# AI in Built Environment DCP4300

Lec09: Computer Vision

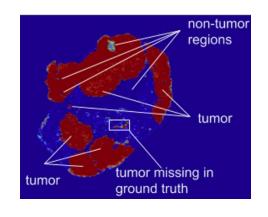
Part A

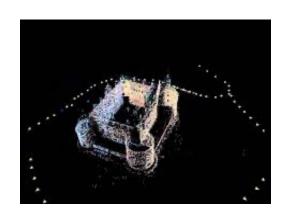
Dr. Chaofeng Wang
Jianhao Gao (TA)
University of Florida
College of Design Construction and Planning

### **Applications of Computer Vision**









Face recognition

Autonomous driving

Disease diagnosis

3D reconstruction

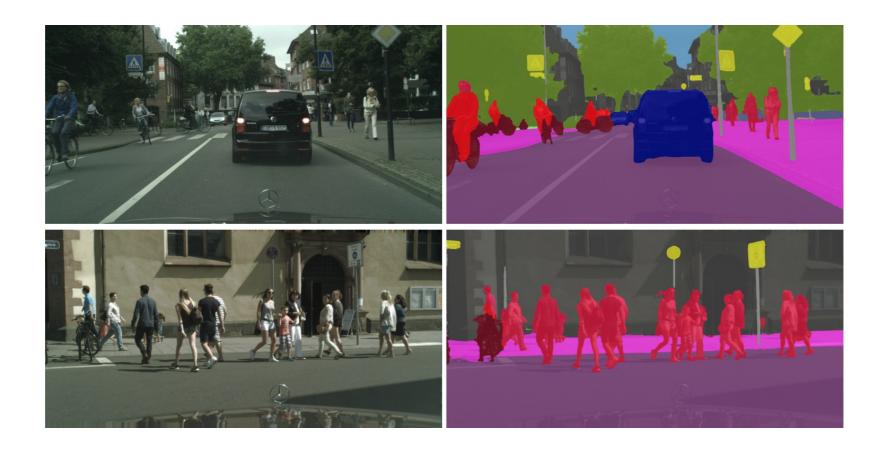
# **Applications of Computer Vision**

### Classification



# **Applications of Computer Vision**

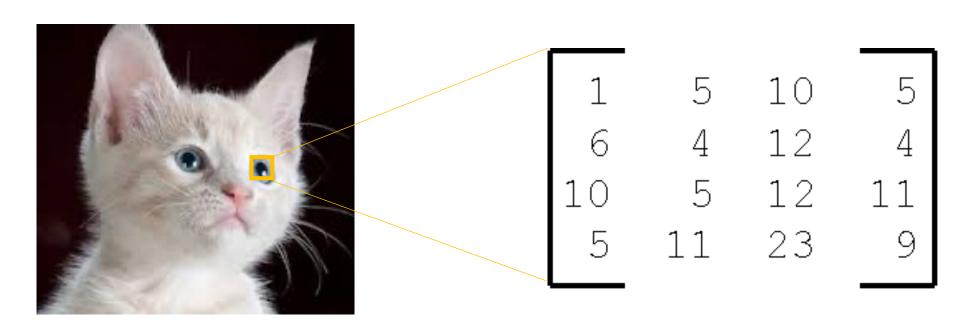
Segmentation



### **Images**

What we see

### What the computer sees



A 256x256 RGB image is a 256x256x3 matrix

### **Images**



Visual Illusion: https://www.youtube.com/watch?v=9Gw23ayxY-I

# **Images**



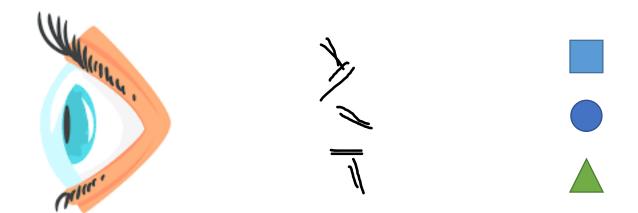


# Vision



It started from the research on cat's vision system

### Vision



simple features

complex features

### The early-stage computer vision

- Edge Detection
- Dilation, Erosion
- •Perspective Transformation
- •Cropping
- Scaling, Interpolations, And Re-Sizing
- Thresholding
- Sharpening
- Blurring
- •Contours
- Line Detection
- Blob Detection

•...

