

EE269

Signal Processing and Quantization for Machine Learning

Dithering and Stochastic Rounding

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Outline

- ▶ Why finite-bit quantization creates *structured artifacts*
- ▶ **Dither**: add noise then quantize (what “dithering” usually means)
- ▶ Fundamental analysis: *linearization*
- ▶ **Subtractive dither (variant)**: exact uniform error
- ▶ **Stochastic rounding**: unbiased randomized rounding
- ▶ Quantization in GPUs
- ▶ Practical takeaways

Recall (Lecture 1): Bennett's theorem is asymptotic

- ▶ For a uniform quantizer with step Δ , the additive model assumes

$$X \mapsto Q(X) = X - \varepsilon, \quad \varepsilon \sim \mathcal{U}(-\Delta/2, \Delta/2), \quad \varepsilon \perp X.$$

- ▶ Bennett's theorem justifies this as $\Delta \rightarrow 0$ (many levels, smooth pdf, no overload).
- ▶ At finite bit-depth, $\varepsilon(x)$ is deterministic and correlated.

Finite rate artifacts: why randomness helps

- ▶ Deterministic quantization maps smooth ramps to a **staircase**
⇒ contouring/banding in images.
- ▶ Quantized sinusoids produce **spurious tones** (harmonics), not white noise.
- ▶ In feedback systems, quantization can create **limit cycles**.

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- ▶ Quantized sinusoids produce **spurious tones** (harmonics), not white noise.
- ▶ In feedback systems, quantization can create **limit cycles**.
- ▶ **Dithering idea:** add small noise before quantization to *randomize the staircase*.
 - ▶ trades structured distortion for “noise-like” distortion
 - ▶ often preferred perceptually (weak grain vs hard bands)

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Motivation

Dithering

Definition

Fundamental property: linearization

Quantization in GPUs: NVFP4

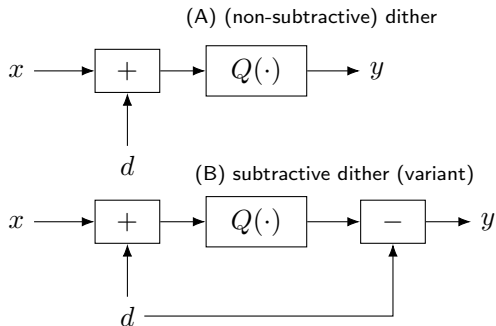
How much dither?

Examples: 1D signals, images and music

Subtractive dithering (variant)

Exact Bennett-like model

Additive dither: two canonical architectures



- ▶ In this lecture we start with (A): add noise then quantize.
- ▶ (B) is a useful *variant* when the same d is known at encoder/decoder.

Uniform rounding quantizer

We use a uniform rounding quantizer with step Δ :

$$Q_{\Delta}(z) \triangleq \Delta \cdot \text{round}\left(\frac{z}{\Delta}\right).$$

Quantization error:

$$e(z) \triangleq Q_{\Delta}(z) - z \in \left[-\frac{\Delta}{2}, \frac{\Delta}{2}\right].$$

- ▶ Without randomization, $e(x)$ is a periodic sawtooth function of x .

Non-subtractive dither (definition)

Let d be a random dither, independent of the signal x .

Non-subtractive dithering:

$$y = Q_{\Delta}(x + d)$$

The reconstruction error is

$$\varepsilon \triangleq y - x = d + e(x + d).$$

- ▶ Benefit: breaks correlation between the signal and the quantization staircase.
- ▶ Cost: d appears directly in the output error.

