

## COM-202: Signal Processing

Chapter 8.b: Quantization

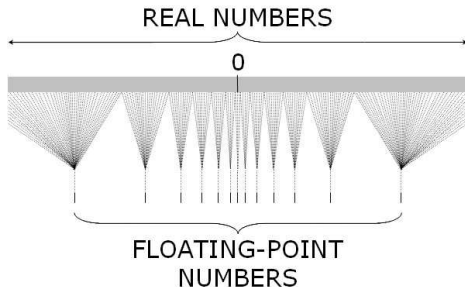
**quantization**

# The digital world

- basic storage unit: the binary digit (bit) with two possible values (0, 1)
- aggregate units: the byte (8 bits), word, dword, etc
- $R$  aggregate bits can hold  $2^R$  distinct integer values

# What about floating point?

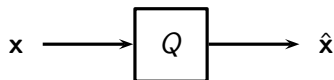
- floating point standards (e.g. IEEE 754) are clever ways of mapping reals to integers
- an  $R$ -bit float can represent at most  $2^R$  distinct values
- a floating point representation partitions the real line into intervals of increasing size and maps them to integers



# Quantization

- digital devices can only deal with integers ( $R$  bits per sample)
- samples of a discrete-time signal must be converted to integers for storage
- the conversion process is called *quantization*
- quantization causes an irreversible loss of information

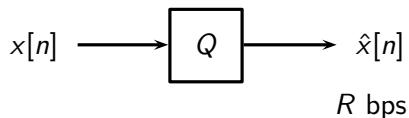
# Quantization schemes



Several factors at play:

- storage budget (bits per sample)
- encoding scheme (fixed point, floating point)
- properties of the input
  - dynamic range
  - probability distribution of samples

# Scalar, memoryless, fixed-rate quantization

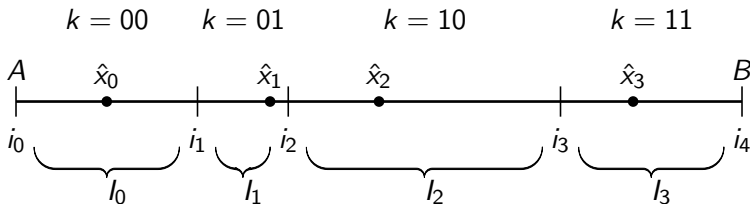


The simplest quantization scheme:

- each sample is encoded individually (*scalar quantization*)
- each sample is quantized independently (*memoryless quantization*)
- each sample is encoded using  $R$  bits (*fixed-rate quantization*)

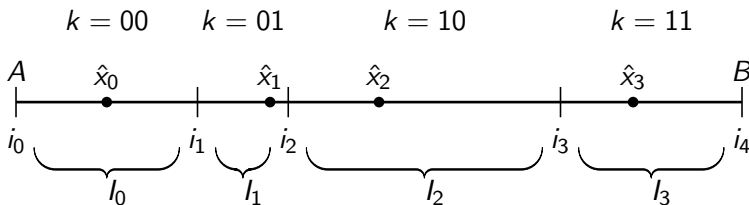
# Typical quantization scheme

- input values are within known bounds  $A \leq x[n] \leq B$
- with  $R$  bits/sample, input range is divided into  $2^R$  intervals  $I_k = [i_k, i_{k+1})$
- each interval is associated to a  $R$ -bit binary number  $k$
- each interval is associated to a representative value  $\hat{x}_k$





# Typical quantization scheme



- what are the optimal interval boundaries  $i_k$ ?
- what are the optimal quantization values  $\hat{x}_k$ ?