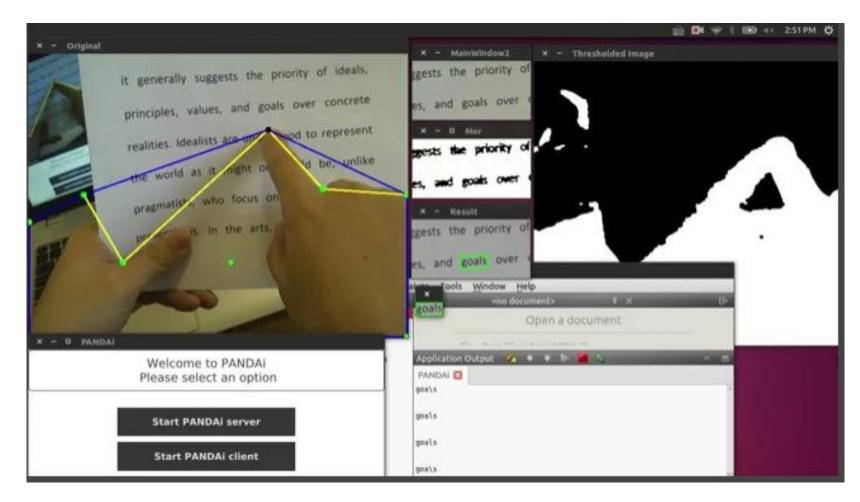




https://opencv.org/

### The early-stage computer vision





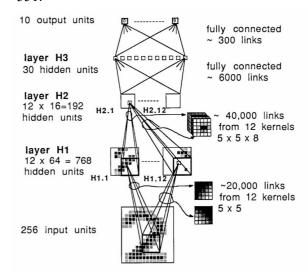
My first computer vision project

### Key points in the history of computer vision

1950 1960 1970 1980 1990 2000 2010 2020

### 1989, Convolutional Neural Networks (CNN/ConvNet)

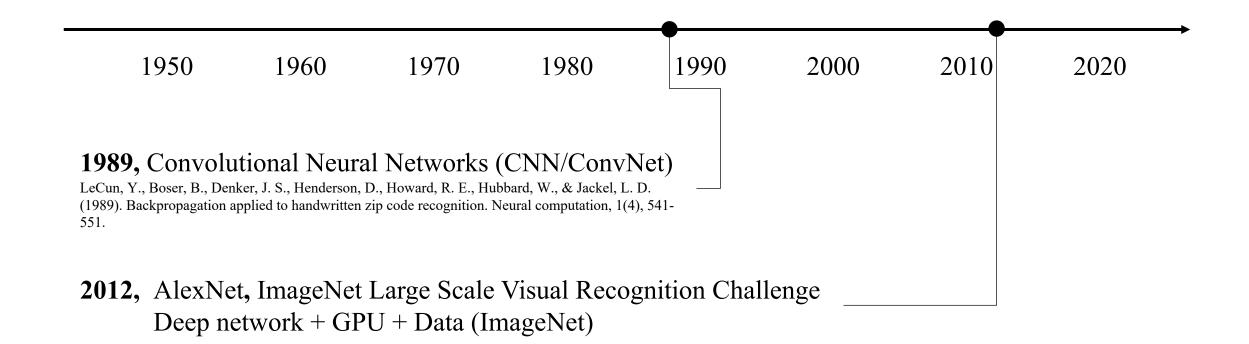
LeCun, Y., Boser, B., Denker, J. S., Henderson, D., Howard, R. E., Hubbard, W., & Jackel, L. D. (1989). Backpropagation applied to handwritten zip code recognition. Neural computation, 1(4), 541-551.



