

Master: INFORMATIQUE  
Parcours: VICO Visual Computing

UE: Multimedia Communication

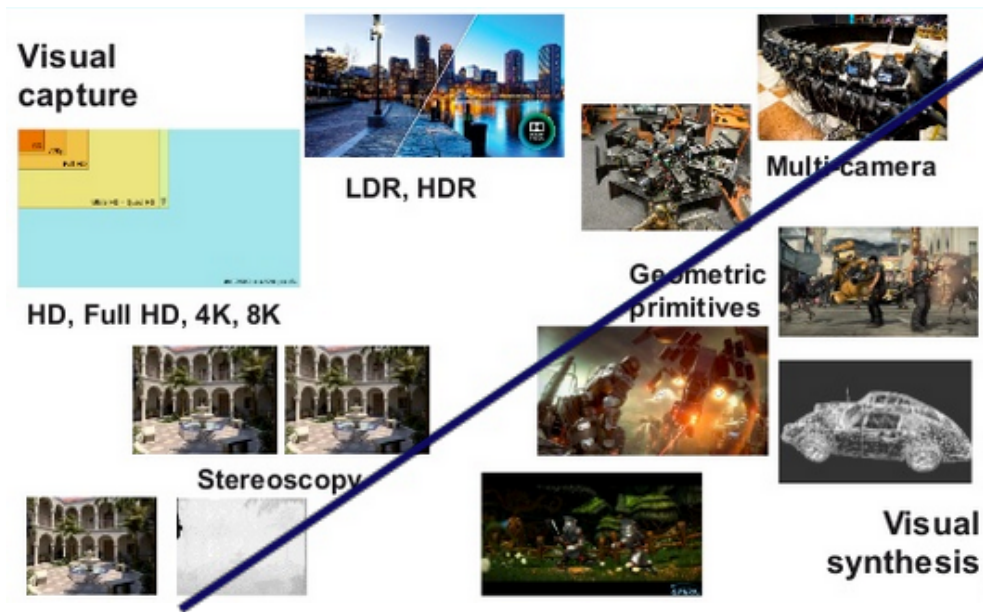
**VQ - Vector Quantization**  
**TSLVQ - Tree Structured Lattice VQ**

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# Plan

1. Context of the study
2. Vector Quantization (VQ)
3. Lattice VQ and Tree-Structured VQ
4. Tree-Structured Lattice VQ (TSLVQ)
5. Experimental results
6. Conclusion

## Convergence between 2 worlds



Point Cloud

- Challenge: Massive 3-D data sets
  - Unstructured millions of points
  - Costly to store/transmit/manipulate
- Goal: Find efficient techniques for representation and compression

- standards

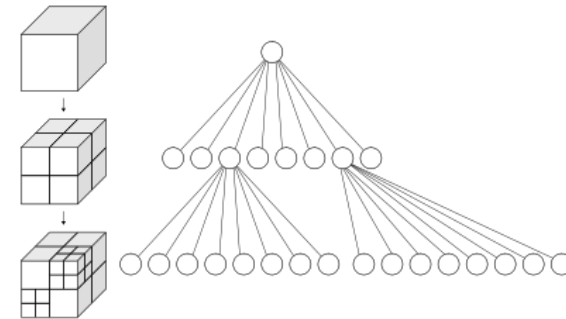
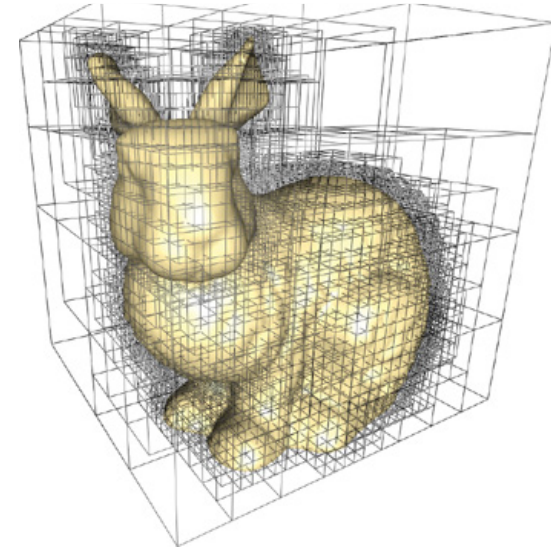
- April 2017: MPEG issued a Call for Proposals on PCC  
=> Final standard in early 2020 with V-PCC & G-PCC

- Octree-based PCC methods

- Point cloud compression with graph transform (Zhang2014)
  - construct graphs on small neighborhoods of occupied voxels
- Extended Shape Adaptive DCT (Cohen2016)
  - represent points (average) on an uniform grid and apply 1-D DCT along each direction

- Tree-Structured Lattice Vector Quantization (TSLVQ) (Ricordell1998)

- truncated lattices embedding
- multi-stage procedure of quantization based on 3x3x3 tree splitting



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## Principe

- Vector Quantizer, dimension  $k$ , size  $L$

$$\begin{aligned} Q : R^k &\longrightarrow \mathcal{D} \\ \mathbf{x} &\longmapsto Q(\mathbf{x}) = \mathbf{y}_i \end{aligned}$$

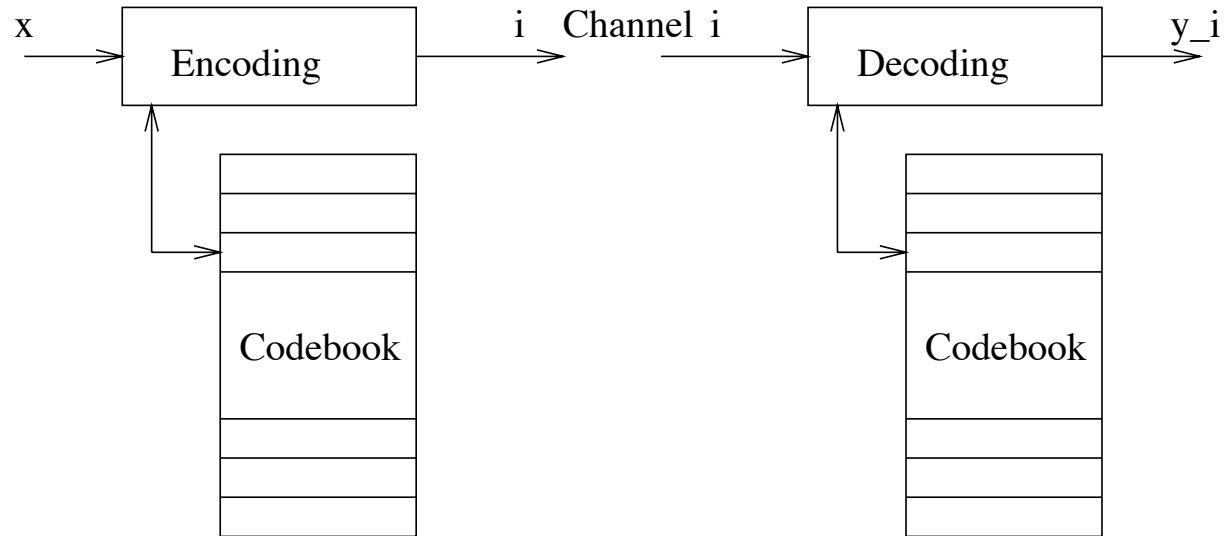
$$\mathcal{D} = \{\mathbf{y}_i \in R^k / i = 1, 2, \dots, L\}$$

