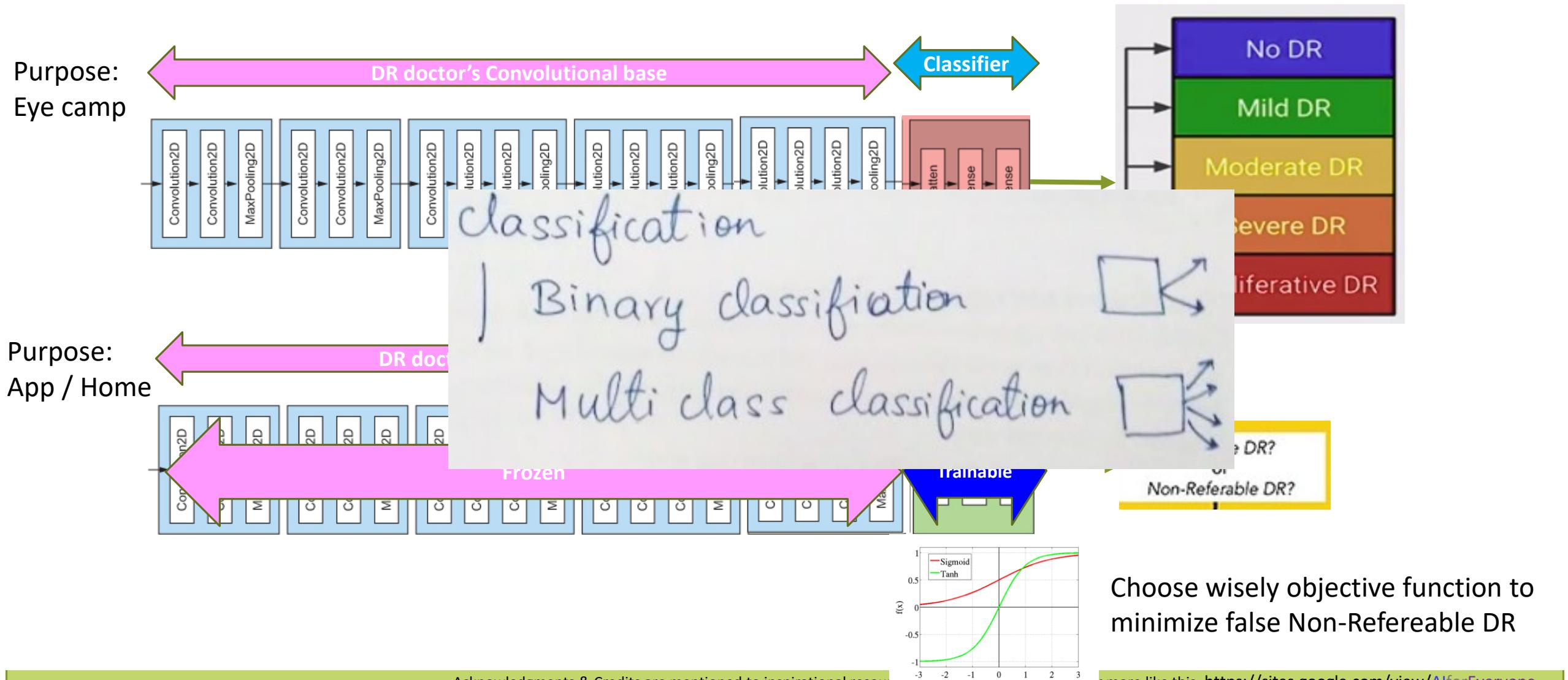
Having to train a image classification model using only very little data is a common situation.



# App Goal: Selfie Binary classifier to alert you for eye check-up



# Multi class classifier → Binary classifier

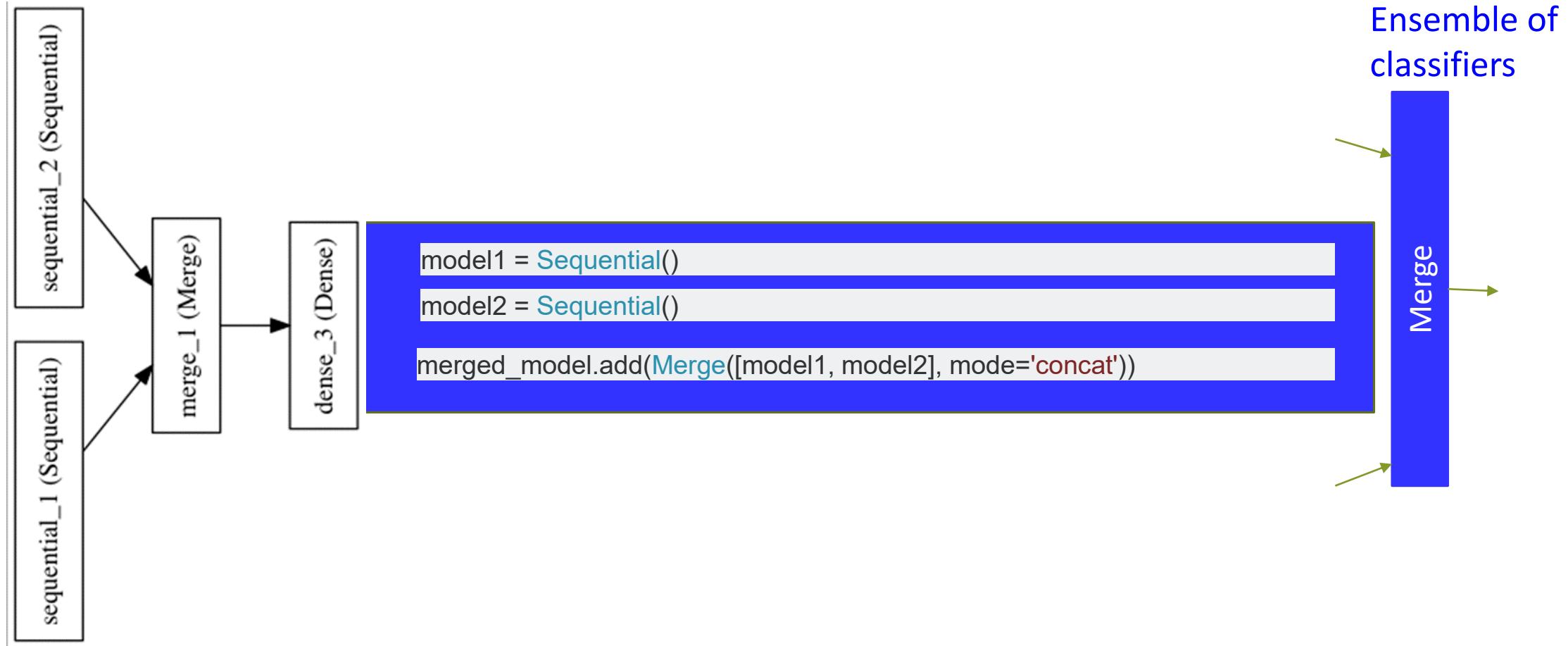


# Cheat sheet : objective function

Choosing the right last-layer activation and loss function for your model

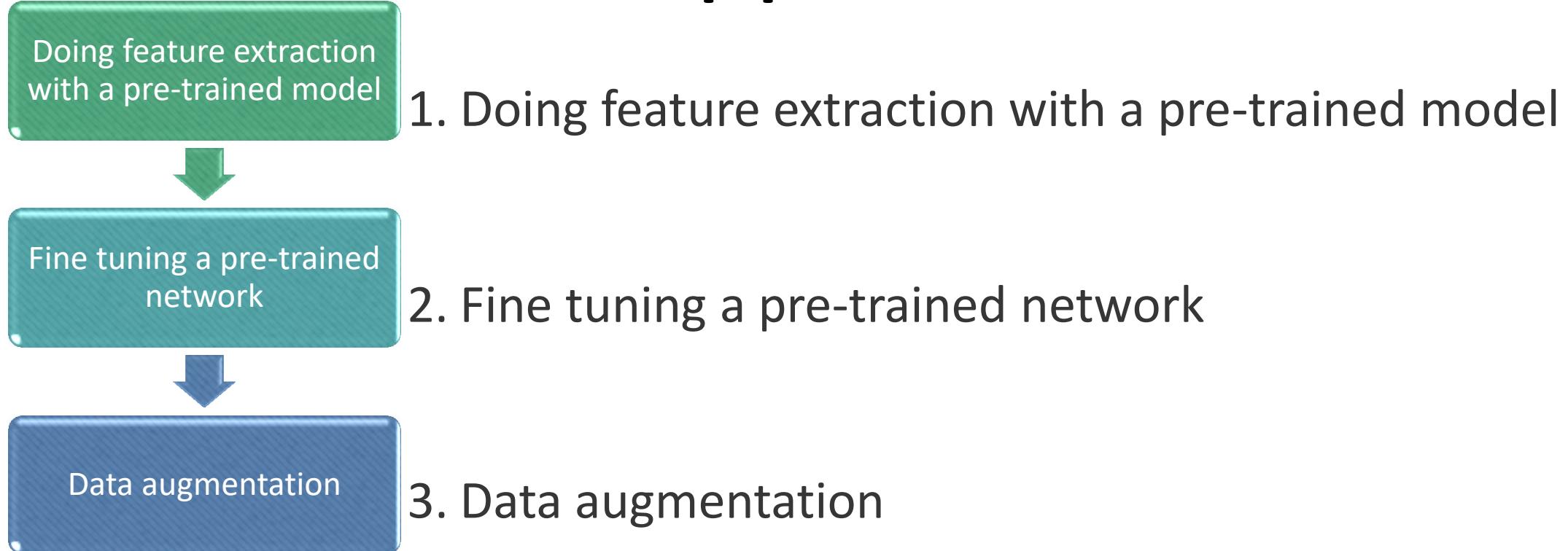
Problem type	Last-layer activation	Loss function
Binary classification	sigmoid	binary_crossentropy
Multiclass, single-label classification	softmax	categorical_crossentropy
Multiclass, multilabel classification	sigmoid	binary_crossentropy
Regression to arbitrary values	None	mse
Regression to values between 0 and 1	sigmoid	mse or binary_crossentropy

