ELEC 221 Lecture 13 The fast Fourier transform

Thursday 20 October 2022

Announcements

- Assignment 4 due next Wednesday
- Quizzes resume on Tuesday
- Tuesday's lecture will be a hands-on (instructions for what to bring will be posted on Piazza)

Last time

We introduced the discrete-time Fourier transform (DTFT):

Inverse DTFT (synthesis equation):

$$x[n] = \frac{1}{2\pi} \int_{za} x(e^{j\omega}) e^{j\omega n} d\omega$$

DTFT (analysis equation):

$$X(e^{i\omega}) = \sum_{n=-\infty}^{\infty} x(n) e^{-i\omega n}$$

Last time

There is a convolution property just like in CT:

$$y[n] = h[n] * \times [n]$$

 $Y(e^{j\omega}) = H(e^{j\omega}) \times (e^{j\omega})$

Same consequences for the impulse response in DT:

$$H(e^{jw}) = \sum_{n=-\infty}^{\infty} h(n) e^{-jwn}$$

$$h[n] = \frac{1}{2\pi} \int_{2\pi} H(e^{jw}) e^{jwn} dw$$

Last time

We looked at some of its key properties.

It is periodic:

$$X(e^{j(\omega+2\pi)})=X(e^{j\omega})$$

There are some convergence criteria:

$$\sum_{n=-\infty}^{\infty} |x[n]| < \infty \qquad \sum_{n=-\infty}^{\infty} |x[n]|^2 < \infty$$

Oppenheim 5.9.

Suppose x[n] is a real signal with spectrum $X(e^{j\omega})$ and we know the following about it:

- 1. x[n] = 0, n > 0
- 2. x[0] > 0
- 3. $\operatorname{Im}(X(e^{j\omega})) = \sin \omega \sin 2\omega$
- 4. $\frac{1}{2\pi} \int_{2\pi} |X(e^{j\omega})|^2 d\omega = 3$

What is x[n]?

Even
$$(x(n)) \leftrightarrow Re(x(e^{ju}))$$

- 1. x[n] = 0, n > 0
- 2. x[0] > 0
- 3. $\operatorname{Im}(X(e^{j\omega})) = \sin \omega \sin 2\omega$
- 4. $\frac{1}{2\pi} \int_{2\pi} |X(e^{j\omega})|^2 d\omega = 3$

Given a real signal x[n], last class we saw that

$$Odd(x[n]) \longleftrightarrow j Im(x(e^{j\omega_j}))$$

We can find the odd part of x[n] by taking the inverse DTFT.

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$$F(Odd(x(n))) = j \cdot Im(X(e^{jw}))$$
$$= F^{-1}(j \cdot Im(X(e^{jw})))$$

$$Odd (x[n]) = F^{-1}(j \cdot Im(x(e^{j\omega}l)))$$

$$= F^{-1}(j \cdot im\omega - j \cdot sin \cdot 2\omega)$$

$$= F^{-1}(\underbrace{e^{j\omega} - e^{-j\omega}}_{2} - (e^{-2j\omega} - e^{-2j\omega}))$$

S[n+1] & ejw.1

€[n-2] ← e-400

 $= F^{-1} \left(\frac{e^{3\omega} - e^{-3\omega}}{2} - \left(e^{-\frac{23\omega}{2}} - e^{-\frac{23\omega}{2}} \right) \right)$ = \frac{1}{2} \Bigg[F^{-1} \left(e^{j\infty} \right) - F^{-1} \left(e^{-2j\infty} \right) + F(e^{-2j\infty} \right) $x[n-n_0] \leftrightarrow e^{\int u \, dx} \, \chi(e^{iu})$ $X(e^{j\omega}) = \sum_{n=0}^{\infty} \delta[n] e^{-j\omega h} = y$

