COMP9517: Computer Vision

Deep Learning Part 1

Dong Gong

https://donggong1.github.io/
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Some slides from Fei-Fei Li et al. and Francois Fleuret

Challenges in CV

Consider object detection as an example:

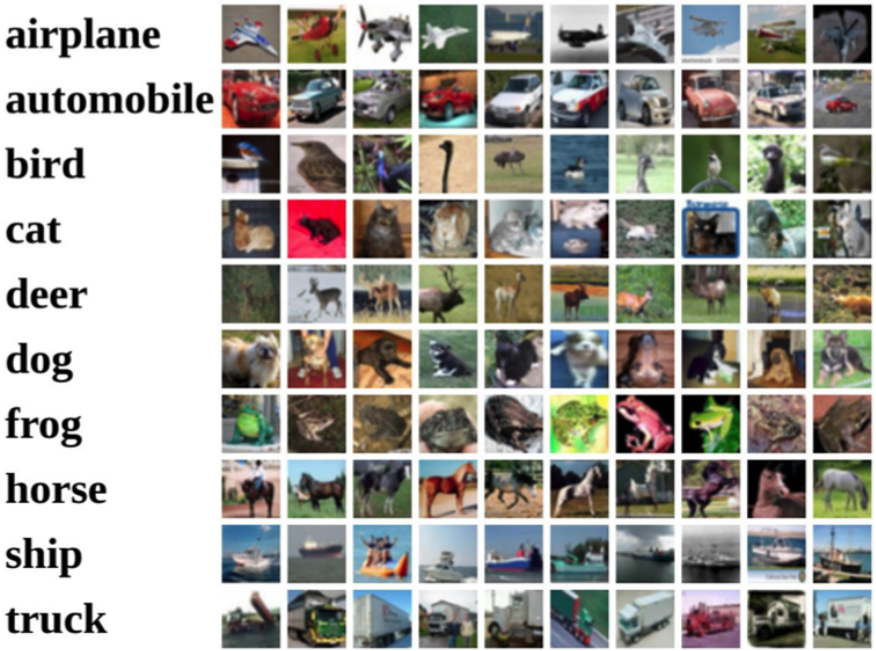
- Variations in viewpoint
- Differences in illumination
- Hidden parts of images
- Background clutter

Content: link

Linear Classifier for Image Classification

Image Classification

Dataset: CIFAR10 [Alex Krizhevsky, “Learning Multiple Layers of Features from Tiny Images”, Technical Report, 2009.]



10 classes
50,000 training images
10,000 testing images

Image Classification

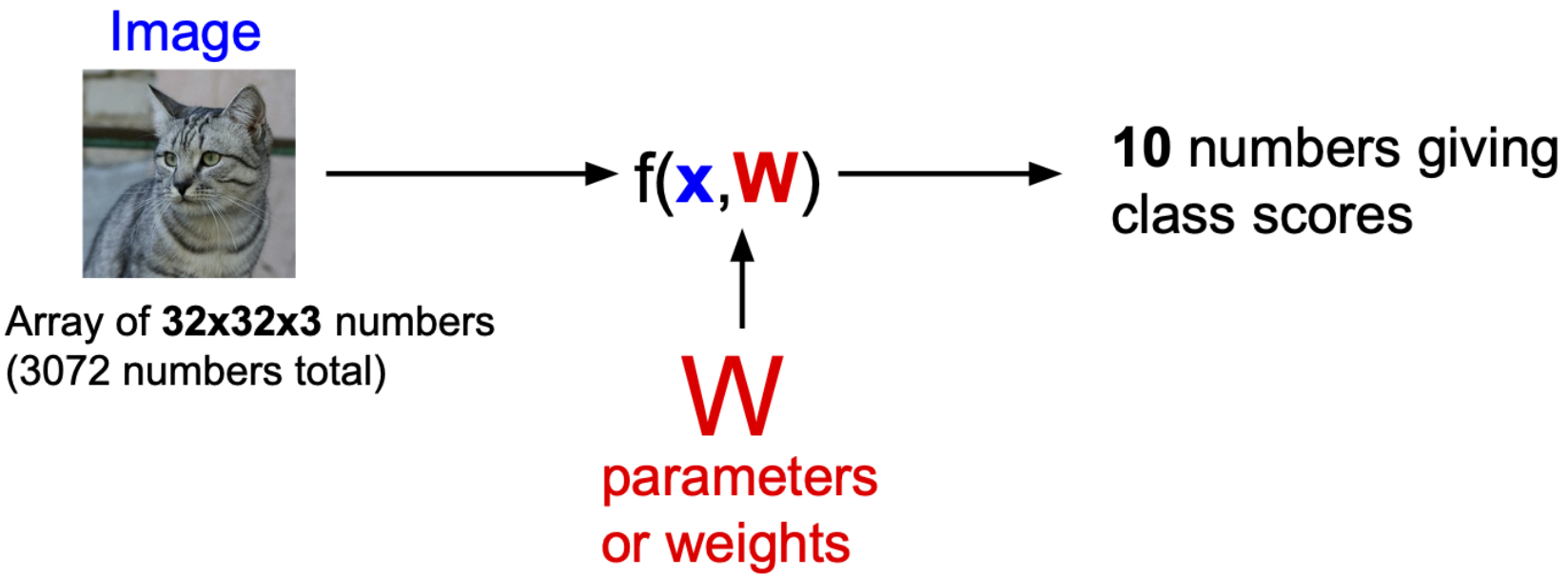


Image Classification

- Image classification with linear classifier

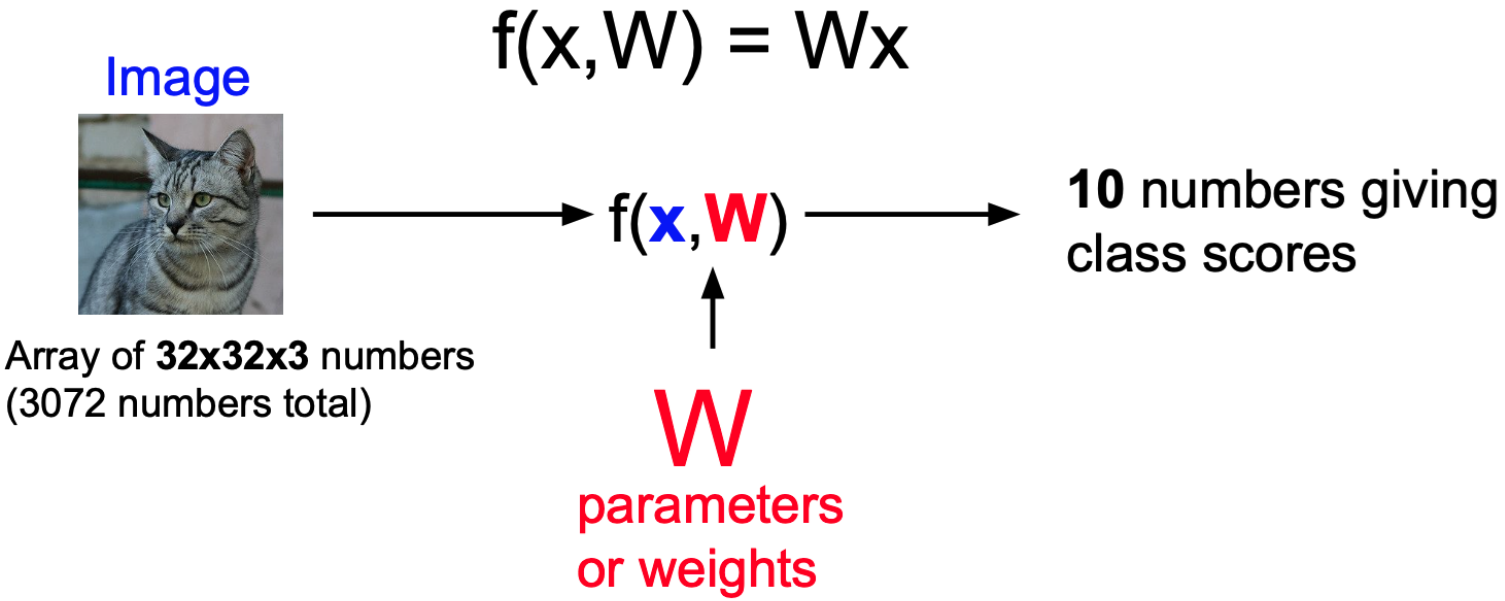


Image Classification

- Image classification with linear classifier

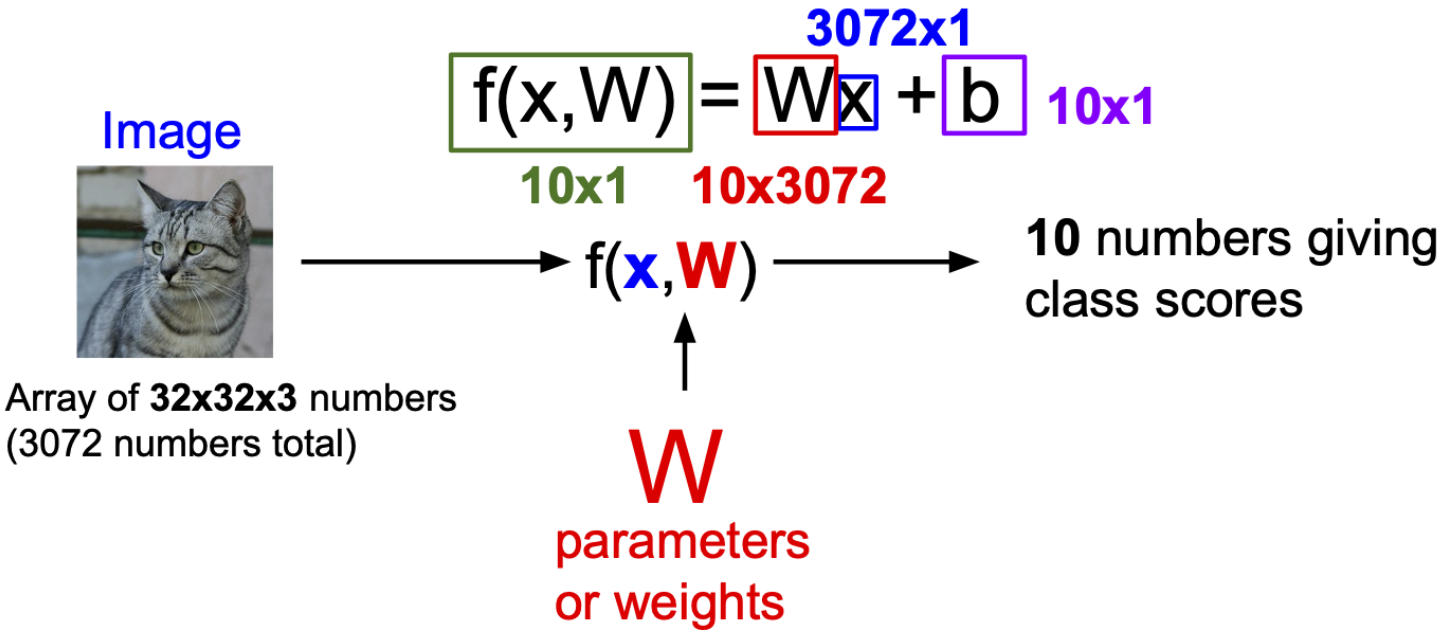


Image Classification

- An image example with 4 pixels and 3 classes.

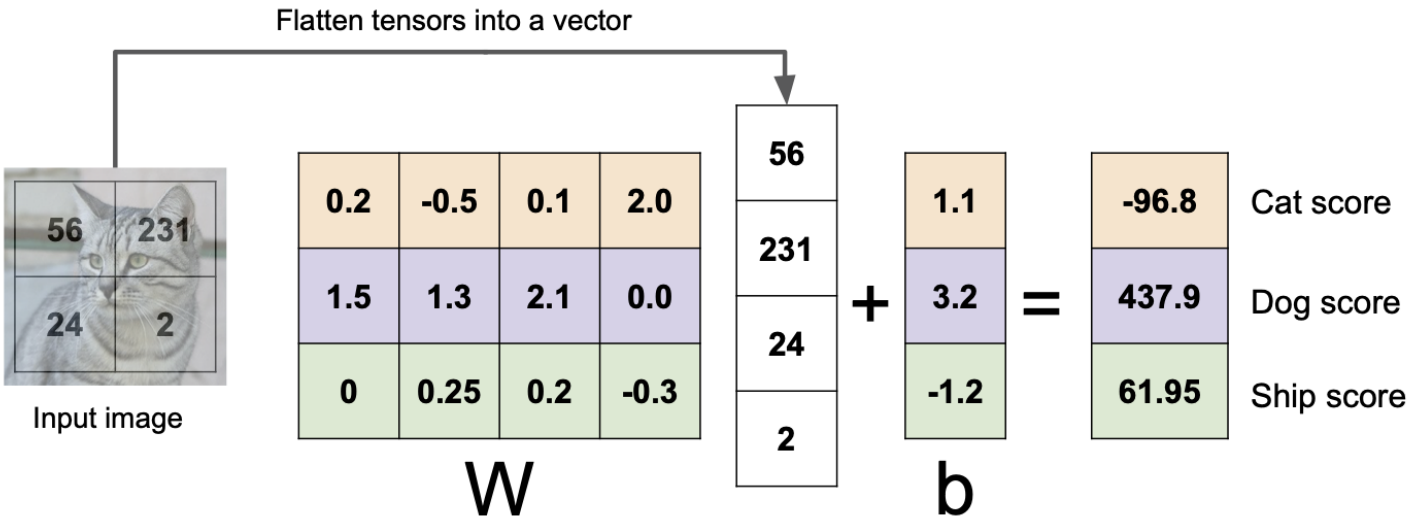
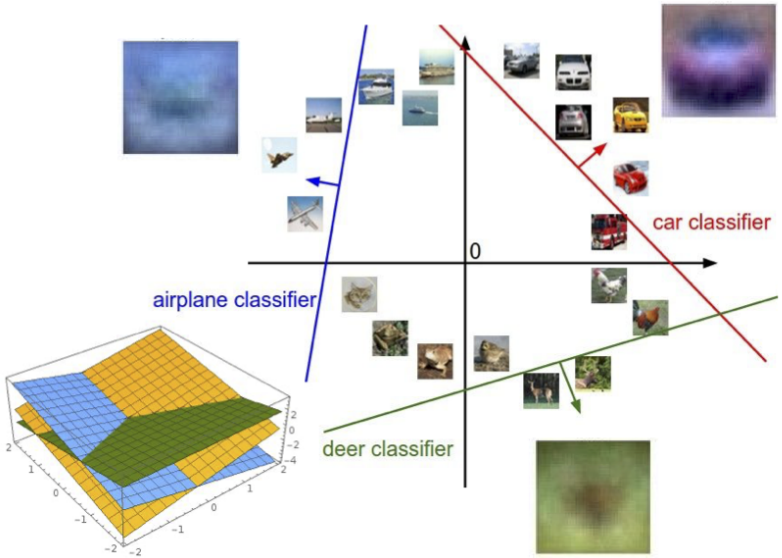


Image Classification

- Interpreting a linear classifier.



$$f(x,W) = Wx + b$$

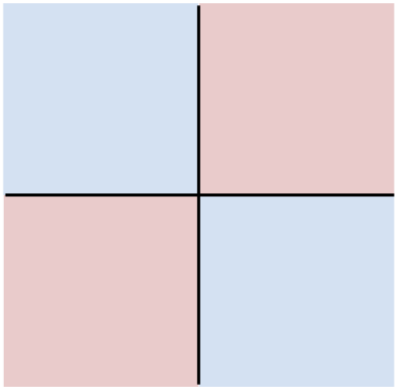
Array of **32x32x3** numbers
(3072 numbers total)

Image Classification

- Hard cases for a linear classifier.