# Merge 2 networks



# How to develop professional solution

## Toolbox to develop professional solution



# How to develop professional solution

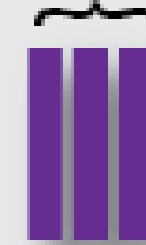
## Load pretrained network

Early layers that learned  
low-level features  
(edges, blobs, colors)



...

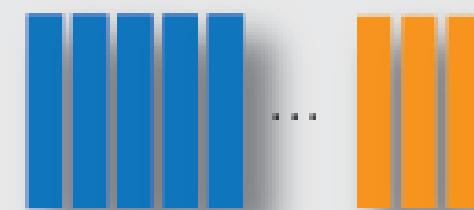
Last layers that  
learned task  
specific features



1 million images  
1000s classes

## Replace final layers

New layers to learn  
features specific  
to your data set



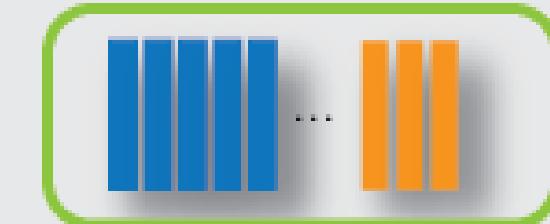
Fewer classes  
Learn faster

## Train network

Training images

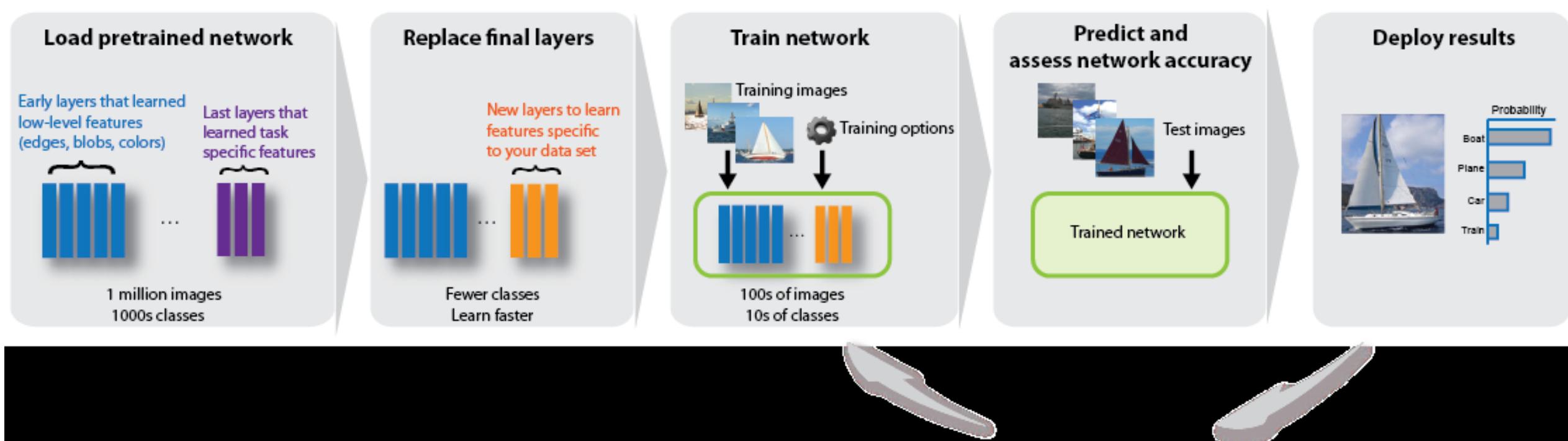


Training options

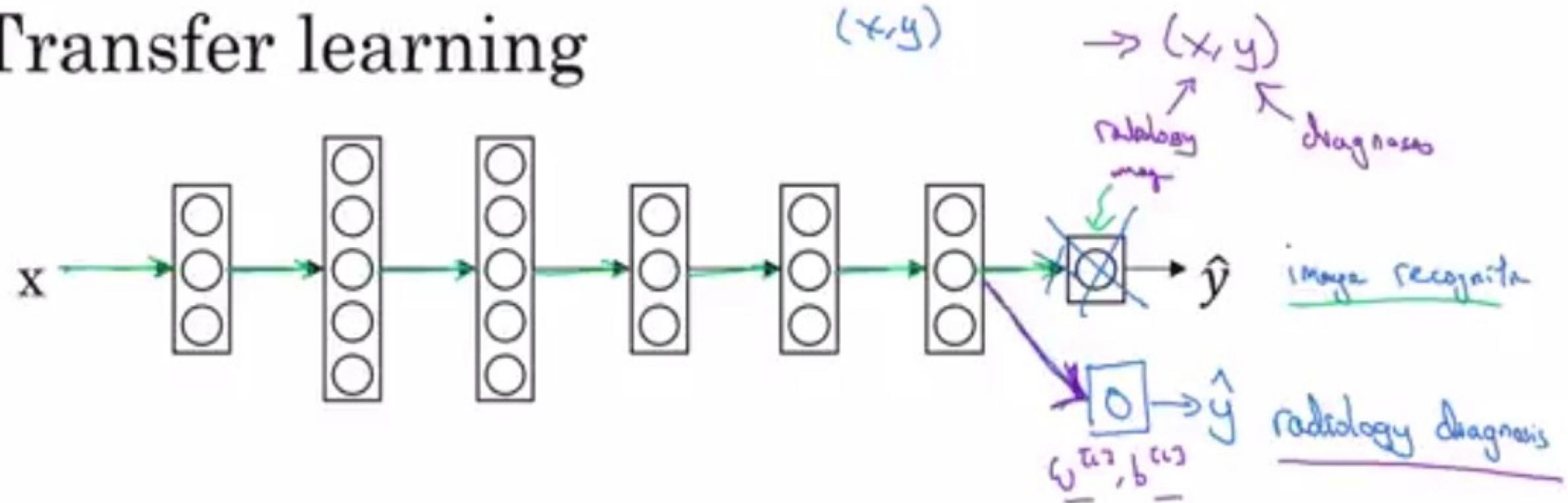


