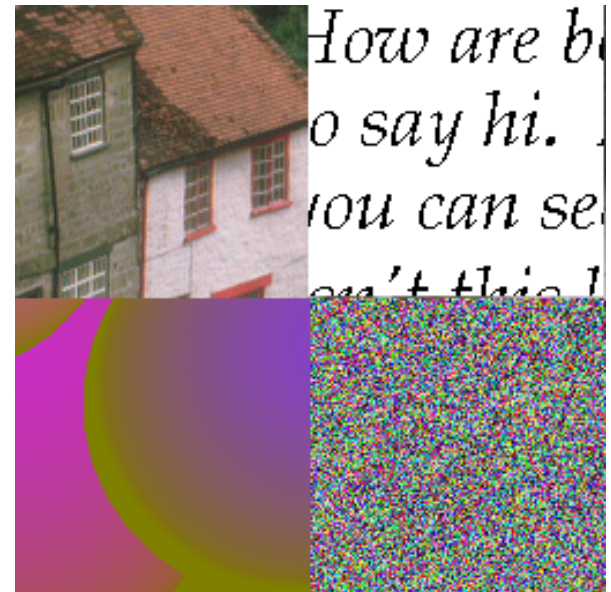


# LOCO and JPEG-LS

A new method for **lossless** and  
**near lossless**  
image compression

Nimrod Peleg  
Update: May 2009



# Credit...

- *Suggested by HP Labs, 1996*
- Developed by: M.J. Weinberger, G. Seroussi and G. Sapiro,

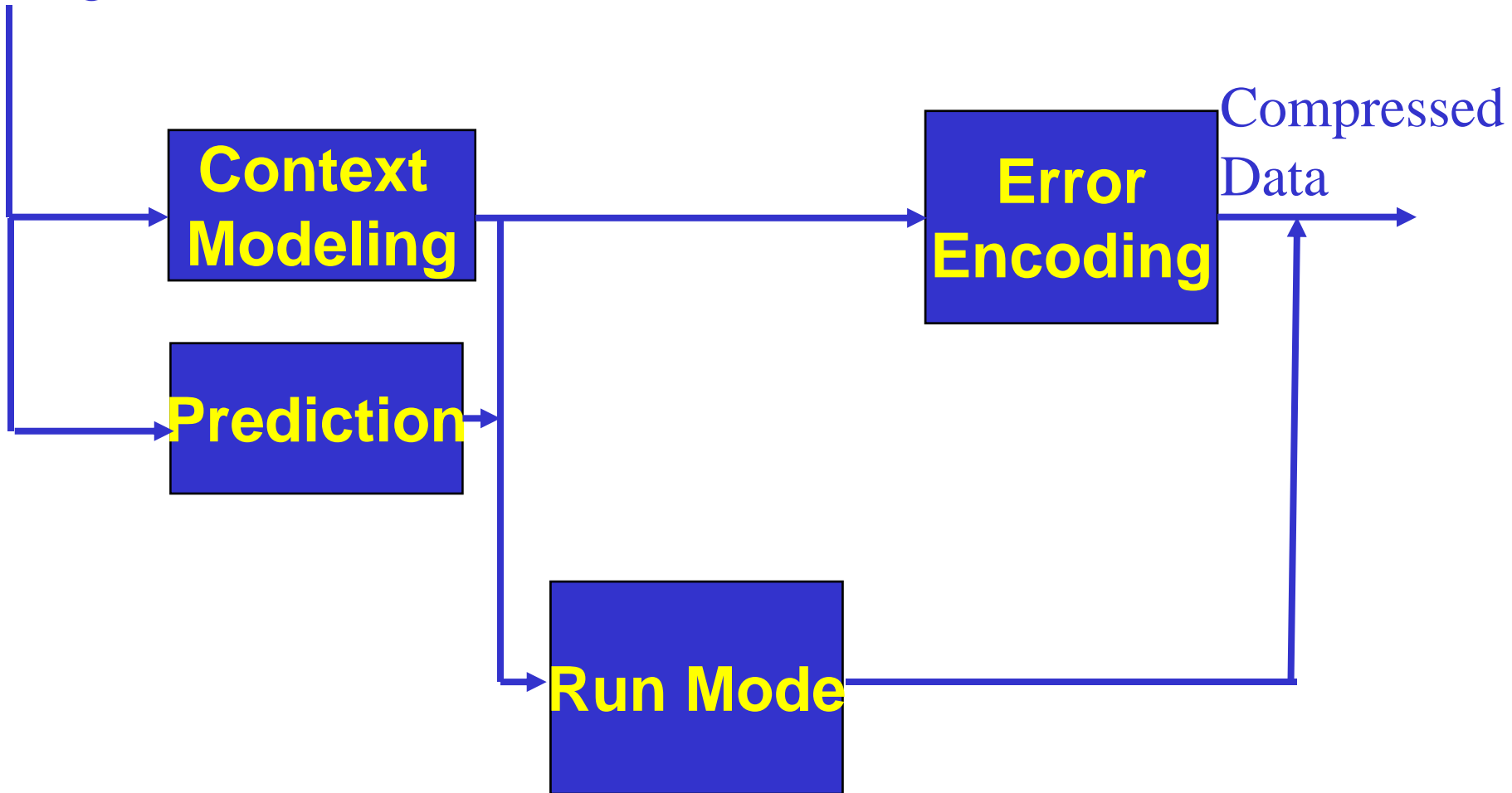
“*LOCO-I: A Low Complexity, Context-Based, Lossless Image Compression Algorithm*”,