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Proof of linearization

Fix $x \in \mathbb{R}$ and write

$$x = k\Delta + r, \quad r \in \left[-\frac{\Delta}{2}, \frac{\Delta}{2}\right).$$

With $d \sim \mathcal{U}[-\Delta/2, \Delta/2]$,

$$x + d \sim \mathcal{U}\left(k\Delta + r - \frac{\Delta}{2}, k\Delta + r + \frac{\Delta}{2}\right),$$

an interval of length Δ , so

$$Q_{\Delta}(x + d) \in \{k\Delta, (k + 1)\Delta\}.$$

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Let

$$p = \mathbb{P}(Q_{\Delta}(x + d) = (k + 1)\Delta \mid x) = \mathbb{P}(x + d > k\Delta + \Delta/2)$$

Since the interval is uniform and centered at x ,

$$p = \frac{r}{\Delta}.$$

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Thus

$$\mathbb{E}[Q_{\Delta}(x + d) \mid x] = p(k + 1)\Delta + (1 - p)k\Delta = k\Delta + \Delta p = k\Delta + r = x.$$

Numerical example (linearization)

Quantize an 8-bit pixel using a 4-bit uniform quantizer.

- ▶ Dynamic range: 0 to 255.
- ▶ Step size: $\Delta = 16$ (levels at $\{\dots, 96, 112, 128, \dots\}$).
- ▶ Choose pixel value $x = 100$.

Write $x = 96 + 4$, so $k\Delta = 96$ and $r = 4$.

Let $d \sim \mathcal{U}(-8, 8)$. Then $x + d \sim \mathcal{U}(92, 108)$. The boundary between 96 and 112 is at 104.

$$\mathbb{P}(Q_{\Delta}(x + d) = 112) = \frac{r}{\Delta} = \frac{4}{16} = \frac{1}{4}$$

$$\mathbb{P}(Q_{\Delta}(x + d) = 96) = 1 - \frac{1}{4} = \frac{3}{4}.$$

Therefore, on average we get

$$\mathbb{E}[Q_{\Delta}(x + d) \mid x] = 112 \frac{1}{4} + 96 \frac{3}{4} = 100.$$

Dithering is stochastic rounding

Let Q_Δ be a uniform scalar quantizer and

$$d \sim \mathcal{U}\left[-\frac{\Delta}{2}, \frac{\Delta}{2}\right].$$

Assumption (no overload): $x \pm \frac{\Delta}{2}$ lies strictly inside the quantizer range.

For fixed x , $x + d$ is uniform over an interval of length Δ . Hence $Q_\Delta(x + d)$ can take only the two neighboring quantization levels.

Let $x \in [t, t + \Delta)$ and define

$$p \triangleq \frac{x - t}{\Delta} = \frac{\text{'distance from } x \text{ to } t\text{'}}{\text{'distance from } t \text{ to } t + \Delta\text{'}}.$$

Then

$$Q_\Delta(x + d) = \begin{cases} t & \text{with probability } 1 - p, \\ t + \Delta & \text{with probability } p. \end{cases}$$

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Then

$$Q_\Delta(x + d) = \begin{cases} t & \text{with probability } 1 - p, \\ t + \Delta & \text{with probability } p. \end{cases}$$

Therefore, $\mathbb{E}[Q_\Delta(x + d) \mid x] = (1 - p)t + p(t + \Delta) = x$.

Stochastic rounding in NVFP4

- ▶ NVIDIA's NVFP4 data format was announced in March 2024 as a key feature of its Blackwell GPU architecture
- ▶ Its representable values are *not uniformly spaced*
- ▶ Each block is first scaled before quantization
- ▶ Popular in LLM inference and training

Stochastic rounding: Instead of always rounding to the nearest value, we randomly round up or down so that the average equals the original number. **How stochastic rounding works in**

NVFP4.

- ▶ After scaling, a real number lies between two neighboring NVFP4 values
- ▶ Call them v_{low} and v_{high}
- ▶ We round to either one at random

round to v_{high} with probability $\frac{x - v_{\text{low}}}{v_{\text{high}} - v_{\text{low}}}$, otherwise round to v_{low} .

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How much dither should we add?

