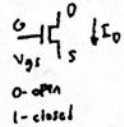
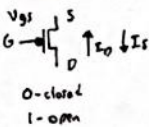


- CMOS (Complementary Metal Oxide Semiconductor)

- NMOS

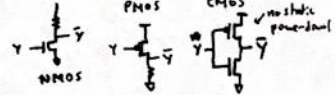


- PMOS



- Logic gates

- Inverter

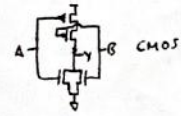


- NAND

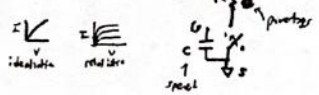
- ring oscillator

- NOR

- odd number



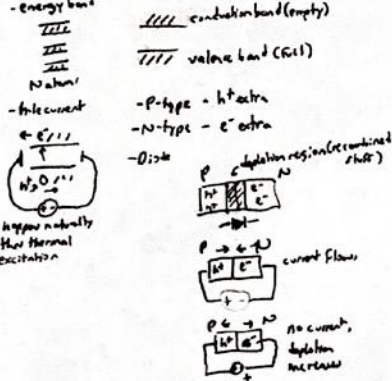
- Transistor Model



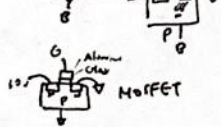
- Q = CV Capacitance

$I = C \frac{dV}{dt}$   
 $V = V_{DD} e^{-t/\tau}$   
 $V = V_{DD} (1 - e^{-t/\tau})$   
 $E = \frac{1}{2} CV^2$   
 $P_{dissipated} = CV^2 f$

- Semiconductors (Silicon)



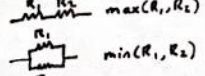
- Transistor



- Inductor

$\phi = LI$   
 $V = \frac{d\phi}{dt} = L \frac{dI}{dt}$   
 $I = I_0 e^{-t/(L/R)}$   
 $V = L \frac{dI}{dt}$   
 $E = \frac{1}{2} LI^2$

- Resistance Approximation



max error = 2c  
 use L for Bode plots  
 $A^0 = \frac{R_1}{R_2} \pm \frac{1}{2} \sqrt{\frac{R_1^2}{L} - \frac{4}{LC}}$   
 no oscillation = c is small, = real  
 $R_{min} \geq 2\sqrt{\frac{L}{C}}$

- Phasors

- Impedance  
 $|Z| = \frac{|V|}{|I|}$   
 $Z = |Z| e^{j\theta}$   
 $Z = x + jy, \bar{Z} = x - jy$   
 Euler's identity  $e^{j\theta} = \cos\theta + j\sin\theta$   
 $\sin\theta = \frac{e^{j\theta} - e^{-j\theta}}{2j}$   
 $\cos\theta = \frac{e^{j\theta} + e^{-j\theta}}{2}$

- Trig Identities  
 $-\sin x = \cos(x - \pi/2)$   
 $-\cos x = \sin(x + \pi/2)$   
 $\#(-\cos x) = \cos(x \pm \pi)$   
 $-\sin(-x) = \sin x$   
 $-\cos(-x) = \cos x$

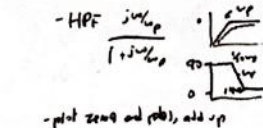
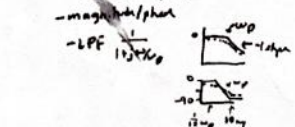
- Phasor  
 $v(t) = V_0 \cos(\omega t + \phi)$   
 $= \frac{V_0}{2} e^{j\phi} e^{j\omega t} + \frac{V_0}{2} e^{-j\phi} e^{-j\omega t}$   
 - coefficient of  $e^{j\omega t}$   
 $\tilde{V} = \frac{V_0}{2} e^{j\phi}$

- Impedance  
 $Z_R = R$   
 $Z_C = \frac{1}{j\omega C}$   
 $Z_L = j\omega L$

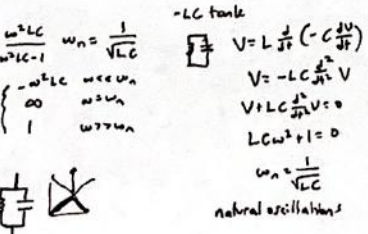
- Transfer Function  
 $H(\omega) = |H(\omega)| e^{j\angle H(\omega)}$   
 $|a \cdot b| = |a| |b|$   
 $\angle \frac{a}{b} = \angle a - \angle b$   
 $\angle \frac{a}{b} = \angle a - \angle b$

