Machine Learning and Deep Learning
Lecture-13

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Overview

- Convolutional Neural Network (CNN)
- Generative Adversarial Network (GAN)

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNN)

- CNNs emerged from the study of the brain’s visual cortex.
- Popular use image recognition (since 1980s).
- Deep neural network does NOT work well for large mage recognition..?
    - For example, a 100×100 pixel image has 10,000 pixels. If the first layer has just 1,000 neurons means a total of 10M connections for just the first layer.
    - CNNs solve it using partially connected layers and weight sharing.
- CNN each layer is represented in 2D which makes it easier to match neurons with their corresponding inputs.

https://poloclub.github.io/cnn-explainer/

CNN VS DNN

- CNNs Layers are designed to process grid-like data. It include convolutional layers that apply filters to the input data to detect features like edges, textures, and patterns.
  - Fewer parameters
  - Less overfits
  - Automatically learns spatial features from images
  - Locally connected network
- Applications: Image and video recognition
- DNNs includes any neural network with multiple layers. It consists of fully connected layers where each neuron is connected to every neuron in the previous layer.
  - More parameters
  - Overfits
  - Require feature engineering
  - Fully connected
- Applications: Used for a wide range of tasks.

Convolutional Neural Networks (CNN)

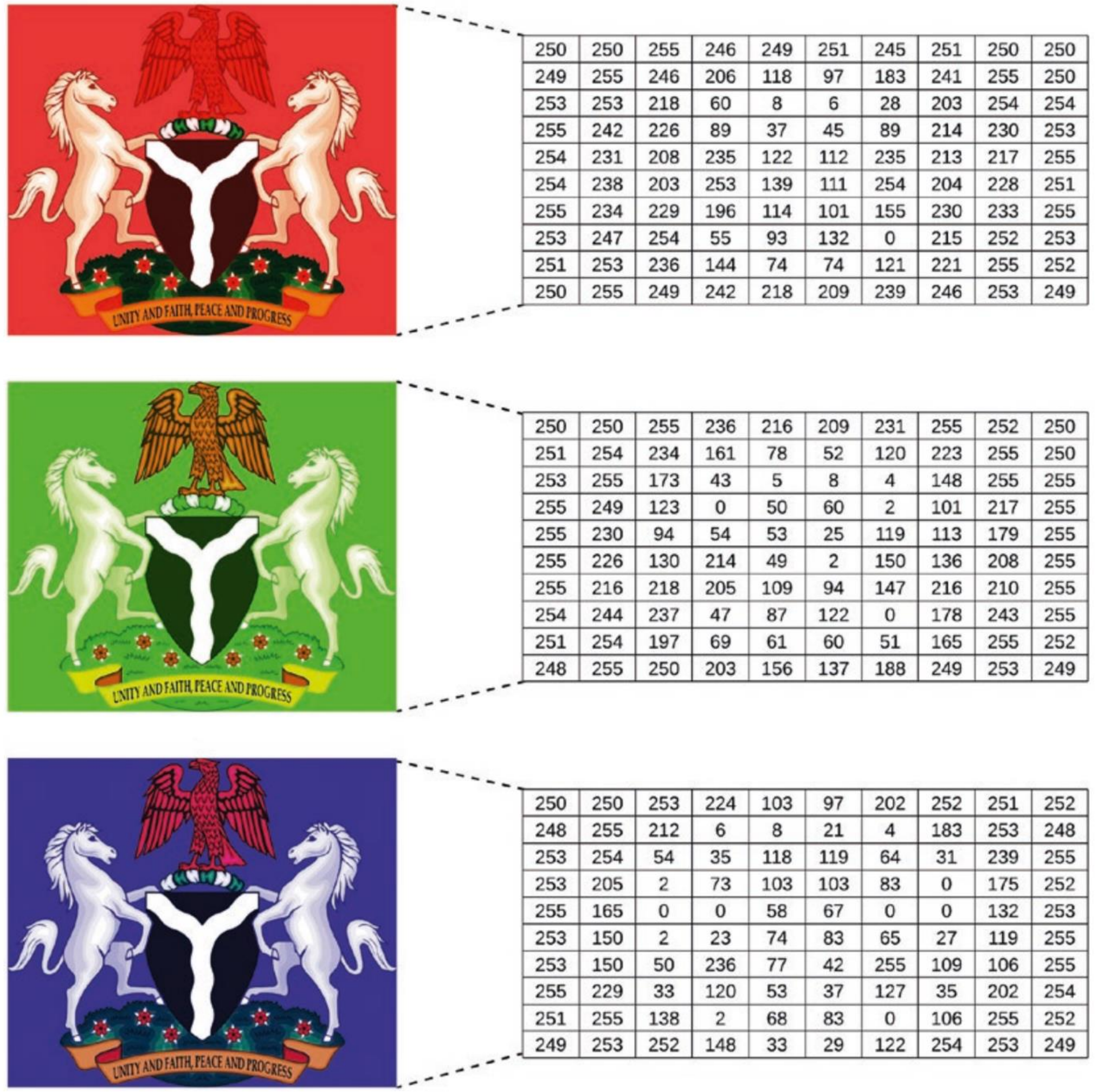
- Convolution is a mathematical operation that slides one function over another and measures the integral of their pointwise multiplication.
- It has deep connections with Fourier transform + Laplace transform.
- Convolutional layers use cross-correlations (similar to convolutions).

- CNN has three fundamental layers: Convolutional layer, Pooling layer, Fully connected layer.
- Convolutional layer is the most important building block of a CNN.
  - During training convolutional layers require a huge amount of RAM.

Convolutional Neural Networks (CNN)

- Coloured image consists red, green, and blue with pixel intensity values from 0 to 255.
- A coloured image has a matrix shape of [height x width x channel].
- Side image of shape [10 x 10 x 3] indicating a 10 x 10 matrix with three channels.

- NN perform image processing on multi-channelled images.
  - Each channel represents a color.
  - Each pixel consists of three channels - RGB
- RGB image can be described as a wxhxn_c matrix, where w, h, and n_c denote width, height, and number of channels respectively.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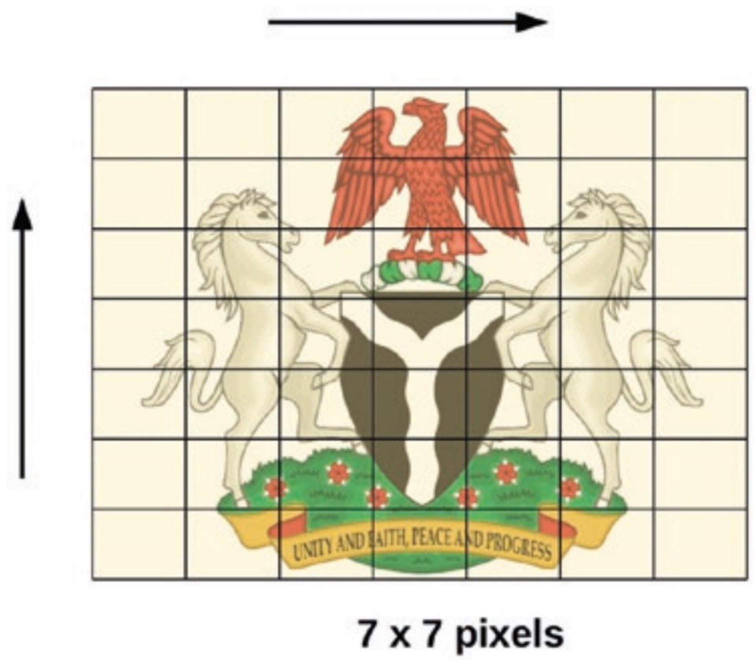
250	250	255	246	249	251	245	251	250	250
249	255	246	206	118	97	183	241	255	250
253	253	218	60	8	6	28	203	254	254
255	242	226	89	37	45	89	214	230	253
254	231	208	235	122	112	235	213	217	255
254	238	203	253	139	111	254	204	228	251
255	234	229	196	114	101	155	230	233	255
253	247	254	55	93	132	0	215	252	253
251	253	236	144	74	74	121	221	255	252
250	255	249	242	218	209	239	246	253	249

