

Day 7: Convolutional Neural Networks

Summer STEM: Machine Learning

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August 11, 2020

Outline

- 1 Motivation**
- 2 Dealing with Images in Computers**
- 3 Convolution**
- 4 Regularization**
- 5 Transfer Learning**

Better performance with images

- Encoding locality
- How does an MLP see an image?
- Is this how we see images?

Examples: Lena & Mandrill



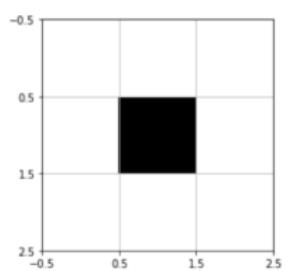
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Images in Computer

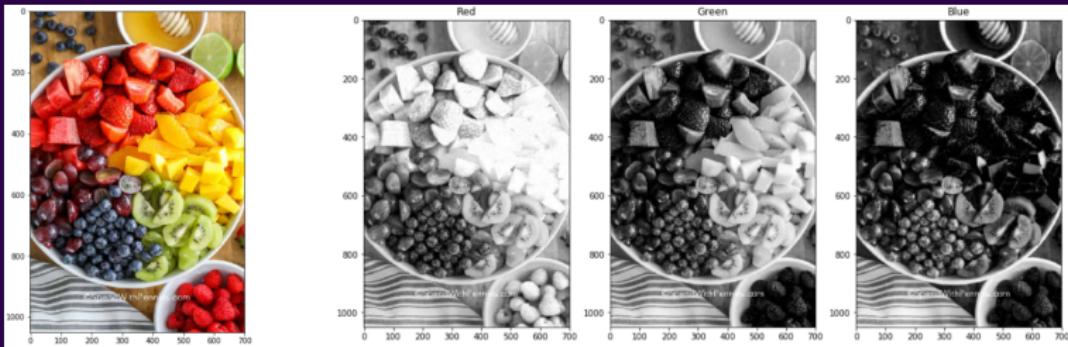
- Images are stored as arrays of quantized numbers in computers
- Gray scale image: 2D matrices with each entry specifying the intensity (brightness) of a pixel
 - Pixel values range from 0 to 255, 0 being the darkest, 255 being the brightest

```
[[255 255 255]
 [255 0 255]
 [255 255 255]]
```



Color Images

- Color image: 3D array, 2 dimensions for space, 1 dimension for color
 - Can be thought of as three 2D matrices stacked together into a cube, each 2D matrix specify the amount of each color: Red ,Green ,Blue value at each pixel



- Shape of this image: (1050,700,3)
 - There are 1050x700 pixels, 3 channels: R,G,B

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Limitations of Fully Connected Network

- Open `lab_mnist.ipynb`
- In MNIST, we used a fully connected network, in which each neuron in the hidden layer is connected to all $28 \times 28 = 784$ pixels.
- Higher definition images often contain millions of pixels → It is not practical to use fully connected networks.
- Fully connected networks treat each individual pixel as a feature, it does not utilize the positional relationship between pixels

Convolution

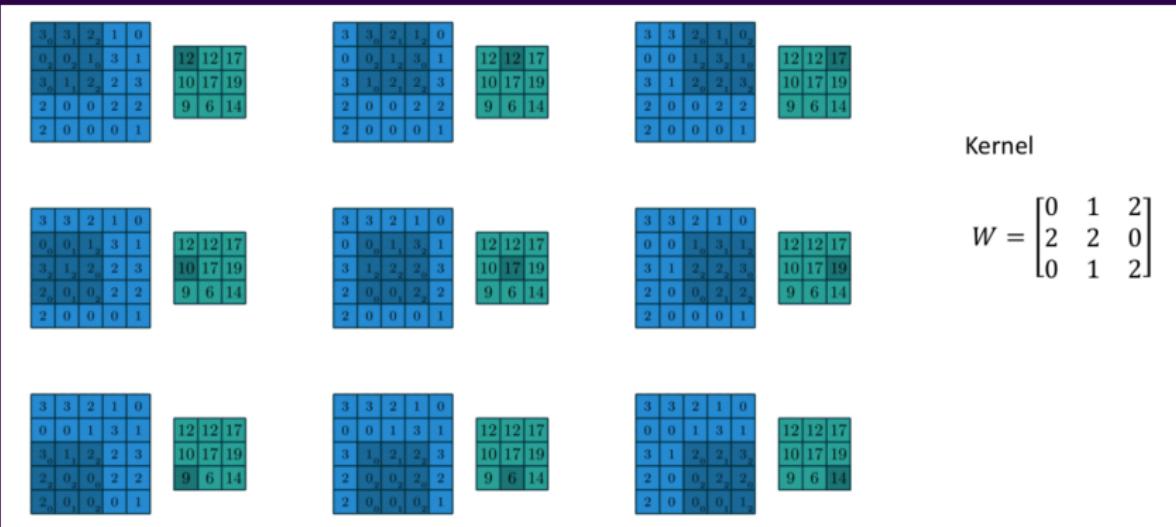
- Introducing a new operation: Convolution
- An operation on an image(matrix) X with a kernel W
- $Z = X \circledast W$

