

Using the Numpy `fft` Library

With `%pylab` loaded all of Numpy is in the namespace, including the `fft` library. To get to these functions you have to use the prefix `fft`

```
In [1]: # %pylab inline
from numpy import *
from matplotlib.pyplot import *
%matplotlib inline
import sk_dsp_comm.sigsys as ss
# import simple_sa_new as sa_new
import scipy.signal as signal
from IPython.display import Audio, display
from IPython.display import Image, SVG

%config InlineBackend.figure_formats=['svg'] # SVG inline viewing
```

```
In [ ]: # Explore with
# press 'tab' following '.' in 'fft' to see the functions
fft.
```

```
In [3]: x1 = ones(10)
x1
```

```
Out[3]: array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])
```

Timing Test

The `FFT` is very fast even without choosing a power of 2.

```
In [11]: # not a power of 2 length
Nfft = 1000
%timeit X1 = fft.fft(x1,Nfft) # zero pad to 1000 points
#X1
```

5.34 μ s $\pm$ 14.9 ns per loop (mean $\pm$ std. dev. of 7 runs, 100,000 loops each)

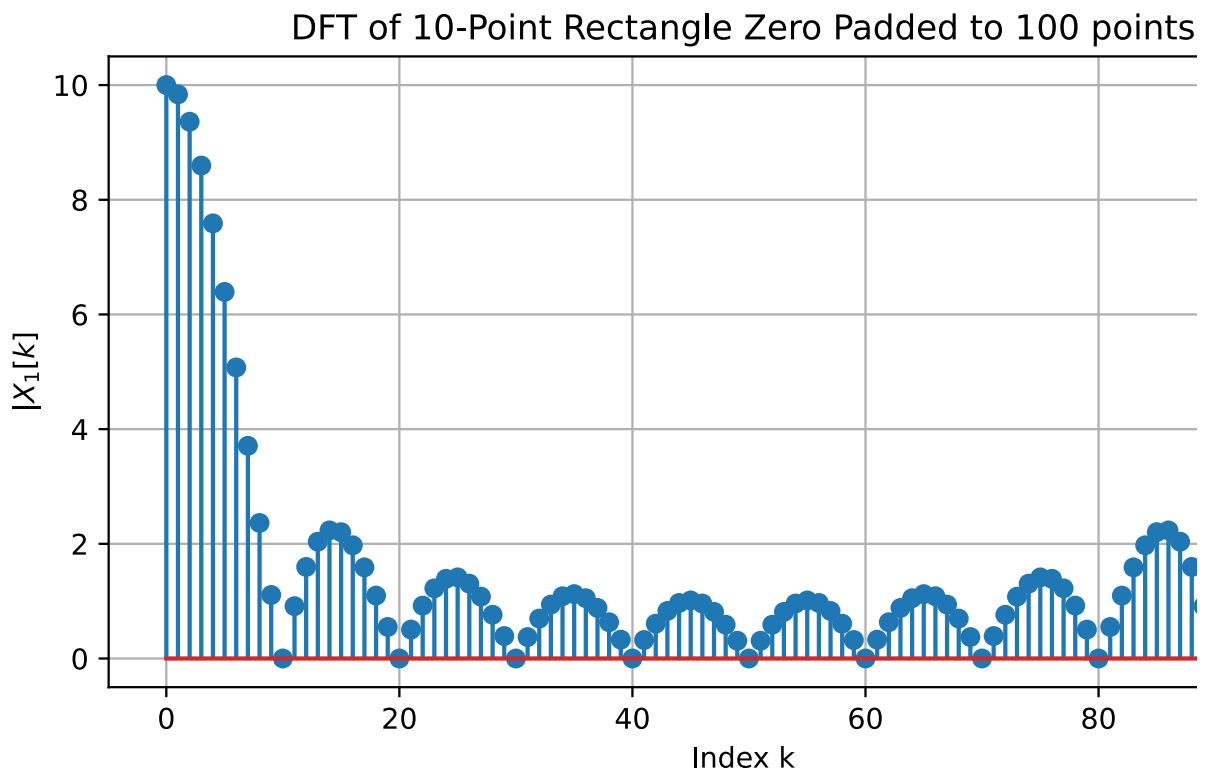
```
In [12]: # choose a power of two length
Nfft = 1024
%timeit X1 = fft.fft(x1,Nfft) # zero pad to 1024
#X1
```

5 μ s $\pm$ 19.4 ns per loop (mean $\pm$ std. dev. of 7 runs, 100,000 loops each)

Zero Padd the DFT (FFT)

Making the DFT act more like the DTFT using zero padding.

```
In [16]: Nfft = 100
X1 = fft.fft(x1,Nfft)
figure(figsize=(8,4))
stem(abs(X1))
title(f'DFT of 10-Point Rectangle Zero Padded to {Nfft} points')
xlabel('Index k')
ylabel(r'$|X_1[k]|$')
grid();
#savefig()
```



