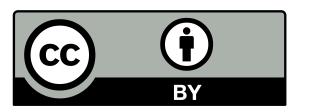
Quantization Digital Audio Coding



Scalar Quantizer

$$[\,\cdot\,]:\mathbb{R} o\mathbb{R}$$

countable range: $|\{[x], x \in \mathbb{R}\}| \le |\mathbb{N}|$

idempotent mapping: $\forall x \in \mathbb{R}, [[x]] = [x]$

Example: rounding functions $\mathbb{R} \to \mathbb{Z} \subset \mathbb{R}$

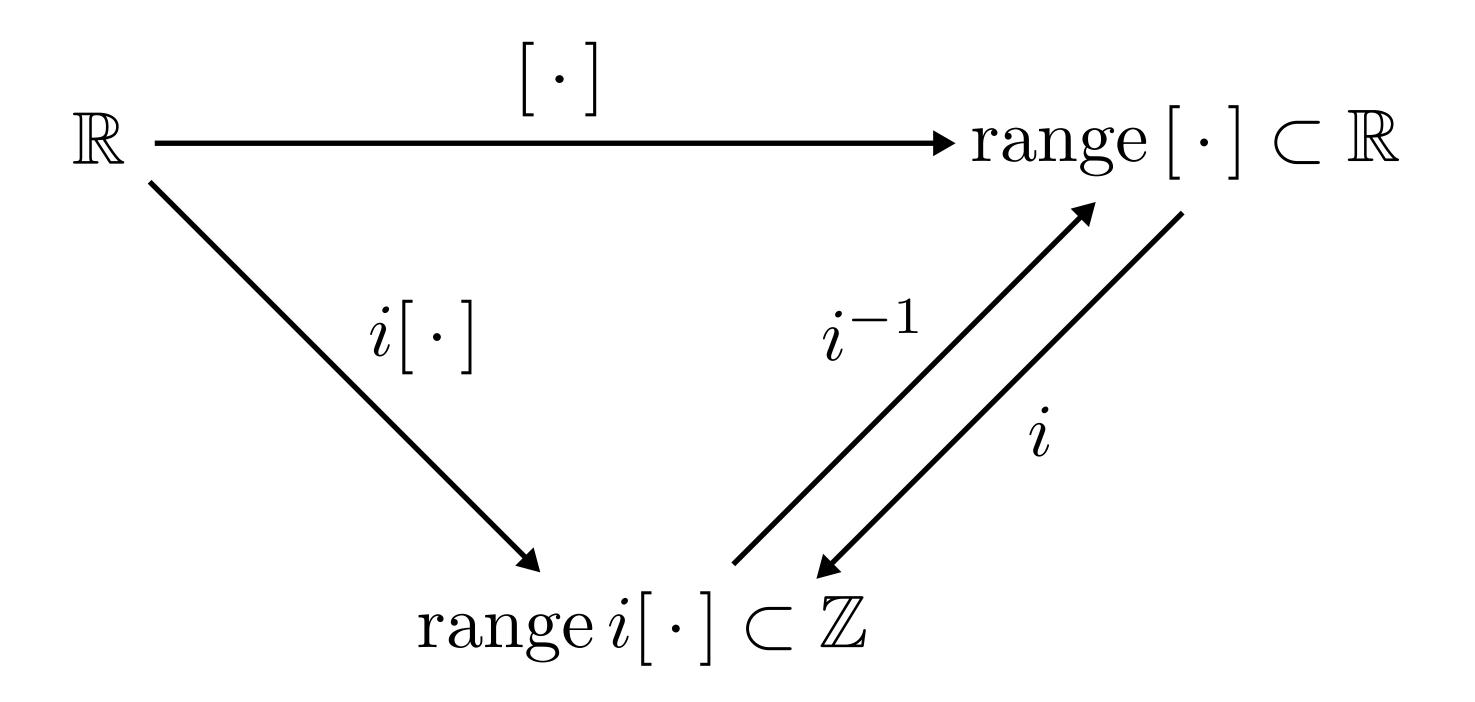
NumPy: floor, ceil, round_

Forward/Inverse Quantizers

forward quantizer: mapping $i[\cdot]: \mathbb{R} \to \mathbb{Z}$ such that i[x] = i[y] iff [x] = [y] $i[\cdot] = i \circ [\cdot]$ where $i: \mathrm{range}[\cdot] \to \mathbb{Z}$ is into

inverse quantizer: i^{-1} : range $i \subset \mathbb{Z} \to \mathbb{R}$ i^{-1} is a left inverse of i. $\forall x \in \mathbb{R}, \ (i^{-1} \circ i)[x] = [x]$