- $R^k$  partition into  $L$  Voronoï cells

$$C_i = \{\mathbf{x} \in R^k / Q(\mathbf{x}) = \mathbf{y}_i\}$$

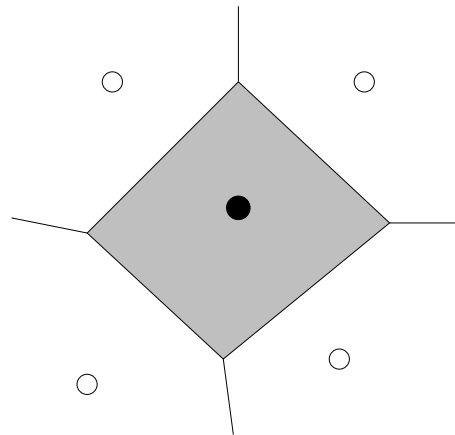
- Coding

6



- Encoding, "Nearest Neighbour" rule

$$C_i = \{ \mathbf{x} \in R^k / Q(\mathbf{x}) = \mathbf{y}_i, \text{ si } d(\mathbf{x}, \mathbf{y}_i) \leq d(\mathbf{x}, \mathbf{y}_j), \forall j \neq i \}$$



## Performance evaluation

- Rate [bpp]

- ▷ Rate constrained :  $R = \frac{1}{k} \cdot \log_2 L$

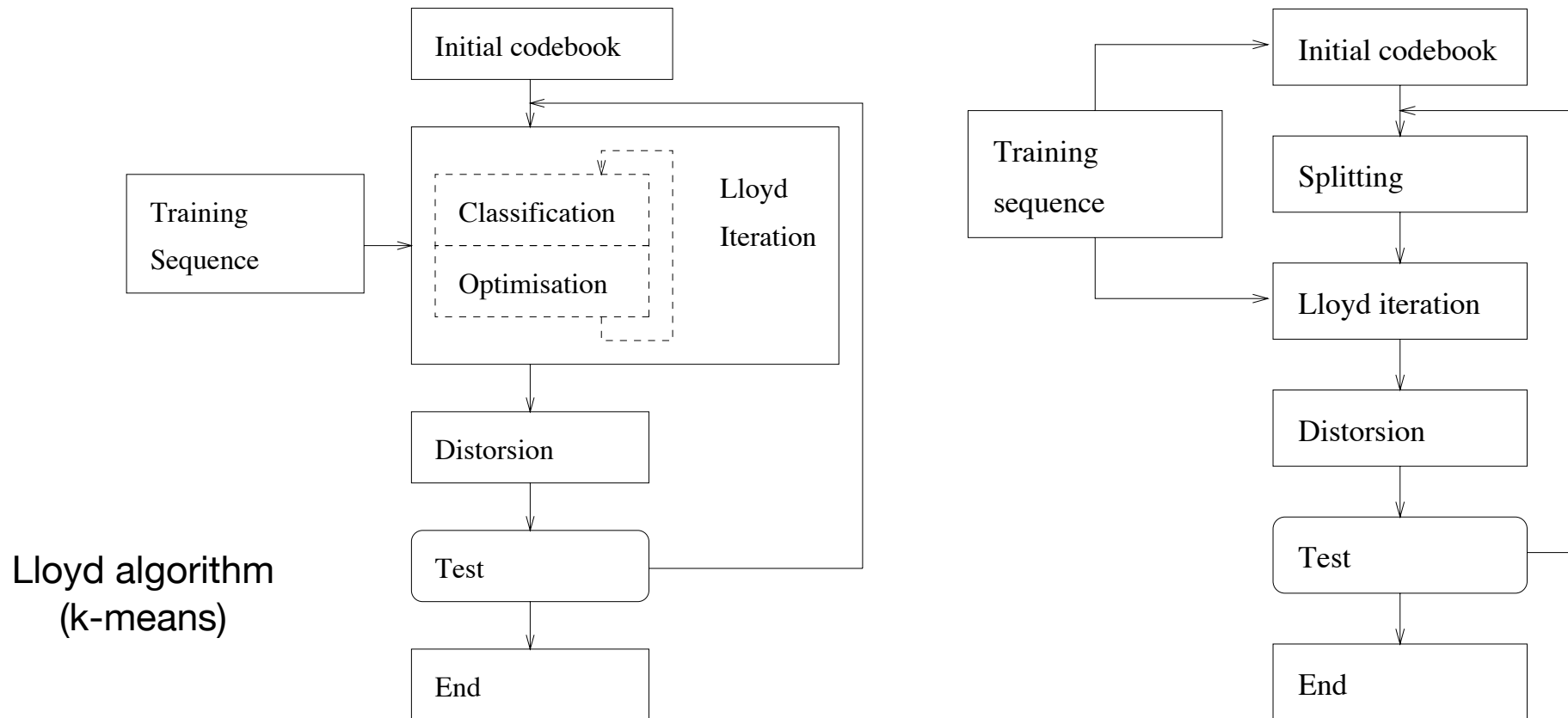
- ▷ Entropy constrained :  $R \simeq H(\mathcal{D})$

- Distorsion

$$D = \frac{1}{k} \sum_{i=1}^L \int_{C_i} L_2(\mathbf{x}, \mathbf{y}_i) \cdot p_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}$$



# (nearly) Optimal VQ



- Training
- Encoding  $\rightarrow$  exhaustive research  $O(L)$

LBG algorithm

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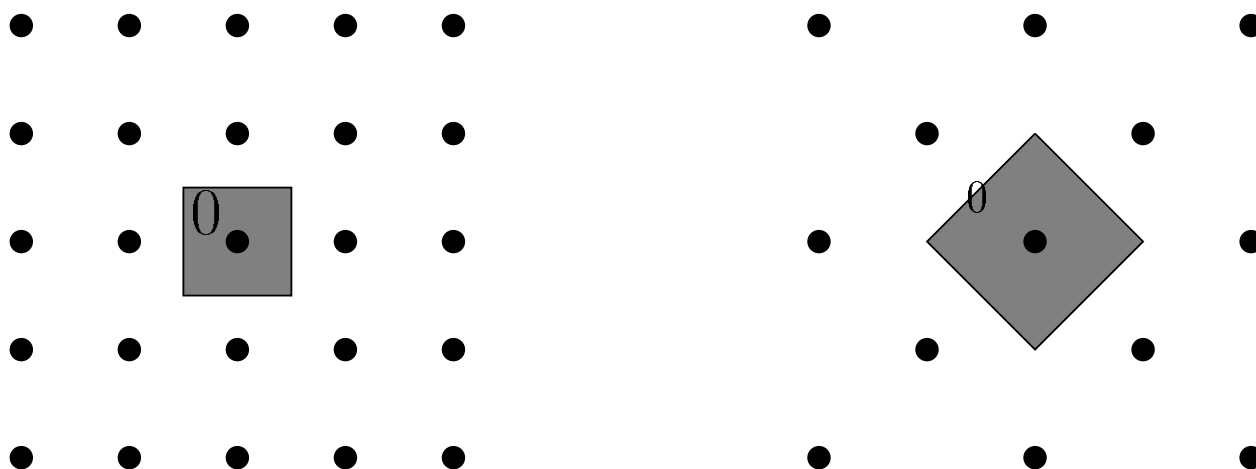
# Lattices $\Lambda$