- Bode Plot  
 - magnitude (log-log plot)  $|H(\omega)|$   
 split piecewise, approximate  
 $\log_{10}(H(\omega)) = m \log_{10}(\omega) + k$   
 - phase (Semi-log)  $\angle H(\omega)$   
 - plotting - approximate  
 - pole except  $\omega_p$  and zero  
 - mte error at  $\omega_p$   
 - magnitude  $\frac{1}{2}$  at  $\omega_p$

- phase  
 $-\tan^{-1}(\frac{1}{10}) = 5.7^\circ$   
 $-\tan^{-1}(10) = 90 - 5.7^\circ$   
 - usually approximate



- plot zero and pole, add up



- Transient State Analysis of Larger Circuits

Matthew Tran  
 EE16B  
 Hello!!

-  $\frac{d}{dt} \tilde{x}(t) = A \tilde{x}(t)$   
 - Change of variables to eigenbasis  
 $\tilde{x}(t) = V \tilde{z}(t)$   
 $\tilde{z}(t) = V^{-1} A V \tilde{z}(t)$   
 $\tilde{z}(t) = e^{\lambda t} \tilde{z}(0)$   
 $\tilde{z}(t) = e^{\lambda t} \tilde{z}(0)$

- Input in Diff Eq

-  $\frac{d}{dt} x(t) = \lambda x(t) + u(t)$   
 - solution  $x(t) = x_0 e^{\lambda t} + \int_0^t u(\tau) e^{\lambda(t-\tau)} d\tau$   
 (only one)  
 - Try  $u(t) = H(t) e^{st}$ ,  $s \neq \lambda$ ,  $H(s) = \frac{1}{s-\lambda}$   
 - solve  $x(t) = (x_0 - H(s)) e^{\lambda t} + H(s) e^{st}$

- Piecewise constant inputs

(1)  $\frac{d}{dt} x(t) = \lambda x(t) + u(t)$   
 (2)  $u(t) = u(i)$  if  $t \in [i\Delta, (i+1)\Delta)$   
 Start at  $x_i[i] = x(i\Delta) \Rightarrow x_i[i+\Delta] = x(i+\Delta)$   
 $\frac{d}{dt} x(t) = \lambda x(t) + u(i)$   
 Guess  $x(t) = \alpha e^{\lambda(t-i\Delta)} + \beta$   
 $\frac{d}{dt} x(t) = \lambda \alpha e^{\lambda(t-i\Delta)} = \lambda x(t) + u(i)$   
 $\Rightarrow \lambda \alpha e^{\lambda(t-i\Delta)} = \lambda (\alpha e^{\lambda(t-i\Delta)} + \beta) + u(i)$   
 $\beta = \frac{-u(i)}{\lambda}$ ,  $x(i\Delta) = x(i)$   
 $x(i) = \alpha + \beta \Rightarrow \alpha = x(i) + \frac{u(i)}{\lambda}$   
 $x(t) = (x(i) + \frac{u(i)}{\lambda}) e^{\lambda(t-i\Delta)} - \frac{u(i)}{\lambda}$   
 $\Rightarrow x(i+\Delta) = x(i) e^{\lambda\Delta} + \frac{e^{\lambda\Delta} - 1}{\lambda} u(i)$

- Can we reach a certain position?

-  $\tilde{x}(i+\Delta) = A \tilde{x}(i) + B u(i) + \tilde{w}(i)$   
 -  $x(i) = A^i x(0) + B \sum_{j=0}^{i-1} A^{i-1-j} u(j)$   
 -  $x(i) = A^i x(0) + A^i B \tilde{u}(i) + B \tilde{u}(i)$   
 - to reach in 3 steps  $\exists F, x^* \in \text{span}(B, AB, A^2B)$  (or  $x^* - A^3 x(0)$ )  
 - Finding A & B, least square  
 $A \tilde{x} = \tilde{b}$ ,  $\tilde{x} = (A^T A)^{-1} A^T \tilde{b}$ ,  $A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix}$  Arc counts for

- Find  $\tilde{z}(t)$ ?

