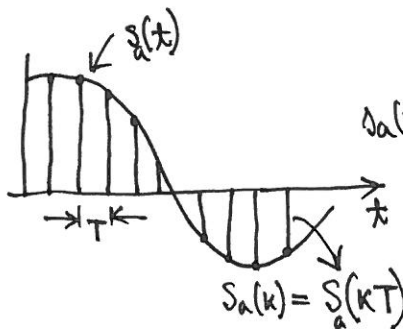


Quantization

①

- In nature, we mostly observe continuous analog signals. For example, speech, image, video.
- Using a sampler, we first sample the continuous signal to a discrete signal. But samples of a discrete signal has infinite resolution (analog).
- For digital processing, we must need a finite bit budget. Or, a finite resolution representation. So, quantization comes into picture.

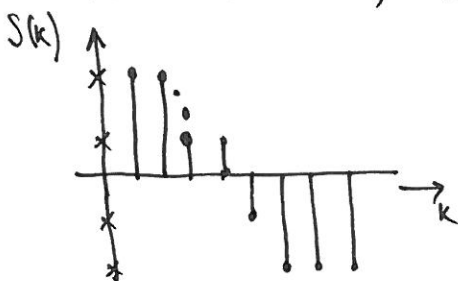


$s_a(t)$: A continuous time domain signal.

$s_a(k) = s_a(kT)$: sampled at each time interval T .

$s(k) = Q[s_a(kT)] = Q(s_a(k))$: If b bits are available, then $s(k)$ can take one out of 2^b different discrete values which are in the range of highest and lowest values of $s_a(k)$.

Let us take $b=2$, and so only 4 values allowed.



$$q(k) = x(k) - \hat{x}(k)$$

= quantization noise.

$$\hat{x}(k) = Q[x(k)]$$

= quantized value of $x(k)$.

(2)

Mean square error (MSE) = $\left(\sum_{\forall k} q^2(k) \right) \frac{1}{\#\text{ } k} = E\{q^2(k)\}$

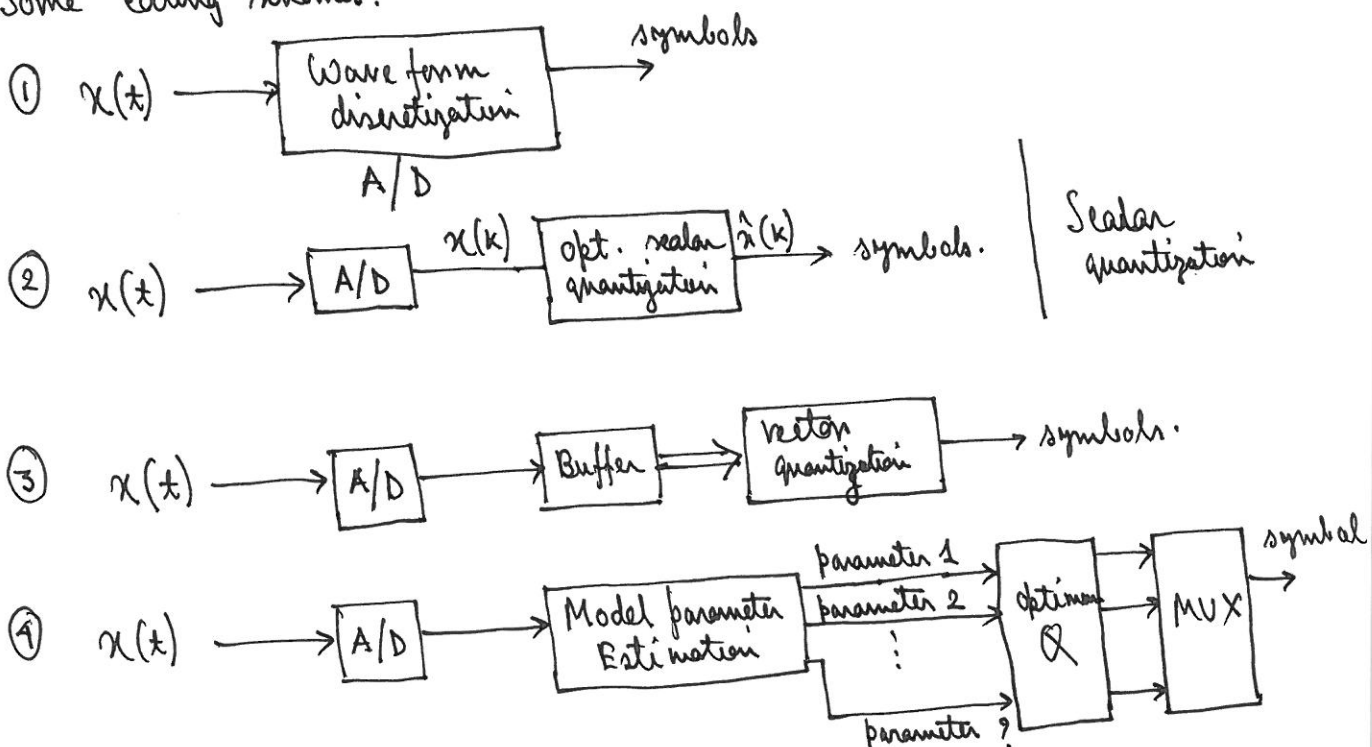
Signal-to-quantization-noise-ratio (SQNR) = $\frac{\sigma_x^2}{\sigma_q^2} = \frac{E\{x^2\}}{E\{q^2\}}$