- Regular arrangement of identical spheres  $\rightarrow$  spheres centers

$0 \rightarrow$  origin

- $Z^k = \{ \mathbf{y} = (y_1, y_2, \dots, y_k)^T \mid y_i \in Z \}$

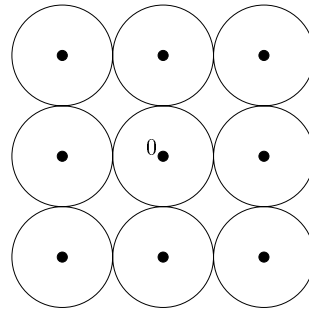
- $D_k = \{ \mathbf{y} = (y_1, y_2, \dots, y_k)^T \mid \mathbf{y} \in Z^k, \sum_{i=1}^k y_i = 0 \pmod{2} \}$



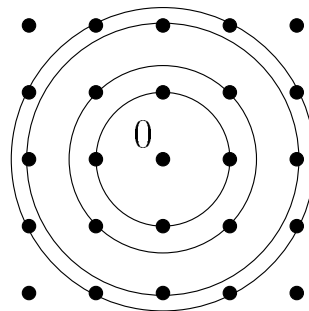
# Characteristics

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- Packing radius  $\rho$



- Series Theta, Nu (Gaidon93), modified Theta (Moureaux94)



- Best quantizing lattices :  $A_2, D_4, E_8, \Lambda_{16}$
- Fast quantizing lattices (Conway and Sloane83) :  $Z^k, D_k, E_8, \Lambda_{16}$   
 $\implies$  complexity  $O(k)$

## Coding scheme

- Lattice Truncation

- ▷ Shape

- ▷ i.i.d Gaussian source  $\rightarrow$  sphere ( $L_2$ )

- ▷ i.i.d Laplacian source  $\rightarrow$  pyramid ( $L_1$ )

- ▷ correlated GG source  $\rightarrow$  ellipse (ponderated  $L_2$ )

- ▷ Truncation energy (Fisher86)  $\mathcal{E}_t \rightarrow$  points number

- Source normalisation

- ▷ before quantization

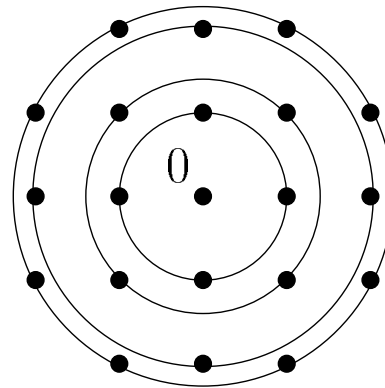
- ▷ scaling factor

## Projection within a sphere

- Sphere radius  $\sqrt{\mathcal{E}_t}$
- Training sequence  $\mathcal{SA} = \{\mathbf{x}_j = (x_1, \dots, x_k)^T \ / \ j = 0, 1, 2, \dots\}$
- Vector energy  $\mathcal{E}(\mathbf{x}) = L_2(\mathbf{x})$
- $\mathcal{E}_{max} = \max_{\mathcal{E}} \{\mathcal{E}(\mathbf{x}) \ / \ \mathbf{x} \in \mathcal{SA}\}$
- Scaling factor  $F = \sqrt{\mathcal{E}_t / \mathcal{E}_{max}}$
  
- Real source  $\rightarrow$  vectors with energy greater than  $\mathcal{E}_{max}$   
are processed separately

## Labeling of the lattice points

- Index calculation  $\rightarrow$  product code (Lamblin88, Moureaux94, Onno95)
  - ▷ sub-index for the sphere energy
  - ▷ sub-index for the point position



## Conclusion

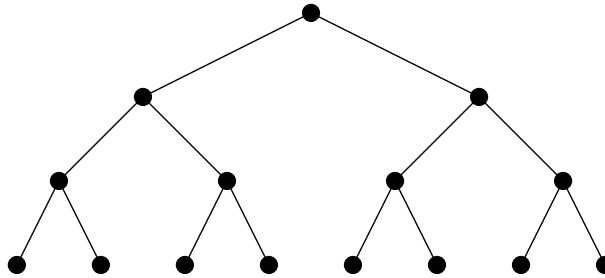
- Advantage
  - ▷ fast quantization
  - ▷ predefined codebook
- Drawback → method for simple sources

⇒ TSLVQ : hierarchical packing of embedded truncated lattices



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- Encoding

- ▷ complexity  $O(\log_B L)$

- ▷ tree storage

- Decoding

- ▷ leaves

- ▷ progressive reconstruction

- Unbalanced tree  $\rightarrow$  variable rate

- ▷ pruning approach (Breiman84, Chou89)

- ▷ greedy approach (Makhoul85, Riskin91)

## Training

Characterisation of each node  $n_i$

- Probability of reaching  $n_i$

$$P(n_i) = \frac{\text{card}(C_{n_i})}{\text{card}(SA)}$$

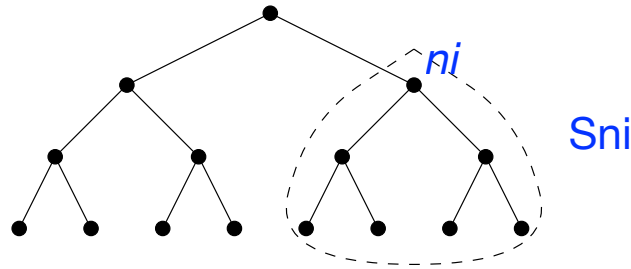
- Average distortion

$$d(n_i) = \frac{1}{\text{card}(C_{n_i})} \cdot \sum_{\mathbf{x} \in C_{n_i}, \mathbf{x} \in SA} \|\mathbf{x} - \mathbf{y}_{n_i}\|^2$$