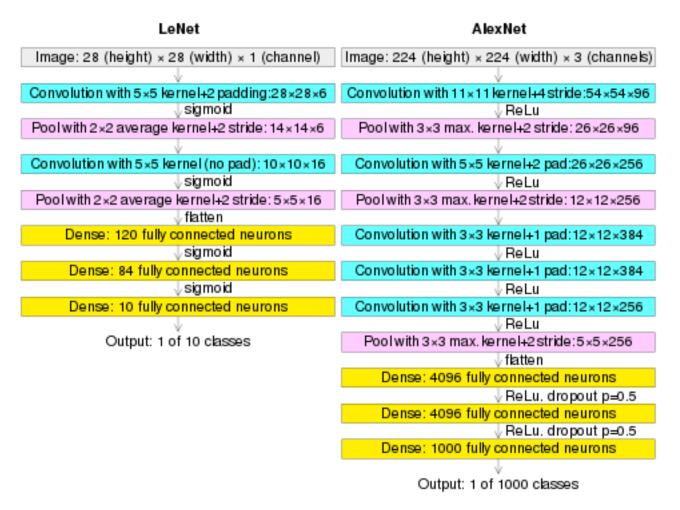


Yann LeCun demonstrating LeNet 1, 1993

### **Key points in the history of computer vision**



#### **Key points in the history of computer vision**



https://en.wikipedia.org/wiki/AlexNet

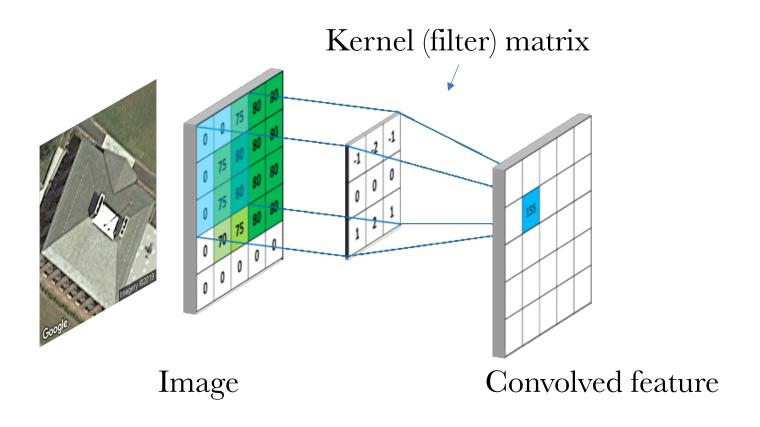


A 24x24 image can be expanded as a vector  $[x_1, x_2, ... x_{576}]$ 

# $X_1$ $B_1$ $\mathbf{X}_2$ 0.3 $B_2$ $X_3$ $B_3$ $X_4$ 0.4 $B_4$ $X_5$ 0.8 $B_5$ $X_{576}$

A brute way...

## **Convolutional layer**



A 2D convolution operation

Input: 5x5x1

Kernel: 3x3

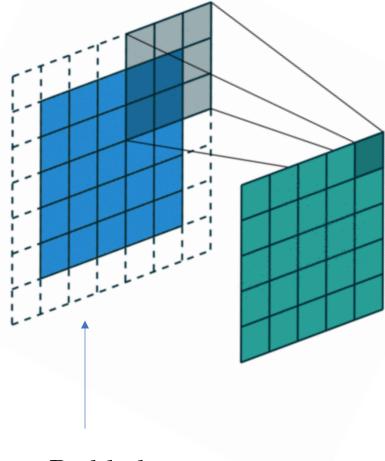
Stride: 1 (size of the 'slide')

Padding: 0

Output: 3x3x1

Purpose: extracting features.

### **Convolutional layer**



Padded

https://github.com/vdumoulin/conv\_arithmetic

Input: 5x5x1

Kernel: 3x3

Stride: 1 (size of the 'slide')

