

Angle Modulation:  $u(t) = A_c \cos(\omega_c t + \varphi(t))$

PM:  $\dot{\varphi}(t) = K_p m(t)$

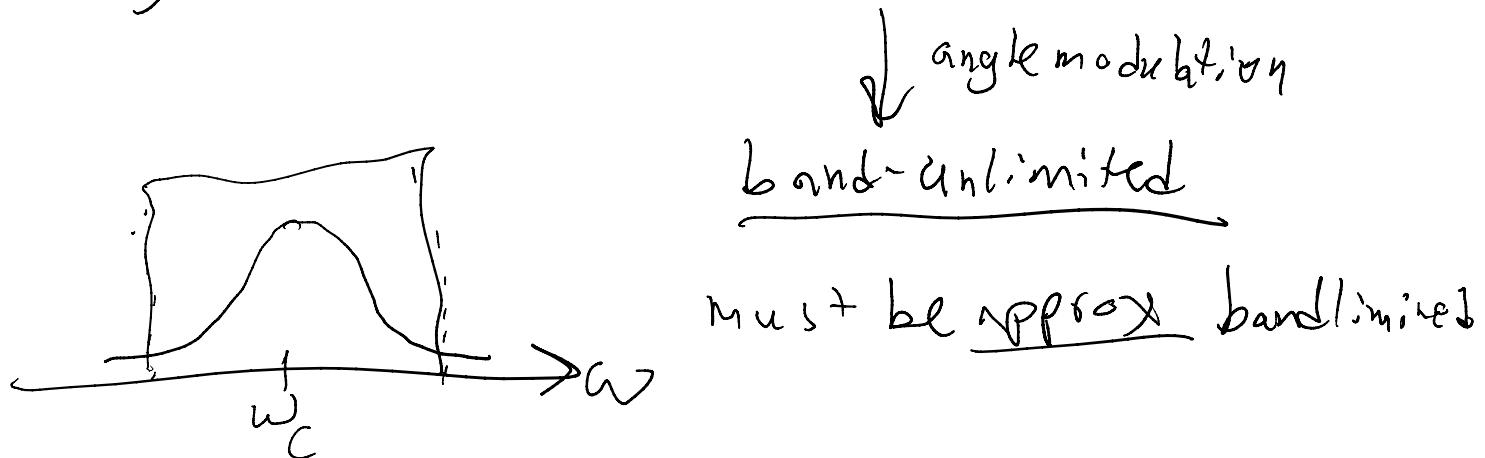
FM:  $\dot{\varphi}(t) = 2\pi K_f \int_{-\infty}^t m(\tau) d\tau$

$$f_i(t) = f_c + \frac{1}{2\pi} \frac{d}{dt} \varphi(t)$$

So FM modulates  $f_i - f_c$

Tuesday, September 29, 2020 6:01 PM

Using the Bessel functions - a tone



must be approx bandlimited

FM  $\rightarrow$  band unlimited  
 $\downarrow$  BRF

band limited ( $\downarrow$  distorted)

$$\text{tone thru PM} \Rightarrow u(t) = \sum_{n=-\infty}^{\infty} A_n J_n(\beta) \cos((\omega_n + n\omega_0)t)$$

$\uparrow$  decays in  $n$

"Rule of Thumb" if all have mod. index  $\beta$ , freq. of tone  $f_0$ , the effective

BW is  $B = 2(\beta + 1)f_0$   $\leftarrow$  both FM and PM  
 centered around  $f_c$

... 1 ... 2 ... 3 ... 4 ... 5 ... 6 ...

concentration

for a tone this gives us 98% of signal power



### Carson's Rule

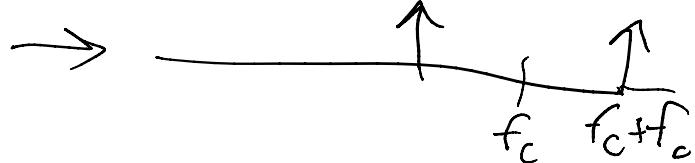
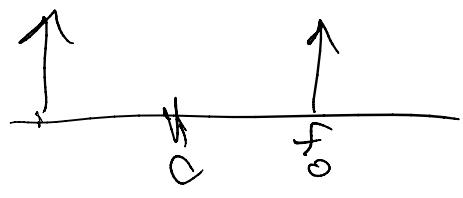
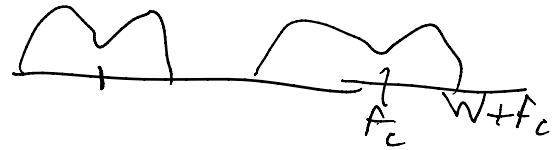
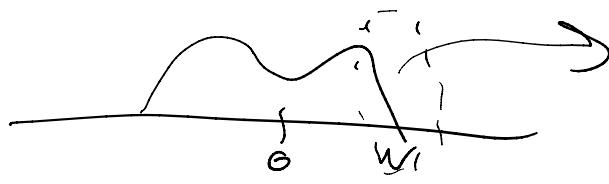
For message signal with BW  $W$ , i.e.  $BW_f$