- Entropy code length

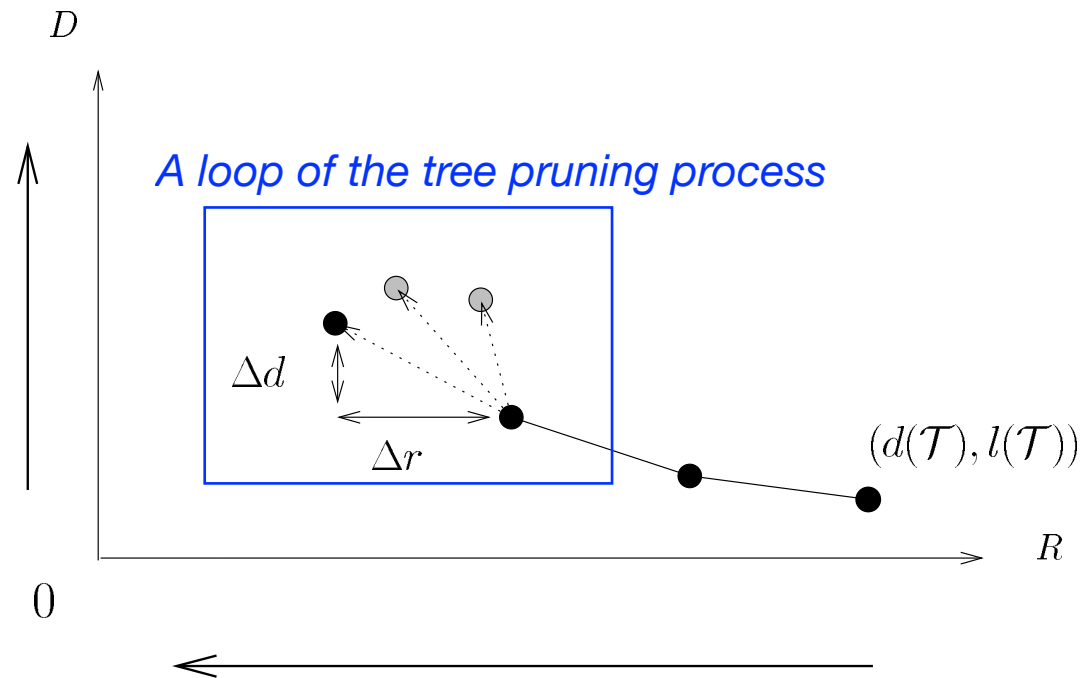
$$r(n_i) = -\log_2 P(n_i)$$

## Tree pruning



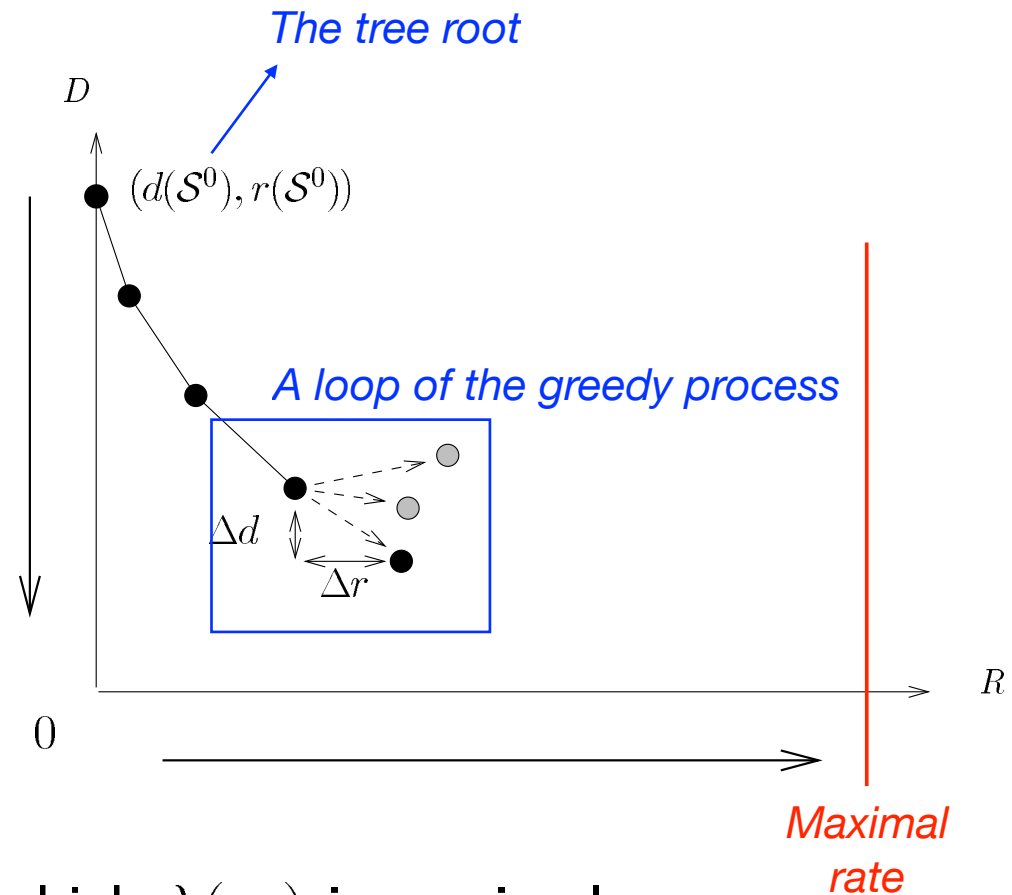
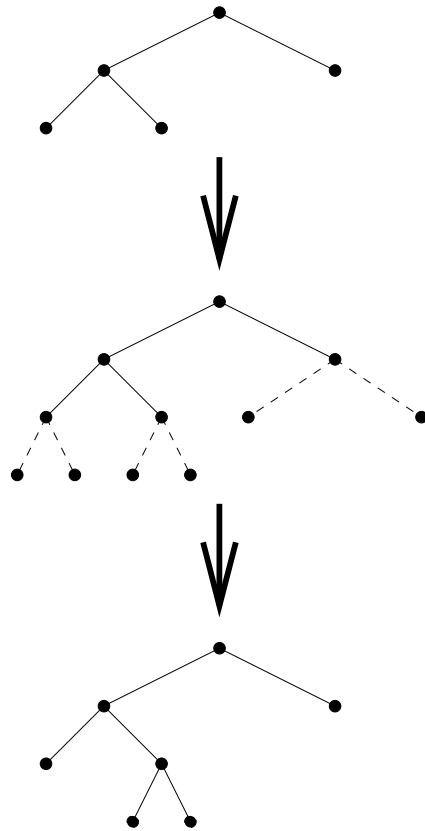
- BFOS algorithm (Breiman84)
  1. complet tree  $\mathcal{T}$
  2. successive pruning
- Characterisation of each branch  $\mathcal{S}_{n_i}$ 
  - ▷ increase in distortion if  $\mathcal{S}_{n_i}$  is removed  $\Delta d(\mathcal{S}_{n_i})$
  - ▷ decrease in rate if  $\mathcal{S}_{n_i}$  is removed  $\Delta r(\mathcal{S}_{n_i})$
  - ▷ **BFOS criterion**  $\lambda(n_i) = \Delta d(\mathcal{S}_{n_i}) / \Delta r(\mathcal{S}_{n_i})$

# Pruning principle



$\implies$  Pruning of the branch for which  $\lambda(n_i)$  is minimal

# Greedy approach



$\implies$  Splitting of the leaf for which  $\lambda(n_i)$  is maximal

## Conclusion

- Pruning algorithm
  - ▷ global approach
  - ▷ storage of the complete tree
- Greedy algorithm
  - ▷ local approach
  - ▷ limited storage