# Optimal Quantization

The optimal quantizer minimizes the energy of the quantization error:

$$e[n] = Q(x[n]) - x[n] = \hat{x}[n] - x[n]$$

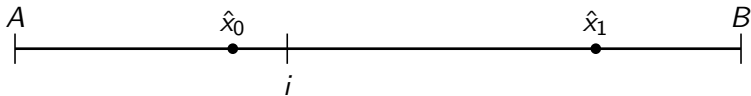
- model  $\mathbf{x}$  as a stochastic process
- find the optimal  $i_k$  and  $\hat{x}_k$  that minimize  $\sigma_e^2 = \text{E} [e^2[n]]$
- optimal quantizer will depend on the input's statistics

# Quantization MSE

$$\begin{aligned}\sigma_e^2 &= \mathbb{E} [(x - Q(x))^2] \\ &= \int_{-\infty}^{\infty} (x - Q(x))^2 f_x(x) dx \\ &= \sum_{k=0}^{2^R-1} \int_{i_k}^{i_{k+1}} (x - \hat{x}_k)^2 f_x(x) dx\end{aligned}$$

find global minimum wrt  $i_k, \hat{x}_k$

## Simple example: optimal one-bit quantizer



3 free parameters:  $i, \hat{x}_0, \hat{x}_1$

## Simple example: optimal one-bit quantizer

$$\sigma_e^2 = \int_A^i (x - \hat{x}_0)^2 f_x(x) dx + \int_i^B (x - \hat{x}_1)^2 f_x(x) dx$$

find  $i, \hat{x}_0, \hat{x}_1$  such that

$$\frac{\partial \sigma_e^2}{\partial i} = \frac{\partial \sigma_e^2}{\partial \hat{x}_0} = \frac{\partial \sigma_e^2}{\partial \hat{x}_1} = 0$$

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## little calculus reminder

$$\frac{\partial}{\partial t} \int_{\alpha}^t f(\tau) d\tau = \frac{\partial}{\partial t} [F(t) - F(\alpha)] = f(t)$$

## Optimal one-bit quantizer: threshold

$$\frac{\partial \sigma_e^2}{\partial i} = \frac{\partial}{\partial i} \left[ \int_A^i (x - \hat{x}_0)^2 f_x(x) dx + \int_i^B (x - \hat{x}_1)^2 f_x(x) dx \right]$$

$$= (i - \hat{x}_0)^2 f_x(i) - (i - \hat{x}_1)^2 f_x(i) = 0$$

$$\Rightarrow (i - \hat{x}_0)^2 - (i - \hat{x}_1)^2 = 0$$

$$\Rightarrow i = \frac{\hat{x}_0 + \hat{x}_1}{2}$$



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## Optimal one-bit quantizer: values

$$\begin{aligned}\frac{\partial \sigma_e^2}{\partial \hat{x}_0} &= \frac{\partial}{\partial x_0} \int_A^i (x - \hat{x}_0)^2 f_x(x) dx \\ &= \int_A^i 2(\hat{x}_0 - x) f_x(x) dx = 0\end{aligned}$$

$$\Rightarrow \hat{x}_0 = \frac{\int_A^i x f_x(x) dx}{\int_A^i f_x(x) dx} \quad (\text{center of mass})$$

$$\Rightarrow \hat{x}_1 = \frac{\int_i^B x f_x(x) dx}{\int_i^B f_x(x) dx}$$

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## For uniformly-distributed input

$$f_x(x) = \frac{1}{B - A}$$

$$\hat{x}_0 = \frac{\int_A^i x \, dx}{\int_A^i dx} = \frac{A + i}{2}$$

$$\hat{x}_1 = \frac{\int_i^B x \, dx}{\int_i^B dx} = \frac{i + B}{2}$$

$$i = \frac{\hat{x}_0 + \hat{x}_1}{2} = \frac{A + B}{2}$$

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## For uniformly-distributed input