the angle-modulated signal is approximately

$$B_c = 2(\beta + 1)W$$

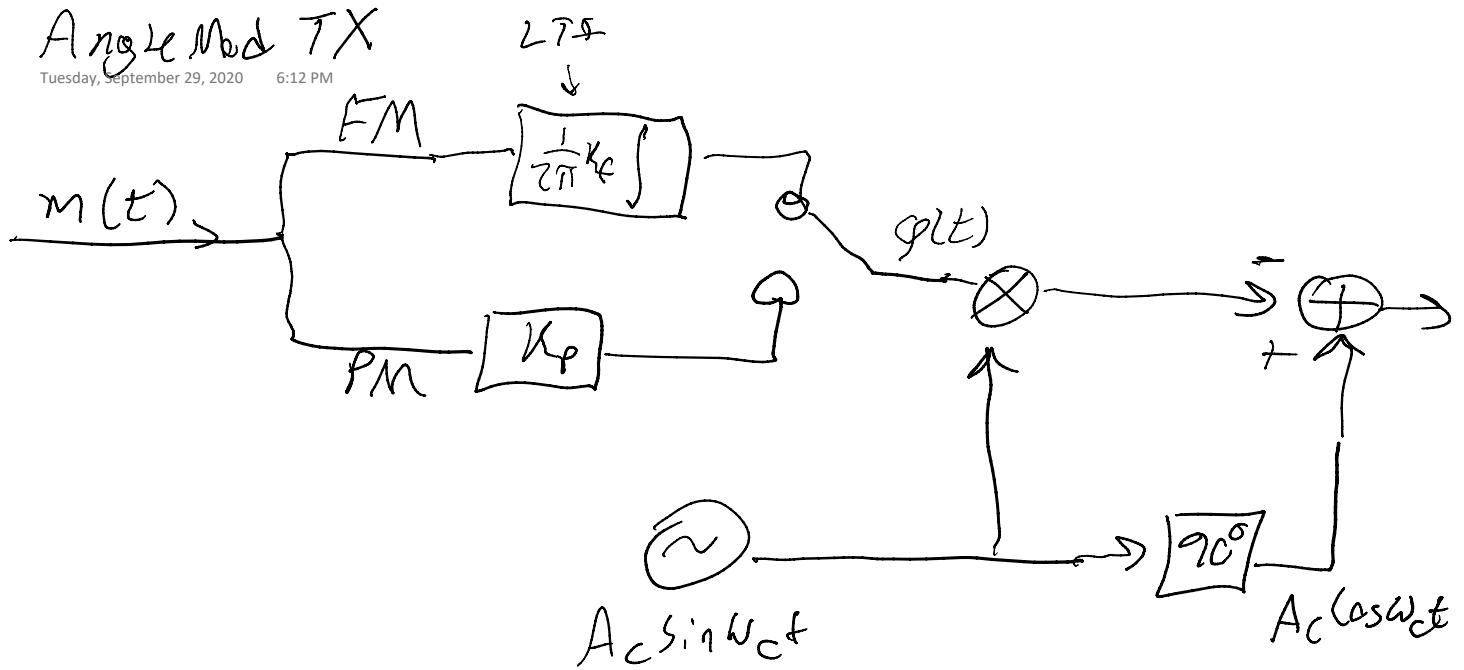
centered about  
 $f_c$

even in AM, had tone freq.  $f_0 \sim$  to  $W$



# Angle Mod TX

Tuesday, September 29, 2020 6:12 PM



$$- \varphi(t) A_c \sin w_ct + A_c \cos w_ct$$

narrowband FM formula  
derived using cos & sin



Less narrowband signal

$$u(t) = A_c \cos(w_c t + \underline{\Phi}(t))$$

pick an integer  $n$  s.t.  $\underline{\Phi}(t)/n$  is small  
(relative to  $2\pi$ )  
so that  
 $\sin \underline{\Phi}_n \approx \underline{\Phi}_n$

more detailed discussion

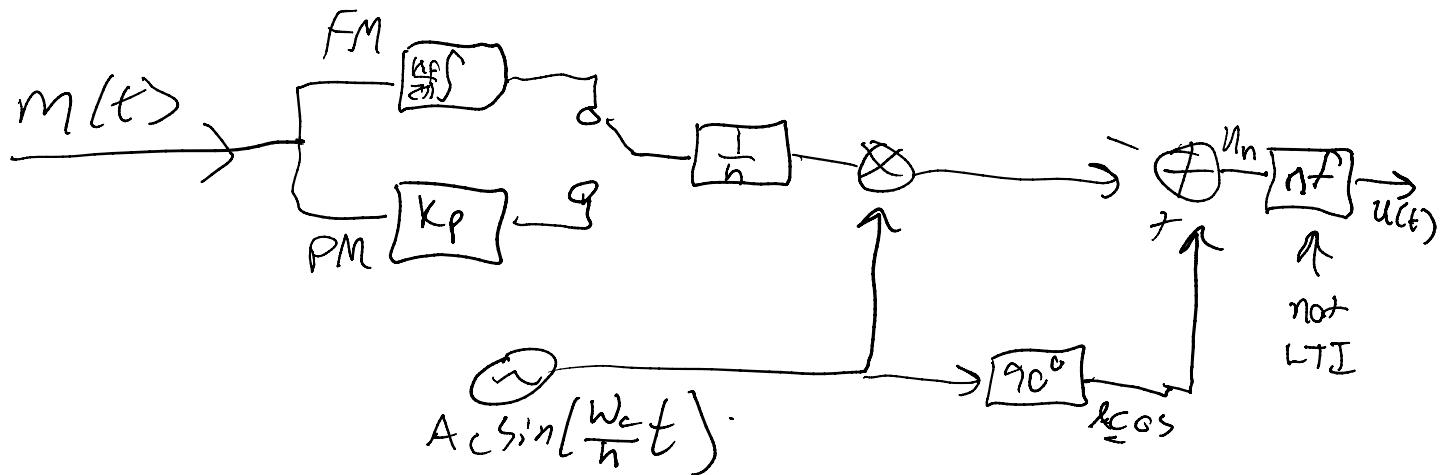
You can always do this so long as  $m$  bounded

$$\text{then } u_n(t) = A_c \cos\left(\frac{\omega_c}{n}t + \frac{\phi(t)}{n}\right) \leftarrow \begin{matrix} \text{narrowband} \\ \text{signal} \end{matrix}$$

Can generate these using the scheme above

And then use "frequency multiplier" by factor  $n$

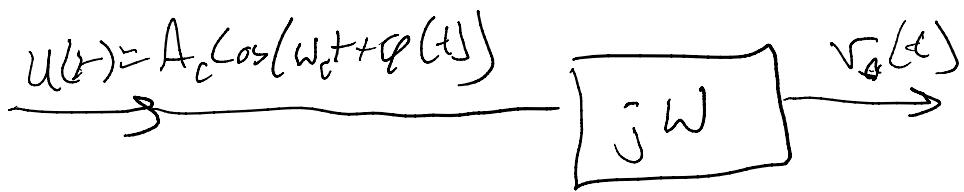
(find in lab)



$$\cos \omega_c t \xrightarrow{\text{multiplier}} \frac{1 + \cos 2\omega_c t}{2}$$

