
525.749 Image Compression, Packet Video and Video Processing

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Lecture 8 - Foundation of Video Coding

Part II: Scalar and Vector Quantization

<http://webdev.apl.jhu.edu/~beser/525759/index.html>

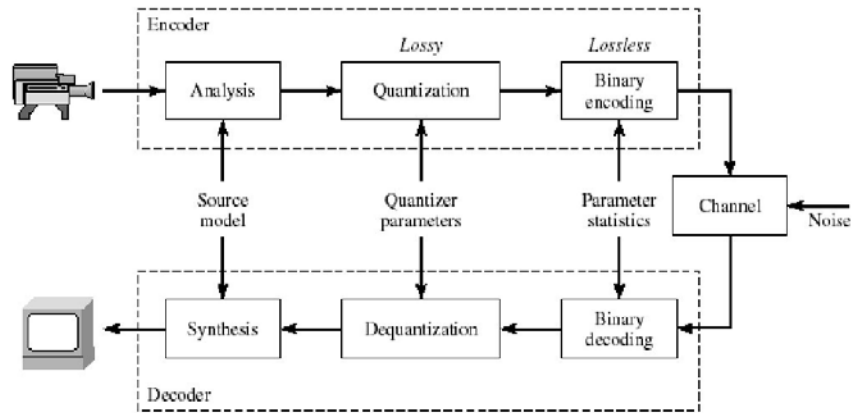
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Outline

-
- Overview of video coding systems
 - Scalar Quantization
 - Vector Quantization
 - Rate-distortion characterization of lossy coding
 - Operational rate distortion function
 - Rate distortion bound (lossy coding bound)

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Components in a Coding System



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Lossy Coding

- **Original source is discrete**
 - Lossless coding: bit rate \geq entropy rate
 - One can further quantize source samples to reach a lower rate
- **Original source is continuous**
 - Lossless coding will require an infinite bit rate!
 - One must quantize source samples to reach a finite bit rate
 - Lossy coding rate is bounded by the mutual information between the original source and the quantized source that satisfy a distortion criterion
- **Quantization methods**
 - Scalar quantization
 - Vector quantization

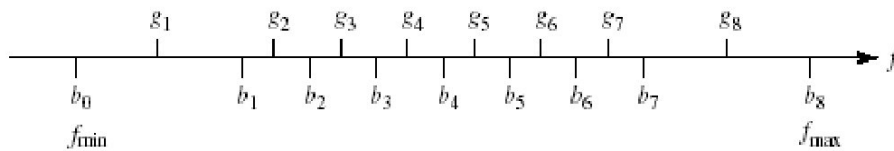
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Scalar Quantization

- General description
- Uniform quantization
- MMSE quantizer
- Lloyd algorithm

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SQ as Line Partition



Quantization Levels: L

Boundary Values: b_i

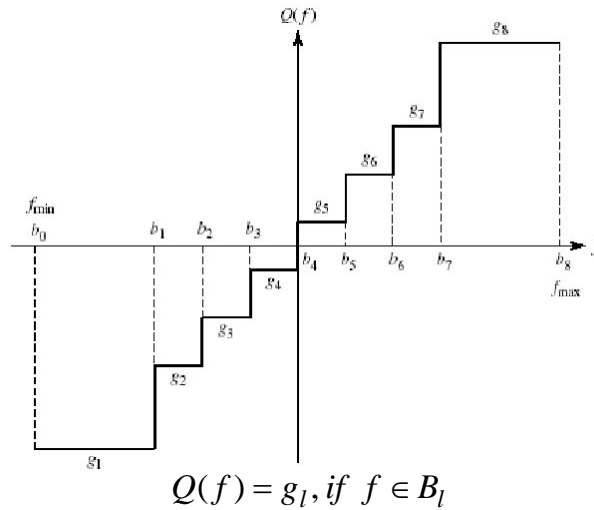
Partition Regions: $B_l = [b_{l-1}, b_l)$