 $Odd(x[n]) = \frac{1}{2} \left[S[n+i] - S[n-i] - S[n-2] \right]$



$$\begin{cases} 1. & x[n] = 0, \quad n > 0 \\ 2. & x[0] > 0 \end{cases}$$

$$\checkmark 3. & \text{Im}(X(e^{j\omega})) = \sin \omega - \sin 2\omega$$

$$4. & \frac{1}{2\pi} \int_{2\pi} |X(e^{j\omega})|^2 d\omega = 3$$

$$Odd(x[n]) = \frac{1}{2} (\delta[n+1] - \delta[n-1] - \delta[n+2] + \delta[n-2])$$

Know that

$$Odd(x[n]) = \frac{x[n] - x[-n]}{2}$$

Allows us to determine that
$$x[n] = 2 \cdot Odd(x[n]) + x[-n]$$

$$= 2 \cdot Odd(x[n]) \quad n < a$$

1.
$$x[n] = 0, \quad n > 0$$

2.
$$x[0] > 0$$

3.
$$\operatorname{Im}(X(e^{j\omega})) = \sin \omega - \sin 2\omega$$

4.
$$\frac{1}{2\pi} \int_{2\pi} |X(e^{j\omega})|^2 d\omega = 3$$

So,

$$X[n] = S[n+1] - S[n+2] + S[n-2] n < 0$$

 $= S[n+1] - S[n+2] n < 0$

1.
$$x[n] = 0, \quad n > 0$$

2. $x[0] > 0$
3. $Im(X(e^{j\omega})) = \sin \omega - \sin 2\omega$
4. $\frac{1}{2\pi} \int_{2\pi} |X(e^{j\omega})|^2 d\omega = 3$

We have

$$\chi[n] = \begin{cases} 0 & n > 0 \\ \frac{??}{??} > 0 & n = 0 \\ \delta[n+1] - \delta[n+2] & n < 0 \end{cases}$$

1.
$$x[n] = 0, n > 0$$

- 2. x[0] > 0
- 3. $\operatorname{Im}(X(e^{j\omega})) = \sin \omega \sin 2\omega$
- 4. $\frac{1}{2\pi} \int_{2\pi} |X(e^{j\omega})|^2 d\omega = 3$

Leverage Parseval's relation:

$$\frac{1}{2\pi} \int_{2\pi} |x(e^{jv})|^2 dw = \sum_{n=-\infty}^{\infty} |x(n)|^2 = 3$$

1.
$$x[n] = 0, \quad n > 0$$

2. $x[0] > 0$

3.
$$Im(X(e^{j\omega})) = \sin \omega - \sin 2\omega$$

4.
$$\frac{1}{2\pi} \int_{2\pi} |X(e^{j\omega})|^2 d\omega = 3$$

$$x[n] = \begin{cases} 0 & n > 0 \\ ?? > 0 & n = 0 \\ \delta[n+1] - \delta[n+2] & n < 0 \end{cases}$$

Structure of x[n] so far means that

$$\sum_{n=-\infty}^{\infty} |x(n)|^2 = \sum_{n=-\infty}^{\infty} |x(n)|^2 = |x(-2)|^2 + |x(-1)|^2 + |x(0)|^2$$

$$= 1 + 1 + |x(0)|^2$$

$$= 3 \qquad x(0) = \pm 1$$

1.
$$x[n] = 0, n > 0$$

- 2. x[0] > 0
- 3. $\operatorname{Im}(X(e^{j\omega})) = \sin \omega \sin 2\omega$
- 4. $\frac{1}{2\pi} \int_{2\pi} |X(e^{j\omega})|^2 d\omega = 3$

$$x[n] = \begin{cases} 0 & n > 0 \\ 1 & n = 0 \\ \delta[n+1] - \delta[n+2] & n < 0 \end{cases}$$

At the end of the day, we can simply write



Today

Learning outcomes:

- Distinguish between the discrete-time Fourier transform and the discrete Fourier transform
- Describe the fast Fourier transform (FFT) algorithm
- Implement a basic FFT algorithm and state its algorithmic scaling

Take another look at the DTFT:

$$X[n] = \frac{1}{2\pi} \int_{2\pi} X(e^{j\omega}) e^{j\omega n} d\omega \quad X(e^{j\omega}) = \sum_{n=-\infty}^{\infty} x[n] e^{-j\omega n}$$

 $X(e^{j\omega})$ is a **continuous function** of ω .