## Demod

Tuesday, September 29, 2020 6:25 PM

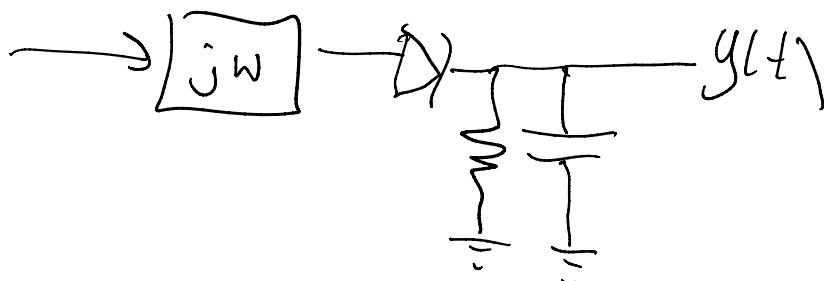


$$v_o(t) = A_c (\omega_c + \dot{\varphi}(t)) (-\sin \omega_c t)$$

$$\stackrel{FM}{=} -A_c (\omega_c + m(t)) \sin \omega_c t$$

Conventional AM

## FM demod



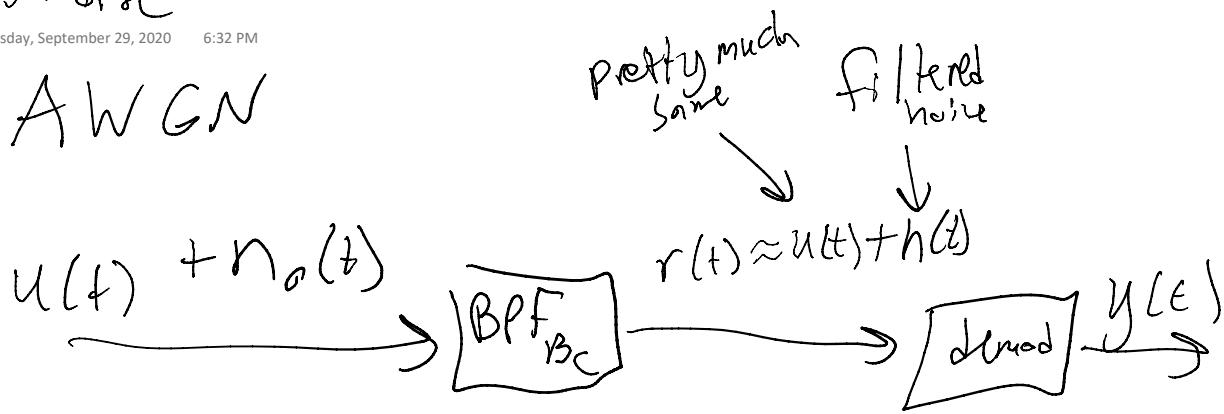
FM has very inexpensive demod  
(no mixer)

PM - backwards IQ demod (like for SSB)  
(can do for FM too)

# Noise

Tuesday, September 29, 2020 6:32 PM

AWGN



$$n(t) = n_I(t) \cos \omega_c t - n_Q(t) \sin \omega_c t$$

$$r(t) = u(t) + n(t)$$

↓ polar form

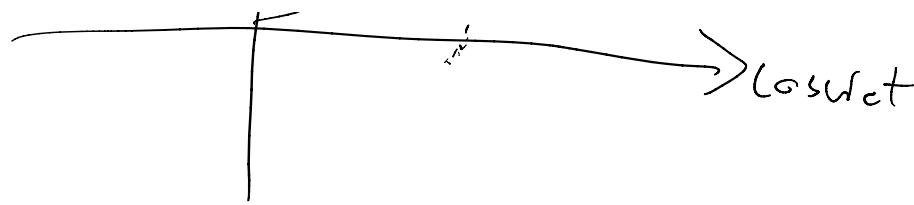
$$= u(t) + \sqrt{n_I^2(t) + n_Q^2(t)} \cos\left(\omega_c t + \arctan\left(\frac{n_Q(t)}{n_I(t)}\right)\right)$$

$$= u(t) + V_n(t) \cos(\omega_c t + \Phi_n(t))$$

↑  
narrowly Vibrating Phasor

$$- \sin \omega_c t$$





~~r(t) = A\_c cos(Φ\_n(t) + φ(t))~~ "drunken phaser"  
 our signal + gaussian  
 - dispersion

Noise power smaller  $\rightarrow \sigma \downarrow$  and the radius of  
 likely uncertainty  $\downarrow$

distinct from AM in that the phase is as vulnerable  
 $\rightarrow$  as the amplitude

$$|r(t)| \approx A_c + V_n(t) \cos(\Phi_n(t) - \varphi(t))$$

$$\angle r(t) \approx \varphi(t) + \arctan\left(\frac{V_n(t) \sin(\Phi_n(t) - \varphi(t))}{A_c + V_n(t) \cos(\Phi_n(t) - \varphi(t))}\right)$$