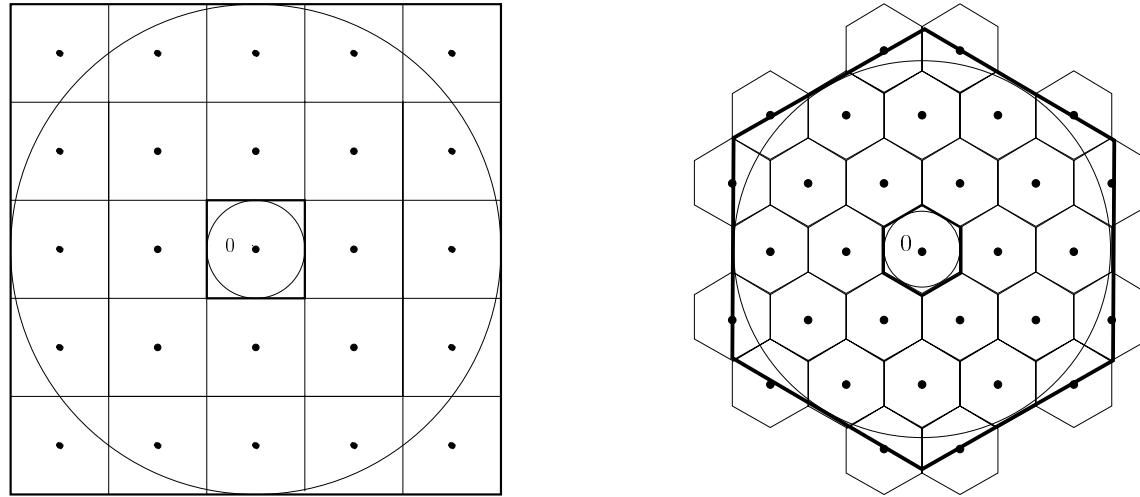
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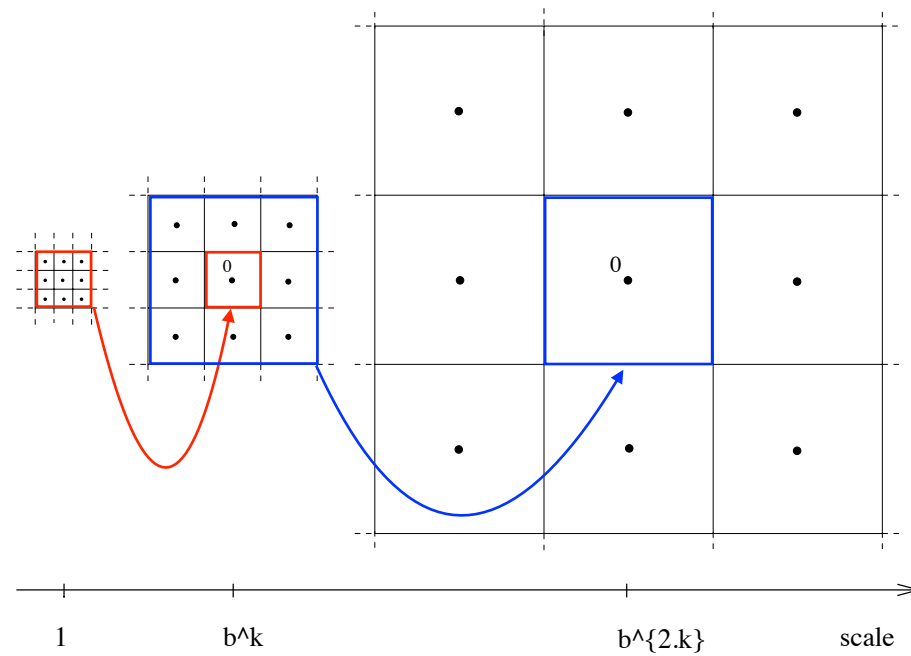


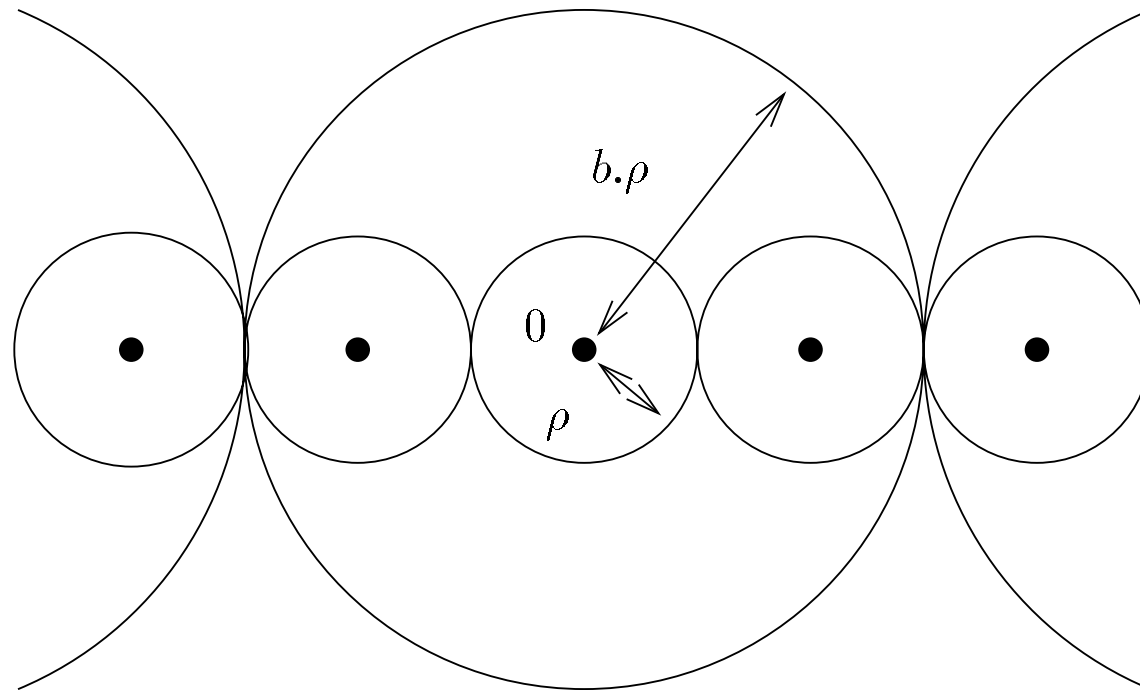
## Embedded Lattices

- Support Lattices  $Z^k, D_k, E_8, \Lambda_{16} \rightarrow$  fastest quantizing algorithms
- **Embedding :**  
by contracting it, embed a truncated lattice in its Voronoï cell
- **Optimal embedding :**  
the rescaled truncated lattice covers exactly the Voronoï cell
- **Sub-optimal embedding :**  
the rescaled truncated lattice covers maximally the Voronoï cell



