

# Single-Gaussian Messages and Noise Thresholds for Low-Density Lattice Codes

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# Background

- Low-density lattice codes (LDLC) are lattices [Sommer, Feder and Shalvi, IT 2008]
- Decoded using belief-propagation, like low-density parity check codes.
- Decoding complexity is linear in the dimension. Dimension  $n=10^5$  possible.
  - “Classical” lattices can be decoded in dimension  $n=2\sim 200$
- Within 0.6 dB of unconstrained power capacity
- Messages (beliefs) are functions, rather than numbers. Existing implementations
  - Quantize the functions
  - Gaussian mixture approximation

## In this talk

- Propose a LDLC decoder: belief-propagation messages approximated by a single Gaussian,
- Single-Gaussian decoding has a noise threshold within 0.1 dB of the quantized-message implementation (that is, 0.7 dB from capacity)
- But, single-Gaussian decoding has much lower complexity than other methods
- Design of regular LDLC lattices  $\alpha=0.7$  is better than  $\alpha$  approaching 1

# Low-Density Lattice Codes (LDLCs)

Sommer, Feder and Shalvi gave a lattice construction and decoding algorithm based upon low-density parity-check codes. Extensive convergence analysis in IT Trans, April 2008.

## Low-Density Parity-Check Codes

- Code over a finite field (binary)
- Sparse parity check matrix

## LDLC

- Lattice: Code over the real numbers

$$\begin{array}{ccc} & \xrightarrow{\quad} & \mathbf{x} = G \cdot \mathbf{b} & \xleftarrow{\quad} \\ & n\text{-dim lattice points} & & n\text{-dim integer vector} \end{array}$$

- $n$ -by- $n$  inverse generator  $H=G^{-1}$  is sparse
- $H$  has row and column weight  $d$
- Non-zero entries in rows and columns:

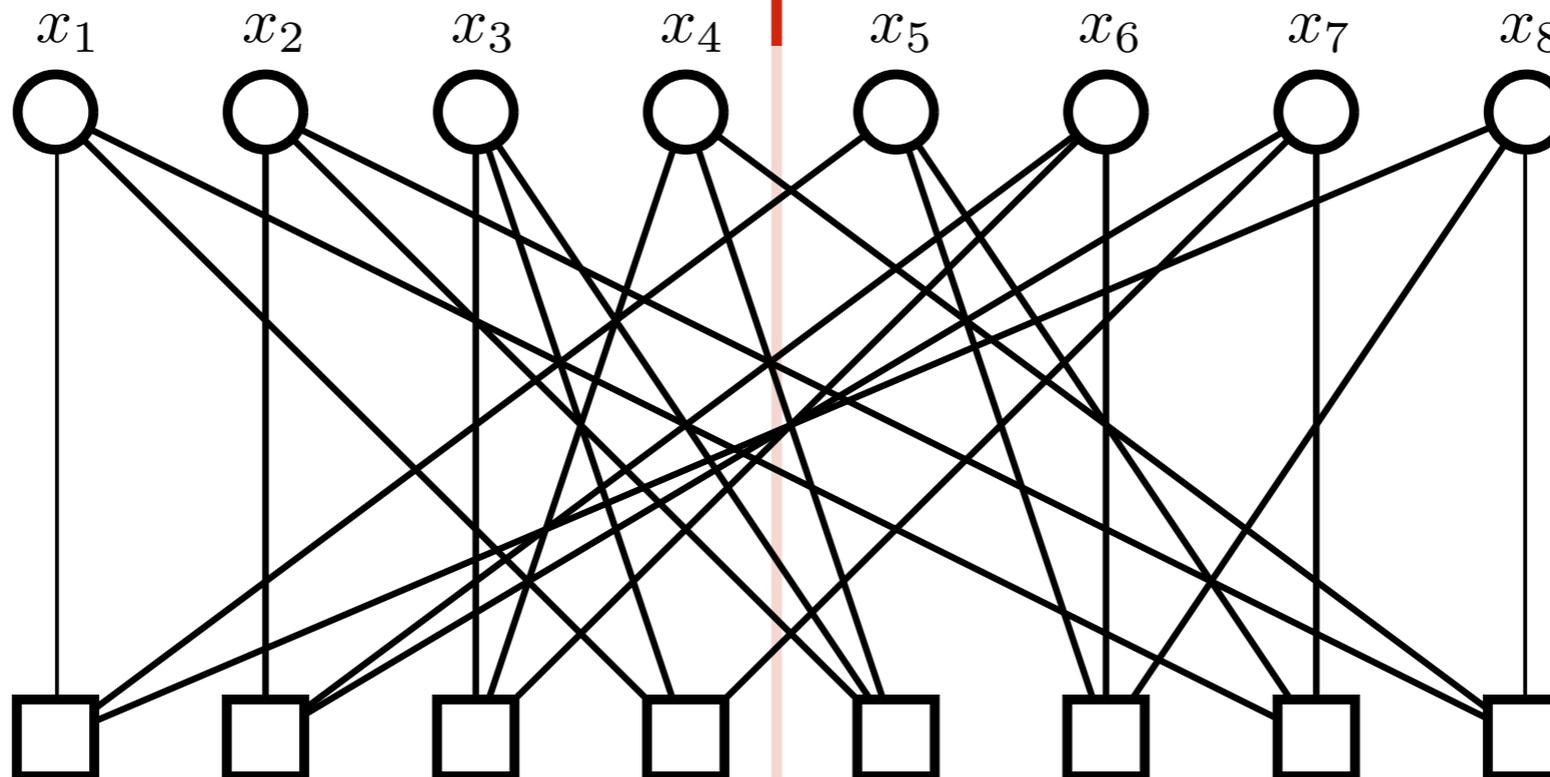
$$\pm\{h_1, h_2, \dots, h_d\}$$

# Low-Density Parity-Check Codes

Variables are from the field

$$x_i \in \{0, 1\}$$

So, messages are scalars (LLRs)



