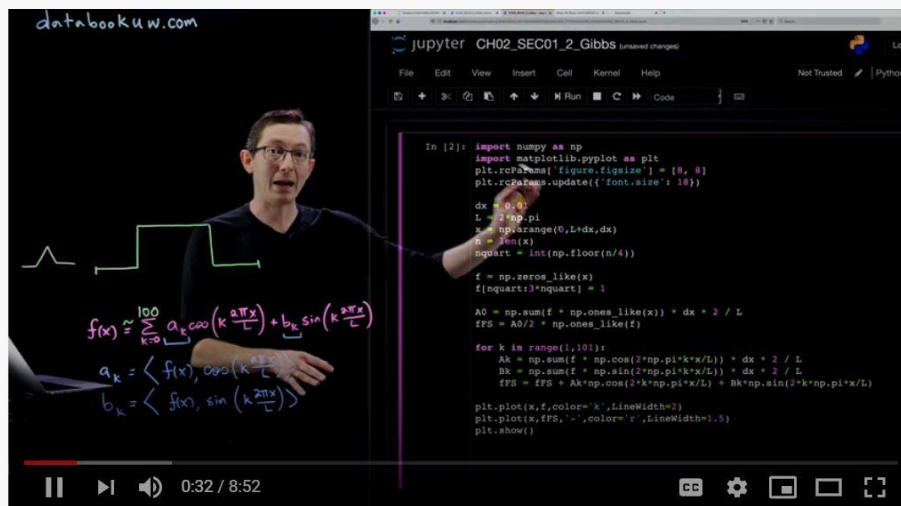


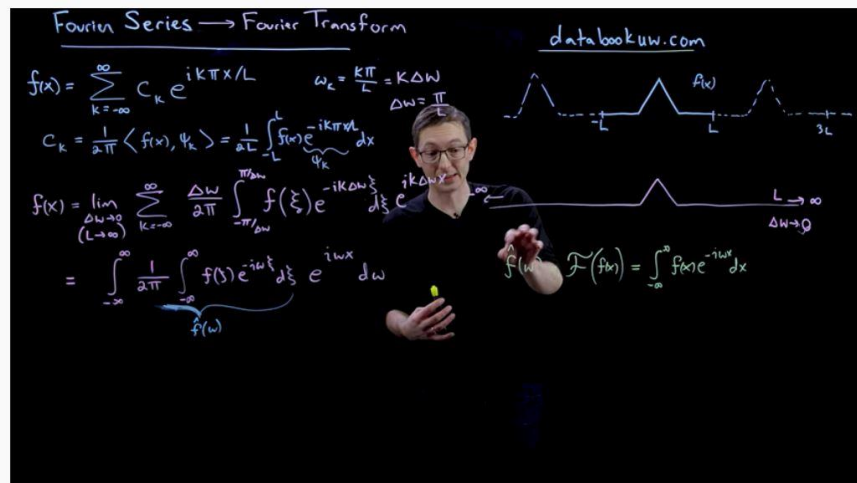
DAILY ASSESSMENT FORMAT

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Course:	Digital Signal Processing	USN:	4AL17EC103
Topic:	Fourier Transforms	Semester & Section:	6-B
Github Repository:	Sachin-Courses		

FORENOON SESSION DETAILS



Fourier Series and Gibbs Phenomena [Python]



Fourier series A fundamental result in Fourier analysis is that if $f(x)$ is periodic and piecewise smooth, then it can be written in terms of a Fourier series, which is an infinite sum of cosines and sines of increasing frequency. In particular, if $f(x)$ is 2π periodic, it may be written as:

$$f(x) = \frac{a_0}{2} + \sum_{k=1}^{\infty} (a_k \cos(kx) + b_k \sin(kx)) .$$

FOURIER SERIES AND FOURIER TRANSFORMS

The coefficients a_k and b_k are given by

$$a_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos(kx) dx$$

$$b_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin(kx) dx,$$

which may be viewed as the coordinates obtained by projecting the function onto the orthogonal cosine and sine basis $\{\cos(kx), \sin(kx)\}_{k=0}^{\infty}$. In other words, the integrals in (2.6) may be re-written in terms of the inner product as:

$$a_k = \frac{1}{\|\cos(kx)\|^2} \langle f(x), \cos(kx) \rangle$$

$$b_k = \frac{1}{\|\sin(kx)\|^2} \langle f(x), \sin(kx) \rangle,$$

where $\|\cos(kx)\|^2 = \|\sin(kx)\|^2 = \pi$. This factor of $1/\pi$ is easy to verify by numerically integrating $\cos(x)^2$ and $\sin(x)^2$ from $-\pi$ to π . The Fourier series for an L -periodic function on $[0, L]$ is similarly given by:

