

2-D DISCRETE FOURIER TRANSFORM

DEFINITION

$$F(k, l) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m, n) \cdot e^{-j2\pi \left(\frac{mk}{M} + \frac{nl}{N} \right)} \quad \text{forward DFT}$$

$$f(m, n) = \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} F(k, l) \cdot e^{+j2\pi \left(\frac{mk}{M} + \frac{nl}{N} \right)} \quad \text{inverse DFT}$$

- The DFT is a **transform** of a discrete, complex 2-D array of size $M \times N$ into another discrete, complex 2-D array of size $M \times N$

Approximates the **Continuous Fourier Transform (CFT)** under certain conditions

Both $f(m, n)$ and $F(k, l)$ are 2-D periodic

Alternate definitions:

- $\frac{1}{MN}$ in inverse definition instead, or $\frac{1}{\sqrt{MN}}$ in forward and inverse definitions ("unitary")
- doesn't matter as long as consistent

2-D DISCRETE FOURIER TRANSFORM

RELATION OF THE DFT TO THE CFT

- One view of the DFT is as an **approximation** to the CFT
- “recipe” to convert CFT to DFT:

1. sample $f(x,y)$

$$f(x,y) \cdot \frac{1}{XY} comb(x/X, y/Y)$$

2. truncate to $MX \times NY$

$$f(x,y) \cdot \frac{1}{XY} comb(x/X, y/Y) \cdot rect(x/MX, y/NY)$$

3. make periodic

$$\begin{aligned} f(x,y) \cdot \frac{1}{XY} comb(x/X, y/Y) \cdot rect(x/MX, y/NY) \\ \ast \ast \frac{1}{MX \cdot NY} comb(x/MX, y/NY) \\ = f_p(m, n) \end{aligned}$$

, i.e. the periodic extension of a 2-D array $f(m,n)$ with sample intervals $X=Y=1$

2-D DISCRETE FOURIER TRANSFORM

4. take CFT

**replicate (aliasing
occurs here)**

**smooth (leakage
occurs here)**

sample



$$[F(u, v) \circledast \circledast \text{comb}(uX, vY) \circledast \circledast MX \cdot NY \text{sinc}(uMX, vNY)] \cdot \text{comb}(uMX, vNY)$$

$$= F_p(k, l)$$

, i.e. the periodic extension of a 2-D array $F(k, l)$ with sample intervals $1/X = 1/Y = 1$

- The arrays f and F are both discrete and periodic in space and spatial frequency, respectively

2-D DISCRETE FOURIER TRANSFORM

CALCULATION OF DFT

- Both arrays $f(m,n)$ and $F(k,l)$ are periodic (period = $M \times N$) and sampled ($X \times Y$ in space, $1/MX \times 1/NY$ in frequency)
 - In the CFT, if one function has compact support (i.e. it is space- or frequency-limited), the other must have ∞ support
 - Therefore, **aliasing** will occur with the DFT, either in space or frequency. If we want the DFT to closely approximate the CFT, aliasing must be minimized in both domains
 - The **Fast Fourier Transform (FFT)** is an efficient algorithm to calculate the DFT that takes advantage of the periodicities in the complex exponential
- Can use 1-D FFT for 2-D DFT (later)