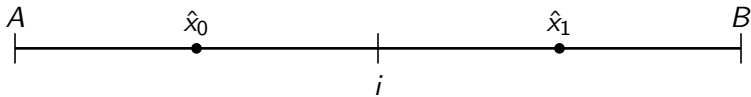
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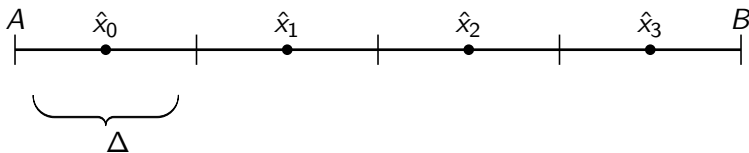
$$i = \frac{\hat{x}_0 + \hat{x}_1}{2} = \frac{A + B}{2}$$

## Optimal one-bit quantizer

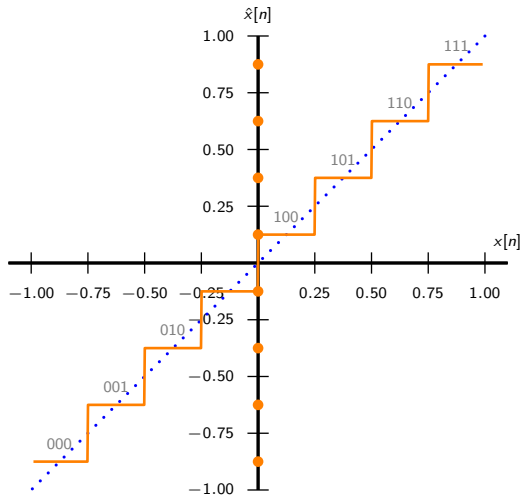


# Uniform quantization of uniform input

- for uniformly-distributed input values, optimal quantizer is uniform
- optimal subdivision:  $2^R$  *equal* intervals of width  $\Delta = (B - A)2^{-R}$
- optimal quantization values are the midpoints of each interval



# Uniform 3-Bit quantization function



# Uniform quantization of uniform input: error analysis

$$\begin{aligned}\sigma_e^2 &= \int_A^B f_x(x)(Q(x) - x)^2 dx \\ &= \sum_{k=0}^{2^R-1} \int_{I_k} f_x(x)(\hat{x}_k - x)^2 dx\end{aligned}$$

$$f_x(s) = \frac{1}{B - A}$$

$$\Delta = \frac{B - A}{2^R}$$

$$I_k = [A + k\Delta, A + (k + 1)\Delta]$$

$$\hat{x}_k = A + (k + 1/2)\Delta$$

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# Uniform quantization of uniform input: error analysis

$$\begin{aligned}\sigma_e^2 &= \sum_{k=0}^{2^R-1} \int_{A+k\Delta}^{A+(k+1)\Delta} \frac{(A + (k + 1/2)\Delta - x)^2}{B - A} dx \\&= \sum_{k=0}^{2^R-1} \int_{-\Delta/2}^{\Delta/2} \frac{x^2}{B - A} dx && x \leftarrow x + A + k(+1/2)\Delta \\&= \frac{2^R}{B - A} \frac{2(\Delta/2)^3}{3} \\&= \frac{\Delta^2}{12}\end{aligned}$$

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# Error analysis

- error energy

$$\sigma_e^2 = \Delta^2/12, \quad \Delta = (B - A)/2^R$$

- signal energy

$$\sigma_x^2 = (B - A)^2/12$$

- signal to noise ratio

$$\text{SNR} = 2^{2R}$$

- in dB

$$\text{SNR}_{\text{dB}} = 10 \log_{10} 2^{2R} \approx 6R \text{ dB}$$

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# The “6dB/bit” rule of thumb

