

## 09.4 four.dft Discrete and fast Fourier transforms

Modern measurement systems primarily construct spectra by sampling an analog electronic signal  $y(t)$  to yield the sample sequence  $(y_n)$  and perform a *discrete Fourier transform*.

### Definition 09 four.6: discrete Fourier transform

The *discrete Fourier transform* (DFT) of a sample sequence  $(y_n)$  of length  $N$  is  $(Y_m)$ , where  $m \in [0, 1, \dots, N - 1]$  and

$$Y_m = \sum_{n=0}^{N-1} y_n e^{-j2\pi mn/N}.$$

The *inverse discrete Fourier transform* (IDFT) reconstructs the original sequence for  $n \in [0, 1, \dots, N - 1]$  and

$$y_n = \frac{1}{N} \sum_{m=0}^{N-1} Y_m e^{j2\pi mn/N}.$$

The DFT  $(Y_m)$  has a frequency interval equal to the sampling frequency  $\omega_s/N$  and the IDFT  $(y_n)$  has time interval equal to the sampling time  $T$ . The first  $N/2 + 1$  DFT  $(Y_m)$  values correspond to frequencies

$$(0, \omega_s/N, 2\omega_s/N, \dots, \omega_s/2)$$

and the remaining  $N/2 - 1$  correspond to frequencies

$$(-\omega_s/2, -(N-1)\omega_s/N, \dots, -\omega_s/N).$$

In practice, the definitions of the DFT and IDFT are not the most efficient methods of computation. A clever algorithm called the *fast Fourier transform* (FFT) computes the DFT much more efficiently. Although it is a good exercise to roll our own FFT, in this lecture we will use `scipy`'s built-in FFT algorithm, loaded with the following command.

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<sup>1</sup>Python code in this section was generated from a Jupyter notebook named `discrete_fourier_transform.ipynb` with a python3 kernel.

```
from scipy import fft
```

Now, given a time series array  $y$  representing  $(y_i)$ , the DFT (using the FFT algorithm) can be computed with the following command.

```
fft(y)
```

In the following example, we will apply this method of computing the DFT.

### Example 09.4 four.dft-1

re: FFT  
of a  
sawtooth  
signal

We would like to compute the DFT of a sample sequence  $(y_n)$  generated by sampling a spaced-out sawtooth. Let's first generate the sample sequence and plot it.

In addition to `scipy`, let's import `matplotlib` for figures and `numpy` for numerical computation.

```
import matplotlib.pyplot as plt  
import numpy as np
```

We define several "control" quantities for the spaced-sawtooth signal.

```
f_signal = 48 # frequency of the signal  
spaces = 1 # spaces between sawteeth  
n_periods = 10 # number of signal periods  
n_samples_sawtooth = 10 # samples/sawtooth
```

These quantities imply several "derived" quantities that follow.

```
••• n_samples_period = n_samples_sawtooth*(1+spaces)  
••• n_samples = n_periods*n_samples_period
```

```

T_signal = 1.0/f_signal # period of signal
t_a = np.linspace(0,n_periods*T_signal,n_samples)
dt = n_periods*T_signal/(n_samples-1) # sample time
f_sample = 1./dt # sample frequency