$\frac{\text{Taylor expansion}}{\text{high SNR}}$

$$\approx \varphi(t) + \frac{V_n \sin(\Phi_n^{(1)}(t) - \varphi(t))}{A_c + V_n(t) \cos(\Phi_n(t) - \varphi(t))}$$

$$\boxed{V_n \ll A_c} \approx \varphi(t) + \frac{V_n}{A_c} \sin(\bar{\Phi}_n(t) - \varphi(t))$$

$$= |r(t)| \cos(\omega_c t + \angle r(t))$$

$$r(t) \approx \left( A_c + V_n(t) \cos(\bar{\Phi}_n(t) - \varphi(t)) \right)$$

$$\times \cos\left(\omega_c t + \varphi(t) + \frac{V_n(t)}{A_c} \sin(\bar{\Phi}_n(t) - \varphi(t))\right)$$

demod  $\rightarrow$  PM; get phase  
FM; get  $f_i$

$$y_{PM}(t) = \varphi(t) + \frac{V_n(t)}{A_c} \sin(\bar{\Phi}_n(t) - \varphi(t))$$

$$\xrightarrow{\text{Signal}} + \xrightarrow{\text{noise}} Y_n = \frac{V_n}{A_c} \sin \bar{\Phi} - \varphi$$

$$y_{FM}(t) = \frac{1}{2\pi} \frac{d}{dt} \left( \varphi + \frac{V_n}{A_c} \sin(\bar{\Phi}_n - \varphi) \right)$$

$$= K_{FM}(t) + \frac{1}{2\pi} Y_n'(t)$$

$$\begin{matrix} T \\ \uparrow \\ \text{Signal + noise} \\ \downarrow \\ C/I \end{matrix}$$

To get  $y = \text{signal} + \text{noise}$ , used a high SNR assumption  
 Functions of  $n_I, n_Q$

$$V_h = \frac{V_n}{A_c} \sin(\Phi - \varphi)$$

Functions of the scheme

$A_c \nearrow$  decreases noise power

in AM, increase  $A_c$ ,  $\text{SNR} \nearrow$  because  $P_B$   
 but noise power is fixed

here  $\nearrow A_c \rightarrow \downarrow N$  but has no  
 effect on S

but still  $\nearrow A_c \rightarrow \text{SNR} \nearrow$

Same effect thru different route

$$Y_n(t) = \frac{V_n(t)}{A_c} \sin(\bar{\Phi}_n(t) - \phi(t))$$

$$= \frac{1}{A_c} (V_n(t) \sin \bar{\Phi}_n \cos \varphi - V_n \cos \bar{\Phi}_n \sin \varphi)$$

$$= \frac{1}{A_c} (n_Q(t) \cos \varphi - n_I(t) \sin \varphi)$$

We had narrowband approx for FM/PM, can apply

$B_C \ggg W$   $\nwarrow$  BW of  $m(t)$  so we can  
 $\approx$  BW of noise

assume  $q(t) \approx \varphi$  approx constant compared to  $\bar{\Phi}_n$

$$Y_n \approx \frac{n_Q(t)}{A_c} \cos \varphi - \frac{n_I(t)}{A_c} \sin \varphi$$

input noise (after filter) I:  $n_I$ , output J:  $\frac{n_Q}{A_c}$   
Q:  $n_Q$ , output Q:  $\frac{n_I}{A_c}$

after demod, at bb

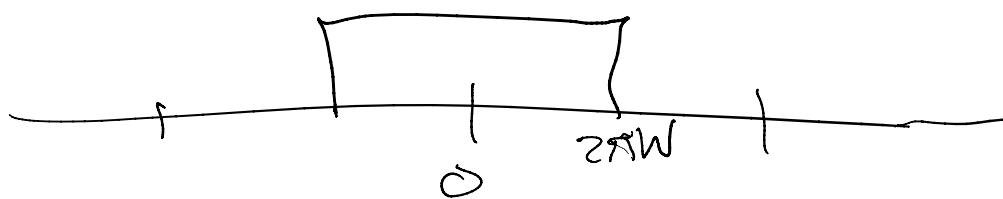
PSD I/Q have same PSD as  $Y_n$

$\uparrow A_c \downarrow P_N$   
only relationship we know

$$S_{Y_n}(w) = S_{\frac{n_Q}{A_c}}(w) = S_{\frac{n_I}{A_c}}(w) = \begin{cases} N_0/A_c^2, & |w| \leq 2BW \\ 0, & \text{else} \end{cases}$$

~ 1 ~ 1 ~ 1

Noise PSD



for PM

for FM,

noise is  $\frac{1}{2\pi} Y_n^1(t)$

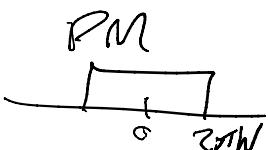
↓ PSD

$$\left| \frac{1}{2\pi} \zeta \omega \right|^2 S_{Y_n}(w)$$

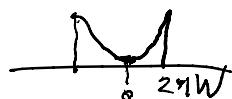
$$\frac{1}{4\pi^2} \omega^2 S_{Y_n}(w)$$

quadratic PSD

baseband case:



FM



$P - \perp P_{..}$

$\text{const } w \text{ . } n_{nn}$

$$P_h = \frac{1}{2\pi} \int S_n(w) dw = \begin{cases} \frac{2N_0 w}{A_c^2}, & \text{PM} \\ \frac{2 w^3 N_0}{3 A_c^2}, & \text{FM} \end{cases}$$

Signal power  $P_s = \begin{cases} K_p^2 P_m, & \text{PM} \\ K_f^2 P_m, & \text{FM} \end{cases}$

$$\boxed{SNR_{PM} = \frac{K_p^2 A_c^2}{2} \frac{P_m}{N_0 w}}$$

$$\boxed{SNR_{FM} = \frac{3 K_f^2 A_c^2}{2 w^2} \frac{P_m}{N_0 w}}$$

← better in narrowband case  
(as  $w \rightarrow SNR \downarrow$   
but  $\uparrow$ )

$$\beta_f = \frac{K_f}{w} \max |m(t)|$$

$$\beta_p = K_p \max |m(t)|$$

$$P_R = A_c^2 / 2$$

$$\boxed{SNR_{PM} = P_R \left( \frac{\beta_p}{\max |m(t)|} \right)^2 \frac{P_m}{N_0 w}}$$

$$SNR_{FM} = \frac{P_R}{N_{cW}} \left( \frac{B_f}{\max(|m(t)|)} \right) \sim \frac{P_m}{N_{cW}}$$

Same formula in terms of mod. index

$\nearrow \beta$  increases SNR

$\nearrow \beta$  also increases  $B_c$  by Carson

$\uparrow$  ex. Power/BW tradeoff

(issue,  $\nearrow \beta$  too much, not narrowband any more, maybe approx falls apart...)

