

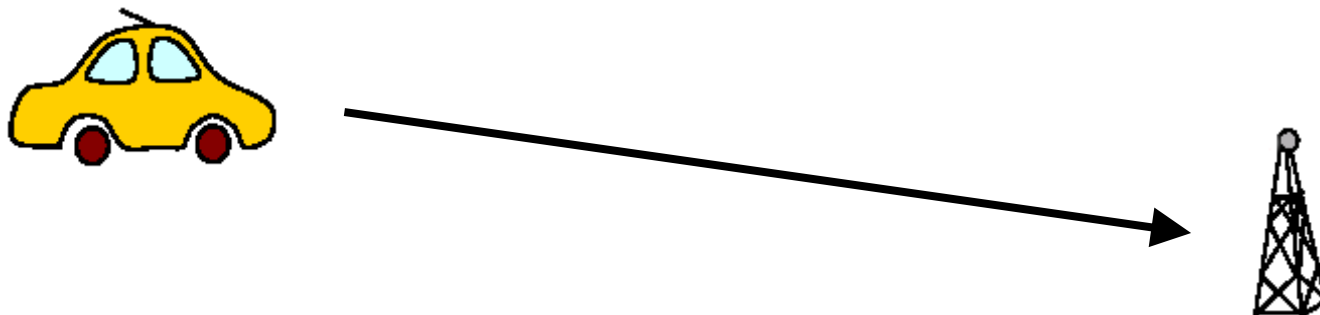
Forschungszentrum Telekommunikation Wien
[Telecommunications Research Center Vienna]

Theory and Design of Turbo and Related Codes

Lecture 3

Jossy Sayir & Gottfried Lechner

The Channel



- The channel is the **link** between the transmitter and the receiver.
- Signals sent by the transmitter will usually be **corrupted** by the channel.
- The corruption of the signal has some **random** source.
- We use channel **models** that approximate real channels.



The channel maps a symbol of the input alphabet to a symbol of the output alphabet (randomly).

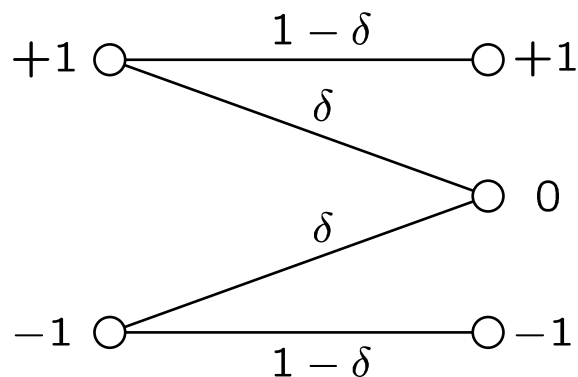
This mapping can be described by the probability of a symbol at the output, given that a symbol at the input has been transmitted.

$$P(Y = y|X = x)$$

Binary Erasure Channel BEC

$$X \in \mathcal{A}_{in} = \{+1, -1\}$$

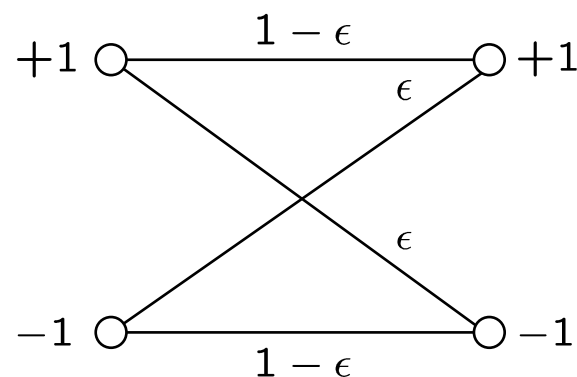
$$Y \in \mathcal{A}_{out} = \{+1, 0, -1\}$$