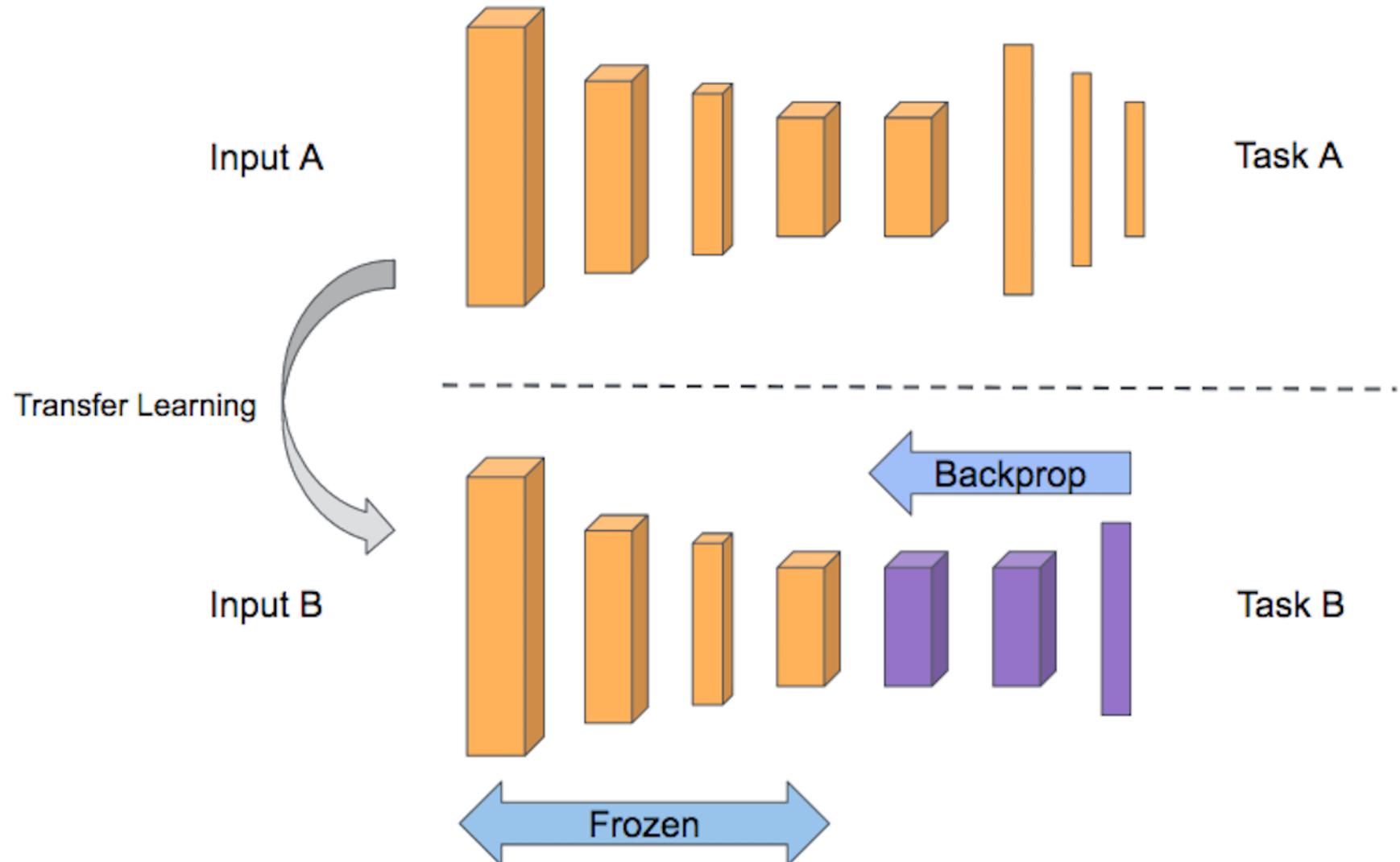
100s of images  
10s of classes

# How to develop professional solution

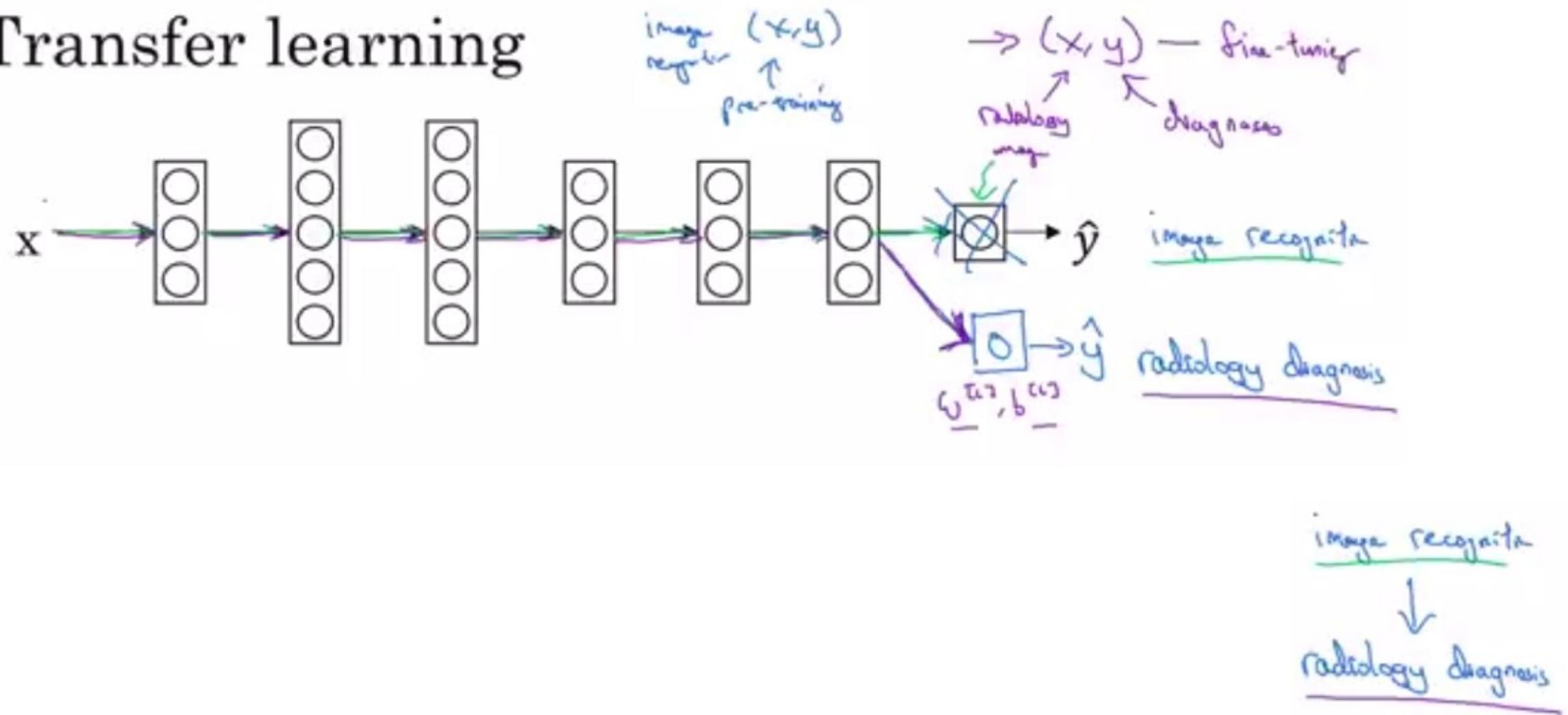


# Transfer learning

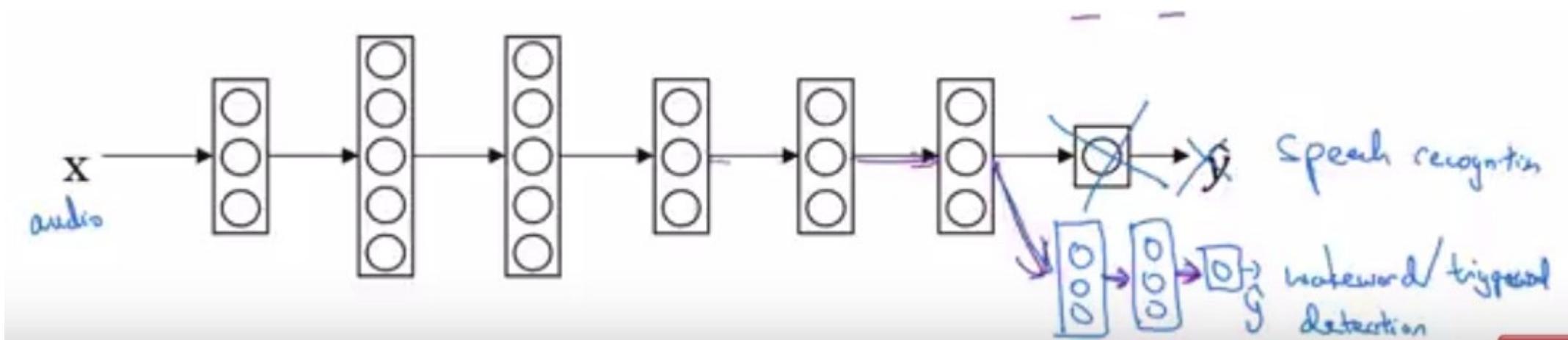




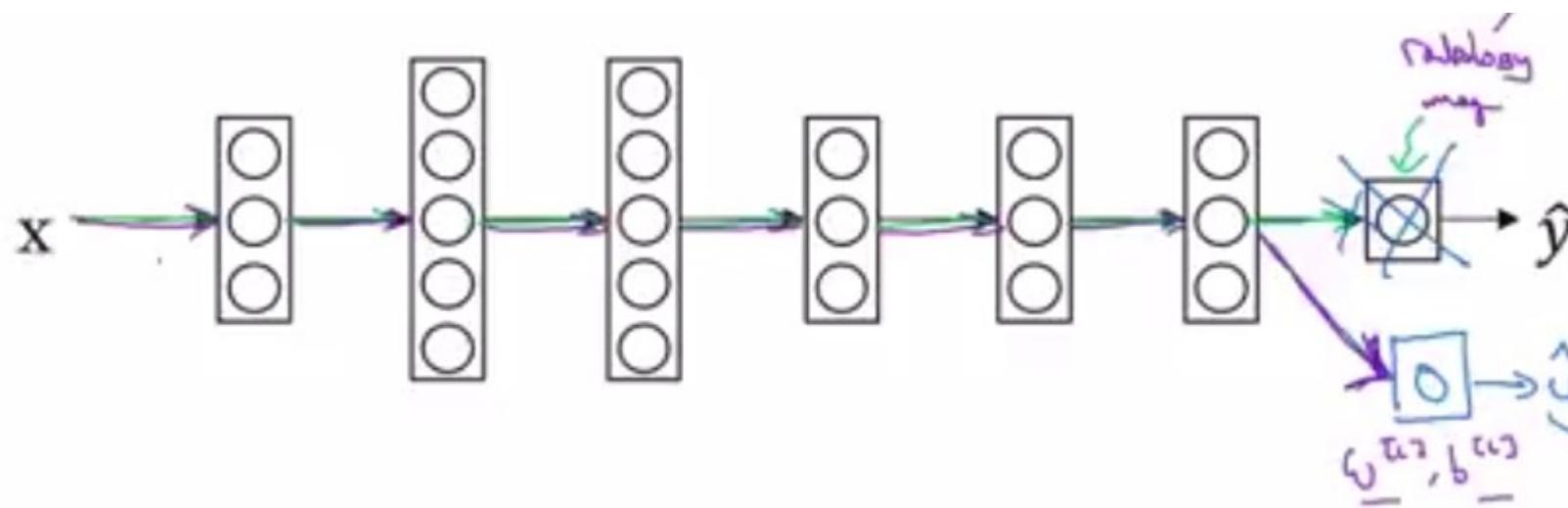
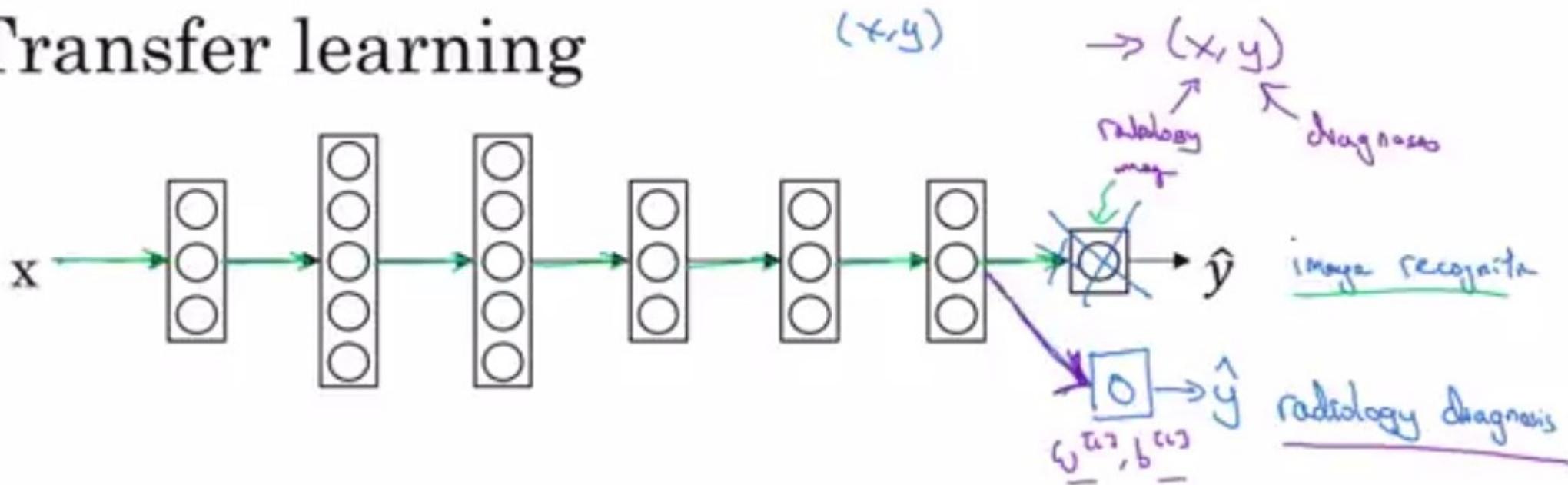
# Transfer learning



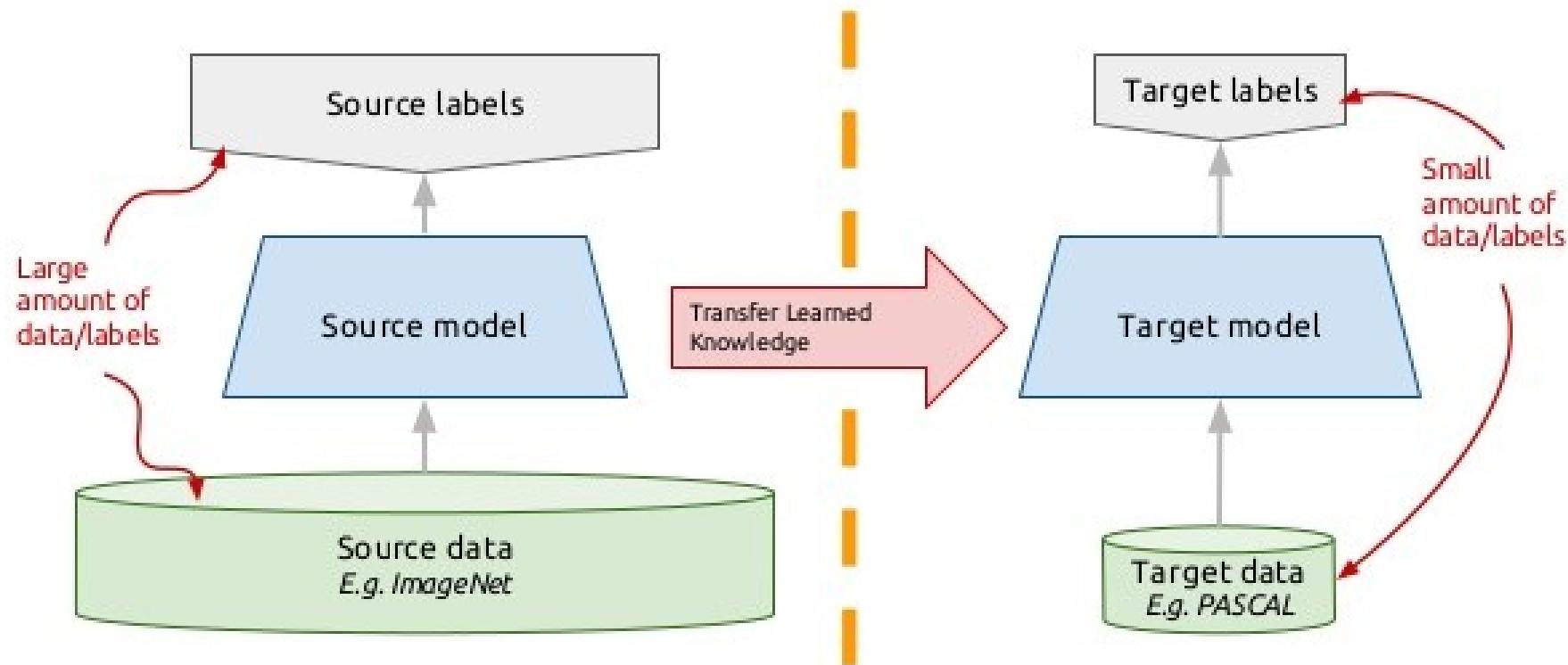
# “Hey Karunya”



