

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

PM:  $\varphi(t) = K_p m(t)$

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

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

So FM modulates  $f_i - f_c$

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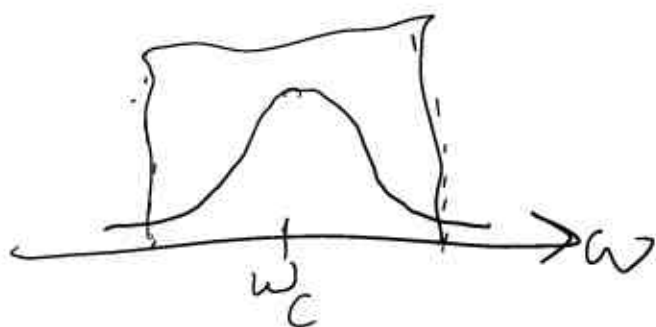
6:01 PM

Using the Bessel funcs - a tone

↓ angle modulation

band-unlimited

must be approx bandlimited



FM → band unlimited  
↓ BRF

band limited (distorted)

$$\text{tone thru PM} \Rightarrow u(t) = \sum_{n=-\infty}^{\infty} A_c J_n(\beta) \cos((\omega_c + n\omega_m)t)$$

↑ decays in  $n$

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

BW is  $B = 2(\beta + 1)f_0$  ← both FM and PM

centered around  $f_c$

... .. 90% ... ..

centered around  $f_c$

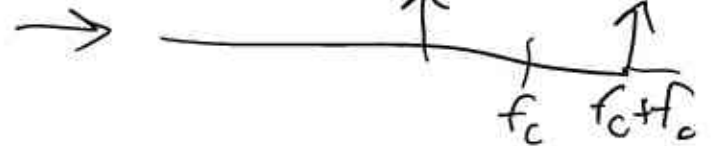
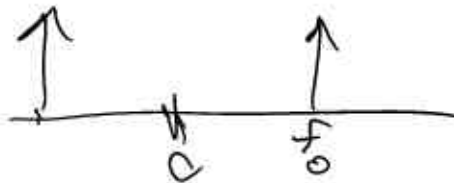
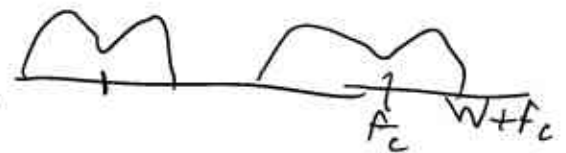
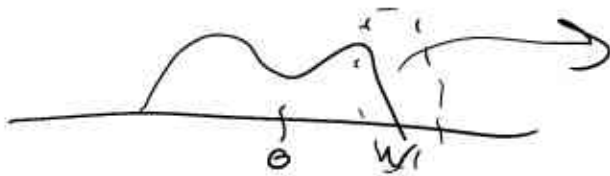
for a tone this gives us 98% of signal power

## Carson's Rule

For message signal with BW  $W$ , the BW of the angle-modulated signal is approximately