250	250	255	236	216	209	231	255	252	250
251	254	234	161	78	52	120	223	255	250
253	255	173	43	5	8	4	148	255	255
255	249	123	0	50	60	2	101	217	255
255	230	94	54	53	25	119	113	179	255
255	226	130	214	49	2	150	136	208	255
255	216	218	205	109	94	147	216	210	255
254	244	237	47	87	122	0	178	243	255
251	254	197	69	61	60	51	165	255	252
248	255	250	203	156	137	188	249	253	249

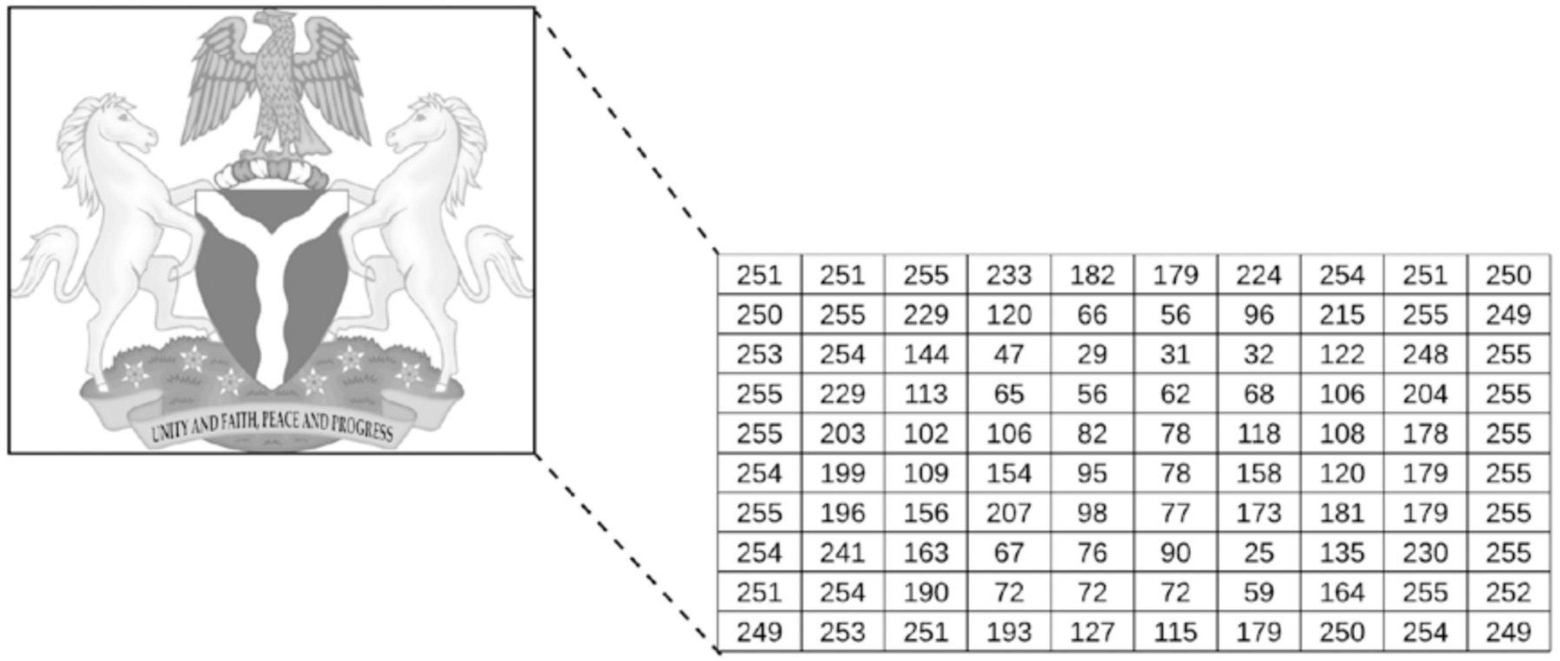
250	250	253	224	103	97	202	252	251	252
248	255	212	6	8	21	4	183	253	248
253	254	54	35	118	119	64	31	239	255
253	205	2	73	103	103	83	0	175	252
255	165	0	0	58	67	0	0	132	253
253	150	2	23	74	83	65	27	119	255
253	150	50	236	77	42	255	109	106	255
255	229	33	120	53	37	127	35	202	254
251	255	138	2	68	83	0	106	255	252
249	253	252	148	33	29	122	254	253	249

Convolutional Neural Networks (CNN)

- Image is depicted as a matrix of pixel intensity values ranging from 0 to 255.
- Grayscale consists of a single channel with 0 representing the black areas and 255 the white regions with the values in between for various shades of Gray.



2-D representation of an image



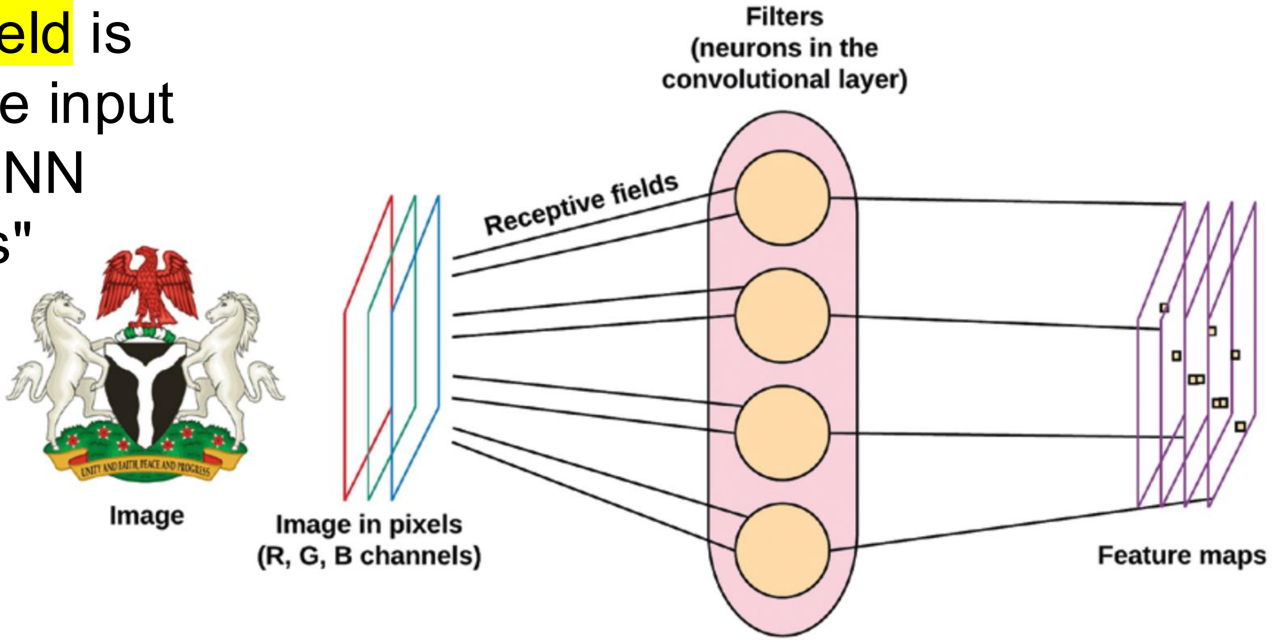
251	251	255	233	182	179	224	254	251	250
250	255	229	120	66	56	96	215	255	249
253	254	144	47	29	31	32	122	248	255
255	229	113	65	56	62	68	106	204	255
255	203	102	106	82	78	118	108	178	255
254	199	109	154	95	78	158	120	179	255
255	196	156	207	98	77	173	181	179	255
254	241	163	67	76	90	25	135	230	255
251	254	190	72	72	72	59	164	255	252
249	253	251	193	127	115	179	250	254	249

10 x 10 grayscale image with its matrix representation.