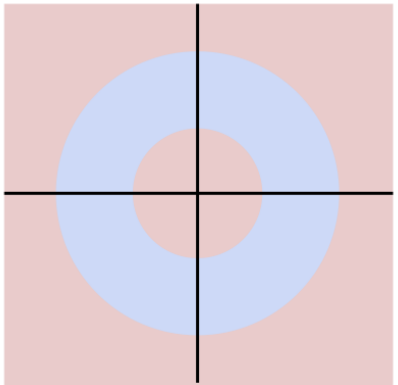
Class 1:
First and third quadrants

Class 2:
Second and fourth quadrants



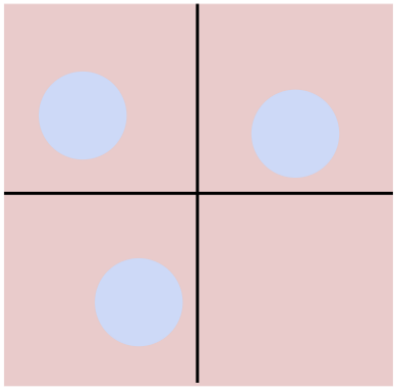
Class 1:
1 <= L2 norm <= 2

Class 2:
Everything else



Class 1:
Three modes

Class 2:
Everything else



From Linear Classifiers to (Non-linear) Neural Networks

Neural Networks

- Starting from the original linear classifier

(**Before**) Linear score function: $f = Wx$

$$x \in \mathbb{R}^D, W \in \mathbb{R}^{C \times D}$$

Neural Networks

- 2 layers

(**Before**) Linear score function: $f = Wx$

(**Now**) 2-layer Neural Network $f = W_2 \max(0, W_1 x)$

$$x \in \mathbb{R}^D, W_1 \in \mathbb{R}^{H \times D}, W_2 \in \mathbb{R}^{C \times H}$$

(In practice we will usually add a learnable bias at each layer as well)

Neural Networks

- 2 layers
- Also called as fully connected network
- Fully connected layer

(**Before**) Linear score function: $f = Wx$

(**Now**) 2-layer Neural Network $f = W_2 \max(0, W_1 x)$

$$x \in \mathbb{R}^D, W_1 \in \mathbb{R}^{H \times D}, W_2 \in \mathbb{R}^{C \times H}$$

“Neural Network” is a very broad term; these are more accurately called “fully-connected networks” or sometimes “multi-layer perceptrons” (MLP)

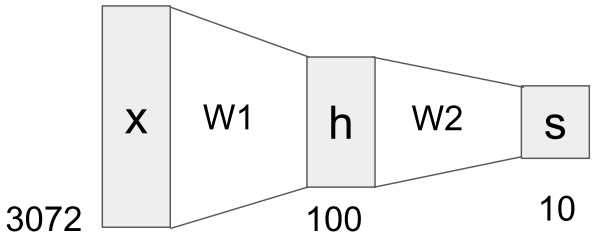
(In practice we will usually add a learnable bias at each layer as well)

Neural Networks

- 2 layers
- Also called as fully connected network
- Fully connected layer

(**Before**) Linear score function: $f = Wx$

(**Now**) 2-layer Neural Network $f = W_2 \max(0, W_1 x)$



$x \in \mathbb{R}^D, W_1 \in \mathbb{R}^{H \times D}, W_2 \in \mathbb{R}^{C \times H}$

Neural Networks

- 3 layers

(**Before**) Linear score function: $f = Wx$

(**Now**) 2-layer Neural Network $f = W_2 \max(0, W_1 x)$

or 3-layer Neural Network

$$f = W_3 \max(0, W_2 \max(0, W_1 x))$$

$$x \in \mathbb{R}^D, W_1 \in \mathbb{R}^{H_1 \times D}, W_2 \in \mathbb{R}^{H_2 \times H_1}, W_3 \in \mathbb{R}^{C \times H_2}$$

(In practice we will usually add a learnable bias at each layer as well)

Neural Networks

- Activation function
- The function $\max(0, z)$ is called the activation function.

(**Before**) Linear score function: $f = Wx$

(**Now**) 2-layer Neural Network $f = W_2 \max(0, W_1 x)$

- What if without the activation function?

Neural Networks

- Activation function
- The function $\max(0, z)$ is called the activation function.

(**Before**) Linear score function: $f = Wx$

(**Now**) 2-layer Neural Network $f = W_2 \max(0, W_1 x)$

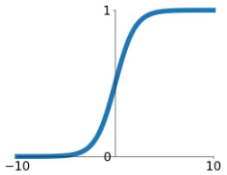
- What if without the activation function?
  - The model will be linear.

Neural Networks

- Activation functions
  - Non-linear functions

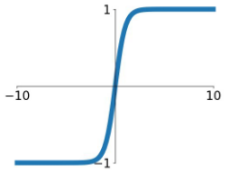
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



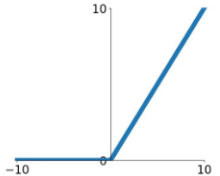
tanh

$$\tanh(x)$$



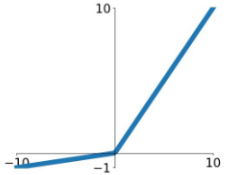
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

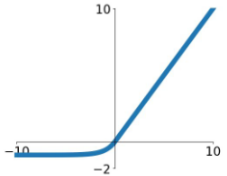


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

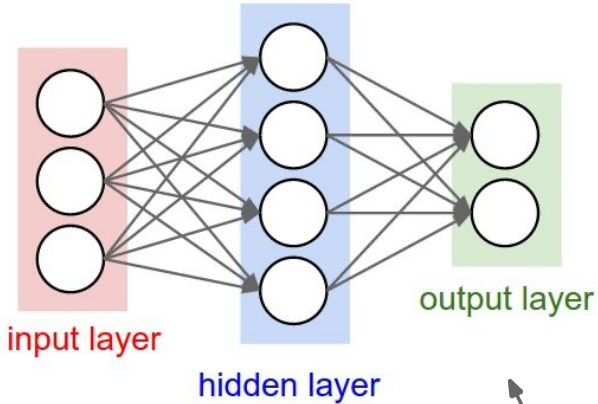
ELU

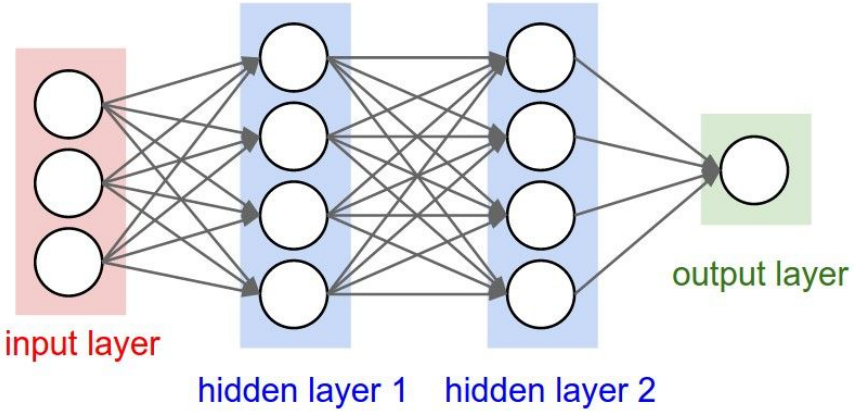
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Neural Networks

- Architectures (for MLP)





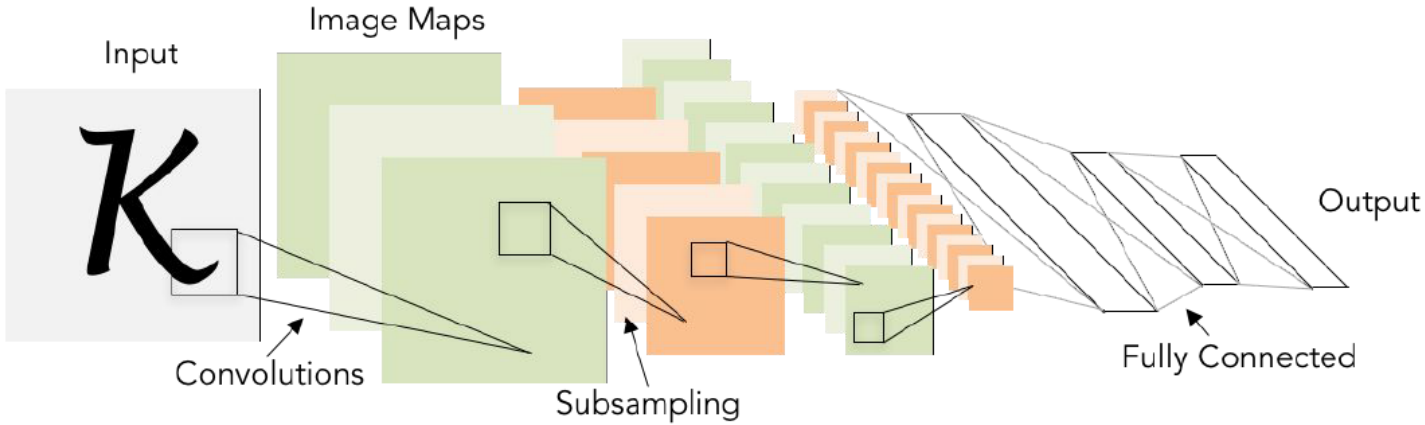
“2-layer Neural Net”, or
“1-hidden-layer Neural Net”

“3-layer Neural Net”, or
“2-hidden-layer Neural Net”

“Fully-connected” layers

Neural Networks

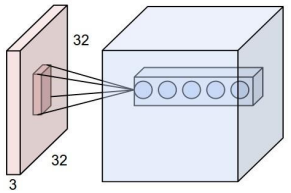
- Architectures (for CNNs)



From Neural Networks to “Deep Learning”

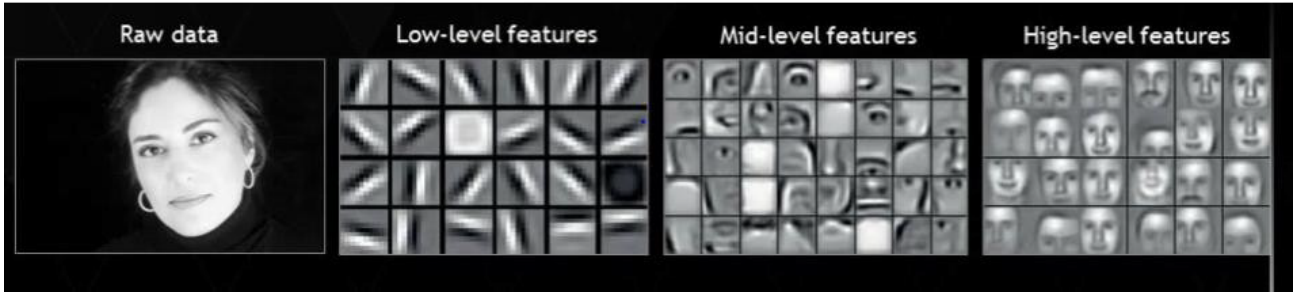
Deep Learning

- Deep learning is a collection of artificial neural network techniques that are widely used at present
- Predominantly, deep learning techniques rely on large amounts of data and deeper learning architectures
- Some well known paradigms for different types of data and applications:
  - **Convolutional Neural Networks (CNNs)**
  - Recurrent Neural Networks
  - Auto-encoders
  - Restricted Boltzmann Machines



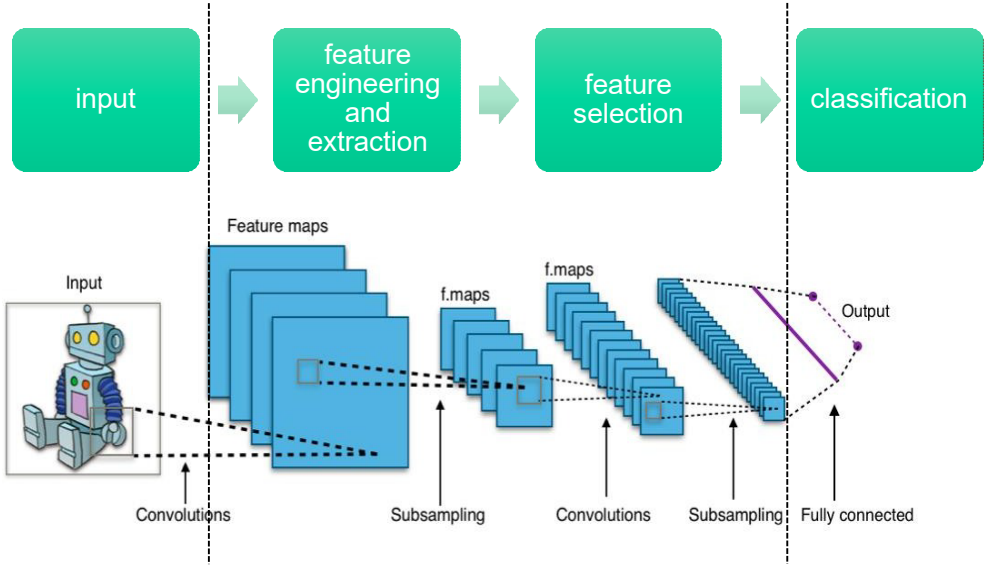
Traditional Approach vs DL

- Convolutional neural networks (CNNs) are a type of DNNs for processing images.
- CNNs can be interpreted as gradually transforming the images into a representation in which the classes are separable by a linear classifier.
- CNNs will try to learn low-level features such as edges and lines in early layers, then parts of objects and then high-level representation of an object in subsequent layers.



http://www.analyticsvidhya.com/blog/2017/04/comparison-between-deep-learning-machine-learning/

Traditional Approach vs DL



https://towardsdatascience.com/convolutional-neural-networks-for-all-part-i-cdd282ee7947

From Neural Networks to “Deep Learning”

Core ideas go back many decades

The **Mark I Perceptron** machine was the first implementation of the perceptron algorithm.

The machine was connected to a camera that used 20×20 cadmium sulfide photocells to produce a 400-pixel image.

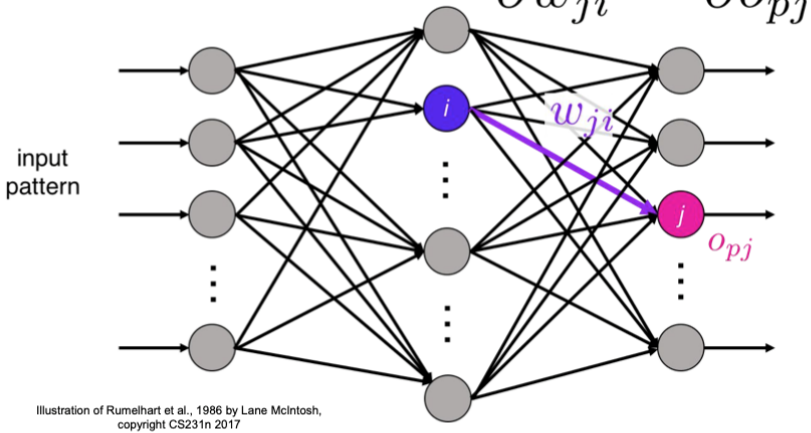
recognized
letters of the alphabet

Frank Rosenblatt, ~1957: Perceptron

From Neural Networks to “Deep Learning”

$$\frac{\partial E_p}{\partial w_{ji}} = \frac{\partial E_p}{\partial o_{pj}} \frac{\partial o_{pj}}{\partial w_{ji}}$$

recognizable math



Rumelhart et al., 1986: First time back-propagation became popular

From Neural Networks to “Deep Learning”

First strong results

Acoustic Modeling using Deep Belief Networks
Abdel-rahman Mohamed, George Dahl, Geoffrey Hinton, 2010
Context-Dependent Pre-trained Deep Neural Networks for Large Vocabulary Speech Recognition
George Dahl, Dong Yu, Li Deng, Alex Acero, 2012

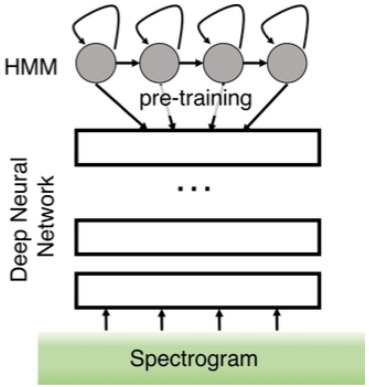
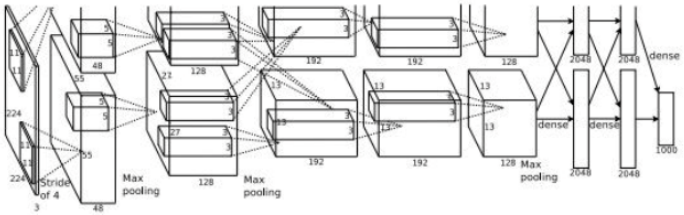


Illustration of Dahl et al. 2012 by Lane McIntosh, copyright CS231n 2017

Imagenet classification with deep convolutional neural networks
Alex Krizhevsky, Ilya Sutskever, Geoffrey E Hinton, 2012



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From Neural Networks to “Deep Learning”

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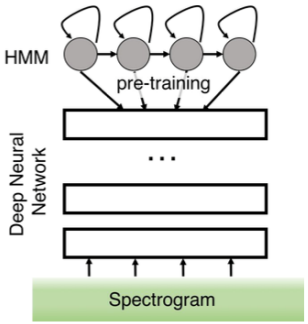
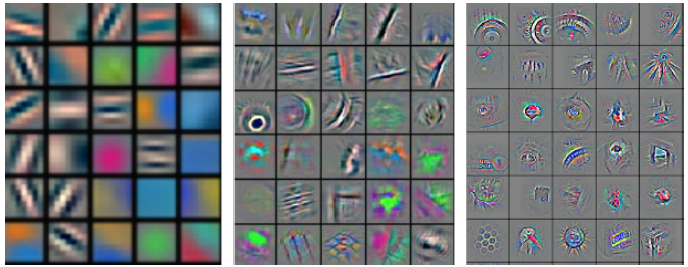
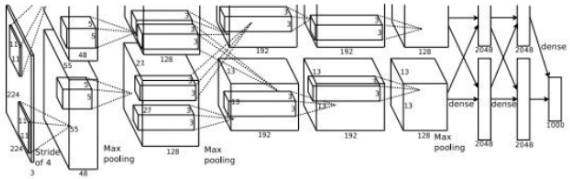


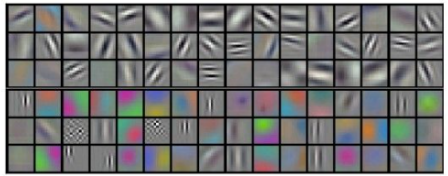
Illustration of Dahl et al. 2012 by Lane McIntosh, copyright CS231n 2017