IEEE Proceedings of Data Compression Conference, pp. 140-149, 1996

# General Block Diagram

Digital Source

Image Data



# Context Based Algorithm

- An efficient coding needs a **statistical model**, for a good prediction of pixel value
- The **statistical distribution** of a pixel is predicted according to the **previous pixels**
- The best distribution for coding is **minimum entropy distribution**
- To achieve it, each pixel is assigned to a “**context**” (728 context types in LOCO)

# Prediction

- After context definition, a **simple prediction** is activated.
- The predictor is **NOT context dependent**, but same for all contexts.
- It's a simple and effective **edge detector**, based on 3 gradients.
- **Prediction error** is calculated between predicted and “real” pixel value.

# Error Coding

- Basic assumption: for each context, a **statistical information** is available.
- A Geometric distribution is assumed for the prediction error, and LOCO uses 2 parameters for each context: **Average** and **Decay factor**.
- LOCO uses a Golomb-Rice entropy coding, which is optimal for two-sided geometric distribution (**it's a 1 parameter Huffman like method**).

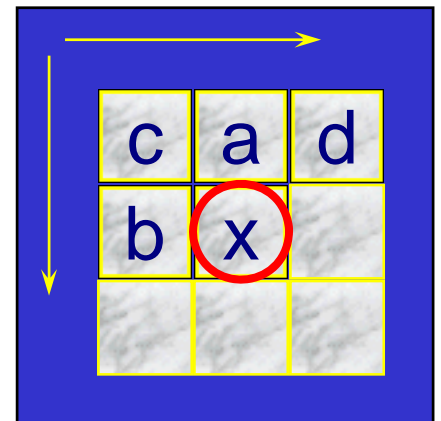
# Why Golomb-Rice ?

The Golomb-Rice technique is simple,  
low-complexity and efficient:

- Huffman-like complexity
- Almost Arithmetic coding efficiency

# Run Mode

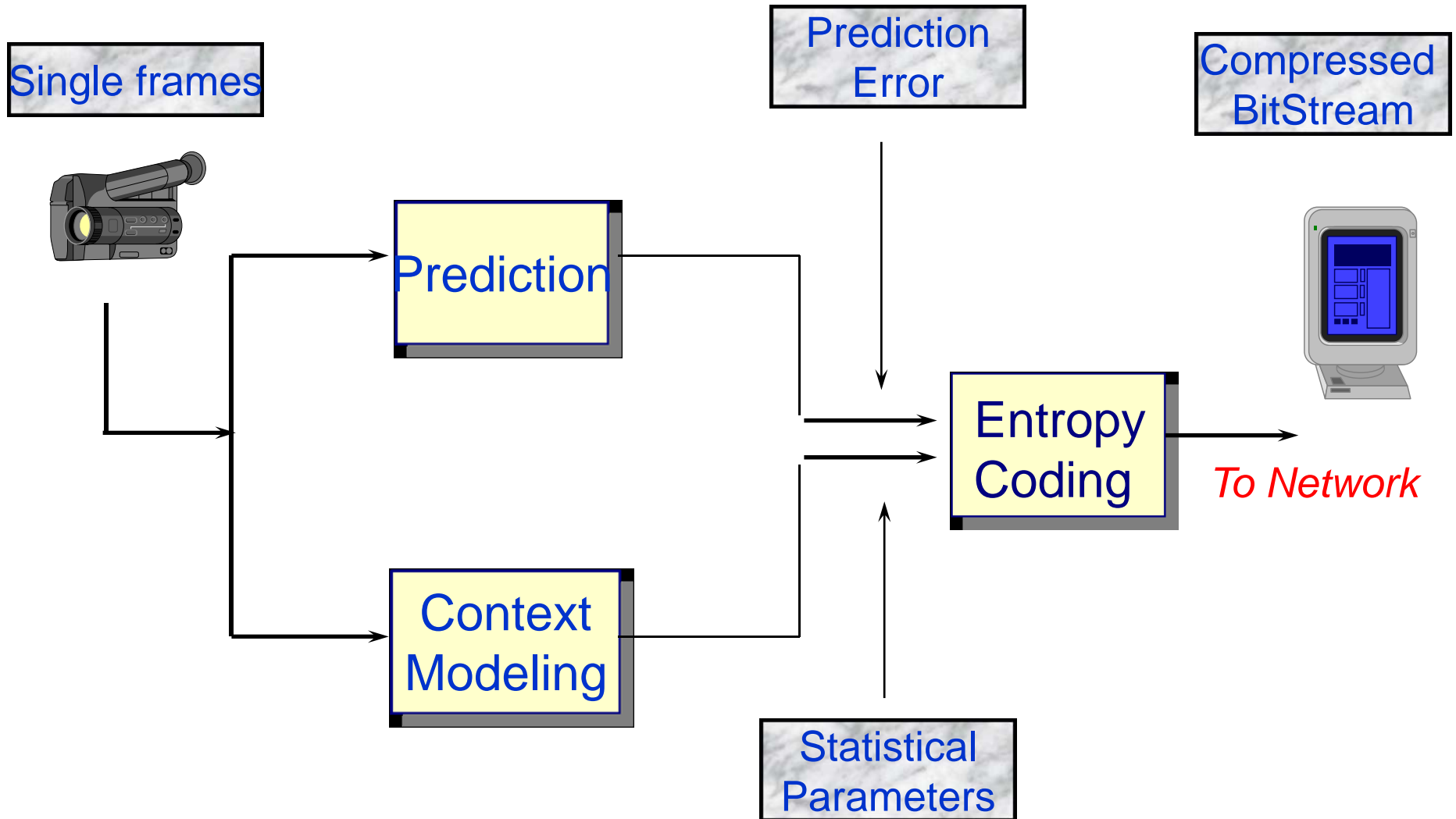
- When **all local gradient are zero**, we can assume that it's a “**smooth**” area in the image.
- In this situation we **skip** the prediction and the prediction error coding stages.
- We go on with the “run-mode” until the condition  **$x=b$  is no more TRUE**.
- This process saves lots of bits for **long runs**.