Reconstruction Values: g_l

Quantizer Mapping: $Q(f) = g_l, \text{if } f \in B_l$

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Function Representation



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Distortion Measure

- General measure:**

$$D_q = E\{d_1(F, Q(F))\} = \int_{f \in B} d_1(f, Q(f)) p(f) df$$

$$= \sum_{l \in L} P(B_l) D_{q,l}$$

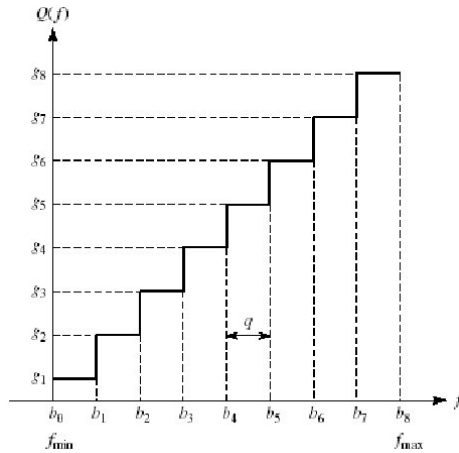
$$D_{q,l} = \int_{f \in B_l} d_1(f, g_l) p(f|f \in B_l) df.$$

- Mean Square Error (MSE)**

$$\sigma_q^2 = E\{F - Q(F)\}^2 = \sum_{l \in L} P(B_l) \int_{b_{l-1}}^{b_l} (f - g_l)^2 p(f|B_l) df.$$

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Uniform Quantization



Uniform Source:

$$p(f) = \begin{cases} 1/B & f \in (f_{\min}, f_{\max}) \\ 0 & \text{otherwise} \end{cases}$$

$$\sigma_q^2 = \frac{q^2}{12} = \sigma_f^2 2^{-2R}$$

$$\begin{aligned} \text{SNR} &= 10 \log_{10} \frac{\sigma_f^2}{\sigma_q^2} \\ &= (20 \log_{10} 2)R := 6.02R(\text{dB}) \end{aligned}$$

$$Q(f) = \left[\frac{f - f_{\min}}{q} \right] * q + \frac{q}{2} + f_{\min}$$

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Minimum MSE (MMSE) Quantizer

Determine b_l, g_l to minimize MSE

$$\sigma_q^2 = E\{F - Q(F)\}^2 = \sum_{l \in L} P(B_l) \int_{b_{l-1}}^{b_l} (f - g_l)^2 p(f|B_l) df.$$

Setting $\frac{\partial \sigma_q^2}{\partial b_l} = 0, \frac{\partial \sigma_q^2}{\partial g_l} = 0$ yields:

$$b_l = \frac{g_l + g_{l+1}}{2}, \text{ or } B_l = \{f : d_1(f, g_l) \leq d_1(f, g_{l'}), \forall l' \neq l\} \text{ (Nearest Neighbor Condition)}$$

$$g_l = E\{F|F \in B_l\} = \int_{B_l} p(f|f \in B_l) df, \quad \text{(Centroid Condition)}$$

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High Resolution Approximation

- For a source with arbitrary pdf, when the rate is high so that the pdf within each partition region can be approximated as flat:

$$\sigma_q^2 = \varepsilon^2 \sigma_f^2 2^{-2R}$$

$$\varepsilon^2 = \frac{1}{12} \left(\int_{-\infty}^{+\infty} \bar{p}(f)^{1/3} df \right)^3, \quad \bar{p}(f) = \sigma_f p(\sigma_f f)$$

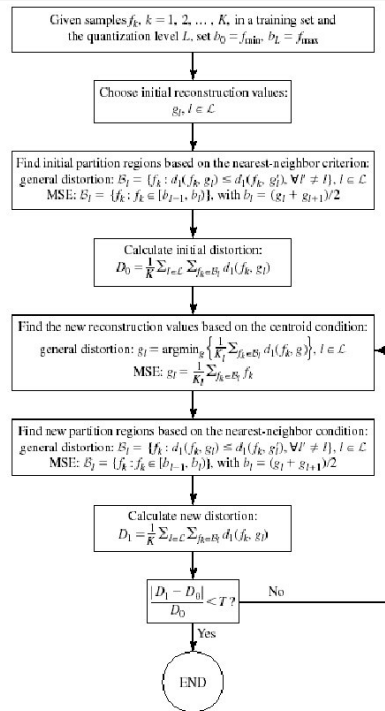
Uniform Source : $\varepsilon^2 = 1$

i.i.d Gaussian Source : $\varepsilon^2 = 2.71$ (w/o VLC)