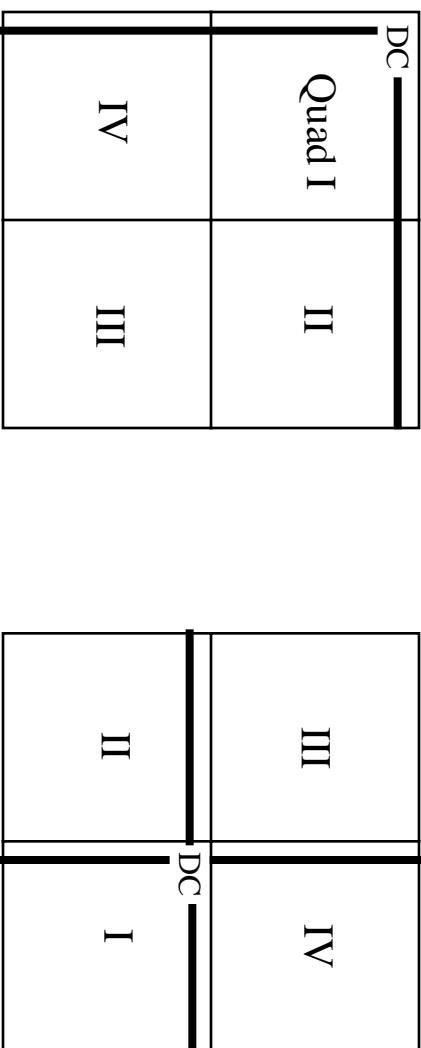
2-D DISCRETE FOURIER TRANSFORM

ARRAY COORDINATES

- The DC term ($u=v=0$) is at $(0,0)$ in the raw output of the DFT (e.g. the Matlab function "fft2")

raw output of DFT

reordered output of DFT



- Reordering puts the spectrum into a "physical" order (the same as seen in optical Fourier transforms) (e.g. the Matlab function "fftshift")
- N and M are commonly powers of 2 for the FFT. Therefore, the DC term is at $(M/2, N/2)$ in the reordered format for $(0,0)$ indexing and at $(M/2+1, N/2+1)$ for $(1,1)$ indexing

2-D DISCRETE FOURIER TRANSFORM

SAMPLE INTERVALS

- *Constraints*

product of physical **sample intervals** in x and u , y and v : $xU = 1/M$, $yV = 1/N$
sampling (replication) frequency in u and v : $u_s = 1/X$, $v_s = 1/Y$

folding frequency in u and v :

$$u_f = 1/2X, v_f = 1/2Y$$

- *For images, a convenient, normalized set of units is*

$$X = Y = 1 \text{ pixel}$$

- *Therefore,*

$$U = 1/M \text{ cycles/pixel}, u_s = 1 \text{ cycle/pixel}, u_f = 1/2 \text{ cycle/pixel}$$

$$V = 1/N \text{ cycles/pixel}, v_s = 1 \text{ cycle/pixel}, v_f = 1/2 \text{ cycle/pixel}$$

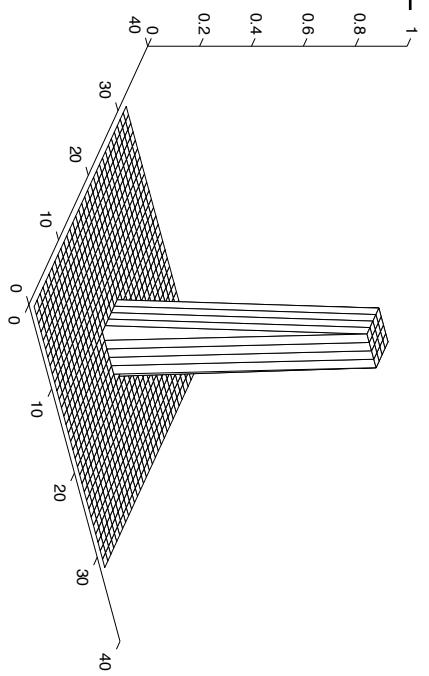
- *Note, in reordered DFT format, u_f and v_f are along the first row and columns of the array*