CNN Components

- Convolution layer is made up of filters and feature maps.
  - Filter [or Kernel] is passed over input image pixels to capture a specific set of features in a process called convolution.
    - Convolution is the process by which a function is applied to a matrix to extract specific information from the matrix.
  - Feature maps are outputs of a filter in a convolutional layer.

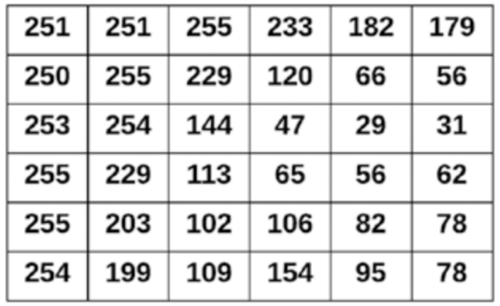
Receptive Field is an area of the input image that CNN neuron "sees"



Design Convolutional layer

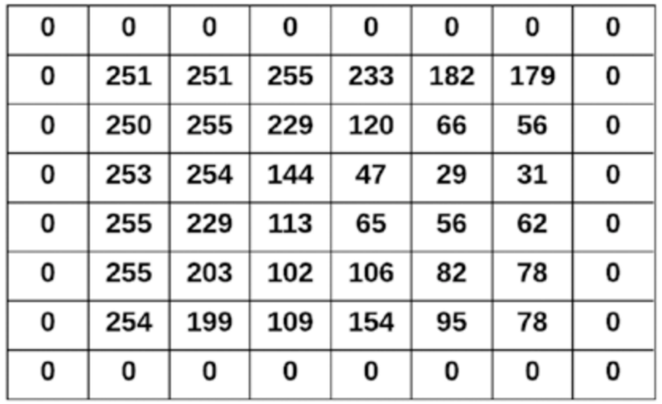
- Considerations to design convolutional layer:
    - Filter size: Neuron’s weights can be represented as a small image size of receptive field.
        - Filters are small matrix used to detect patterns in an image.
        - Different filters detect edges, textures, and shapes.
        - A n×n filter slides over image and performs dot product (convolution).
    - Stride of filter: [Step Size] determines how many pixel steps filter makes when moving from one image activation to another (default 1).
    - Padding for input layer: Zero padding is used to pad borders of image pixels with a defined layer of zeros.
    - Larger stride --> smaller feature map (less details, faster)

without zero padding



251	251	255	233	182	179
250	255	229	120	66	56
253	254	144	47	29	31
255	229	113	65	56	62
255	203	102	106	82	78
254	199	109	154	95	78

with zero padding

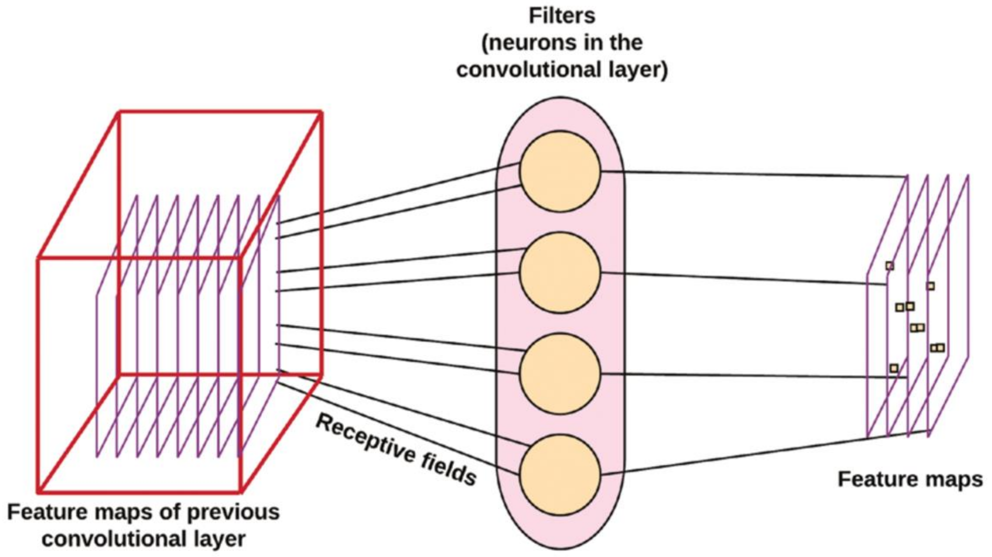


0	0	0	0	0	0	0	0
0	251	251	255	233	182	179	0
0	250	255	229	120	66	56	0
0	253	254	144	47	29	31	0
0	255	229	113	65	56	62	0
0	255	203	102	106	82	78	0
0	254	199	109	154	95	78	0
0	0	0	0	0	0	0	0

CNN Components

- Feature Maps are output matrix of a filter in a convolutional layer.
  - Expose patterns of input image (such as horizontal lines, vertical lines).
  - Multiple filters = Multiple feature maps.
  - Deeper CNN: Inputs to a deeper convolutional layer are feature maps of previous layer.

- Pooling layer summarizes image features learned in previous network layers.
  - Pooling Layer: follow one or more convolutional layers.
  - Common type of pooling layer is Max pooling layer.
  - Goal: to reduce feature map of convolutional layer.


Filters
(neurons in the convolutional layer)
Receptive fields
Feature maps
Feature maps of previous convolutional layer

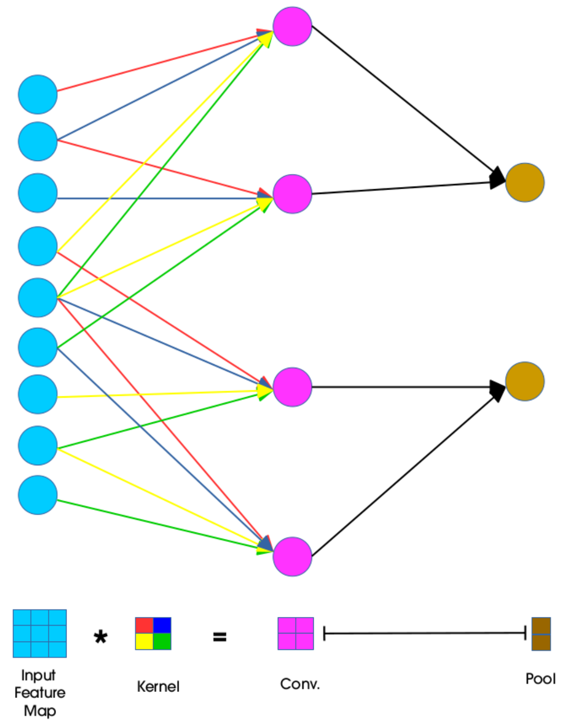
If we have a 32×32 RGB image and apply 32 filters, we get 32 feature maps.
Reason: Each filter processes the image to extract different features, resulting in a separate feature map for each filter.