Bound for Gaussian Source : $\varepsilon^2 = 1$

Lloyd Algorithm

- Iterative algorithms for determining MMSE quantizer parameters
- Can be based on a pdf or training data
- Iterate between centroid condition and nearest neighbor condition



Vector Quantization

- General description
- Nearest neighbor quantizer
- MMSE quantizer
- Generalized Lloyd algorithm

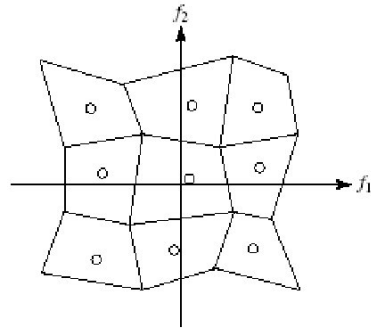
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Vector Quantization: General Description

- **Motivation:** quantize a group of samples (a vector) together, to exploit the correlation between these samples
- Each sample vector is replaced by one of representative vectors (or patterns) that often occur in the signal
- **Applications:**
 - Color quantization: Quantize all colors appearing in an image to N colors for display on a monitor that can only display N distinct colors at a time – Adaptive palette
 - Image quantization: Quantize every NxN block into one of the typical patterns (obtained through training). More efficient with larger block size, but block size are limited by complexity.

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VQ as Space Partition



Original vector: $f \in R^N$

Quantization levels: L

Partition regions: B_l

Reconstruction vector (codeword): g_l

Quantizer mapping: $Q(f) = g_l, \text{ if } f \in B_l$

Codebook: $C = \{g_l, l = 1, 2, \dots, L\}$

Bit rate: $R = \frac{1}{N} \log_2 L$

Every point in a region (B_l) is replaced by (quantized to) the point indicated by the circle (g_l)

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Distortion Measure

General measure:

$$D_q = E\{d_N(F, Q(F))\} = \int_B p_N(f) d_N(f, Q(f)) df$$

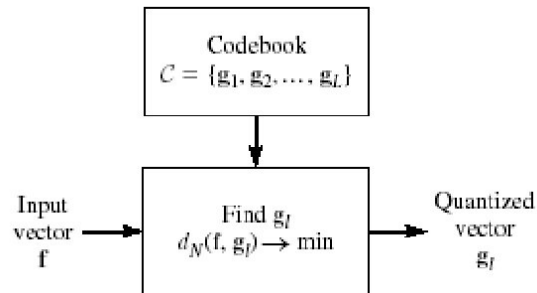
$$= \sum_{l=1}^L P(B_l) D_{q,l}$$

$$D_{q,l} = E\{d_N(F, Q(F)) | F \in B_l\} = \int_{f \in B_l} P_N(f | f \in B_l) d_N(f, g_l) df,$$

$$\text{MSE: } d_N(f, g) = \frac{1}{N} \sum_{n=1}^N (f_n - g_n)^2,$$

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Nearest Neighbor (NN) Quantizer



$$B_l = \{f \in R^N : d_N(f, g_l) \leq d_N(f, g_{l'}), \forall l' \neq l\}$$

Challenge: How to determine the codebook?