2-D DISCRETE FOURIER TRANSFORM

Reordering the 2-D DFT

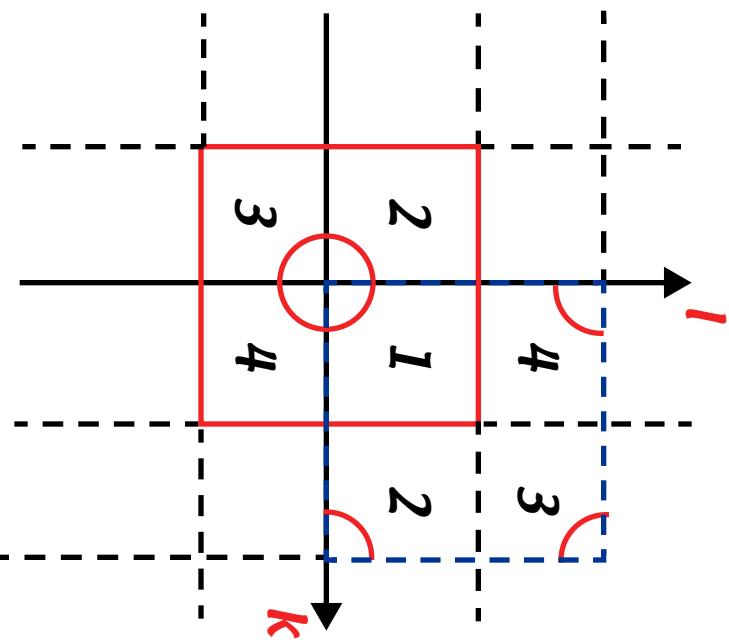
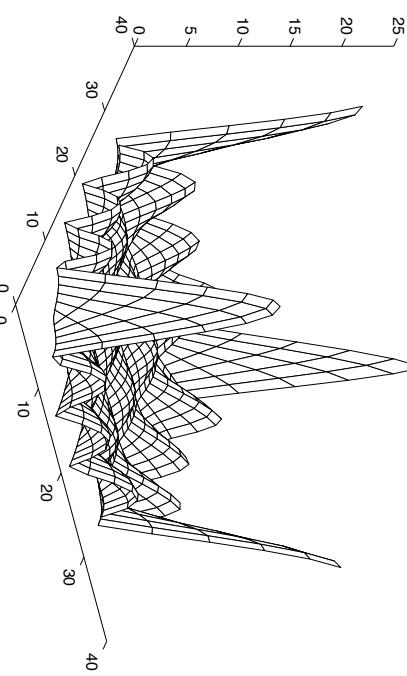
- “origin-centered” display