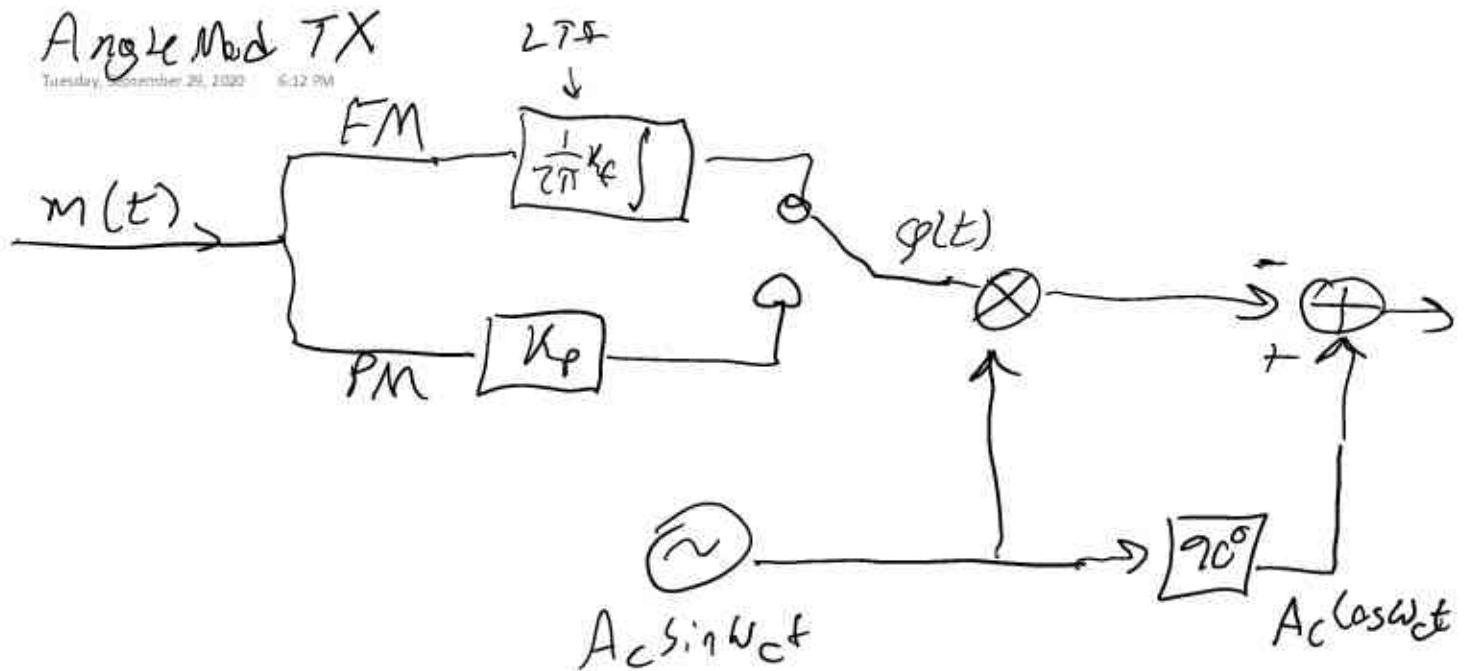
$$B_c = 2(\beta + 1)W \quad \text{centered about } f_c$$

even in AM, the tone freq.  $f_o \sim W$



# Angle Mod TX

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$$- \phi(t) A_c \sin \omega_c t + A_c \cos \omega_c t$$

narrow band FM formula  
derived using  $\cos \theta \approx 1$   
 $\sin \theta \approx \theta$

Less narrow band signal

$$u(t) = A_c \cos(\omega_c t + \Phi(t))$$

Pick an integer  $n$  s.t.  $\Phi(t)/n$  is small

(relative to  $2\pi$   
so that  
 $\sin \Phi/n \approx \Phi/n$ )

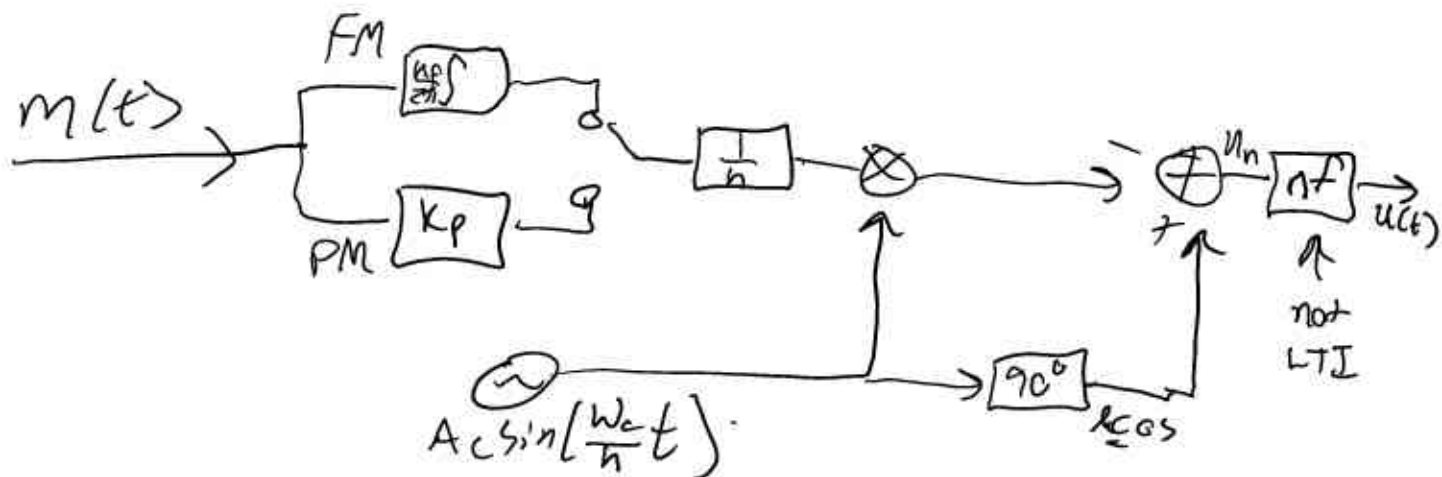
1104... 1112... 1112... 1112...