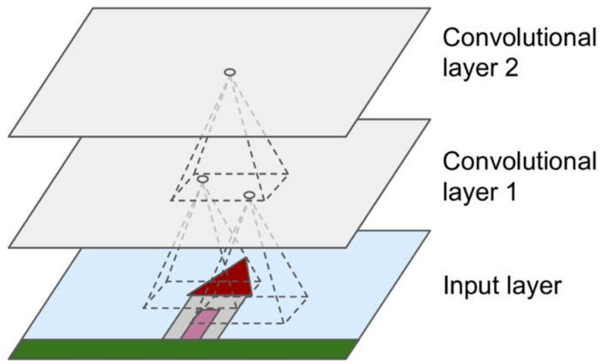
Choosing "Correct" Kernel Size

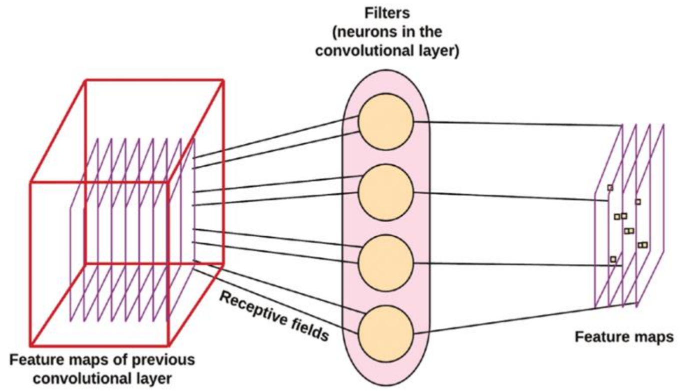
- Kernel size determines the receptive field of each convolutional operation.
- kernel size should be chosen based on the data characteristics.
- Detection of fine-grained details --> smaller kernel sizes [capture local information].
- Detection of larger patterns --> larger kernel sizes [capture global information].
- Smaller input sizes works well with smaller kernel sizes.
- Larger input sizes can accommodate larger kernel sizes [resource intensive].
- Stacking multiple layers with small kernel sizes can help preserve information.
- Very large kernel sizes may result in over smoothing or loss of fine-grained details.

Convolutional Layer

- Neurons in first convolutional layer are connected only to pixels in their receptive fields (BUT not to all pixels).
- Each neuron in second convolutional layer is connected only to neurons located within a small rectangle in first layer.
- It allows network to concentrate on small low-level features in first hidden layer, then assemble them into larger higher-level features in next hidden layer, and so on.

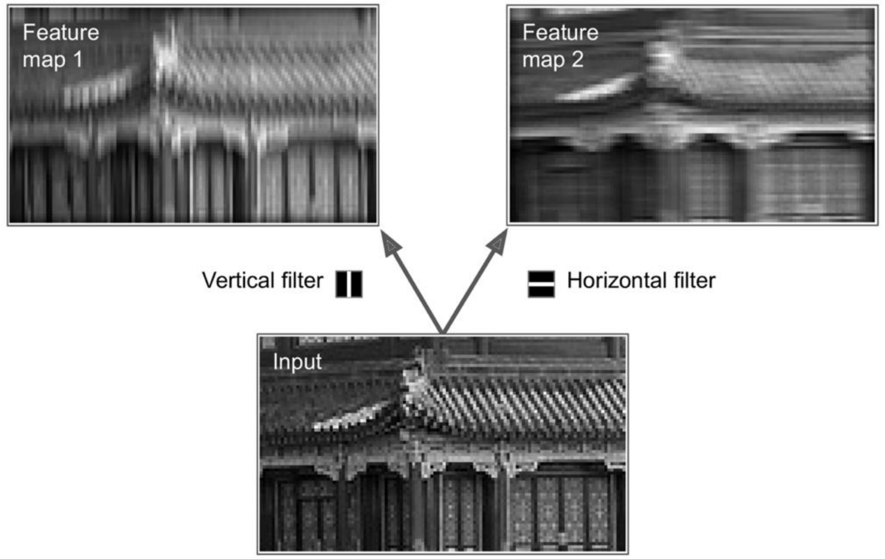





Filters (neurons in the convolutional layer)
Receptive fields
Feature maps
Feature maps of previous convolutional layer

Convolutional Layer

- Neuron's weights can be represented as a small image size of receptive field.
- Feature map highlights areas in an image that activate filter (or convolution kernels) most.
- All neurons in a feature map share same parameters which dramatically reduces number of parameters in model.
- Once CNN has learned to recognize a pattern in one location, it can recognize it in any other location.
  - DNN can recognize only at particular location.



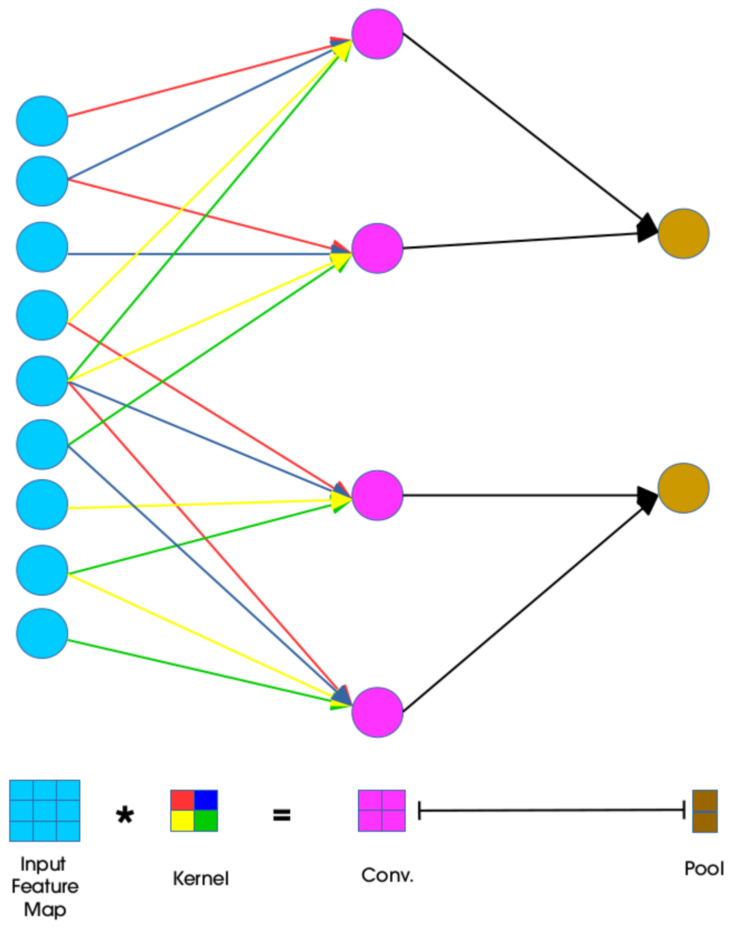
CNN Components

- Fully Connected Network (FCN) layer is feedforward neural network or multilayer perceptron (MLP).
    - These layers typically have a non-linear activation function (softmax).
    - FCN is the final layer of CNN.