*A more detailed Description*

# General Scheme



# *Context Modeling*

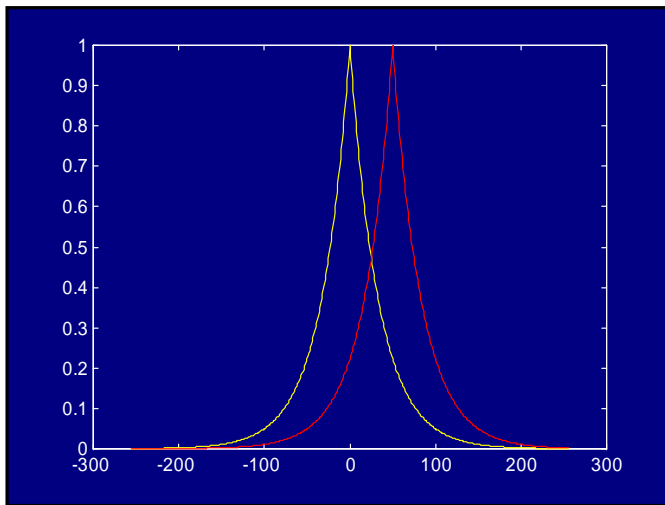
Every pixel is assigned to a context based on locally calculated parameters.

*Why ?*

Prediction errors for pixels in same context, have the same **statistical distribution**.

*The assumption is -*

The prediction error is distributed as a **two sided geometric distribution**.



- The extinction factor is context dependent.
- There is systematic bias for every context.

# Calculating the context number

There is a tradeoff between the **number** of contexts and the **quality** of the estimated statistics for each context.

*In the LOCO algorithm:*

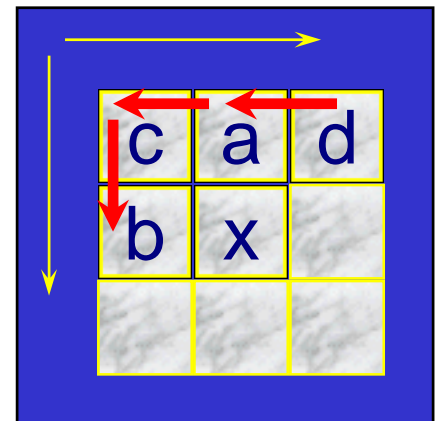
There are 728 contexts created by using the **local**