# check nodes < # variable nodes

$$x_1 + x_2 + x_3 = 0 \text{ (over field)}$$

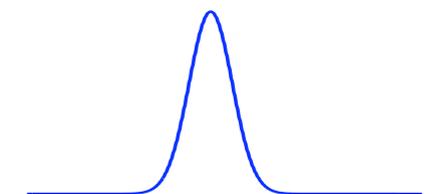
Approaches BIAWGN channel capacity

# Low-Density Lattice Codes (LDLC)

Variables are real numbers

$$x_i \in \mathbb{R}$$

So, messages are functions (!)



# check nodes = # variable nodes

$$x_1 + x_2 + x_3 = b \text{ (over real numbers)}$$

$b$  is an integer

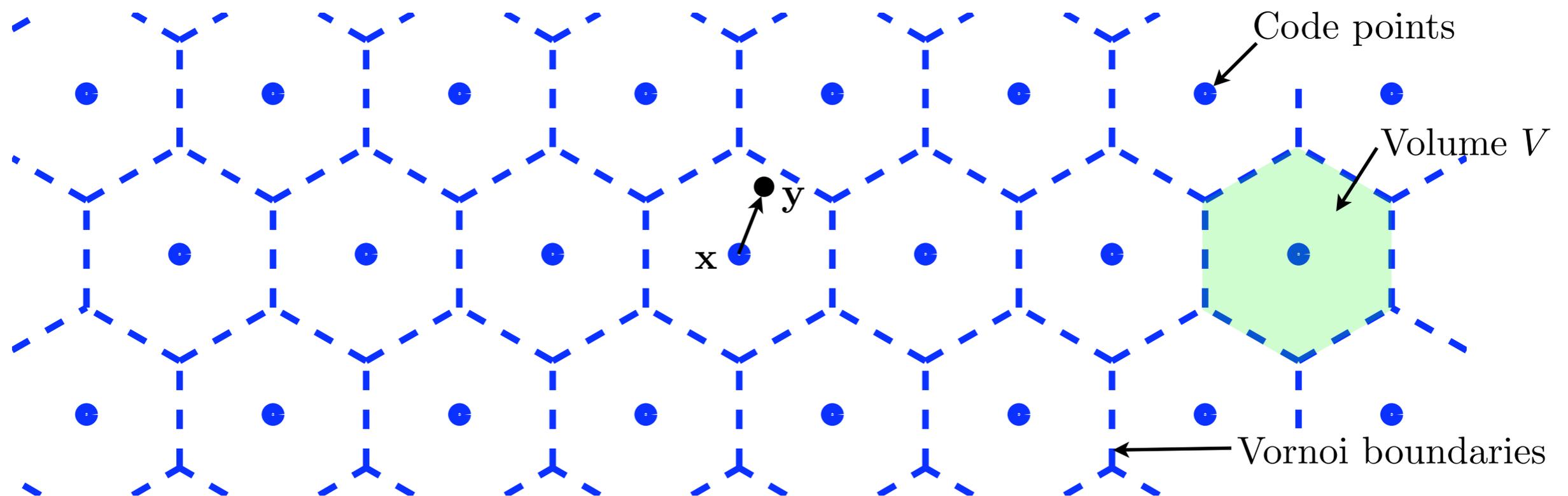
Comes within 0.6 dB of unconstrained power AWGN channel capacity.

# Channel Model: Unconstrained Power Transmission

- Use entire lattice for transmission
  - The code is linear!
- Reliable “communication” [Poltyrev, etc.] if and only if

$$\text{SNR} \geq 2\pi e, \quad \text{SNR} = \frac{\sqrt[n]{V^2}}{\sigma^2} \quad \text{Noise power } \sigma^2$$

- Transmit power is unconstrained; no shaping region.



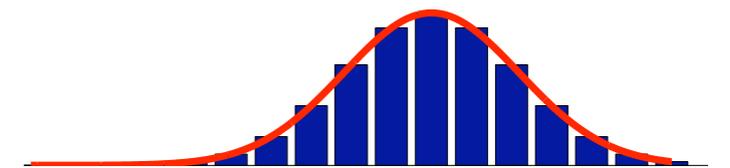
# Implementations of LDLC Decoders

How to represent messages, which are functions?

0. **Exact** True message is a mixture of Gaussians, but number is exponential in iterations.

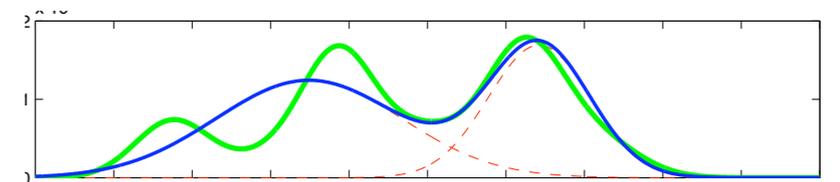
1. **Quantization** of the the messages [Sommer et al.]

