The Discrete Fourier Transform (DFT)

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Sampling Periodic Functions

Given a function of period, T, *i.e.*,

$$f(t) = f(t+T)$$

choose N and **sample** $f(t)$ within the interval, $0 \le t \le T$, at N equally spaced points, $n\Delta t$, where $n = 0, 1, \ldots, N-1$ and $\Delta t = T/N$. The result is a discrete function of period, N, which can be represented as a vector, $\mathbf{f}$, in $\mathbb{R}^N$ (or $\mathbb{C}^N$) where $f_n = f(n\Delta t)$:

$$\mathbf{f} = \begin{bmatrix} f_0 \\ f_1 \\ \vdots \\ f_{N-1} \end{bmatrix}.$$

Inner Product of Discrete Periodic Functions

We can define the *inner product* of two discrete functions of period, N, as follows:

$$\langle \mathbf{f}, \mathbf{g} \rangle = \sum_{n=0}^{N-1} f_n^* \, g_n.$$

Kronecker Delta Basis

$$(\mathbf{k}_m)_n = \delta_{mn} = \begin{cases} 1 & \text{if } m = n \\ 0 & \text{otherwise} \end{cases}$$

Example:

$$\mathbf{k}_2 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Because $\langle \mathbf{k}_{m_1}, \mathbf{k}_{m_2} \rangle$ equals zero when $m_1 \neq m_2$ and one when $m_1 = m_2$, the set of $\mathbf{k}_m$ for $0 \leq m < N$ form an orthonormal basis for $\mathbb{R}^N$ (or $\mathbb{C}^N$) and therefore for discrete functions of period, N.

Sampled Harmonic Signal Basis

A sampled harmonic signal is a discrete function of period, N:

$$W_{n,m} = \frac{1}{\sqrt{N}} e^{\,j2\pi m \frac{n}{N}}$$

where m is frequency and n is position. A sampled harmonic signal of frequency, m, can be represented by a vector of length N:

$$\mathbf{w}_m = \begin{bmatrix} W_{0,m} \\ W_{1,m} \\ \vdots \\ W_{N-1,m} \end{bmatrix} = \frac{1}{\sqrt{N}} \begin{bmatrix} e^{\,j2\pi m \frac{0}{N}} \\ e^{\,j2\pi m \frac{1}{N}} \\ \vdots \\ e^{\,j2\pi m \frac{(N-1)}{N}} \end{bmatrix}.$$

Sampled Harmonic Signal Basis (contd.)

How “long” is a sampled harmonic signal?

$$\begin{aligned}
\|\mathbf{w}_m\| &= \langle \mathbf{w}_m, \mathbf{w}_m \rangle^{\frac{1}{2}} \\
&= \left(\sum_{n=0}^{N-1} \frac{1}{\sqrt{N}} e^{-j2\pi m \frac{n}{N}} \frac{1}{\sqrt{N}} e^{\,j2\pi m \frac{n}{N}} \right)^{\frac{1}{2}} \\
&= \left(\sum_{n=0}^{N-1} \frac{1}{N} \right)^{\frac{1}{2}} \\
&= 1
\end{aligned}$$

Sampled Harmonic Signal Basis (contd.)

What is the "angle" between two sampled harmonic signals, $\mathbf{w}_{m_1}$ and $\mathbf{w}_{m_2}$, when $m_1 \neq m_2$?

$$
\begin{aligned}
\langle \mathbf{w}_{m_1}, \mathbf{w}_{m_2} \rangle &= \frac{1}{N} \sum_{n=0}^{N-1} e^{-j2\pi m_1 \frac{n}{N}} e^{j2\pi m_2 \frac{n}{N}} \\
&= \frac{1}{N} \sum_{n=0}^{N-1} e^{j2\pi (m_2 - m_1) \frac{n}{N}} \\
&= \frac{1}{N} \sum_{n=0}^{N-1} \left(e^{j2\pi \frac{(m_2 - m_1)}{N}} \right)^n
\end{aligned}
$$

Sampled Harmonic Signal Basis (contd.)

