Day 7: Convolutional Neural Networks

Summer STEM: Machine Learning

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Outline

Better performance with images

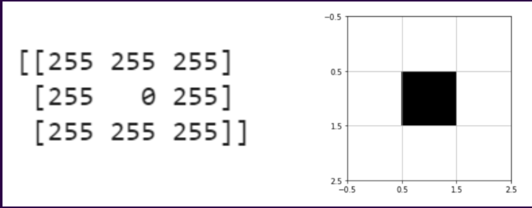
- Encoding locality
- How does an MLP see an image?
- Is this how we see images?

Examples: Lena & Mandrill


Outline

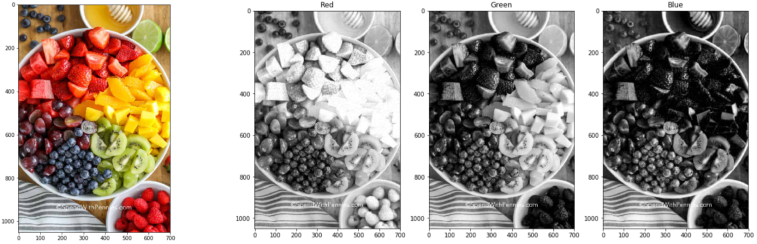
Images in Computer

- 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



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

Outline

Limitations of Fully Connected Network

- In MNIST, we used a fully connected network, in which each neuron in the hidden layer is connected to all 28x28 $=$ 784 pixels
- Higher definition images often contain millions of pixels $\rightarrow$ It is not practical to use fully connected network

Limitations of Fully Connected Network

- In MNIST, we used a fully connected network, in which each neuron in the hidden layer is connected to all 28x28 = 784 pixels
- Higher definition images often contain millions of pixels $\rightarrow$ It is not practical to use fully connected network
- Fully connected network treat each individual pixel as a feature, it does not utilize the positional relationship between pixels

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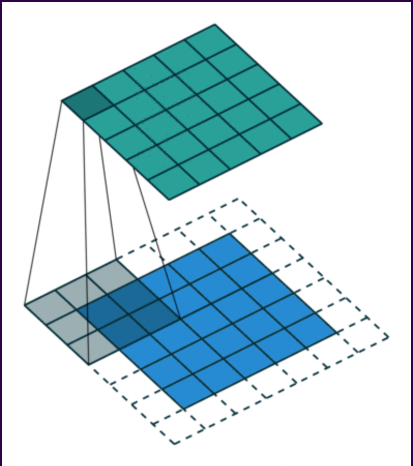
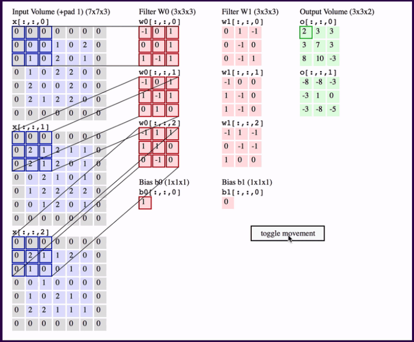
Convolution

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

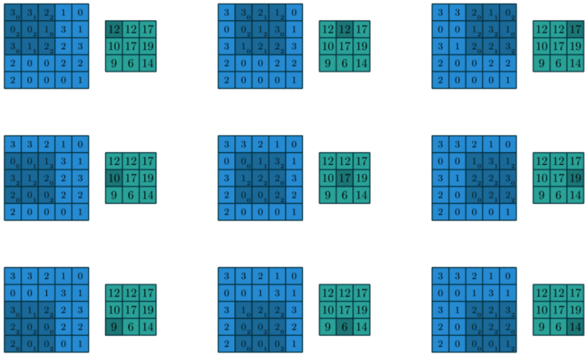
Some Animations, Source: https://towardsdatascience.com



Some Animations, Source: https://cs231n.github.io/convolutional-networks/



Example of a Convolultion



Kernel

$$W = \begin{bmatrix} 0 & 1 & 2 \\ 2 & 2 & 0 \\ 0 & 1 & 2 \end{bmatrix}$$

Why Convolution?