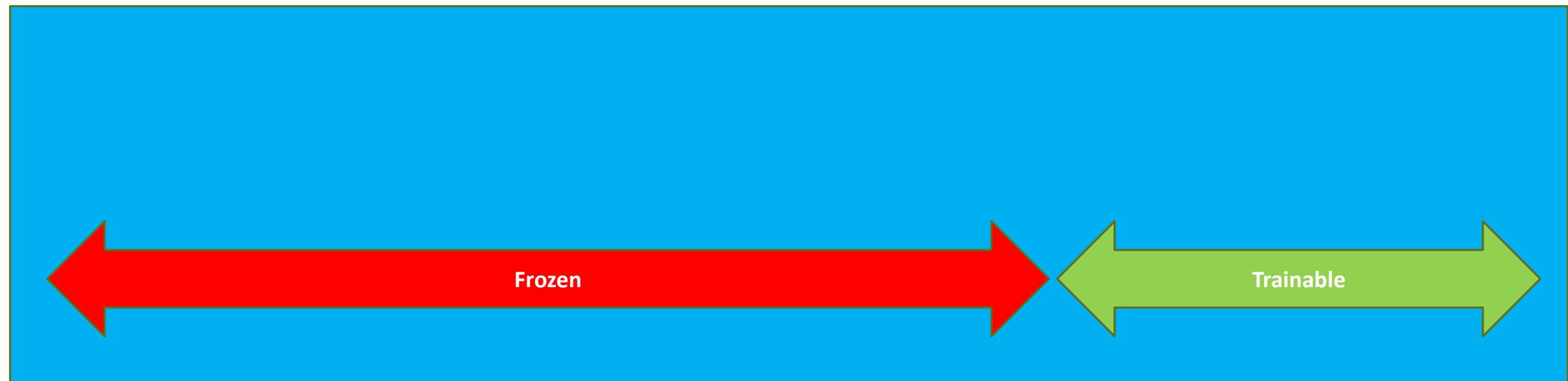
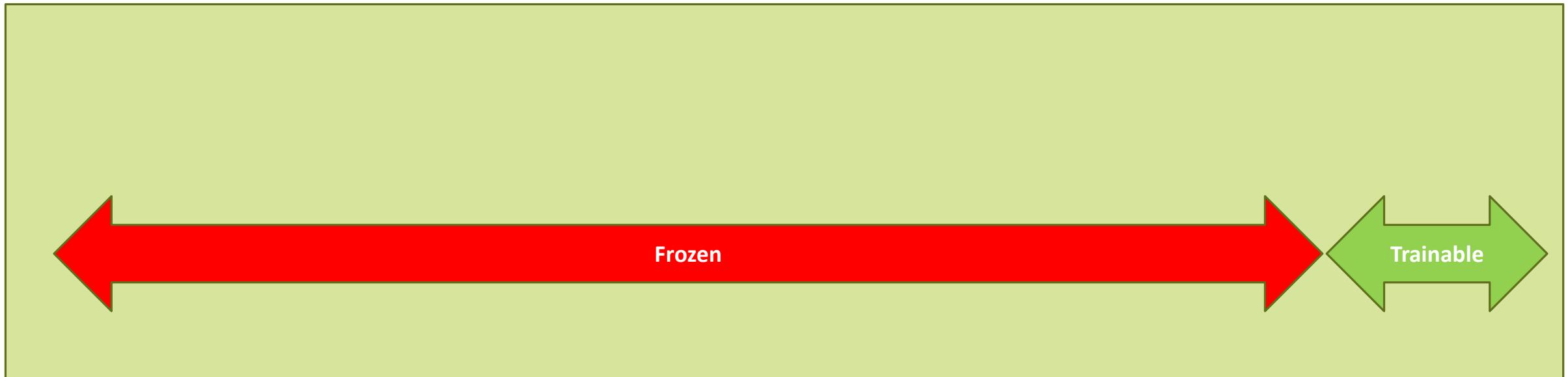
# Transfer learning



