Techniques for Video Compresson and Analysis (5LSE0), Module 02 - A

Scalar Quantization

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slides version 1.0

Techniques for Video Compresson and Analysis (5LSE0), Module 02 - A

Mod 02 - A, Part 1

Characterization of Quantizers

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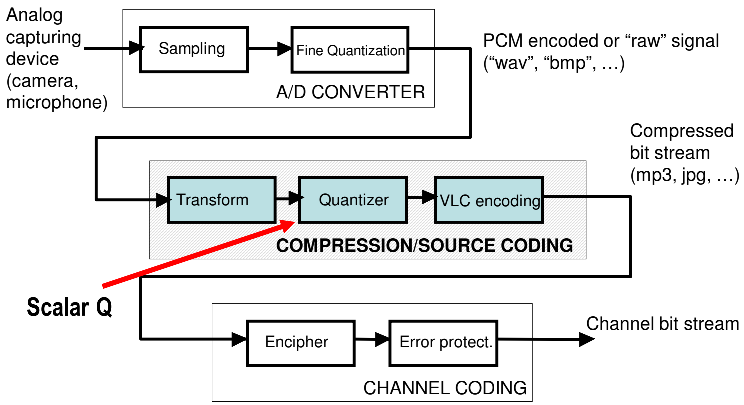
System Overview



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Why can Signals be Compressed? – (1)

Because infinite accuracy of signal amplitudes is (perceptually) irrelevant

Question 1:

What is the *best possible* trade-off between required bit rate and resulting distortion?

(Rate-Distortion Theory)

Question 2:

How do we *implement* a system that gives us that best possible trade-off?

(Scalar and Vector Quantization Theory)

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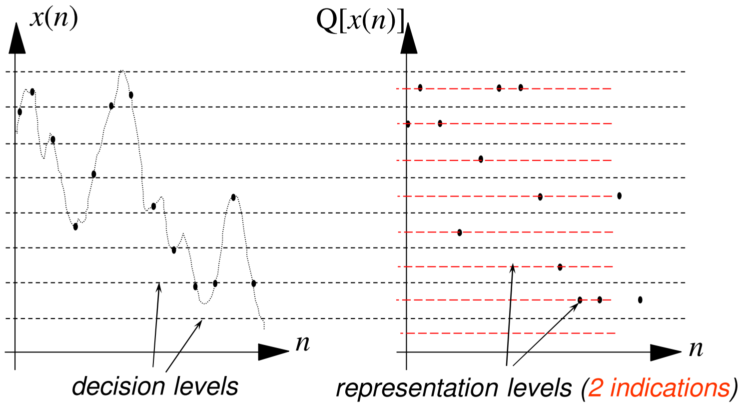
Quantization Process – (1)



Quantization Process – (2)

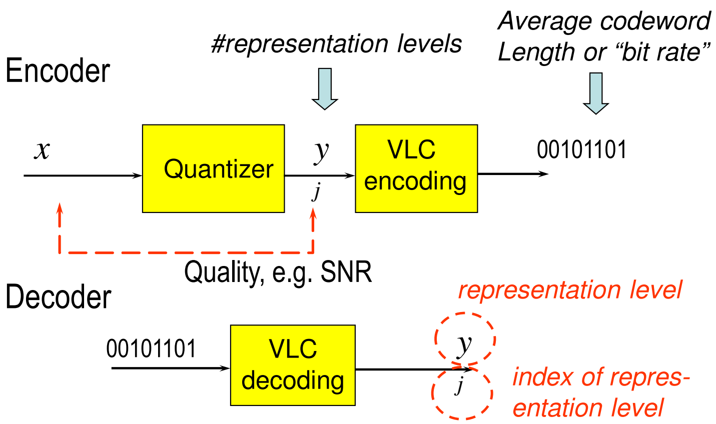
* **Quantization: Map a continuous-valued signal value $x(n)$ onto a (limited set of) discrete-valued signals values $y(n)$:**

$$y(n) = Q[x(n)]$$

  such that $y(n)$ is good approximation of $x(n)$.