$f(m,n)$



$|F(k,l)|$

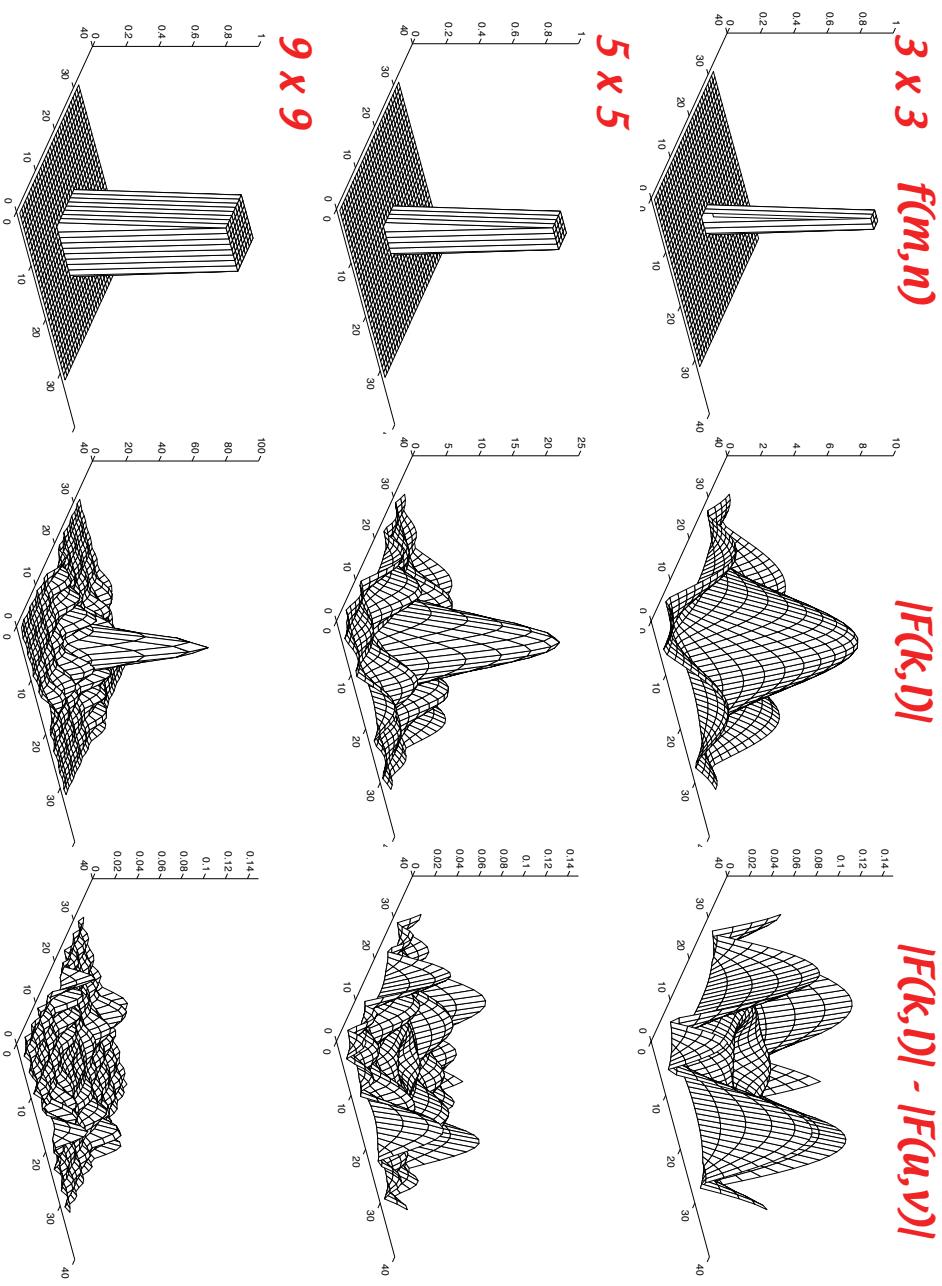
origin-centered
 $|F(k,l)|$



2-D DISCRETE FOURIER TRANSFORM

Aliasing in the frequency domain

- DFT of discrete approximation to a $\text{rect}(x/W, y/W)$ function

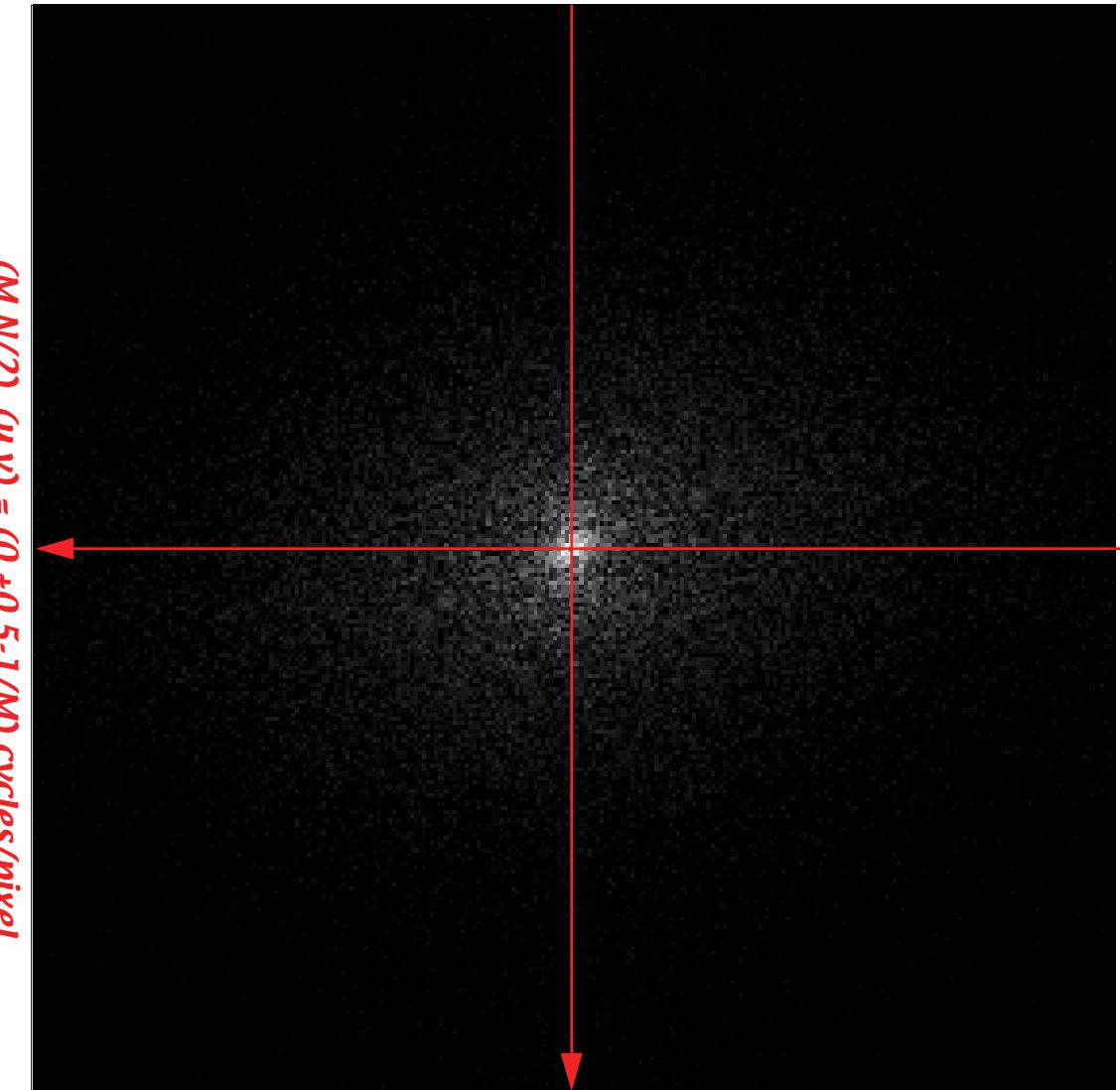


2-D DISCRETE FOURIER TRANSFORM

Digital image power spectrum (squared amplitude of F) coordinates

$(0,0)$
 $(u,v) = (-0.5, -0.5)$
cycles/pixel

$(M/2, N)$
 $(u,v) = (+0.5-1/N, 0)$
cycles/pixel



$(M,N/2), (u,v) = (0, +0.5-1/M)$ cycles/pixel

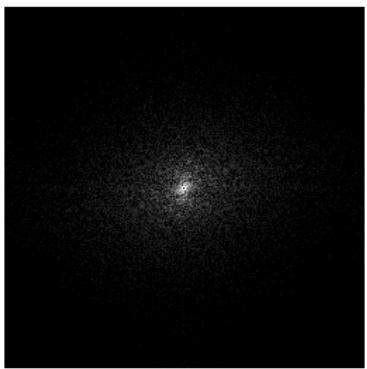
(M,N)
 $(u,v) = (+0.5-1/N,$
 $+0.5-1/M)$
cycles/pixel