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

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

Can generate these using the scheme above

And then use "frequency multiplier" by factor  $n$   
(find in lab)



$n=2$

$$\cos \omega_c t \rightarrow \frac{1 + \cos 2\omega_c t}{2}$$

Demod

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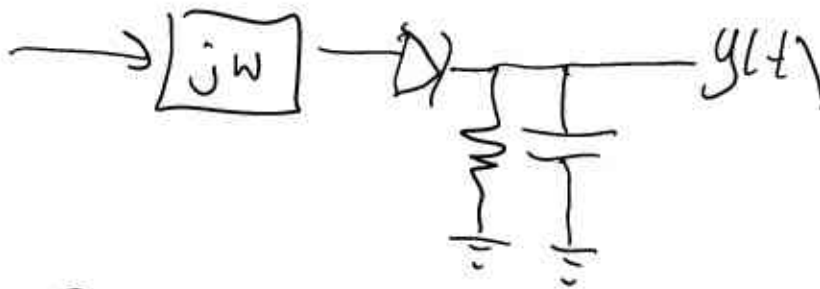


$$v_o(t) = A_c (\omega_c + \phi'(t)) (-\sin \omega_c t)$$

$$\stackrel{\text{FM}}{=} \underbrace{-A_c (\omega_c + m(t)) \sin \omega_c t}_{\text{Conventional AM}}$$

Conventional AM

FM demod



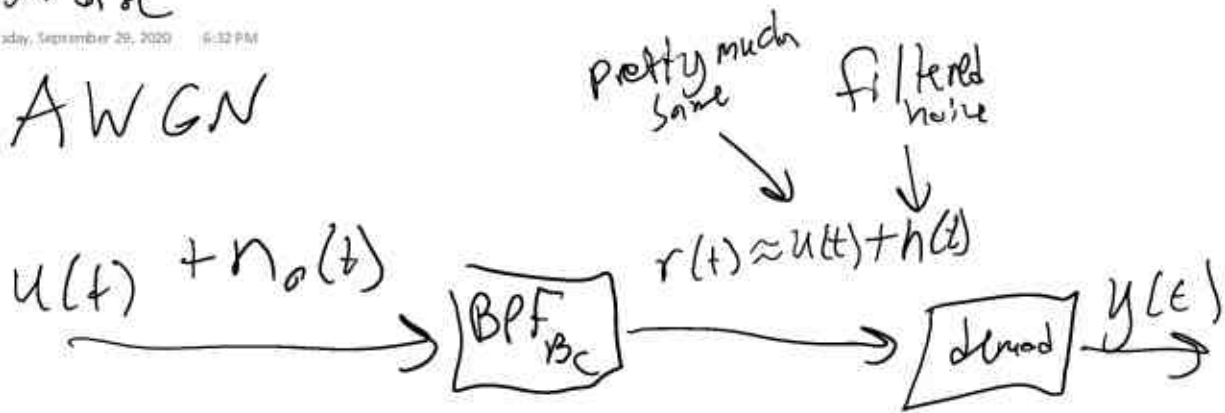
FM has very inexpensive demod  
(no mixer)