Some Animations, Source:
<https://towardsdatascience.com>

Some Animations, Source:

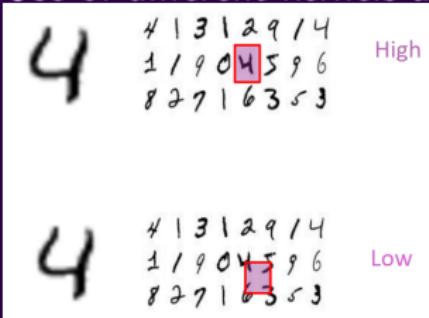
<https://cs231n.github.io/convolutional-networks/>

Example of a Convolution



Why Convolution?

- With convolution, each output pixel depends on only the neighboring pixels in the input
- This allows us to learn the positional relationship between pixels
- Use of different kernels allows us to detect features



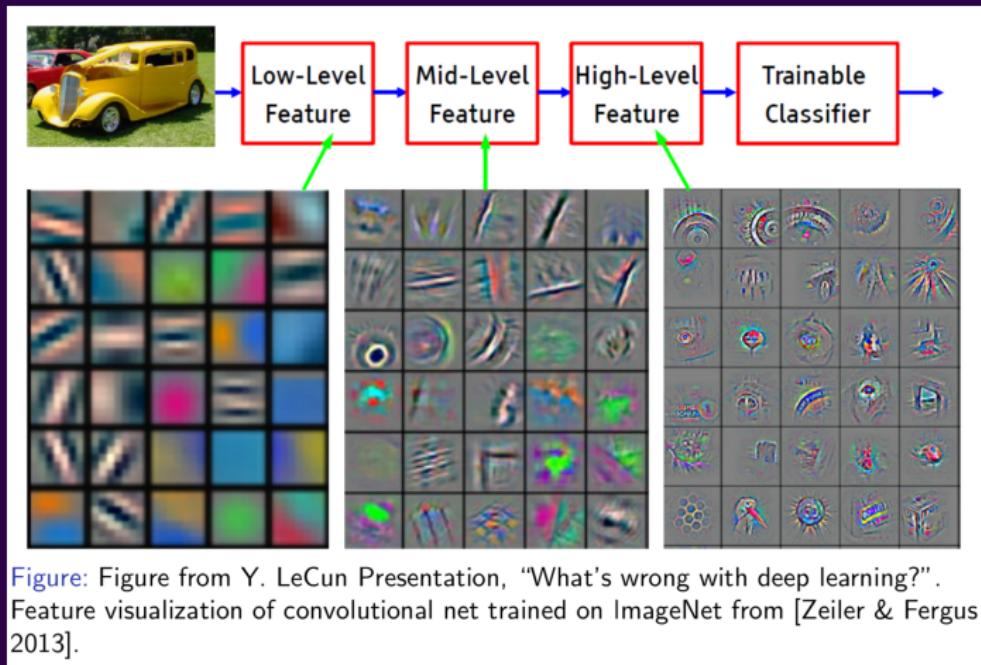
Understand Kernels

Open `demo_kernels.ipynb`

Convolution for Multiple Channels

- A kernel for each channel. Could be same kernel, or different
- Perform a convolution for each of the channel, with the respective kernel
- Sum the results