DFT and IDFT

Consider some basic DFT/IDFT operations using `fft.fft` as a fast and efficient version of the theoretical DFT and `fft.ifft` as a fast and efficient version of the theoretical IDFT.

```
In [ ]: x3 = [1,2,3,4,5]
X3 = fft.fft(x3)
X3
```

```
Out[ ]: array([15. +0.j          , -2.5+3.4409548j , -2.5+0.81229924j,
               -2.5-0.81229924j, -2.5-3.4409548j ])
```

```
In [ ]: x3p = fft.ifft(X3)
        x3p.real
```

```
Out[ ]: array([1., 2., 3., 4., 5.])
```

- From the above we see that the `ifft` does return the original sequence. We take the real part to rove any small numerical precision errors which introduce small imaginary parts. Since we start a real sequence we should end up with a real sequence.

```
In [9]: Y1 = fft.fft([1,1,2,2])
        Y1
```

```
Out[9]: array([ 6.+0.j, -1.+1.j,  0.+0.j, -1.-1.j])
```

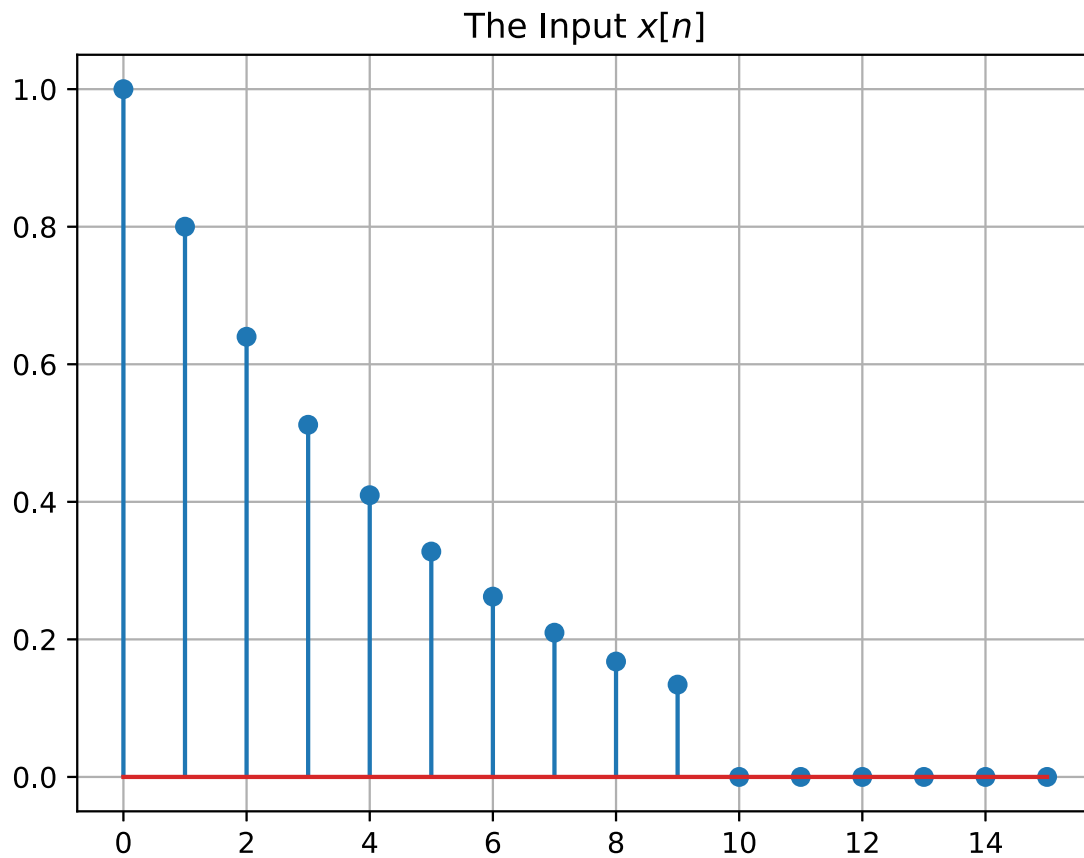
```
In [10]: y1 = fft.ifft(Y1)
         y1.real
```

```
Out[10]: array([1., 1., 2., 2.])
```