Forward/Inverse Quantizers

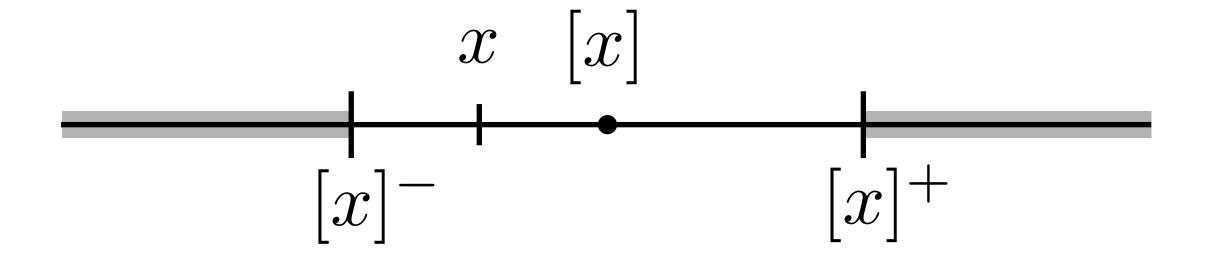


Quantization Step

Assume that for every $x \in \mathbb{R}$,

$$V_x = \{ y \in \mathbb{R}, [y] = [x] \}$$

is an interval.



We define the decision values:

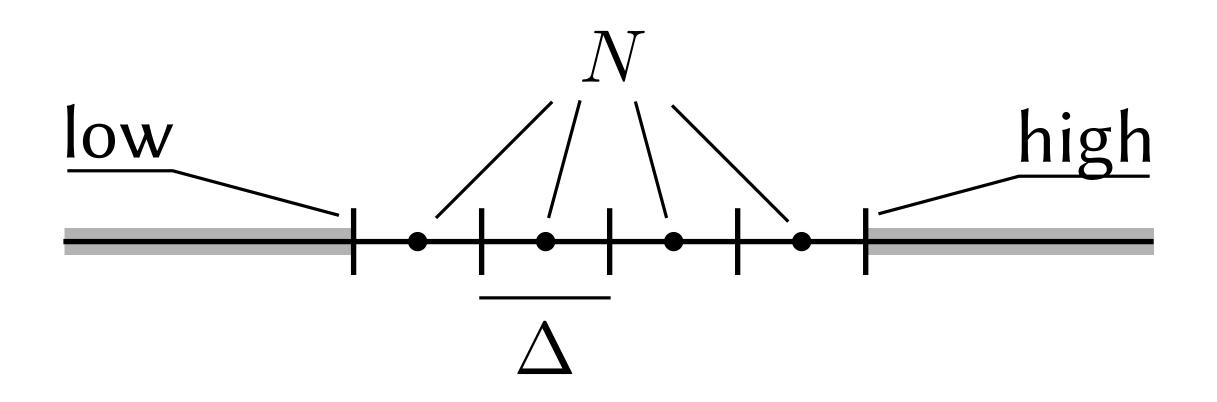
$$[x]^- = \inf V_x$$
 and $[x]^+ = \sup V_x$

and the quantization step:

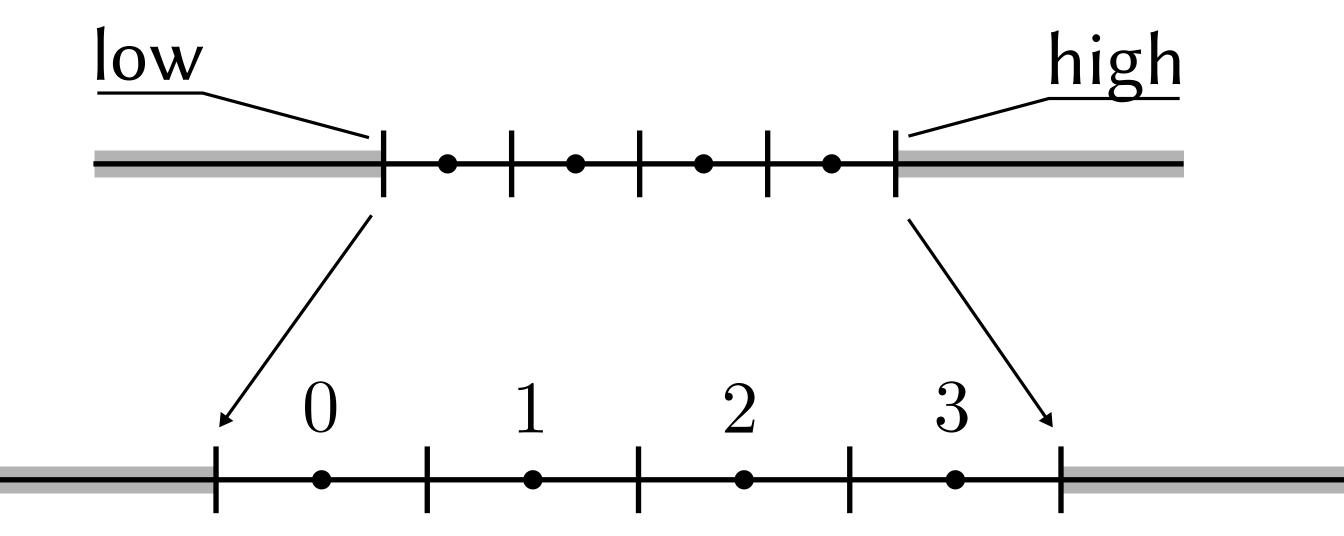
$$\Delta(x) = [x]^+ - [x]^-$$

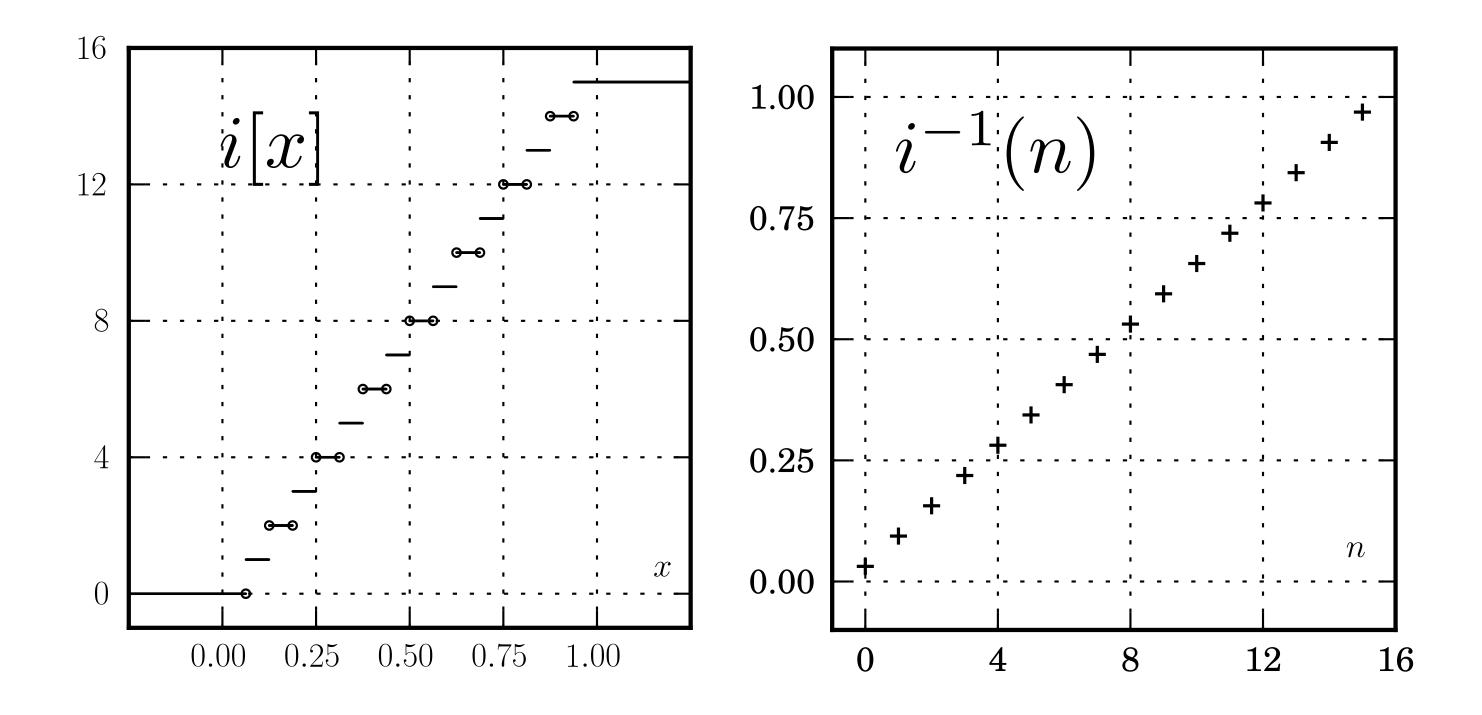
```
class Uniform(Quantizer):
```

```
def __init__(self, low=0.0, high=1.0, N=2**8):
    self.low, self.high = float(low), float(high)
    self.N = N
    self.delta = (self.high - self.low) / self.N
```



```
class Uniform(Quantizer): (continued)
  def encode(self, data):
    data = clip(self.data, self.low, self.high)
    flints = round_((self.data - self.low) / self.delta - 0.5)
    return array(flints, dtype=long)
  def decode(self, i):
    return self.low + (i + 0.5) * self.delta
```