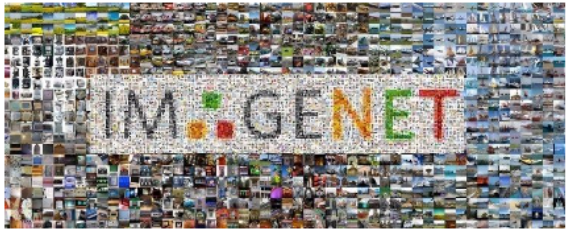


Visual features extracted in different layers in CNN

Imagenet classification with deep convolutional neural networks
Alex Krizhevsky, Ilya Sutskever, Geoffrey E Hinton, 2012







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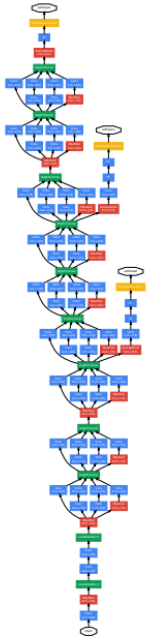
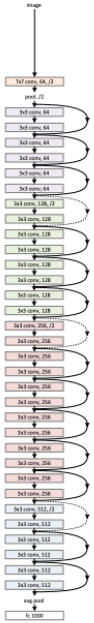
From Neural Networks to “Deep Learning”



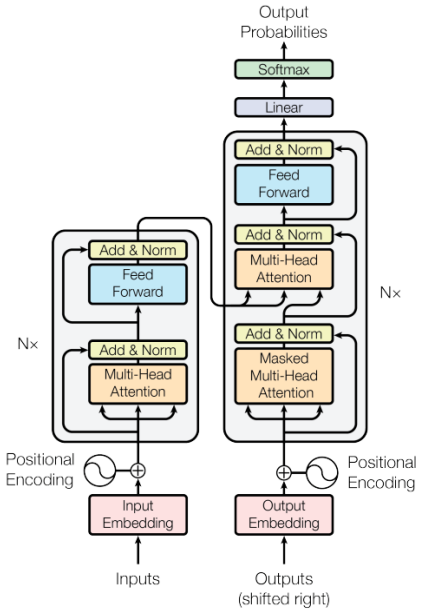
GoogleNet (Szegedy et al., 2015)



ResNet (He et al., 2015)

From Neural Networks to “Deep Learning”

Transformer

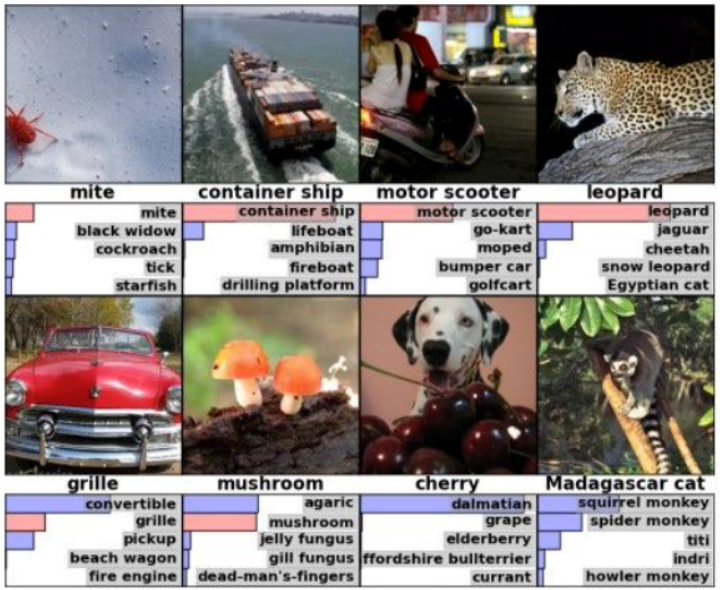


(Vaswani et al., 2017)

From Neural Networks to “Deep Learning”

- DL is everywhere

Classification



Retrieval

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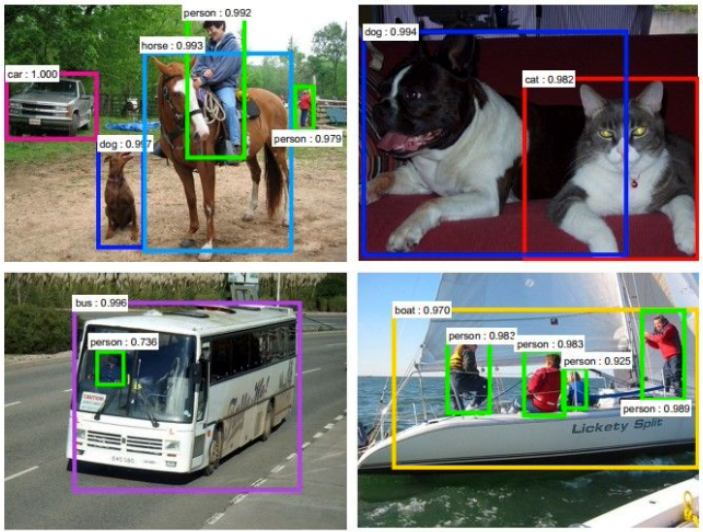
From Neural Networks to “Deep Learning”

- DL is everywhere

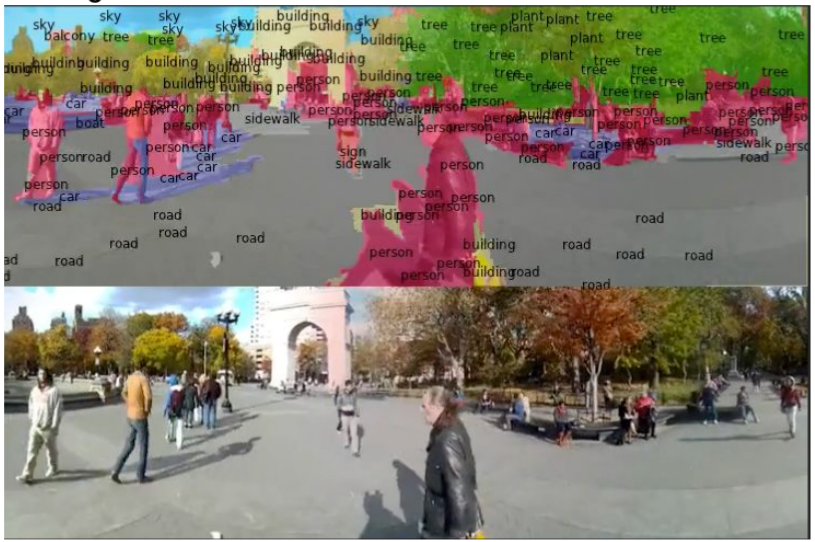
Detection



Figures copyright Shaoqing Ren, Kaiming He, Ross Girschick, Jian Sun, 2015. Reproduced with permission.

[Faster R-CNN: Ren, He, Girshick, Sun 2015]

Segmentation



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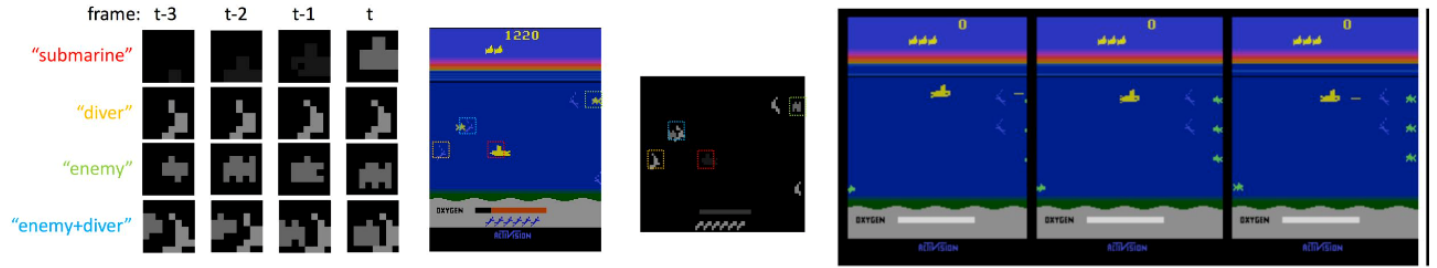
[Farabet et al., 2012]

From Neural Networks to “Deep Learning”

- DL is everywhere

Images are examples of pose estimation, not actually from Toshev & Szegedy 2014. Copyright Lane McIntosh.

[Toshev, Szegedy 2014]



[Guo et al. 2014]

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From Neural Networks to “Deep Learning”

- DL is everywhere

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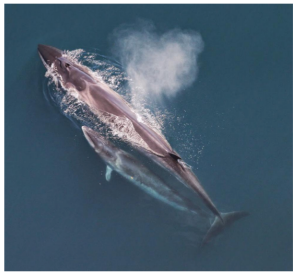
self-driving cars



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Whale recognition, Kaggle Challenge

Photo and figure by Lane McIntosh; not actual example from Mnih and Hinton, 2010 paper.

Mnih and Hinton, 2010

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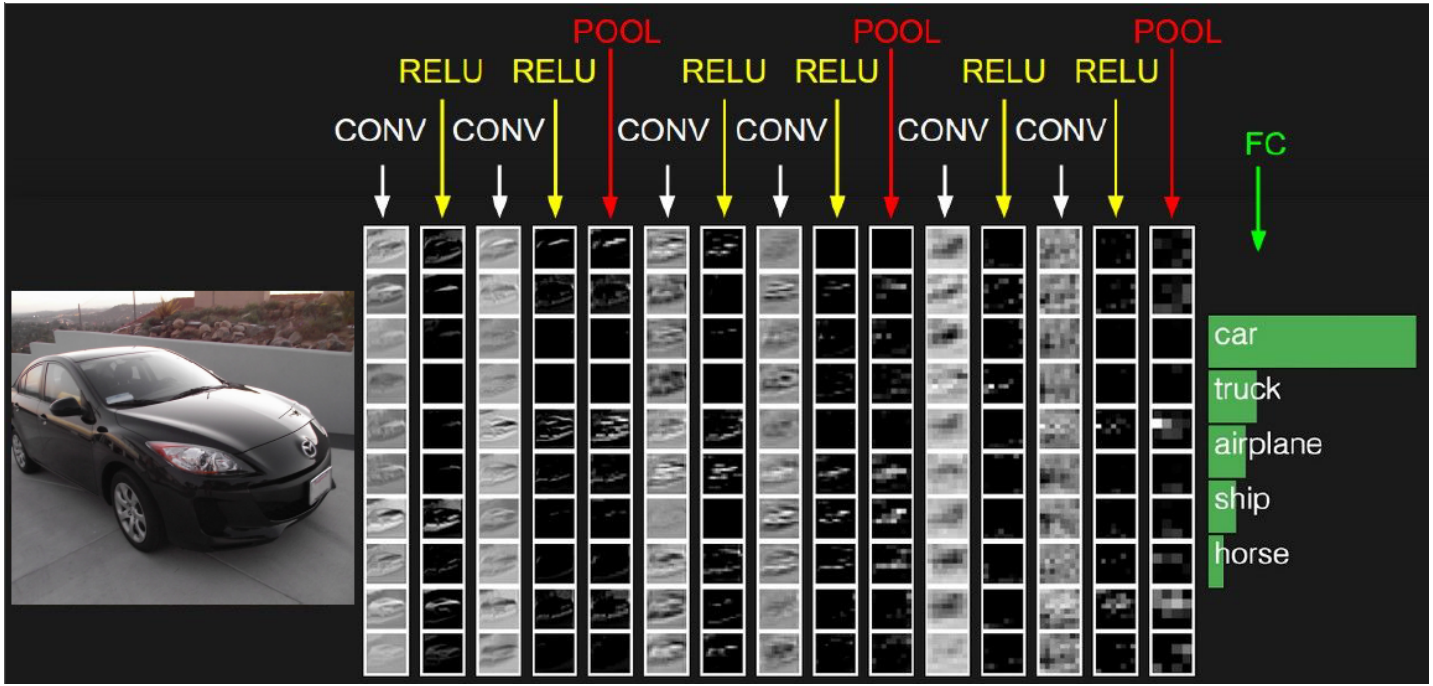
Starry Night and Tree Roots by Van Gogh are in the public domain
Bokeh image is in the public domain
Stylized images copyright Justin Johnson, 2017;

Gatys et al, “Image Style Transfer using Convolutional Neural Networks”, CVPR 2016
Gatys et al, “Controlling Perceptual Factors in Neural Style Transfer”, CVPR 2017

Convolutional Neural Network (CNN), from MLP to CNN

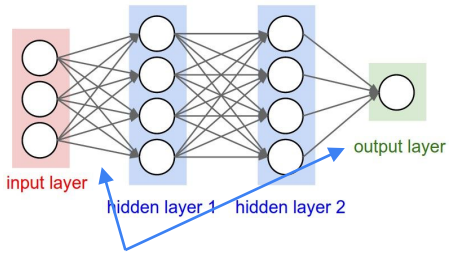
An overview of a CNN



CNNs

- CNNs are made up of neurons with learnable weights, as other to regular Neural Networks
- CNN architecture assumes that inputs are images
  - Using specific assumptions for images
  - So that we have local features
  - Which allows us to
    - encode certain properties in the architecture that makes the forward pass more efficient and
    - significantly reduces the number of parameters needed for the network

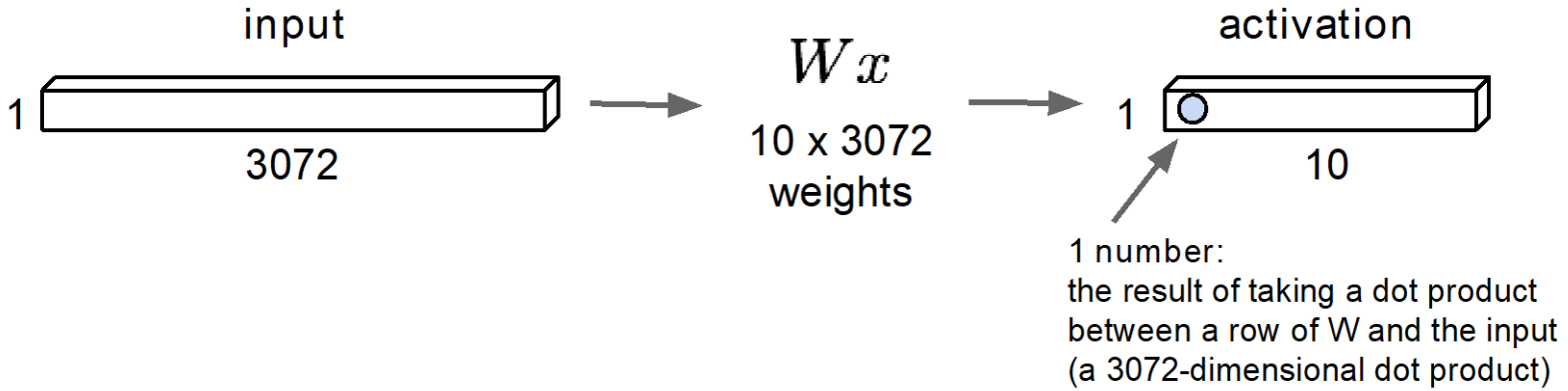
Convolutional Neural Networks (CNNs)



FC layer

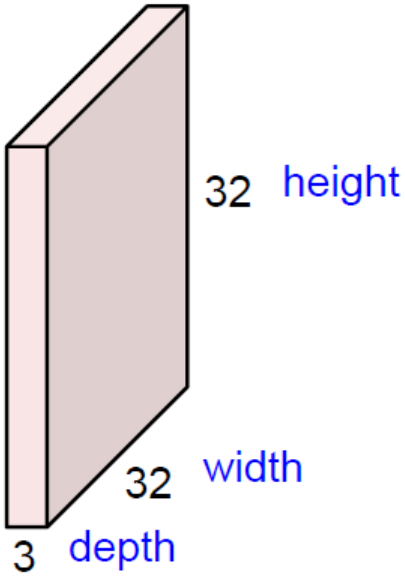
- Recap: fully connected (FC) layer
- A linear model, not CNNs.
- A components of CNNs

32x32x3 image -> stretch to 3072 x 1



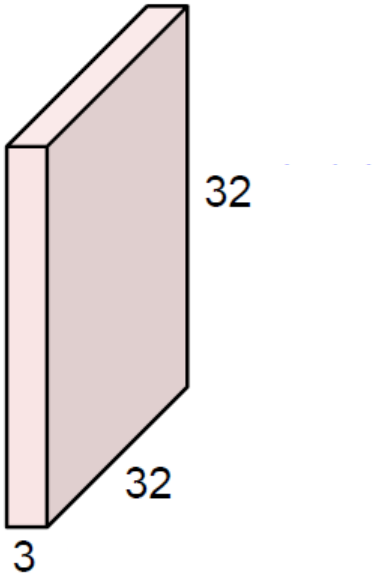
Convolution Layer (2D)