## Transfer learning: idea

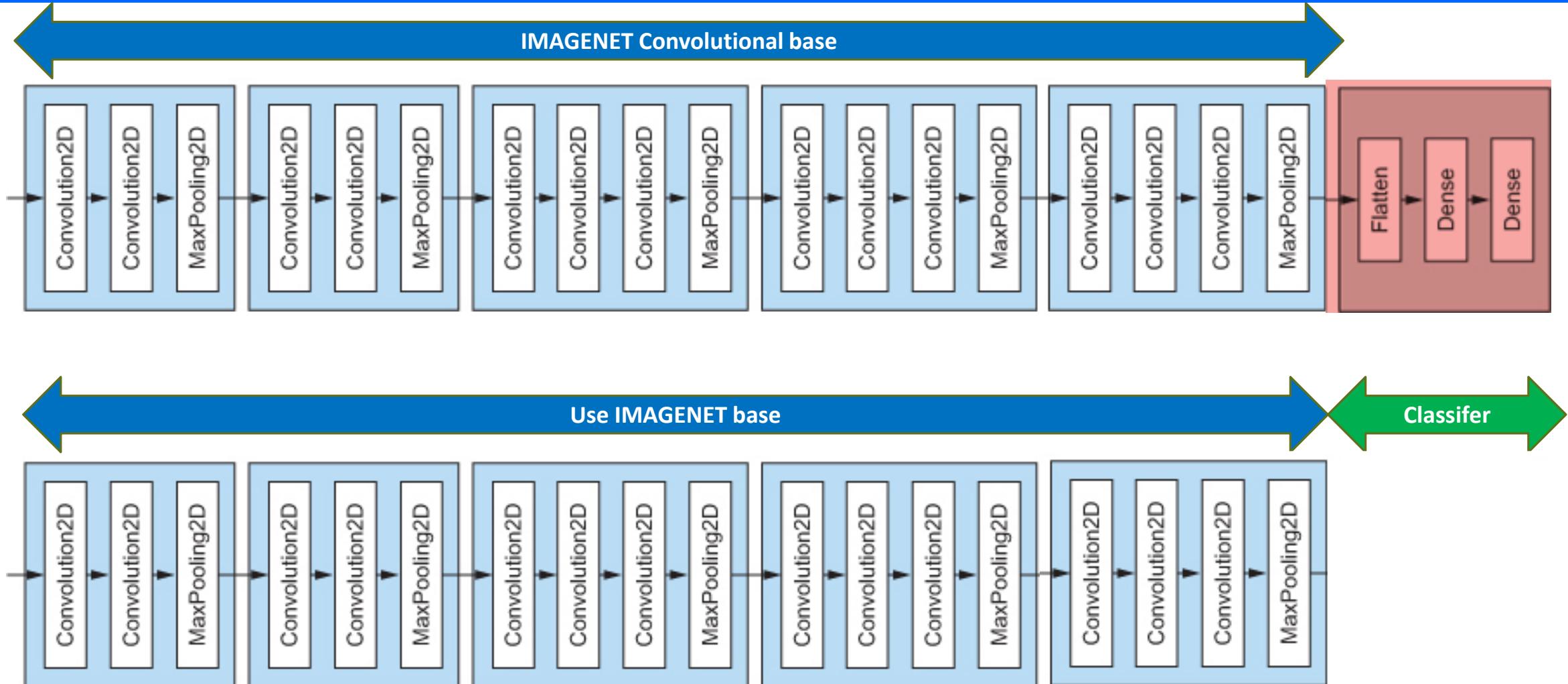


# Network 1 or Network 2



# Network 1

Doing feature extraction with a pre-trained model

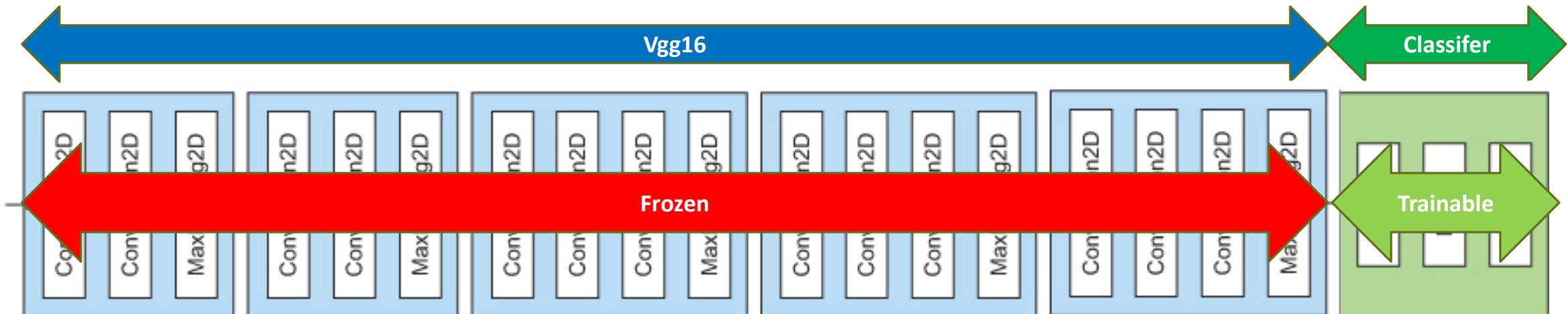


# Network 1

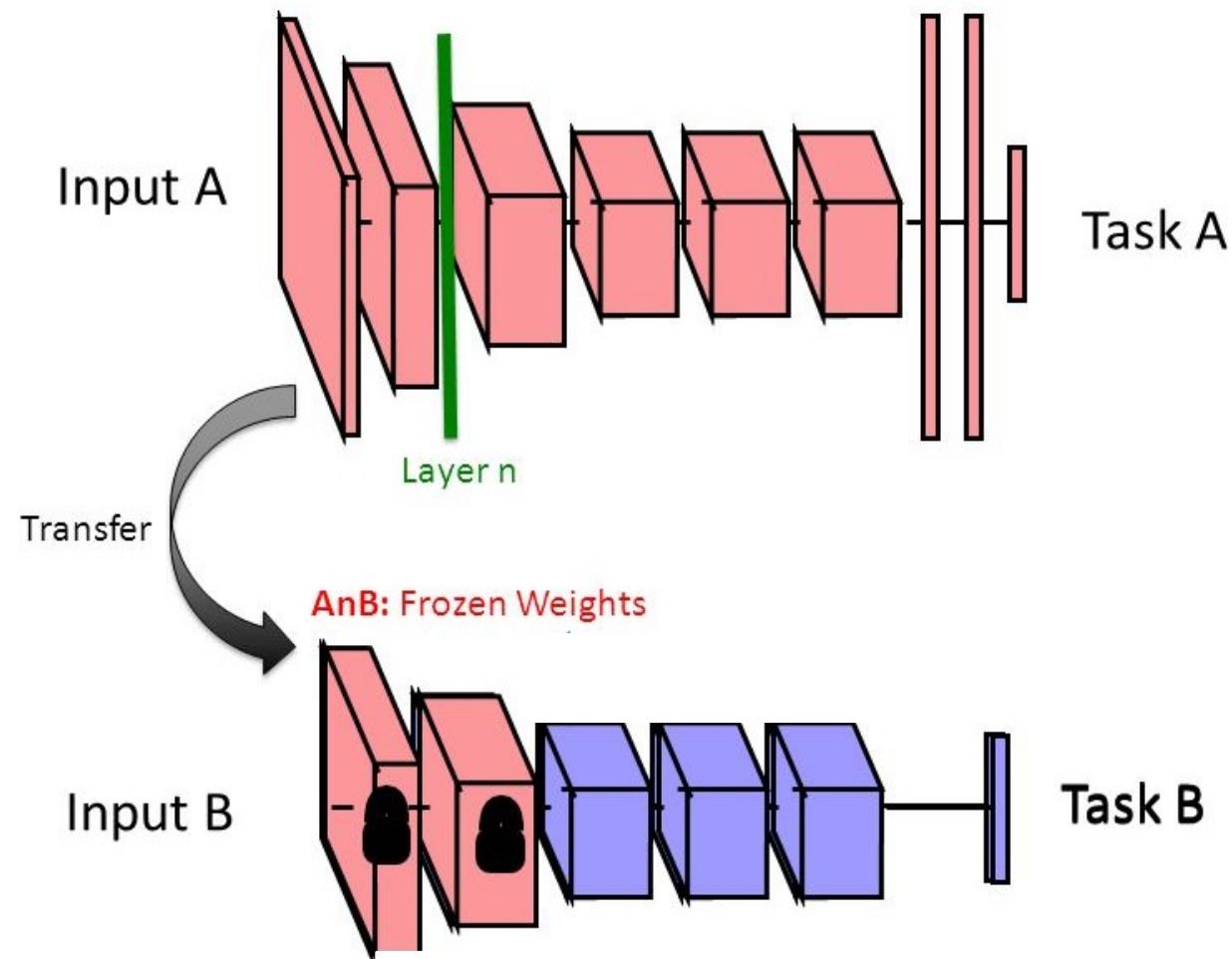
Doing feature extraction with a pre-trained model

LAYER	TRAINABLE
vgg16	False
flatten_1	True
dense_1	True
dense_2	True

convbase.trainable = **False**



# Re-purposing neural nets



# When does transfer transfer makes says

- Image recognition - Million examples
- Radiology recognition – 100 examples
- Speech – 10, 000 hr data
- Wake word – 1 hr data

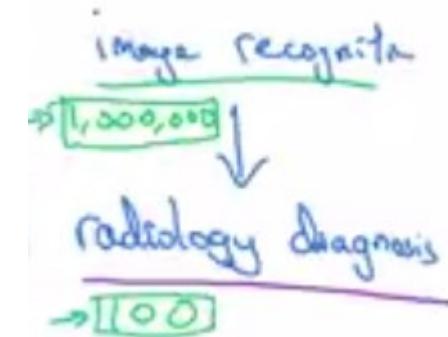
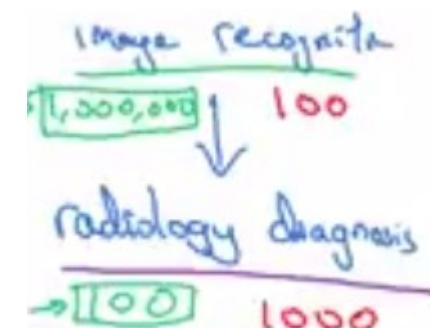
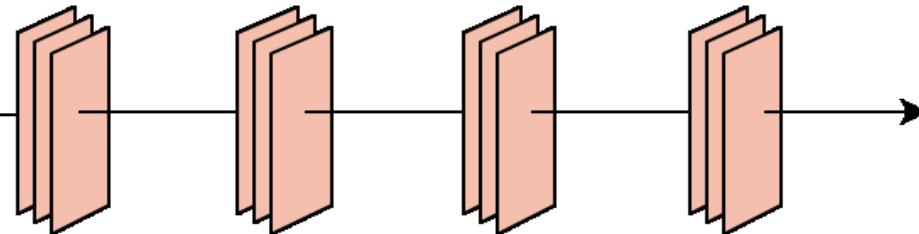


image ( $x, y$ )  
regular ↑  
pre-training  
 $\rightarrow (x, y)$  — fine-tuning  
radiology ↓ diagnosis



Source Task

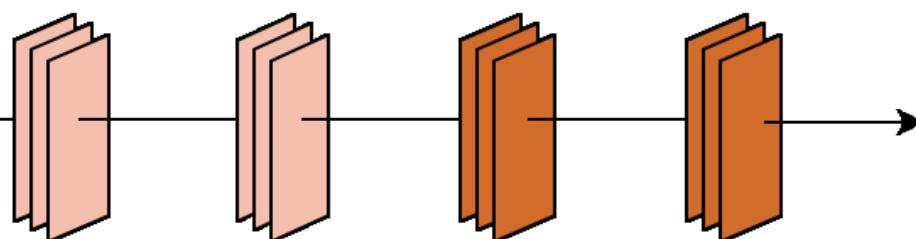


Transfer pre-trained  
parameters to new task

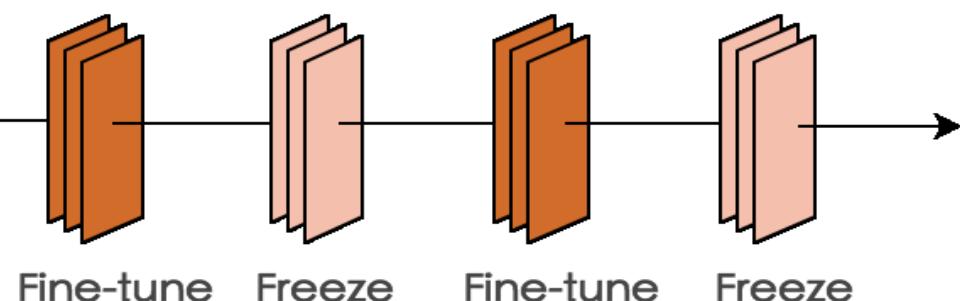
Target Task

Which layers to freeze and which layers to fine-tune?  
(per instance)