**Gradients:**

$$D1 = d - a$$

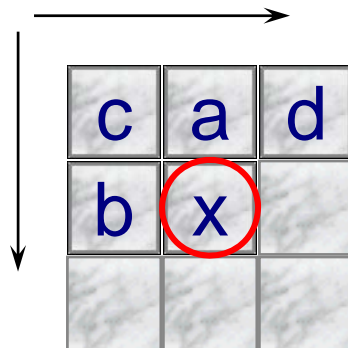
$$D2 = a - c$$

$$D3 = c - b$$



# Prediction

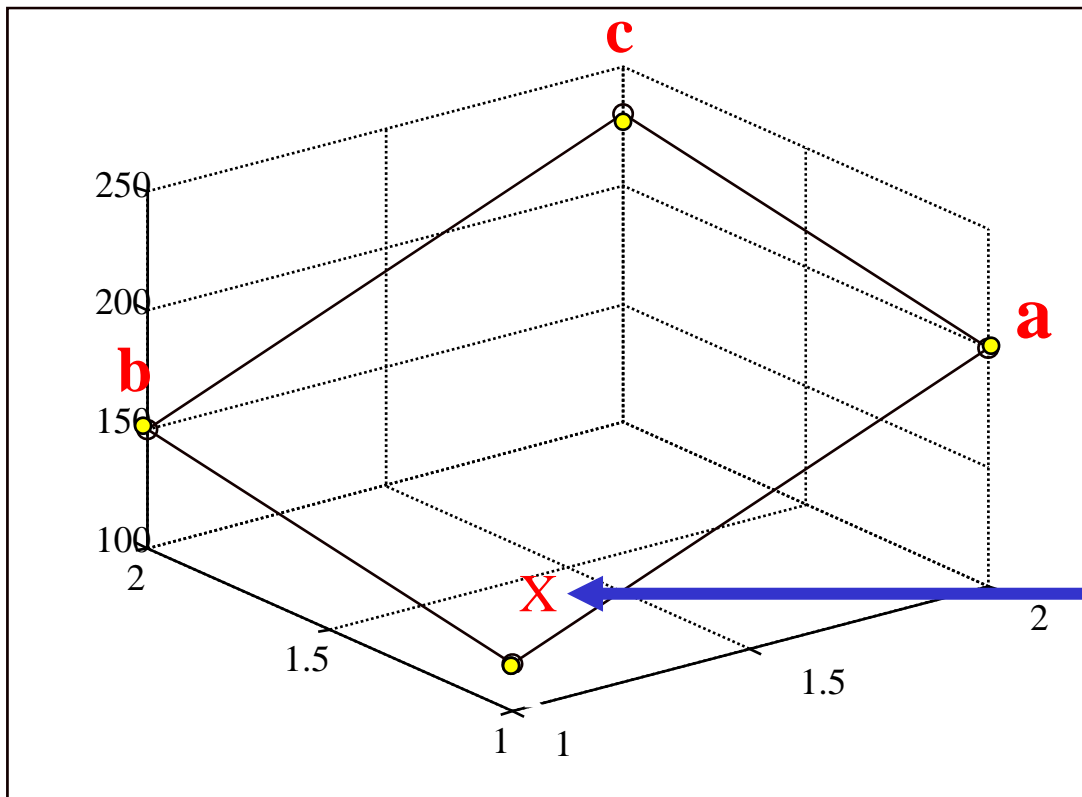
The Loco **predictor** is “casual”, it uses nearby pixels which already have been scanned



$$Px = \begin{cases} \min(a,b) & c \geq \max(a,b) \\ \max(a,b) & c \leq \min(a,b) \\ a+b-c & \textit{otherwise} \end{cases}$$

Why ????

# The principle :

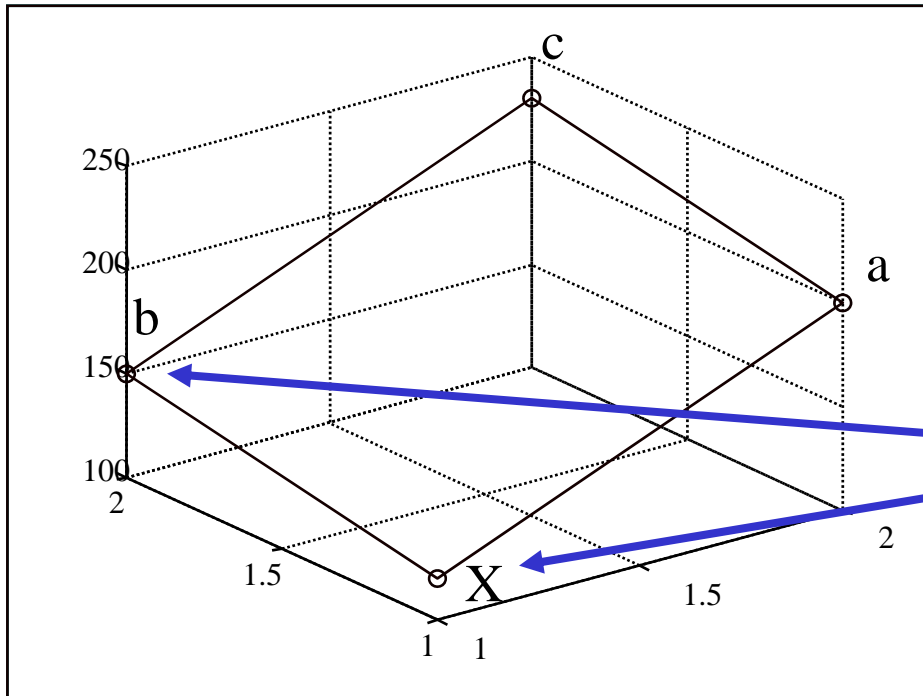


The assumption is

:

'**x**' should be on the same plane created by **a**, **b** and **c**.