```

We want an interval of ramp followed by an interval of “space” (zeros). The following method of generating the sampled signal  $y$  helps us avoid *leakage*, which we’ll describe at the end of the example.

```

arr_zeros = np.zeros(n_samples_sawtooth) # frac of period
arr_ramp = np.arange(n_samples_sawtooth) # frac of period
y = [] # initialize time sequence
for i in range(n_periods):
    y = np.append(y,arr_ramp) # ramp
    for j in range(spaces):
        y = np.append(y,arr_zeros) # space

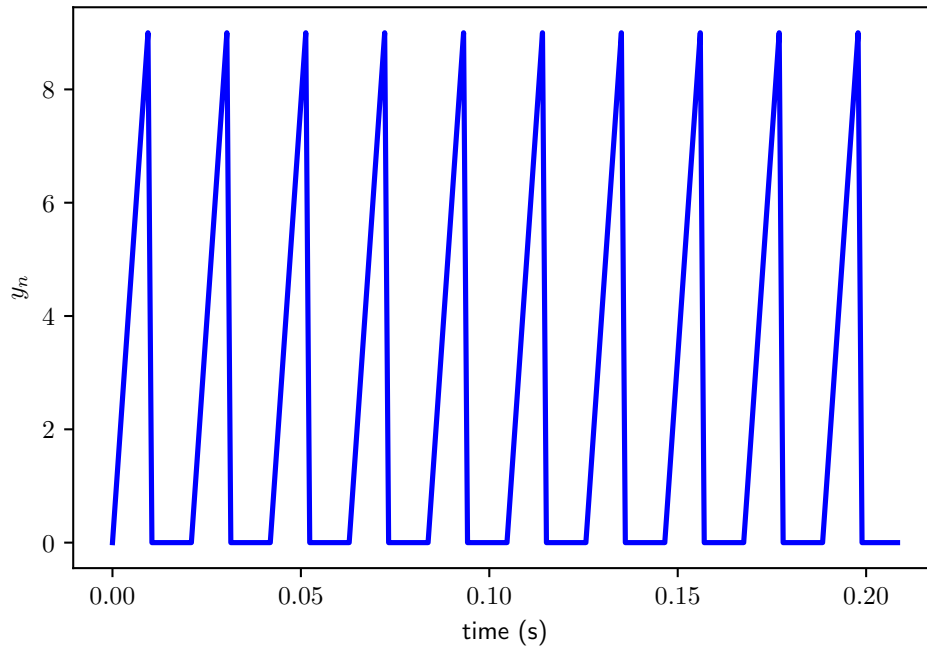
```

We plot the result in [Fig. dft.1](#), generated by the following code.

```

fig, ax = plt.subplots()
plt.plot(t_a,y,'b-',linewidth=2)
plt.xlabel('time (s)')
plt.ylabel('$y_n$')
plt.show()

```



**Figure dft.1:** the sawtooth signal in the time-domain.

Now we have a nice time sequence on which we can perform our DFT. It's easy enough to compute the FFT.

```
Y = fft(y)/n_samples # FFT with proper normalization
```

Recall that the latter values correspond to negative frequencies. In order to plot it, we want to rearrange our  $Y$  array such that the elements corresponding to negative frequencies are first. It's a bit annoying, but *c'est la vie*.

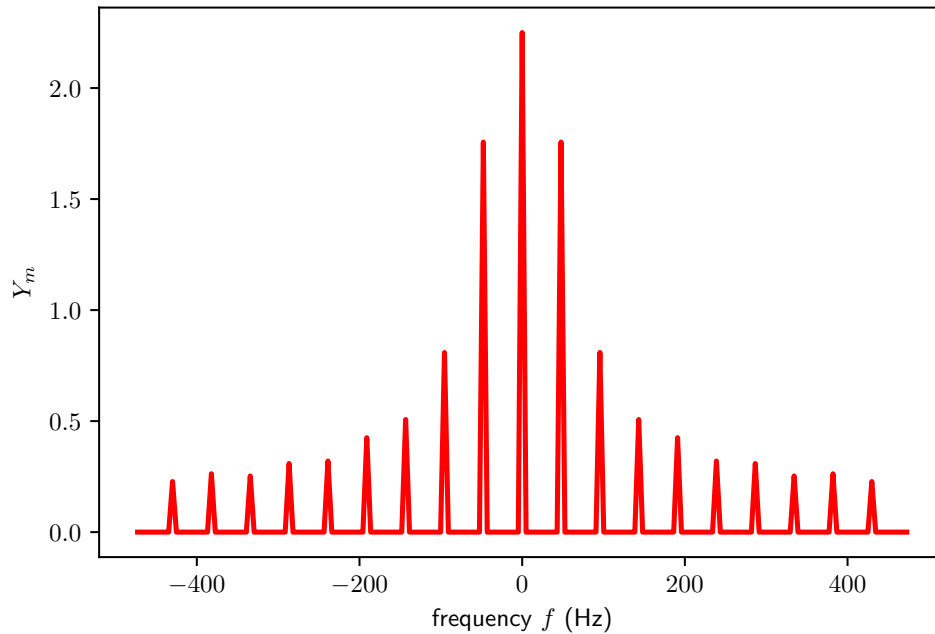
```
Y_positive_zero = Y[range(int(n_samples/2))]
Y_negative = np.flip(
    np.delete(Y_positive_zero,0),0
)
Y_total = np.append(Y_negative,Y_positive_zero)
```