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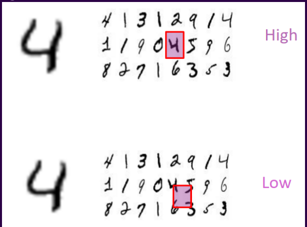
- With convolution, each output pixel depends on only the neighboring pixels in the input
- This allows us to learn the positional relationship between pixels
- Use of different kernels allows us to detect features

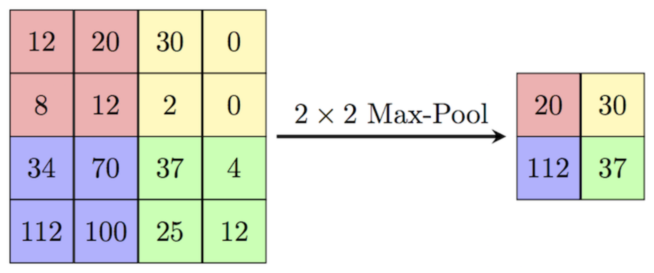


Convolution for Multiple Channels

- 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

Max-Pooling

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

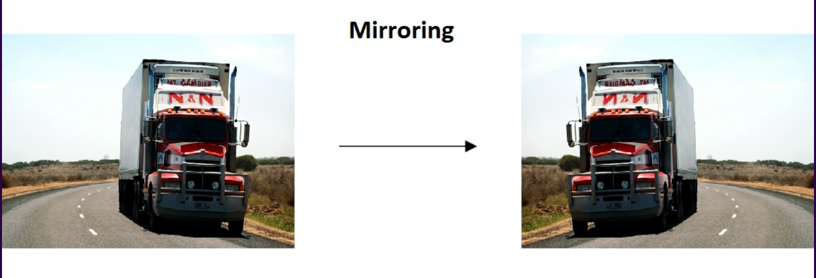


Outline

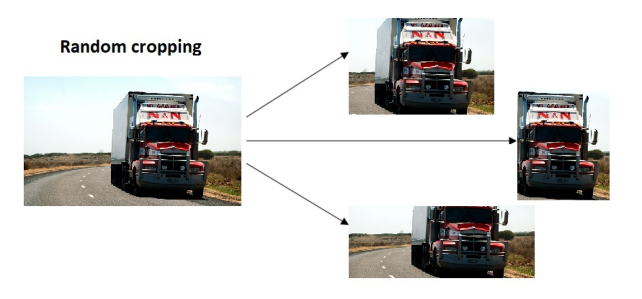
Data augmentation

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

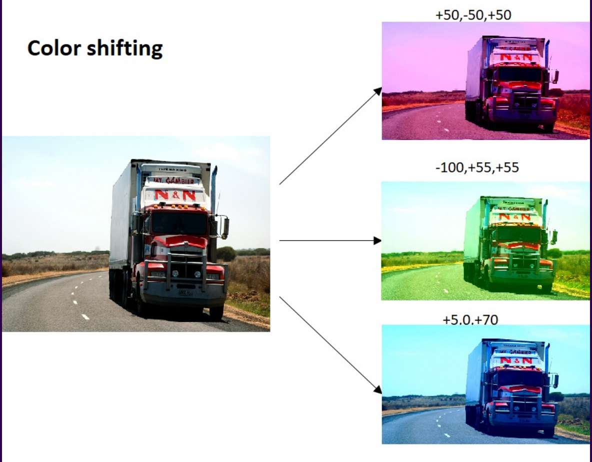
Data augmentation



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-33288db9

Outline

Data Normalization

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

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- Standard deviation : $\sigma \ (= \sqrt{\sigma^2})$
- **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

- **Proof :**

$$\bar{x'} = \frac{1}{N}\sum_{i=1}^{N} x_i'$$
$$= \frac{1}{N}\sum_{i=1}^{N} \frac{x_i - \bar{x}}{\sigma}$$
$$= \frac{1}{N\sigma}(\sum_{i=1}^{N} x_i - \sum_{i=1}^{N} \bar{x})$$

Data Normalization

- **Proof :**

$$
\begin{aligned}
\bar{x'} &= \frac{1}{N}\sum_{i=1}^{N} x'_i \\
&= \frac{1}{N}\sum_{i=1}^{N} \frac{x_i - \bar{x}}{\sigma} \\
&= \frac{1}{N\sigma}\left(\sum_{i=1}^{N} x_i - \sum_{i=1}^{N} \bar{x}\right) \\
&= \frac{1}{N\sigma}(N\bar{x} - N\bar{x}) = 0
\end{aligned}
$$

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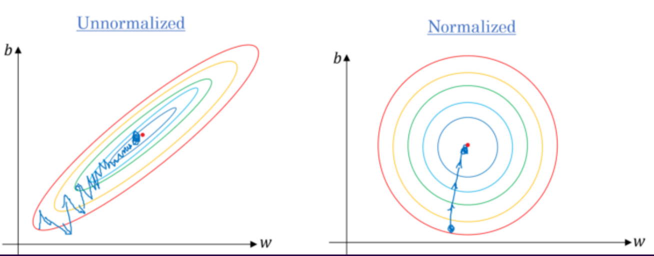
Data Normalization