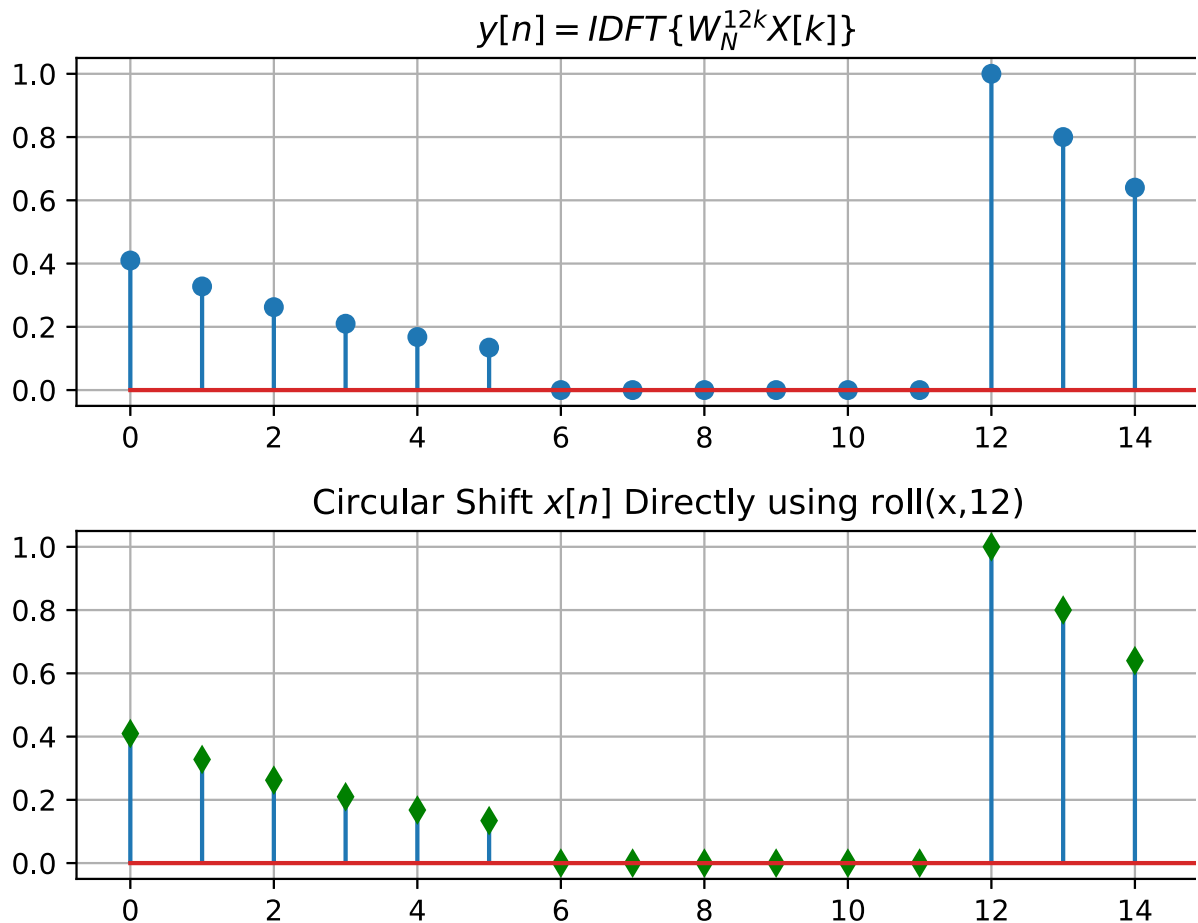
Circular Shift

Consider a basic circular shift in the DFT/IDFT domain and compare it with the `numpy` function `roll`. Define a truncated exponential as the input sequence. Then shift it to the right by 12 samples out of the total length of 16 samples.

```
In [17]: n = arange(16)
         a = 0.8
         x = a**n * ss.direct(n,10)
         stem(n,x)
         title(r'The Input $x[n]$')
         grid();
```



```
In [18]: k = arange(16)
X = fft.fft(x)
Y = X*exp(-1j*2*pi/16*k*12) #
y = fft.ifft(Y).real
subplot(211)
stem(n,y)
title(r'$y[n] = \text{IDFT}\{W_N^{12k}X[k]\}$')
grid();
subplot(212)
stem(n,roll(x,12),markerfmt='gd')
title(r'Circular Shift $x[n]$ Directly using roll(x,12)')
grid();
tight_layout()
```



Quick Circular Shift Example

```
In [19]: n = arange(8)
x = [1,1,1,1,1,0,0,0]
# Shift to left by 1
y = fft.ifft(exp(1j*2*pi*1*n/8)*fft.fft(x)).real
y
```

```
Out[19]: array([1.00000000e+00, 1.00000000e+00, 1.00000000e+00, 1.00000000e+00,
0,
0.00000000e+00, 0.00000000e+00, 5.55111512e-17, 1.00000000e+00,
0])
```

Circular Convolution

Following the notes example 7.2, we circularly convolve $x_1[n]$ and $x_2[n]$ using the DFT/IDFT.