(assume both $x(k)$ and $q(k)$ are zero mean signals).

What we want? (a) σ_q^2 as minimum as possible given bit budget.
other way (b) Bit budget as minimum as possible given a maximum allowable σ_q^2 .

An understanding of channel symbols (some codes over channel)
Explain

Some coding schemes:

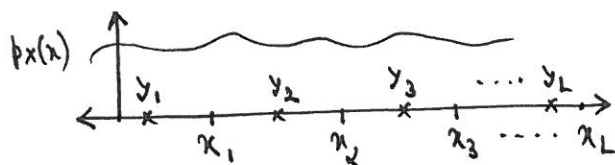


Scalar Quantization

- Mapping of x to a finite set of symbols. x is real valued.

$$-\alpha \leq x \leq +\alpha$$

- Intervals of x : I_k , $1 \leq k \leq L$
(finite no) $I_k: x_{k-1} \leq x \leq x_k$



- Reconstructed value for each interval I_k : y_k (real valued quantity)
(Quantized)

$$y = Q(x) : \text{quantization of } x \text{ to } y.$$

$$y \in \{y_k\}_{k=1}^L$$

$$q = x - Q(x) = x - y.$$

- Minimize σ_q^2 for a fixed L . ($L = 2^b$)

$$\sigma_q^2 = E\{q^2\} = E\{(x-y)^2\}$$

$$= \int_{-\alpha}^{+\alpha} (x-y)^2 p_x(x) dx$$

$$= \sum_{k=1}^L \int_{x_{k-1}}^{x_k} (x-y_k)^2 p_x(x) dx$$

[$p_x(x)$: pdf of x]

- Optimal quantizer: Solve $\{x_k, y_k; 1 \leq k \leq L\}$ such that σ_q^2 is minimum

Design of optimal quantizer

• For most of the pdfs, there is no closed form solution for the ~~para~~ parameters $\{x_k, y_k\}$ to design an optimal quantizer.

• Lloyd-Max Algo : Two steps (Iteration)

① solve for $\{y_k\}$ given $\{x_k\}$.

② solve for $\{x_k\}$ given $\{y_k\}$.

Theorem: $\{x_k^t, y_k^t, 1 \leq k \leq L\}$ leads to lower δ_q^2 than the case $\{x_k^{t-1}, y_k^{t-1}, 1 \leq k \leq L\}$ where t is the iteration index.

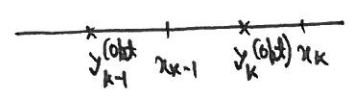
$$\delta_q^2 = \sum_{k=1}^L \int_{x_{k-1}}^{x_k} (x - y_k)^2 p_x(x) dx.$$

Step 1: $\frac{\partial \delta_q^2}{\partial y_k} = 0, \forall k.$

$$w, \int_{x_{k-1}}^{x_k} 2(x - y_k) (-1) p_x(x) dx$$

$$w, y_k^{(opt)} = \frac{\int_{x_{k-1}}^{x_k} x p_x(x) dx}{\int_{x_{k-1}}^{x_k} p_x(x) dx} \rightarrow \text{centroid} \dots \textcircled{a}$$

Step 2: Given $\{y_k^{(opt)}\}_{k=1}^L.$



For $x > x_k, (x - y_k)^2 < (x - y_{k-1})^2$

$$w, x^2 - 2xy_k + y_k^2 < x^2 - 2xy_{k-1} + y_{k-1}^2$$

$$w, 2xy_k - 2xy_{k-1} + y_{k-1}^2 - y_k^2 > 0$$

$$w, 2x(y_k - y_{k-1}) - (y_k + y_{k-1})(y_k - y_{k-1}) \geq 0 \quad [\because y_k - y_{k-1} > 0]$$

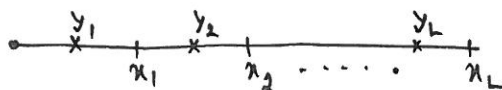
$$w, 2x - (y_k + y_{k-1}) > 0$$

$$w, x > \frac{1}{2} (y_k + y_{k-1})$$

$$w, x_{k-1}^{(opt)} = \frac{1}{2} (y_k + y_{k-1}) \dots \textcircled{b}$$

Sequential Lloyd-Max (LM) Algorithm

(5)



0. Initialize: choose $\{y_k^0\}$, $k=1$
1. Solve for ~~$\{x_k^0\}$~~ $\{x_k^*\}_{k=1}^L$ using equation (b').
2. Solve for $\{y_k^*\}$, using equation (a).
3. Till convergence.