In FM, most noise is at higher freqs,

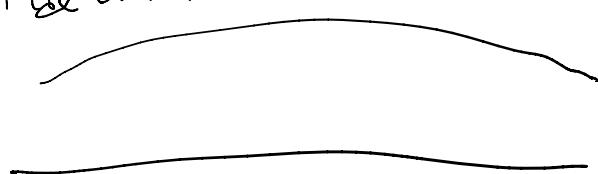
= Pre-emphasis filter amplifies high-freq before mod.

Pre-emp.

SNR  $\sim$  const

after demod

Pre-emp.



de emphasis filter

- inf M, higher freq. SE € more noise

## Wrap-up of Analog

Tuesday, September 29, 2020 7:24 PM

BW-efficiency: SSB-AM > DSSB-AM >> FM / PM  
↑  
VSB-AM

Power-efficiency: FM / PM >> AM > conventional AM

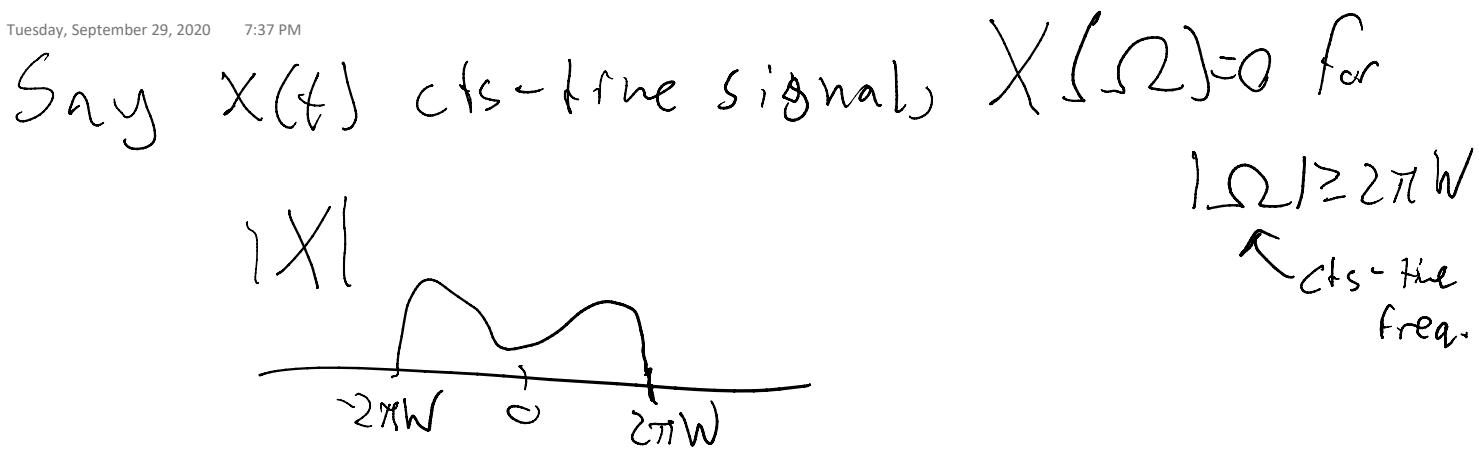
↑ highest SNR

Cost implementation: Conv. AM > FM > everything else  
↓  
cost ratios! (I, Q demod, mixer)

A&D

Tuesday, September 29, 2020 7:32 PM

- Review of sampling theory / DTFT
- Quantization (discrete-time vs. digital)
- Coding Intro
- Intro to decision theory
  - dive into Modulationschemes



Nyquist Sampling Thm; The sampled signal  $x[n] = x(nT_s)$  can "perfectly reconstruct" the signal  $x(t)$  so long as

$$\frac{1}{T_s} = f_s \geq 2W$$

$$x(t) = \sum_{n=-\infty}^{\infty} x(nT_s) \sin\left(\frac{t}{T_s} - n\right)$$

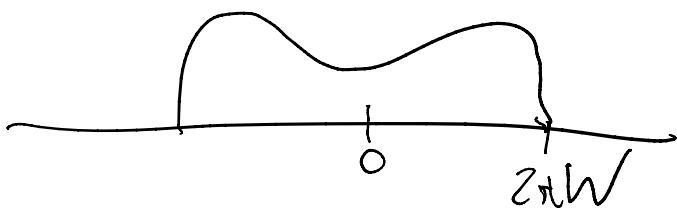
is the perfect reconstruction

# Def (DTFT)

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

- 1)  $X(\omega)$  is  $2\pi$ -periodic
- 2)  $X: \mathbb{R} \rightarrow \mathbb{C}$