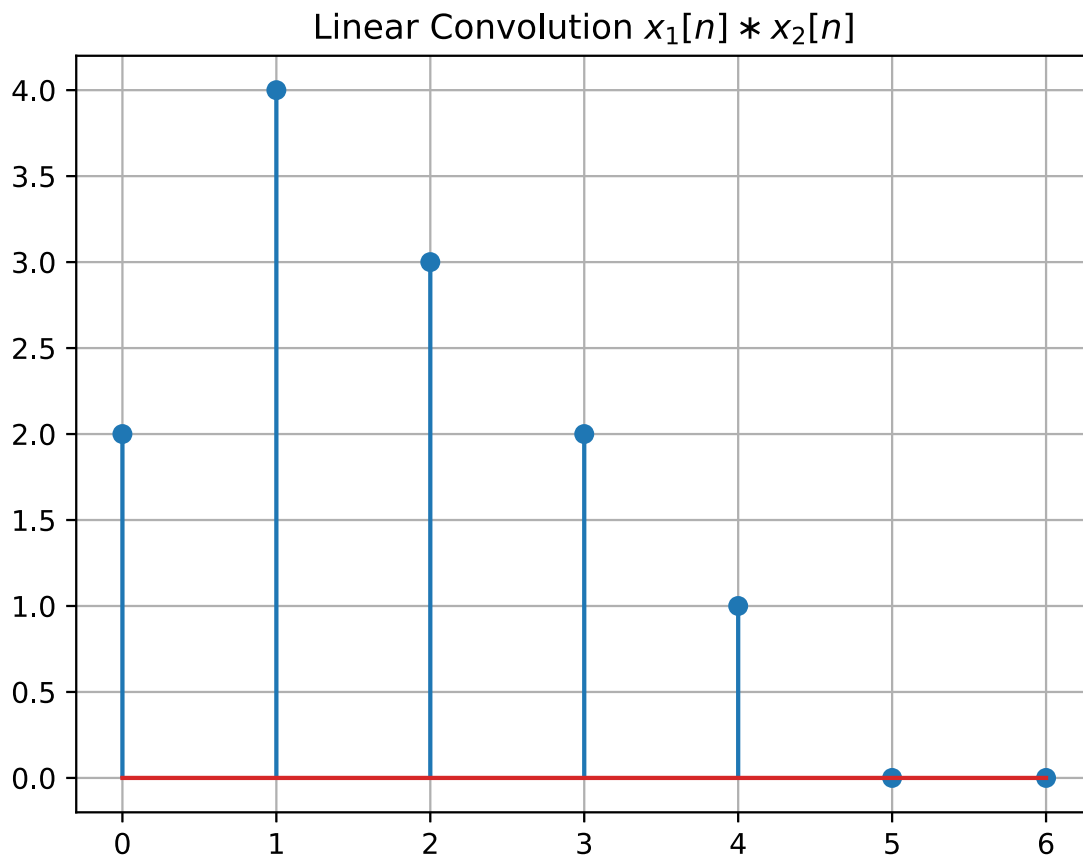
```
In [20]: x1 = [2,2,1,1]
x2 = [1,1,0,0]
```

```
In [21]: X3 = fft.fft(x1)*fft.fft(x2)
x3 = fft.ifft(X3)
x3.real
```

```
Out[21]: array([3., 4., 3., 2.])
```

- Consider the linear convolution of $x_1[n]$ and $x_2[n]$ using the DFT/IDFT. We know that to make circular convolution behave as linear convolution we must zero pad the sequence up to $N = L + P - 1 = 4 + 4 - 1 = 7$. First we compute the linear convolution for reference using the `signal.convolve` function:

```
In [22]: stem(signal.convolve(x1,x2))
title(r'Linear Convolution $x_1[n] \ast x_2[n]$')
grid();
```