* **Important: # bits to represent $y(n)$.**
  (= average codeword length per representation level)
* **Design/Optimization Problem**
  – What positions of the "*decision levels*"
  – What positions of the "*representation levels*"

Quantization Process – (3)

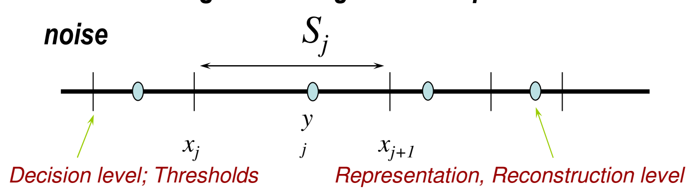


Formal Quantization Definition

* **Given amplitude x, divide domain of x into K non-overlapping intervals S_k:**

$$S_k = \{x \mid x_k < x \le x_{k+1}\} \qquad k = 1,2,...,K$$

* **If x falls in S_j then it is represented by y_j.**
* **Quantization gives *coding errors or quantization noise***



Quantizer Characteristics – (1)

- Signals values are assumed to lie symmetrically around zero

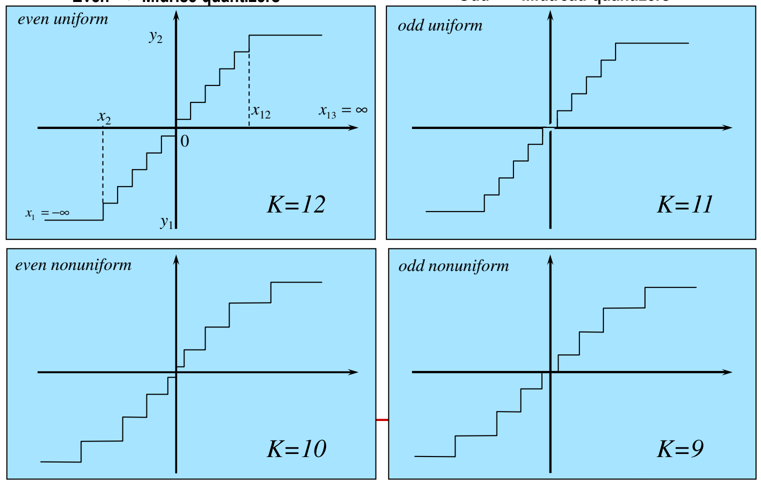
⇨ Quantizers are usually *symmetric about origin*

- Quantizer choices:
  - Odd or even number of levels?
  - Uniform or non-uniform quantizers?
  - Way of optimizing the quantizer?

"structure" (odd/even number of levels, uniform/non-uniform)
"design" (way of optimizing the quantizer)

Quantizer Characteristics – (2)

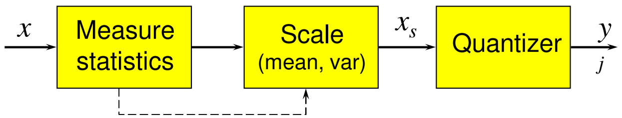
Even = > Midrise quantizers Odd = > Midtread quantizers



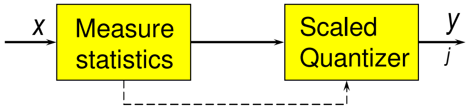
Preprocessing for Quantization – (1)

- Only *prototype* quantizers are designed
  - Signal is assumed to be zero-mean, unity variance

Scale signal values to be quantized



Scale quantizer itself



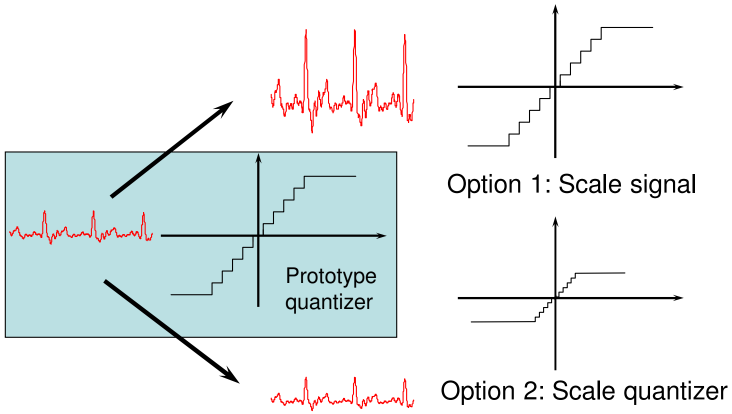
Overall Quantization Error with Pre-proc.