## Hierarchy of embedded lattices





*(lower scale lattice)*

- Packing radius of the support lattice :  $\rho$

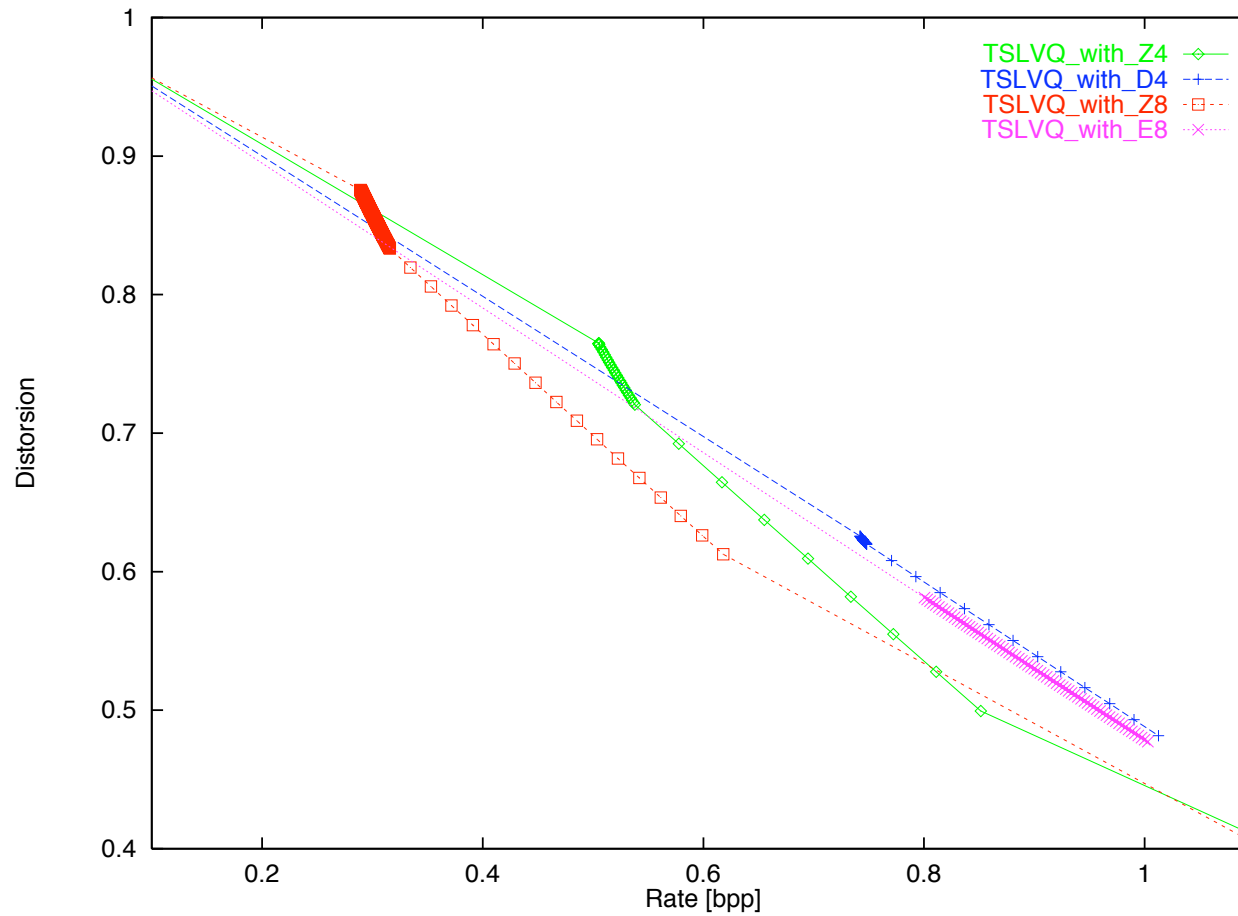
*(next higher scale lattice)*

- Packing radius of the dilated lattice :

