Chapter: Interpreting DFT Output and Understanding **Fundamental Frequency**

Chapter Objective

To clearly understand:

- What each DFT/FFT output value means
- · How to calculate and interpret frequency bins
- What "fundamental frequency" is and why it matters
- How sampling rate and FFT size affect frequency resolution
- · How to read FFT plots with confidence

1. What Does the DFT Actually Do?

The Discrete Fourier Transform (DFT) takes a time-domain signal and decomposes it into a set of **sinusoids** of different frequencies, amplitudes, and phases.

The DFT is defined as:

$$X[k] = \sum_{n=0}^{N-1} x[n] \cdot e^{-j2\pi kn/N}$$

Where:

- x[n]: input signal (time domain)
- X[k]: output spectrum (frequency domain)
- N: number of samples
- k: index of the DFT bin Each X[k] tells you how much of frequency f_k is present in the original signal.

♦ 2. Frequency of Each Bin — The Key Formula

To map a DFT bin k to its real-world frequency:

$$f_k = rac{k}{N} \cdot f_s$$

Where:

- f_k : frequency represented by bin k
- f_s : sampling rate (Hz)
- N: number of samples (FFT size) This tells us that:
- X[0] = DC (0 Hz)
- X[1] = fundamental frequency
- ullet X[k] = contains the strength (amplitude & phase) of f_k

3. What Is the Fundamental Frequency?

The **fundamental frequency** is the smallest frequency that your DFT can detect — it's the spacing between each frequency bin:

$$f_{ ext{fundamental}} = rac{f_s}{N}$$

It sets the frequency resolution of your FFT.

Example:

If:

- $f_s = 800 \, \mathrm{Hz}$
- N = 8

Then:

- $f_{
 m fundamental} = rac{800}{8} = \boxed{100 \ {
 m Hz}}$
- Bin k=1 represents 100 Hz
- Bin $k=2 \rightarrow$ 200 Hz, and so on.

This means: You can't detect anything in between these bins! If your signal has a frequency at 125 Hz, it won't appear clearly unless you increase N.

4. Interpreting DFT Output: Magnitude and Phase

Each X[k] is a **complex number**:

$$X[k] = \operatorname{Re}(X[k]) + j \cdot \operatorname{Im}(X[k])$$

From this you can derive:

• Amplitude (strength of that frequency):

$$|X[k]| = \sqrt{\mathrm{Re}^2 + \mathrm{Im}^2}$$

• Phase (angle/offset of that frequency):

$$\angle X[k] = an^{-1} \left(rac{ ext{Im}}{ ext{Re}}
ight)$$

Use these to:

- Visualize the spectrum
- Reconstruct or modify specific frequency components

 \bigcirc 5. Symmetry of DFT for Real Signals If your input x[n] is real (not complex), then:

$$X[N-k] = \overline{X[k]}$$
 (complex conjugate)

This means:

- You only need to look at the first N/2+1 bins
- The second half of the spectrum mirrors the first
 That's why NumPy's np.fft.rfft() (real FFT) gives only the meaningful part.

6. How to Read FFT Plots import numpy as np import matplotlib.pyplot as plt fs = 800

```
N = 8
t = np.arange(N) / fs
x = np.cos(2 * np.pi * 100 * t) # Cosine at 100 Hz
X = np.fft.fft(x)
freqs = np.fft.fftfreq(N, d=1/fs)
plt.stem(freqs, np.abs(X), use_line_collection=True)
plt.title("DFT Magnitude Spectrum")
plt.xlabel("Frequency (Hz)")
plt.ylabel("Amplitude")
plt.grid(True)
plt.show()

Interpreting the Plot
```

Bin k	Frequency f_k	Meaning
0	0 Hz (DC)	Average value (bias)
1	100 Hz	Main peak — cosine frequency
2	200 Hz	No content here
4	400 Hz (Nyquist)	Half the sampling rate
5–7	Mirror of bins 1–3	Symmetric, usually ignored for real signals
Quick Practice Example		
Given:		

- $\bullet \ f_s=1000\ \mathrm{Hz}$
- N = 500

Then:

- ullet Fundamental frequency $f_{
 m fund}=1000/500=2$ Hz
- $\bullet~$ Bin k=100 = $2\times100=200~{\rm Hz}$
- You can only resolve multiples of 2 Hz

Key Takeaways

Concept	Key Point	
DFT output $X[k]$	Complex value for frequency f_k	
Frequency per bin	$f_k=rac{k}{N}f_s$	
Fundamental frequency	Smallest detectable frequency = f_s/N	
FFT resolution	Increase N for finer resolution	
Real signal DFT	Symmetric — use first $N/2+1$ bins	
FFT plots	Show magnitude (amplitude) of each frequency	

What's Next?

In the next section, we'll:

- Apply these fundamentals to **real noisy signals**
- See how **FIR filters** change the spectrum
- Compare before/after FFT plots