Introduction to Convolutional Neural Networks

Applied Machine Learning

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Topics

- Motivation: Why we need CNN?
- What is the principle of convolution?
- From ANN to CNN
- CNN Architecture

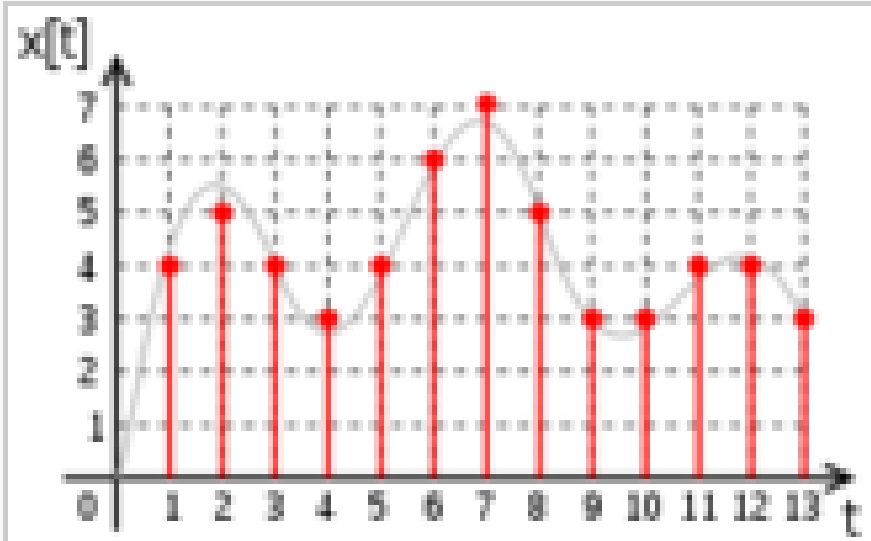
Motivation for CNN

- Suppose we are required to perform image classification on a colour image of 100 x 100 dimensions.
- If we are to implement this brute force using a standard feed forward neural network that has an input, hidden and an output layer, how many model parameters we need for: hidden units (nh) = 1000, output classes = 10 and Softmax output layer
- Input layer = 10k pixels * 3 = 30k, weight matrix for hidden to input layer = 1k * 30k = 30 M and output layer matrix size = 10 * 1000 = 10k
- We can easily see that the parameters blow up if we need to process larger sized images because an image is 2 dimensional and has a depth also if the colour information is to be taken in to account
- One way to handle this is by extracting the features using image processing techniques (pre processing) and presenting a lower dimensional input to the Neural Network. But this requires expert engineered features and hence domain knowledge
- Can we do better by using some properties of images?
- CNNs allow us to substantially reduce the model parameters without needing to perform hand crafted feature engineering

Convolution: From first principles

What is a digital signal?

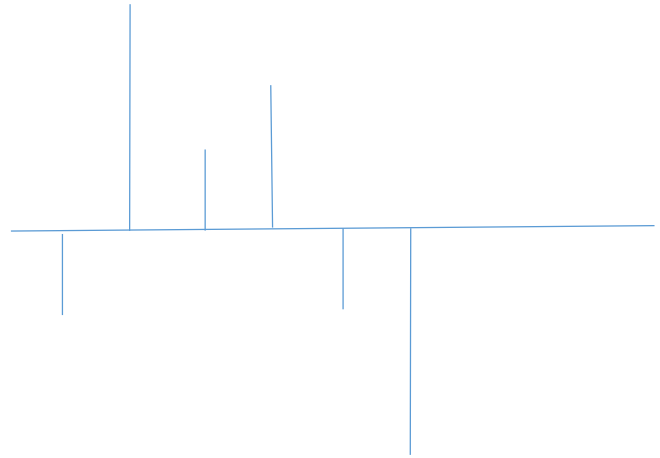
- Refer books on DSP for formal definitions.
- For the purpose of our course and discussions we will use the following working definition: A digital signal is an entity in digital form that carries the information we want to process.
- Examples:
  - An image (gif file)
  - Audio file
  - Text file
  - Facebook posts
  - Tweets



In signal processing, a digital signal is an abstraction that is discrete in time and amplitude, meaning it only exists at certain time instants.

What is a system?

- For the purpose of our class, we consider the system as a function that transforms the input signal.
- A linear system satisfies the properties of:
  - Scaling
  - Superposition
- Shift Invariant Systems: If the input is shifted by a distance k, the output is also shifted exactly by the same distance.
- A linear shift invariant system is both linear as well as shift invariant.
- If a system is linear shift invariant, its output is fully characterized by its impulse response and is determined as the convolution of the input and the impulse response
- Important implications:
  - Impulse Response fully characterizes the system and so we can treat the system as a black box.
  - Inputs can be looked at as scaling factors to the impulse response and so don't play a role in modifying the nature of output except for scaling



Convolution

$Convolution\ in\ 1\ Dimension$:

$$y[n] = \sum_{k=-\infty}^{k=\infty} x[k]h[n-k]$$

$Convolution\ in\ 2\ Dimensions$:

$$y[n_1, n_2] = \sum_{k1=-\infty}^{k1=\infty} \sum_{k2=-\infty}^{k2=\infty} x[k_1, k_2]h[(n_1 - k_1), (n_2 - k_2)]$$

CNNs for applications that involve images

- Why CNNs are more suitable to process images?
- Pixels in an image correlate to each other. However, nearby pixels correlate stronger and distant pixels don’t influence much
  - Local features are important: Local Receptive Fields
- Affine transformations: e.g the class of an image doesn’t change with respect to translation. So we can build a feature detector that can look for a particular feature (e.g an edge) anywhere in the image plane by moving across. A convolutional layer may have several such filters constituting the depth dimension of the layer.

Before we discuss CNNs…

- CNNs operate on images that have a 2d surface and a depth in terms of RGB colours. Hence they are 3 dimensional.
- The standard neural network architecture has a linear input layer structure.
- When we discuss CNN architecture, it helps to decouple in our minds the abstraction CNNs deal with and the practical realization of these principles on a linear layer based neural network architectures.

CNN Architecture – Refer Slides from Andrej Karpathy's course (Stanford)

FNN to CNN: Conceptual Understanding

- Inputs
  - The input layer of FNN is a linear arrangement of input elements. This is typically represented as an input vector.
  - CNNs operate on a 3d input “volume”.
- Hidden Layers of the architecture
  - Neural networks use one or more hidden layers with the units typically performing some non linear transformations (e.g tanh)
  - Convolutional networks use: convolutional layers and pooling layers
    - Local receptive fields and shared weights for a given filter across the complete input
    - Strides
    - Filters arranged depthwise: small size
- Output layer
  - In a traditional NN the output layer (such as Softmax or Logistic) connect to the linear hidden layer in a fully connected pattern
  - CNNs follow a similar pattern where the “volume” represented by the final internal layer is fully connected to the output layer