- Scaling procedure: $x_s = \dfrac{x-\mu_x}{\sigma_x}$
- Rescaling procedure: $\hat{x} = \sigma_x y + \mu_x = \sigma_x \hat{x}_s + \mu_x$
- Overall effect: Quantization noise variance is scaled with : σ_x^2

$$\sigma_q^2 = E[(\hat{x}-x)^2] = E[(\sigma_x \hat{x}_s - \sigma_x x_s)^2] = \sigma_x^2 E[(\hat{x}_s - x_s)^2]$$
$$= \sigma_x^2 \sigma_{q,\text{prototype}}^2$$

⇒ *Quantization noise variance is linearly proportional to the variance of the signal to be quantized*

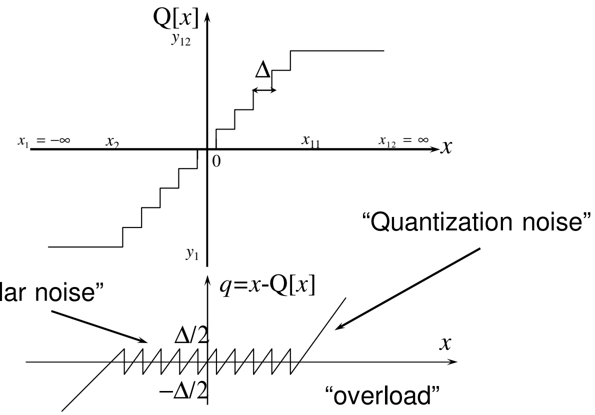
Preprocessing for Quantization – (2)



Quantizer Characteristics – (3)

* **Design of quantizer is optimization problem**
  – Find optimal values for decision and representation levels
* **Two approaches:**
  – Exploit knowledge of probability density function (PDF) of x to find optimum given #representation levels
    • Uniform quantization: easily solved and implemented
    • Non-uniform quantization: more difficult with limited gain
  – Select uniform quantizer with variable coarseness; determine effective #representation levels during applications
    • More practical; this is what JPEG/MPEG do
    • Choices inspired by theory

Quantization Noise / Types – (1)

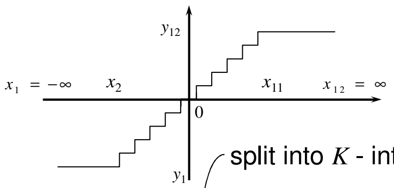


Quantization Noise / Variance – (2)

* **Quantification of (average) quantization error:**
  Variance of the quantization noise: $q=x - Q[x]$
* **Need to model probability density of** x: $p_X(x)$
* **Quantization noise variance:**

$$\sigma_q^2 = \int_{-\infty}^{\infty} \underbrace{(x - Q[x])^2}_{\text{Amount of error}} \underbrace{p_X(x)\,\mathrm{d}x}_{\text{Probability of amount}}$$

Quantization Noise / Variance – (3)



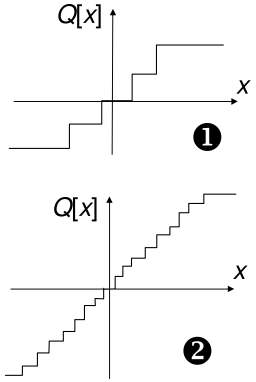
split into K - intervals

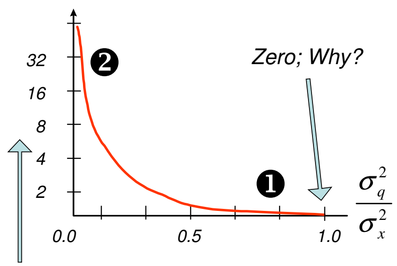
$$\sigma_q^2 = \int_{-\infty}^{\infty} (x - Q[x])^2 \, p_X(x)\,\mathrm{d}x = \sum_{k=1}^{K} \int_{x_k}^{x_{k+1}} (x - y_k)^2 \, p_X(x)\,\mathrm{d}x$$