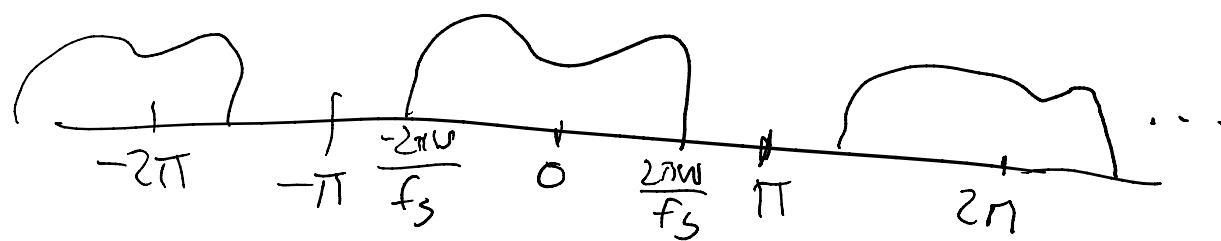
$X(\omega)$



$$\downarrow f_s > 2\omega$$

$$\boxed{\omega_s = 2\pi f_s = \Omega / f_s} \leftarrow$$

$X(\omega)$



if  $f_s < 2W$ , these overlap, and I get aliasing

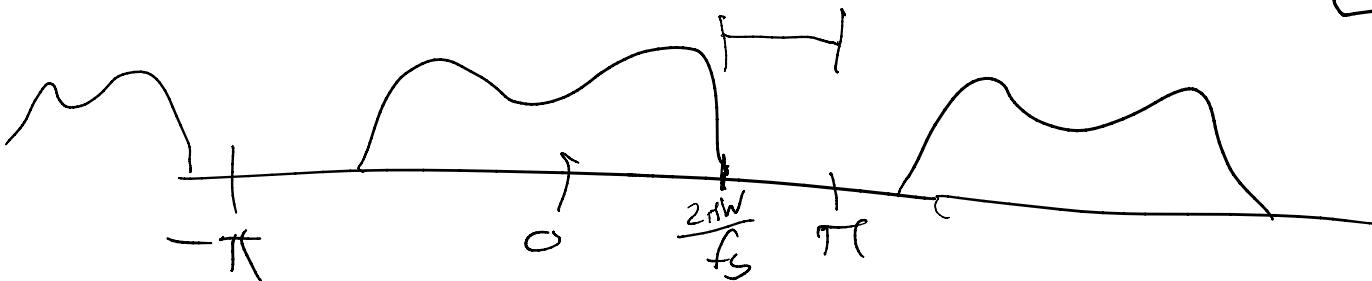


1) Nyquist Rate. The slowest you can sample a bandlimited signal and still avoid aliasing ( $f_s = 2W$ )

2) Nyquist Frequency: If I sample at  $f_s$ , what is the highest freq. of a signal that will not be aliased (cutoff of the anti-aliasing filter)  
( $f_c = f_s/2$ )

3) Guard Band

in  $W_d$  is  $\pi - \frac{2\pi W}{f_s}$   
guard band: or in  $f$  is  $[f_s - 2W]$



QuantizationEx Scalar quantization

Represent my signal using  $N$  possible values

$$\hat{x}_i, i=1, 2, \dots, N. \text{ Commonly } N=2^k$$

Discrete-time signal with values in  $\mathbb{R}$

partitioning  $\mathbb{R}$  into  $N$  intervals,  $R_i, i=1, \dots, N$

s.t. the quantization map is given by

$$Q(x[n]) = \hat{x}[n] = \hat{x}_i \text{ for } x[n] \in R_i$$

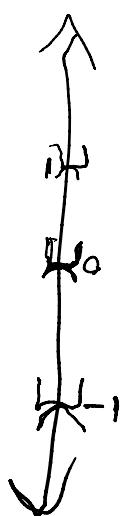
$$N=4$$

$$R_1 = (-\infty, -1)$$

$$R_2 = [-1, 0)$$

$$R_3 = [0, 1)$$

$$R_4 = [1, \infty)$$

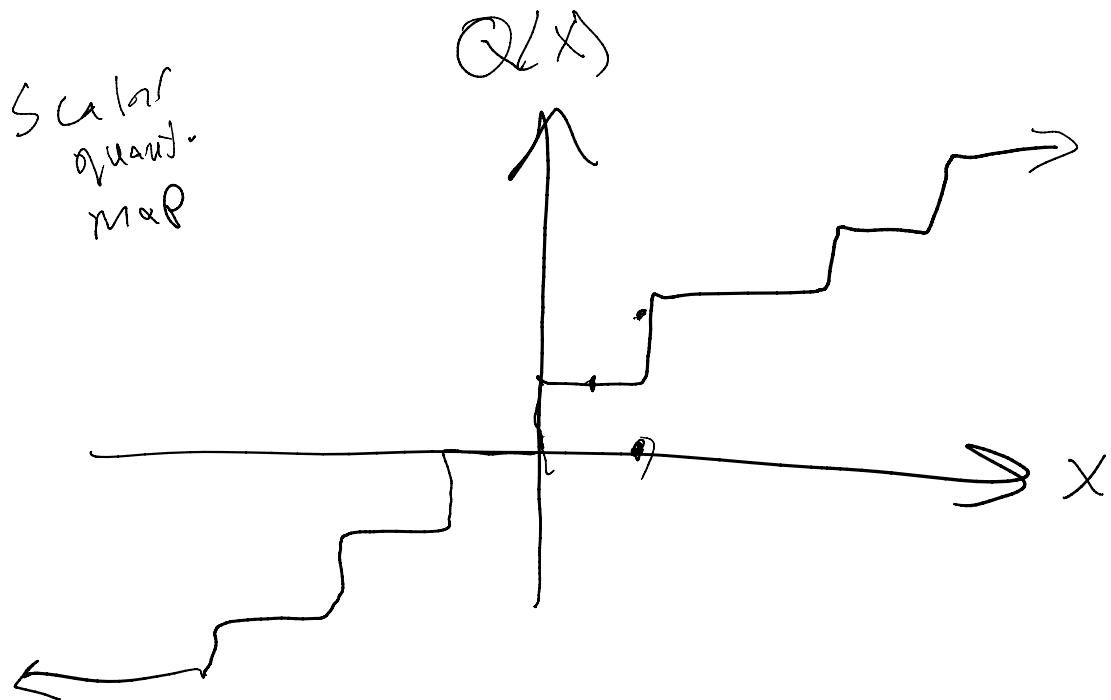


$$\begin{array}{ll} \hat{x}_1 = -2 & \hat{x}_3 = 0 \\ \hat{x}_2 = -1 & \hat{x}_4 = 1 \end{array}$$

$$\text{m.m. W.D. } \approx \infty$$

$$\hat{x}_- \approx 10$$

Ex. rep.  $\hat{x}_1$  as 00       $\hat{x}_3$  as 10  
 $\hat{x}_2$  as 01       $\hat{x}_4$  as 11



Q:

I have  $N$ -level quantization scheme,  
how many bits do I need to rep. 1 value

A:  $\lceil \log_2 N \rceil$

we are wasteful when  $N \neq 2^k$

Quantization  $\rightarrow$  Distortion

↳ 1.01  
(Quantization noise)