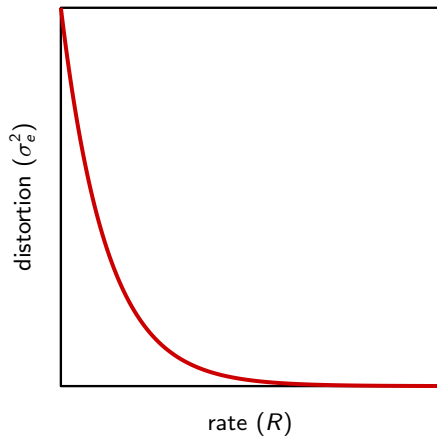
- a compact disk has 16 bits/sample:

$$\text{max SNR} = 96\text{dB}$$

- a DVD has 24 bits/sample:

$$\text{max SNR} = 144\text{dB}$$

# Rate/Distortion Curve



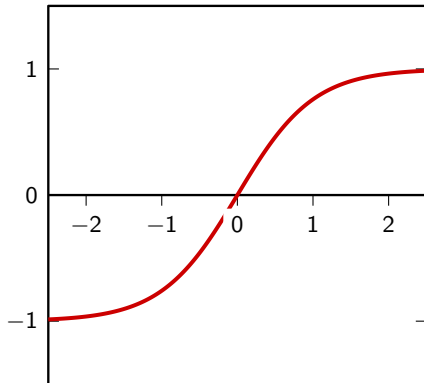
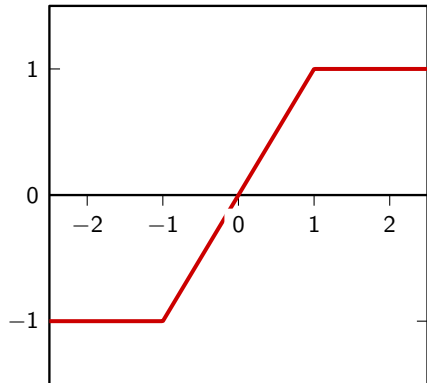
## Other quantization errors

If input is not bounded to  $[A, B]$  several options; eg:

- clip samples to  $[A, B]$ : linear distortion (can be put to good use in guitar effects!)
- smoothly saturate input: this simulates the saturation curves of analog electronics



## Clipping vs saturation



# Analysis of the quantization error

- so far we have only a *quantitative* result on the error (its power)
- to understand the distortion we need the error's spectrum
- quantizer is nonlinear: impossible to compute the spectrum exactly
- the common approach is to make *assumptions* on the error statistics

# High-resolution hypothesis

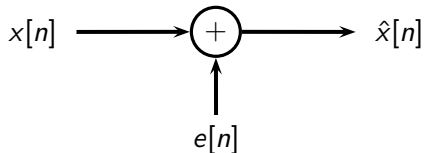
drastic simplification of the problem: if

- input samples are iid (they are not)
- $R$  is relatively large

then we can try to use the following model:

- error samples are iid
- error is uncorrelated to the signal
- quantization error equivalent to additive white noise with  $P_e(\omega) = \Delta^2/12$

# High-resolution hypothesis



problems with this model:

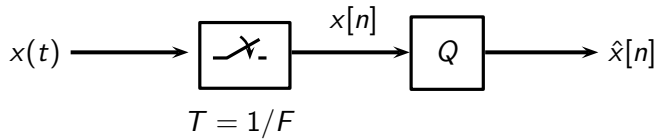
- error is not random!
- error is not white or uncorrelated to the input

common approaches:

- use *dithering* to whiten the noise spectrum
- use *feedback* in the quantization loop to perform *noise shaping*

**oversampled A/D conversion**

## A/D conversion



$$\hat{\mathbf{x}} = \mathbf{x} + \mathbf{e}$$

# Oversampled A/D

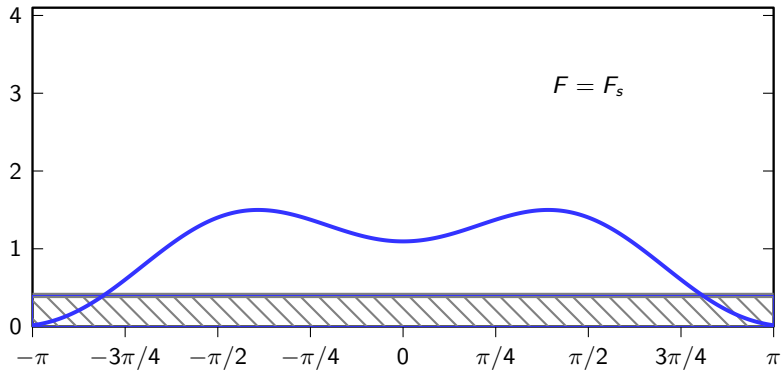
Key assumptions on quantization error:

- $e$  is a white noise process, independent of  $x$
- PSD of quantization noise is flat,  $P_e(\omega) = \frac{\Delta^2}{12}$
- PSD of quantization noise is independent of sampling rate  $F$

Key observations:

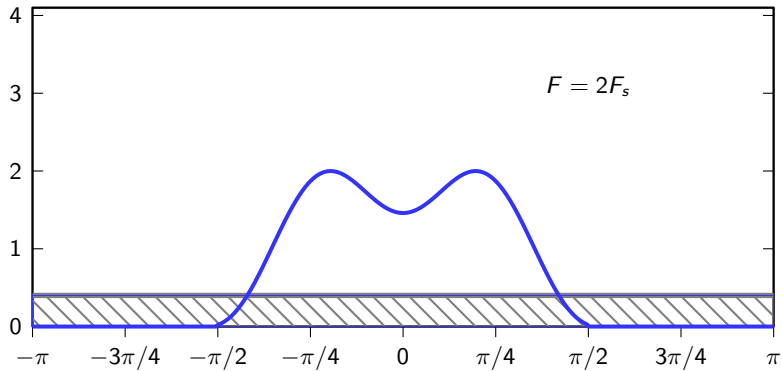
- $x(t)$  is  $F_s$ -BL
- spectrum of sampled signal is  $X(\omega) = FX(\frac{\omega}{2\pi}F)$
- with  $N$ -times oversampling, spectral support is  $[-\pi/N, \pi/N]$