A standard choice is **one-LSB uniform dither**:

$$d \sim \mathcal{U}\left(-\frac{\Delta}{2}, \frac{\Delta}{2}\right)$$

- ▶ large enough to randomize the fractional part modulo Δ
- ▶ minimal support that yields the exact linearization result $\mathbb{E}[Q_{\Delta}(x + d) \mid x] = x$

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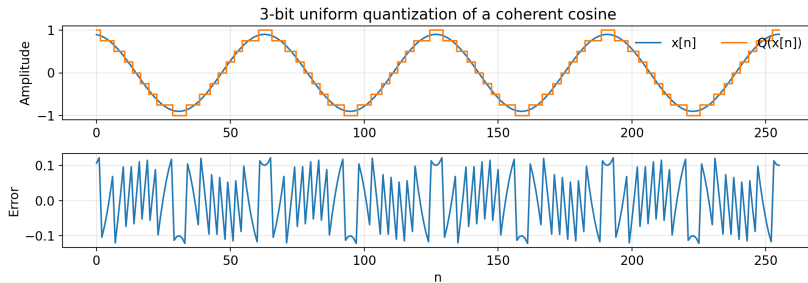
- ▶ large enough to randomize the fractional part modulo Δ
- ▶ minimal support that yields the exact linearization result
 $\mathbb{E}[Q_{\Delta}(x + d) \mid x] = x$

If the dither amplitude is much smaller than Δ , artifacts remain; if much larger, you add unnecessary noise.

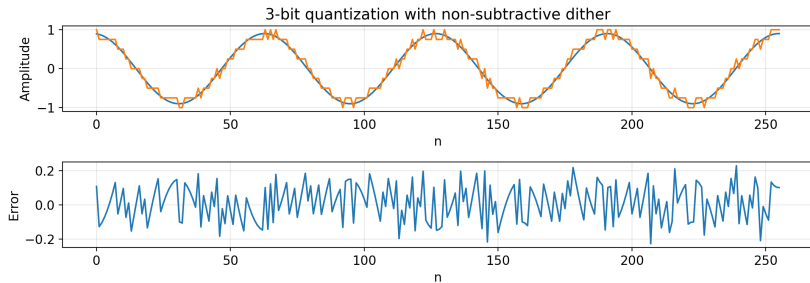
▶ Examples

- ▶ dithering in 1D signals
- ▶ dithering in images
- ▶ dithering in audio
- ▶ spectrum (later)

Quantization of a pure sine wave



Dithered quantization of a pure sine wave



Uniform quantization of an image

- ▶ values in $[0, 100]$ and threshold at 50

8 bit



85%
75%
55%
45%
25%
15%

1 bit



85%
75%
55%

Adding noise

8 bit

85%
75%
55%
45%
25%
15%

8 bit (noise added)

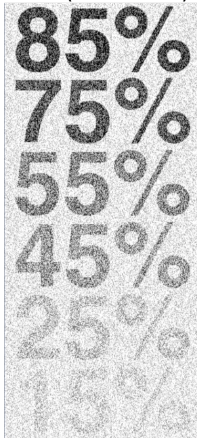
85%
75%
55%
45%
25%
15%

Dithering: Add noise and quantize

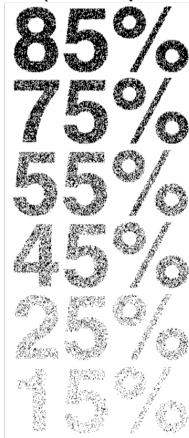
8 bit



8 bit (noise added)

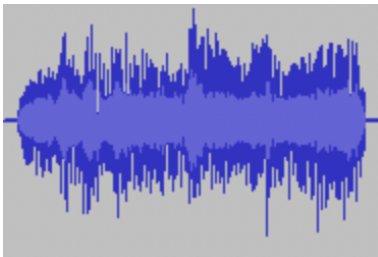


1 bit (noise & quantize)

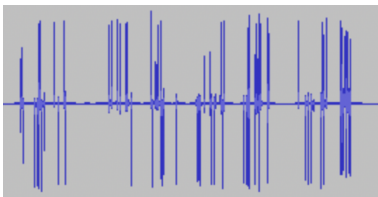


Dithering in music

- ▶ original audio



- ▶ 1-bit quantization



- ▶ 1-bit quantization with dithering

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Subtractive dither: the key simplification

In subtractive dither,

$$y = Q_{\Delta}(x+d)-d \quad \Rightarrow \quad \varepsilon \triangleq y-x = Q_{\Delta}(x+d)-(x+d) = e(x+d).$$

- ▶ The reconstruction error equals the quantization error of the *dithered input*.
- ▶ If $(x+d) \bmod \Delta$ is uniform, then ε becomes uniform.