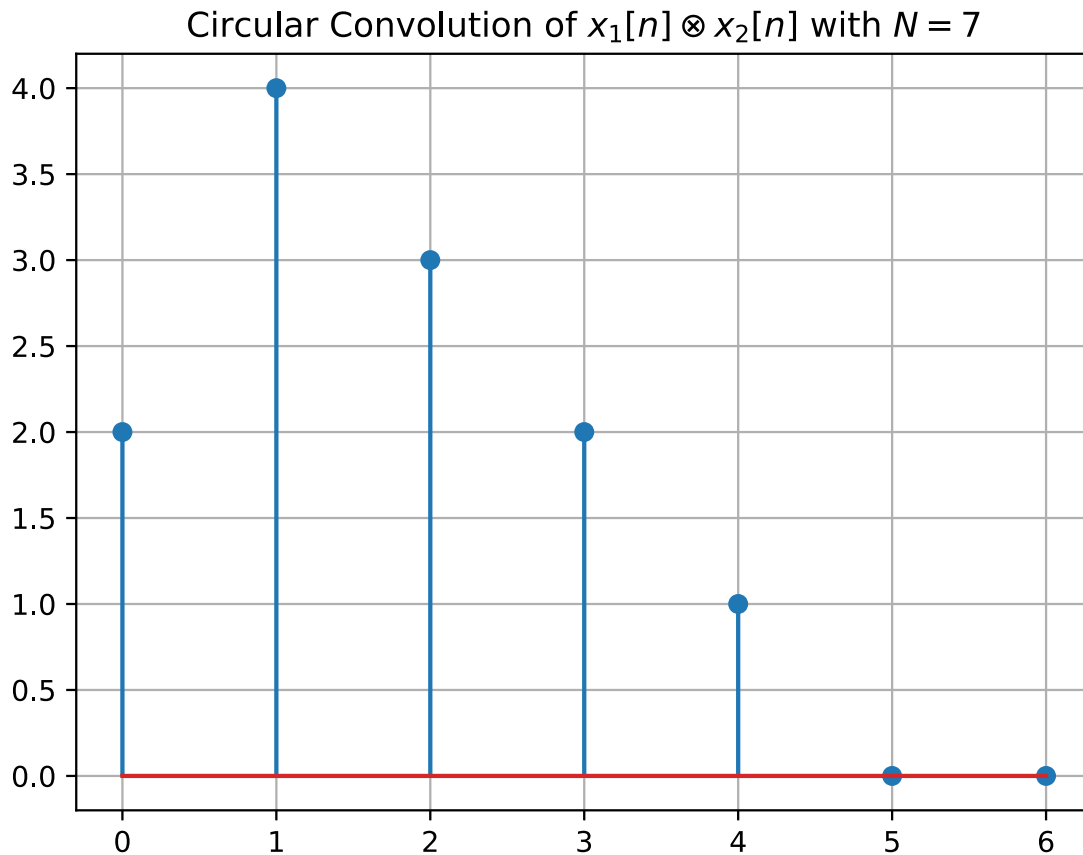


- Now zero pad the circular convolution result and place all the calculations in one line:

```
In [23]: # Verify as a circular convolution
N = 7
x3_circ = fft.ifft(fft.fft(x1,N)*fft.fft(x2,N),N).real
x3_circ
```

```
Out[23]: array([ 2.00000000e+00,  4.00000000e+00,  3.00000000e+00,  2.00000000e+00,
                1.00000000e+00,  2.53765263e-16, -2.53765263e-16])
```

```
In [24]: stem(x3_circ.real)
title(r'Circular Convolution of  $x_1[n] \otimes x_2[n]$  with  $N = 7$ ')
grid();
```



- The results agree; circular convolution can emulate linear convolution!

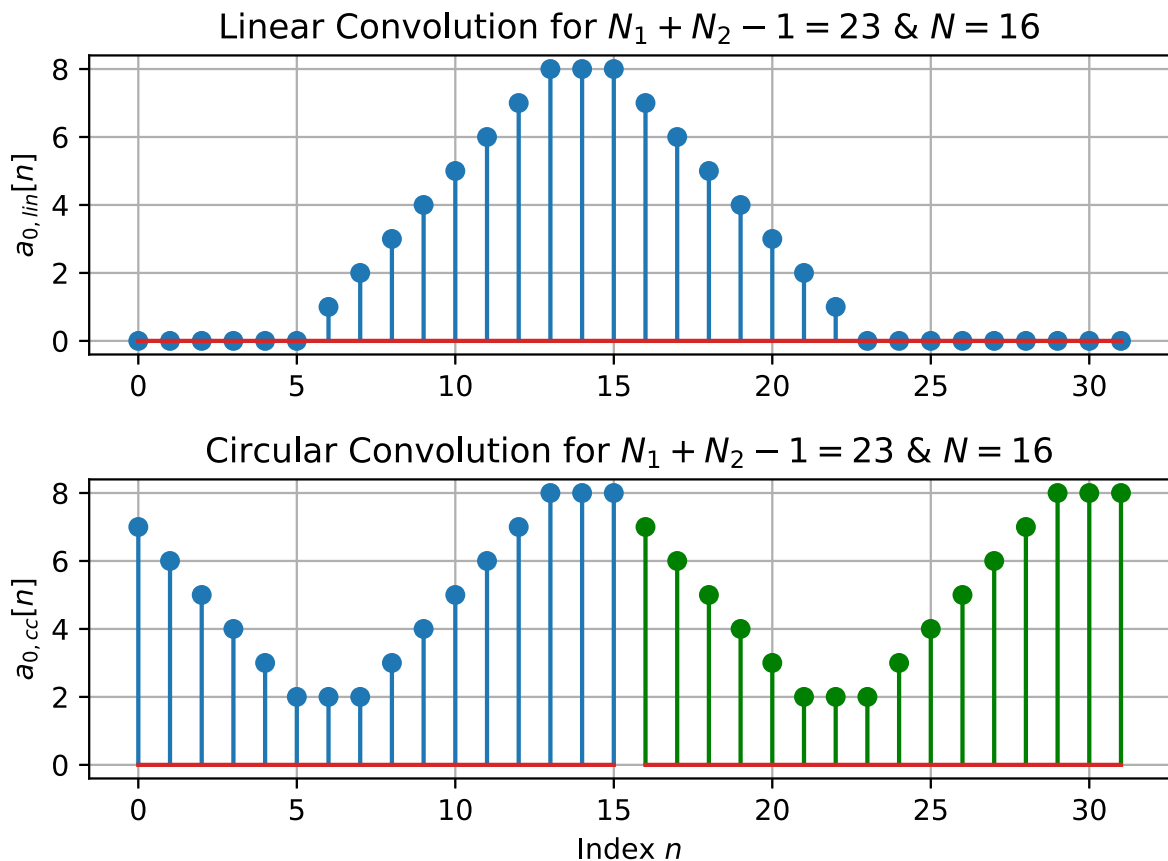
Notes Example 7.4

```
In [51]: # Define the sequences
figure(figsize=(6,4.5))
N = 16 # try 20 and 24 to see need for N >= 23
nN = arange(2*N)
a1 = hstack((ones(10), zeros(len(nN)-10)))
a2 = array([0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1])
# Linear convolution
subplot(211)
a0 = signal.lfilter(a2,1,a1)
stem(nN,a0)
title(f'Linear Convolution for  $N_1+N_2-1=23$  &  $N={N}$ ')
ylabel(r'$a_{\{0,lin\}}[n]$')
grid();
```

```

# Circular convolution using the FFT/IFFT (DFT/IDFT)
# Take real-part since we know convolution is real &
# a very small imaginary part may (will) exist
a0_circ = real(fft.ifft(fft.fft(a1,N)*fft.fft(a2,N)))
subplot(212)
stem(nN[:N],a0_circ)
stem(nN[N:],a0_circ,'g', markerfmt='go')
title(f'Circular Convolution for $N_1+N_2-1=23$ & $N={N}$')
ylabel(r'$a_{0,cc}[n]$')
xlabel(r'Index $n$')
grid();
tight_layout()