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Complexity of NN VQ

- Complexity analysis:
 - Must compare the input vector with every codewords
 - Each comparison takes N operations
 - Need $L=2^{\{NR\}}$ comparisons
 - Total operation = $N 2^{\{NR\}}$
 - Total storage space = $N 2^{\{NR\}}$
 - Both computation and storage requirement increases exponentially with N!
- Example:
 - $N=4 \times 4$ pixels, $R=1$ bpp: $16 \times 2^{16} = 2^{20} = 1$ Million operation/vector
 - Apply to video frames, 720×480 pels/frame, 30 fps:
 $2^{20} * (720 \times 480 / 16) * 30 = 6.8 \text{ E}+11$ operations/s !
 - When applied to image, block size is typically limited to $\leq 4 \times 4$
- Fast algorithms:
 - Structured codebook so that one can conduct binary tree search
 - Product VQ: can search subvectors separately

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MMSE Vector Quantizer

- **Necessary conditions for MMSE**

- Nearest neighbor condition

$$B_l = \{f : d_N(f, g_l) \leq d_N(f, g_{l'}), \forall l' \neq l\}.$$

- Generalized centroid condition:

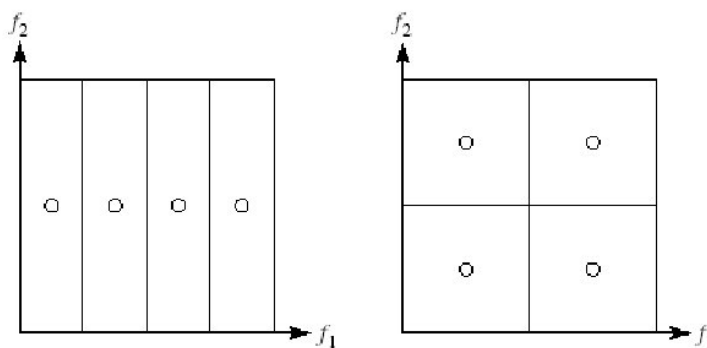
$$g_l = \arg \min_g E\{d_N(F, g) | F \in B_l\}.$$

- MSE as distortion:

$$g_l = \int_{B_l} p(f|f \in B_l) f df = E\{F | F \in B_l\}.$$

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Caveats



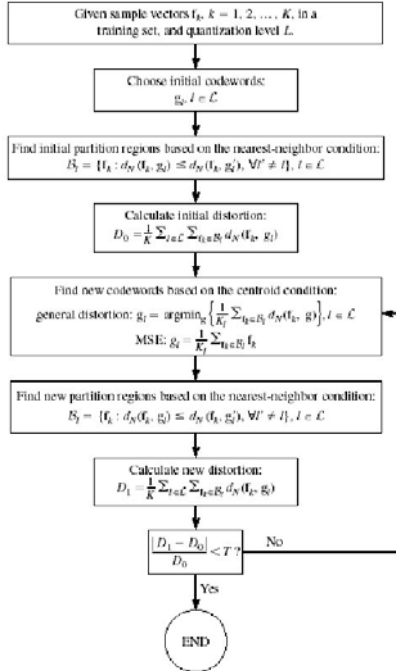
Both quantizer satisfy the NN and centroid condition, but the quantizer on the right is better!

NN and centroid conditions are necessary but NOT sufficient for MSE optimality!

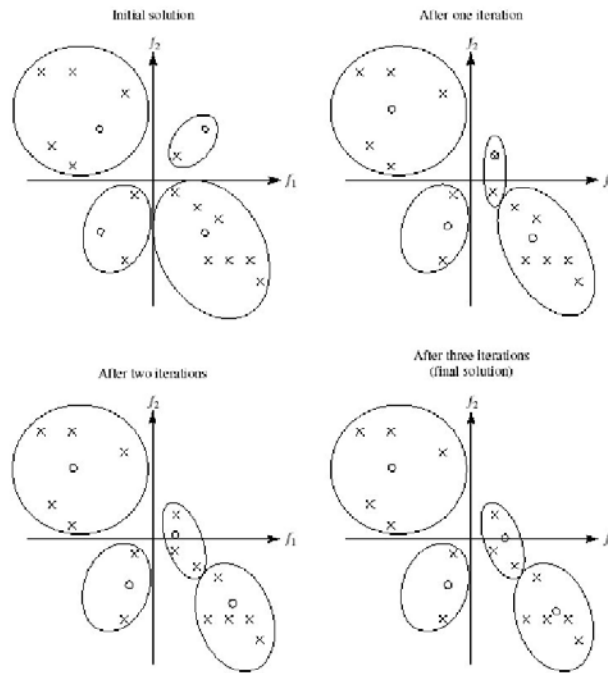
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Generalized Lloyd Algorithm (LBG Algorithm)