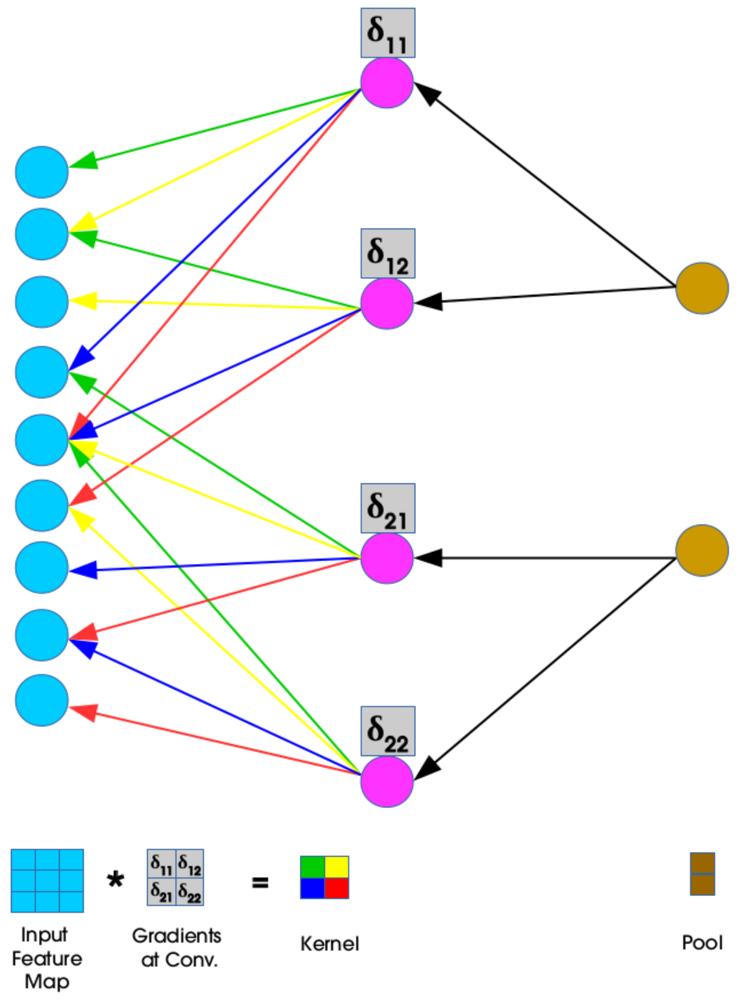
- CNN Modeling:
    - First layer following input layer of images must be a convolutional layer for extracting image features.
    - Pooling layers typical follow a set of one or more convolutional layers.

Convolution Layer Training Process

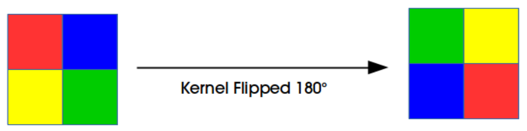
Forward Propagation



Backpropagation



No learning takes place on the pooling layers!!

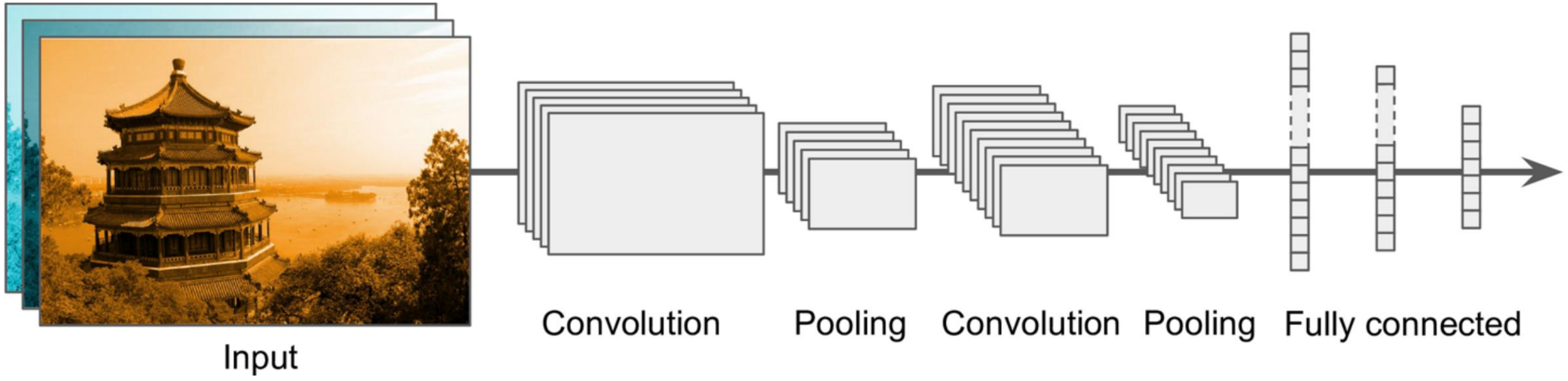


Gradients ==> $\delta_{11},\delta_{12},\delta_{21},\delta_{22}$

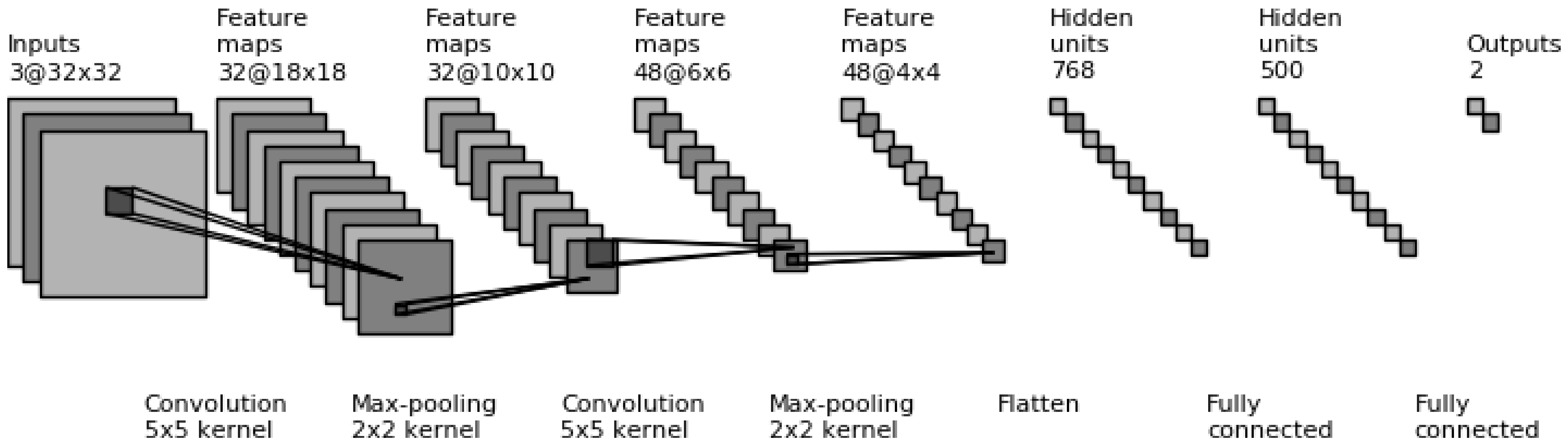
https://www.jefkine.com/general/2016/09/05/backpropagation-in-convolutional-neural-networks/

CNN Components

- CNN Modeling:
  - Fully connected layer must be final layer of CNN (called dense layer).
    - Contains ReLU, softmax activation function to give probabilities of class membership.
  - CNN may include one or more Dropout layers to prevent network overfitting.