Uniform(low=0.0, high=1.0, N=2**4)

```
>>> uniform = Uniform(low=-1.0, high=1.0, N=2**4)
>>> uniform(1.0)
0.9375
>>> uniform(0.0)
0.0625 — mid-rise
>>> uniform = Uniform(low=-1.0, high=1.0, N=2**4-1)
>>> uniform(1.0)
0.933333333333333
>>> uniform(0.0)
    — mid-tread
0.0
```

Random Variables

 $X \in \mathbb{R}$, density p.

$$P([X] = [x]) = P_X \{ y \in \mathbb{R}, [y] = [x] \}$$
$$= \int_{[x]^-}^{[x]^+} p(y) \, dy$$

High Resolution assumption:

$$\approx p(x) \times \Delta(x)$$

Optimal Quantizer Criteria: Entropy

The entropy of [X] is maximal when all events

$$[X] = [x], x \in \mathbb{R}$$

are equally likely, that is when:

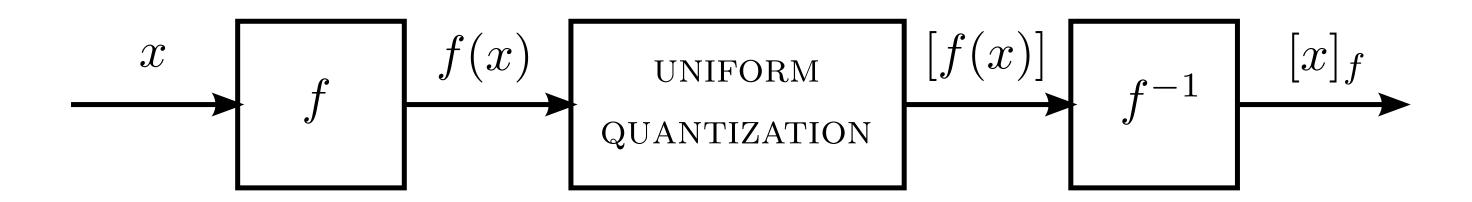
$$\Delta(x) \propto \frac{1}{p(x)}$$

Nonlinear Quantizers

Select a characteristic function f and define

$$[\cdot]_f = f^{-1} \circ [\cdot] \circ f$$

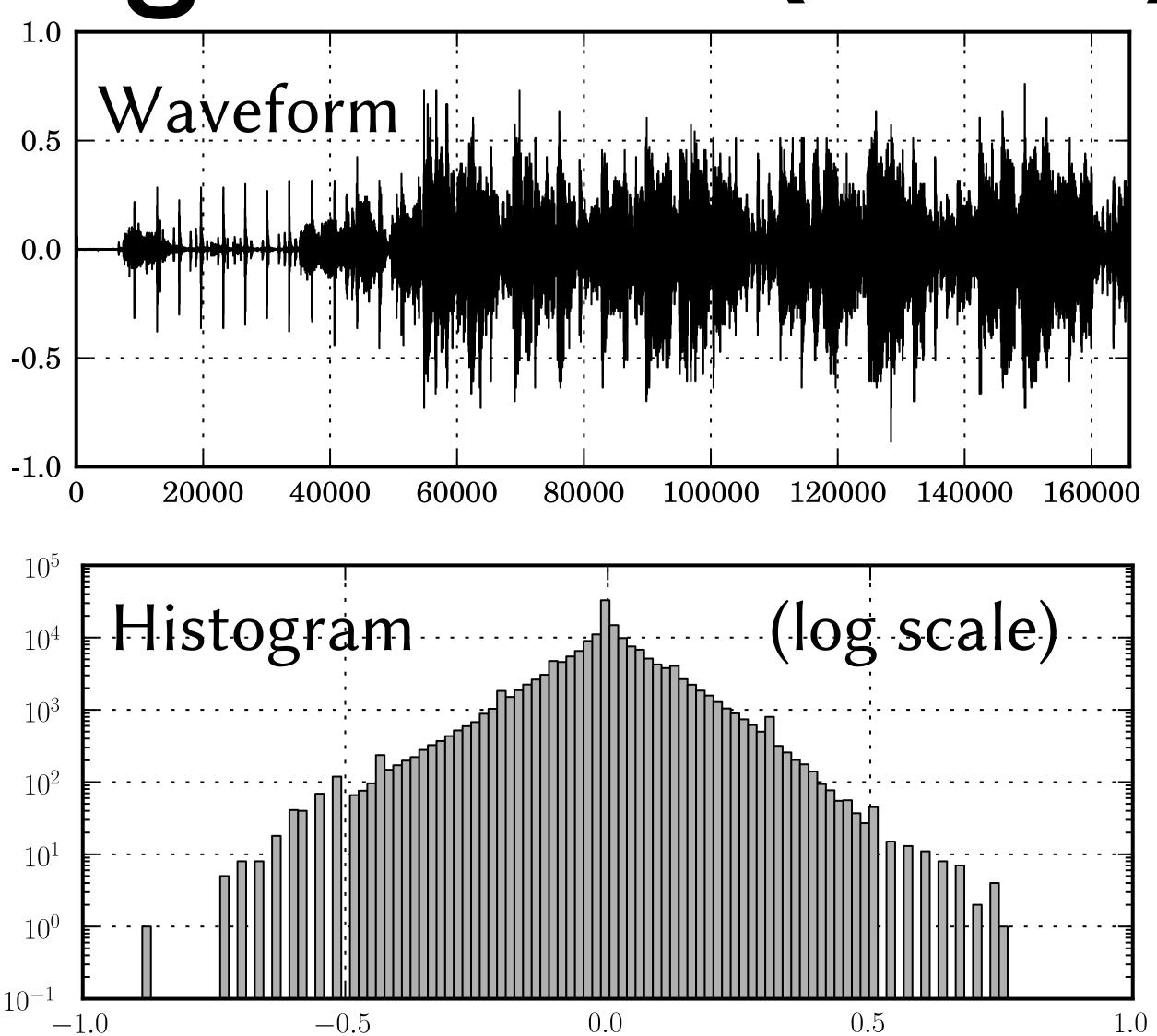
where is [·] a uniform quantizer.



Under the high resolution assumption:

$$\Delta_f(x) \propto \frac{1}{f'(x)} \qquad \left(\Delta_f(x) = \frac{\Delta_{[\cdot]}}{f'(x)}\right)$$

"legende.au" (NeXT)



Nonlinear Quantizer Maximal Entropy

If we model the distribution of values with:

$$p(x) \propto \exp(-a|x|)$$

the optimal quantizer satisfies:

$$\Delta(x) \propto \exp(a|x|)$$
 and $f'(x) \propto \exp(-a|x|)$

Setting f(0) = 0 and f'(0) = a yields:

$$f(x) = \text{sgn}(x)(1 - e^{-a|x|})$$

$$f^{-1}(x) = -\frac{\operatorname{sgn}(x)}{a} \log(1 - |x|)$$

Nonlinear Quantizer

Setting
$$f(0) = 0$$
 and $f'(0) = a$ yields:
$$f(\mathbb{R}) = (-1, 1)$$

Given implementations **f** and **f_inv** of the characteristic function and of its inverse, we define the optimal 8-bit quantizer with:

uniform = Uniform(low=-1.0, high=1.0, N=2**8-1) quantizer = NonLinear(f, f_inv, uniform)