32x32x3 image -> preserve spatial structure

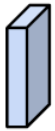


Convolution Layer

32x32x3 image

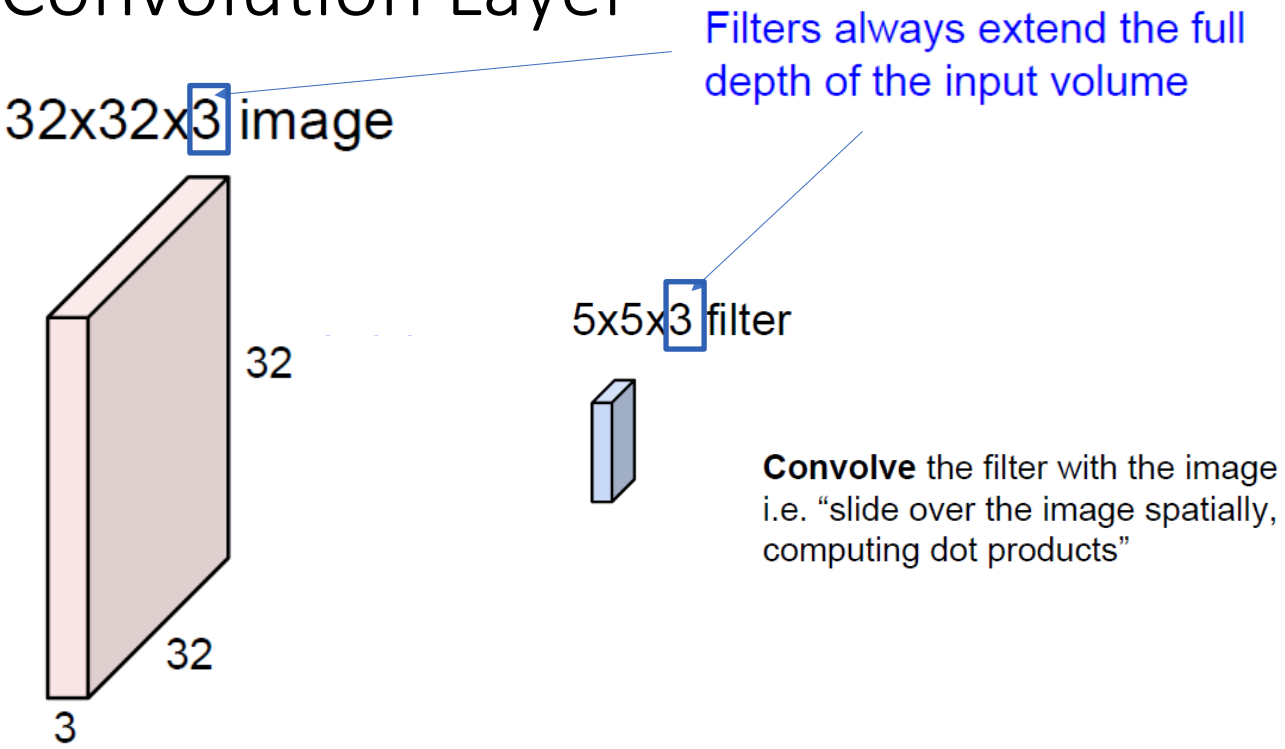


5x5x3 filter



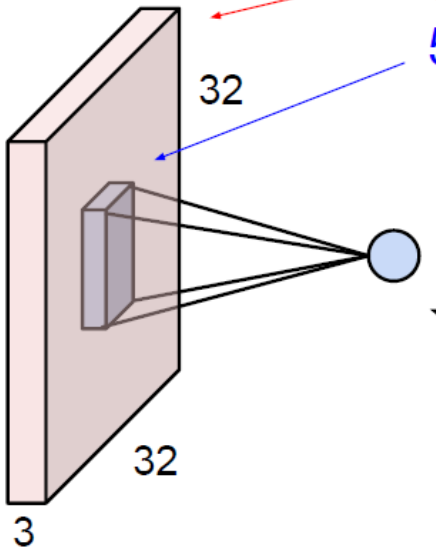
Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Convolution Layer



Convolve the filter with the image
i.e. “slide over the image spatially, computing dot products”

Convolution Layer



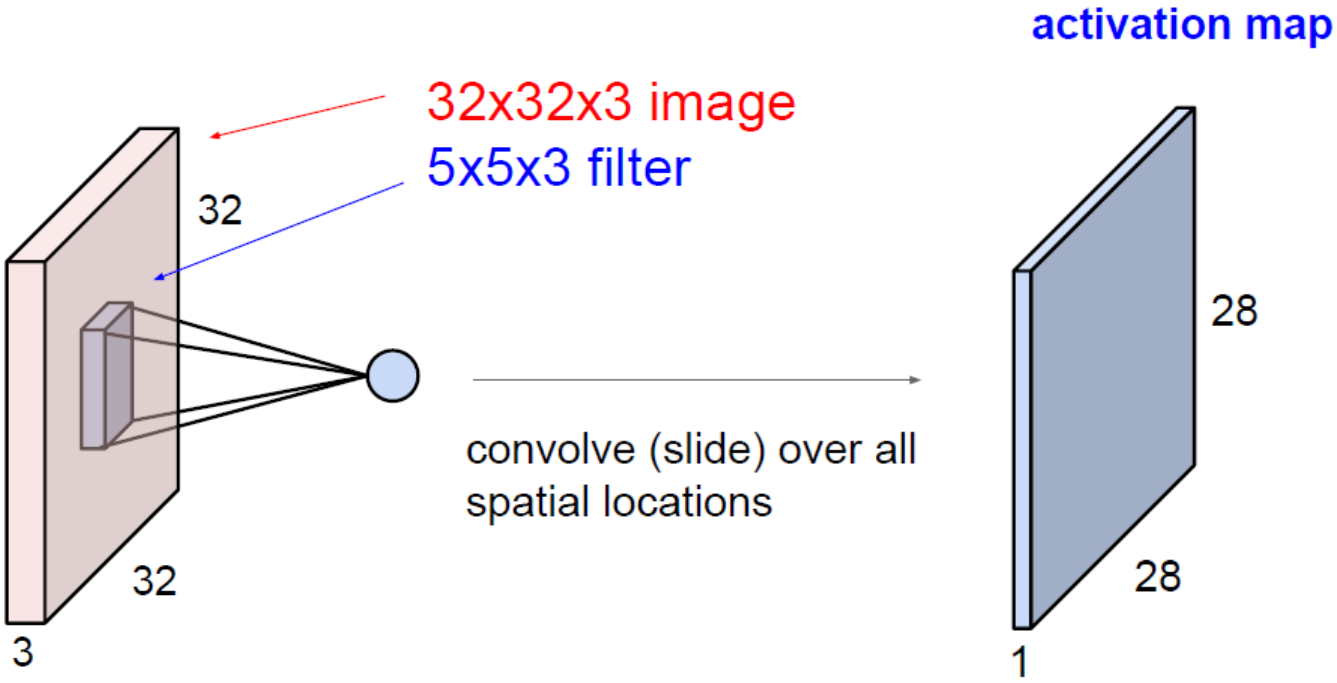
32x32x3 image

5x5x3 filter w

1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

Convolution Layer

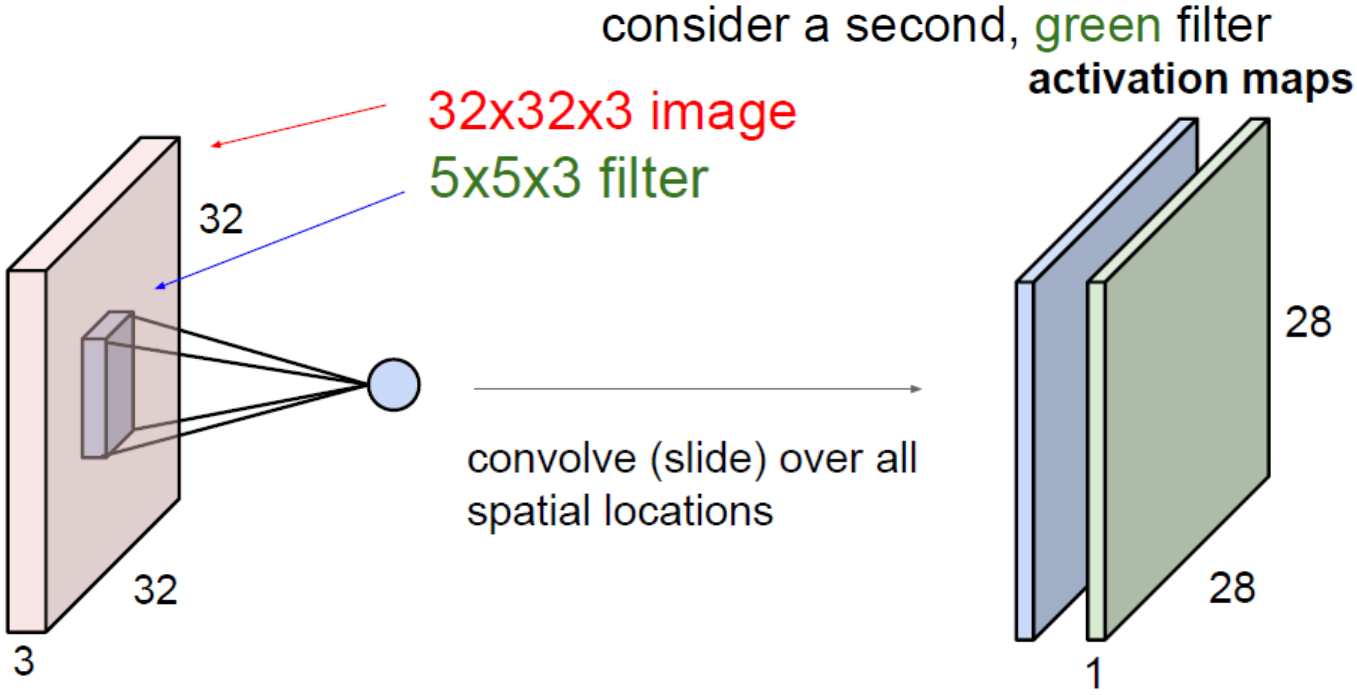


Noticed the difference on size?
Why?

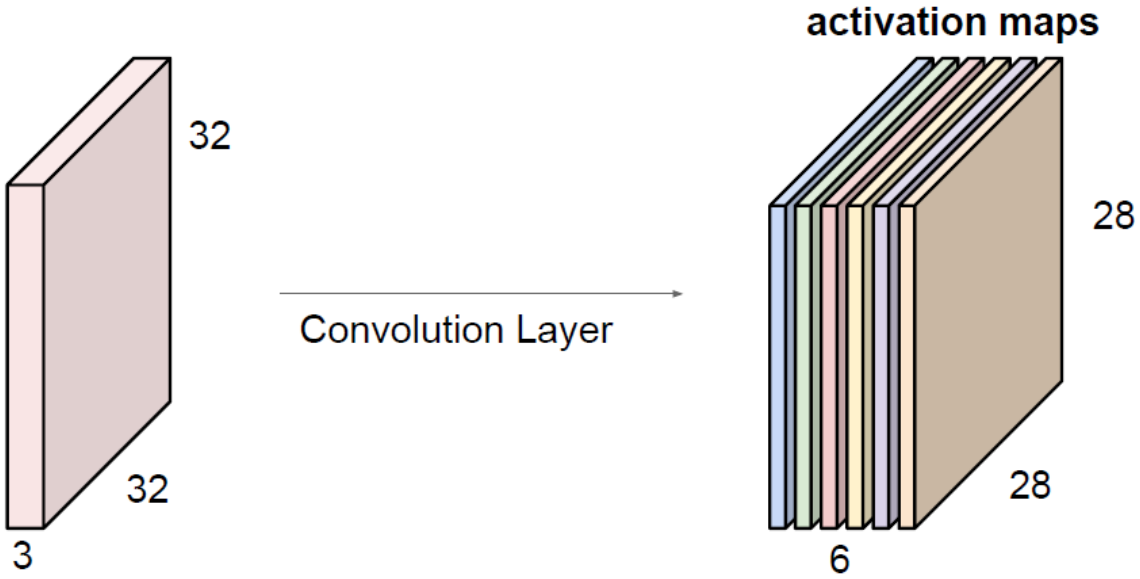
CNN: Convolutional Layer

- The output of the Conv layer can be interpreted as holding neurons arranged in a 3D volume.
- The Conv layer's parameters consist of a set of **learnable filters**. Every filter is small spatially (along width and height), but extends through the full depth of the input volume.
- During the forward pass, each filter is slid (convolved) across the width and height of the input volume, producing a 2-dimensional activation map of that filter.
- Network will learn filters (via backpropagation) that activate (through the activation function) when they see some specific type of feature at some spatial position in the input.

Convolution Layer



For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

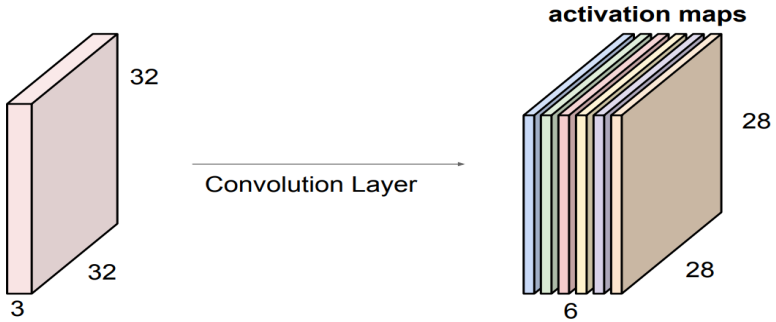


We stack these up to get a "new image" of size 28x28x6!

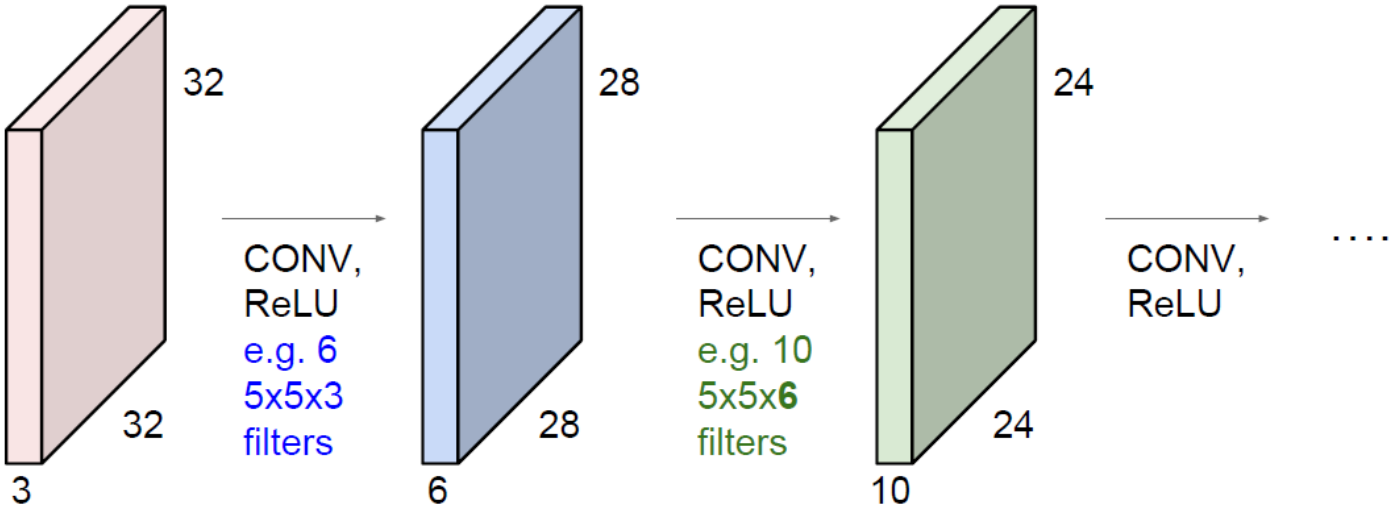
CNN: Convolutional Layer

- Stacking these activation maps for all filters along the depth dimension forms the full output volume
- Every entry in the output volume can thus also be interpreted as an output of a neuron that looks at only a small region in the input and ***shares parameters*** with neurons in the same activation map (since these numbers all result from applying the same filter)