$$b \cdot \rho \text{ avec } b \in \mathbf{R} \ / \ b > 1$$

$$\implies b = 2 \cdot n + 1 \ / \ n \in \mathbf{N}^*$$

# Optimal lattice

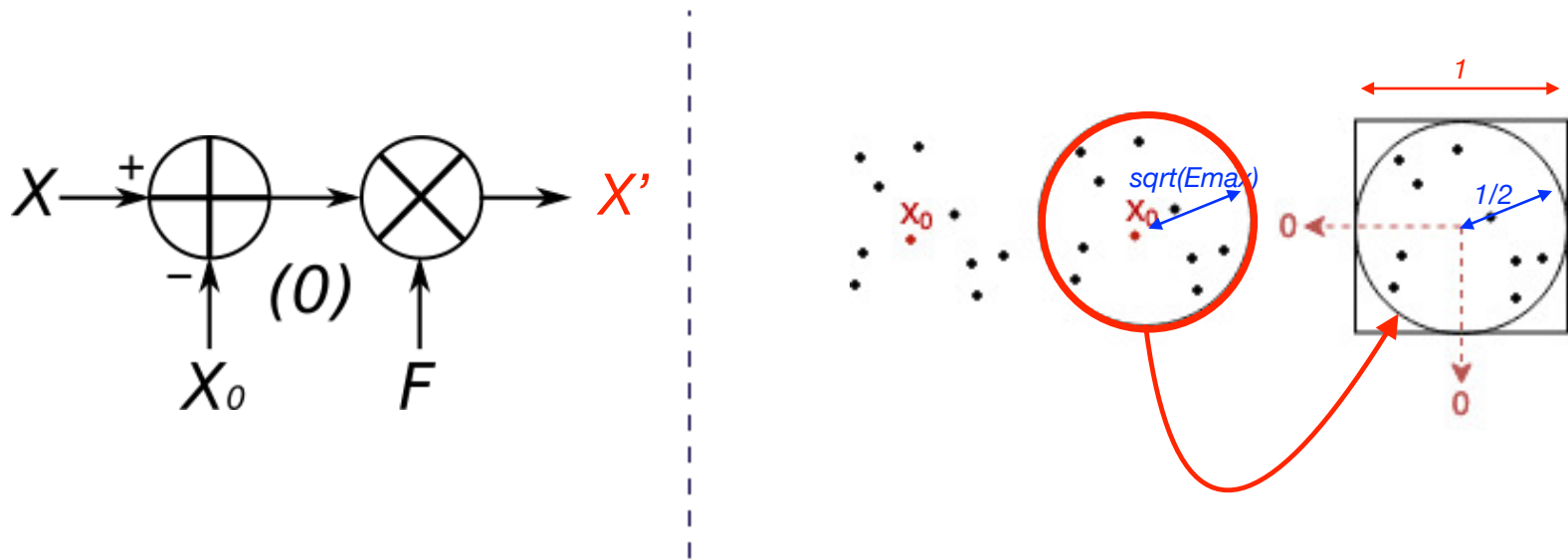


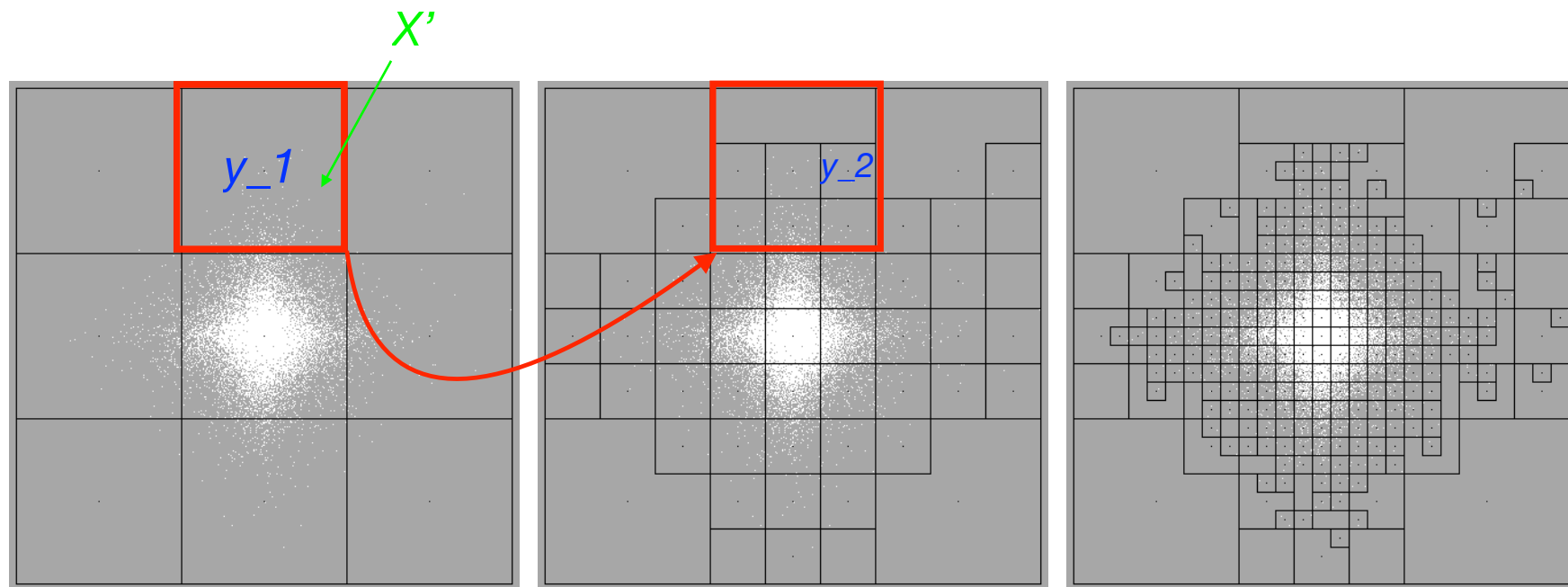
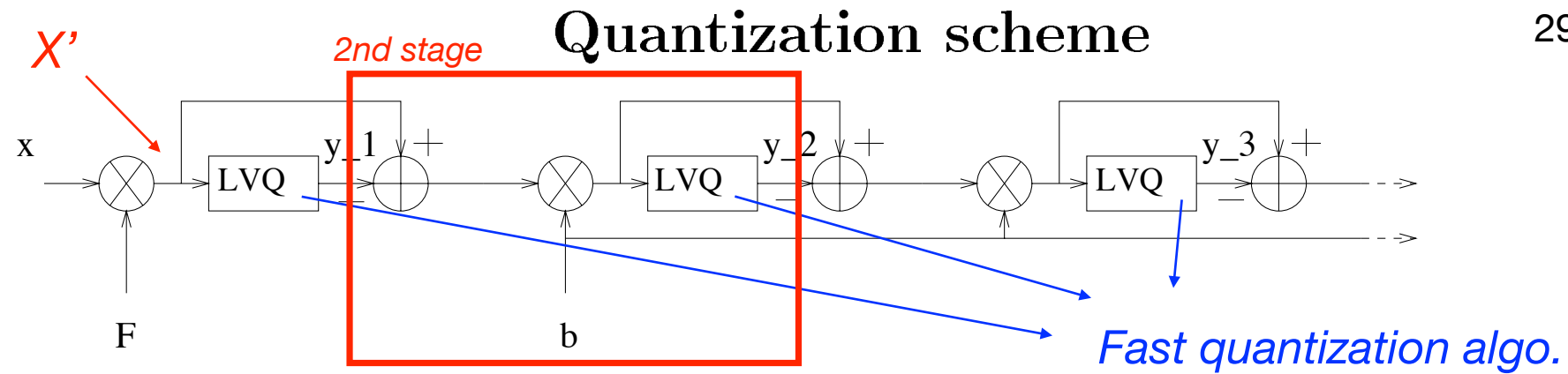
$\Rightarrow Z^k$  is optimal

- Step (0): Initialization

- The points set is normalized:
  - centering the points ( $\mathbf{X}_0$  : points mean)
  - Scaling data with the factor  $F = \frac{1}{2\sqrt{E_{max}}}$

$$F = (1/2) / \text{sqrt}(E_{max})$$





- A tree-structured codebook
- Progressive splitting  $\rightarrow b = b_{min} = 3$

## Conclusion

- Partition of the space according to :
  - ▷ the source distribution
  - ▷ the rate vs. distortion tradeoff
- Simple labeling method
- $Z^k \rightarrow$  simple processing for the outlying source vectors
- Fast quantizing  $\rightarrow$  complexity  $O(h.k)$
- Bit allocation

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## ■ Steps (1) and (2): Splitting