Theorem (uniform subtractive dither)

Claim. Let $d \sim \mathcal{U}(-\Delta/2, \Delta/2)$ be independent of x . In subtractive dithering:

$$y = Q_{\Delta}(x + d) - d$$

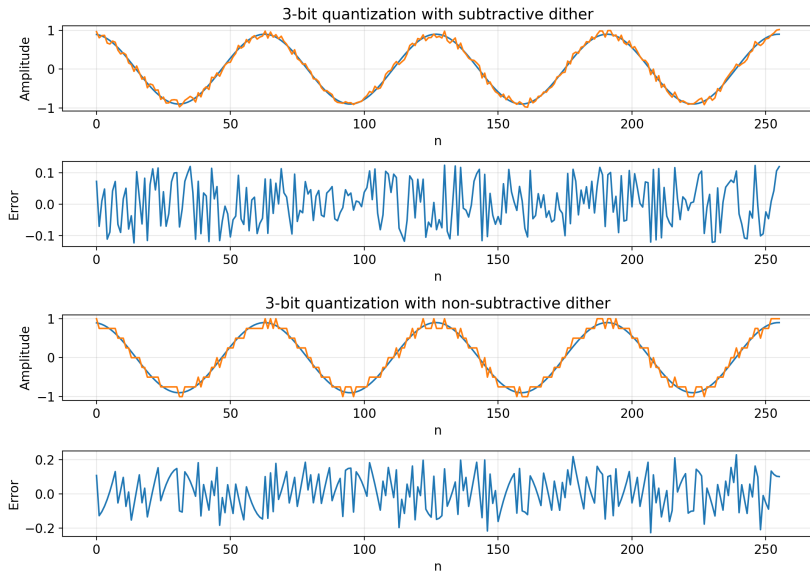
the error $\varepsilon = y - x$ satisfies

$$\varepsilon \sim \mathcal{U}\left(-\frac{\Delta}{2}, \frac{\Delta}{2}\right), \quad \varepsilon \perp x$$

Quantization error and the signal are independent (see appendix for the proof). Consequently,

$$\mathbb{E}[\varepsilon \mid x] = 0, \quad \mathbf{Var}(\varepsilon) = \frac{\Delta^2}{12}.$$

Subtractive vs non-subtractive dithering of a sine wave



Summary

- ▶ Bennett's theorem explains when quantization error *looks* uniform in the high-rate regime.
- ▶ Dithering is a way to *engineer* this behavior at finite rate.
 - ▶ non-subtractive dither: linearizes in expectation (good for images)
 - ▶ subtractive dither: gives uniform, input-independent error (great for analysis) but need to make the noise sequence available at the receiver
- ▶ Stochastic rounding is an unbiased randomized quantizer; tightly related to dither.
- ▶ NVFP4 utilizes stochastic rounding for unbiasedness.

Appendix: Why subtractive dither gives signal-independent noise

Let $d \sim \mathcal{U}(-\Delta/2, \Delta/2)$ and define

$$z = x + d, \quad \hat{x} = Q_{\Delta}(z) - d.$$

Quantization depends only on the position of z within a cell. Write $x = k\Delta + r$ with $r \in [-\Delta/2, \Delta/2)$, so

$$z = k\Delta + (r + d).$$

Since d is uniform over one full quantization step, the random variable $(r + d)$ is uniform over an interval of length Δ , independent of r .

Wrapping any length- Δ interval into one cell produces a uniform variable on $[-\Delta/2, \Delta/2)$, hence

$$e \triangleq \hat{x} - x \sim \mathcal{U}(-\Delta/2, \Delta/2),$$

with a distribution that does not depend on x .

Conclusion: Subtractive dither yields uniform, signal-independent noise.