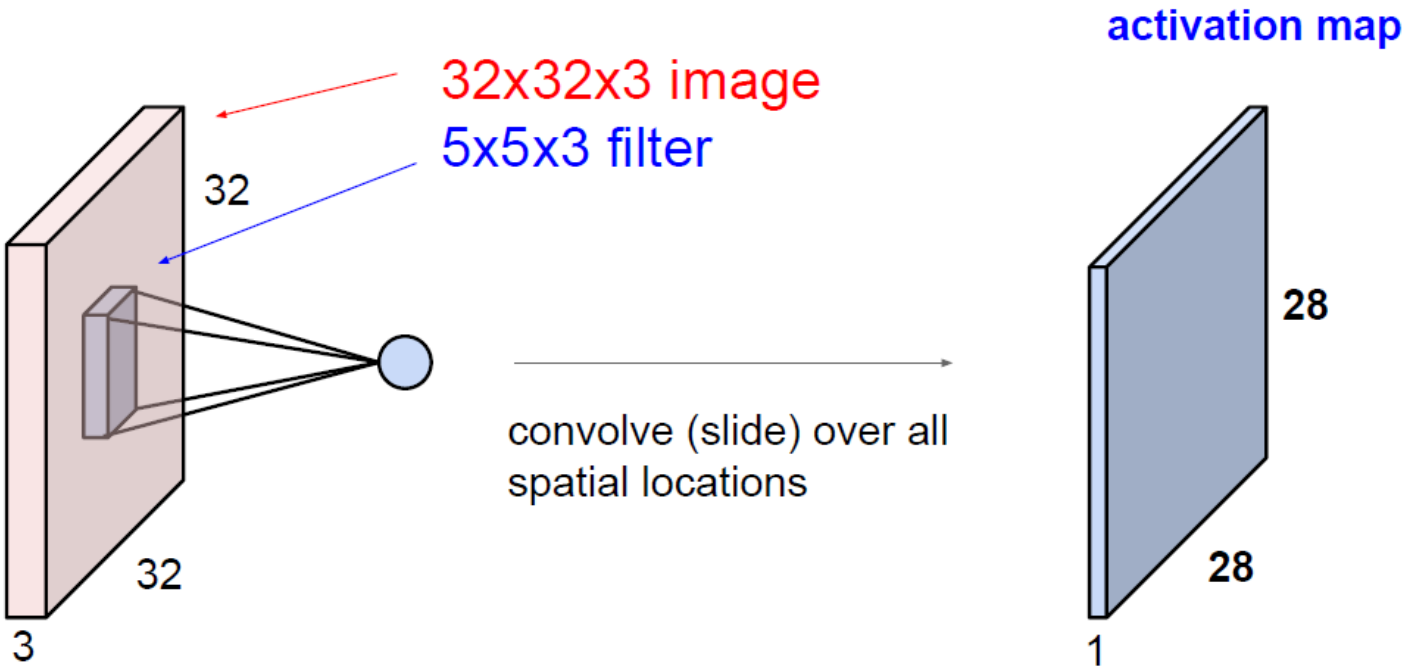
With 6 filters, we get
6 activation maps



Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



A closer look at spatial dimensions:

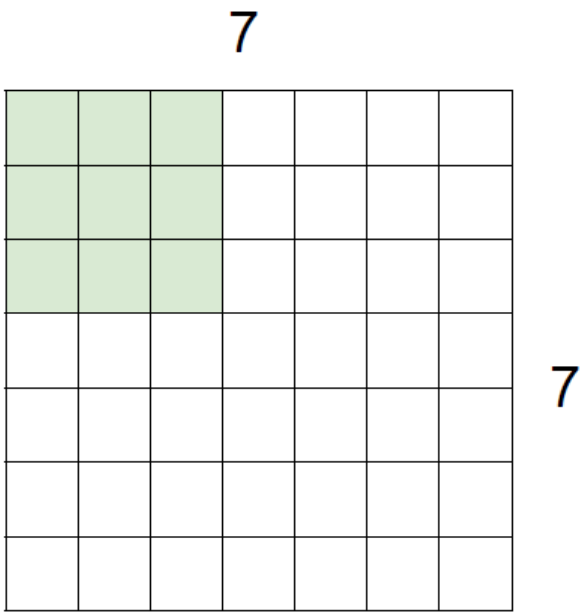


CNN: Convolutional Layer

Local Connectivity

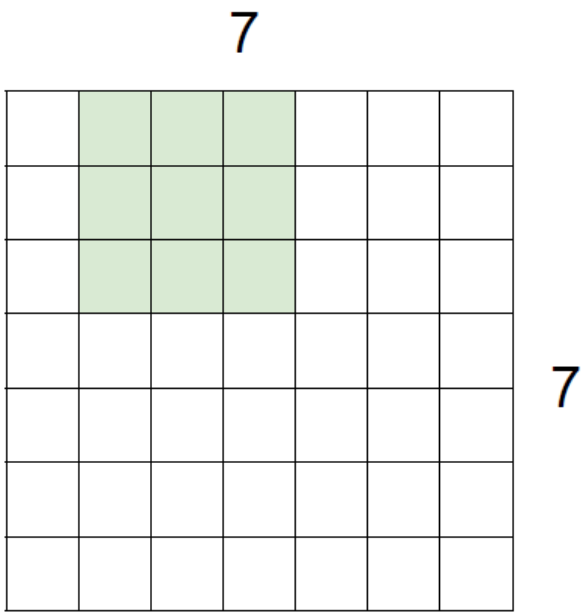
- As we have realized by now, it is impractical to use fully connected networks when dealing with high dimensional images/data
- Hence the concept of local connectivity: each neuron only connects to a local region of the input volume.
- The spatial extent of this connectivity is a concept called ***receptive field*** of the neuron.
- The extent of the connectivity along the depth axis is always equal to the depth of the input volume.
- The connections are local in space (along width and height), but always full along the entire depth of the input volume.

A closer look at spatial dimensions:



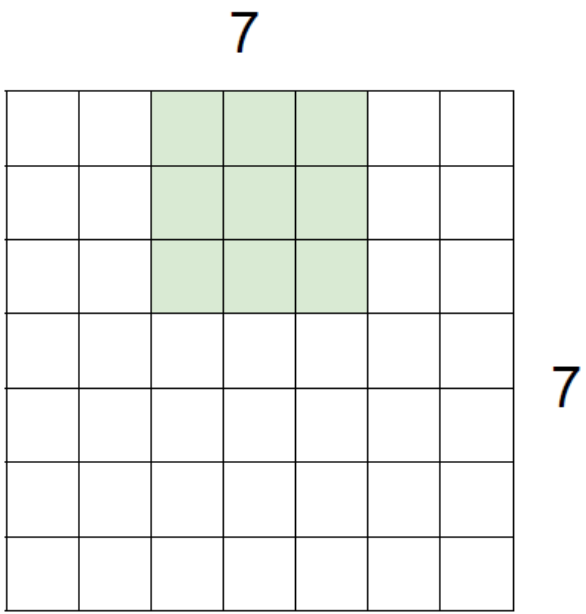
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



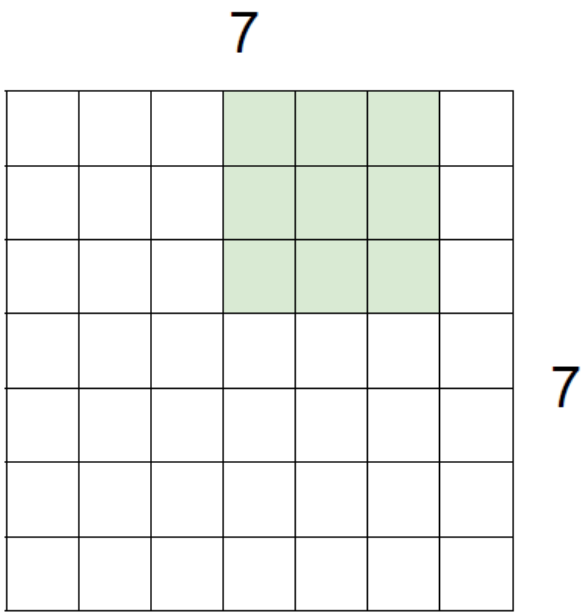
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



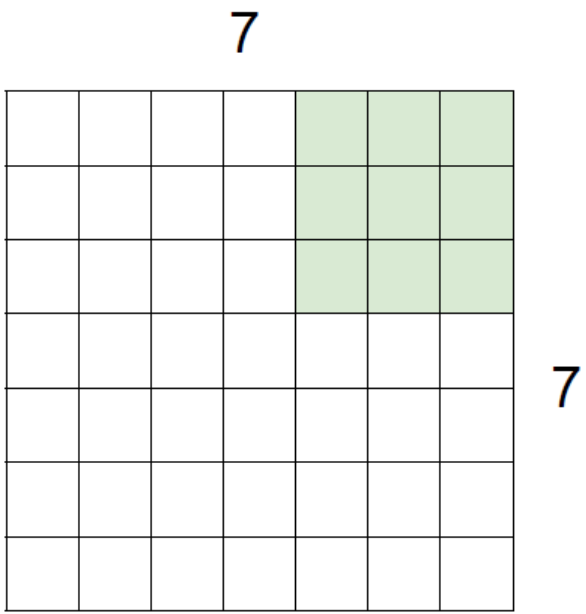
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

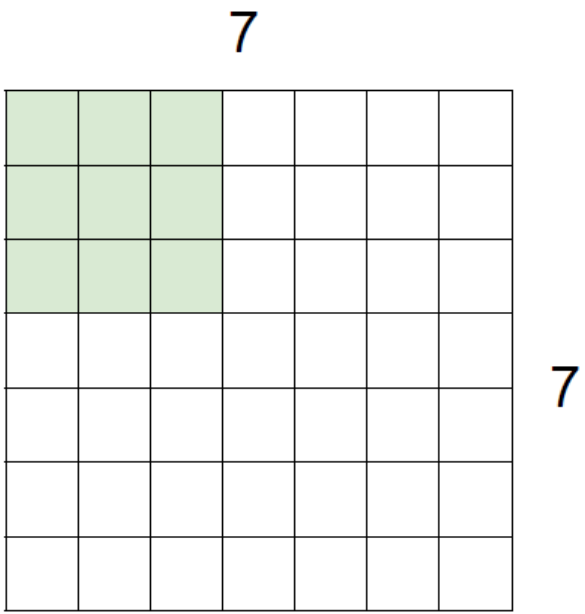
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

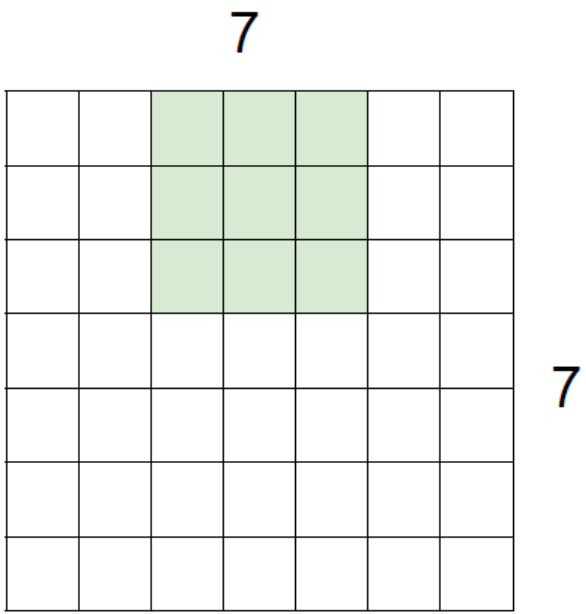
=> 5x5 output

A closer look at spatial dimensions:



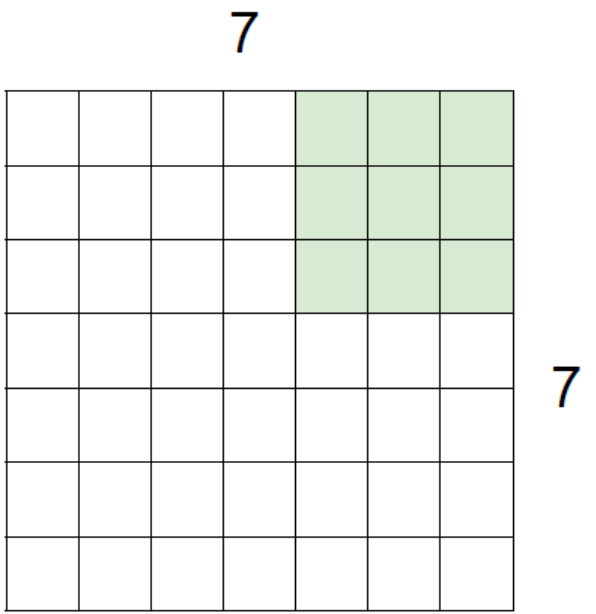
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

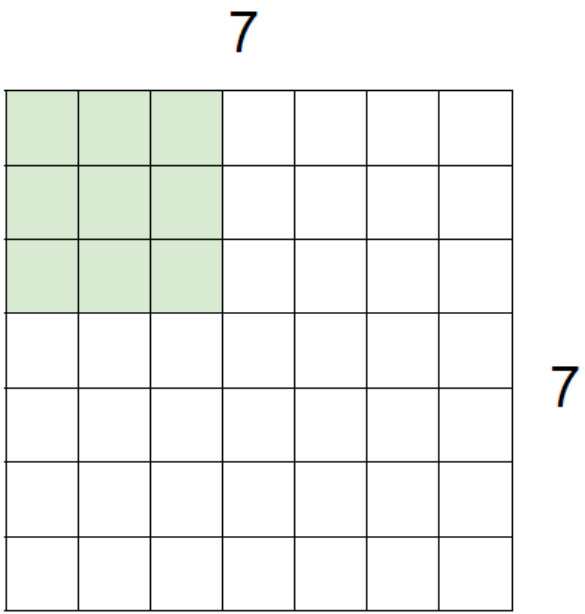
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

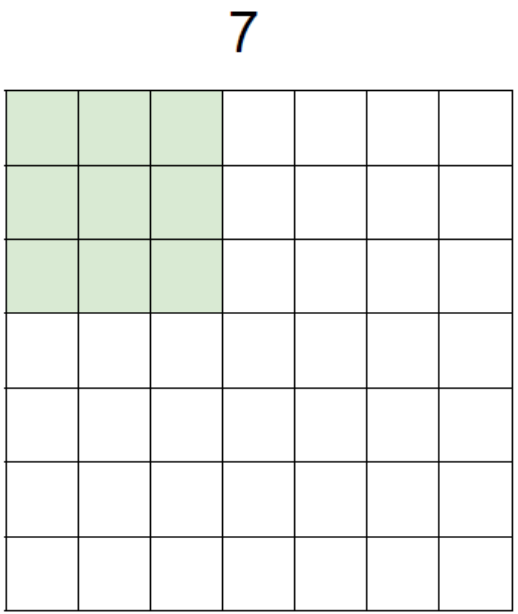
=> 3x3 output!

A closer look at spatial dimensions:



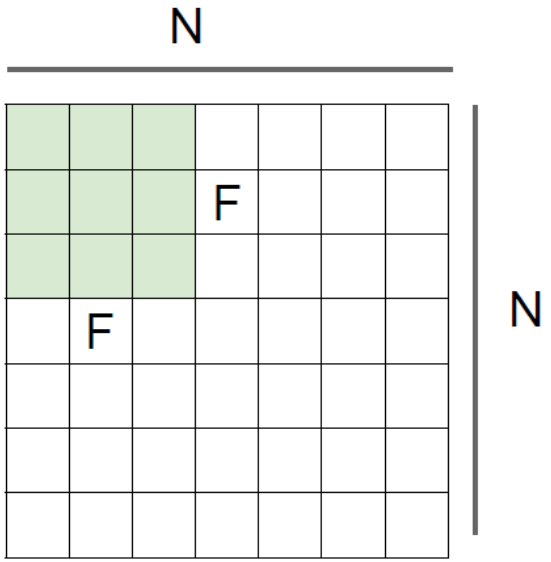
7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

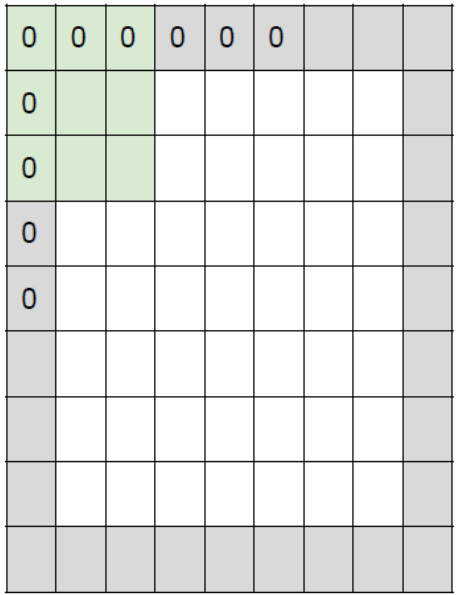
doesn't fit!
cannot apply 3x3 filter on
7x7 input with stride 3.



Output size:
(N - F) / stride + 1

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

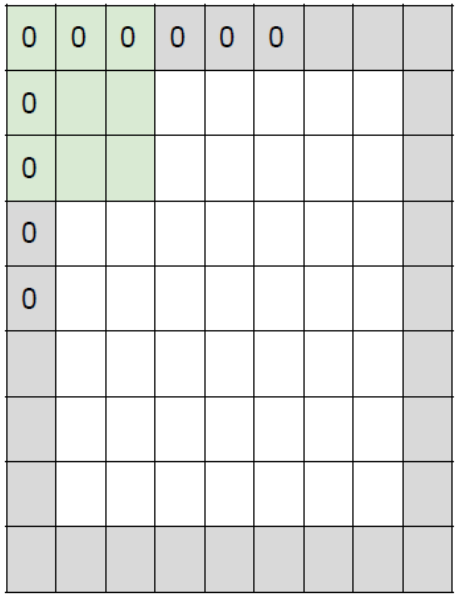
In practice: Common to zero pad the border



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

(recall:)
(N - F) / stride + 1

In practice: Common to zero pad the border



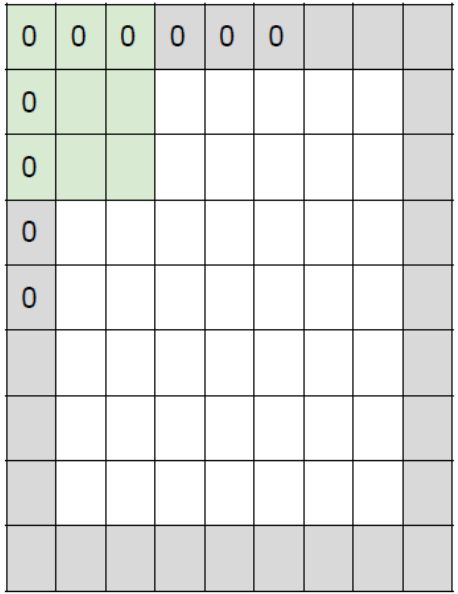
e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

(recall:) N will not be 7 after padding.