- observation matrix  $\tilde{y}(t) = C \tilde{z}(t)$   
 - consider system w/ inputs to get  $\tilde{z}(t)$   
 - assuming model scalar (parallel system) if not scalar  
 - want randomized  $u(i)$  bc could have linear dependence  
 - consider  $x(i) = a x(i) + b u(i) + w(i)$  least square  $\begin{bmatrix} a(i) \\ b(i) \\ w(i) \end{bmatrix} = \begin{bmatrix} x(i) \\ u(i) \\ 0 \end{bmatrix}$   
 - basically variable for each component

- Stability?

- Scalar (1)  $x(i+\Delta) = \alpha x(i) + u(i) + w(i)$  // no dependence, min var.  
 (2)  $x(i+\Delta) = \frac{1}{2} x(i) + u(i) + w(i)$  //  $\frac{1}{2}, \frac{1}{2}, \dots = 0$  no effect  
 (3)  $x(i+\Delta) = 2x(i) + u(i) + w(i)$  //  $2, 2, \dots = \infty$  unstable  
 - Stable  $|\lambda_i(A)| < 1$  Remember  $A \tilde{z}(t) = \lambda \tilde{z}(t)$   
 - unstable  $|\lambda_i(A)| \geq 1$   $A \tilde{0} = \lambda \tilde{0}$  det(A-AI) = 0

- Real inductor (has R)

$Z = j\omega L + R + \frac{1}{j\omega C}$   
 $Z(\omega = \frac{1}{RC}) = R$   
 $Q = \frac{\omega L}{R} = \frac{1}{\omega RC}$

- Controller Canonical Form (CCF)

- $\tilde{A} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \\ a_0 & a_1 & \dots & a_{n-1} \end{bmatrix}$ ,  $\tilde{B} = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}$ ,  $\tilde{C}(s) = \begin{bmatrix} x(t) \\ \vdots \\ z(t) \end{bmatrix}$
- $z(t+1) = a_n z(t) + a_{n-1} z(t-1) + \dots + a_1 z(t-(n-1)) + u(t)$
- controllable system of form  $\dot{z}(t+1) = \tilde{A}z(t) + \tilde{B}u(t)$
- Find  $T$  s.t.  $\tilde{z} = Tz$ ,  $\tilde{A} = TAT^{-1}$ ,  $\tilde{B} = TB$ 
  - $R_n = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix}$
  - $\tilde{A} = R_n^{-1} A^n \tilde{b}$  gives coefficients of characteristic poly.  $F A$
  - find  $\tilde{R}_n = \begin{bmatrix} \tilde{b} & A\tilde{b} & \dots & A^{n-1}\tilde{b} \end{bmatrix}$ , again  $\tilde{a} = \tilde{R}_n^{-1} \tilde{A}^n \tilde{B}$
  - $T = \tilde{R}_n R_n^{-1}$
  - if use feedback  $u(t) = \tilde{K}\tilde{z} = Kz$ ,  $\tilde{K} = -KT^{-1}$ , we get  $T(A+BK)T^{-1} = \tilde{A} + \tilde{B}\tilde{K}$
- Allstate conversion - coefficient matching
  - $\tilde{A}$  and  $A$  have same characteristic polynomial
  - check for controllability first
  - $\det(K\tilde{A} - \lambda I) = \lambda^n - a_{n-1}\lambda^{n-1} - \dots - a_0$