CNN Example


Inputs
3@32x32
Feature maps
32@18x18
Feature maps
32@10x10
Feature maps
48@6x6
Feature maps
48@4x4
Hidden units
768
Hidden units
500
Outputs
2
Convolution
5x5 kernel
Max-pooling
2x2 kernel
Convolution
5x5 kernel
Max-pooling
2x2 kernel
Flatten
Fully connected
Fully connected

Code Snippet

```
# Convolutional base using a common pattern: a stack  of Conv2D and MaxPooling2D layers.
# CNN takes tensors of shape (image_height, image_width, color_channels), color_channels  refers to
(R,G,B) to support the format of CIFAR images.

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
```

Layer Type	Filters	Kernel Size	Activation	
Conv2D	32	(3,3)	ReLU	This sample network processes 32x32 RGB images, extracting features through convolution and reducing spatial dimensions through pooling.
MaxPooling2D	-	(2,2)	-	
Conv2D	64	(3,3)	ReLU	
MaxPooling2D	-	(2,2)	-	
Conv2D	64	(3,3)	ReLU	

Output is flattened and passed through dense layers for classification.

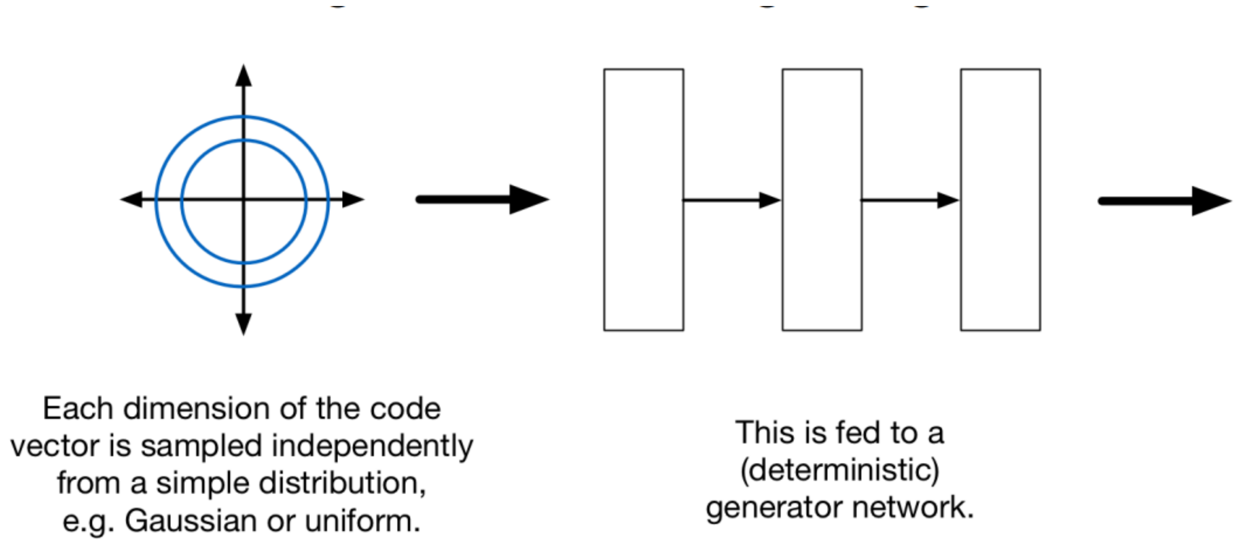
Recap: CNN

- CNN consists of Convolutional layer, Pooling layer, and Fully connected layer.
    - Convolutional layer is made up of filters (convolution kernels) and feature maps.
- Key considerations for designing a convolutional layer include:
    - Filter size: A neuron’s weights can be represented as a small image size, which is its receptive field.
    - Stride of filter: determines how many pixel steps the filter takes when moving across the image (a stride of 1 is typical).
    - Pooling layers typically follow one or more convolutional layers.
        - Goal is to reduce the feature map size from the convolutional layer.
- All neurons within a feature map share the same parameters.
- Training Process:
    - Forward Propagation: No learning occurs in the pooling layers.
    - Backpropagation: Network's weights are adjusted based on the error in its predictions. convolutional layers require a huge amount of RAM.

Adversarial Examples

Generative Models

- Generative models learn a mapping from random noise vectors to things that look like, e.g., images.


Each dimension of the code vector is sampled independently from a simple distribution, e.g. Gaussian or uniform.
This is fed to a (deterministic) generator network.

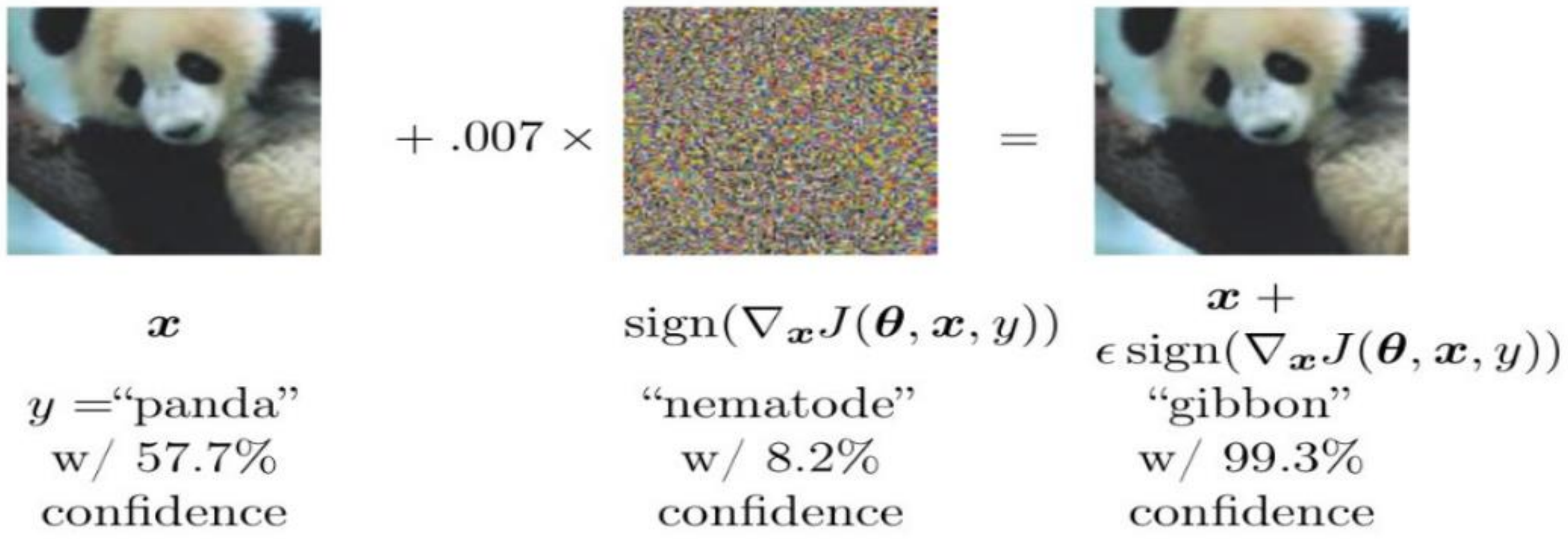
- Need to have some criterion for evaluating image quality, then compute gradient wrt to parameters,
- Update parameters for better image.