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

Noise

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AWGN



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

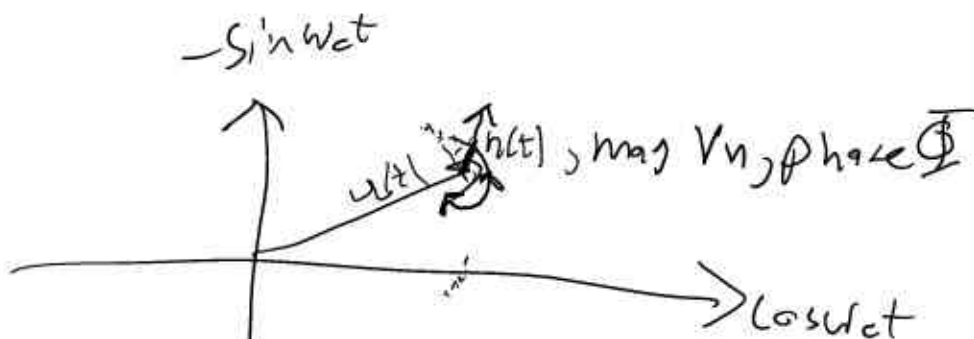
$$r(t) = u(t) + n(t)$$

↓ Polar form

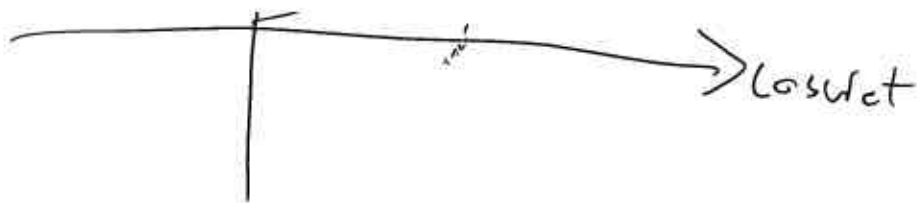
$$= u(t) + \sqrt{n_I^2(t) + n_Q^2(t)} \cos \left( \omega_c t + \arctan \left( \frac{n_Q(t)}{n_I(t)} \right) \right)$$


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

↑  
narrowly vibrating phasor








 "drunken phaser"  
 our signal + gaussian  
 - distortion

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

distinct from AM in that the phase is as vulnerable  
 as the amplitude

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

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

Taylor  
 approx  
 high SNR

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

(noise is small)

$$\left[ \begin{array}{l} \text{high SNR} \\ V_n \ll A_c \end{array} \right] r(t) \approx \varphi(t) + \frac{V_n}{A_c} \sin(\Phi_n(t) - \varphi(t))$$

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

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

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

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

$$\begin{array}{c} \uparrow \\ \text{signal} \end{array} + \begin{array}{c} \uparrow \\ \text{noise} \end{array} = Y_n = \frac{V_n}{A_c} \sin \Phi - \varphi$$

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

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

↑ ↑  
Signal + noise

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

Functions of  $n_c, n_q$

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

↑  
Functions of the channel

$A_c \uparrow$  decreases noise power

in AM, increase  $A_c$ ,  $SNR \uparrow$  because  $P_B$  but noise power is fixed