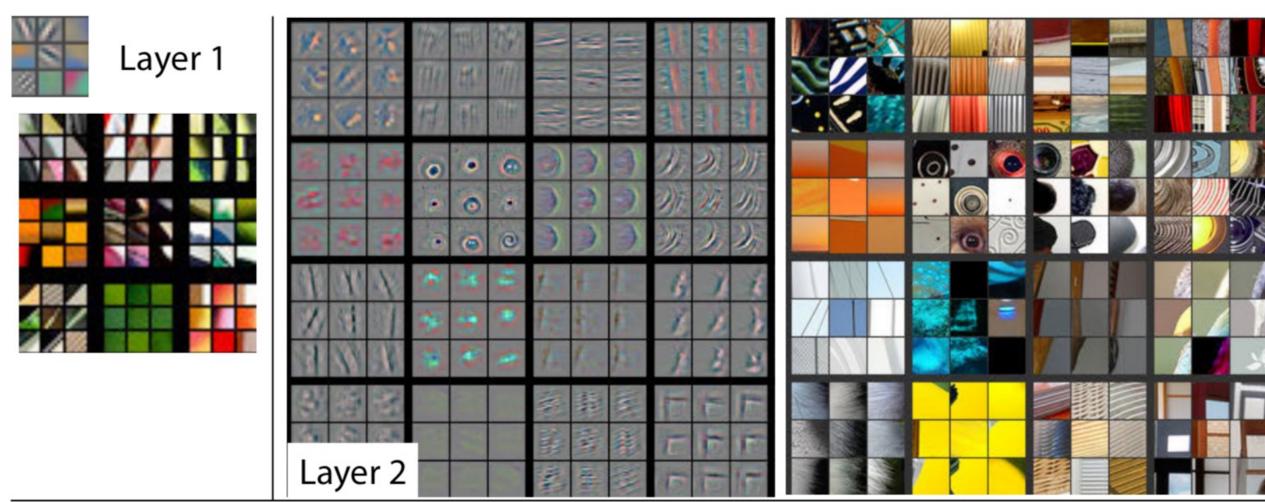
Padding: 1

Output: 5x5x1

Purpose: extracting features.

# Learn features hierarchically

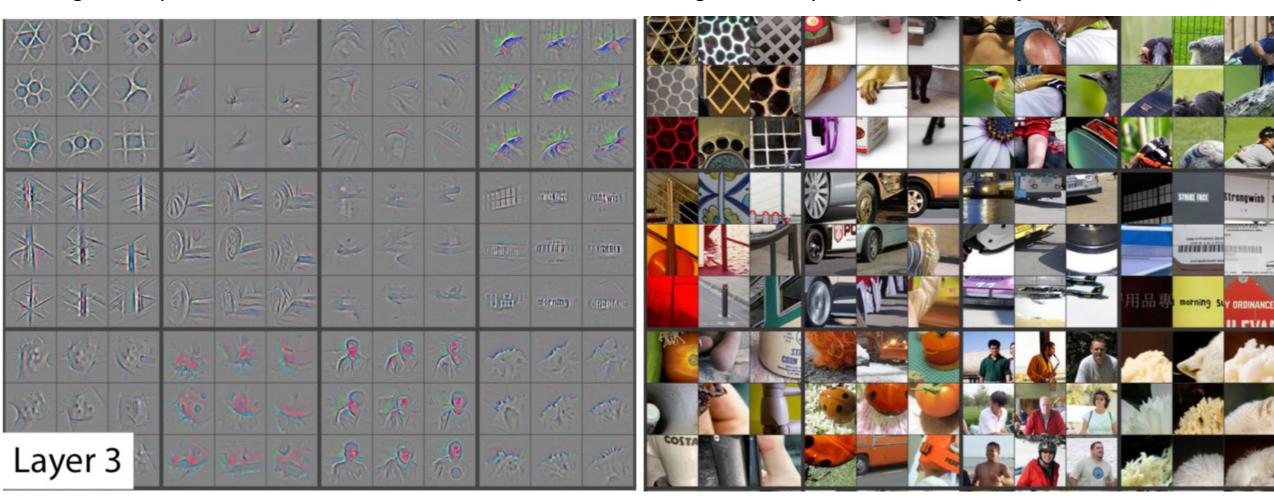
The first layers of CNN detect general features: Edges, Corners, Circles, Blobs colors, ...



Zeiler, Matthew D., and Rob Fergus. "Visualizing and understanding convolutional networks." European conference on computer vision. Springer, Cham, 2014.

## Learn features hierarchically

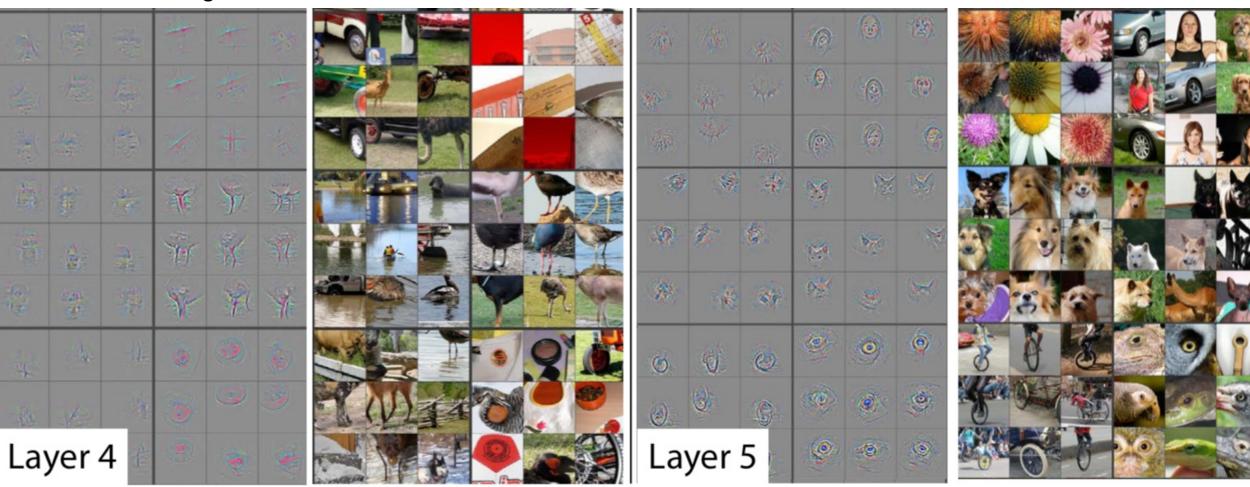
As it goes deeper into the CNN, it starts to detect more concrete things such as eyes, faces, and full objects.