*For example :*

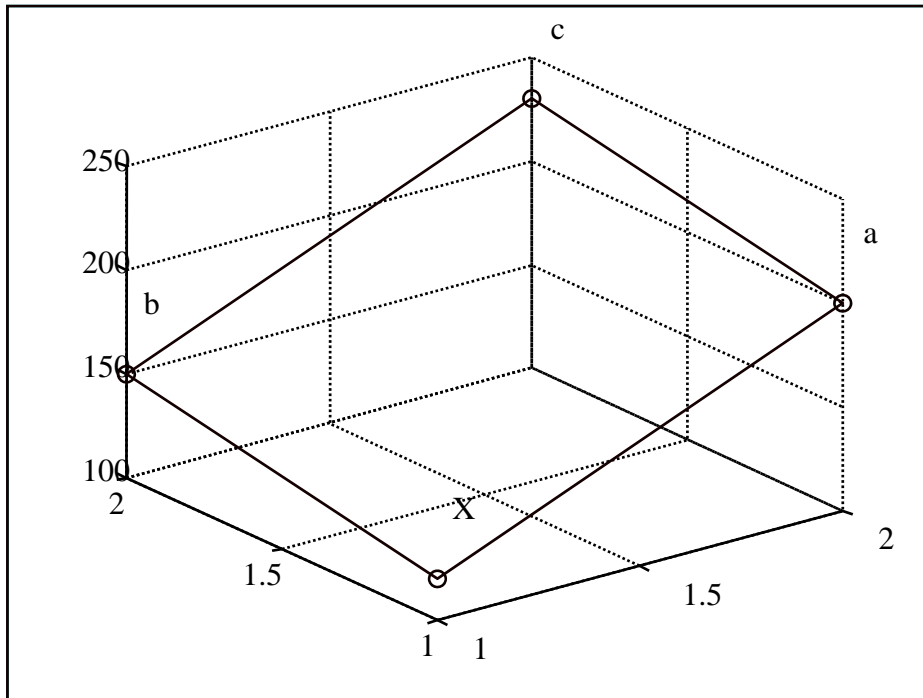


Here, the lowest value **x** can get is the value of **b** (from what we “have”).

$$Px = \begin{cases} \min(a,b) & c \geq \max(a,b) \\ \max(a,b) & c \leq \min(a,b) \\ a+b-c & \text{otherwise} \end{cases}$$



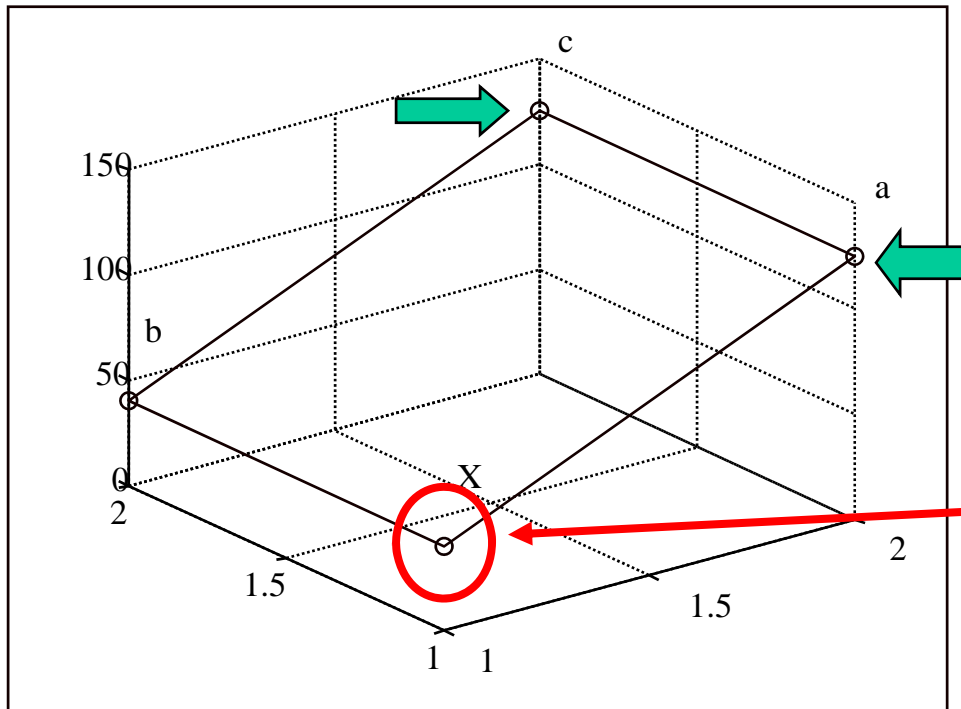
# Why not take the Average ?



$$x = \frac{a + b + c}{3}$$

*Let's take a look on this case -*

When **c** is very close to **a** . . .