• Now all we need is a corresponding frequency array.

```
freq_total = np.arange(  
    -n_samples/2+1,n_samples/2  
) * f_sample/n_samples
```

The plot, created with the following code, is shown in [Fig. dft.2](#).

```
fig, ax = plt.subplots()  
plt.plot(freq_total, abs(Y_total), 'r-', linewidth=2)  
plt.xlabel('frequency $f$ (Hz)')  
plt.ylabel('$Y_m$')  
plt.show()
```



• **Figure dft.2:** the DFT spectrum of the sawtooth function.

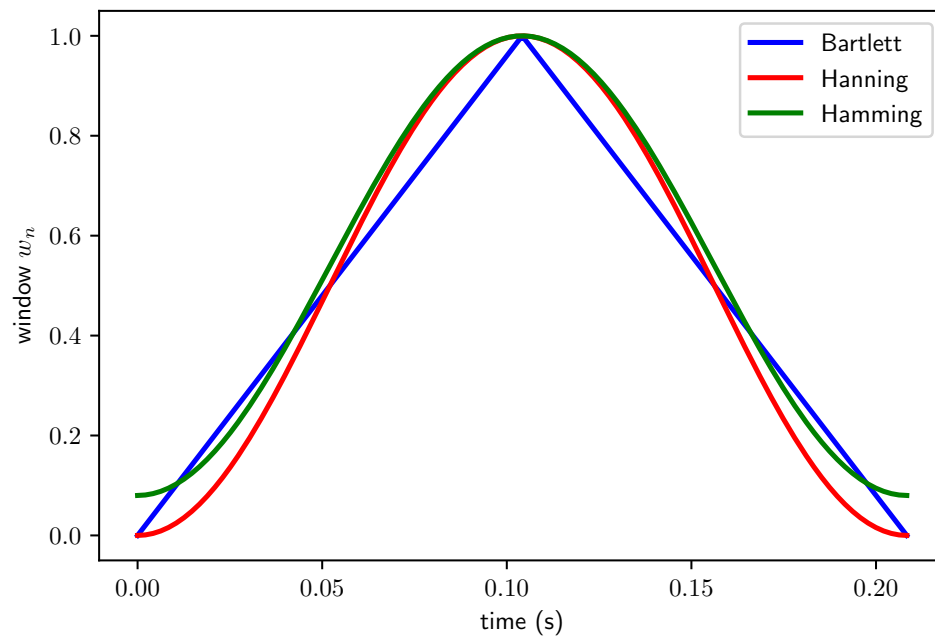
## Leakage

The DFT assumes the sequence  $(y_n)$  is periodic with period  $N$ . An implication of this is that if any periodic components have period  $N_{\text{short}} < N$ , unless  $N$  is divisible by  $N_{\text{short}}$ , spurious components will appear in  $(Y_n)$ . Avoiding leakage is difficult, in practice. Instead, typically we use a *window function* to mitigate its effects. Effectively, windowing functions—such as the *Bartlett*, *Hanning*, and *Hamming windows*—multiply  $(y_n)$  by a function that tapers to zero near the edges of the sample sequence. *Numpy* has several window functions such as `bartlett()`, `hanning()`, and `hamming()`.

Let's plot the windows to get a feel for them – see [Fig. dft.3](#).

```
bartlett_window = np.bartlett(n_samples)
hanning_window = np.hanning(n_samples)
hamming_window = np.hamming(n_samples)

fig, ax = plt.subplots()
plt.plot(t_a, bartlett_window,
         'b-', label='Bartlett', linewidth=2)
plt.plot(t_a, hanning_window,
         'r-', label='Hanning', linewidth=2)
plt.plot(t_a, hamming_window,
         'g-', label='Hamming', linewidth=2)
plt.xlabel('time (s)')
plt.ylabel('window $w_n$')
plt.legend()
plt.show()
```



**Figure dft.3:** three window functions to minimize leakage.