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

but still  $\uparrow A_c \rightarrow SNR \uparrow$

Same effect thru different route

$$Y_n(t) = \frac{V_n(t)}{A_c} \sin(\Phi_n(t) - \phi(t))$$

$$= \frac{1}{A_c} (V_n(t) \sin \Phi_n \cos \phi - V_n \cos \Phi_n \sin \phi)$$

$$= \frac{1}{A_c} (N_Q(t) \cos \phi - N_I(t) \sin \phi)$$

we have a narrowband approx for FM/PM, can apply

$B_c \gg W$   $\nwarrow$  BW of  $m(t)$  so we can  
 $\nwarrow$  BW of noise

assume  $\phi(t) \approx \phi$  approx constant compared to  $\Phi_n$

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

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

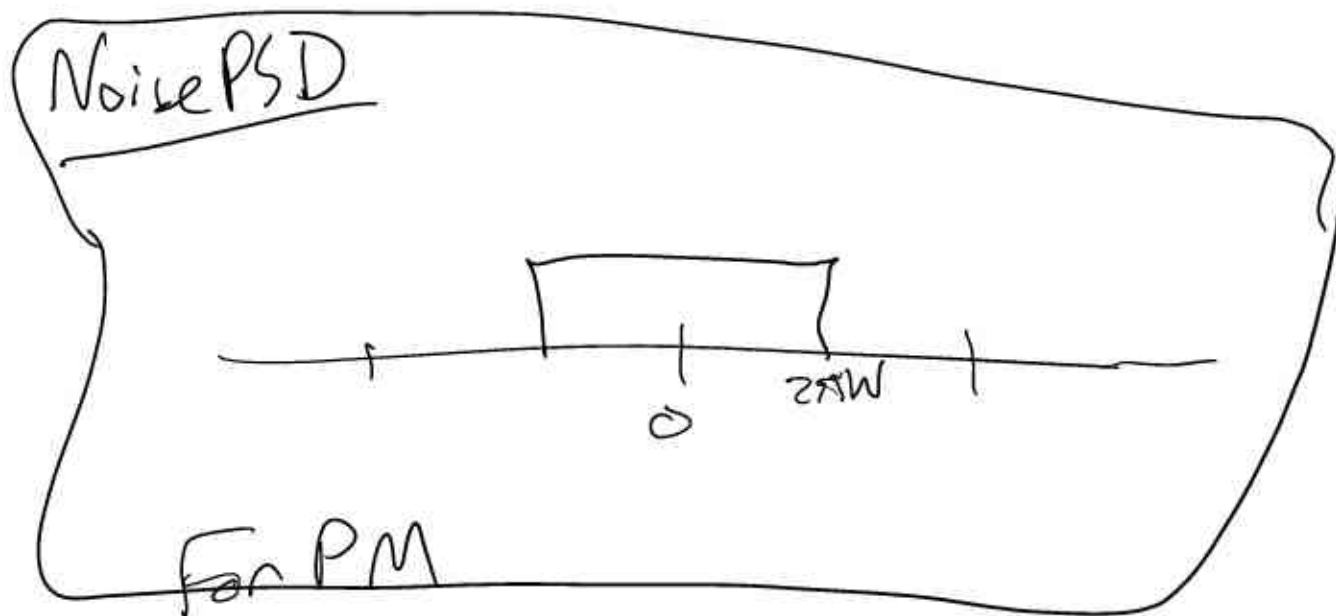
after demod, get b/b

PSD  $\downarrow$   $I/Q$  have same PSD as  $Y_n$

$\nearrow A_c \rightarrow P_N$   
 only relationship we have now

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

not N/T



for FM,  
noise is  $\frac{1}{2\pi} \dot{Y}_n(t)$

↓ PSD

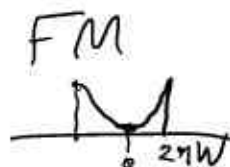
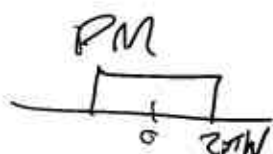
$$\left| \frac{1}{2\pi j\omega} \right|^2 S_{Y_n}(\omega)$$

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



quadratic PSD

baseband case:



$$P = \frac{1}{2} P_n$$

$$P = N_0 W \cdot P_n$$

$$P_h = \frac{1}{2\pi} \int S_n(\omega) d\omega = \begin{cases} \frac{2N_0 W}{A_c^2}, PM \\ \frac{2W^3 N_0}{3A_c^2}, FM \end{cases}$$

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

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

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

← better in narrowband case  
(as  $W \uparrow$ ,  $SNR \downarrow$ )  
bad!

$$B_f = \frac{K_f}{W} \max |m(t)|$$

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

$$P_R = A_c^2 / 2$$

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

$$SNR_{PM} = K \left( \frac{P_F}{\max(|m(t)|)} \right)^2 \frac{P_m}{N_c W}$$

Same formula in terms of mod. index

$\uparrow \beta$  increases SNR

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

$\uparrow$  ex. Power/BW tradeoff

(issue,  $\uparrow \beta$  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-emph.

$SNR \sim \text{const}$

after demod

Post-emph

de emphasis filter

- in FM, higher freq. see more noise



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↑  
USB-AM

↑ highest SNR

car radios!

(I, Q demod, held an iter)

A → D

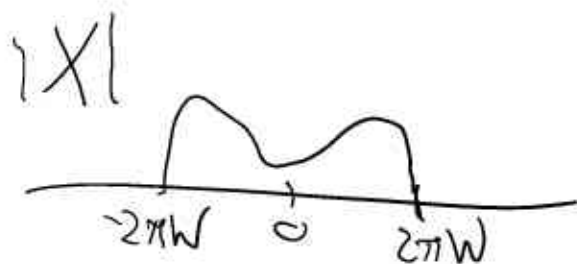
Tuesday, September 29, 2020 7:32 PM

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

Say  $x(t)$  cts-time signal,  $X(\Omega) = 0$  for

$$|\Omega| \geq 2\pi W$$

← cts-time  
freq.