- Linearization

- Linear (FC) properties iff
  - scaling  $\forall \alpha (F(\alpha x)) = \alpha F(x)$
  - superposition  $F(x_1 + x_2) = F(x_1) + F(x_2)$
- Linearization of function  $f(x)$ 
  - expand about  $x^*$
  - $f_L(x^* + \delta x) \approx f(x^*) + m \delta x$
  - $\delta y = f_L(x^* + \delta x) - f(x^*) = m \delta x$
- Linearity for system
  - input  $u(t) \rightarrow \begin{cases} \text{input} \\ \text{output} \end{cases}$   $y(t) = \mathcal{L}\{u(t)\}$  functional
  - not same as  $y(t) = \mathcal{L}\{u(t)\}$  function
  - function
    - easy: if know  $\delta$ , compute  $y(t)$  if know  $u(t)$
  - functional (capture memory)
    - need to know all  $u(t)$
    - ex.  $y(t) = \mathcal{L}\{u(t)\} \approx \int_{t-1}^t u(\tau) d\tau$
  - system linear iff
    - scaling  $\mathcal{L}\{k u(t)\} = k \mathcal{L}\{u(t)\}$
    - superposition  $\mathcal{L}\{u_1(t) + u_2(t)\} = \mathcal{L}\{u_1(t)\} + \mathcal{L}\{u_2(t)\}$
    - ex.  $\frac{d}{dt} f(x) = b u(t)$  is linear iff  $f(x)$  is linear
- Linearization of ODE about operating point
  - $\dot{x} = f(x) + b u(t)$ , but  $f(x)$  nonlinear
  - 1) choose given input  $u(t) = u^*$  // constant w/ time
  - 2)  $x(t) = x^*$  solve  $f(x^*) = -b u^*$  for  $x^*$
  - 3) Define  $\delta x(t) = x(t) - x^*$ ,  $\delta u(t) = u(t) - u^*$ 
    - output deviation input perturbation
  - 4) Suppose  $\delta u(t)$  is small
  - 5) Assume  $\delta x(t)$  is small (big assumption, not always true)
  - 6)  $\dot{\delta x}(t) = f(x^*) + m \delta x(t) + b \delta u(t)$

- Linearization of Vector Case

- $\tilde{f}(\tilde{x}) = \begin{bmatrix} f_1(x_1, x_2, \dots) \\ f_2(x_1, x_2, \dots) \\ \vdots \\ f_n(x_1, x_2, \dots) \end{bmatrix}$
- $\tilde{f}(x^* + \delta x) \approx \tilde{f}(x^*) + J_{\tilde{f}} \delta x$  at  $x^*$

- Speed up OMP

- 1) find max column, add but orthogonalize
- 2)  $\tilde{Q} = (A^T A)^{-1} A^T b = A^T \tilde{b}$

- Gram Schmidt

- don't forget to normalize too  $\text{proj}_a \tilde{b} = \frac{a \cdot \tilde{b}}{\|a\|^2} a$
- BIBO - bounded input, bounded output

- Schur Form =  $A = Q T Q^*$

- basically  $\text{eig}(A)$
- real, symmetric  $A = P \Lambda P^T$

- Spectral Theorem

- real, symmetric  $A = P \Lambda P^T$

- SVD (Singular Value Decomposition)

- $A = U \Sigma V^T$
- $U, V$  unitary,  $\Sigma$  diagonal
- $\sigma_i \geq 0$

- outer products

- Moore Penrose Pseudo Inverse

- $A^+ = V \tilde{\Sigma} U^T$
- solves  $A \tilde{x} = \tilde{b}$  w/ min  $\|\tilde{x}\|$
- $\tilde{\Sigma} = \begin{bmatrix} \sigma_1 & & & 0 \\ & \sigma_2 & & 0 \\ & & \ddots & \\ & & & \sigma_r \\ & & & & 0 \end{bmatrix}$  pad 0s when needed
- get for min energy

- Calculation Frobenius Norm

$$\|A\|_F = \sqrt{\sum_{i,j} |a_{ij}|^2} = \sqrt{\text{Tr}\{A^T A\}} = \sqrt{\sum_{i=1}^n \sigma_i^2}$$

$$A = U \Sigma V^T = \sum_{i=1}^r \sigma_i u_i v_i^T$$

- calculation - A-norm

- 1)  $A^T A$  dim  $n \times n$
- 2) find  $\lambda_i$  and  $\tilde{v}_i$
- 3) for  $\sigma_i = \sqrt{\lambda_i}$  multiply by  $\tilde{v}_i$ , make  $V$  unitary  $u_i$  if necessary, use Gram Schmidt
- 4)  $\tilde{u}_i = \frac{A \tilde{v}_i}{\sigma_i}$

- for compression error

$$\|A - \tilde{A}\| = \sqrt{\sum_{i=r+1}^n \sigma_i^2}$$

- PCA (Principal Component Analysis)