```



Overlap and Add Transform Domain Filtering

Consider a long sequence being filter by an FIR filter. The overlap-and-add method simplifies the process by breaking the input $x[n]$ into short subsequences, which are individually zero padded.

```

In [30]: n = arange(60)
x = cos(2*pi*n/20)
h = ones(5)/5

```

```

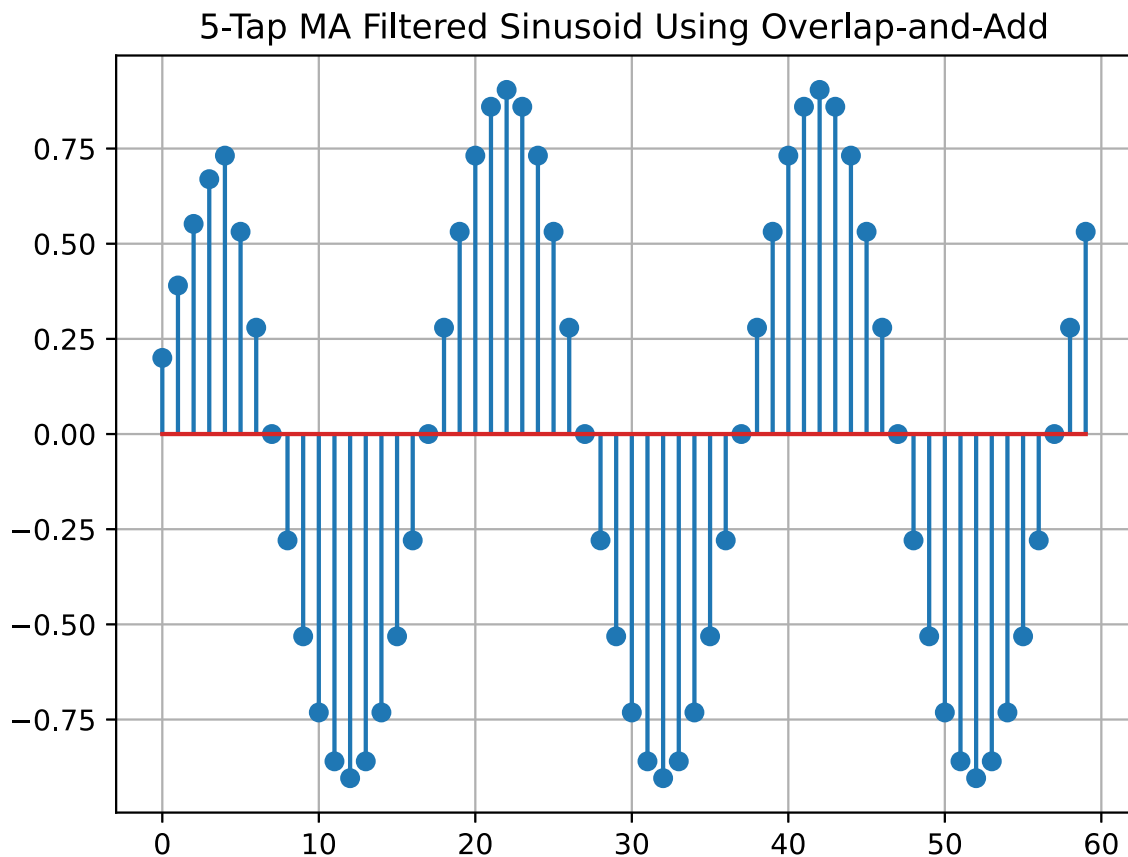
In [33]: # Overlap and Add

```



```
y, y_mat = ss.oa_filter(x,h,20,True)
# Overlap and Save
# y, y_mat = ss.os_filter(x,h,20,True)
```

```
In [32]: stem(n,y)
title(r'5-Tap MA Filtered Sinusoid Using Overlap-and-Add')
grid();
```



```
In [42]: y_mat.shape
# stem(y_mat[3,:])
```

```
Out[42]: (4, 60)
```