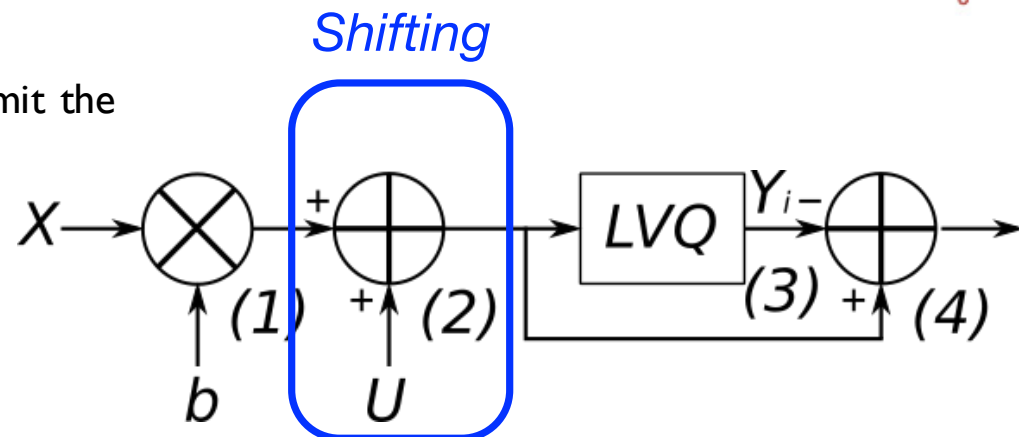
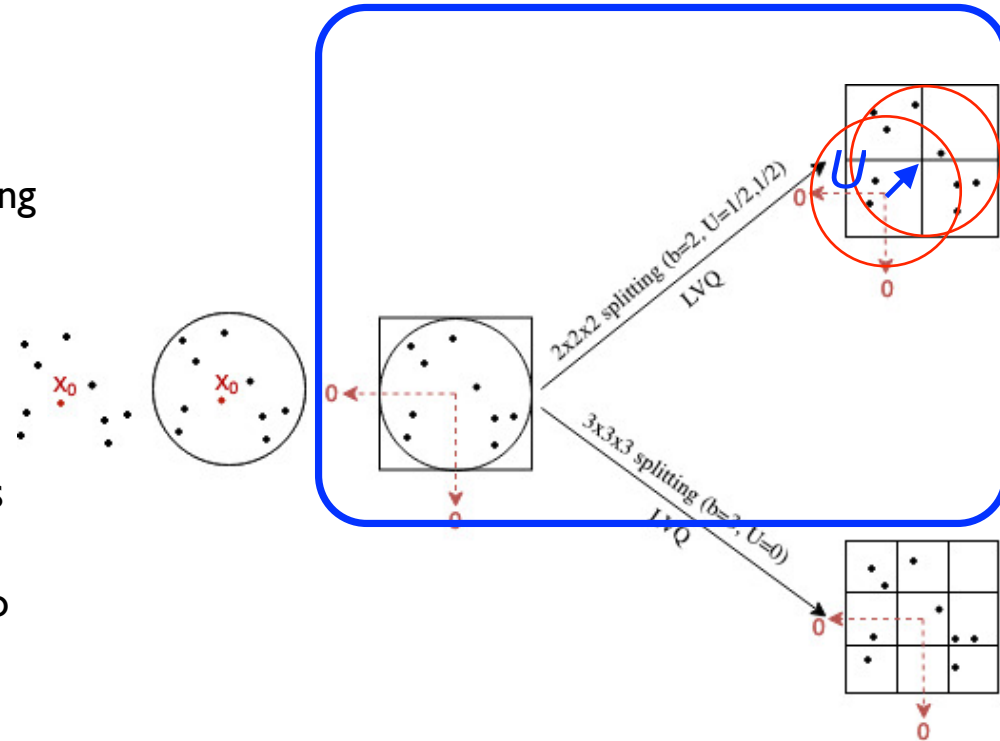
- Scaling the input vector  $\mathbf{X}$  by  $\mathbf{b}$  then shifting by  $\mathbf{U}$
- Splitting the cube in  $2 \times 2 \times 2$  ( $\mathbf{b}=\mathbf{2}$ ,  $\mathbf{U}=(1/2, 1/2, 1/2)$ ) or in  $3 \times 3 \times 3$  ( $\mathbf{b}=\mathbf{3}$ ,  $\mathbf{U}=(0, 0, 0)$ )

## ■ Step (3): Projection into truncated lattices

- Fast quantization algorithm is then used to produce by rounding the corresponding reproduction vector  $\mathbf{Y}_i$

## ■ Step (4): Recentering

- The output vector is centered to permit the next quantization level

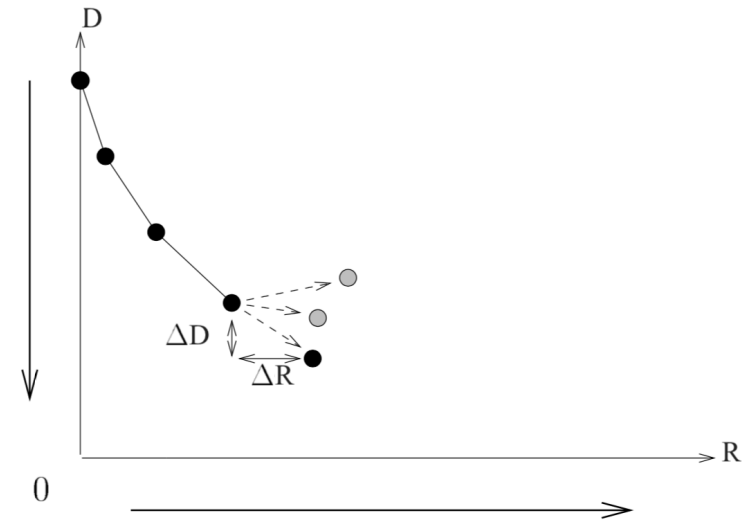


## Iterative Process

- Tree structure design : Greedy approach
  - Cube  $\mathbf{C}_i$  to split
  - Adapted splitting method (2x2x2 vs. 3x3x3)
- Lagrangian optimization technique
  - Multiplier associated to each node  $\lambda = \frac{\Delta D}{\Delta R}$

### Globally:

- 2 possible splittings by node for all nodes → The best  $\lambda$   
 → Maximal decrease in distortion, minimal increase in rate

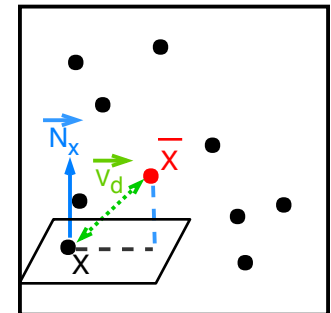
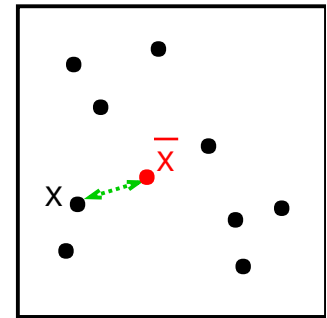


**Locally:**

- Increase in rate  $\Delta R$ : tree encoding cost
- Decrease in distortion  $\Delta D$ : 2 local metrics

□ Point-to-Point metric  $D_{P2Point}(X, \bar{X}) = \sum_{X \in C_i} d(X, \bar{X})$

□ Point-to-Plane metric  $D_{P2Plane}(X, \bar{X}) = \sum_{X \in C_i} \|\vec{v}_d(X, \bar{X}) \cdot \vec{N}_{X_i}\|$



Iterative Process Stop: number of leaves / depth is reached

- Each occupied leaf: Output point

- Objective Comparison: *TSPLVQ* method
  - 3 splitting schemes
    - Only 3x3x3
    - Only 2x2x2
    - 2x2x2 vs. 3x3x3
  - 2 local metrics
    - Point2Point
    - Point2Plane (in **Bold**)

PC Images	MPEG G-PCC	Our approach		
		3x3x3	2x2x2	hybrid
<i>Soldier</i>	16.48	18.72	11.2816	18.70
		<b>19.02</b>	<b>14.32</b>	<b>14.45</b>
<i>Long Dress</i>	16.53	18.74	9.28	<b>15.89</b>
		<b>19.89</b>	<b>61.08</b>	<b>17.74</b>
<i>Loot</i>	16.54	15.33	18.77	<b>15.36</b>
		<b>17.65</b>	<b>10.49</b>	<b>19.13</b>

Comparison of symmetric **MSE** metric

*source: ICIP'2019*

■ Subjective Comparison: *Visual rendering result of Soldier point cloud*