- $A$  -  $n \times m$
- $\tilde{A}$  - mean centered
- Covariance Matrix  $S = \frac{1}{n} \tilde{A}^T \tilde{A}$   $n \times n$  - diagonal has biggest values absolute value-wise
- Correlation Matrix
  - divide by  $\sigma_i$  of  $S_i$
  - diagonal  $U$
  - $r_i$  is correlation between dim
  - not always good tho

- PCA -  $S = P \Lambda P^T$

- $\tilde{p}_i$  are direction of correlation
- $\lambda_i$  is covariance

- SVD connection

$$\tilde{A} = U \Sigma V^T \Rightarrow S = V \tilde{\Sigma} U^T \Rightarrow \frac{1}{n} \tilde{A}^T \tilde{A} = V \begin{bmatrix} \frac{\sigma_1^2}{n} & & & 0 \\ & \frac{\sigma_2^2}{n} & & 0 \\ & & \ddots & \\ & & & \frac{\sigma_r^2}{n} \\ & & & & 0 \end{bmatrix} V^T = P \Lambda P^T \Rightarrow \lambda_i = \frac{\sigma_i^2}{n}$$

- Approximation Curves

- Pwl (Piecewise Linear) - lines
- Zero (Zero Order Hold) - constant between points, jumps
- sinc  $\tilde{f}(t) = \sum_{k=-\infty}^{\infty} \tilde{f}(k) \phi(t-k)$
- sinc  $\tilde{f}(t) = \begin{cases} \frac{\tilde{f}(t)}{t} & \text{if } t \neq 0 \\ \tilde{f}(0) & \text{if } t = 0 \end{cases}$
- Polynomial

- Hermitian matrix - same as complex transpose

- To find char.  $\lambda$  of observation matrix  $C$ , just plug in  $\tilde{C}$  instead of  $\tilde{z}$  to get new char poly

$$\tilde{C} V(t) = C U(t) - \beta$$

$$\begin{bmatrix} \tilde{C}(1) & \dots & \tilde{C}(n) \\ \vdots & \ddots & \vdots \\ \tilde{C}(1) & \dots & \tilde{C}(n) \end{bmatrix} \begin{bmatrix} V(1) \\ \vdots \\ V(n) \end{bmatrix} = \begin{bmatrix} \beta \\ \vdots \\ \beta \end{bmatrix}$$

- Discrete Fourier Transform (DFT)

- Digital Signal Processing (DSP)

- take snippets of signal and process  
 $x(t) = A_1 + A_2 \cos(2\pi f_1 t + \theta_1) + A_3 \cos(2\pi f_2 t + \theta_2) + \dots$   
 think of  $A_1$  as fundamental component,  $A_2 \cos(2\pi f_1 t + \theta_1)$  as 2<sup>nd</sup> harmonic, etc.  
 - phases -  $A_1 \cos(2\pi f_1 t + \theta_1) = \frac{A_1}{2} e^{j\theta_1} e^{j2\pi f_1 t} + c.c.$

- Complex review

-  $j = \sqrt{-1}$ ;  $a = a_r + ja_i$ ;  $\bar{a} = a_r - ja_i$   
 $-a\bar{a} = a_r^2 + a_i^2$ ;  $|a| = \sqrt{a_r^2 + a_i^2} = \sqrt{a\bar{a}}$   
 - de Moivre's/Euler's formula -  $e^{j\theta} = \cos\theta + j\sin\theta$   
 $-e^{-j\theta} = \cos\theta - j\sin\theta$  (graphically true)  
 $-\cos\theta = \frac{1}{2}(e^{j\theta} + e^{-j\theta})$   
 $-\sin\theta = \frac{1}{2j}(e^{j\theta} - e^{-j\theta})$   
 - Polar Form -  $a = a_r + ja_i = M e^{j\theta}$   $M = |a|$ ,  $\theta = \tan^{-1}(\frac{a_i}{a_r})$   
 $-x^k = M^k e^{jk\theta}$   
 - roots of unity (1) -  $\omega_N = e^{j\frac{2\pi}{N}}$   $\Rightarrow \omega_N^N = 1$   $\omega_N \neq 1$