$$x_{avg} \approx \frac{2a + b}{3}$$

But,

$$P_X = b$$

# *Prediction Example*

Original Image



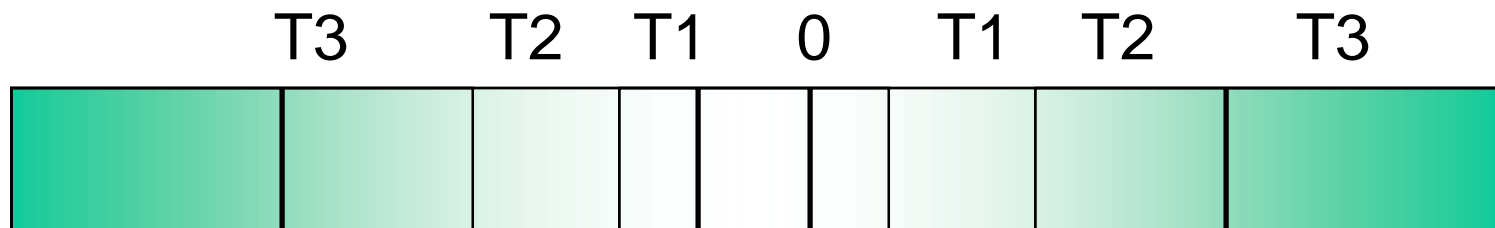
Predicted Image (SNR=25.3dB)



and more details...

# The Quantizer

The gradients are quantized by a **9 level** quantizer



( Q1, Q2, Q3 )



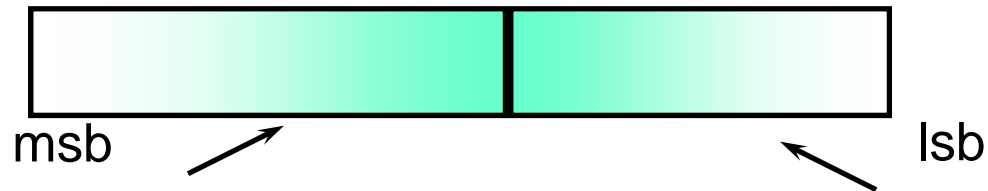
The context number - Q

# Entropy Coding

Golomb-Rice is an optimal entropy coder for geometric distribution

## Golomb - Rice Codes

- Does not require tables (vs. Huffman)
- One parameter only:  $k$



8-k bits  
By unary presentation

k bits  
By binary presentation

# Golomb-Rice coding example

$k = 2$

Let's take the number:  $x=14$   $\rightarrow$  **0000 1110**

**Unary presentation of  $11_2 (= 3_{10}) = 000_1$**

Unary Code  
**000**



Separating one

**1**

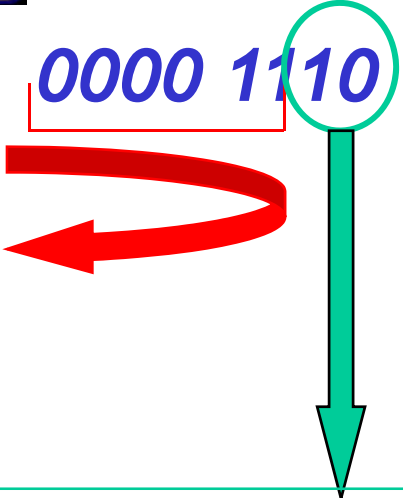


Binary Code  
**10**



*The BitStream*

**Binary presentation - 10**



# *Run mode*

A special mode which allows efficient compression of a **sequence of pixels** with same value.

*For example*

⋮





*In Lossy Mode*

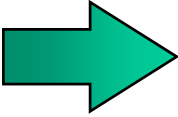
# *Lossy Mode*



Maximal allowed restoration error per pixel ~~= 0~~ *NEAR*

## *The method :*

The prediction error is quantized by a  $2Near + 1$  step quantizer .

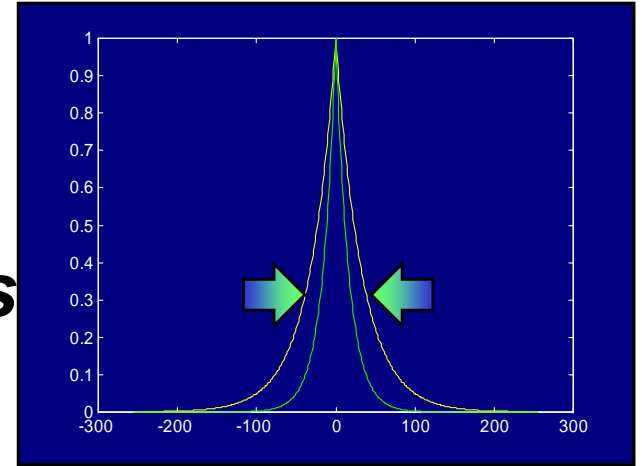
*Prediction Error*   $\left[ \frac{\textit{Prediction Error}}{2Near + 1} \right]$