Feature Maps

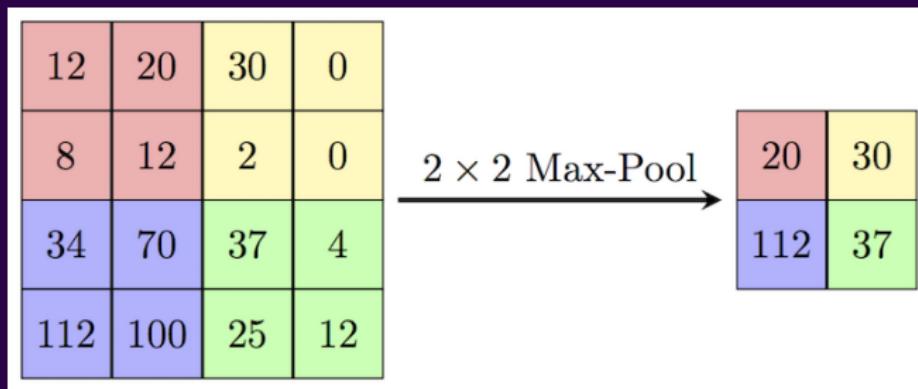


Demo: Building a CNN

Open `demo_cnn.ipynb`

Max-Pooling

- Down-samples the inputs
- Provides translation invariance. Why?
- Apply after activation!



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Data Augmentation

- Image classification is a difficult task
- We need more data !
- Labeling is expensive and time-consuming.
- How can we create new images ?