- complex vectors/matrices

-  $\vec{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_N \end{bmatrix}$   $\|\vec{x}\| = \sqrt{|x_1|^2 + \dots + |x_N|^2} = \langle \vec{x}, \vec{x} \rangle$   
 $\langle \vec{x}, \vec{y} \rangle = \vec{y}^H \vec{x}$  Hermitian inner product  
 $-\vec{y}^H = \vec{y}^T$  Hermitian = complex conjugate transpose

- DFT matrix

-  $N \times N$ , indices start at 0,  $F_N$   
 $-F_N = \begin{bmatrix} \omega_N^{0 \cdot 0} & \omega_N^{0 \cdot 1} & \dots & \omega_N^{0 \cdot (N-1)} \\ \omega_N^{1 \cdot 0} & \omega_N^{1 \cdot 1} & \dots & \omega_N^{1 \cdot (N-1)} \\ \vdots & \vdots & \ddots & \vdots \\ \omega_N^{(N-1) \cdot 0} & \omega_N^{(N-1) \cdot 1} & \dots & \omega_N^{(N-1) \cdot (N-1)} \end{bmatrix}$   $\omega_N^{ij} = (e^{j\frac{2\pi}{N}})^{ij}$  entry  
 $-F_N = \begin{bmatrix} 1 & 1 & \dots & 1 \\ \omega_N & \omega_N^2 & \dots & \omega_N^{N-1} \\ \vdots & \vdots & \ddots & \vdots \\ \omega_N^{N-1} & \omega_N^{2(N-1)} & \dots & \omega_N^{(N-1)^2} \end{bmatrix}$   $\vec{y}_k = \begin{bmatrix} \omega_N^{0 \cdot k} \\ \omega_N^{1 \cdot k} \\ \vdots \\ \omega_N^{(N-1) \cdot k} \end{bmatrix}$

- Properties

- 1) symmetric
- 2)  $\|\vec{y}_k\| = \sqrt{N}$ , bc  $\|\vec{y}_k\| = 1$
- 3)  $\langle \vec{y}_k, \vec{y}_l \rangle = 0$  if  $k \neq l$ , orthogonal
- 4)  $F_N^{-1} = \frac{1}{N} F_N^*$   $\leftrightarrow F_N^* F_N = N I$
- 5)  $\vec{y}_k = \frac{1}{\sqrt{N}} F_N \vec{x}$   $F_N = \begin{bmatrix} \omega_N^{0 \cdot k} \\ \omega_N^{1 \cdot k} \\ \vdots \\ \omega_N^{(N-1) \cdot k} \end{bmatrix}$  complex conjugate transpose  
 $\vec{y}_k = \frac{1}{\sqrt{N}} \begin{bmatrix} 1 \\ \omega_N^k \\ \vdots \\ \omega_N^{(N-1)k} \end{bmatrix}$  complex conjugate transpose

- Frequency separation

-  $x(t) = A_2 \cos(2\pi f_2 t + \theta_2)$ ,  $T = \frac{1}{f_2}$ ,  $t \in [0, T]$   
 -  $M$  is max considered frequency  
 $N = 2M + 1$  samples  
 $\omega = \frac{2\pi}{N}$   $\omega_N = e^{j\omega}$   
 $-x(k\Delta) = A_2 \cos(2\pi f_2 k\Delta + \theta_2) = A_2 \cos(\frac{2\pi}{N} k + \theta_2)$   
 $= \frac{A_2}{2} e^{j\theta_2} e^{j\frac{2\pi}{N} k} + c.c. = C_2 \omega_N^{k \cdot 1}$   
 $-\vec{y}_k = \begin{bmatrix} 1 \\ \omega_N \\ \vdots \\ \omega_N^{N-1} \end{bmatrix} = C_2 \begin{bmatrix} \omega_N^{0 \cdot 1} \\ \omega_N^{1 \cdot 1} \\ \vdots \\ \omega_N^{(N-1) \cdot 1} \end{bmatrix} + c.c.$   
 $\vec{y}_k = \frac{1}{\sqrt{N}} \begin{bmatrix} 1 \\ \omega_N^k \\ \vdots \\ \omega_N^{(N-1)k} \end{bmatrix}$  entries  $\vec{y}_k$   
 $-F_N \vec{y}_k = N \begin{bmatrix} 1 \\ \omega_N^k \\ \vdots \\ \omega_N^{(N-1)k} \end{bmatrix}$  1 value matches and peak at c.c.  $\neq N-1$