Binary Symmetric Channel BSC

$$X \in \mathcal{A}_{in} = \{+1, -1\}$$

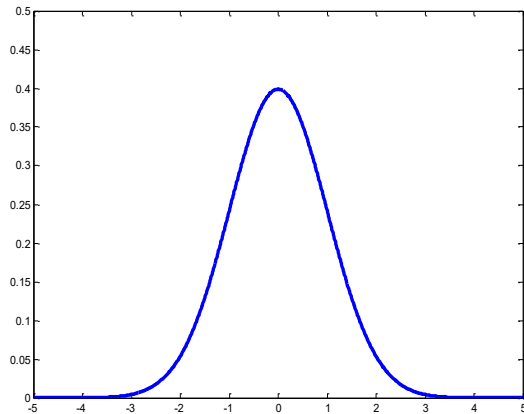
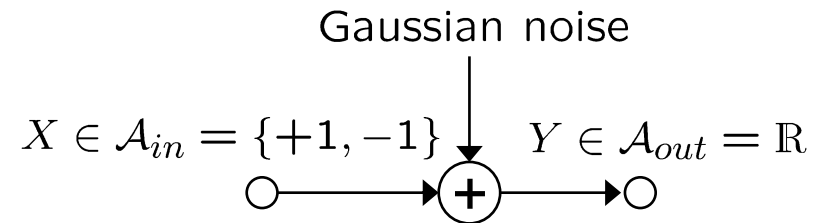
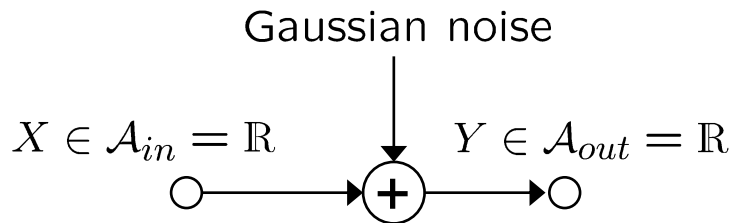
$$Y \in \mathcal{A}_{out} = \{+1, -1\}$$



Does the decoding algorithm of lecture 1 also work for a BSC?

Additive White Gaussian Noise AWGN

Binary Input AWGN BIAWGN

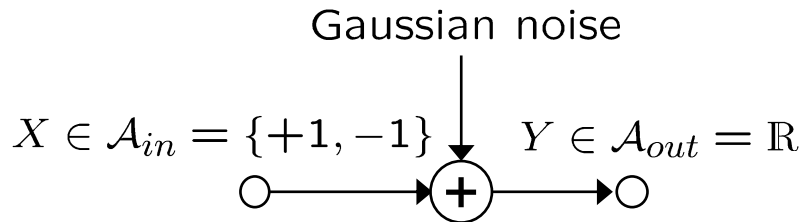


$$P(Y = y|X = x) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(y-x)^2}{2\sigma^2}}$$

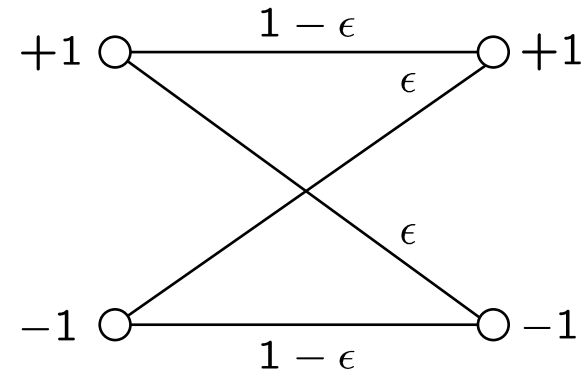
Carl Friedrich Gauss 1777-1855



A BIAWGN channel with "hard decision" becomes a BSC.

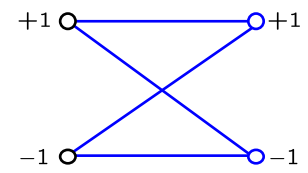
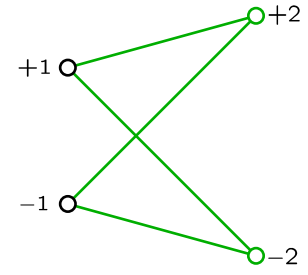
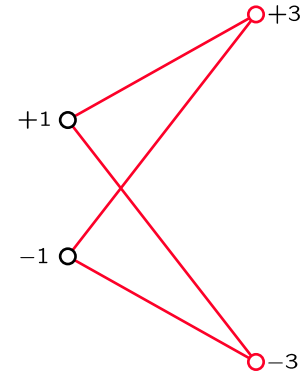
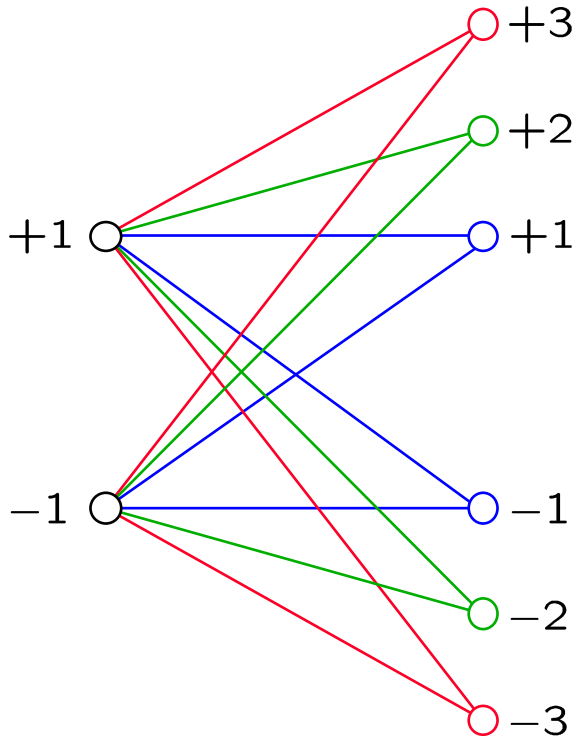


$$P(Y = y|X = x) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(y-x)^2}{2\sigma^2}}$$



$$\epsilon = P(Y > 0|X = -1) = \int_0^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(y+1)^2}{2\sigma^2}} dy$$