- 1) How does this affect the SNR?
- 2) How does this affect the spectrum? ← harder

Def Squared Error Distortion for quantizer

Quantized signal  $X[n]$  is given by

$$(X[n] - Q(x[n]))^2 \equiv \tilde{x}^2$$

This varies with  $n$

Def The average distortion (or mean square error) is given by

$$D = E[\tilde{x}^2]$$

Ex.  $X(t)$  white Gaussian C-mean

$$S_X(\omega) = \begin{cases} 2, & |\frac{\omega}{2\pi}| < 100\text{Hz} \\ 0, & \text{else} \end{cases}$$

Sample  $X_a$  at Nyquist ( $f_s = 200\text{ Hz}$ )

Let's say I use 8-level quantizer

$$R_1 = (-\infty, -60), R_2 = (-60, -40), \dots, R_7 = (40, 60), R_8 = (60, \infty)$$

$$\hat{x}_1 = -70, \hat{x}_2 = -50, \hat{x}_3 = -30, \dots, \hat{x}_8 = 70$$

Rate: 3 bits/sample (8 level)

200 samples/second

$$R = 600 \text{ bits/second}$$

$$D = E[X - Q(x)]^2 = \int_{-\infty}^{\infty} (x - Q(x))^2 f_x(x) dx$$

$f_X(x)$  is pdf of  $X$  which has  $S_X(\omega) = \begin{cases} 2, & |f| < 100 \\ 0, & \text{else} \end{cases}$

we know  $R_X(0) = \sigma^2 = E[X^2]$

$$\sigma^2 = R_X(2) \Big|_{\omega=0} = \int_{-\infty}^{\infty} \frac{1}{2\pi} S_X(\omega) e^{j\omega 2} d\omega \Big|_{\omega=0}$$

$$= \frac{1}{2\pi} \int_{-2\pi(100)}^{2\pi(100)} 2 dw = 400$$

$$f_X(x) = \frac{1}{\sqrt{2\pi(400)}} e^{-x^2/800}$$

$$\begin{aligned} D &= \int_R (x - Q(x))^2 f_X(x) dx \\ &= \sum_{i=1}^8 \int_{R_i} (x - \hat{x}_i)^2 f_X(x) dx \end{aligned}$$

$\uparrow$        $\uparrow$   
closed form      closed form

→ MATLAB

$$\boxed{D \approx 33.38}$$

$$\overline{D} \approx 33.38$$

$$\text{Mean-Squared error} = \boxed{\text{Quantization noise}}$$

Def for r.v.  $X$ , quantizer  $Q$

The signal-to-quantization noise ratio (SQNR)

is  $SQNR = \frac{E[X^2]}{E[(X-Q(X))^2]}$  power of  
a r.v.

Ex.  $E[X^2] = 400$ ,  $D = 33.38$ ,  $SQNR \approx 11.98$

$$SQNR_{dB} = 10 \log_{10}(11.98) = 10.78 \text{ dB}$$

Find the best quantizer

Optimal = greatest possible SQNR  
 or  
 for fixed power  
 lowest possible D

### Uniform Case

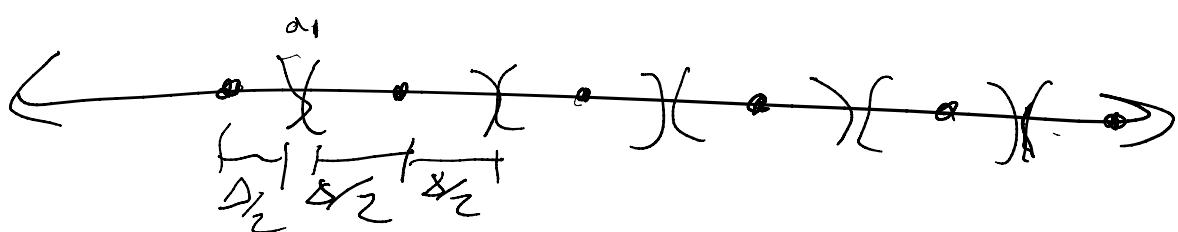
Every regions same size i.e.  $R_i = (a_i, a_{i+1})$

$$\text{then } a_{i+1} - a_i = \Delta$$

for  $i=1, \dots, N-1$  because  $R_1 = (-\infty, a_0)$   
 $R_N = (a_{N-1}, \infty)$

we choose  $\hat{x}_i = a_i + \frac{\Delta}{2}$ , for  $i=1, \dots, N-1$

$$\hat{x}_N = a_{N-1} + \frac{\Delta}{2}$$



$$D = P_1, \dots, P_{N-1}, P_N, \dots, P_\infty, z_n$$

$$D = \int_{-\infty}^{\cdot} (x - (a_1 - \Delta/2))^2 f_x(x) dx + \int_{a_{N-1}}^{\cdot} (x - (a_{N-1} + \Delta/2))^2 f_x(x) dx$$

$$+ \sum_{i=1}^{N-2} \int_{a_i + (i-1)\Delta}^{a_i + \Delta} (x - (a_1 + (i-1)\Delta + \Delta/2))^2 f_x(x) dx$$

# parameters = 2,  $a_1, \Delta$

if I know I want N-level quantizer

To find optimal quantizer,

minimize  $D(a_1, \Delta)$  in  $\mathbb{R}^2$

have a functional form, easy to search the 2-d space  
using SGD for example

Non-uniform case

$$R_i = (a_i, a_{i+1})$$

$$D = \sum_i \int_{R_i} (x - \hat{x}_i)^2 f_x(x) dx$$

$\alpha_1, \dots, \alpha_{N-1}$  are all parameters

$\hat{x}_1, \dots, \hat{x}_N$  are all parameters

$2N-1$  parameters

$$\frac{\partial D}{\partial \alpha_i} = f_x(\alpha_i)((\alpha_i - \hat{x}_i)^2 - (\alpha_i - \hat{x}_{i+1})^2) = 0$$

$$\alpha_i = \frac{1}{2}(\hat{x}_i + \hat{x}_{i+1})$$

So analytically, the  $\alpha_i$  are best chosen as the midpoints,

$$\text{can show analytically that } \frac{\partial D}{\partial \hat{x}_i} = 0 \rightarrow \hat{x}_i = \frac{\int_{\alpha_{i-1}}^{\alpha_i} x f_x(x) dx}{\int_{\alpha_{i-1}}^{\alpha_i} f_x(x) dx}$$