Normalized measure: Signal-to-Noise-Ratio (SNR):

$$SNR = 10\log_{10}\frac{\sigma_x^2}{\sigma_q^2}\ \text{(dB)}$$

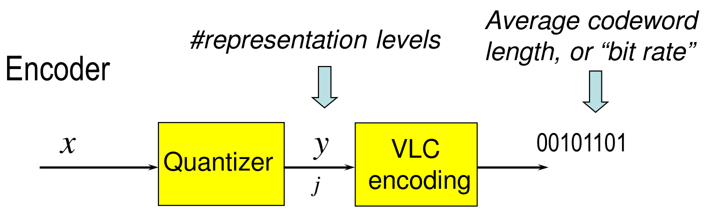
Bit Rate versus Distortion – (1)





#representation levels
~ average code word length
~ bit rate

Terminology for using quantizers



* **Representation levels coded in $\lceil \log_2(K) \rceil$ bits: *Fixed-rate quantization***
* **Representation levels coded in $H(Y)$ bits: *Quantization with entropy encoding***
* **(Later: *Entropy-constrained quantization*)**

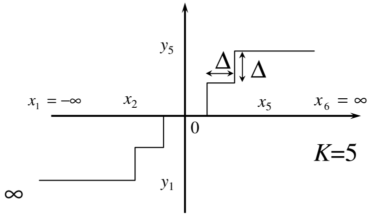
Bit Rate versus Distortion – (2)

* **Performance of quantizer is determined by**
  - the number of representation levels (bit rate or average codeword length R)
  - the quality σ_q^2 or SNR
* **Fixed-rate quantizer design:**

  For given K, find the quantizer characteristic with smallest σ_q^2

5 LSE0 - Mod 02 – A, Part 2
Uniform Quantization

R-D Optimal Design: Uniform Quantizer – (1)



* **Given:**
  $x_1 = -\infty \qquad x_{L+1} = \infty$

$$x_{k+1} - x_k = \Delta \qquad\qquad y_k = \frac{(x_{k+1} + x_k)}{2}$$

* **Find Δ such that σ_q^2 is minimized**

R-D Optimal Design: Uniform Quantizer – (2)

$$\min_{\Delta} \sum_{k=1}^{K} \int_{x_k}^{x_{k+1}} (x - y_k)^2 \, p_X(x) \, \mathrm{d}x$$

For values of K>3, this requires numerical optimization

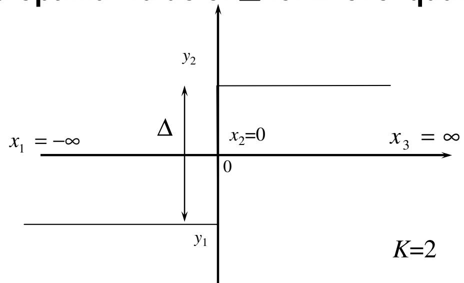
R	Δ/σ_x (=1)			SNR (dB)		
bit/sample)	Uniform	Gaussian	Laplace	Uniform	Gaussian	Laplace
1	1.732	1.596	1.414	6.02	4.40	3.01
2	0.866	0.996	1.087	12.04	9.25	7.07
3	0.433	0.586	0.731	18.06	14.27	11.44
4	0.217	0.335	0.461	24.08	19.38	15.96
5	0.108	0.188	0.280	30.10	24.57	20.60
6	0.054	0.104	0.166	36.12	29.83	25.36
7	0.027	0.057	0.096	42.14	35.13	30.23
8	0.013	0.031	0.055	48.17	40.34	35.14

smaller D: "finer" quantizer

more difficult to quantize

Example: Two-Level Quantizer – (1)