- About 1024 quantization points gets good performance

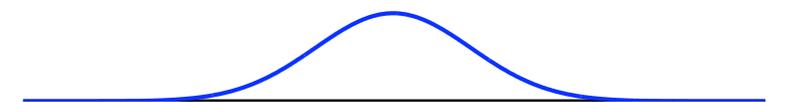


2. **Mixture of Gaussians** — Approximate the message with a mixture of Gaussians [joint work with Justin Dauwels]

- Uses a "Gaussian Mixture Reduction Algorithm"
- preserves Gaussian nature of messages, low memory requirements.
- Further improvements: Yona and Feder, ISIT 2009

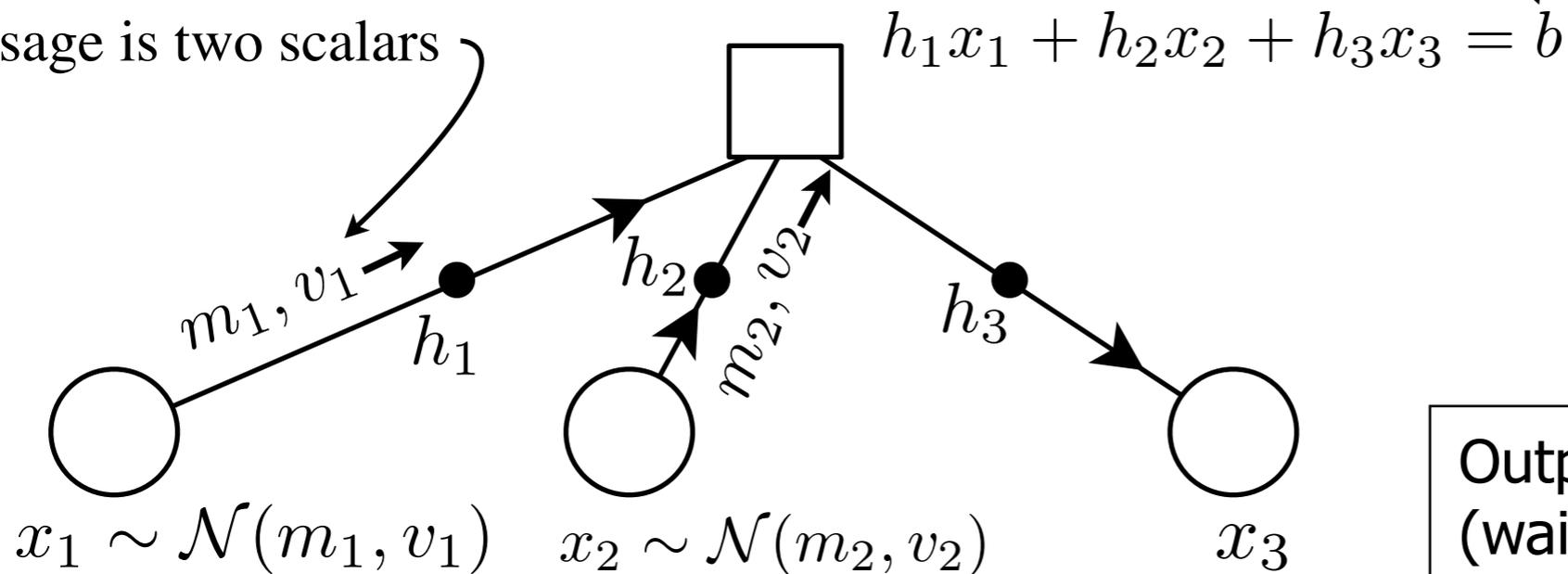


3. **Single Gaussian (this talk)** Approximate the message with a single Gaussian



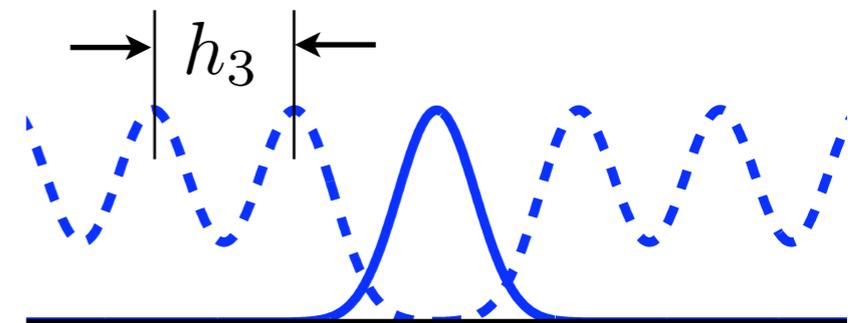
# Single Gaussian Decoder: Check Node (Easy Part)

Message is two scalars



Unknown integer

Output: Single Gaussian  
(wait for shift-and-repeat)



Input: Single Gaussian

Check node function is quite simple:

$$m_3 = -\frac{h_1m_1 + h_2m_2}{h_3}$$

$$v_3 = \frac{h_1^2v_1 + h_2^2v_2}{h_3^2}$$

# Moment Matching — Gaussian Approximation

Let  $X$  be the mixture of two Gaussians  $X_1$  and  $X_2$ :

$$\begin{aligned} X &= X_1 + X_2 \\ &= c_1 \mathcal{N}(m_1, v_1) + c_2 \mathcal{N}(m_2, v_2). \end{aligned}$$

Let  $Y$  be the single Gaussian (mean  $m_Y$ , variance  $v_Y$ ) which approximates  $X$ . Then,  $\text{KL}(X||Y)$  is minimized when:

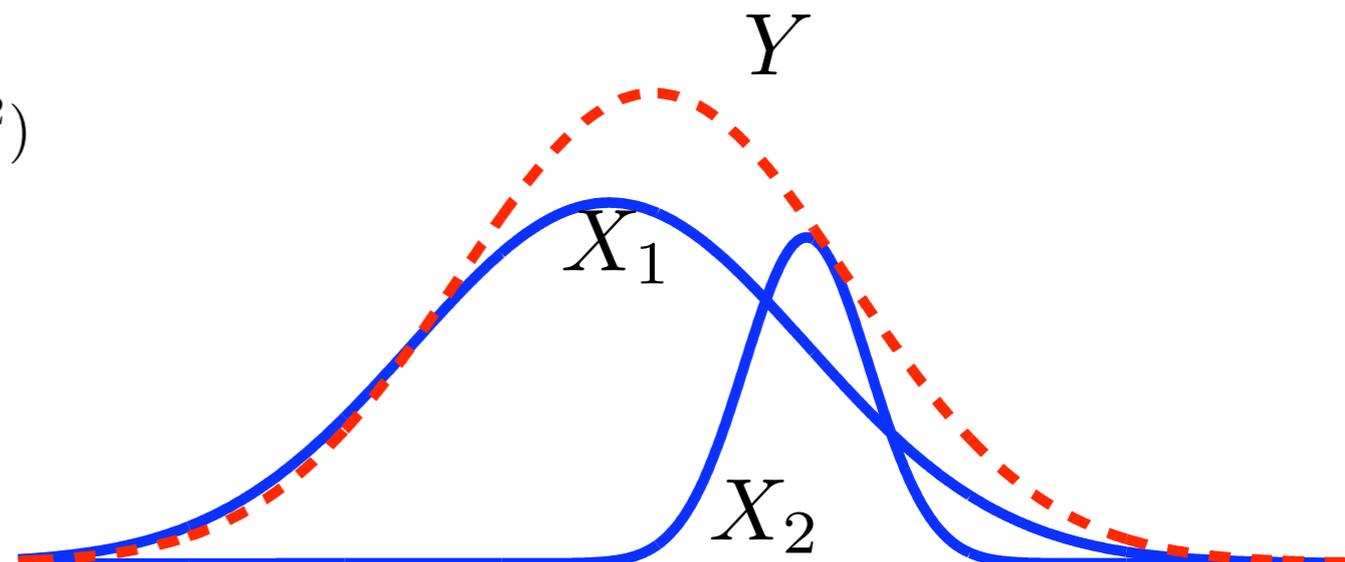
$$\begin{aligned} E[Y] &= E[X] \quad (\text{first moment}) \\ E[Y^2] &= E[X^2] \quad (\text{second moment}) \end{aligned}$$

Then,

$$\begin{aligned} m_Y = E[Y] &= c_1 m_1 + c_2 m_2 \\ E[Y^2] &= \sum_i c_i \cdot (v_i + m_i^2) \end{aligned}$$

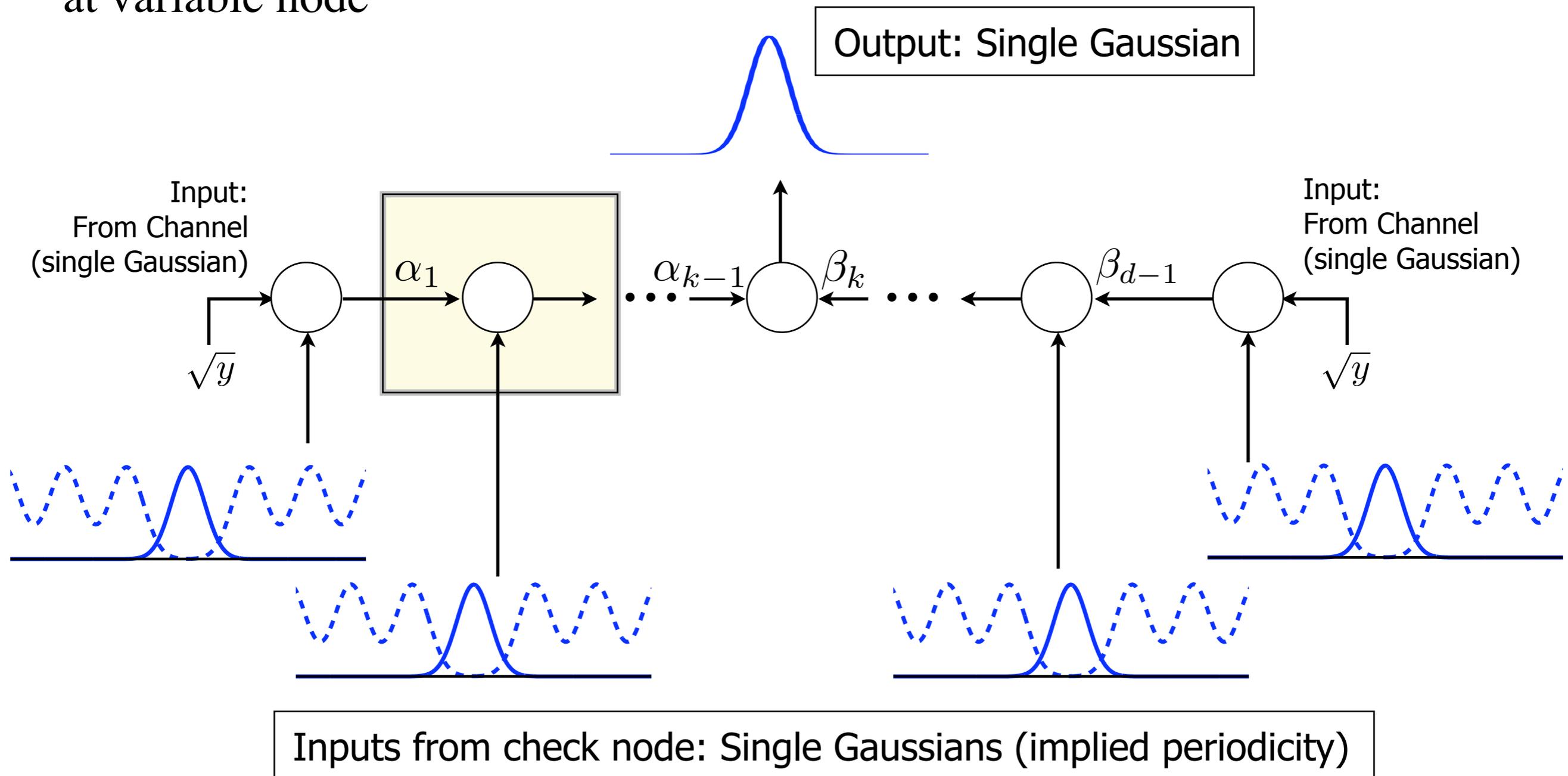
Of course:

$$v_Y = E[Y^2] - E[Y]^2$$

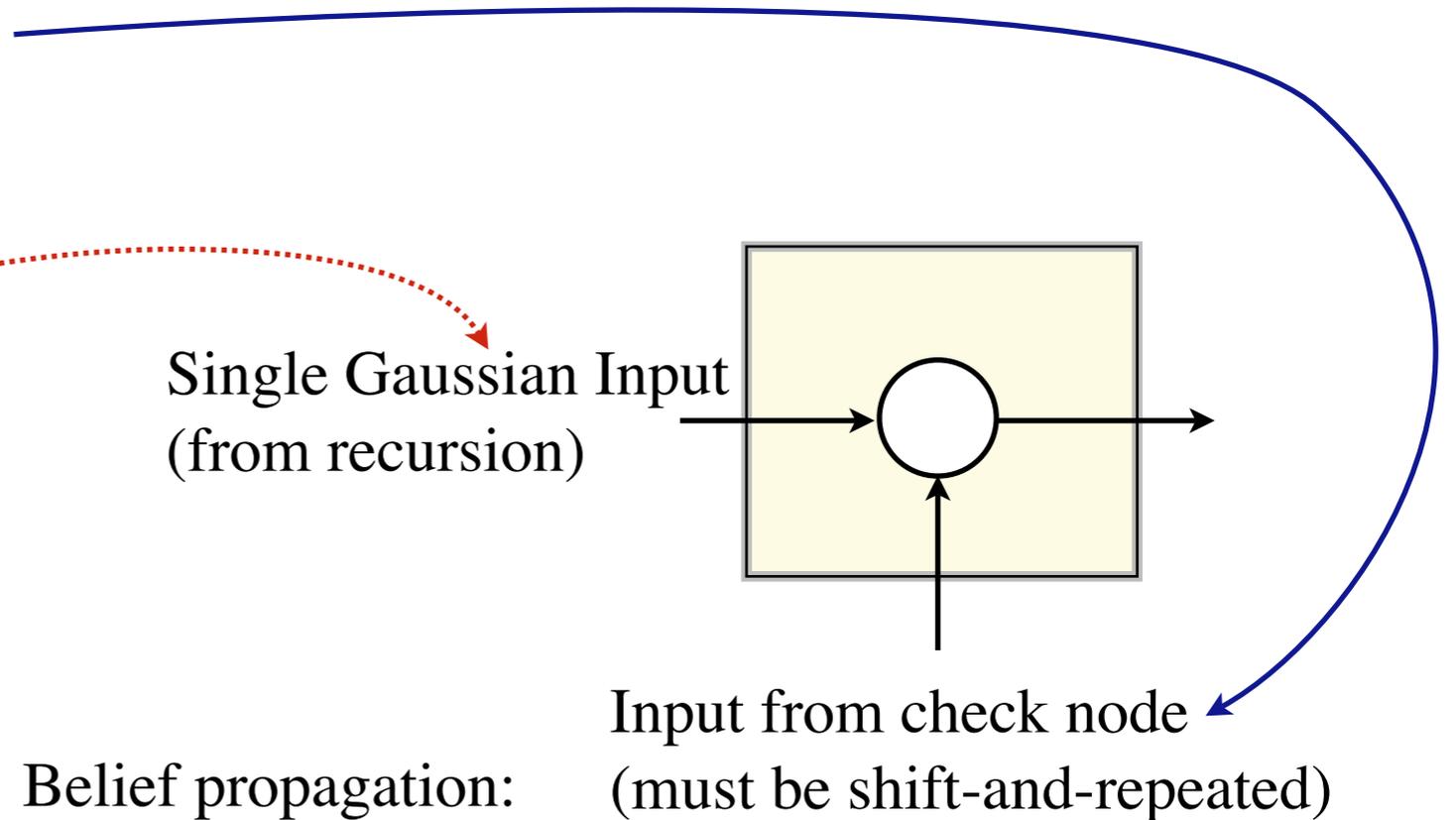
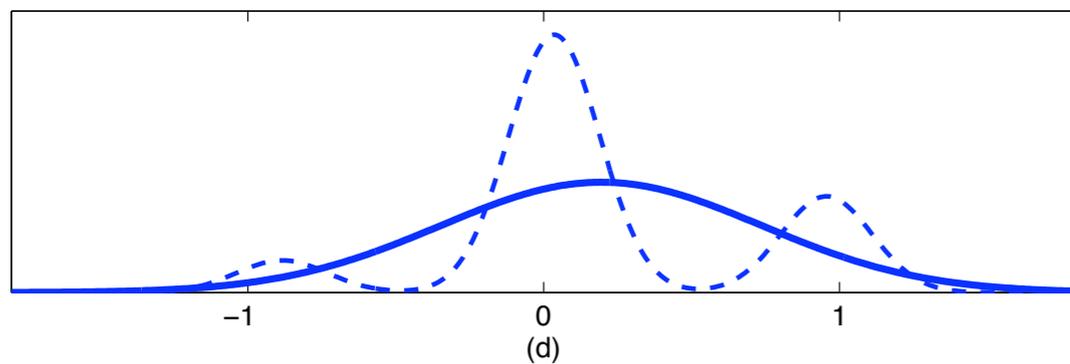