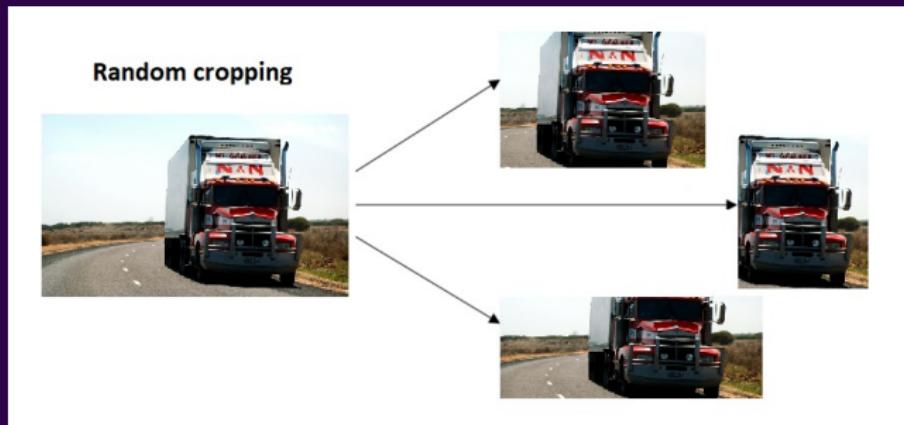
Data Augmentation



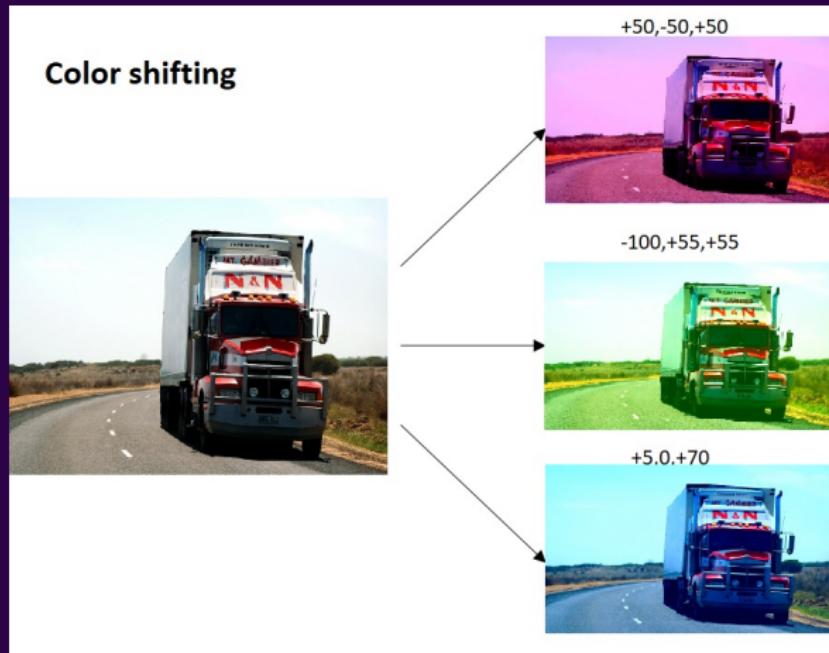
Mirroring



Data Augmentation

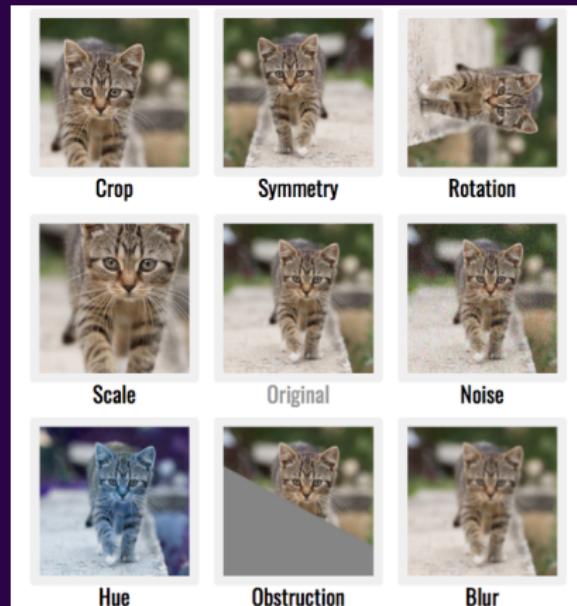


Data Augmentation



<http://datahacker.rs/deep-learning-data-augmentation>

Data Augmentation



<https://medium.com/@wolframalphav1.0/easy-way-to-improve-image-classifier-performance-part-1-mixup-augmentation-with-codes-33288db9f8e0>

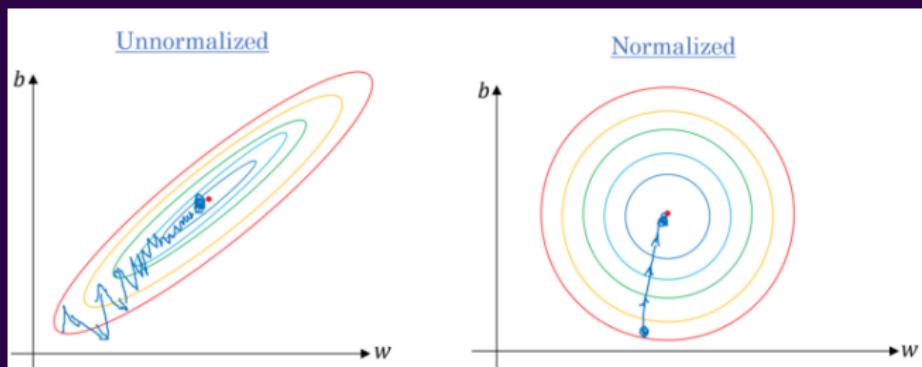
Data Normalization

- Given the dataset (x_i, y_i) for $i = 1, 2, \dots, N$
- Mean: $\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$
- Variance: $\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2$
- Standard deviation : σ ($= \sqrt{\sigma^2}$)

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- Variance: $\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2$
- Standard deviation : σ ($= \sqrt{\sigma^2}$)
- **Normalization** : Replace each x_i by $x'_i = \frac{x_i - \bar{x}}{\sigma}$
- The new dataset will have a mean of 0 and a variance of 1.

Data Normalization



<https://towardsdatascience.com/gradient-descent-algorithm-and-its-variants-10f652806a3>

Batch Normalization

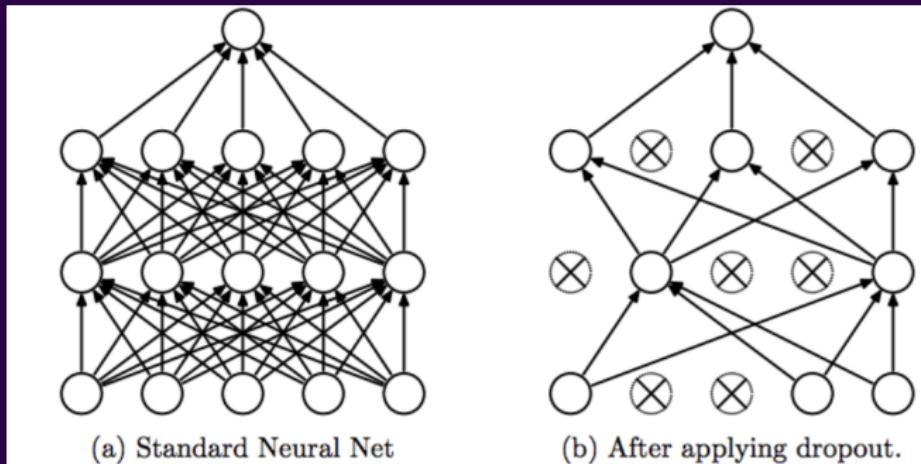
- We normalize the inputs to the network. Why not do that for the inputs to the hidden layers?
- Batch norm: normalize the inputs to a layer for each mini-batch.
- Apply before activation!