Consider what we have been doing in Python so far:

We are computing a Fourier spectrum here. The signal is discrete and finite, and the spectrum is also discrete and finite. What is this thing?

Recall how we derived the DTFT. We had some signal, and considered a periodic extension of it.

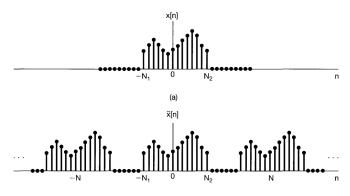
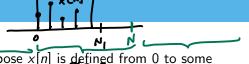


Image credit: Oppenheim chapter 5.1



Without loss of generality, suppose x[n] is defined from 0 to some $N_1 \leq N$.

We can define $\tilde{x}[n]$ as a periodic function with period N. Then, it has Fourier series coefficients

Ck =
$$\frac{1}{N} \sum_{n \neq \langle N \rangle} \tilde{x}(n) e^{-jk \cdot \frac{2\pi n}{N}}$$

= $\frac{1}{N} \sum_{n=0}^{N-1} x(n) e^{-jk \cdot \frac{2\pi n}{N}}$

These N-1 coeffcients are known as the **discrete Fourier** transform of x[n].

Generally we write

$$X[k] = 1 \sum_{n=0}^{N-1} x(n) e^{-jk2\pi n}$$

$$k=0,1,...,N7$$
Why are these interesting a

First, we can recover x[n] from them:

$$X[n] = \sum_{k=0}^{N-1} \tilde{X}[k] e^{jk \frac{2\pi n}{N}} n = 0,..., N-1$$

More importantly, these are related to the discrete-time Fourier transform:

$$X(e^{j\omega} = \sum_{n=-\infty}^{\infty} x(n) e^{-j\omega n}$$

If the signal is only defined from 0 to N-1,

$$\chi(e^{j\omega}) = \sum_{n=0}^{N-1} \chi(n) e^{-j\omega n}$$

What if we sample this signal at particular values of $k\omega = k2\pi/N$?

$$X(e^{j \cdot k \cdot \frac{2\pi}{N}}) = \sum_{n=0}^{N-1} x(n) e^{-jk \cdot \frac{2\pi n}{N}} = N \cdot \tilde{X}(k)$$

$$= \sum_{n=0}^{N-1} x(n) e^{-jk \cdot \frac{2\pi n}{N}} = N \cdot \tilde{X}(k)$$

The discrete Fourier transform is a set of equally spaced samples of the full discrete-time Fourier transform.

Key point 1: Any signal x[n] can be uniquely specified by a finite set of samples from its DTFT (i.e., its DFT).

How do we actually compute the DFT?

$$\overset{\sim}{\chi}(k) = \overset{\sim}{\eta} \overset{\sim}{\sum} x[n] e^{-jk \cdot 2\pi n}$$

$$\overset{\sim}{\chi}(0) = \overset{\sim}{\eta} \overset{\sim}{\sum} x[n] = \overset{\sim}{\eta} (x[0] + x[1] + \dots + x[N-1])$$

$$\overset{\sim}{\chi}(1) = \overset{\sim}{\eta} \overset{\sim}{\sum} x[n] = \overset{\sim}{\eta} (x[0] + x[1] e^{-j(N-1)2\pi n/N} = \overset{\sim}{\eta} (x[0] + x[1] e^{-j(N-1)2\pi n/N}$$

This is just a big matrix multiplication!