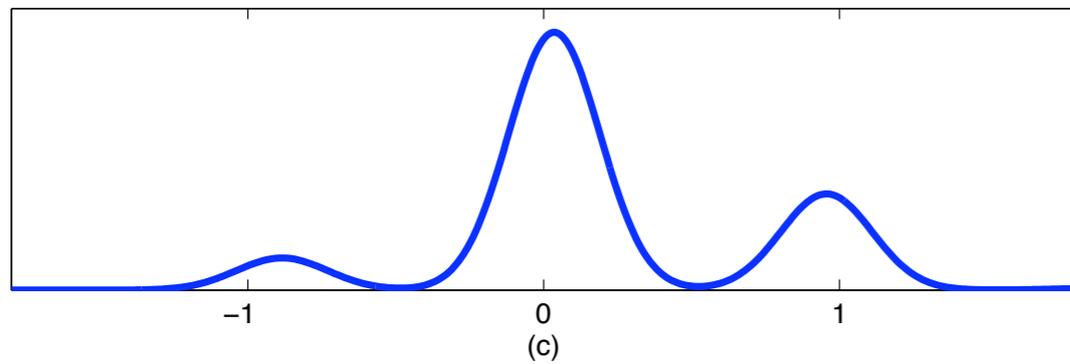
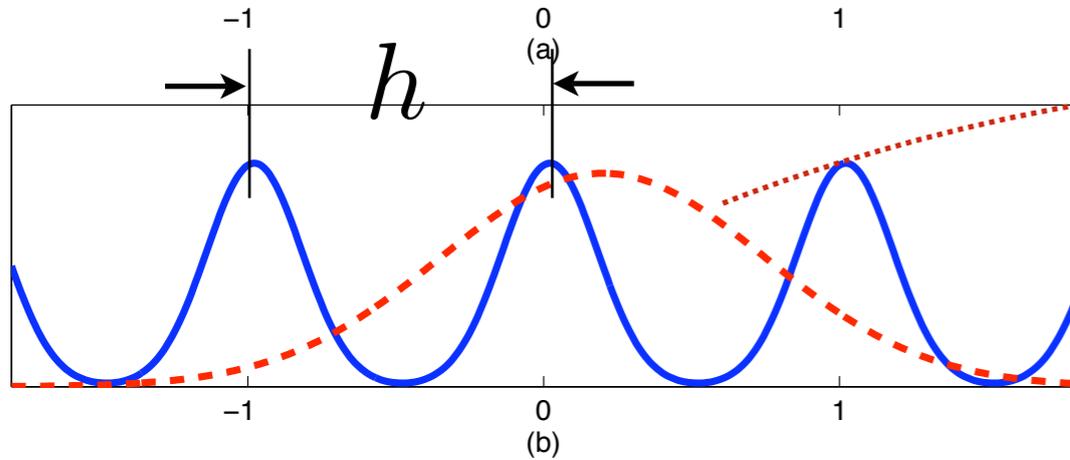
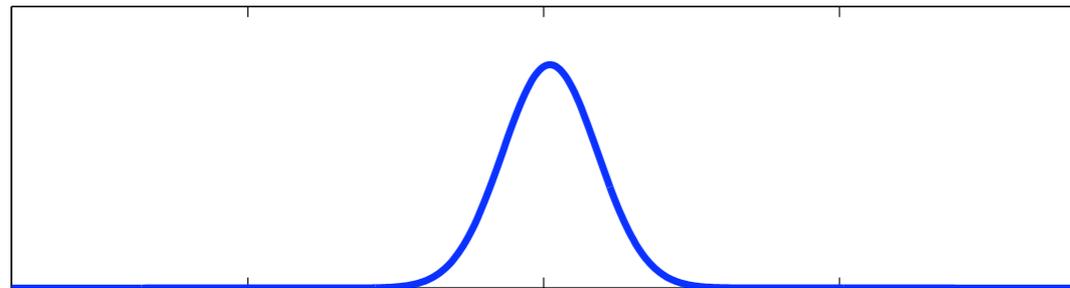