Zeiler, Matthew D., and Rob Fergus. "Visualizing and understanding convolutional networks." European conference on computer vision. Springer, Cham, 2014.

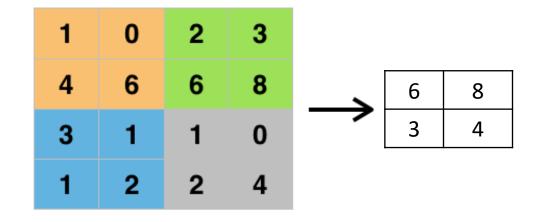
## Learn features hierarchically

More concrete things ...



Zeiler, Matthew D., and Rob Fergus. "Visualizing and understanding convolutional networks." European conference on computer vision. Springer, Cham, 2014.

## **Pooling layer**



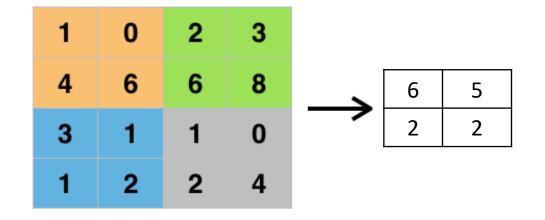
Max pooling Average pooling L2-norm polling

. . .

Max pooling

Purpose: extracting dominant feature and reduce dimensionality

## **Pooling layer**



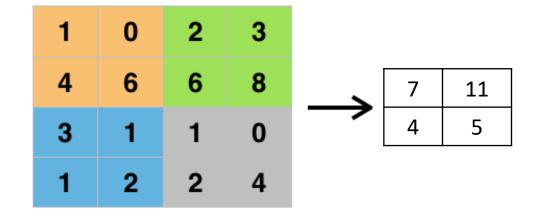
Max pooling Average pooling L2-norm pooling

. . .

Average pooling

Purpose: extracting dominant feature and reduce dimensionality

### **Pooling layer**



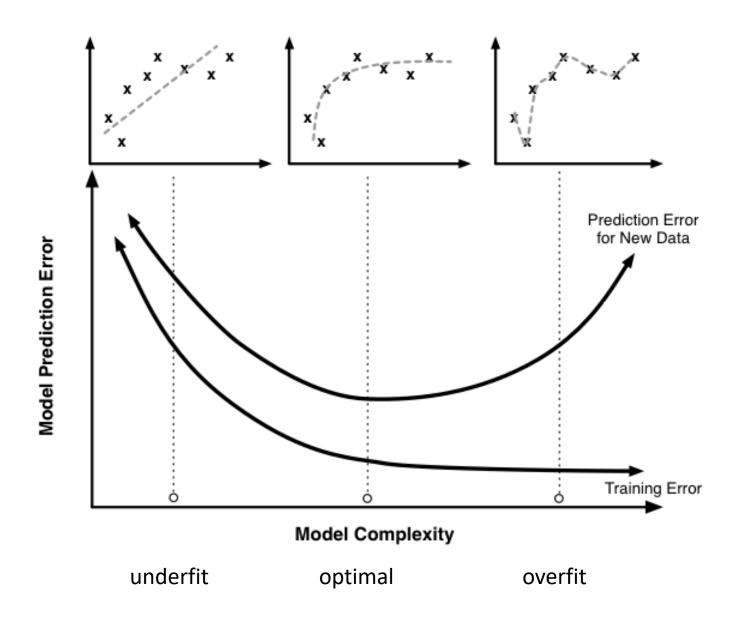
Max pooling
Average pooling
L2-norm pooling

. . .