2-D DISCRETE FOURIER TRANSFORM

EXAMPLES OF IMAGE POWER SPECTRA



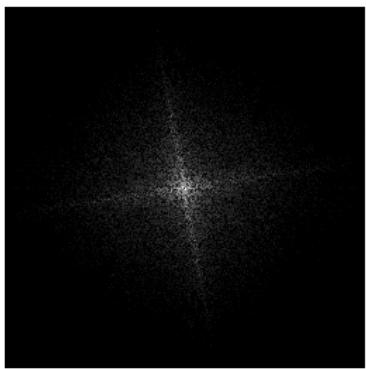
desert



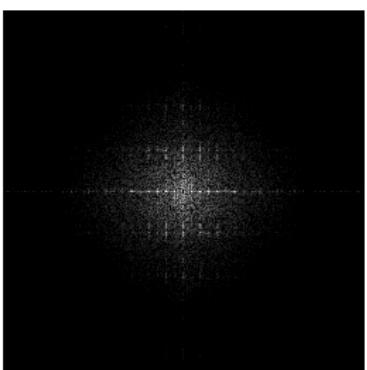
streets



fields



railroad



2-D DISCRETE FOURIER TRANSFORM

DISPLAY OF POWER SPECTRA

- Large dynamic range
- amplitude at zero-frequency dominates

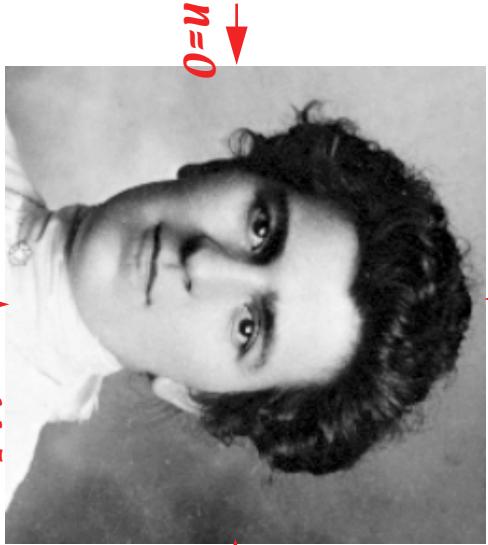
Power Spectra Display

- Mask zero-frequency term to zero
- Contrast stretch with square-root transform
- Repeat contrast stretch as needed

2-D DISCRETE FOURIER TRANSFORM

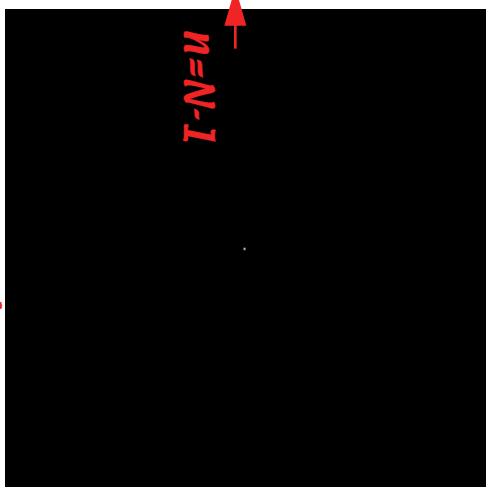
Example

$$\downarrow m=0$$



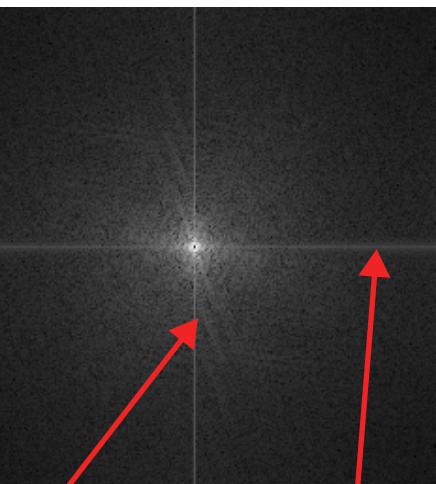
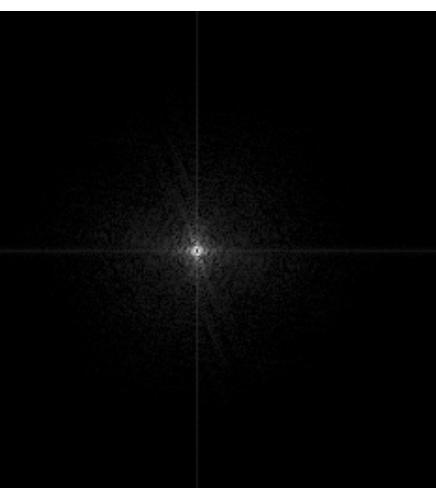
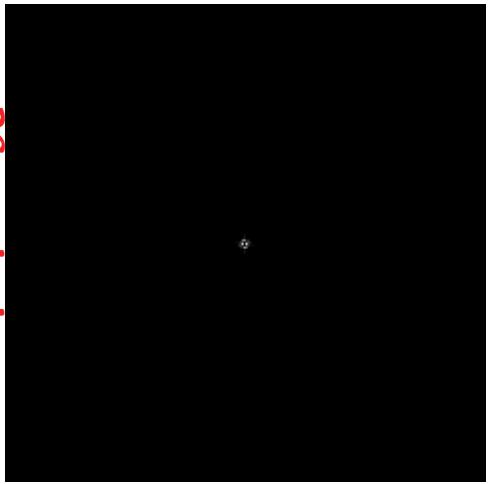
$$\uparrow m=M-1$$

power spectrum



DC masked

due to periodic border at $m=0$ and $M-1$



$$^2\sqrt{2}$$

$$^4\sqrt{2}$$

$$^8\sqrt{2}$$

2-D DISCRETE FOURIER TRANSFORM

This section is from lecture notes by my late friend and colleague, Professor Steve Park, of the College of William and Mary, Virginia