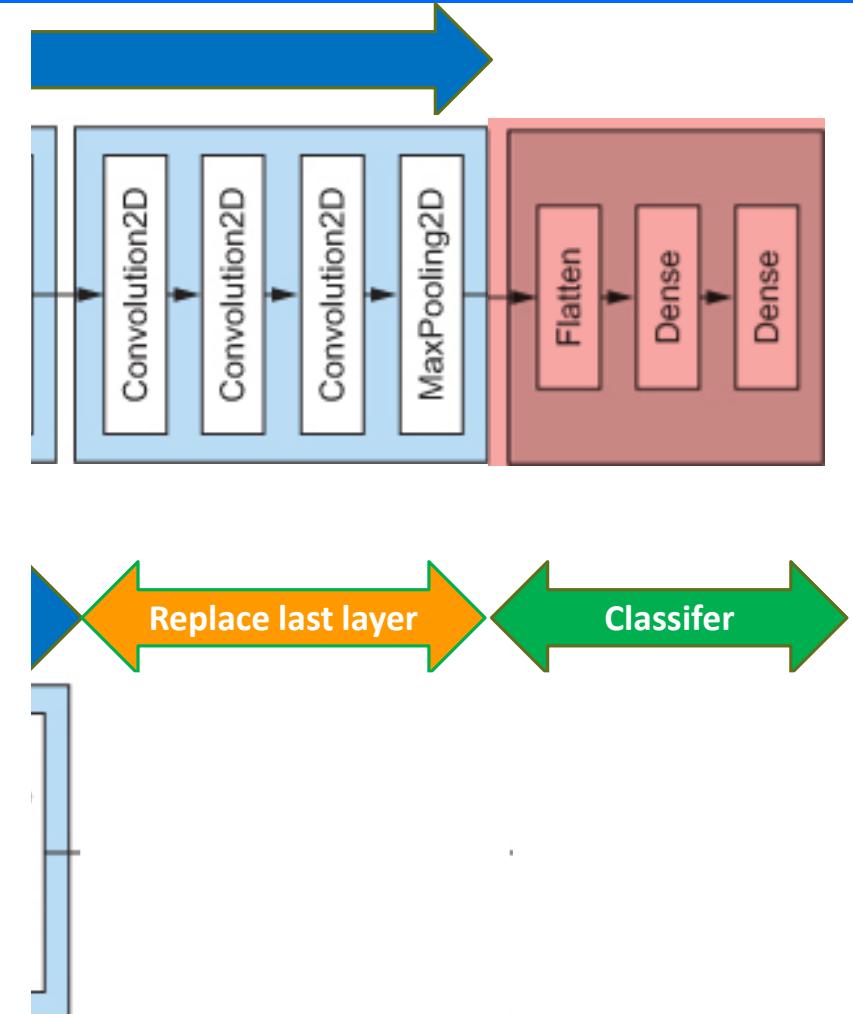
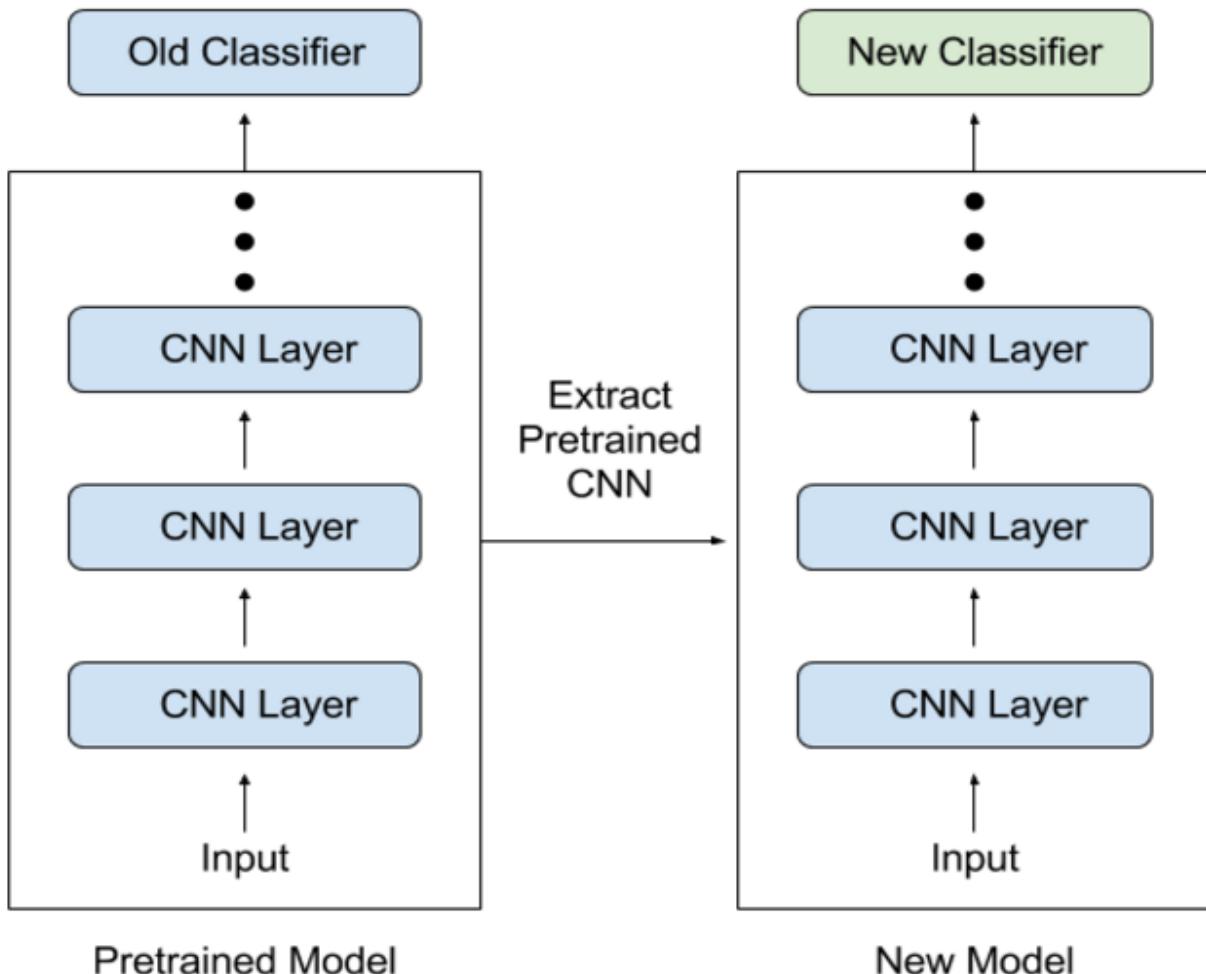
Training Example



Training Example



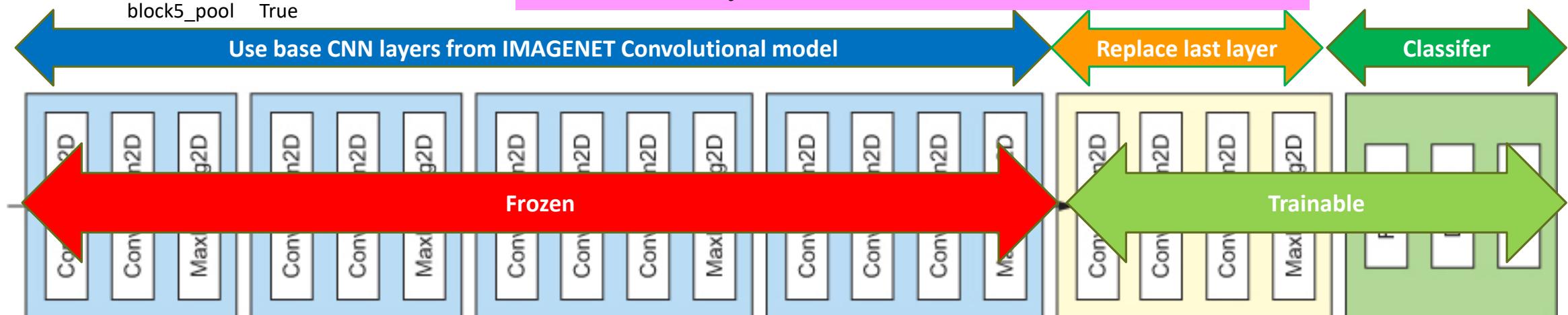
# Network 2



# Network 2

```
block1_conv1 False
block1_conv2 False
block1_pool False
block2_conv1 False
block2_conv2 False
block2_pool False
block3_conv1 False
block3_conv2 False
block3_conv3 False
block3_pool False
block4_conv1 False
block4_conv2 False
block4_conv3 False
block4_pool False
block5_conv1 True
block5_conv2 True
block5_conv3 True
block5_pool True
```

```
convbase.trainable = True
isblock5conv1crossed = False;
for ainsidelayer in convbase.layers:
    layername = ainsidelayer.name
    if layername == 'block5_conv1':
        isblock5conv1crossed = True;
    if isblock5conv1crossed:
        ainsidelayer.trainable = True
        print("Setting trainable for " + str(layername))
    else:
        ainsidelayer.trainable = False
```



# Data Augmentation

```
imageGeneratorDataAugumented =  
    ImageDataGenerator(rescale=1.0/255,  
                       rotation_range=0.01,  
                       width_shift_range=0.01,height_shift_range=0.01,  
                       shear_range=0.01,zoom_range=0.01,  
                       horizontal_flip=True, fill_mode='nearest')
```

## Data Augmentation:

a. No augmentation (= 1 image)



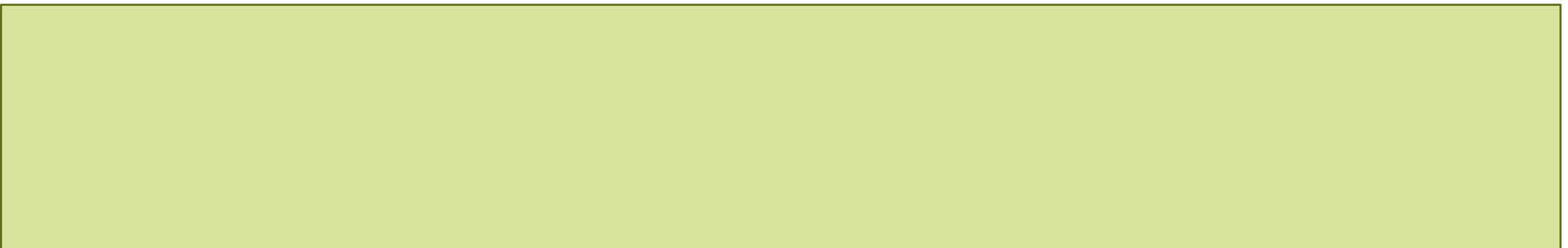
224x224  
→



b. Flip augmentation (= 2 images)