*And the profit is . . .*

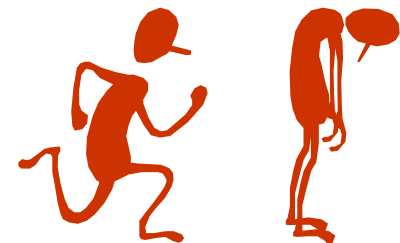


- **Narrower** geometric distribution

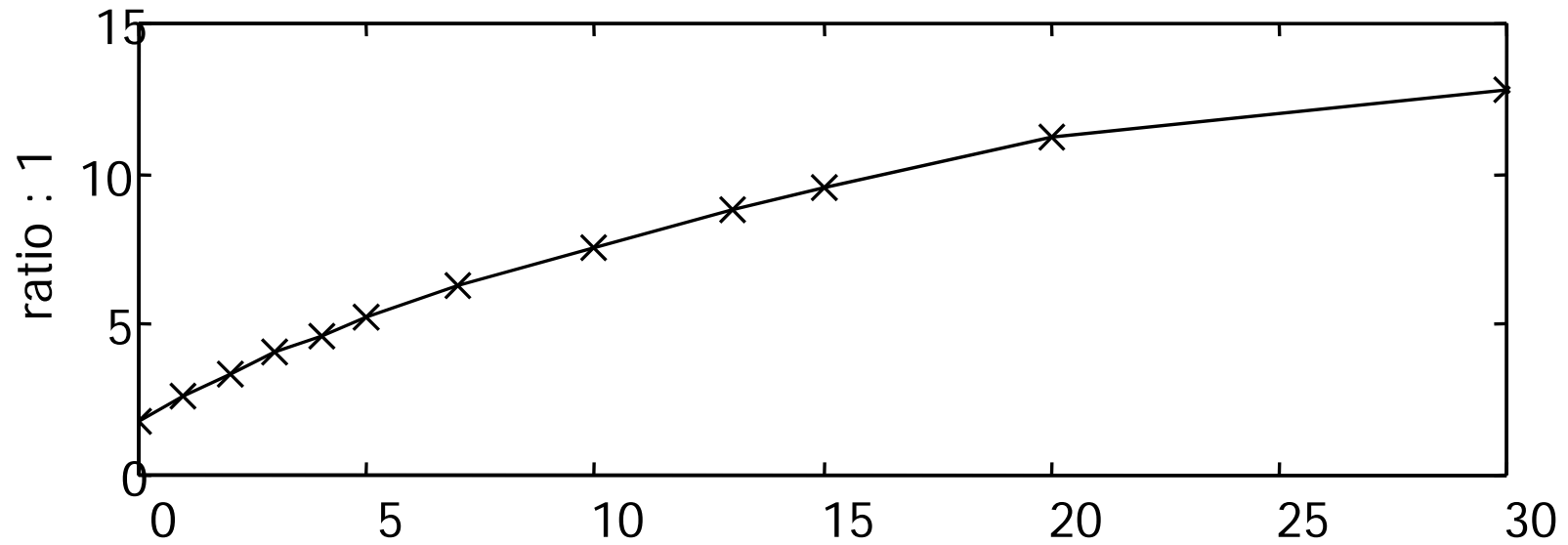
**➔** **Shorter Golomb-Rice Codes**



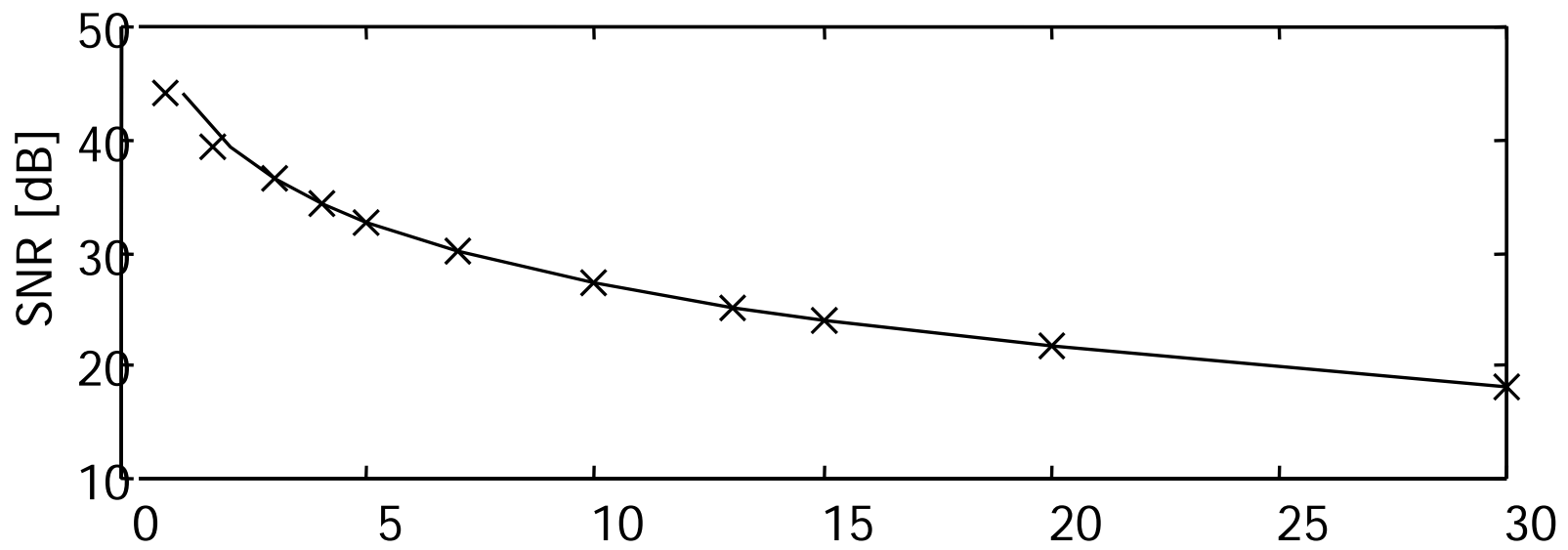
- Spending more time in Run-Mode



Compression ratio vs. Near



SNR vs. Near



# Explanation

(last graph: Lena for different Near values)

ניתן לראות, שבערכים נמוכים העלייה ביחס הדחיסה ליניארית עם Near, אולם