Batch Normalization

```
model = models.Sequential()  
# More layers  
model.add(layers.Conv2D(64, (3, 3)))  
model.add(layers.BatchNormalization())  
model.add(layers.Activation('relu'))  
# More layers  
model.add(layers.Flatten())  
model.add(layers.Dense(64))  
model.add(layers.BatchNormalization())  
model.add(layers.Activation('relu'))  
model.add(layers.Dense(1, activation='sigmoid'))
```

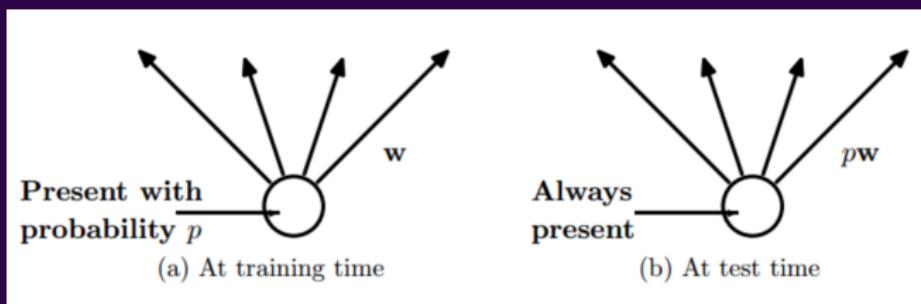
Dropout

- Patented by Google
- Randomly disable neurons and their connections between each other.



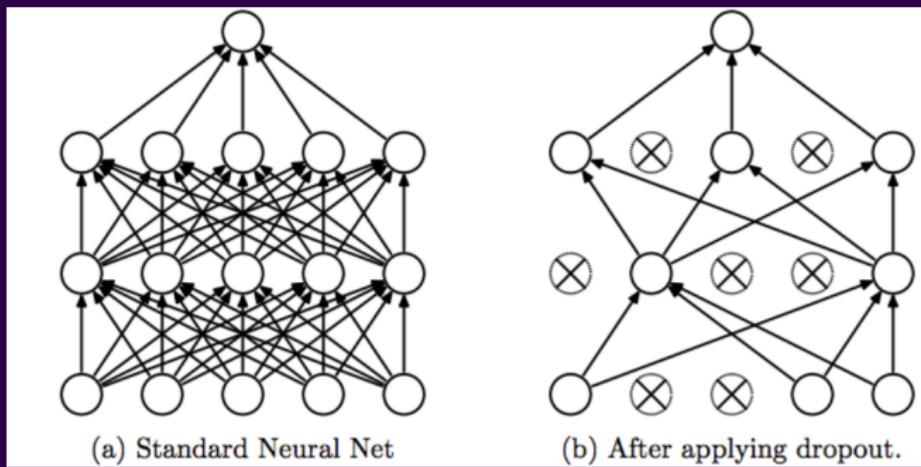
Dropout

- In train mode, each neuron is present with probability p .
- In eval mode, multiply the weights with p .
- Apply after activation!