Putting into the context

Panda

Gibbon

Misclassification



$+ .007 \times$
$=$
$\boldsymbol{x}$
$y =$"panda"
w/ 57.7%
confidence
$\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"nematode"
w/ 8.2%
confidence
$\boldsymbol{x} + \epsilon\, \text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"gibbon"
w/ 99.3%
confidence

Adversarial Examples

- ML models consistently misclassify adversarial examples from dataset
    - such that perturbed input results in model outputting an incorrect answer with high confidence.
    - ML models misclassify examples that are only slightly different from correctly classified examples drawn from data distribution.
    - Adversarial examples are inputs formed by applying small but intentionally worst-case perturbations.

Adversarial Examples

- ML models such as DNN, clustering, Naive Bayes, Decision tree, Multilayer Perceptron, SVM are not attacked resilient.

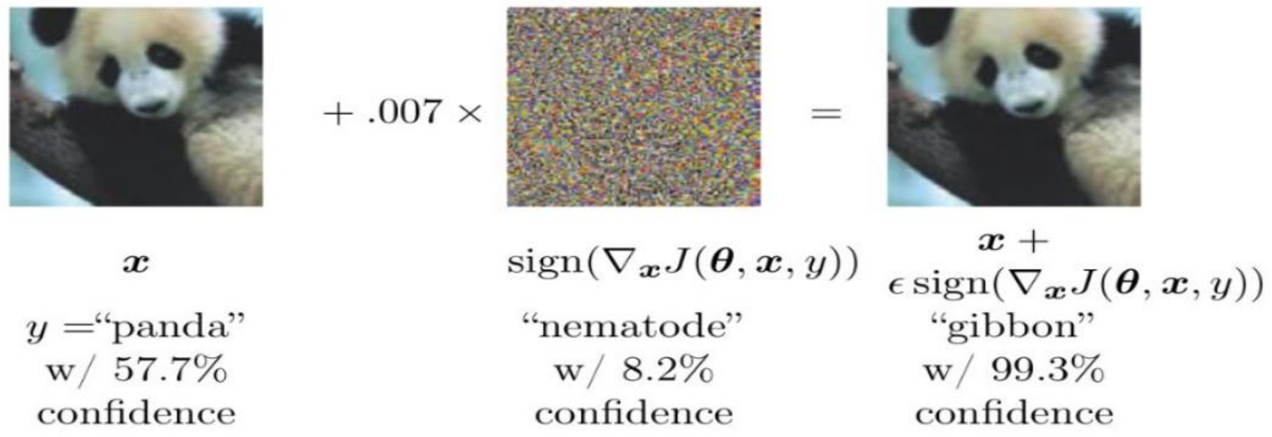
- Injection of adversarial/malicious data into training datasets that can caused decreased performance/ model failure is known as poisoning.

  - Malicious users add malicious data with similar features of original data and wrong labels.

  - Malicious users might know the training data distribution; also learning algorithm.

Adversarial Examples

- A model is performing a task (e.g. classification) with some level of success.
- An adversary is attacking that model.
- Objective: to perform the task (maintaining a similar accuracy) under attack.


$+ .007 \times$
$=$
$\boldsymbol{x}$
$y =$"panda"
w/ 57.7%
confidence
$\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"nematode"
w/ 8.2%
confidence
$\boldsymbol{x} + \epsilon \, \text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"gibbon"
w/ 99.3%
confidence

- Forms of adversarial image attacks:
  - Untargeted adversarial attacks: *cannot* control output label of adversarial image.
  - Targeted adversarial attacks: *can* control output label of image.

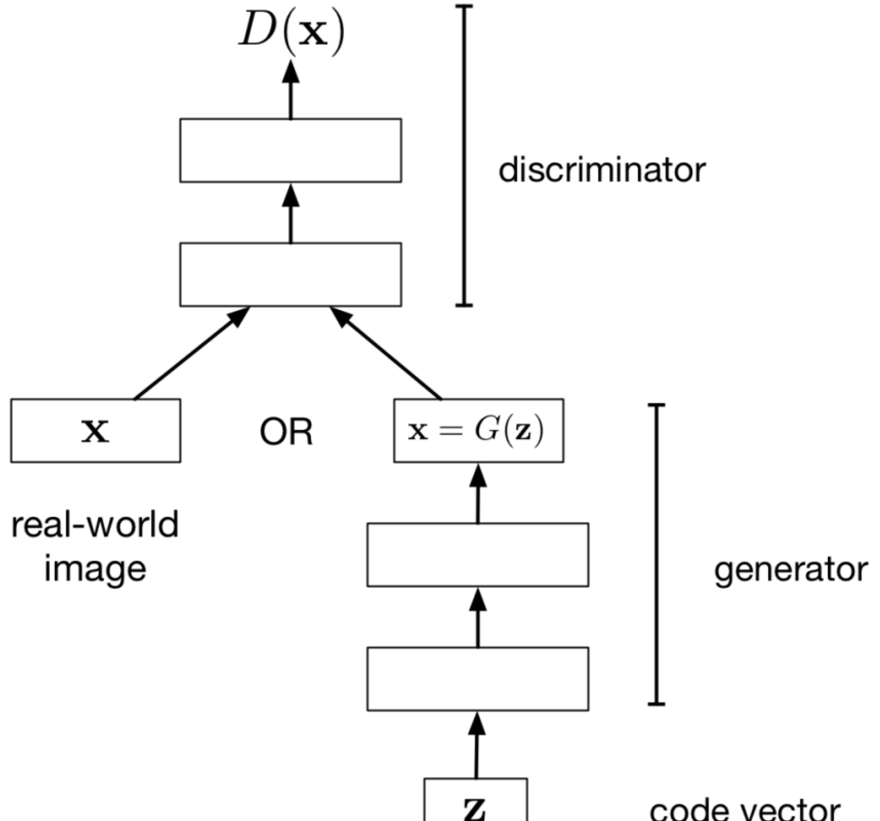
Adversarial Examples

- Two types of attacks in DL: White-Box and Black-Box attacks
  - White-Box: Attacker has access to training method (data/network initialization/ algorithm/hyperparameter).
    - Small perturbations --> bad performance.
  - Black-Box attacks: Attacker does not have complete access to network training method.

- We need robust models: weight decay and dropout do not work.
- Approach: Brute force method to generate adversarial examples and train model using them (Adversarial training).

Generative Adversarial Networks

- Generative Adversarial Networks (GANs): train two different networks
  - Generator network tries to produce realistic-looking samples
  - Discriminator network tries to figure out whether an image came from training set or generator network
  - Generator network tries to fool the discriminator network.



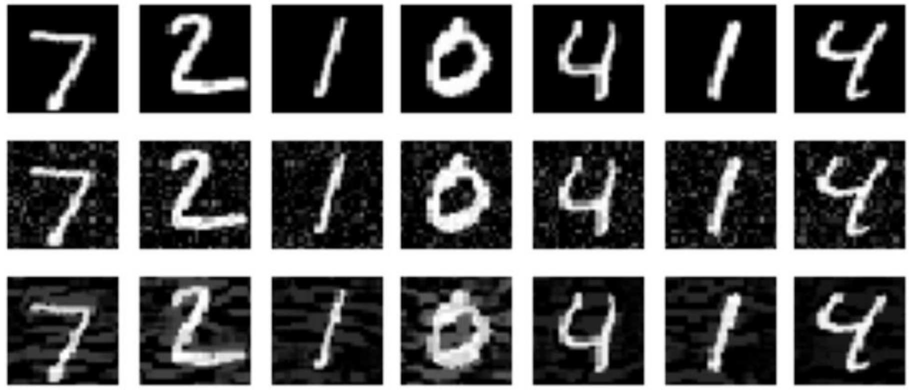
Adversarial Examples

- Fast Gradient Sign Method (FGSM) effective method to generate adversarial images.