(N - F) / stride + 1

7x7 output!

In practice: Common to zero pad the border



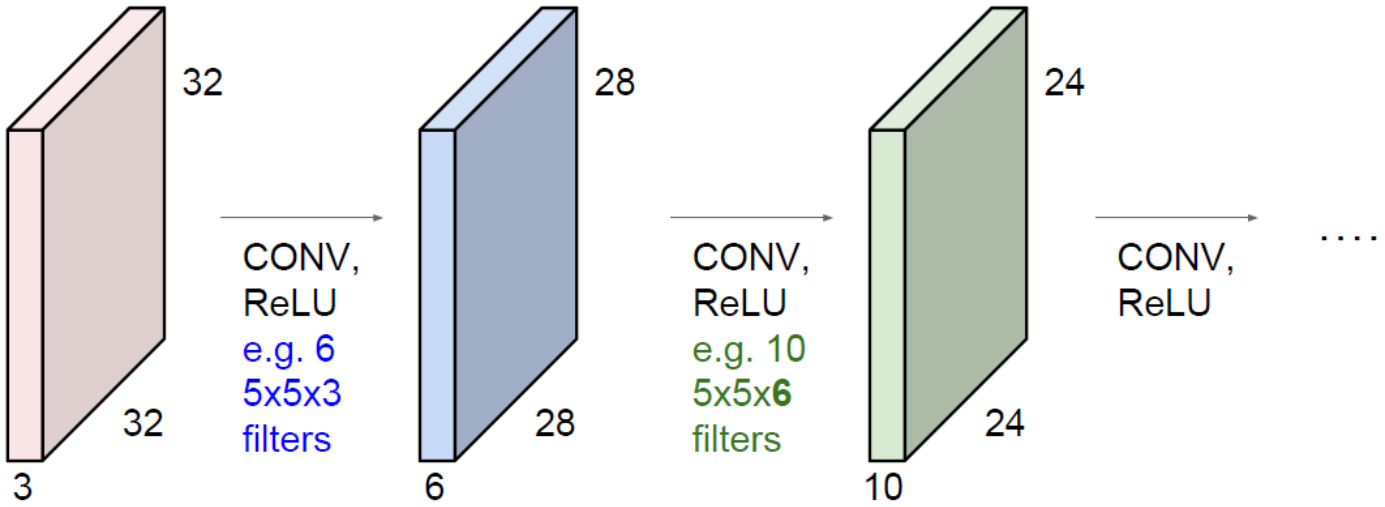
e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

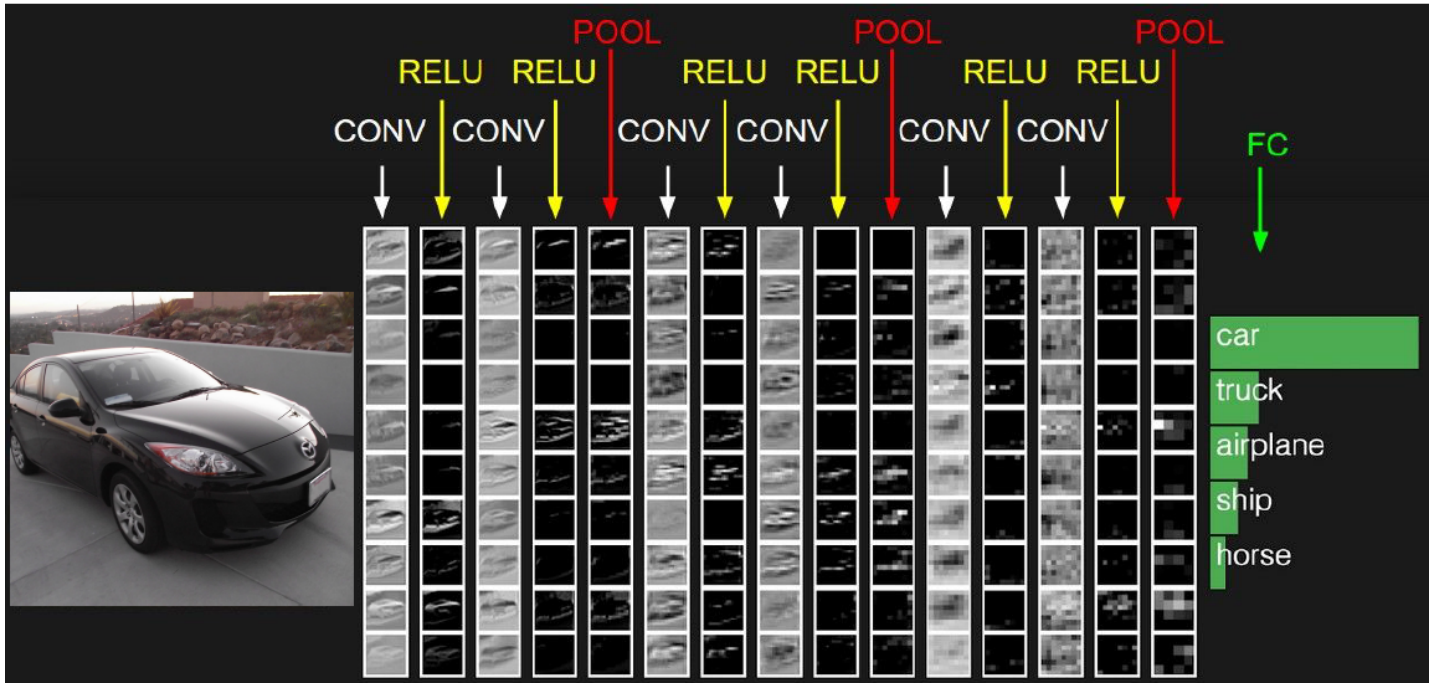
Other padding operations: replication padding, reflection padding …

Remember back to…

E.g. 32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially! (32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn't work well.

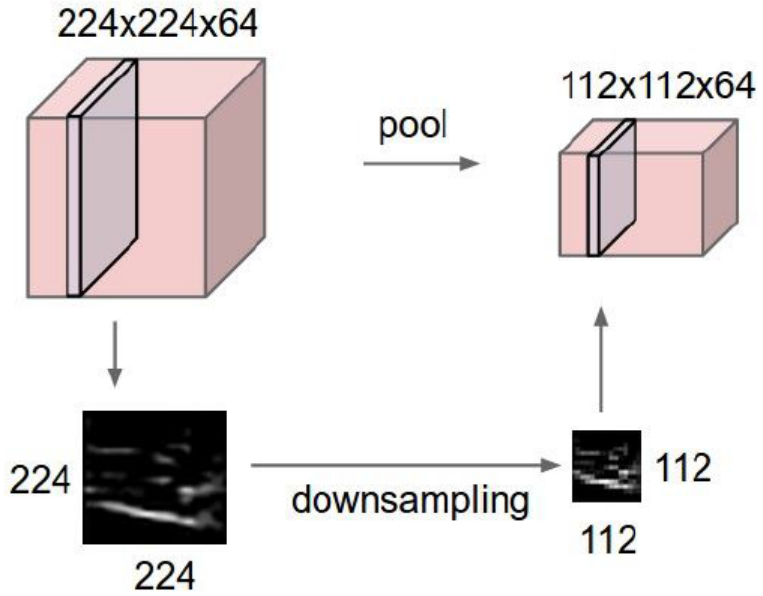


two more layers to go: POOL/FC

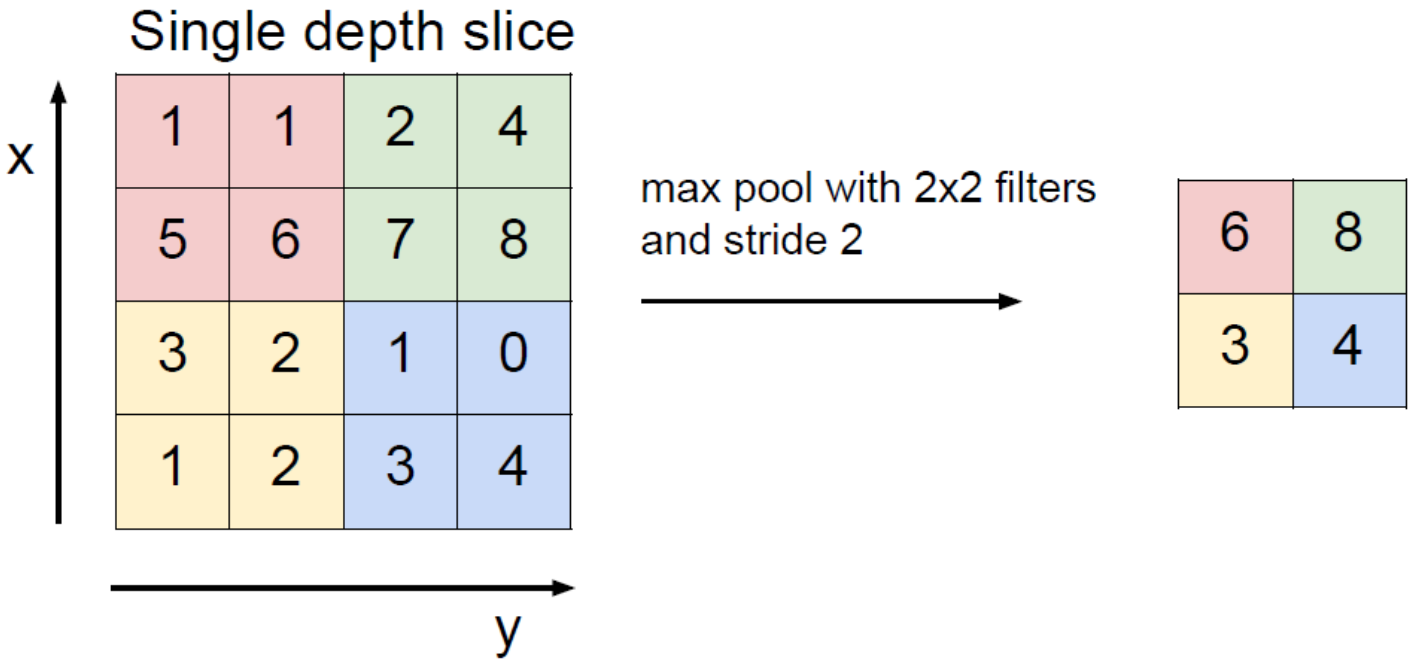


Pooling layer

- makes the representations smaller and more manageable
- operates over each activation map independently:



Max Pooling



Other pooling operations: average/median pooling …

Pooling layer: summary

Let's assume input is W_1 x H_1 x C
Conv layer needs 2 hyperparameters:

- The spatial extent **F**
- The stride **S**

This will produce an output of W_2 x H_2 x C where:

- $W_2 = (W_1 - F)/S + 1$
- $H_2 = (H_1 - F)/S + 1$

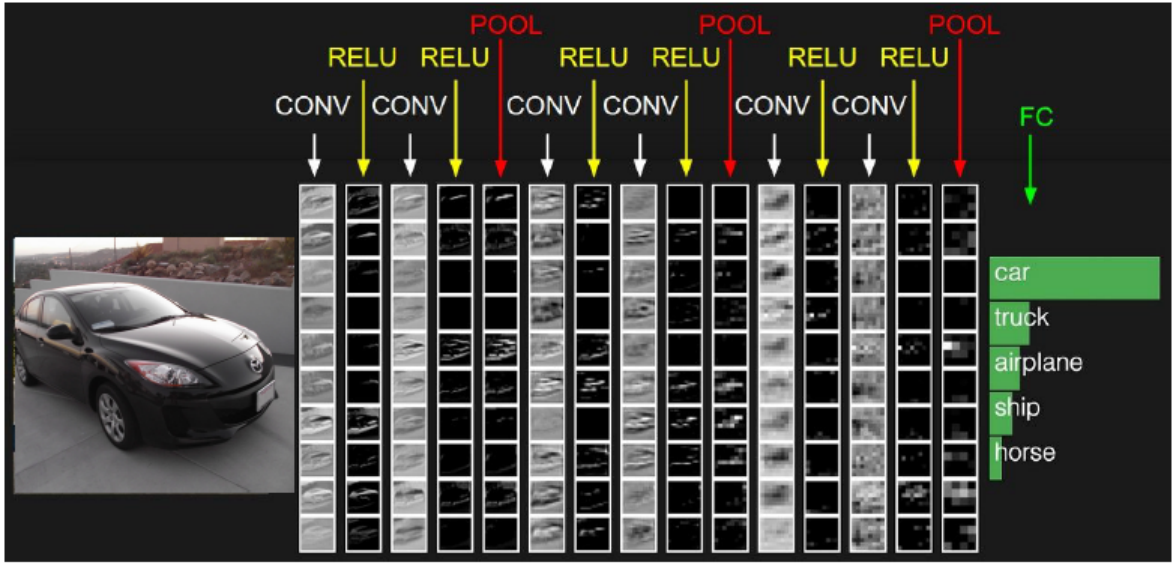
Number of parameters: 0

CNN: Pooling Layer

- The function of pooling layer
  - to progressively reduce the spatial size of the representation to reduce the number of parameters and computation in the network, and
  - hence to also control overfitting
- The Pooling Layer operates
  - independently on every depth slice of the input and resizes it spatially, typically using the MAX operation (ie: max pooling)
  - The most common form is a pooling layer with filters of size 2x2 applied with a stride of 2, which downsamples every depth slice in the input by 2 along both width and height, discarding 75% of the activations

Fully Connected Layer (FC layer)

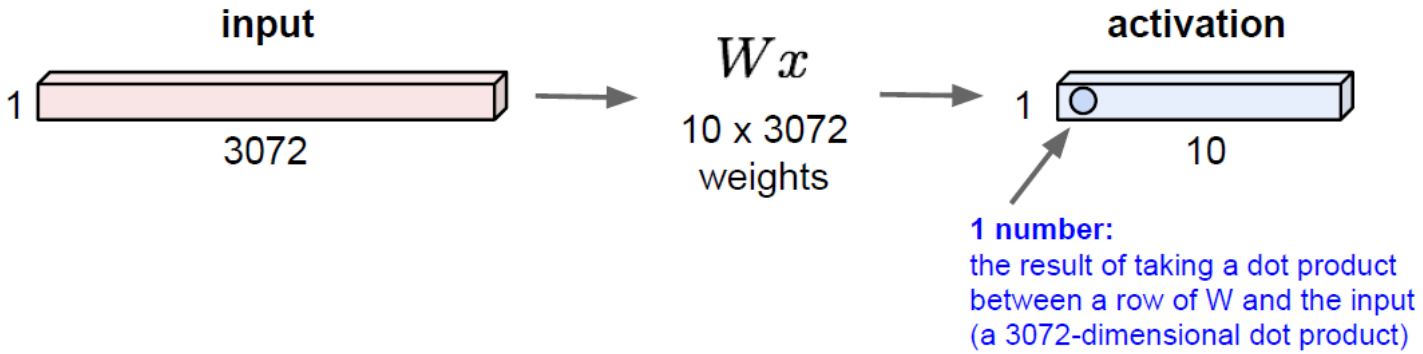
- Contains neurons that connect to the entire input volume, as in ordinary Neural Networks



Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1

Each neuron looks at the full input volume



Summary of CNNs

- ConvNets stack CONV,POOL,FC layers
- Trend towards smaller filters and deeper architectures
- Trend towards getting rid of POOL/FC layers (just CONV)
- Historically architectures looked like **[(CONV-RELU)*N-POOL?]*M-(FC-RELU)*K,SOFTMAX,** where N is usually up to ~5, M is large, 0 <= K <= 2.
    - but recent advances such as ResNet/GoogLeNet have challenged this paradigm

Training CNNs/Deep Neural Networks

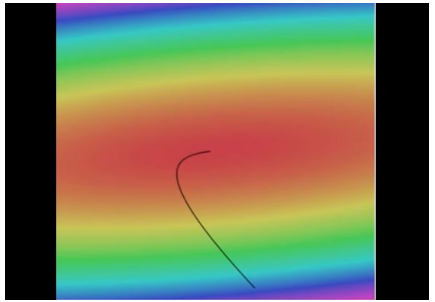
Some slides at this part are from Dr Sonit Singh sonit.singh@unsw.edu.au

CNN: Training

- A loss function is used to compute the model's prediction accuracy from the outputs
  - Most commonly used: categorical cross-entropy loss function

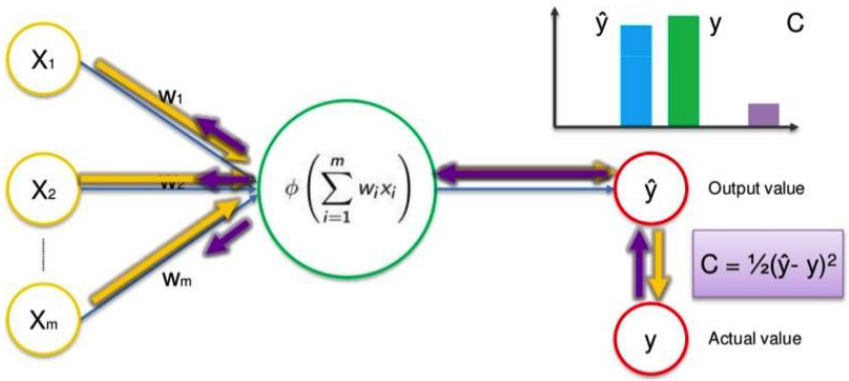
$$H(y, \hat{y}) = \sum_i y_i \log \frac{1}{\hat{y}_i} = -\sum_i y_i \log \hat{y}_i$$