Centroid

but still, this is only constraining a  $2N-1$  parameter optimization problem

→ use SGD still, but constrained

→ use SGD still, but constrained  
to  $a_i \rightarrow$  midpt of  $\hat{X}$ , and  $\hat{X}$  being centers  
 $\alpha R_i$

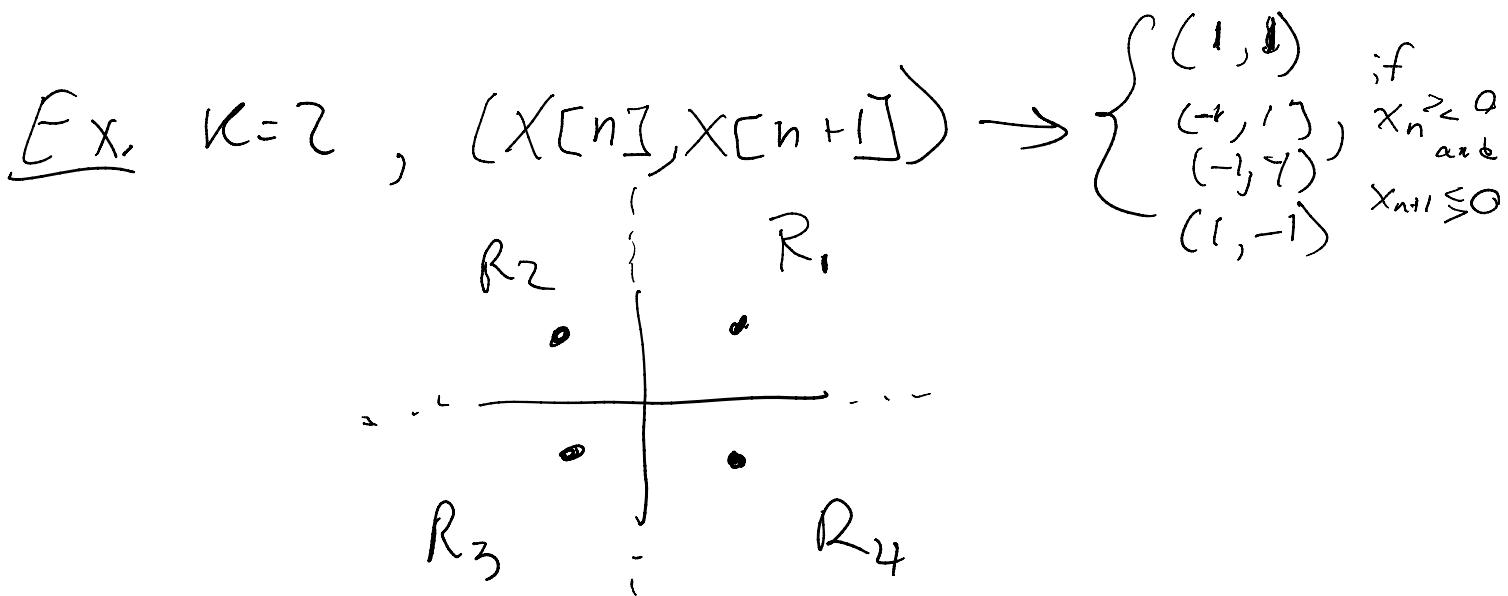
Optimal quantizer "findable" by SGD if  $X$ ,  
Var given, easier in uniform case

Scalar quantization:  $x[n] \xrightarrow{Q} \hat{x}[n] \in \mathbb{R}$

Vector quantization: map multiple time instances to one quantized value

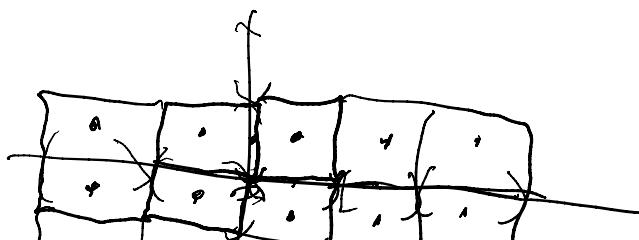
$$(x[n_1], \dots, x[n_K]) \xrightarrow{Q} \hat{x}_i \in \mathbb{R}^K$$

$\in \mathbb{R}^K$

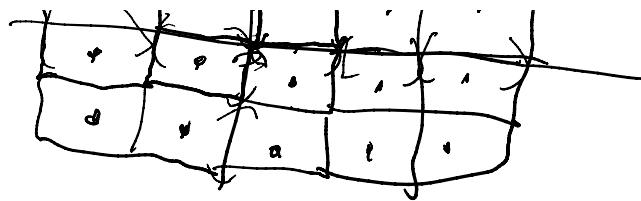


if I'm quantizing pairwise

uniform scalar  $\rightarrow$  what is uniform vector?



Cartesian Product  
of  
two uniform



or  
two uniform  
scalar, i.e. rectangles

My decision regions can have arbitrary shape in  
arbitrary dimension — pretty crazy!

Optimality - still use SGD in very high dim.

→ still, centroids of decision regions are plain

Quantizing in  $\mathbb{R}^n$  with  $K$  quant. regions  
( $K$  values)

$$\begin{pmatrix} x_{[1]} \\ \vdots \\ x_{[n+1]} \end{pmatrix} \rightarrow \hat{x}_i \in \mathbb{R}^m, i=1, \dots, k$$

$m$  signal values →  $K$  quantized values

$\lceil \log_2 K \rceil$  bits required to rep.  $m$  signal vals

$$R = \frac{\log_2 K}{m} \text{ bits/sample}$$