- Start with initial codewords
- Iterate between finding best partition using NN condition, and updating codewords using centroid condition

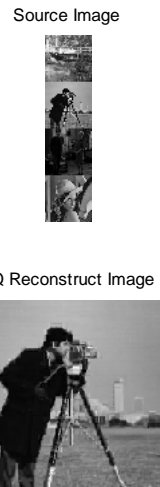
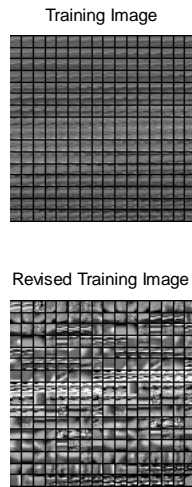


Example



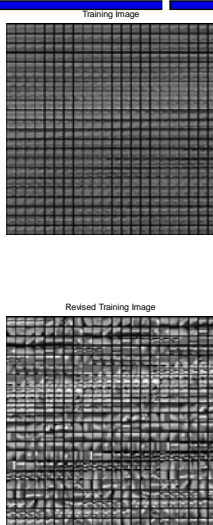
LBG Example

- Training data created by concatenating 4 images
- Process chip size as 8x8
- Quantization set to 256
- Requires 61 iterations
- 175 unique codes found



Large Code Book Example: LBG

- Training data created by concatenating 4 images
- Process chip size as 8x8
- Quantization set to 512
- Requires 59 iterations
- 159 unique codes found



Rate Distortion Bounds

- **Why is this important:**
 - Rate distortion bounds implies that as you quantize the data, you introduce error
 - This quantization changes the data rate of the code
 - If you design a quantizer, you are trading code efficiency with distortion
 - » Optimal quantizers provide the most data with minimal error
 - The models for data will provide the probabilistic basis for determining the quality of the quantizer.

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Rate-Distortion Characterization of Lossy Coding

- **Operational rate-distortion function of a quantizer:**
 - Relates rate and distortion: $R(D)$
 - A vector quantizer reaches different point on its $R(D)$ curve by using different number of codewords
 - Can also use distortion-rate function $D(R)$

- **Rate distortion bound for a source**

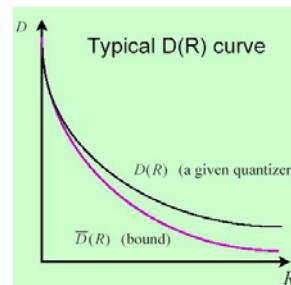
- Minimum rate R needed to describe the source with distortion $\leq D$

$$\bar{R}(D) = \lim_{N \rightarrow \infty} \min_{q_N(g|f) \in Q_{n,N}} R_N(D; q_N(g|f))$$

$$Q_{D,N} = \{q_N(g|f) : E\{d_N(F,G)\} \leq D\}$$

- **RD optimal quantizer:**

- Minimize D for given R or vice versa



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Lossy Coding Bound (Shannon Lossy Coding Theorem)

$$\bar{R}(D) = \lim_{N \rightarrow \infty} \min_{q_N(g|f) \in Q_{D,N}} R_N(D; q_N(g|f))$$

$$Q_{D,N} = \{q_N(g|f) : E\{d_N(F, G)\} \leq D\}$$

$$\bar{R}(D) = \lim_{N \rightarrow \infty} \min_{q_N(g|f) \in Q_{D,N}} \frac{1}{N} I_N(F; G).$$

$I_N(F, G)$: mutual information between F and G , information provided by G about F

Mutual Information measures the mutual dependence of two variables

$$I_N(F; G) = \sum_{f \in F} \sum_{g \in G} p(f, g) \log \frac{p(f, g)}{p(f)p(g)}$$