Substituting α for $e^{j2\pi\frac{(m_2-m_1)}{N}}$ yields

$$\langle \mathbf{w}_{m_1}, \mathbf{w}_{m_2} \rangle = \frac{1}{N}\sum_{n=0}^{N-1} \alpha^n$$

afterwhich the following identity:

$$\sum_{n=0}^{N-1} \alpha^n = \frac{1-\alpha^N}{1-\alpha}$$

can be applied to yield

$$\langle \mathbf{w}_{m_1}, \mathbf{w}_{m_2} \rangle = \frac{1}{N}\left(\frac{1-\alpha^N}{1-\alpha}\right).$$

Sampled Harmonic Signal Basis (contd.)

Since $\alpha = e^{j2\pi\frac{(m_2-m_1)}{N}}$, it follows that

$$\begin{aligned}\alpha^N &= e^{j2\pi(m_2-m_1)\frac{N}{N}}\\ &= e^{j2\pi(m_2-m_1)}.\end{aligned}$$

Because $e^{j2\pi k} = 1$ for all integers, $k \neq 0$, and because $(m_2 - m_1) \neq 0$ is an integer, it follows that $\alpha^N = 1$ yet $\alpha \neq 1$. Consequently,

$$\begin{aligned}\langle \mathbf{w}_{m_1}, \mathbf{w}_{m_2} \rangle &= \frac{1}{N}\left(\frac{1-\alpha^N}{1-\alpha}\right)\\ &= 0.\end{aligned}$$

In summary, because $\langle \mathbf{w}_{m_1}, \mathbf{w}_{m_2} \rangle = 0$ when $m_1 \neq m_2$ and $\langle \mathbf{w}_{m_1}, \mathbf{w}_{m_2} \rangle = 1$ when $m_1 = m_2$, the set of $\mathbf{w}_m$ for $0 \leq m < N$ form an orthonormal basis for $\mathbb{R}^N$ (or $\mathbb{C}^N$) and therefore for discrete functions of period, N.

The Discrete Fourier Transform (DFT)

- **Question** What are the coefficients of $\mathbf{f}$ in the sampled harmonic signal basis?
- **Answer** Take inner products of $\mathbf{f}$ with the finite set of sampled harmonic signals, $\mathbf{w}_m$, for $0 \leq m < N$.

The result is the *analysis formula* for the DFT:

$$\begin{aligned} F_m &= \langle \mathbf{w}_m, \mathbf{f} \rangle \\ &= \langle \frac{1}{\sqrt{N}} e^{j2\pi m \frac{n}{N}}, \mathbf{f} \rangle \\ &= \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} f_n e^{-j2\pi m \frac{n}{N}} \end{aligned}$$

where $\mathbf{F}$ is used to denote the discrete Fourier transform of $\mathbf{f}$. The function can be reconstructed using the *synthesis formula* for the DFT:

$$f_n = \frac{1}{\sqrt{N}} \sum_{m=0}^{N-1} F_m e^{j2\pi m \frac{n}{N}}.$$

The DFT in Matrix Form

The analysis formula for the DFT:

$$F_m = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} f_n e^{-j2\pi m \frac{n}{N}}$$

can be written as a matrix equation:

$$\begin{bmatrix} F_0 \\ \vdots \\ F_{N-1} \end{bmatrix} = \begin{bmatrix} W^*_{0,0} & \cdots & W^*_{0,N-1} \\ \vdots & \ddots & \vdots \\ W^*_{N-1,0} & \cdots & W^*_{N-1,N-1} \end{bmatrix} \begin{bmatrix} f_0 \\ \vdots \\ f_{N-1} \end{bmatrix}$$

where $W^*_{m,n} = \frac{1}{\sqrt{N}} e^{-j2\pi m \frac{n}{N}}$.

More concisely:

$$\mathbf{F} = \mathbf{W}^* \mathbf{f}.$$

The DFT in Matrix Form (contd.)