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

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

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

is the perfect reconstruction

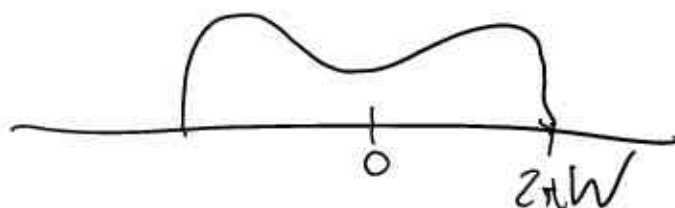
# Def (DTFT)

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

1)  $X(\omega)$  is  $2\pi$ -periodic

2)  $X: \mathbb{R} \rightarrow \mathbb{C}$

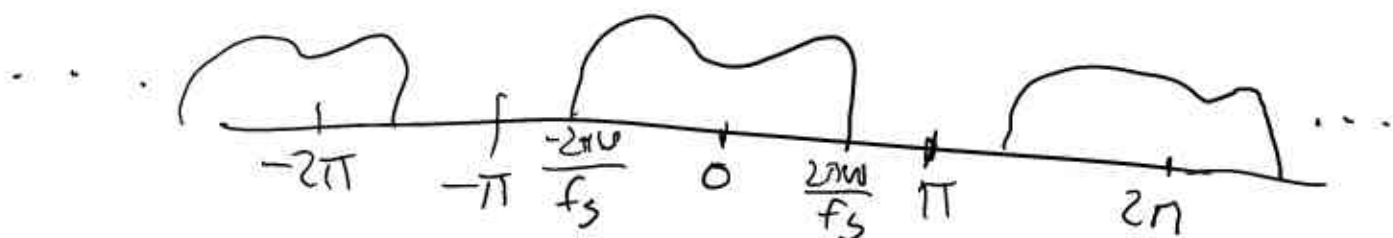
$X(\Omega)$



$$\downarrow f_s > 2W$$

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

$X(\omega)$



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

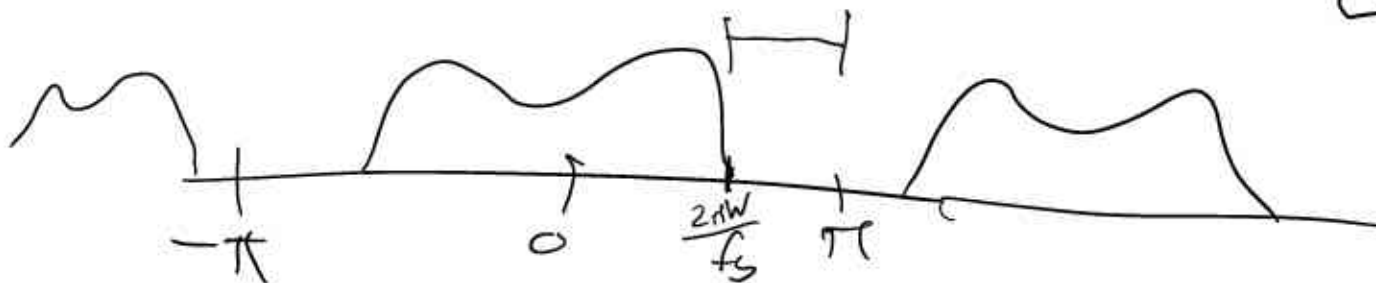


1) Nyquist Rate. the slowest you can sample a bandlimited signal and still avoid aliasing ( $f_s = 2W$ )

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

guard band: in  $\omega$  is  $\pi - \frac{2\pi W}{f_s}$   
or in  $f$  is  $\boxed{f_s - 2W}$