## Oversampled A/D

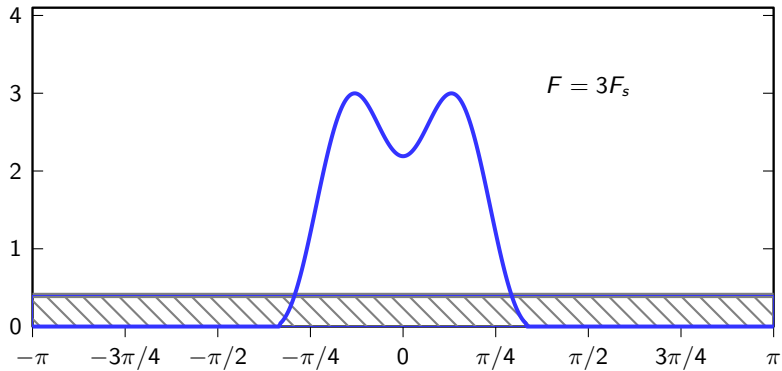




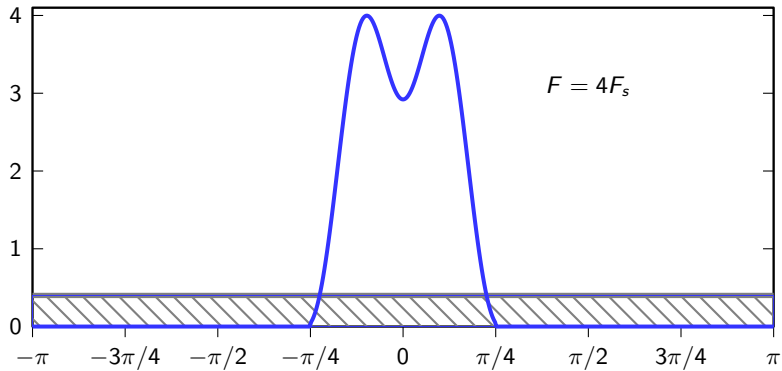
## Oversampled A/D



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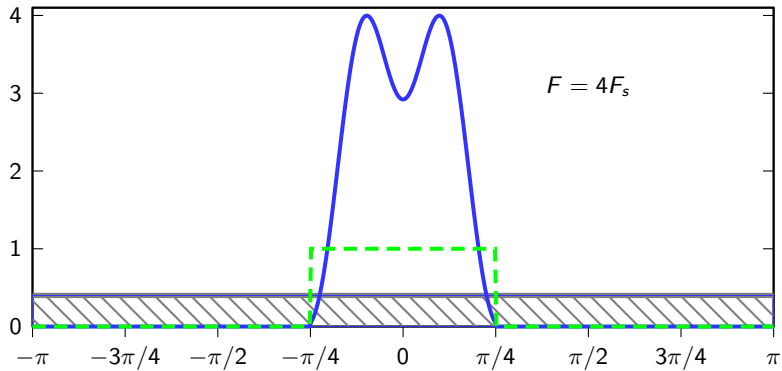


# Oversampled A/D

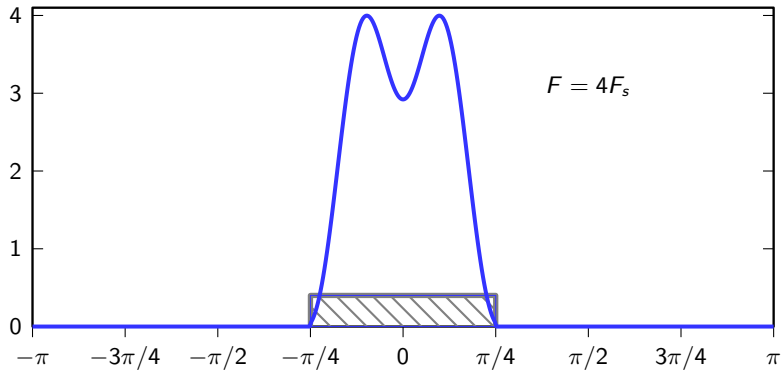
Idea:

- oversample by a factor of  $N$
- signal's spectral support shrinks
- if quantization noise remains independent, its PSD remains flat
- filter out the quantization noise out of band
- downsample back to  $F_s$

# Oversampled A/D

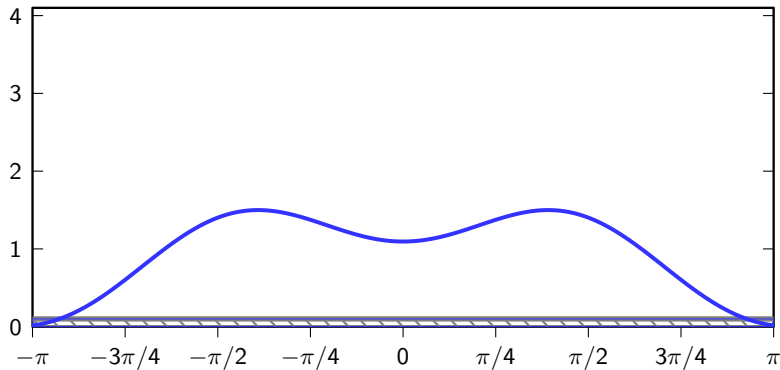


## Oversampled A/D

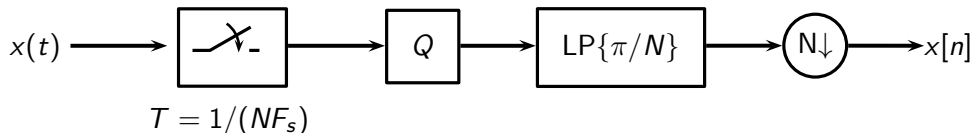


## Oversampled A/D

after downsampling by  $N$ ,  $X_o(\omega) = (1/N)X(\omega/N)$



## Oversampled A/D



- in theory, SNR at the output is  $N$  times better
- 3dB gain per octave (i.e. per doubling of the sampling rate)
- but key assumptions (independence of error) breaks down fast...