- **Proof :**

$$
\begin{aligned}
\sigma_{x'}^2 &= \frac{1}{N}\sum_{i=1}^{N}(x_i' - \bar{x'})^2 \\
&= \frac{1}{N}\sum_{i=1}^{N}(x_i' - 0)^2 \\
&= \frac{1}{N}\sum_{i=1}^{N}(\frac{x_i - \bar{x}}{\sigma})^2 \\
&= \frac{1}{\sigma^2}\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2 \\
&= \frac{1}{\sigma^2}\sigma^2 = 1
\end{aligned}
$$

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!

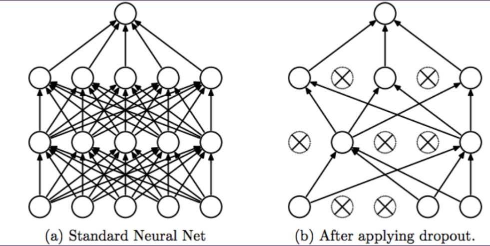
Batch Normalization

```
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'))
```

Outline

Dropout

- Patented by Google
- Randomly disable neurons and their connections between each other.
- Reduce complex co-adaptive relationships between neurons.



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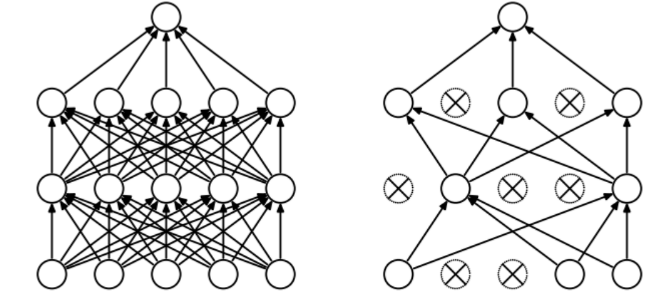
Dropout

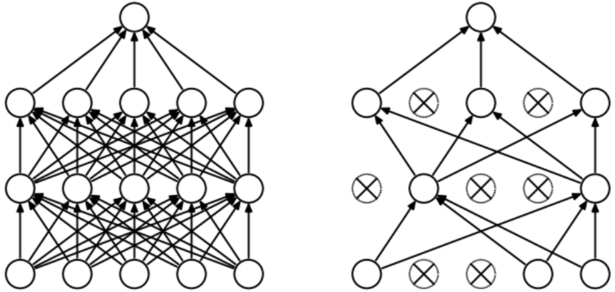
- This is the same as using a neural network with the same amount of layers but less neurons per layer.
- The more neurons the more powerful the neural network is, and the more likely it is to overfit.



(a) Standard Neural Net (b) After applying dropout.

Dropout

- This also means that the model can not rely on any single feature, therefore would need to spread out the weights.



(a) Standard Neural Net (b) After applying dropout.

Outline

Open Source Implementation

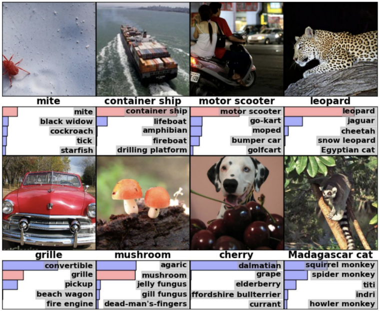
- If you are interested in building on top of a deep learning research paper it is a good idea to first go online and see if there is a nice open source implementation instead of starting from scratch.
- If you are in the field of computer vision, many networks would require an extensive hyperparameter 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

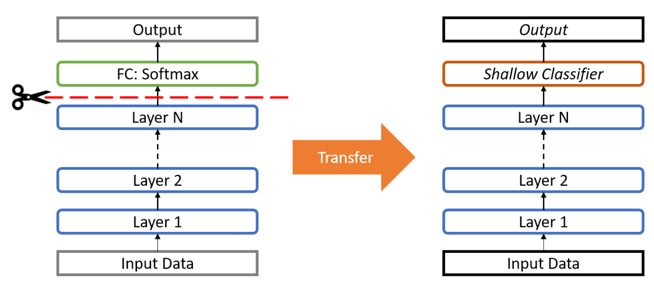
ImageNet Challenge

IMAGENET

- 1,000 object classes (categories).
- Images:
  - 1.2 M train
  - 100k test.



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_transfer_learning_dog_cat.ipynb`