- The training objective is to minimise this loss
- The loss guides the backpropagation process to train the CNN model
- Gradient descent based methods, such as Stochastic gradient descent and the Adam optimizer, are commonly used algorithms for optimisation



CNN: Training

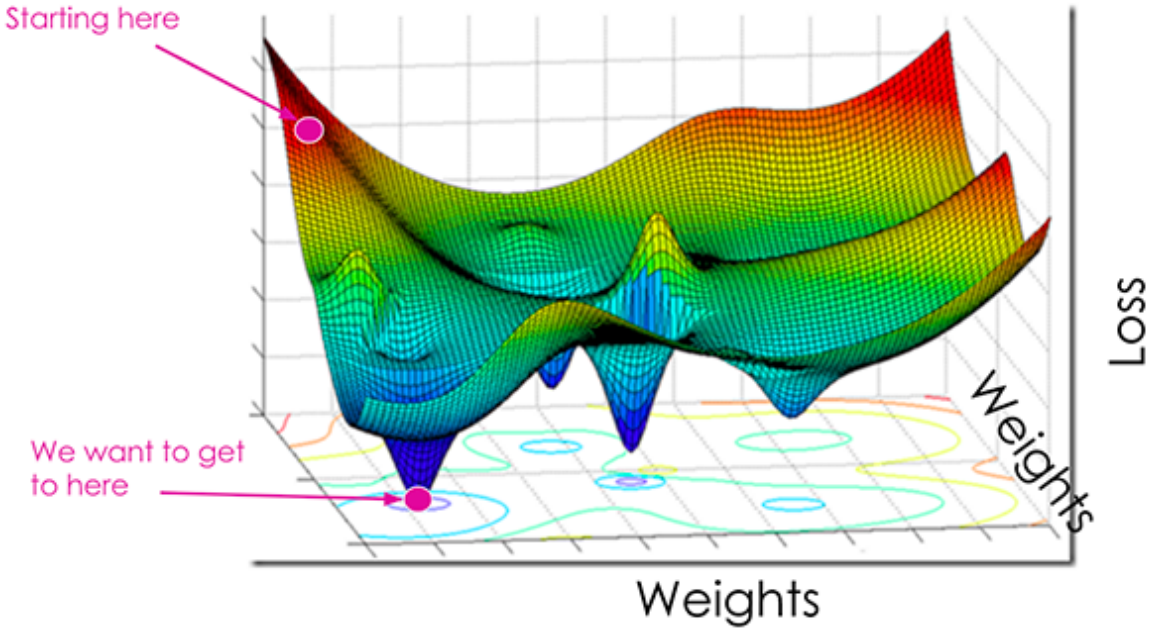
- Backpropagation in general:



https://www.superdatascience.com/blogs/artificial-neural-networks-backpropagation

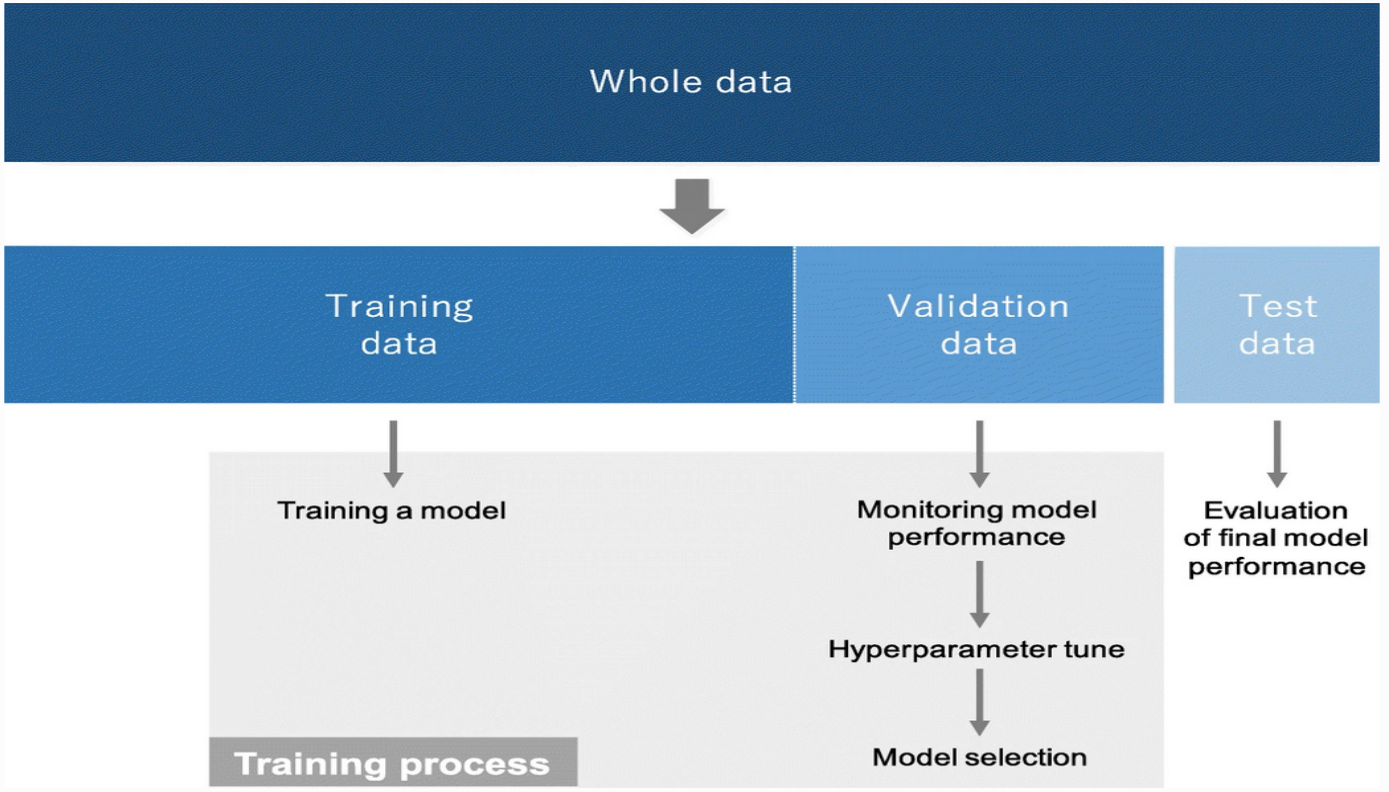
- Calculating gradients for gradient descent
- Directly deriving and calculating gradient is difficult, due to the complexity of DNNs

Why training Deep Neural Networks is hard?



Credit: Adrian Rosebrock, PyImageSearch, https://www.pyimagesearch.com/2019/10/14/why-is-my-validation-loss-lower-than-my-training-loss/

Training Methodology



Source: Yamashita R. et al. (2018) Convolutional neural networks: an overview and applications in radiology

Data Augmentation

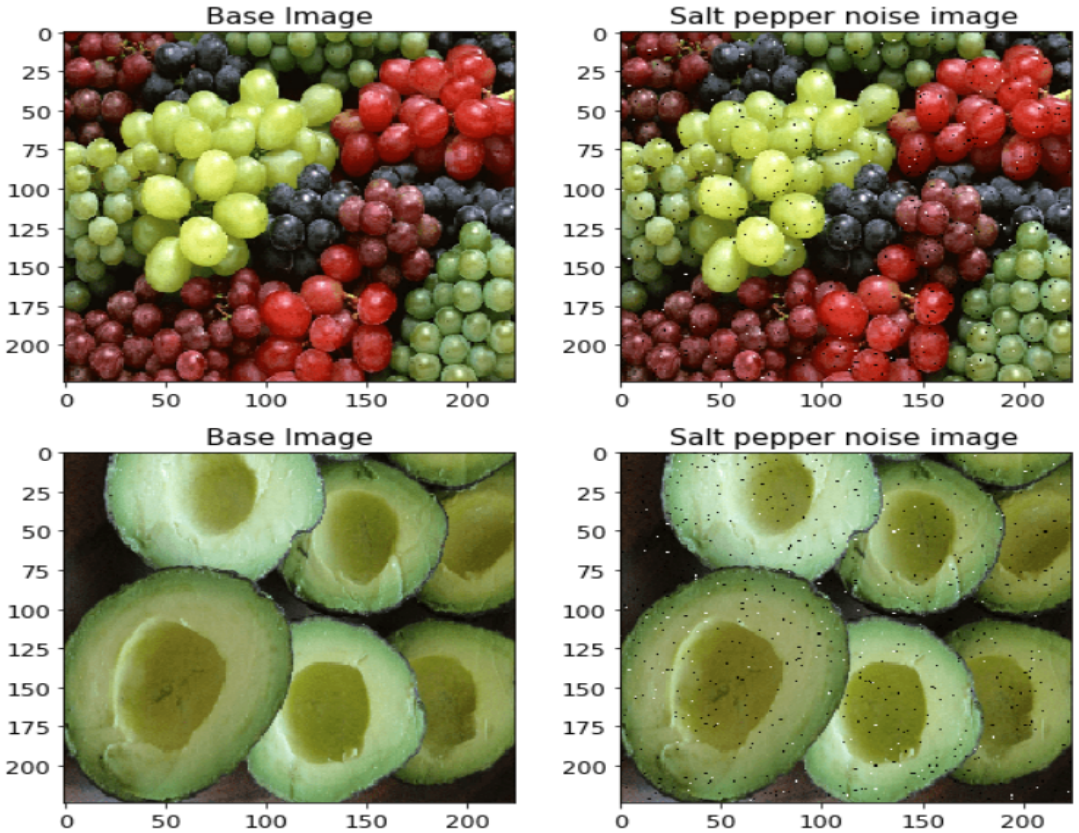
- Data augmentation generate different versions of a real dataset artificially to increase its size
- Improving the robustness of the networks
- We use data augmentation to handle data scarcity and insufficient data diversity
- Data augmentation helps to increase performance of deep neural networks

- Common augmentation techniques:
  - Adding noise
  - Cropping
  - Flipping
  - Rotation
  - Scaling
  - Translation
  - Brightness
  - Contrast
  - Saturation
  - Generative Adversarial Networks (GANs)

Source: 13 Data Augmentation Techniques. https://research.aimultiple.com/data-augmentation-techniques/

Data Augmentation

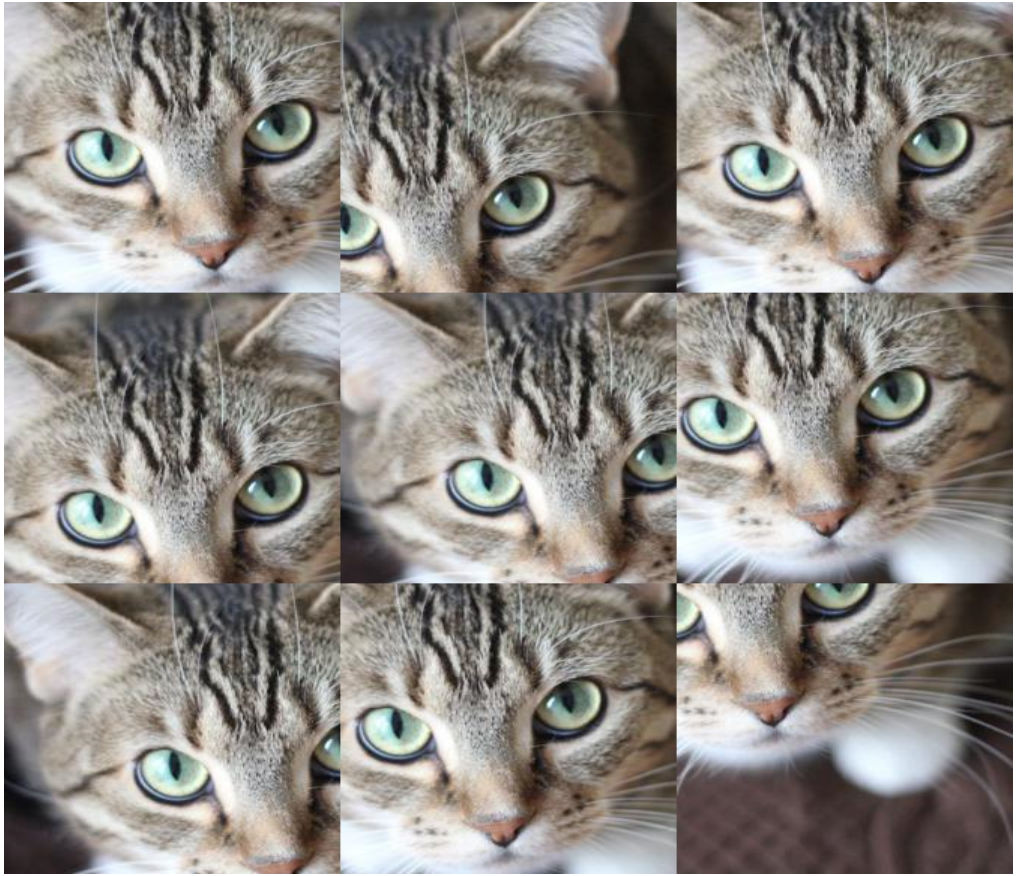
- Adding noise



Source: 13 Data Augmentation Techniques. https://research.aimultiple.com/data-augmentation-techniques/

Data Augmentation

- Cropping



Source: 13 Data Augmentation Techniques. https://research.aimultiple.com/data-augmentation-techniques/

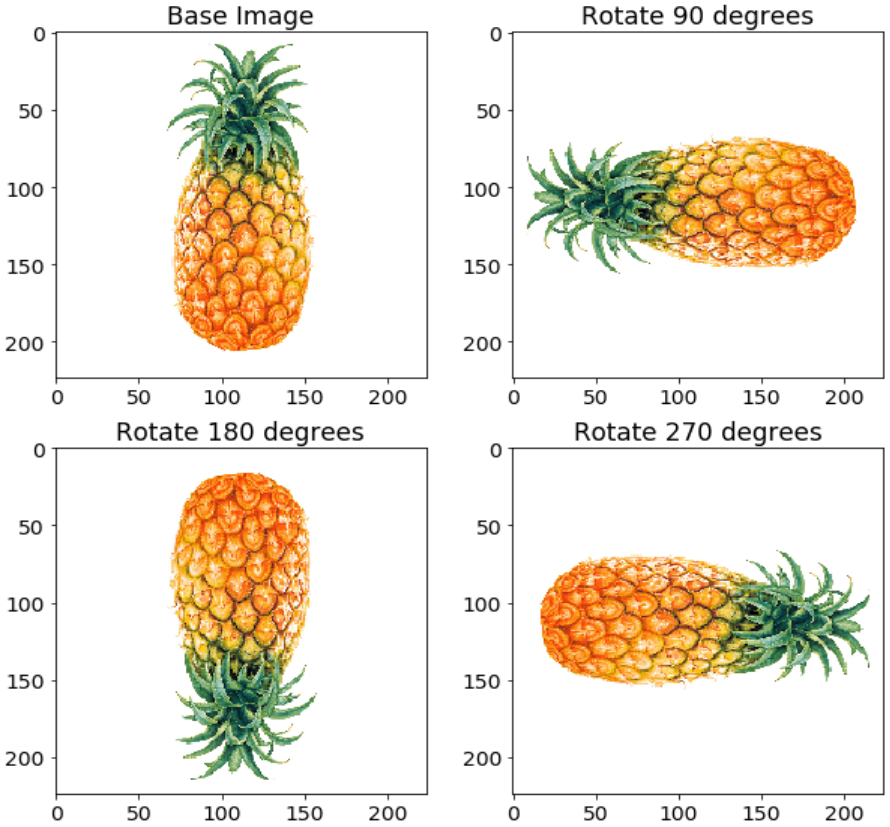
Data Augmentation

- Flipping

Source: 13 Data Augmentation Techniques. https://research.aimultiple.com/data-augmentation-techniques/