* **Find optimal value of Δ for 2 level quantizer**



$$\sigma_q^2 = \sum_{k=1}^{K} \int_{x_k}^{x_{k+1}} (x - y_k)^2 \, p_X(x) \, \mathrm{d}x = \int_{-\infty}^{0} (x + \frac{\Delta}{2})^2 \, p_X(x) \, \mathrm{d}x + \int_{0}^{\infty} (x - \frac{\Delta}{2})^2 \, p_X(x) \, \mathrm{d}x$$

Two-Level Quantizer – (2)

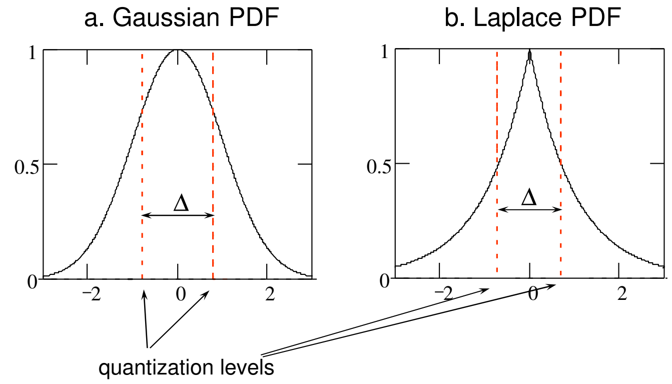
$$\sigma_q^2 = \int_{-\infty}^{0} (x + \frac{\Delta}{2})^2 \, p_X(x)\, \mathrm{d}x + \int_{0}^{\infty} (x - \frac{\Delta}{2})^2 \, p_X(x)\, \mathrm{d}x$$

$$= \sigma_x^2 + \frac{\Delta^2}{4} - 2\Delta \int_0^{\infty} x p_X(x)\, \mathrm{d}x$$

$$\Rightarrow \Delta_{\text{optimal}} = \min_{\Delta} \sigma_q^2 = 4\int_0^{\infty} x p_X(x)\, \mathrm{d}x = 2E[|X|]$$

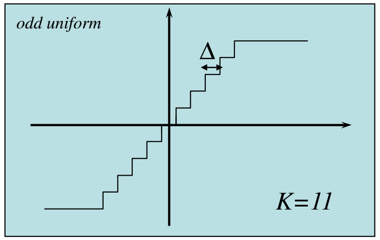
PDF	Δ/σ_x	σ_q^2	SNR (dB)
Uniform	1.732	0.250	6.02
Gaussian	1.596	0.363	4.40
Laplace	1.414	0.500	3.01
Gamma	1.154	0.667	1.76

Two-Level Quantizer – (3)



Implementation of Uniform Quantizer

* **The quantizer**
  - Odd
  - Uniform
  - K = 11 output levels



can be implemented by:

$$Q[x] = y_j = \Delta\,\mathrm{nint}\left(\frac{x}{\Delta}\right) = \Delta\left\lfloor \frac{x}{\Delta} + \frac{1}{2} \right\rfloor$$

$$j = \mathrm{nint}\left(\frac{x}{\Delta}\right) = \left\lfloor \frac{x}{\Delta} + \frac{1}{2} \right\rfloor$$

5LSE0 Mod 02 - A, Part 3

Non-Uniform Quantization

Non-Uniform Quantizer / 2 Approaches

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1. **Preprocessing of x by non-linear function followed by uniform quantizer (not discussed here…)**
   - Companding (compression-expanding)
   - Simple implementation
   - Popular for audio: logarithmic curves
     - A-law (Europe)
     - and µ-law (USA, Japan)
2. **Lloyd-Max quantizers, minimization of σ_q^2**
   - Complex design
   - More complex implementation than uniform quantizer
   - Additional gain is typically limited when combined with VLC

Lloyd-Max Quantizer – (1)