Optimal Quantization $\xrightarrow{\text{leads to}}$ Non-uniform Quantization
for an arbitrary pdf

Some properties for Opt. Quantization

$$\begin{aligned} \textcircled{1} \text{ Mean } E[q] &= E\{x - Q(x)\} \\ &= \sum_{k=1}^L \int_{x_{k-1}}^{x_k} (x - y_k) p_X(x) dx \\ &\quad \int_{x_{k-1}}^{x_k} x p_X(x) dx \\ \text{For opt. Q. } y_k &= \frac{\int_{x_{k-1}}^{x_k} x p_X(x) dx}{\int_{x_{k-1}}^{x_k} p_X(x) dx} \end{aligned}$$

$$\therefore E[q] = \sum_{k=1}^L \left[\int_{x_{k-1}}^{x_k} x p_X(x) dx - \int_{x_{k-1}}^{x_k} x p_X(x) dx \right] = 0$$

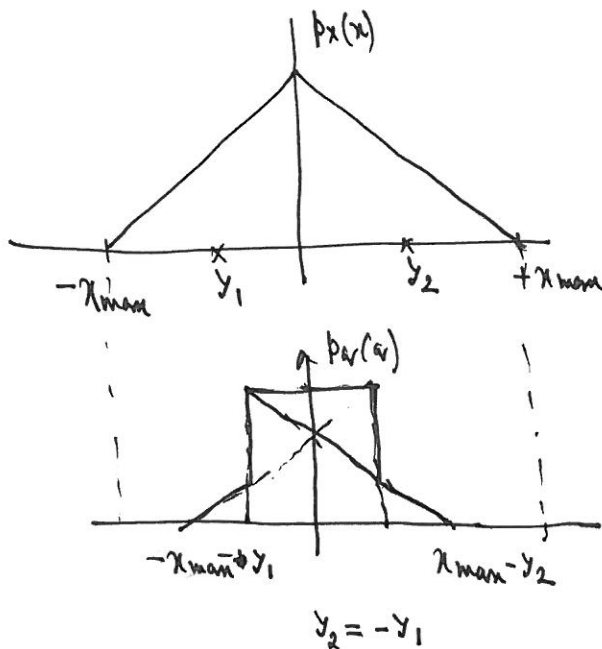
Quantization noise q is always zero mean.

② PDF of q

⑥

$$q = x - Q(x) \\ = x - y_k \quad \text{when } x_{k-1} \leq x \leq x_k \quad (x \in I_k), \quad \forall k.$$

$$\begin{aligned} p_q(q) &= \sum_{k=1}^L P(x \in I_k) p_q(q = x - y_k | x \in I_k) \\ &= \sum_{k=1}^L P(x \in I_k) \cdot \frac{p_q(q = x - y_k, x \in I_k)}{P(x \in I_k)} \\ &= \sum_{k=1}^L p_q(q = x - y_k, x \in I_k) \\ &= \sum_{k=1}^L p_x(x = q + y_k, x \in I_k) \end{aligned}$$

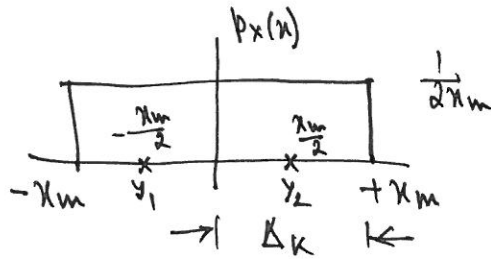


- As L increases, $p_q(q)$ becomes more narrow.
- Bounded $p_x(x) \Rightarrow$ bounded $p_q(q)$.
- In general $p_q(q)$ is not-uniform. But for large L , it may be approximated as uniform.
- If $p_x(x)$ is uniform, then $p_q(q)$ is uniform.