- **Compact notation**
- **Generalizable to other transforms**

$$\bullet \text{ DFT definition } F(k, l) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m, n) \cdot e^{-j2\pi \left(\frac{mk}{M} + \frac{nl}{N} \right)}$$

let $W_M(m, k) = e^{-j2\pi \left(\frac{mk}{M} \right)}$, where W_M is $M \times M$, W_N is $N \times N$

$$W_N(n, l) = e^{-j2\pi \left(\frac{nl}{N} \right)}$$

$$\text{then } F(k, l) = \frac{1}{MN} \sum_{m=0}^{M-1} W_M(m, k) \sum_{n=0}^{N-1} f(m, n) W_N(n, l) = \frac{1}{MN} W_M f W_N,$$

which is the *forward* transform

2-D DISCRETE FOURIER TRANSFORM

- Note that

$$W_M^* W_M = W_M W_M^* = MI_M \text{ (M x M identity matrix)}$$

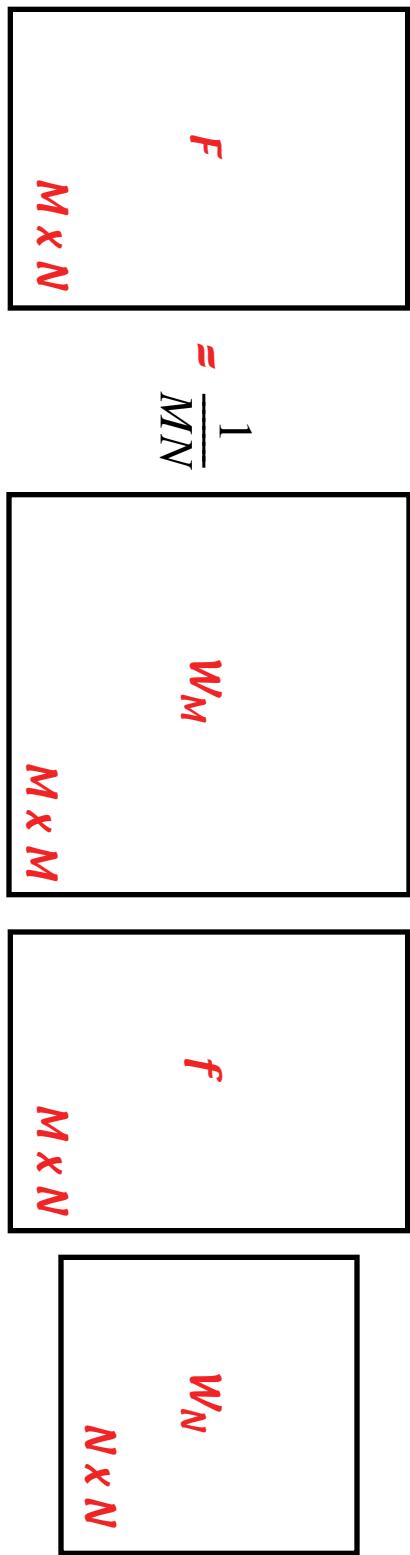
$$W_N^* W_N = W_N W_N^* = NI_N \text{ (N x N identity matrix)}$$

then,

$$\begin{aligned} W_M^* F W_N^* &= \frac{1}{MN} (W_M^* W_M) f(W_N W_N^*) \\ &= \frac{1}{MN} (MI_M) f(NI_N) \quad , \text{ which is the } \textcolor{red}{\text{inverse}} \text{ transform} \\ &= f \end{aligned}$$