1. Take input image --> Make prediction (using CNN).
2. Compute loss of prediction based on *true* class label.
3. Calculate gradients of loss with respect to input image.
4. Compute gradient sign --> Use to construct adversarial image (output).

Adversarial Training

- Models learns to classify correctly adversarial examples.
- Classifiers uses a loss function to minimize model prediction errors.
- After training, attacker uses loss function to maximize model prediction error
  - 1. Compute its gradient with respect to model input
  - 2. Take the sign of gradient and multiply it by a threshold



- Normal (top)
- Noisy (middle)
- Adversarial (bottom)

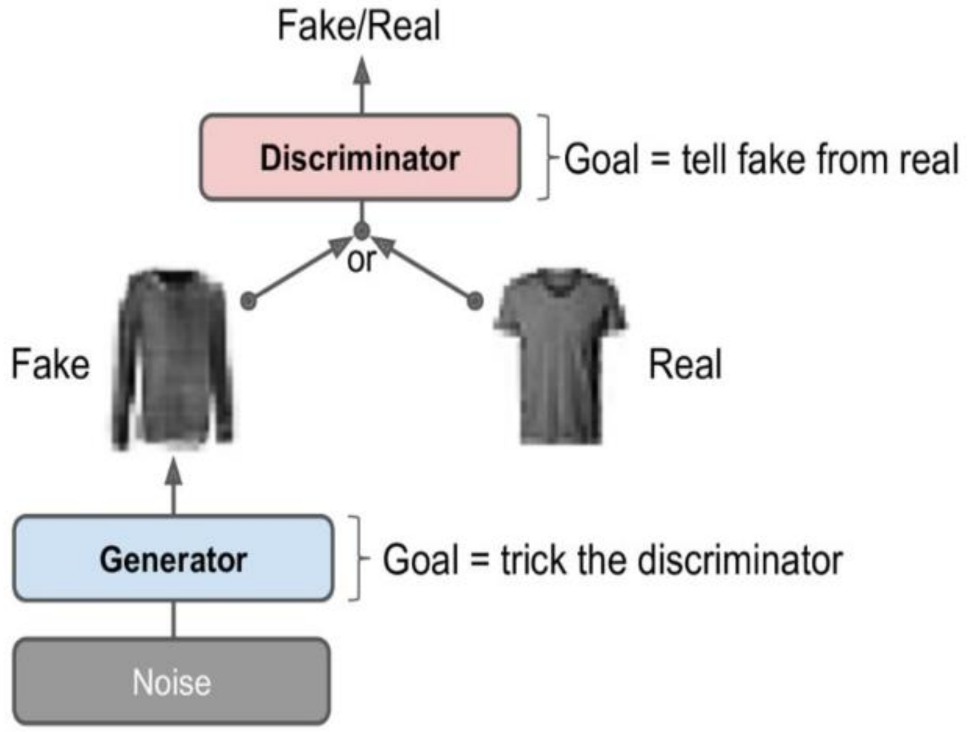
Adversarial training

- Adversarial training is process of training a model to correctly classify both unmodified examples and adversarial examples.
  - Adv: robust adversarial examples, generalize performance for original examples.
- Virtual adversarial training [VAT]* extends idea of adversarial training to semi-supervised regime and unlabelled examples.
  - VAT uses an efficient approximation to maximize the likelihood of the model while promoting the model's local distributional smoothness on each training input data point.
- Traditional adversarial and virtual adversarial training can be interpreted as regularization strategy and as defence against malicious inputs.

*Takeru Miyato, Shin-ichi Maeda, Masanori Koyama, Ken Nakae, and Shin Ishii. Distributional smoothing with virtual adversarial training. In ICLR, 2016.

Generative Adversarial Networks (GANs)

- Idea: Let NNs to compete against each other to perform better.
- GAN composed of two neural networks with different objectives
  - Generator: Takes a random distribution as input (typically Gaussian) and outputs some data typically, an image.
  - Discriminator: Takes either a fake image from generator or a real image from training set as input and guess whether input image is fake or real.



Generative Adversarial Networks

- Each training iteration is divided into two phases:
  - Discriminator training: Batch of real images (label 1) is sampled from training set and is completed with an equal number of fake images (label 0) produced by the generator. [Uses binary cross-entropy as loss function].
  - Generator training: Produce another batch of fake images, and once again discriminator is used to tell whether images are fake or real. Do not add real images in the batch, and all labels are set to 1 (real).
    - Never actually sees any real images.

SELU (Scaled Exponential Linear Unit) [2017] aims to automatically normalize the output of neurons during training. [variation of **ReLU**]

```
codings_size = 30
generator = keras.models.Sequential([
keras.layers.Dense(100, activation="selu",
input_shape=[codings_size]),
keras.layers.Dense(150, activation="selu"),
keras.layers.Dense(28 * 28, activation="sigmoid"),
keras.layers.Reshape([28, 28])
])
```

```
discriminator = keras.models.Sequential([
keras.layers.Flatten(input_shape=[28, 28]),
keras.layers.Dense(150, activation="selu"),
keras.layers.Dense(100, activation="selu"),
keras.layers.Dense(1, activation="sigmoid")
])

gan = keras.models.Sequential([generator, discriminator])
```

Difficulties of Training GANs

1. Generator and discriminator constantly try to outsmart each other lead to no player would be better off changing their own strategy, assuming other players do not change theirs.

2. Generator produces perfectly realistic images and discriminator is forced to guess (50% real, 50% fake) (Not guaranteed).

3. Generator’s outputs gradually become less diverse (called mode collapse).

4. Generator and discriminator are constantly pushing against each other, parameters may end up oscillating and becoming unstable.

Deep Convolutional GANs: DCGANs

- DCGANs (2015): Based on deeper convolutional nets for larger images.

- Guidelines to building DCGANs:
  - Replace any pooling layers with strided convolutions (discriminator) and transposed convolutions (generator).
  - Use Batch Normalization in both generator and discriminator, except in generator’s output layer and discriminator’s input layer.
  - Remove fully connected hidden layers for deeper architectures.
  - Use ReLU activation in generator for all layers except output layer, which should use tanh.
  - Use leaky ReLU activation in discriminator for all layers.

Recap: GANs

- GANs are a framework for training generative models.
- These models learn to map random noise vectors to outputs that resemble a particular data distribution, such as images.

- Core idea: To have two neural networks compete against each other:
  - Generator Network: This network takes a random distribution (typically Gaussian) as input and tries to produce realistic-looking samples, such as images.
  - Discriminator Network: This network takes either a fake image from the generator or a real image from the training set as input.

- Each training iteration in a GAN is divided into two phases:
  - Discriminator Training: A batch of real images (labelled as 1) is sampled from the training set and combined with an equal number of fake images (labelled as 0) produced by the generator.
  - Generator Training: The generator produces another batch of fake images. The discriminator is then used to evaluate these fake images, but this time all the labels are set to 1 (real).

- The constant competition between the generator and discriminator can lead to a situation where neither network improves significantly, and the process does not converge to a stable equilibrium.