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∗ **Minimizes quantization noise variance, without enforcing any* structure onto decision thresholds and representation levels**

$$\min \sigma_q^2 = \min \sum_{k=1}^{K} \int_{x_k}^{x_{k+1}} \left(x - y_k\right)^2 p_X(x)\,\mathrm{d}x$$

for:

$x_k \qquad k = 2,3,\ldots,K$

$y_k \qquad k = 1,2,\ldots,K$

** except for symmetry of the quantizer*

Lloyd-Max Quantizer – (2)

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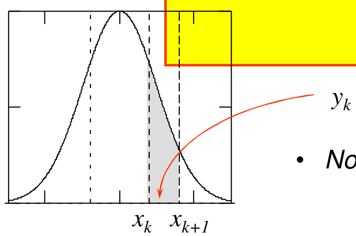
∗ **General solution is given by implicit expressions:**

$$x_k = \frac{1}{2}\left(y_{k-1} + y_k\right) \qquad y_k = \frac{\int_{x_k}^{x_{k+1}} x\,p_X(x)\,\mathrm{d}x}{\int_{x_k}^{x_{k+1}} p_X(x)\,\mathrm{d}x}$$



- *Note the structure of the formulas*
  - *Middle of two representation levels*
  - *Weighted average decision levels*

Lloyd-Max Quantizer – (3)

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∗ **Property of solution:**
- *if* x_k are known $\Rightarrow y_k$ are known
- *if* y_k are known $\Rightarrow x_k$ are known

∗ **Iterative design necessary** — initial choice, “seed”

$x_1 = -\infty$

Assume: $x_2 = g \quad \Rightarrow \quad y_1 = \dfrac{\int_{x_1}^{x_2} x\,p(x)\,\mathrm{d}x}{\int_{x_1}^{x_2} p(x)\,\mathrm{d}x} \quad \Rightarrow \quad y_2 = 2x_2 - y_1$

Solve x_3 from: $y_2 = \dfrac{\int_{x_2}^{x_3} x\,p(x)\,\mathrm{d}x}{\int_{x_2}^{x_3} p(x)\,\mathrm{d}x} \quad \Rightarrow \quad y_3 = 2x_3 - y_2$

etcetera

Lloyd-Max / Iterative Solution Scheme

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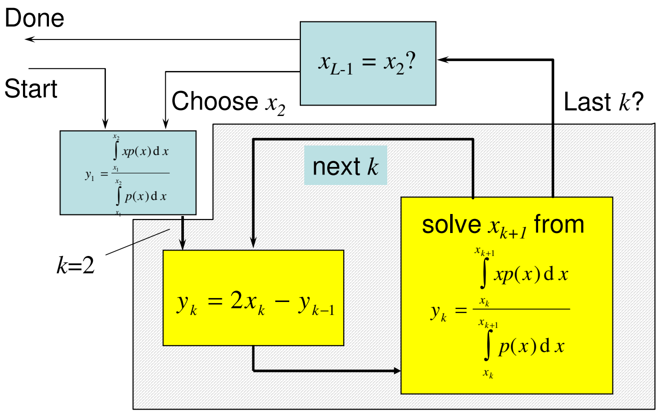

Lloyd-Max / Example iterative Q design

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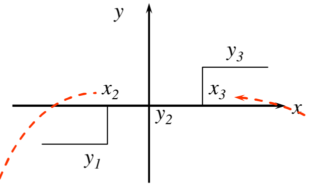

	Iteration			
	1	2	3	4
Assume x_2	-1.000	-0.500	-0.75	-0.612
y_1	-1.525	-1.141	-1.329	-1.224
y_2	-0.475	0.141	-0.171	0.000
y_3	-0.028	0.827	0.368	1.224
x_3	0.419	1.513	0.909	0.612

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Examples of Lloyd-Max Quantizers

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* **For *uniform PDF*, Lloyd-Max quantizer is *uniform***