- Periodic waveforms

-  $T$ -periodic if  $x(t+T) = x(t)$  for all  $t$   
 $-f_0 = \frac{1}{T}$  fundamental freq  
 - make any  $T$ -periodic apply Fourier  $p(t) = F(y(t))$   
 - Fourier series can make any signal w/ sine waves  
 $-x(t) = \sum_{l=0}^{\infty} B_l \cos(2\pi l f_0 t + \theta_l) = \sum_{l=-\infty}^{\infty} A_l e^{j2\pi l f_0 t}$   
 $-A_l = \frac{1}{T} \int_0^T e^{-j2\pi l f_0 t} x(t) dt$ , each integer  $l$   
 $-N = 2M + 1$  samples,  $k = \frac{t}{\Delta}$   $x(k\Delta) = \sum_{l=-M}^M X_l e^{j\frac{2\pi}{N} k l}$   $\vec{x} = F_N^* \vec{X} = N F_N^{-1} \vec{X}$   
 $\vec{X} = \begin{bmatrix} X_0 \\ \vdots \\ X_M \end{bmatrix}$  DFT,  $k$  is  $\begin{bmatrix} -M \\ \vdots \\ M \end{bmatrix}$   $\vec{X}$  is  $\begin{bmatrix} X_0 \\ \vdots \\ X_M \end{bmatrix}$   $\vec{X}$  is  $\begin{bmatrix} X_0 \\ \vdots \\ X_M \end{bmatrix}$

- Interpolation by basis functions

-  $y(t) = \sum_k x_k \phi_k(t)$ ;  $\phi_k(t)$  continuous time basis  
 $-y(t) = \sum_{k=0}^{N-1} y_k \phi(t-k\Delta)$   
 - need  $\phi(0) = 1$  and  $\phi(k\Delta) = 0$   $k \neq 0$   
 - Zero Order Hold (ZOH) -   
 - Piecewise Linear (PL) -   
 $-\text{sinc}(t) = \frac{\sin(\pi t)}{\pi t}$   $\phi(t) = \text{sinc}(\frac{t}{\Delta})$

- Interpolation by Global Polynomials

- Lagrange Interpolation  
 $-y(t) = \sum_{i=0}^{N-1} a_i t^i$ , need  $y(k\Delta) = y_k(k\Delta)$   
 $-N-1$  equations -  $y_k(k\Delta) = a_0 + a_1(k\Delta) + \dots + a_{N-1}(k\Delta)^{N-1}$   
 $-\begin{bmatrix} y_0(0) \\ \vdots \\ y_{N-1}(N-1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & \Delta & \dots & \Delta^{N-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & (N-1)\Delta & \dots & ((N-1)\Delta)^{N-1} \end{bmatrix} \begin{bmatrix} a_0 \\ \vdots \\ a_{N-1} \end{bmatrix}$   
 $\vec{y} = V \vec{a}$   
 - Vandermonde structure -  $\det(V) = (N-1)! \Delta^{N-1} \neq 0$   
 - always a unique soln  
 - Lagrange Interpolation  $y_k(x) = \prod_{j=0, j \neq k}^{N-1} \frac{(x-x_j)}{(x_k-x_j)}$   
 $-y(t) = \sum_{i=0}^{N-1} y_i(t) L_i(t)$

- Extra

- LTI - linear time invariant system  
 $-Y(z) = H(z) X(z)$   
 - impulse condition  $\delta[n]$  input  
 - BIBO - bounded input, bounded output  
 - DFT coeffs  $\frac{N}{2} e^{j\theta} \cos(\frac{2\pi}{N} t + \theta)$   
 $= \frac{N A_2}{2} e^{j\theta}$   
 $-\frac{d}{dt} \vec{x}(t) = A \vec{x}(t)$   
 - if eigenvalue real and negative  $\rightarrow$  stable  
 - oscillates if imaginary part  
 - stable if negative eigenvalues  
 -  $k$ -means  
 - clarify and recalculate  
 - clusters  
 - SVD good for pseudo inverse  
 - solve for system w/ min error norm  
 - DFT - think of like counting number of waves in sample window