Higher output Alphabet



- We use only **binary input** channels in this course.
- Channels are **memoryless**.
- Fully described by their **transition probabilities**.
- All channels satisfy a **symmetry** property

$$P(Y = y|X = x) = P(Y = -y|X = -x)$$

In the end we are only interested which binary digit was transmitted.

Therefore, we have to compare probabilities of +1 or -1 conditioned on our observation.

$$P(X = +1|Y = y) \geq P(X = -1|Y = y)$$

$$P(X = +1|Y = y) - P(X = -1|Y = y) \geq 0$$

$$\frac{P(X = +1|Y = y)}{P(X = -1|Y = y)} \geq 1$$

$$\log \frac{P(X = +1|Y = y)}{P(X = -1|Y = y)} \geq 0$$

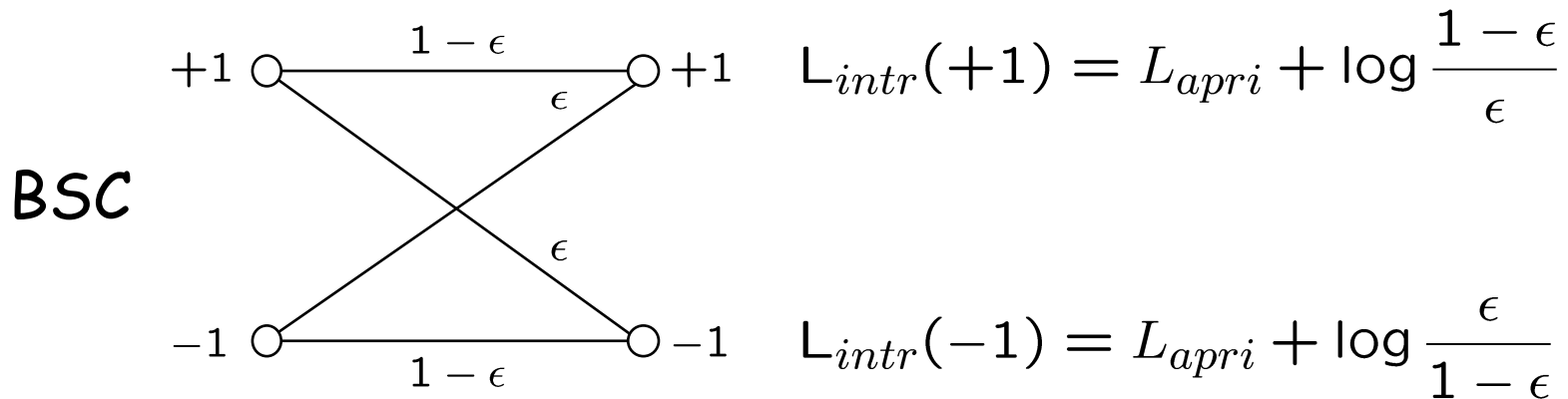
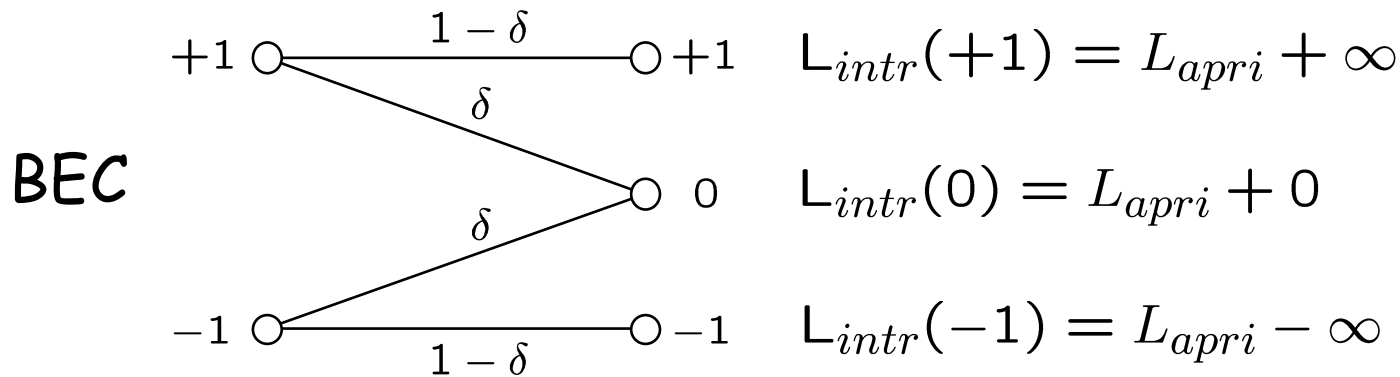
Log-Likelihood Ratio