		K=2, 1 *bit/sample*		*K*=4, 2 *bit/sample*		*K*=8, 3 *bit/sample*		*K*=16, 4 *bit/sample*	
PDF	k	x_k	y_k	x_k	y_k	x_k	y_k	x_k	y_k
Gaussian	1	0.000	0.798	0.000	0.453	0.000	0.245	0.000	0.128
	2			0.982	1.510	0.501	0.756	0.258	0.388
	3					1.050	1.344	0.522	0.657
	4					1.748	2.152	0.800	0.942
	5							1.099	1.256
	6							1.437	1.618
	7							1.844	2.069
	8							2.401	2.733
Laplace	1	0.000	0.707	0.000	0.402	0.000	0.233	0.000	0.124
	2			1.127	1.834	0.533	0.833	0.264	0.405
	3					1.253	1.673	0.567	0.729
	4					2.380	3.087	0.920	1.111
	5							1.345	1.578
	6							1.878	2.178
	7							2.597	3.017
	8							3.725	4.432

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Uniform quantizer versus Lloyd-Max

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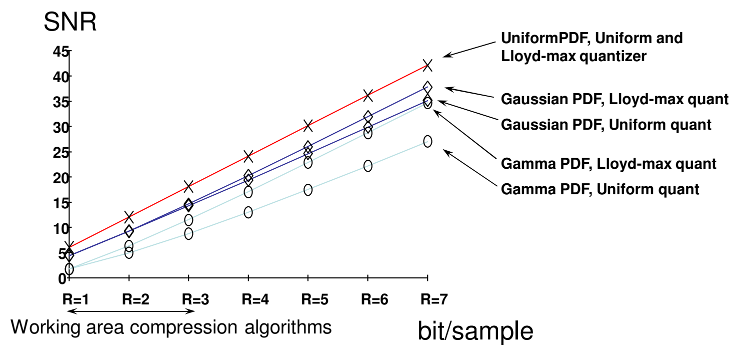
For relevant bit rates, Lloyd-Max does often not pay off.



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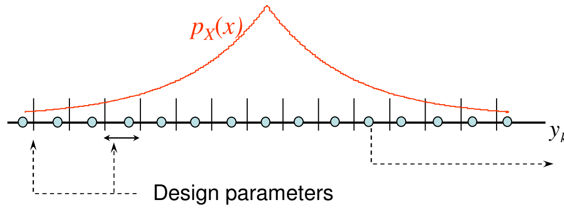
Entropy-Constrained Quantization

* **To find the overall optimal result, quantizer and entropy coder must be *jointly* designed**
  – Complex optimization problem
  – Reasonable approximations are obtained by *Uniform Threshold Quantizers (UTQ)*

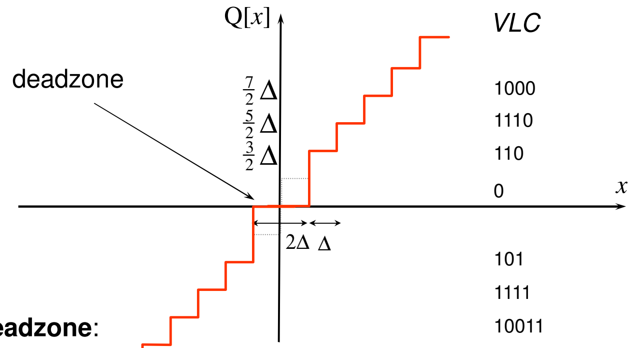


$$y_k = \frac{\int_{x_k}^{x_{k+1}} x p_X(x) dx}{\int_{x_k}^{x_{k+1}} p_X(x) dx}$$

Quantization in Practice – (1)

* **Uniform quantizers are preferred**
  – Implementation and limited loss compared to Lloyd-Max
  – Easily scalable (one parameter: step size Δ)
* ***Odd* quantizers are often preferred over *even* because of the presence of a representation level at zero**
  – In good compression scheme many (near-)zero values occur
  – Zeroes efficiently coded by an entropy coder (runlength coding)
  – Audio: Companding is usual
* **Image/video coding :** No companding
  – Uniform quantizer with *deadzone* is typical

Quantization in Practice – (2)



Deadzone:
* Improves noise robustness of coding system
* "Stimulates" truncation to zero: can be coded efficiently