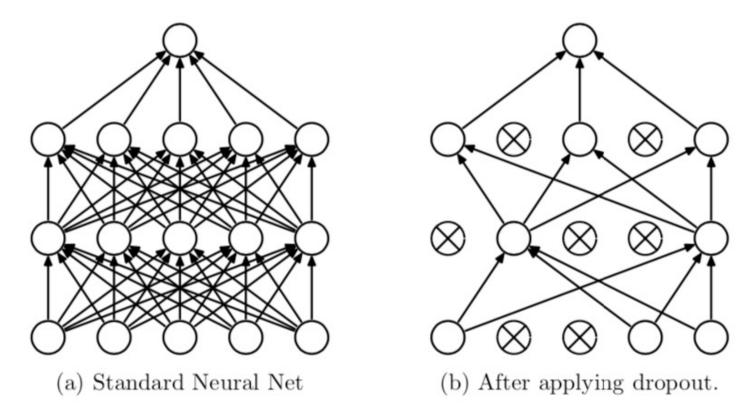
L2-norm pooling

Purpose: extracting dominant feature and reduce dimensionality

# What is a good model?



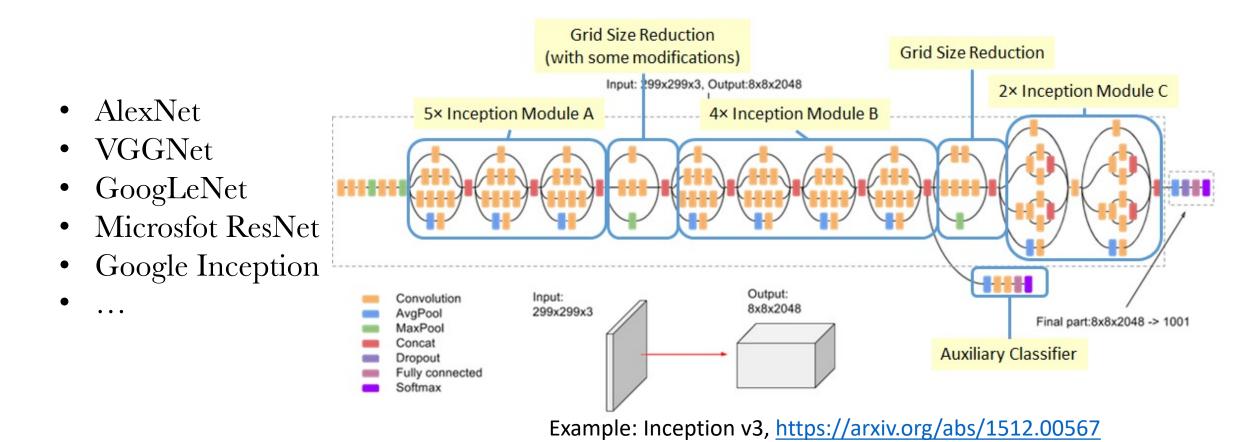
### **Dropout layer**



Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. The journal of machine learning research, 15(1), 1929-1958. <a href="https://www.cs.toronto.edu/~hinton/absps/JMLRdropout.pdf">https://www.cs.toronto.edu/~hinton/absps/JMLRdropout.pdf</a>

Purpose: fight overfitting

### Popular deep CNN architectures



Build one from scratch (ResNet)

https://www.analyticsvidhya.com/blog/2021/08/how-to-code-your-resnet-from-scratch-in-tensorflow/

### **Transfer Learning**

The weights in a pretrained neural network is the leaned knowledge.

So a deep CNN trained on a large dataset contains knowledge (weights) that can be used to understand basic features in any given new image. This is the concept of transfer learning.

To do transfer learning, we

- Freeze the first layers of the pretrained neural network. These are the layers that detect general features that are common across all domains.
- Then we finetune the deeper layers with our own training data and add new layers to classify new categories included in our training dataset.

## **Transfer Learning: Fine tuning**

Take a pre-trained model (with learned weights) as base model

Base model

Add a header and train with the base model's weights frozen

Base model New header

Unfreeze the base model and train

Base model New header

### **Demo: Classification of satellite images**

Will do this demo in a Jupyter notebook on Google Colab:

https://colab.research.google.com/drive/1EKUEZEVgtWTfDTdR1grtAorMq3ZGLxmR?usp=sharing











Gabled





Hipped