

Lab 5: Convolution

10/14/2022

Linear Shift Invariant Systems

- *Linear* systems all obey the principles of homogeneity and superposition
 - Linear operators *respect certain relationships between input elements, meaning that those relationships are preserved in the output*
 - $L(a \cdot x) = a \cdot L(x) \rightarrow$ respects/preserves scaling
 - $L(x + y) = L(x) + L(y) \rightarrow$ respects/preserves addition
- *Shift Invariant* systems respect a different relationship between input elements...“shifting”
 - $L(\text{shift}(x)) = \text{shift}(L(x))$
 - What the heck is a shift? Shifts change the position of elements in the input vector
 - $\text{shift}(x[i]) = x[i + n]$ for some fixed value of n
 - Shift with $n = 2$:

$$\text{shift} \begin{pmatrix} x \\ x \\ x \\ x \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \end{pmatrix}$$

LSI Systems as Matrices

- Linear System $\rightarrow$ We can describe the transformation with a matrix
 - First column is output of system in response to first basis/impulse vector
 - Subsequent columns are outputs in response to the other basis vectors, but these inputs are by definition shifted versions of the same vector $\rightarrow$ for LSI systems we only need to test the output to one input.

$$L \left(\begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix} \right) = \begin{pmatrix} k1 \\ k2 \\ 0 \\ 0 \end{pmatrix} \rightarrow M = \begin{pmatrix} k1 & 0 & 0 & 0 \\ k2 & k1 & 0 & 0 \\ 0 & k2 & k1 & 0 \\ 0 & 0 & k2 & k1 \end{pmatrix}$$

LSI Systems as Matrices

- LSI system/convolution matrices also have a nice interpretation from the “rows,” perspective: the output at a given index is the inner product of part of the input with a reversed order copy of the kernel

$$\begin{pmatrix} k1 & 0 & 0 & 0 \\ k2 & k1 & 0 & 0 \\ 0 & k2 & k1 & 0 \\ 0 & 0 & k2 & k1 \\ 0 & 0 & 0 & k2 \end{pmatrix} \begin{pmatrix} S_1 \\ S_2 \\ S_3 \\ S_4 \end{pmatrix} = \begin{pmatrix} out_1 \\ out_2 \\ out_3 \\ out_4 \\ out_5 \end{pmatrix}$$

- So, in the usual way that we use the dot product to be a similarity measure, we can say that the output of an LSI (or equivalently, the convolution of the input signal with the characteristic kernel) at a given position, is a measure of how similar part of the input is to the kernel
- This is the “sliding dot product,” interpretation.

LSI Systems as Matrices

- Terminology:
 - The matrix that represents a LSI system is called a “**convolution matrix**.”
 - The response to the first impulse vector, or the first column of the convolution matrix, is called the “**impulse response**,” or “**kernel**,” of the operator.
 - We will often use the phraseology: “the output of an LSI system is the convolution of the input signal with the kernel.”

Why Bother?

- When there is meaningful structure *between elements of the input signal*, describing the input-output function as an LSI system (or alternatively, describing the output as *the convolution of the input with some fixed kernel*) ensures that same structure is preserved in the output signal.
 - What kinds of signals have the type of structure that convolution respects?
 - Time-series data, images, time-series of images, etc.
- Practical Benefits
 - Reduced degrees of freedom (overfitting/model complexity reduction)

$$M = \begin{pmatrix} k1 & 0 & 0 & 0 \\ k2 & k1 & 0 & 0 \\ 0 & k2 & k1 & 0 \\ 0 & 0 & k2 & k1 \end{pmatrix}$$

If inputs are related by some shift....



Shift Invariant System

Then outputs are related by the same shift



Shift Invariant System

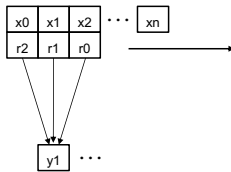


Finite Dimensional Signals: Boundary Conditions

- Recall our definition of shift invariance
 - $\text{shift}(x[i]) = x[i + n]$ for some fixed value of n
 - Or in general for finite LSI systems the definition of convolution is
 - $y[n] = \sum_k x[k]r[n - k]$ What happens when $k > n$?
- For finite dimensional inputs, this definition cannot make sense everywhere...
 - Defining "shift invariance," in these trouble spots $\Leftrightarrow$ deciding on a set of boundary conditions
 - 3 most common are
 - Zero Padding ('same', 'valid', 'all')
 - Circular Boundary Conditions
 - Mirrored Boundary Conditions

Zero Padding: 'full', 'same', and 'valid'

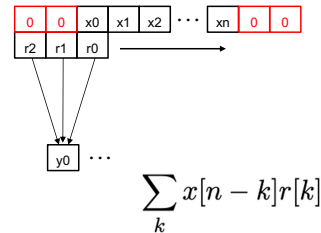
- 'valid' option: only consider the outputs where all terms in definition are known



- Only consider outputs where the kernel is entirely within the signal

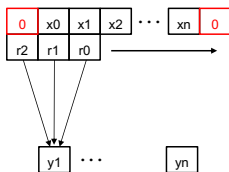
Zero Padding: 'full', 'same', and 'valid'

- 'full' option: use every possible datapoint, assuming the unknown values are zero.



Zero Padding: 'full', 'same', and 'valid'

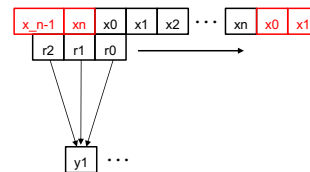
- 'same' option: zero pad on each side by an amount that makes the output size equal to the input size.



- It is often convenient for either theoretical or practical reason for the output to have the same dimensionality as the input.

Circular/Periodic Boundary Conditions

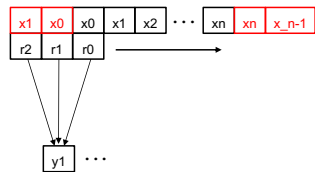
- Rather than assume unknown values are zero, assume values "wrap around"



- Similar to full but with different assumption about missing values

Mirrored Boundary Conditions

- Padded values are the “reflection,” or values near the boundary



- Similar to full but with different assumption about missing values

2-D Extensions

- Everything discussed so far has a direct extension to the two dimensional case:
 - Shift invariance: LSI systems are invariant to shifts in both directions (two dimensional data structures, i.e. images, can be shifted in two directions independently).
 - Padding: zeros surround data structure on both sides
 - Other boundary conditions: can be independently applied to each dimension
 - Visual: a 360 degree panoramic photo might be taken to have circular boundary conditions along one dimension (horizontal), but use zero padding along the other