# Single Gaussian Decoder: Variable Node (Hard Part)

Forward-backward algorithm  
at variable node



# Variable Node One-Step Function



Belief propagation:  
Multiply

Moment Matching  
Approximation



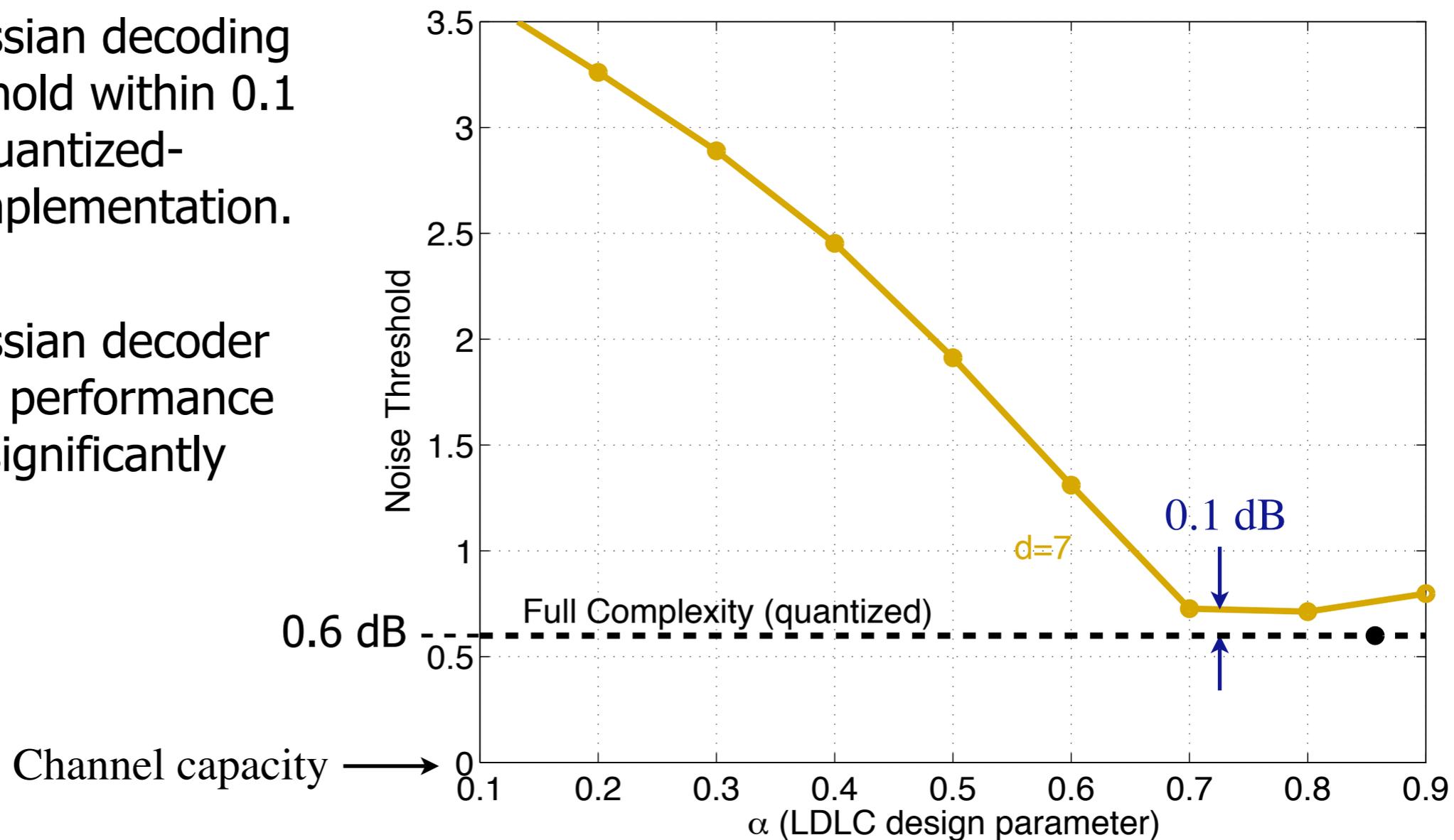
# Complexity Measure: Can you write the decoding rule on one slide?

	Variable Node	Check Node
Quantized message	128-point DFT	Sum of 1024 numbers
Multiple Gaussians	Gaussian Mixture Reduction: <ul style="list-style-type: none"> <li>• Compute pair-wise distance between <math>M^2</math> Gaussians</li> <li>• Repeatedly combine Gaussians</li> </ul>	
Single Gaussian	$m = v' \sum_{b \in \mathcal{B}} \left( \frac{b}{v_c h} + \frac{m_c}{v_c} + \frac{m_a}{v_a} \right) \exp \left( -\frac{1}{2} \frac{(b/h + m_c - m_a)^2}{v_c + v_a} \right)$ $v = v' - m^2 + v'^2 \sum_{b \in \mathcal{B}} \left( \frac{b}{v_c h} + \frac{m_c}{v_c} + \frac{m_a}{v_a} \right)^2 \exp \left( -\frac{1}{2} \frac{(b/h + m_c - m_a)^2}{v_c + v_a} \right)$	$m = m_a + m_c$ $v = v_a + v_c$
Binary LDPC (log domain)	$x_a + x_c$	$\text{sgn}(x_a, x_b) \cdot 2 \tanh^{-1} \left( \log \left  \tanh \frac{x_a}{2} \right  + \log \left  \tanh \frac{x_b}{2} \right  \right)$

- Single-Gaussian decoder is considerably simpler than previous methods
- Single-Gaussian decoder is more complicated than binary LDPC, but at least the decoding rule fits on the page.

# Noise Thresholds — Monte Carlo Density Evolution

- Single-Gaussian decoding noise threshold within 0.1 dB of the quantized-message implementation.
- Single-Gaussian decoder has a slight performance loss but is significantly simpler.