$$\begin{bmatrix} \chi[0] \\ \chi[1] \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & \cdots & 2 & 1 \\ 1 & e^{j2N} & \cdots & e^{-2\pi} & \frac{(N-1)}{N} \\ \vdots & \ddots & \ddots & \vdots \\ \chi[N-1] \end{bmatrix} \begin{bmatrix} \chi[0] \\ \chi[N-1] \end{bmatrix} \begin{bmatrix} \chi[0] \\ \chi[N-1] \end{bmatrix}$$

We typically define $\zeta = e^{-2\pi j/N}$ (Nth root of unity):

$$\begin{bmatrix} \tilde{X}[0] \\ \tilde{X}[1] \\ \dots \\ \tilde{X}[N-1] \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & \zeta & \zeta^2 & \cdots & \zeta^{N-1} \\ 1 & \zeta^2 & \zeta^4 & \cdots & \zeta^{2(N-1)} \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 1 & \zeta^{N-1} & \zeta^{2(N-1)} & \cdots & \zeta^{(N-1)(N-1)} \end{bmatrix} \begin{bmatrix} x[0] \\ x[1] \\ \dots \\ x[N-1] \end{bmatrix}$$



This matrix is very beautiful:

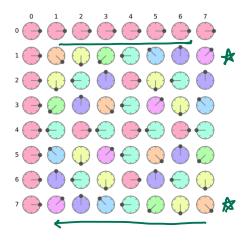


Image credit: Darnling - Own work. CCBY-SA4.0 https://creativecommons.org/licenses/by-sa/4.0

Key point 2: There is an efficient algorithm for the DFT: the **fast Fourier transform**.

$$\overset{\text{m.}}{X}[k] = \frac{1}{N} \sum_{n=0}^{N-1} x[n] e^{-jk \cdot \frac{2\pi n}{N}}$$

$$\times [n] = \sum_{k=0}^{N-1} \overset{\text{of }}{X}[k] e^{-jk \cdot \frac{2\pi n}{N}}$$

These correspond (almost) to:

```
>>> X_k = np.fft.fft(xn)
>>> xn = np.fft.ifft(X_k)
```

Note that in NumPy, the normalization convention is "backwards":

Implementation details

There are many ways to define the DFT, varying in the sign of the exponent, normalization, etc. Ir this implementation, the DFT is defined as

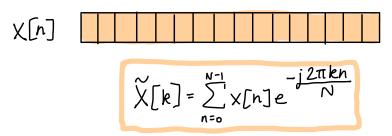
$$A_k = \sum_{m=0}^{n-1} a_m \exp\left\{-2\pi i \frac{mk}{n}\right\} \qquad k = 0, \dots, n-1.$$

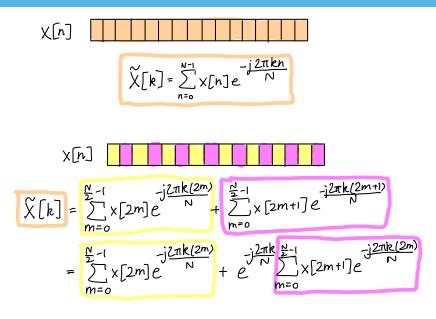
To match the convention we use in class, you need to specify:

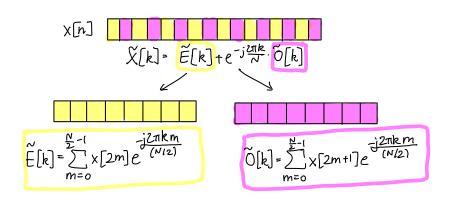
The most famous FFT algorithm is the **Cooley-Tukey algorithm**: it computes the DFT using a divide and conquer method.

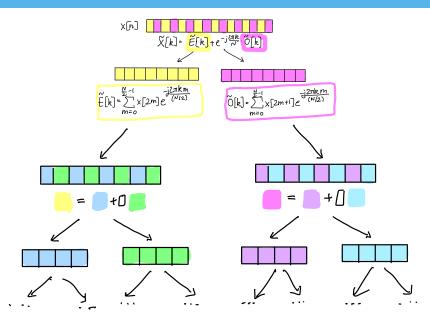
Nicest case to analyze is when N is a power of 2.