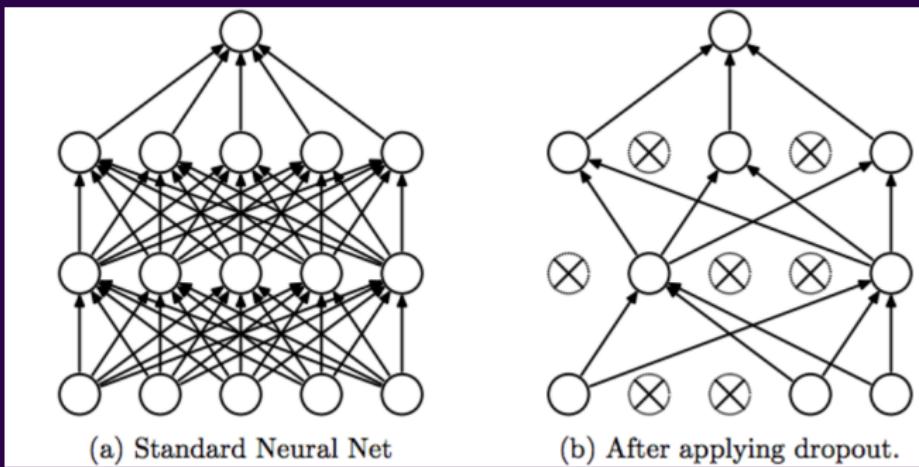
Dropout

- This is the same as using a neural network with the same amount of layers but less neurons per layer.
- The more neurons the more powerful the neural network is, and the more likely it is to overfit.



Dropout

- This also means that the model can not rely on any single feature, therefore would need to spread out the weights.
- When spreading out the weights the size also shrinks, thus giving a similar effect to L2 regularization



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Open Source Implementation

- If you are interested in building on top of a deep learning research paper it is a good idea to first go online and see if there is a nice open source implementation instead of starting from scratch.
- If you are in the field of computer vision, many networks would require an extensive hyperparameter search and multiple GPUs to train, this process might take weeks.
- People now open source their results along with the weights and these can be seen as a nice initialization to your application.

Imagenet Challenge

ImageNet Challenge



The ImageNet Challenge features a grid of images and their corresponding labels. The grid is organized into four columns:

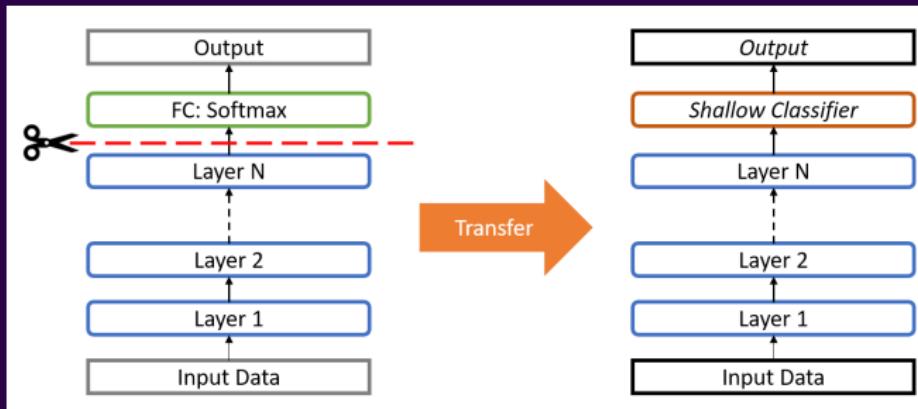
- mite**: Includes images of a red mite, a black widow, a cockroach, a tick, and a starfish.
- container ship**: Includes images of a container ship, a lifeboat, an amphibian, a fireboat, and a drilling platform.
- motor scooter**: Includes images of a motor scooter, a go-kart, a moped, a bumper car, and a golfcart.
- leopard**: Includes images of a leopard, a jaguar, a cheetah, a snow leopard, and an Egyptian cat.

Below the first row, there are three more rows of images and labels:

- grille**: Includes images of a red convertible grille, a beach wagon grille, and a fire engine grille.
- mushroom**: Includes images of agaric mushrooms, jelly fungi, gill fungi, and dead-man's-fingers.
- cherry**: Includes images of cherries and a dalmatian dog.
- Madagascar cat**: Includes images of a squirrel monkey, a spider monkey, a titi, an indri, and a howler monkey.

At the bottom right of the slide, there is a NYU Tandon School of Engineering logo.

Transfer Learning



<https://www.oreilly.com/library/view/hands-on-transfer-learning/9781788831307/d94586c6-1c46-4794-aded-22442a4f81d8.xhtml>

Transfer Learning

- You can freeze the early layers and replace the last few layers to match your own application needs (e.g. different number of classes, different activation functions).
- Only train the replaced layers and use the weights of the early layers "as-is".
- This is similar to transferring the knowledge from one network to another, thus the name transfer learning.

Lab: Cats vs. Dogs

Open `lab_cats_vs_dogs.ipynb`