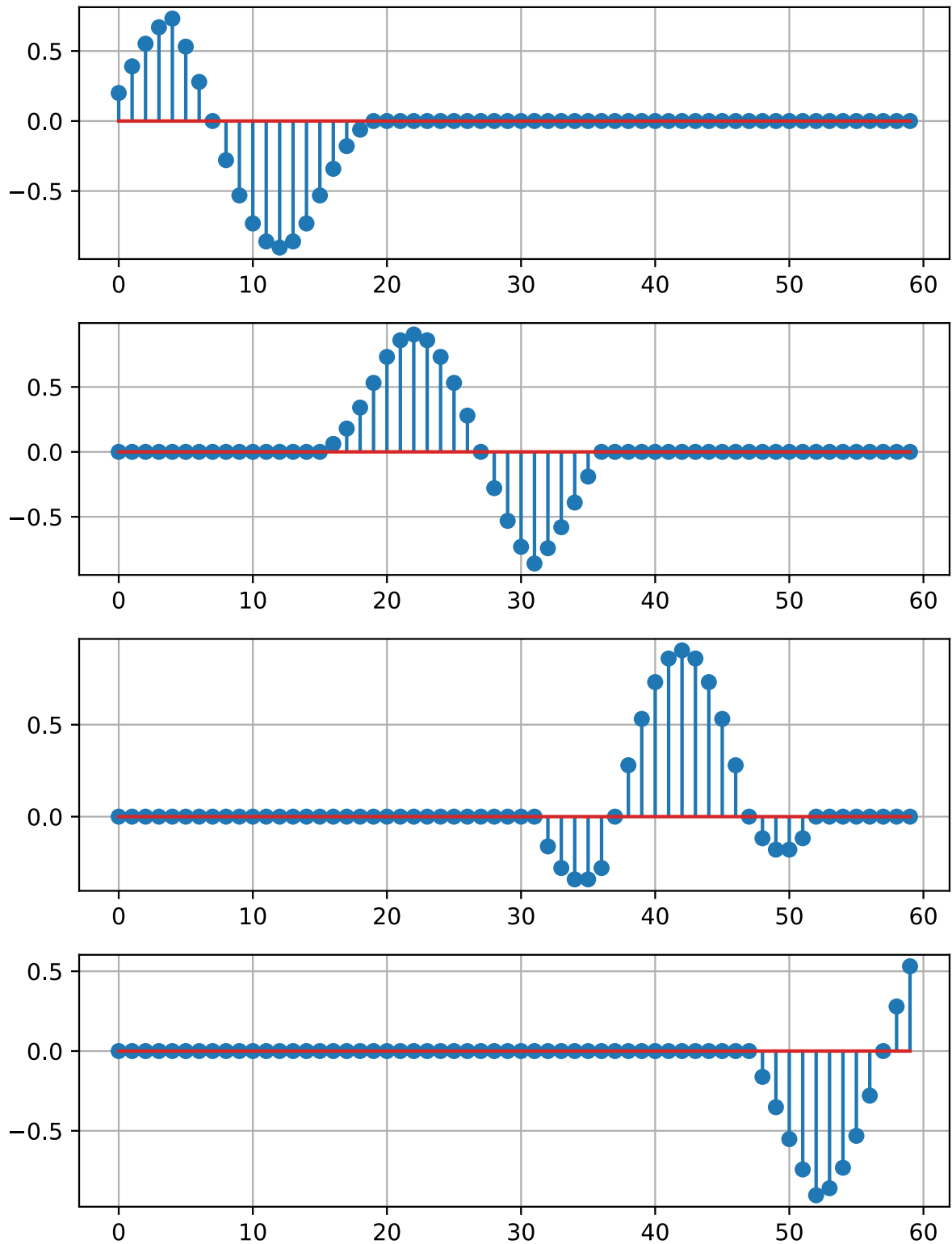
Vizualize How the Overlap and Save Forms the Output

Filter a possibly infinite sequence using the FFT we can use overlap and save or overlap and add techniques. Recall the `fft_filter_bank()` function in Project 2 (Fall 2025) uses the overlap and save method.

```
In [54]: figure(figsize=(6,8))
subplot(4,1,1)
stem(n,y_mat[0,:])
title(r'Decomposition of Output into 4 Overlapping Filtered Subsequenc
```