2-D DISCRETE FOURIER TRANSFORM

Matrix Dimensionality Diagram ($M > N$)



$$F = \frac{1}{MN} W_M f W_N$$

- Diagram for inverse transform is similar, except no $1/MN$ factor

- Note, this representation is possible because the 2-D DFT kernel is

$$e^{-j2\pi \left(\frac{mk}{M} + \frac{nl}{N} \right)} = e^{-j2\pi \left(\frac{mk}{M} \right)} e^{-j2\pi \left(\frac{nl}{N} \right)}$$

2-D DISCRETE FOURIER TRANSFORM

CALCULATING THE 2-D DFT

$$F = \frac{1}{MN} W_M f W_N$$

- **Step 1**

write image as $f = [f_1 | f_2 | \dots | f_N]$ where f_1, f_2, \dots, f_N are the **image columns** of length M

then,

$$\begin{aligned} F &= \frac{1}{N} \left[\frac{1}{M} W_M f_1 | \frac{1}{M} W_M f_2 | \dots | \frac{1}{M} W_M f_N \right] W_N \\ &= \frac{1}{N} [F_1 | F_2 | \dots | F_N] W_N \end{aligned}$$

where **each column is a 1-D DFT of length M of the image columns**

2-D DISCRETE FOURIER TRANSFORM

- **Step 2**

form matrix transpose $F^t = \frac{1}{N} W_N^t$ note, W is symmetric $W_N^t = W_N$

$$\begin{bmatrix} F_1^t \\ F_2^t \\ \vdots \\ F_N^t \end{bmatrix}$$

- **Step 3**

partition image matrix by columns

$$= [g_1 | g_2 | \dots | g_M], \text{ where each column is an array of length } N$$

$$\begin{bmatrix} F_1^t \\ F_2^t \\ \vdots \\ F_N^t \end{bmatrix}$$

2-D DISCRETE FOURIER TRANSFORM

$$\text{then } F^t = \left[\frac{1}{N} W_N g_1 \mid \frac{1}{N} W_N g_2 \mid \cdots \mid \frac{1}{N} W_N g_N \right]$$

where **each column is a 1-D DFT of length N**

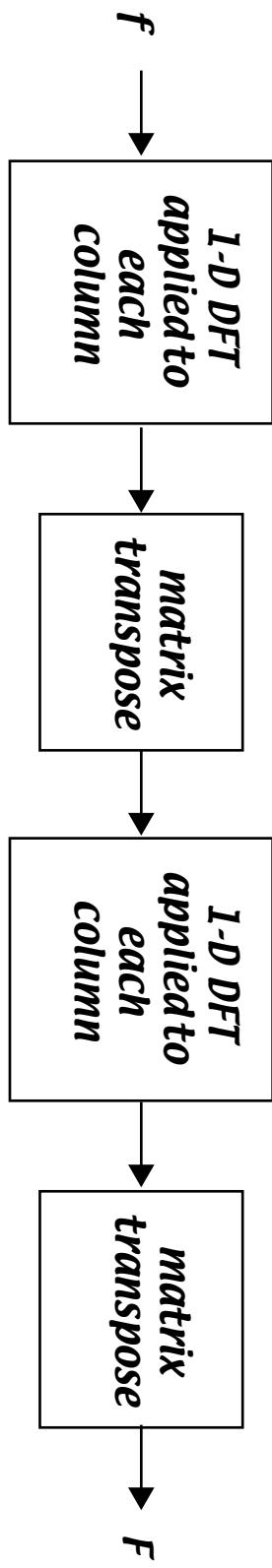
$$\text{therefore } F^t = [G_1 \mid G_2 \mid \cdots \mid G_M]$$

- **Step 4**

transpose F^t to get F

2-D DISCRETE FOURIER TRANSFORM

Calculating the 2-D DFT - Summary



N 1-D DFTs of length M
 $N(M\log_2 M)$ operations

- $N(M\log_2 M) + M(N\log_2 N) = MN\log_2(MN)$ total operations

assumes 1-D FFT is used and M, N are powers of 2

- Compares to M^2N^2 total operations for “brute force” 2-D DFT