# Noise Thresholds — Regular Code Design

LDLC sparse matrix non-zero entries:

$$h_1 \geq h_2 \geq \dots \geq h_d$$

Characterized by parameter  $\alpha$ :

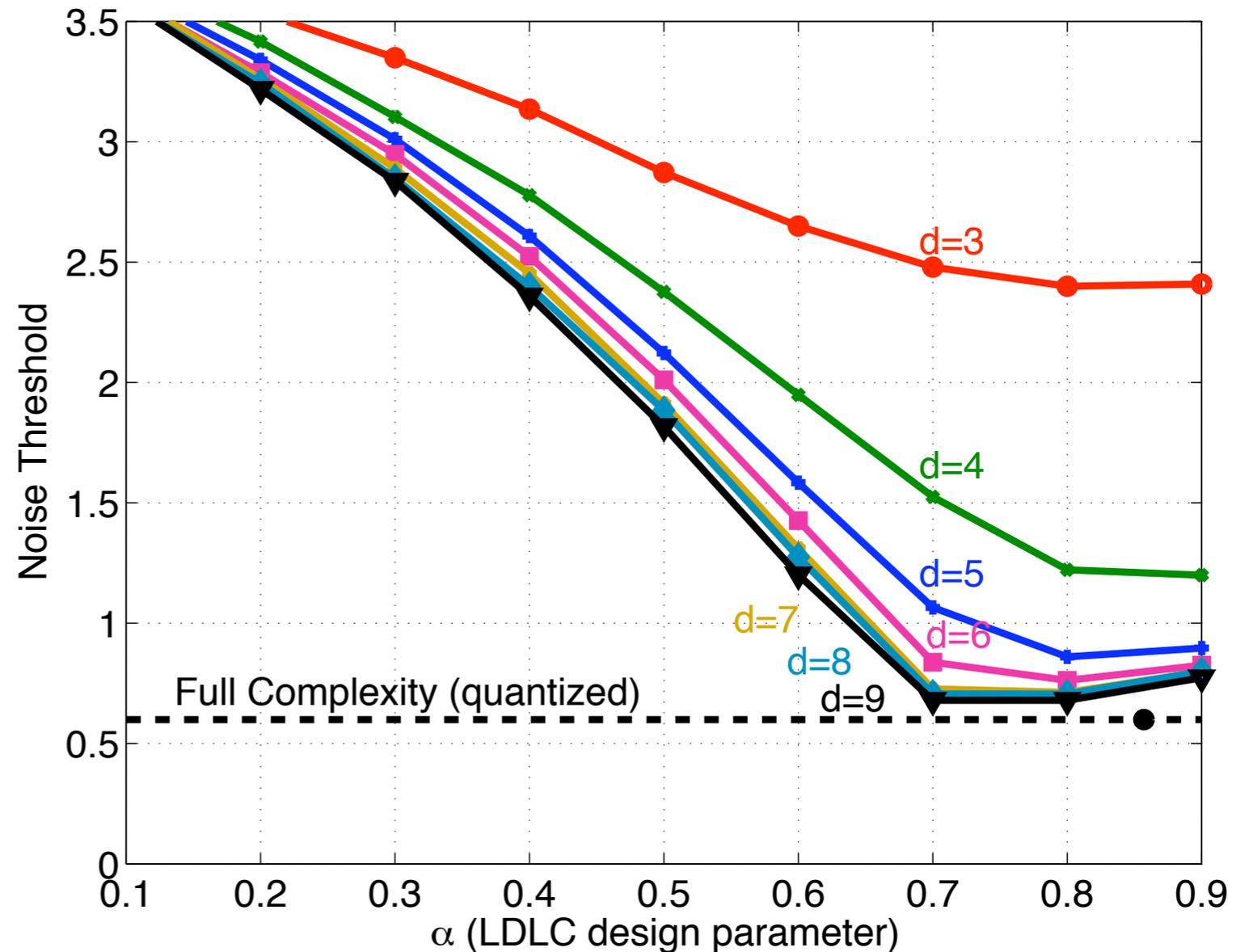
$$\alpha = \frac{h_2^2 + h_3^2 + \dots + h_d^2}{h_1^2} \geq 0$$

Theorem [Sommer, et al.]: Convergence is exponentially fast for  $\alpha \leq 1$ .

It was noted,

$$\alpha \rightarrow 1$$

gave good performance.



- Even alpha =0.7 is slightly better than other higher values.
- Increasing d beyond 7 gives little benefit (same as Sommer et al.)

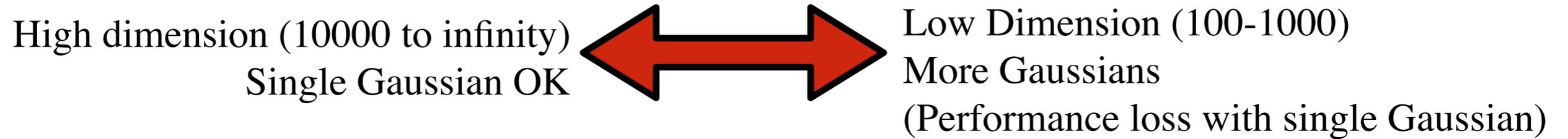
# Conclusion

- **Proposed** a single-Gaussian decoder for LDLC lattices
- **Complexity** is much lower than previous methods — we could write the decoding rule on one slide
- **Performance:** Minimal loss, noise threshold 0.1 dB away from more complicated decoder.
- **Code Design** Regular codes found that  $\alpha \rightarrow 1$  wasn't always best, slight gain by picking  $\alpha = 0.7$

# What about finite or smaller dimension?

## "Low" dimension lattices (dimension 100-1000)

- Single Gaussian numerical results poor.
- Multiple Gaussian decoder works OK at low dimension.



- Suggestion: modify BP decoder to improve convergence at low dimensions