Data Augmentation

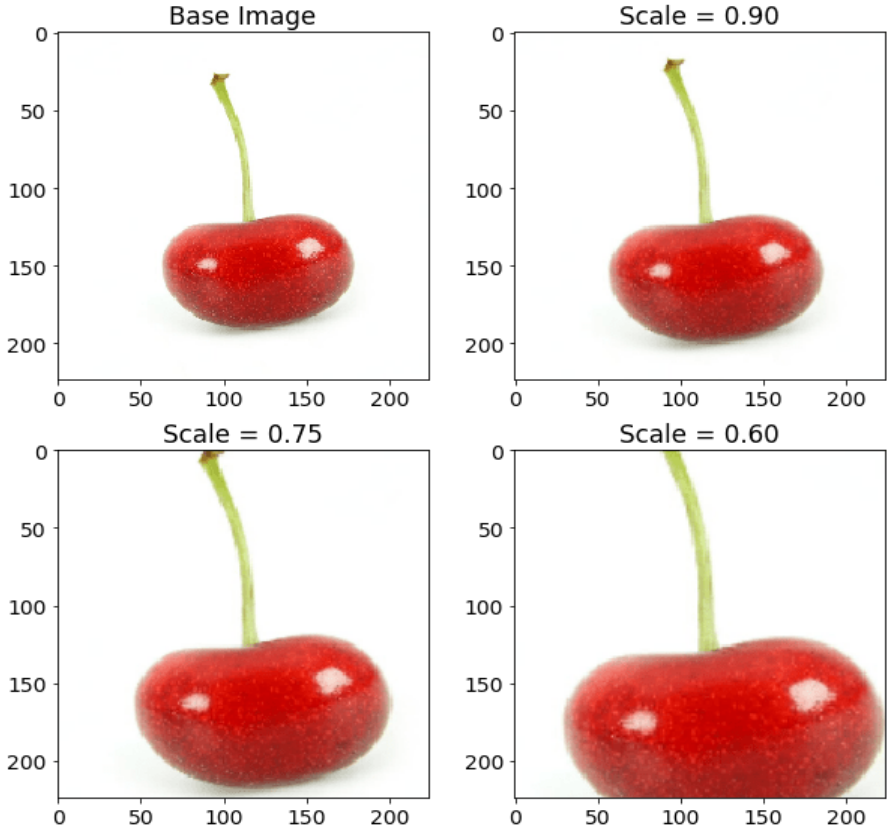
- Rotation



Source: 13 Data Augmentation Techniques. https://research.aimultiple.com/data-augmentation-techniques/

Data Augmentation

- Scaling



Source: 13 Data Augmentation Techniques. https://research.aimultiple.com/data-augmentation-techniques/

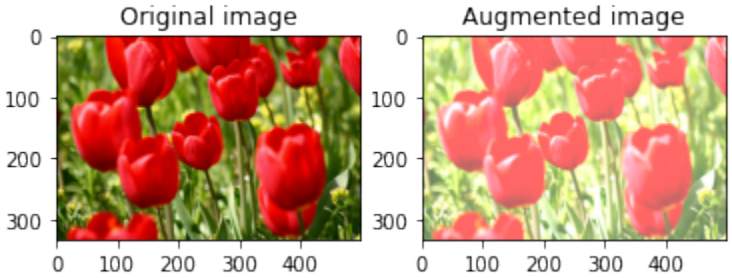
Data Augmentation

- Translation

Source: 13 Data Augmentation Techniques. https://research.aimultiple.com/data-augmentation-techniques/
https://nanonets.com/blog/data-augmentation-how-to-use-deep-learning-when-you-have-limited-data-part-2/

Data Augmentation

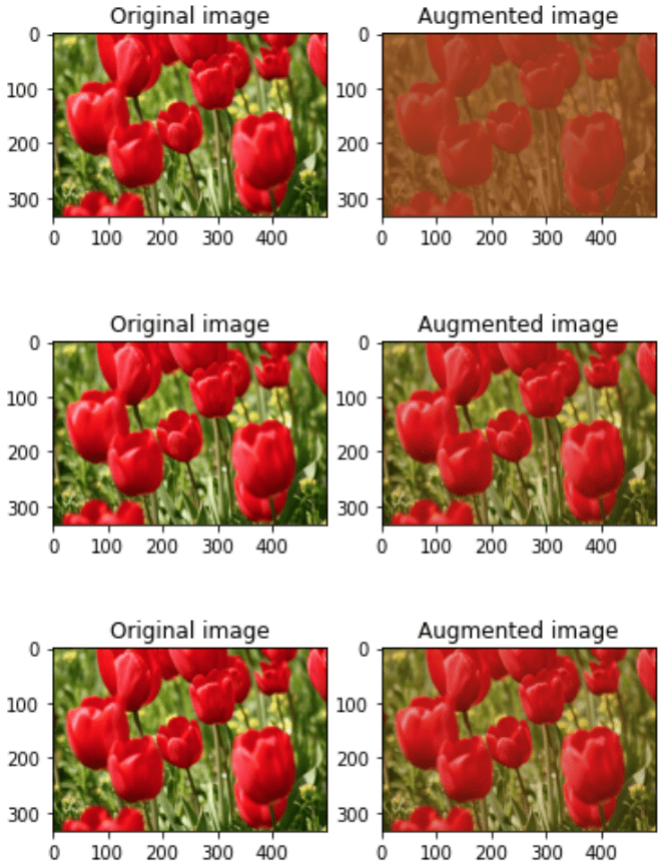
- Brightness



Source: 13 Data Augmentation Techniques. https://research.aimultiple.com/data-augmentation-techniques/

Data Augmentation

- Contrast



Source: 13 Data Augmentation Techniques. https://research.aimultiple.com/data-augmentation-techniques/

Regularization: Weight Decay

- It adds a penalty term to the loss function on the training set to reduce the complexity of the learned model
- Popular choice for weight decay:
  - L1: The L1 penalty aims to minimize the absolute value of the weights

$$L(x, y) \equiv \sum_{i=1}^{n} (y_i - h_\theta(x_i))^2 + \lambda \sum_{i=1}^{n} |\theta_i|$$

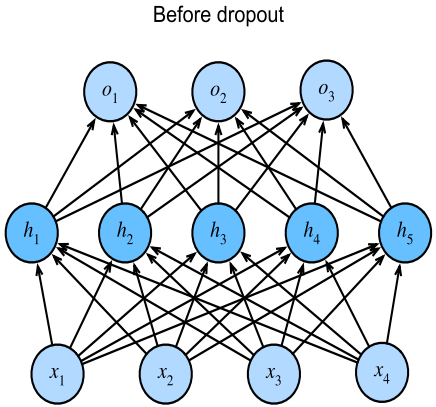
  - L2: The L2 penalty aims to minimize the squared magnitude of the weights

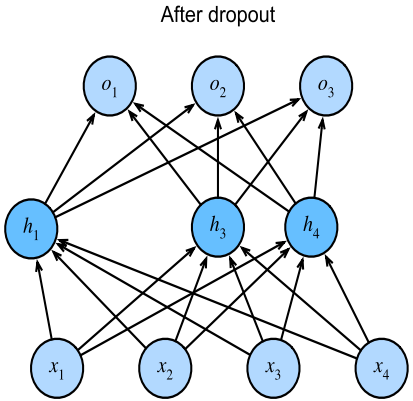
$$L(x, y) \equiv \sum_{i=1}^{n} (y_i - h_\theta(x_i))^2 + \lambda \sum_{i=1}^{n} \theta_i^2$$

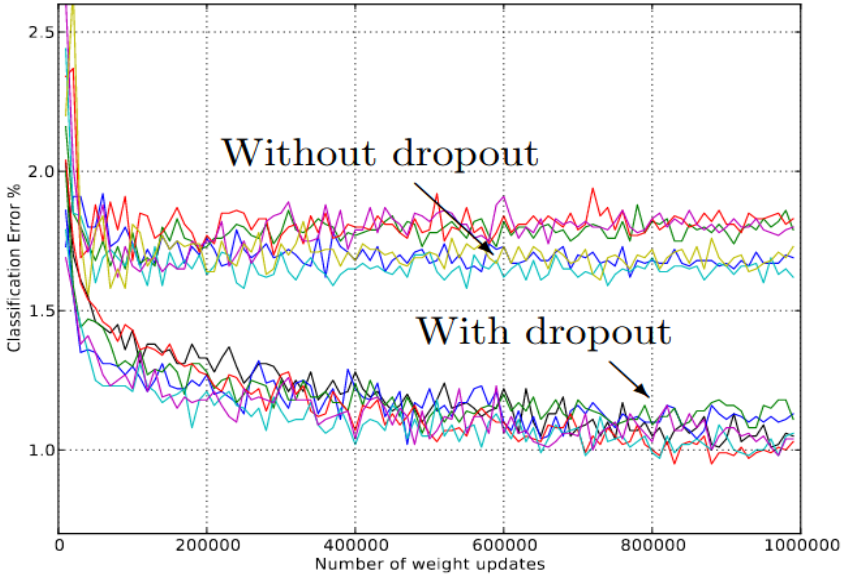
Credit: 5 Techniques to Prevent Overfitting in Neural Networks. https://www.kdnuggets.com/2019/12/5-techniques-prevent-overfitting-neural-networks.html

Regularization: Dropout

- L1 and L2 reduce overfitting by modifying the cost function
- Dropout modify the network by randomly dropping neurons from the neural network during training
- Dropout is an efficient way to average many large neural networks



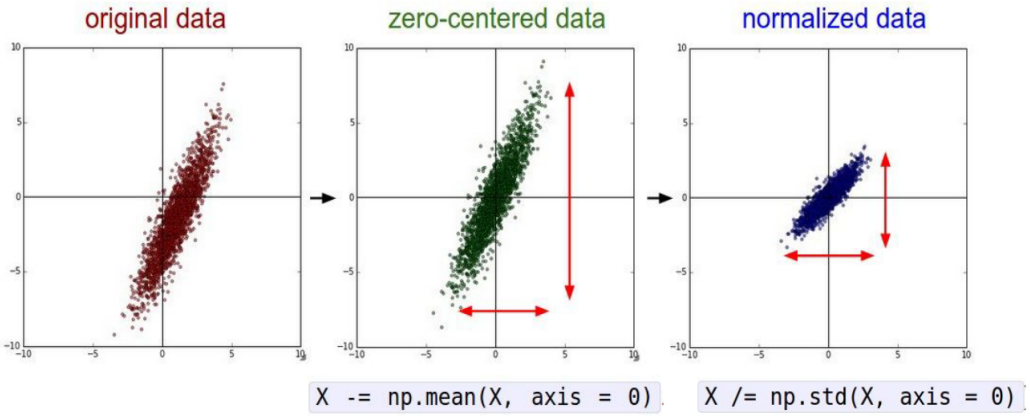




Credit: Srivastava et al., Dropout: A Simple Way to Prevent Neural Networks from Overfitting. JMLR, 2014
https://colab.research.google.com/github/d2l-ai/d2l-en-colab/blob/master/chapter_multilayer-perceptrons/dropout.ipynb

Data Preprocessing

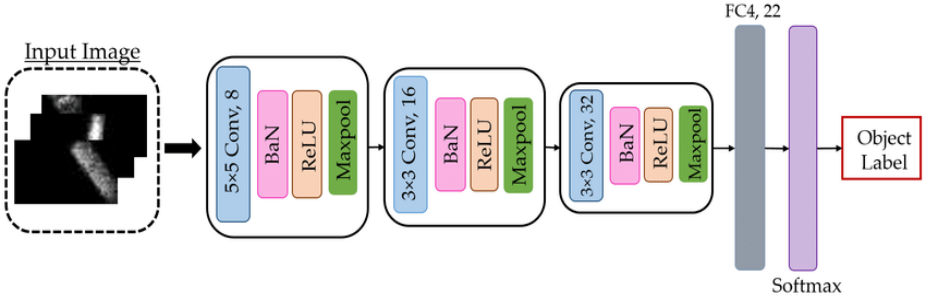
- The pixel values in images must be scaled prior to given as input to deep neural networks for training or evaluation
- Three main types of pixel scaling:
  - **Pixel Normalization**: scale pixel values to the range 0-1
  - **Pixel Centering**: scale pixel values to have a zero mean
  - **Pixel Standardization**: scale pixel values to have a zero mean and unit variance

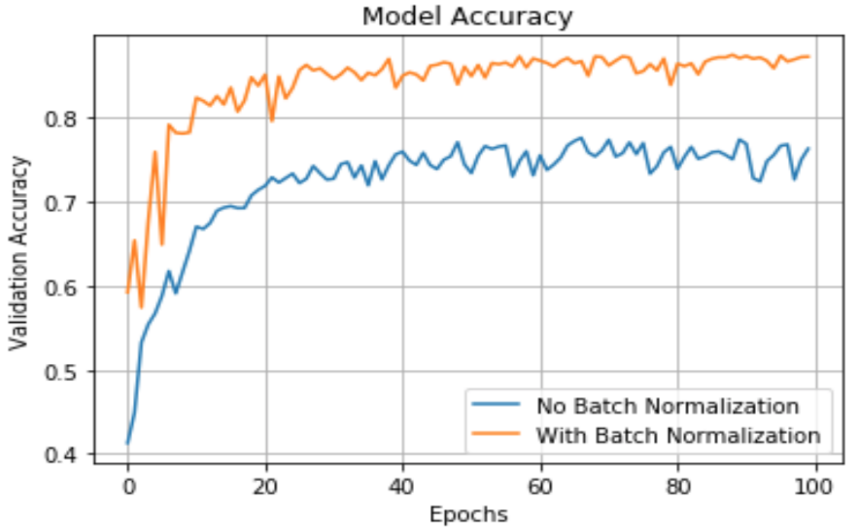


Credit: Stanford CS231n course slides.
Machine Learning Mastery: How to Normalize, Center, and Standardize Image Pixels in Keras

Batch Normalization

- Enables stable training
- Reduces the **internal covariate shift**
- Accelerates the training process
- Reduces the dependence of gradients on the scale of the parameters

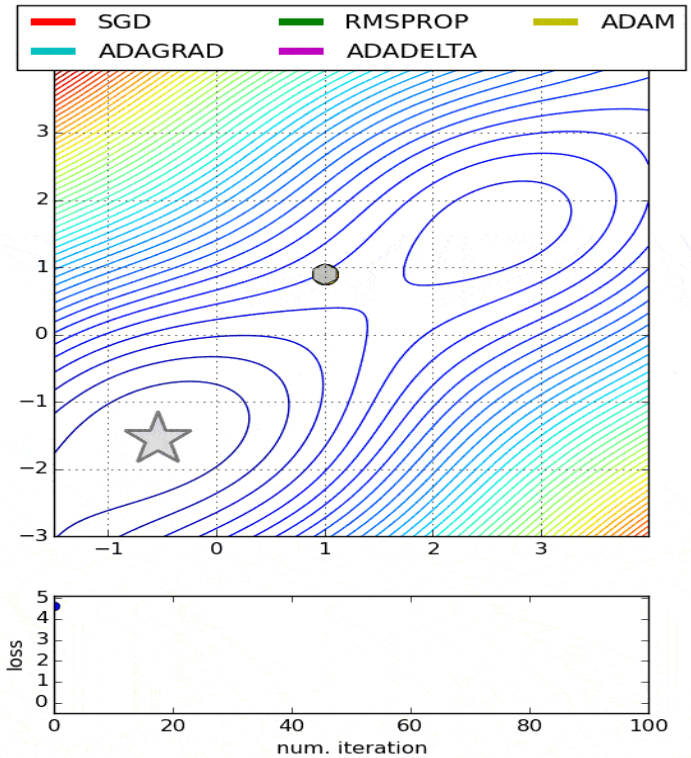




Source: LearnOpenCV: Batch Normalization in Deep Networks. https://learnopencv.com/batch-normalization-in-deep-networks/

Choice of Optimizers

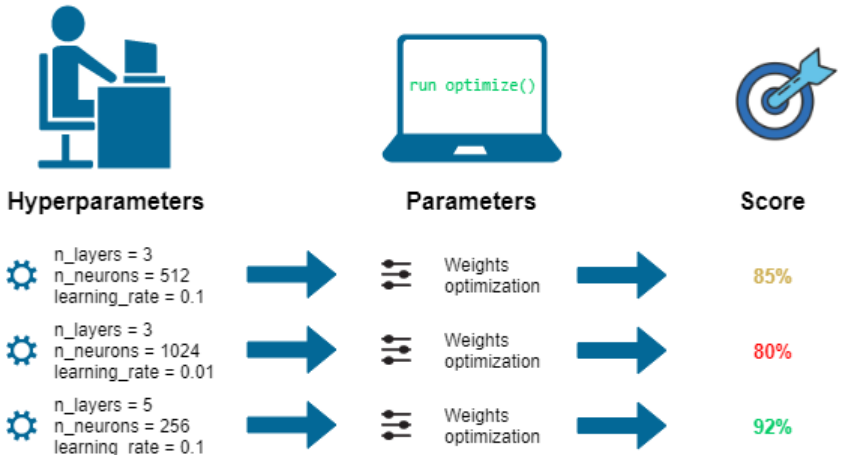
- Choosing right optimizer helps to update the model parameters and reducing the loss in much less effort
- Most DL frameworks supports various optim
  - Stochastic Gradient Descent (SGD)
  - Momentum
  - Nesterov Accelerated Gradient
  - AdaGrad
  - AdaDelta
  - Adam
  - RMSProp



Source: Towards Data Science. Various Optimization Algorithms For Training Neural Network https://towardsdatascience.com/optimizers-for-training-neural-network-59450d71caf6

Tuning Hyperparameters

- Hyperparameters are all parameters which can be arbitrarily set by the user before starting training
- Hyperparameters are like knobs or dials of the network (model)
- An optimization problem: We aim to find the right combinations of their values which can help us to find either the minimum (e.g., loss) or the maximum (e.g., accuracy) of a function
- Many hyperparameters to tune:
  - Learning rate
  - No. of epochs
  - Dropout rate
  - Batch size
  - No. of hidden layers and units
  - Activation function
  - Weight initialization
  - …



Source: KDnuggets: Practical Hyperparameter Optimization. https://www.kdnuggets.com/2020/02/practical-hyperparameter-optimization.html

Deep Learning Frameworks/Packages