Symmetric Uniform PDF :

(7)

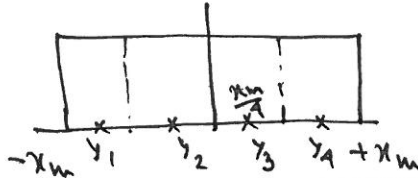
1 bit



$$\Delta_k = \frac{x_m - (-x_m)}{2} = \frac{2x_m}{2}$$

$$\sigma_q^2 = \int_{-x_m}^0 \left(x - \left(-\frac{x_m}{2}\right)\right) p_x(x) dx + \int_0^{x_m} \left(x - \frac{x_m}{2}\right) p_x(x) dx.$$

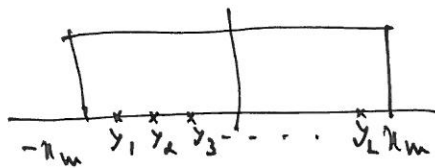
2 bit



$$\Delta_k = \frac{2x_m}{4}$$

H.w. Can we find $\sigma_q^2 = ?$

$L = 2^L$ bit



Now, $\sigma_q^2 = \frac{x_m^2}{3}.$

H.w.
check: $\text{SNR} = L^2 = 2^{2R}$
 $\text{SNR}|_{\text{dB}} = 10 \log_{10} L^2 = 10 \log_{10} 2^{2R} = 6.02R \text{ dB}$

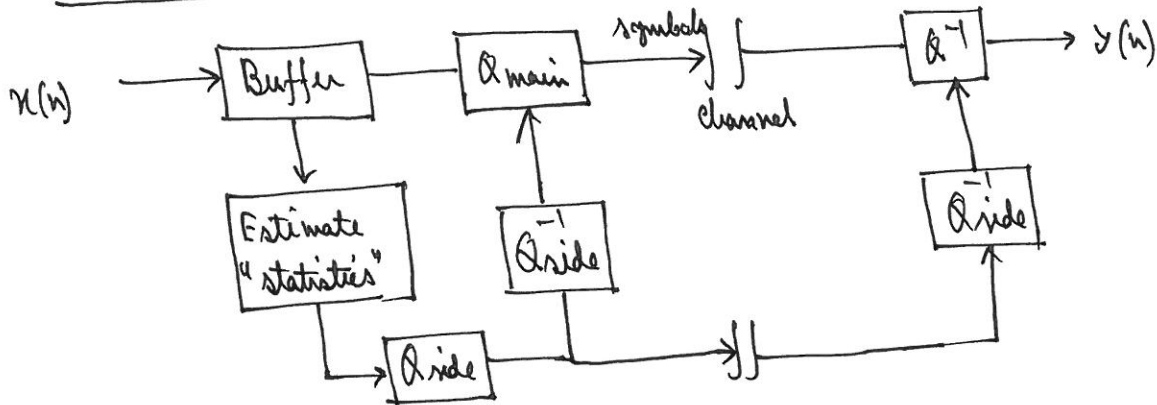
← I think this result should come. Please check it. (H.w.).

Adaptive Quantization

(8)

- Suppose $p_x(x)$ changing with "time"
- But all our design tricks are ~~mainly~~ mainly for stationary pdf.

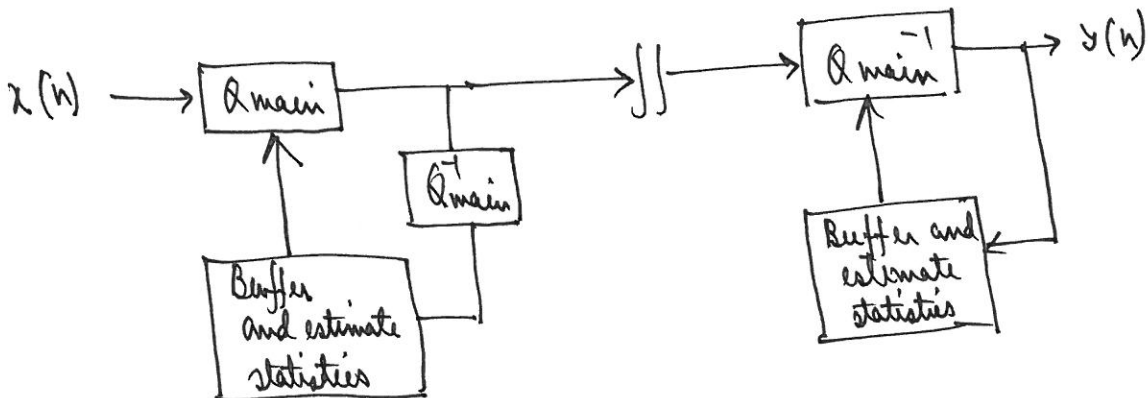
// Forward Adaptation (AQF)



Total Rate = $R_{main} + R_{side}$
Buffer delay of N samples.

$N \rightarrow$ number of learning samples.
 $R_{side} \propto \frac{1}{N}$

// Backward Adaptation (AOB)



Receiver is more complex than AQF

Delay: NO (one sample)

Statistics is approximated by quantized samples : To have synchrony between T_x and R_x
 N is not a problem.