# Quantization

## Ex 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

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

$N=4$

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

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

$$R_3 = [0, 1)$$

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



$$\hat{x}_1 = -2$$

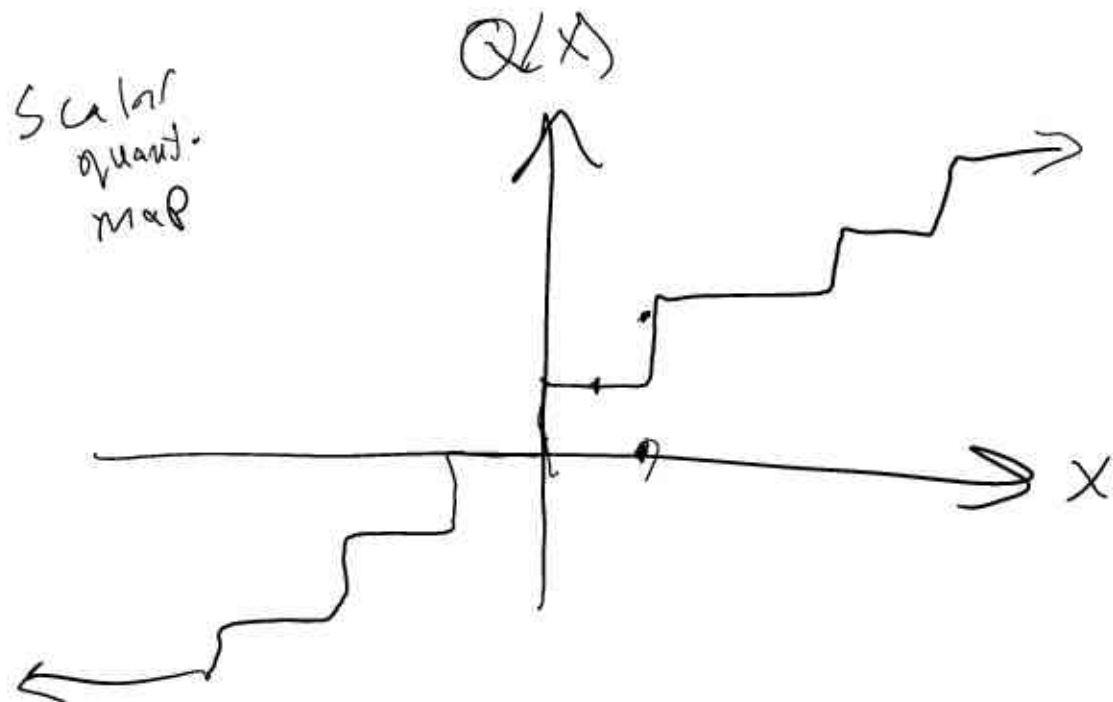
$$\hat{x}_3 = 0$$

$$\hat{x}_2 = -1$$

$$\hat{x}_4 = 1$$

$$n \text{ v.p.d. } \hat{x} \sim 00 \quad \hat{x} \sim 10$$

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



Distortion  
(Quantization noise)

1) How does this affect the SNR?

2) How does this affect the spectrum?  $\leftarrow$  harder

Def Squared Error Distortion for quantizer

$Q$  and signal  $x[n]$  is given by

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

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

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

let's say I use 8-level quantizer

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

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

Rate: 3 bits/sample (8 level)  
200 samples/second

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

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

$f_X(x)$  is pdf of  $X$  which has  $S_X(\omega) = \begin{cases} 2, & |\omega| < 100 \\ 0, & \text{else} \end{cases}$   
 we know  $R_X(0) = \sigma^2 = E[X^2]$

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

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

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

$$D = \int_{\mathbb{R}} (x - Q(x))^2 f_X(x) dx$$

$$= \sum_{i=1}^8 \int_{R_i} (x - \hat{x}_i)^2 f_X(x) dx$$

↑  
closed form

↑  
closed form

→ MATLAB

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

$$D \approx 33.38$$

$$\text{Mean-squared error} = \text{quantization noise}$$

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

The signal-to-quantization noise ratio (SQNR)

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

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  $D$

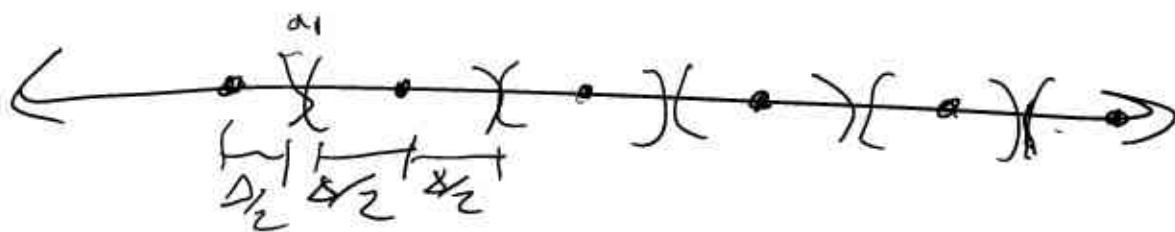
Uniform case

Every region same size i.e.  $R_i = (a_i, a_{i+1})$   
then  $a_{i+1} - a_i = \Delta$

for  $i = 1, \dots, N-1$  because  $R_1 = (-\infty, a_1)$   
 $R_N = (a_{N-1}, \infty)$