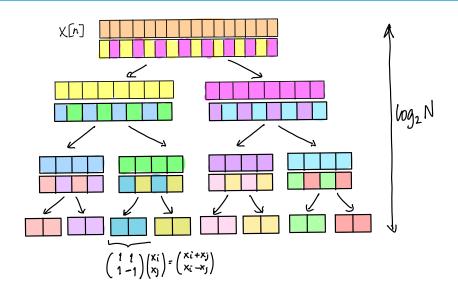
Suppose we would like to compute the kth element of the DFT.











But wait!

We get something for free.

$$\widetilde{X}[k] = \sum_{n=0}^{N-1} x(n) e$$

$$= \sum_{n=0}^{N[2-1]} x[2m] e$$

$$= \sum_{m=0}^{N[2-1]} x[2m] e$$

$$= \widetilde{E}[k] + e^{jk \cdot (\frac{2\pi}{N})} \widetilde{O}[k]$$

$$\widetilde{X}[k + N[2] \rightarrow \widetilde{X}[k]$$

Recall that there is some symmetry between positive/negative values in Fourier coefficients.

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$$\begin{split} \tilde{X}[k+N/2] &= \sum_{m=0}^{N/2-1} x[2m] e^{-j\frac{2\pi}{N/2}km} e^{-j2\pi m} \\ &+ e^{-j(k+N/2)\frac{2\pi}{N}} \sum_{m=0}^{N/2-1} x[2m+1] e^{-j\frac{2\pi}{N/2}km} e^{-j2\pi m} \end{split}$$

$$= \sum_{m=0}^{N/2-1} x[2m]e^{-j\frac{2\pi}{N/2}km} + e^{-j(k+N/2)\frac{2\pi}{N}} \sum_{m=0}^{N/2-1} x[2m+1]e^{-j\frac{2\pi}{N/2}kt}$$

$$\tilde{X}[k+N/2] = \sum_{m=0}^{N/2-1} x[2m]e^{-j\frac{2\pi}{N/2}km}
+e^{-jk\frac{2\pi}{N}}e^{-j\pi} \sum_{m=0}^{N/2-1} x[2m+1]e^{-j\frac{2\pi}{N/2}km}
= \sum_{m=0}^{\mathbb{Z}} \widetilde{\mathbb{E}}[k] - e^{-j\frac{2\pi}{N/2}km} \widetilde{\mathbb{O}}[k]
= \sum_{m=0}^{\infty} x[2m]e^{-j\frac{2\pi}{N/2}km}
-e^{-jk\frac{2\pi}{N}} \sum_{m=0}^{N/2-1} x[2m+1]e^{-j\frac{2\pi}{N/2}km}
= \widetilde{\mathbb{E}}[k] - e^{-jk\frac{2\pi}{N}} \widetilde{\mathbb{O}}[k]$$

Only need to compute the first 1/2 of values in each subdivision of the problem.

At the end of the day, the complexity of the FFT is $O(N \log_2 N)$ -way better than $O(N^2)$ matrix multiplication!

Let's program it. We will compare:

- The naive matrix multiplication version
- A naive implementation of the FFT
- NumPy's FFT

If you want to dig deeper:

https://nbviewer.org/url/jakevdp.github.io/downloads/notebooks/UnderstandingTheFFT.ipynb

Recap

Today's learning outcomes were:

- Distinguish between the discrete-time Fourier transform and the discrete Fourier transform
- Describe the steps of the fast Fourier transform (FFT) algorithm
- Implement a basic FFT algorithm and state its algorithmic scaling

What topics did you find unclear today?

For next time

Content:

■ Hands-on: 2D Fourier analysis and image processing

Action items:

- 1. Quiz 6 on Tuesday
- 2. Assignment 4 due on Wednesday
- 3. Check Piazza for instructions on what to bring for next class

Recommended reading:

- From today's class: Oppenheim extension problems 5.53-5.54
- For next class: research the 2D DFT