בערכים גבוהים של Near כמעט ואין שיפור ביחס הדחיסה. הסיבה לכך, היא שה- LOCO מאבד את ה- Contexts בערכי Near גבוהים, ולכן מאבד את יעילותו. גם איכות התמונה הדחוסה בערכים הגבוהים ירודה ביותר, כפי שניתן לראות מגרף ה- SNR.

# Different Near values compression

Near = 3

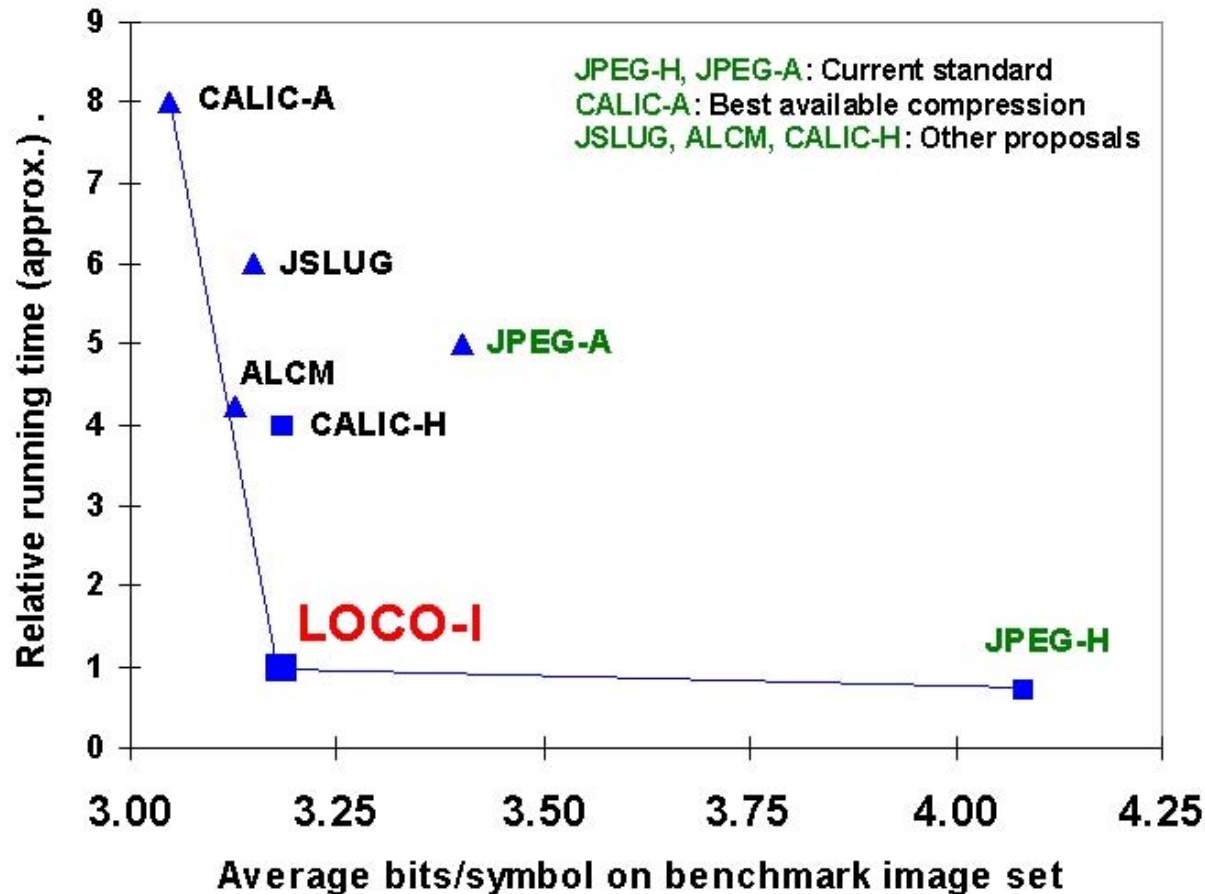


Near = 10



# Benchmark Comparison

## Compression vs. Complexity trade-off



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