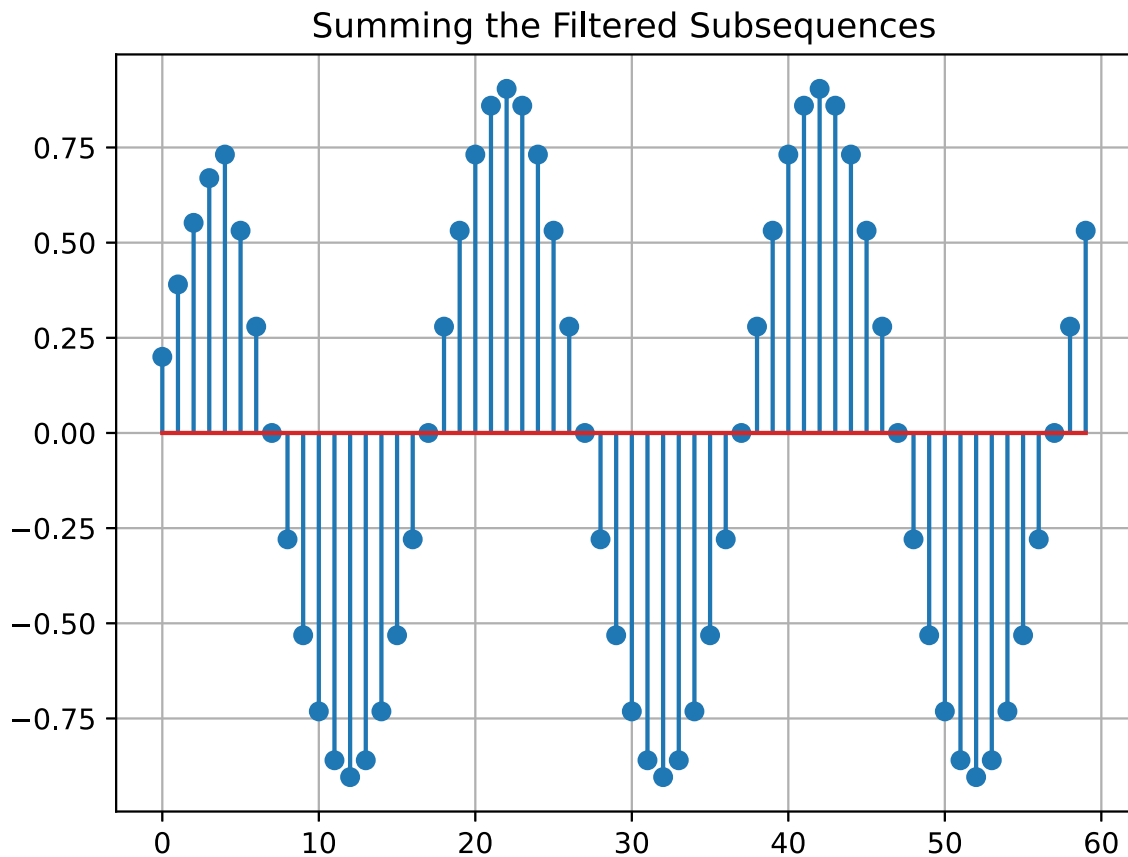
```
grid();  
subplot(4,1,2)  
stem(n,y_mat[1,:])  
grid();  
subplot(4,1,3)  
stem(n,y_mat[2,:])  
grid();  
subplot(4,1,4)  
stem(n,y_mat[3,:])  
grid();  
tight_layout()
```

Decomposition of Output into 4 Overlapping Filtered Subsequence



- The subplots above are the filter outputs from the overlapping of 4 filtered subsequences. If we add each row in the `y_mat` matrix we obtain the overlap-and-add output

```
In [44]: stem(sum(y_mat,0))
         title(r'Summing the Filtered Subsequences')
         grid();
```



FFT-Based FIR Filtering from Scratch

```
In [43]: def fft_os_fir(x,N_fft,b):
         """
         Overlap and Save FIR filtering

         y = fft_os_fir(x,N_fft,b)

         x = real input signal ndarray
         N_fft = FFT half length, i.e. overlap length N
         b = real FIR filter coefficients of length <= N_fft

         y = filtered output (real as input is real)

         Mark Wickert October 2021
         """
         b_zp = zeros(2*N_fft) # zero pad coeff. array
         b_zp[:len(b)] = b # place coeff. at the start
         B_zp = fft.fft(b_zp) # transform filter coeff.
         N_out_buf = len(x)//(N_fft) # Number of output buffers
         y = zeros(N_fft*N_out_buf) # define the output array
         x_state = zeros(N_fft) # state array to hold past inputs
```

```
for k in range(N_out_buf):
    # Fill 2*N_fft array with old and new subarrays
    x_in = hstack((x_state, x[k*N_fft:(k+1)*N_fft]))
    Y_all = B_zp*fft.fft(x_in) # freq. domain filter
    y_all = fft.ifft(Y_all) # back to time domain
    # save the upper index points real-part
    y[k*N_fft:(k+1)*N_fft] = y_all[N_fft:].real
    x_state = x[k*N_fft:(k+1)*N_fft]
return y
```