$$f(x) = \frac{a_0}{2} + \sum_{k=1}^{\infty} \left(a_k \cos\left(\frac{2\pi kx}{L}\right) + b_k \sin\left(\frac{2\pi kx}{L}\right) \right),$$

with coefficients a_k and b_k given by

$$a_k = \frac{2}{L} \int_0^L f(x) \cos\left(\frac{2\pi kx}{L}\right) dx$$

$$b_k = \frac{2}{L} \int_0^L f(x) \sin\left(\frac{2\pi kx}{L}\right) dx.$$

The DFT is tremendously useful for numerical approximation and computation, but it does not scale well to very large n , as the simple formulation involves multiplication by a dense $n \times n$ matrix, requiring $O(n^2)$ operations. In 1965, James W. Cooley (IBM) and

John W. Tukey (Princeton) developed the revolutionary fast Fourier transform (FFT) algorithm [137, 136] that scales as $O(n \log(n))$. As n becomes very large, the $\log(n)$ component grows slowly, and the algorithm approaches a linear scaling. Their algorithm was based on a fractal symmetry in the Fourier transform that allows an n dimensional DFT to be solved with a number of smaller dimensional DFT computations. Although the different computational scaling between the DFT and FFT implementations may seem like a small difference, the fast $O(n \log(n))$ scaling is what enables the ubiquitous use of the FFT in real-time communication, based on audio and image compression

Discrete Fourier transform

Although we will always use the FFT for computations, it is illustrative to begin with the simplest formulation of the DFT. The discrete Fourier transform is given by:

$$\hat{f}_k = \sum_{j=0}^{n-1} f_j e^{-i2\pi jk/n},$$

and the inverse discrete Fourier transform (iDFT) is given by:

$$f_k = \frac{1}{n} \sum_{j=0}^{n-1} \hat{f}_j e^{i2\pi jk/n}.$$

Thus, the DFT is a linear operator (i.e., a matrix) that maps the data points in f to the frequency domain \hat{f} :

$$\{f_1, f_2, \dots, f_n\} \xrightarrow{\text{DFT}} \{\hat{f}_1, \hat{f}_2, \dots, \hat{f}_n\}.$$

For a given number of points n , the DFT represents the data using sine and cosine functions with integer multiple so fundamental frequency, $\omega_n = e^{-2\pi i/n}$. The DFT may be computed by matrix multiplication:

$$\begin{bmatrix} \hat{f}_1 \\ \hat{f}_2 \\ \hat{f}_3 \\ \vdots \\ \hat{f}_n \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & \omega_n & \omega_n^2 & \dots & \omega_n^{n-1} \\ 1 & \omega_n^2 & \omega_n^4 & \dots & \omega_n^{2(n-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega_n^{n-1} & \omega_n^{2(n-1)} & \dots & \omega_n^{(n-1)^2} \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ \vdots \\ f_n \end{bmatrix}.$$

Fast Fourier transform to compute derivatives:

```
n = 128;
L = 30;
dx = L/(n);
x = -L/2:dx:L/2-dx;
f = cos(x).*exp(-x.^2/25);
% Function df = -(sin(x).*exp(-x.^2/25) + (2/25)*x.*f);
% Derivative
%% Approximate derivative using finite Difference... for
kappa=1:length(df)-1
dfFD(kappa) = (f(kappa+1)-f(kappa))/dx;
end dfFD(end+1) = dfFD(end);
%% Derivative using FFT (spectral derivative)
fhat = fft(f); kappa = (2*pi/L)*[-n/2:n/2-1];
kappa = fftshift(kappa);
% Re-order fft frequencies dfhat = i*kappa.*fhat;
dfFFT = real(ifft(dfhat));
%% Plotting commands plot(x,df,'k','LineWidth',1.5),
hold on plot(x,dfFD,'b--','LineWidth',1.2)
plot(x,dfFFT,'r--','LineWidth',1.2)
legend('True Derivative','Finite Diff.','FFT Derivative')
```

Code to simulate the 1D heat equation using the Fourier transform.

```

a = 1;           % Thermal diffusivity constant
L = 100;        % Length of domain
N = 1000;       % Number of discretization points
dx = L/N;
x = -L/2:dx:L/2-dx; % Define x domain

% Define discrete wavenumbers
kappa = (2*pi/L)*[-N/2:N/2-1];
kappa = fftshift(kappa); % Re-order fft wavenumbers

% Initial condition
u0 = 0*x;
u0((L/2 - L/10)/dx:(L/2 + L/10)/dx) = 1;

% Simulate in Fourier frequency domain
t = 0:0.1:10;
[t,uhat]=ode45(@(t,uhat) rhsHeat(t,uhat,kappa,a),t,fft(u0));

for k = 1:length(t) % iFFT to return to spatial domain
    u(k,:) = ifft(uhat(k,:));
end

```