The synthesis formula for the DFT:

$$f_n = \frac{1}{\sqrt{N}} \sum_{m=0}^{N-1} F_m e^{\,j2\pi m \frac{n}{N}}$$

can also be written as a matrix equation:

$$\begin{bmatrix} f_0 \\ \vdots \\ f_{N-1} \end{bmatrix} = \begin{bmatrix} W_{0,0} & \cdots & W_{0,N-1} \\ \vdots & \ddots & \vdots \\ W_{N-1,0} & \cdots & W_{N-1,N-1} \end{bmatrix} \begin{bmatrix} F_0 \\ \vdots \\ F_{N-1} \end{bmatrix}$$

where $W_{m,n} = \frac{1}{\sqrt{N}} e^{\,j2\pi m \frac{n}{N}}$. More concisely:

$$\mathbf{f} = \mathbf{W}\mathbf{F}.$$

Note: Because only the **product** of frequency, m, and position, n, appears in the expression for a sampled harmonic signal, it follows that $W_{m,n} = W_{n,m}$. Therefore $\mathbf{W} = \mathbf{W}^{\mathrm{T}}$. The only difference between the matrices used for the forward and inverse DFT's, *i.e.*, $\mathbf{W}^*$ and $\mathbf{W}$, is conjugation.

The DFT in Matrix Form (contd.)

A matrix product, $\mathbf{y} = \mathbf{A}\mathbf{x}$, can be interpreted in two different ways.

1. The i-th component of $\mathbf{y}$ is the inner product of $\mathbf{x}$ with the i-th row of $\mathbf{A}$:

$$\begin{bmatrix} y_0 \\ \vdots \\ y_{N-1} \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} A_{0,0} & \dots & A_{0,N-1} \end{bmatrix} \begin{bmatrix} x_0 \\ \vdots \\ x_{N-1} \end{bmatrix} \\ \vdots \\ \begin{bmatrix} A_{N-1,0} & \dots & A_{N-1,N-1} \end{bmatrix} \begin{bmatrix} x_0 \\ \vdots \\ x_{N-1} \end{bmatrix} \end{bmatrix}$$

2. The vector, $\mathbf{y}$, is a linear combination of the columns of $\mathbf{A}$. The i-th column is weighted by x_i:

$$\begin{bmatrix} y_0 \\ \vdots \\ y_{N-1} \end{bmatrix} = x_0 \begin{bmatrix} A_{0,0} \\ \vdots \\ A_{N-1,0} \end{bmatrix} + \cdots + x_{N-1} \begin{bmatrix} A_{0,N-1} \\ \vdots \\ A_{N-1,N-1} \end{bmatrix}$$

The DFT in Matrix Form (contd.)

Both ways of looking at matrix product are equally correct. However, it is useful to think of the analysis formula, $\mathbf{F} = \mathbf{W}^*\mathbf{f}$, the first way:

$$\begin{bmatrix} F_0 \\ \vdots \\ F_{N-1} \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} W^*_{0,0} & \cdots & W^*_{0,N-1} \end{bmatrix} \begin{bmatrix} f_0 \\ \vdots \\ f_{N-1} \end{bmatrix} \\ \vdots \\ \begin{bmatrix} W^*_{N-1,0} & \cdots & W^*_{N-1,N-1} \end{bmatrix} \begin{bmatrix} f_0 \\ \vdots \\ f_{N-1} \end{bmatrix} \end{bmatrix}$$

i.e., F_m is the inner product of $\mathbf{f}$ with the m-th row of $\mathbf{W}$. Conversely, it is useful to think of the synthesis formula, $\mathbf{f} = \mathbf{W}\mathbf{F}$, the second way:

$$\begin{bmatrix} f_0 \\ \vdots \\ f_{N-1} \end{bmatrix} = F_0 \begin{bmatrix} W_{0,0} \\ \vdots \\ W_{N-1,0} \end{bmatrix} + \cdots + F_{N-1} \begin{bmatrix} W_{0,N-1} \\ \vdots \\ W_{N-1,N-1} \end{bmatrix}$$

i.e., $\mathbf{f}$ is a linear combination of the columns of $\mathbf{W}$. The m-th column is weighted by F_m.