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Lossy Coding Bound (Shannon Lossy Coding Theorem)

$Q_{D,N}$: all coding schemes (or mappings $q(g|f)$) that satisfy distortion criterion $d_N(f, g) \leq D$

$$\bar{R}_L(D) \leq \bar{R}(D) \leq \bar{R}_G(D),$$

$$\bar{R}_L(D) = \bar{h}(F) - \frac{1}{2} \log_2 2\pi e D = \frac{1}{2} \log_2 \frac{Q(F)}{D},$$

$\bar{R}_G(D)$: RD bound for Gaussian source with the same variance

$\bar{R}_L(D)$: is the Shannon lower bound

$\bar{h}(F)$: entropy of source F

$Q(F)$: is the entropy power of F

For a Gaussian source, $\bar{R}_L(D) = \bar{R}_G(D)$

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Bit Rate Limits

- Among all sources with the same variance, The Gaussian source requires the highest bit rate to satisfy the same distortion criteria.
- Optimal coding scheme that achieves the RD bound is the one in which the quantization error sequence is i.i.d. Gaussian source with variance D , with a differential entropy

$$\frac{1}{2} \log_2 2\pi e D$$

- The lower bound is the difference between the differential entropy of the original source and that of the quantization error.

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RD Bound for Gaussian Source

- i.i.d. 1-D Gaussian: $\bar{D}(R) = \sigma^2 2^{-2R}$.

$$\bar{R}(D) = \begin{cases} \frac{1}{2} \log_2 \frac{\sigma^2}{D} & 0 \leq D < \sigma^2 \\ 0 & D \geq \sigma^2 \end{cases}$$

- i.i.d. N-D Gaussian with independent components

$$\bar{R}(D) = \frac{1}{2} \log_2 \frac{(\prod_n \sigma_n^2)^{1/N}}{D}, \quad \bar{D}(R) = \left(\prod_n \sigma_n^2 \right)^{1/N} 2^{-2R}.$$

where $D \leq \min\{\sigma_n^2\}$

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i.i.d. Vector Gaussian Source with Correlated Components

- If $[C]$ represents the covariance matrix of the N components of each vector sample and let:

$$\lambda_n, n = 1, 2, \dots, N$$

- Represent the eigenvalues of $[C]$, RD bound for this source is given by

$$\begin{cases} R(\alpha) = \frac{1}{N} \sum_n \max\left\{0, \frac{1}{2} \log_2 \frac{\lambda_n}{\alpha}\right\} \\ D(\alpha) = \frac{1}{N} \sum_n \min\{\alpha, \lambda_n\} \end{cases}$$

where $\alpha \in (0, \max\{\lambda_n\})$

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For Small Distortion

- When D is sufficiently small that the preceding reduces to:

$$\bar{R}(D) = \frac{1}{2} \log_2 \frac{\left(\prod_n \lambda_n\right)^{1/N}}{D} = \frac{1}{2} \log_2 \frac{|\det[C]|^{1/N}}{D},$$

$$\bar{D}(R) = \left(\prod_n \lambda_n\right)^{1/N} 2^{-2R} = |\det[C]|^{1/N} 2^{-2R}.$$

- Obtained by transforming the original vector using a transform matrix consisting of the eigenvectors of $[C]$ and then applying the RD Bound to the transformed vector which will now have independent components.

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Summary

- **Coding system:**
 - original data -> model parameters -> quantization-> binary encoding
- **Quantization:**
 - Scalar quantization:
 - » Uniform quantizer
 - » MMSE quantizer (Nearest neighbor and centroid condition)
 - Vector quantization
 - » Nearest neighbor quantizer
 - » MMSE quantizer
 - » Generalized Lloyd algorithm
 - Uniform quantizer
 - » Can be realized by lattice quantizer (not discuss here)
- **Rate distortion characterization of lossy coding**
 - Bound on lossy coding
 - Operational RD function of practical quantizers

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Homework

- **Reading assignment:**
 - Sec. 8.5-8.7, 8.3.2,8.3.3

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