Noise and SNR

Given a random value X and a quantizer $[\cdot]$, the quantizer **noise** B is defined by:

$$[X] = X + B$$

and the signal-to-noise ratio (SNR) by:

$$SNR^2 = \frac{\mathbb{E}X^2}{\mathbb{E}B^2}$$

or in decibels by:

$$SNR [dB] = 10 \log_{10} SNR^2$$

SNR: Number of Bits

Consider a n-bit nonlinear quantizer with

$$f([-1,1]) = [-1,1]$$

The high-resolution assumption yields

$$\mathbb{E} B^2 \simeq \frac{1}{12} \mathbb{E} \Delta(X)^2$$
 and $\Delta(x) = \frac{2^{-n+1}}{f'(x)}$

and as a consequence

$$SNR [dB] \approx 6.0 \times n + c(f)$$

Optimal Quantizer Criteria: SNR

The best characteristic function is solution of:

$$\min_{f'} \int_{-1}^{1} \frac{1}{f'(x)^2} p(x) \, dx$$

subject to
$$f(1) - f(-1) = 2$$

Solution: $f'(x) \propto p(x)^{1/3}$

(Reminder: $f'(x) \propto p(x)$ optimal for the entropy.)

Logarithmic Quantizers

Consider the probability distribution:

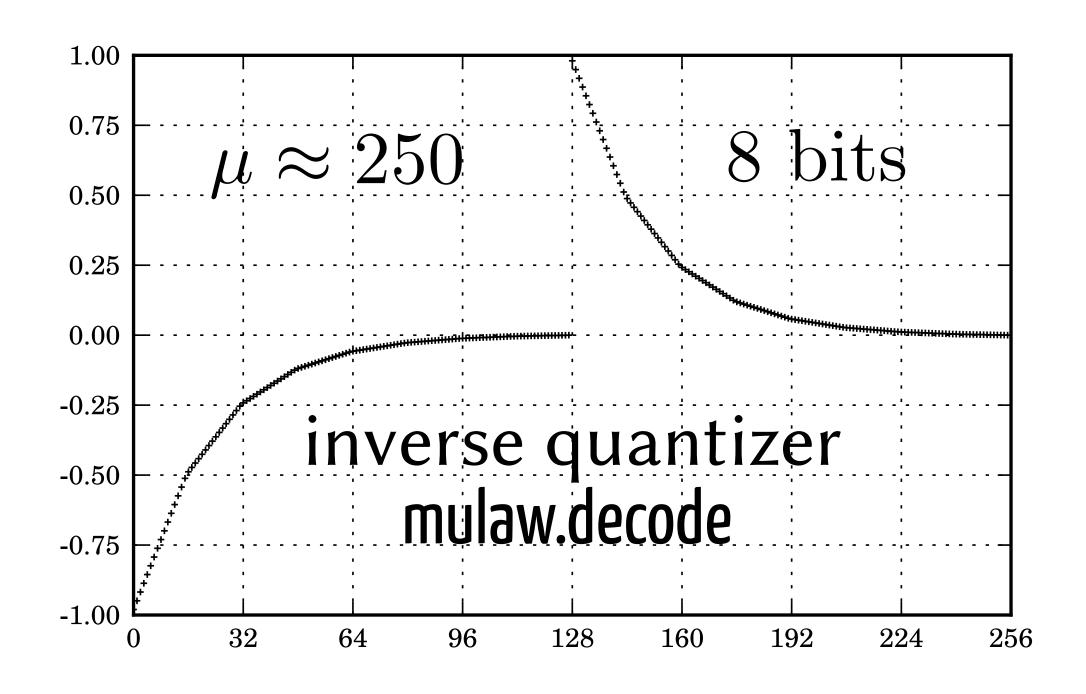
$$p(x) \propto \begin{vmatrix} \frac{1}{1+\mu|x|} & \text{if } |x| \leq 1.0, \\ 0 & \text{otherwise.} \end{vmatrix}$$

The optimal quantizer w.r.t. entropy such that f([-1,1]) = [-1,1] is defined by:

$$f(x) = \text{sgn}(x) \frac{\log(1 + \mu|x|)}{\log(1 + \mu)}$$

µ-law

Implements a piecewise approximation of f. Part of the G.711 (ITU-T) standard.



Used in Sun/NeXT AU file format.