# Training with Generator



# The science behind how computers see

## Visual world

The visual world is fundamentally translation invariant

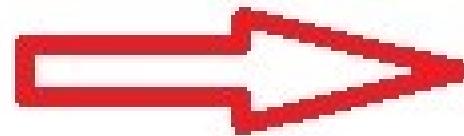
The visual world is fundamentally spatially hierarchical

## What do CNN learn?

CNN learn patterns that are translation invariant

CNN learn spatial hierarchies of patterns

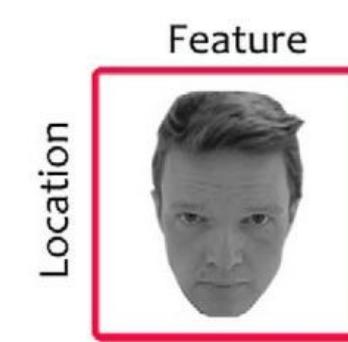
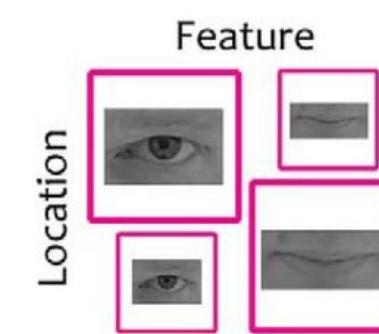
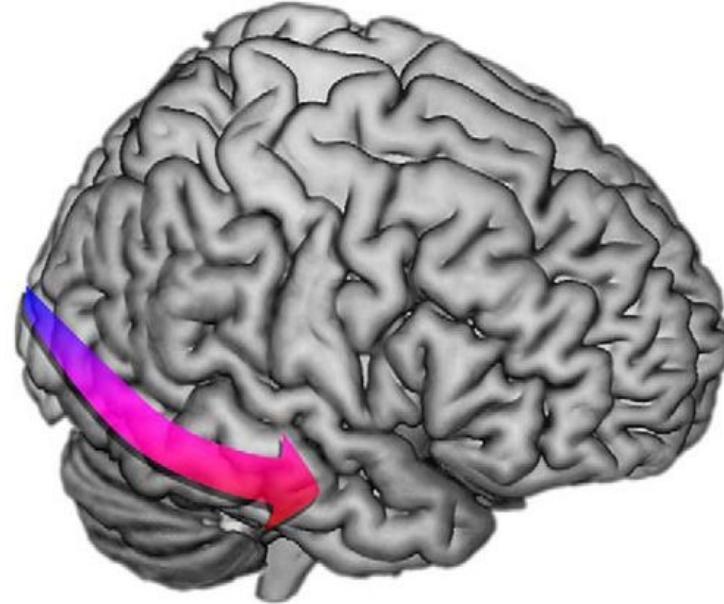
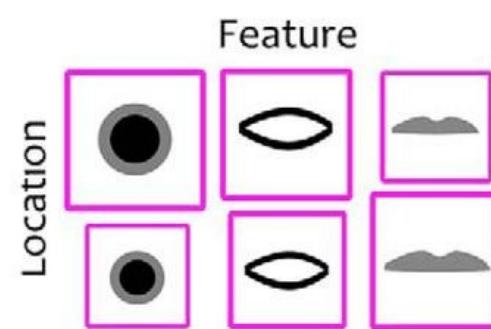
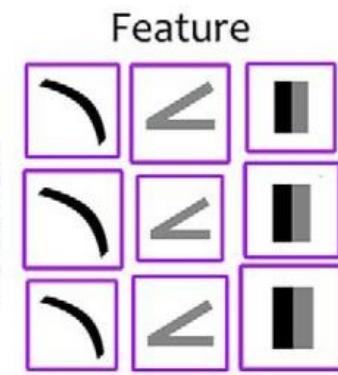
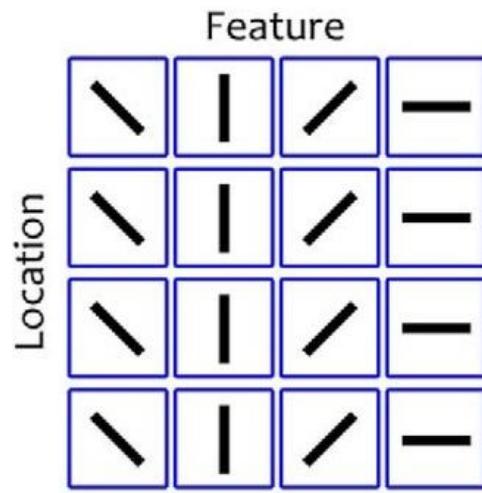
# The visual world is fundamentally translation invariant



train

detect

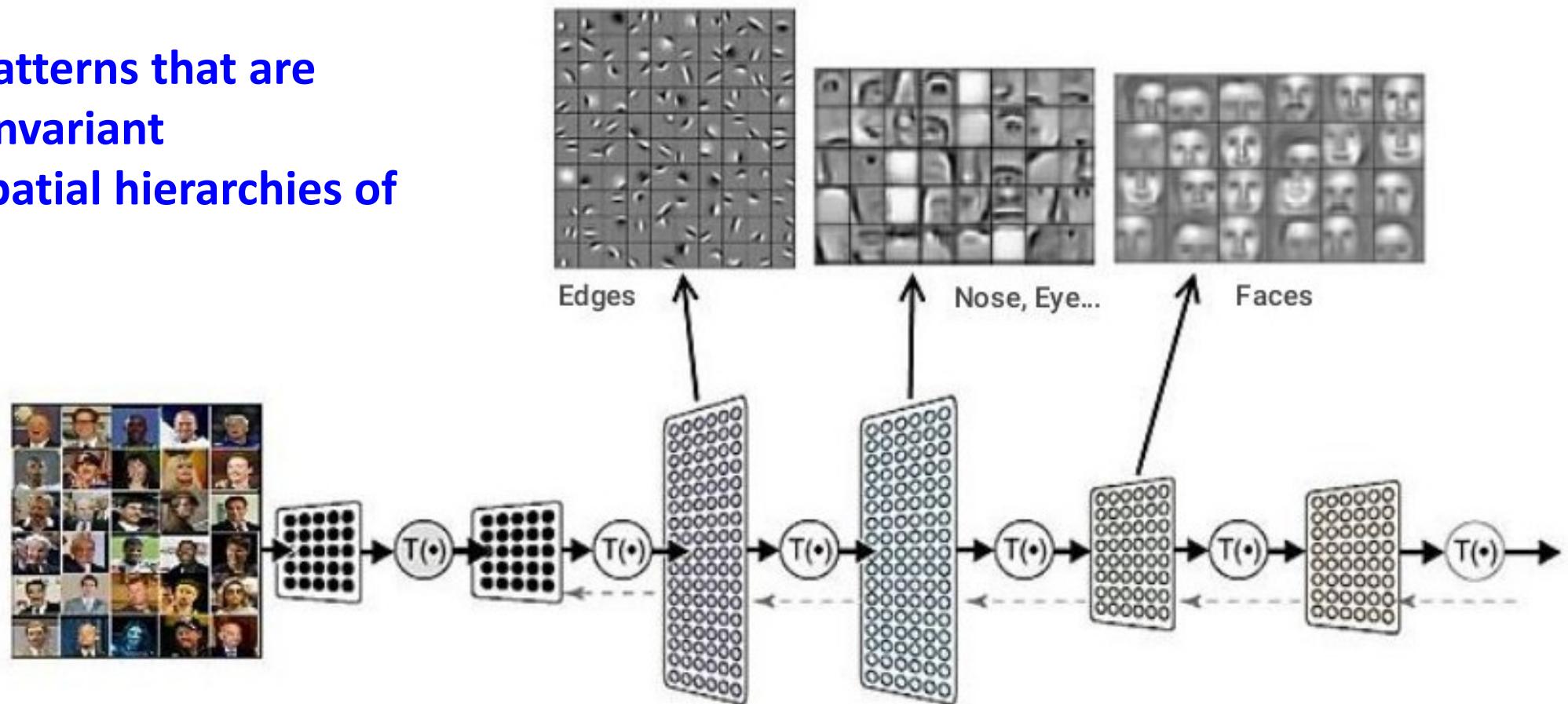
# The visual world is fundamentally spatially hierarchical



# What CNN learns?

A deep neural network consists of a **hierarchy of layers**, whereby each layer **transforms the input data** into more abstract representations (e.g. edge -> nose -> face). The output layer combines those features to make predictions.

- CNN learn patterns that are translation invariant**
- CNN learn spatial hierarchies of patterns**



# Hands-on

- How to use Transfer learning
  - [2\\_2\\_image\\_classification\\_cats\\_part2\\_using\\_Pretrained\\_model.ipynb](#)
- Transfer learning in medical images
  - [4\\_Medical\\_image\\_classification .ipynb](#)