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

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



$$D = \int_{-\infty}^{a_1} \dots \int_{a_{N-1}}^{\infty} \dots$$

$$D = \int_{-\infty}^{\cdot} (x - (a_1 - \Delta/2))^2 f_X(x) dx + \int_{a_{N-1}}^{\cdot} (x - (a_N + \Delta/2))^2 f_X(x) dx \\ + \sum_{i=1}^{N-2} \int_{a_i + (i-1)\Delta}^{a_i + \Delta} (x - (a_i + (i-1)\Delta + \Delta/2))^2 f_X(x) dx$$

# parameters =  $Z$ ,  $a_1, \Delta$

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  $Z$ -d space  
using SGD for example

Non-uniform case

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

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

$a_1, \dots, a_{N-1}$  are all parameters

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

$2N-1$  parameters

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

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

So analytically, the  $a_i$  are best chosen as the mid points,

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

Centroid

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

$\rightarrow$  use SGD still, but constrained



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

Optimal quantizer "findable" by SGD iff  $X$ ,

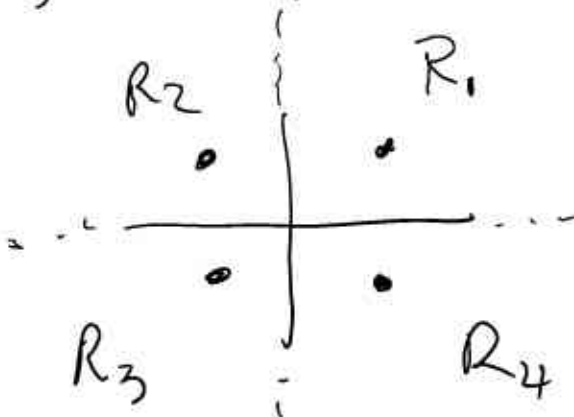
$N$  are given, easier in uniform case

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

Vector quantization: map multiple time instances to one quantized value

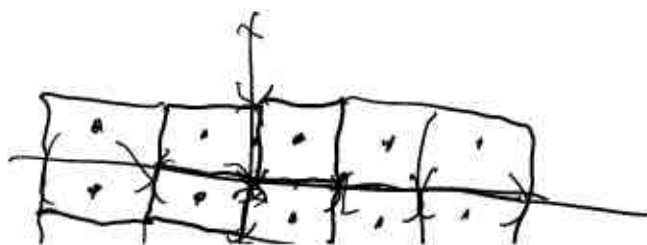
$$(x[n_1], \dots, x[n_k]) \xrightarrow{Q} \hat{x}_i \in \mathbb{R}^k$$

Ex.  $k=2$ ,  $(x[n], x[n+1]) \rightarrow \begin{cases} (1, 1) & \text{if } x_n \geq 0 \text{ and } x_{n+1} \geq 0 \\ (-1, 1) & \text{if } x_n < 0 \text{ and } x_{n+1} \geq 0 \\ (-1, -1) & \text{if } x_n < 0 \text{ and } x_{n+1} < 0 \\ (1, -1) & \text{if } x_n \geq 0 \text{ and } x_{n+1} < 0 \end{cases}$

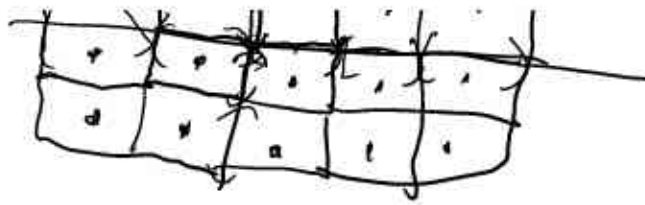


if I'm quantizing pairwise

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 optimal

Quantizing in  $\mathbb{R}^n$  with  $K$  quant. regions  
( $K$  values)  $\begin{pmatrix} x^{(1)} \\ \vdots \\ x^{(n+m)} \end{pmatrix} \rightarrow \hat{x}_i \in \mathbb{R}^m, i=1, \dots, K$

$m$  signal values  $\rightarrow K$  quantized values

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

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