<u>Matrix Diagonalization</u>

A vector, $\mathbf{x}$, is a **right** eigenvector when $\mathbf{Ax}$ points in the same direction as $\mathbf{x}$ but is (possibly) of different length:

$$\lambda\mathbf{x} = \mathbf{Ax}$$

A vector, $\mathbf{y}$, is a **left** eigenvector when $\mathbf{y}^{\mathrm{T}}\mathbf{A}$ points in the same direction as $\mathbf{y}^{\mathrm{T}}$ but is (possibly) of different length:

$$\lambda\mathbf{y}^{\mathrm{T}} = \mathbf{y}^{\mathrm{T}}\mathbf{A}$$

A diagonalizable matrix of rank, N, has N linearly independent right eigenvectors

$$\mathbf{x}_0, \ldots, \mathbf{x}_{N-1}$$

and N linearly independent left eigenvectors

$$\mathbf{y}_0, \ldots, \mathbf{y}_{N-1}$$

which share the N eigenvalues

$$\lambda_0, \ldots, \lambda_{N-1}.$$

Matrix Diagonalization (contd.)

Such a matrix can be factored as follows:

$$\mathbf{A} = \mathbf{X}\mathbf{D}\mathbf{Y}^{\mathrm{T}}$$

where the i-th column of $\mathbf{X}$ is $\mathbf{x}_i$ and the i-th row of $\mathbf{Y}^{\mathrm{T}}$ is $\mathbf{y}_i$ and $\mathbf{D}$ is diagonal with $D_{i,i} = \lambda_i$:

$$\mathbf{D} = \begin{bmatrix} \lambda_0 & 0 & \ldots & 0 \\ 0 & \lambda_1 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \lambda_{N-1} \end{bmatrix}$$

We also observe that

$$\mathbf{X}\mathbf{Y}^{\mathrm{T}} = \mathbf{I}$$

i.e., $\mathbf{X}$ and $\mathbf{Y}^{\mathrm{T}}$ are inverses. We say that $\mathbf{A}$ has been *diagonalized*. Stated differently, in the basis formed by its right eigenvectors, the linear operator, $\mathbf{A}$, is represented by the diagonal matrix, $\mathbf{D}$.

Matrix Diagonalization (contd.)

When $\mathbf{A}$ is real and symmetric, *i.e.*, $\mathbf{A} = \mathbf{A}^{\mathrm{T}}$, the left and right eigenvectors are the **same**. Consequently, $\mathbf{X} = \mathbf{Y}$. In this case, $\mathbf{A}$ can be factored as follows:

$$\mathbf{A} = \mathbf{X}\mathbf{D}\mathbf{X}^{\mathrm{T}}$$

Since $\mathbf{X}\mathbf{X}^{\mathrm{T}} = \mathbf{I}$, we conclude that the eigenvectors of $\mathbf{A}$ form an orthonormal basis.

Matrix Diagonalization (contd.)

The hermitian transpose, $\mathbf{A}^{\mathrm{H}}$, of a complex matrix, $\mathbf{A}$, is defined to be $(\mathbf{A}^*)^{\mathrm{T}}$. When $\mathbf{A}$ is complex and symmetric, the left and right eigenvectors are **complex conjugates**. In this case, $\mathbf{A}$ can be factored as follows:

$$\mathbf{A} = \mathbf{X}\mathbf{D}\mathbf{X}^{\mathrm{H}}$$

When the matrix of eigenvectors, $\mathbf{X}$, is also symmetric, *i.e.*, $\mathbf{X} = \mathbf{X}^{\mathrm{T}}$, the above simplifies to:

$$\mathbf{A} = \mathbf{X}\mathbf{D}\mathbf{X}^*$$

Convolution of Discrete Periodic Functions

Let **f** and **g** be vectors in $\mathbb{R}^N$. Because **f** and **g** represent discrete functions of period, N, we adopt the convention that $f(k \pm N) = f(k)$. The k-th component of the *convolution* of **f** and **g** is then

$$\{\mathbf{f} * \mathbf{g}\}_k = \sum_{j=0}^{N-1} f_j \, g_{k-j}.$$

Example of Discrete Periodic Convolution

Calculate $\{\mathbf{f} * \mathbf{g}\}_k$ when

$$\mathbf{g} = \begin{bmatrix} 2 & 1 & 0 & \ldots & 0 & 1 \end{bmatrix}^{\mathrm{T}}$$

Since $\mathbf{f} * \mathbf{g} = \mathbf{g} * \mathbf{f}$ and since

$$\{\mathbf{g} * \mathbf{f}\}_k = \sum_{j=0}^{N-1} g_j f_{k-j}$$

it follows that

$$\begin{aligned}
\{\mathbf{f} * \mathbf{g}\}_k &= g_0 f_k + g_1 f_{k-1} + \cdots + g_{N-1} f_{k-(N-1)} \\
&= 2 f_k + 1 f_{k-1} + 1 f_{k-(N-1)} \\
&= f_{k-1} + 2 f_k + 1 f_{k+1}
\end{aligned}$$

This operation performs a local weighted averaging of $\mathbf{f}$.

Circulant Matrices

The convolution formula for discrete periodic functions

$$\{\mathbf{f} * \mathbf{g}\}_k = \sum_{j=0}^{N-1} f_j g_{k-j}$$

can be written as a matrix equation:

$$\mathbf{f} * \mathbf{g} = \mathbf{C}\mathbf{f}$$

where $C_{k,j} = g_{k-j}$:

$$\mathbf{C} = \begin{bmatrix} g_0 & g_{N-1} & g_{N-2} & \cdots & g_1 \\ g_1 & g_0 & g_{N-1} & \cdots & g_2 \\ g_2 & g_1 & g_0 & \cdots & g_3 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ g_{N-1} & g_{N-2} & g_{N-3} & \cdots & g_0 \end{bmatrix}$$

Matrices like **C** are termed *circulant*. It is a fact that the right eigenvectors of **all** circulant matrices are sampled harmonic signals. Furthermore, the left eigenvectors of **all** circulant matrices are sampled conjugated harmonic signals.

Diagonalization of Circulant Matrices

Consequently, **any** circulant matrix, **C**, can be factored as follows:

$$\mathbf{C} = \mathbf{W}\mathbf{D}\mathbf{W}^*$$

where $W_{m,n} = e^{\,j2\pi m \frac{n}{N}}$ and

$$\mathbf{D} = \begin{bmatrix} G_0 & 0 & \dots & 0 \\ 0 & G_1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & G_{N-1} \end{bmatrix}$$

Here $D_{m,m} = G_m$, the m-th coefficient of the discrete Fourier transform of **g**. We can use this result to compute $\mathbf{f} * \mathbf{g}$

$$\mathbf{f} * \mathbf{g} = \mathbf{W}\mathbf{D}\mathbf{W}^*\mathbf{f}$$

This is just the *Convolution Theorem*. Multiplication with a circulant matrix, **C**, in the space domain is multiplication with a diagonal matrix, **D**, in the frequency domain.

Polynomial Multiplication

$$
\begin{aligned}
p(x) &= p_0x^0 + p_1x^1 + p_2x^2 + \cdots + p_mx^m \\
q(x) &= q_0x^0 + q_1x^1 + q_2x^2 + \cdots + q_nx^n
\end{aligned}
$$

$$
\begin{gathered}
p(x)q(x) = p_0q_0x^0 + \\
(p_0q_1 + p_1q_0)x^1 + \\
(p_0q_2 + p_1q_1 + p_2q_0)x^2 + \\
(p_0q_3 + p_1q_2 + p_2q_1 + p_3q_0)x^3 + \\
(p_0q_4 + p_1q_3 + p_2q_2 + p_3q_1 + p_4q_0)x^4 + \\
\vdots \\
(p_0q_{n+m} + p_1q_{n+m-1} + \cdots + p_{n+m-1}q_1 + p_{n+m}q_0)x^{n+m}
\end{gathered}
$$

Polynomial Multiplication (contd.)

$$\begin{aligned} r(x) &= p(x)q(x) \\ &= r_0x^0 + r_1x^1 + r_2x^2 + \cdots + r_{n+m}x^{n+m} \end{aligned}$$

where

$$\begin{aligned} r_i &= p_0q_i + p_1q_{i-1} + \cdots + p_{i-1}q_1 + p_iq_0 \\ &= \sum_{j=0}^{i} p_jq_{i-j} \\ &= \sum_{j=-\infty}^{\infty} p_jq_{i-j} \\ &= \{\mathbf{p} * \mathbf{q}\}_i \end{aligned}$$