$$\begin{aligned}
 L(X|Y = y) &= \log \frac{P(X = +1|Y = y)}{P(X = -1|Y = y)} \\
 &= \log \frac{P(Y = y|X = +1) \cdot P(X = +1)}{P(Y = y|X = -1) \cdot P(X = -1)} \\
 &= \underbrace{\log \frac{P(Y = y|X = +1)}{P(Y = y|X = -1)}}_{\text{channel L-value}} + \underbrace{\log \frac{P(X = +1)}{P(X = -1)}}_{\text{a-priori L-value}}
 \end{aligned}$$

$$L_{X,intr}(y) = L_{X,ch}(y) + L_{X,apri}$$

Note: $L_{X,intr}(y)$ is only a function of y - not of x !
 We will omit the subscript X if it is clear from the context.

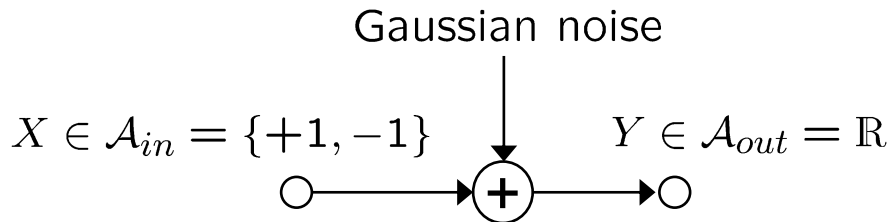
LLR of some Channels



Note the symmetry of the channels.

LLR of some Channels

BIAWGN



$$\begin{aligned}
 L_{ch}(y) &= \log \frac{P(Y = y|X = +1)}{P(Y = y|X = -1)} \\
 &= \log \frac{\frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(y-1)^2}{2\sigma^2}}}{\frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(y+1)^2}{2\sigma^2}}} \\
 &= \frac{-(y-1)^2 + (y+1)^2}{2\sigma^2} = \frac{2y}{\sigma^2}
 \end{aligned}$$

The L-Value of the channel is a scaled version of the received value y .

$$L_{intr}(y) = \frac{2y}{\sigma^2} + L_{apri}$$

The scaling determines the weighting between observation and a-priori information.

LLR Arithmetic



Joachim Hagenauer (TU Munich)
A great advocate of LLR arithmetic.

$$\sum_{j=1}^J \boxplus L(u_j) = \log \frac{1 + \prod_{j=1}^J \tanh(L(u_j)/2)}{1 - \prod_{j=1}^J \tanh(L(u_j)/2)}$$

$$= 2 \operatorname{artanh} \left(\prod_{j=1}^J \tanh(L(u_j)/2) \right)$$

430 IEEE TRANSACTIONS ON INFORMATION THEORY, VOL. 42, NO. 2, MARCH 1995

variable U . The sign of $L_U(u)$ is the hard decision and the magnitude $|L_U(u)|$ is the reliability of this decision. Unless stated otherwise, the logarithm is the natural logarithm.

If the binary random variable U is conditioned on a different random variable or vector Y , then we have a conditioned log-likelihood ratio $L_{U|Y}(u|y)$ with

$$L_{U|Y}(u|y) = \log \frac{P_{Y|U}(y|u=+1)}{P_{Y|U}(y|u=-1)}$$

$$= \log \frac{P_Y(y|u=+1)}{P_Y(y|u=-1)} + \log \frac{P_{Y|U}(y|u=+1)}{P_{Y|U}(y|u=-1)}$$

$$= L_U(u) + L_{Y|U}(y|u)$$

(2)

When there is no danger of confusion, we will henceforth skip the indices for the probabilities and the log-likelihood ratios. Notice that the joint log-likelihood $L(u, y)$ is equal to the conditioned log-likelihood $L(u|y)$ since the probability $P(y)$ term can be canceled out. Using the relations

$$P(u_1 \oplus u_2 = +1) = P(u_1 = +1) \cdot P(u_2 = +1) + (1 - P(u_1 = +1)) \cdot (1 - P(u_2 = +1))$$

(3)

with

$$P(u = +1) = \frac{e^{L(u)}}{1 + e^{L(u)}}$$

(4)

it is easy to prove for statistically independent random variables U_1 and U_2

$$L(u_1 \oplus u_2) = \log \frac{1 + e^{L(u_1)} e^{L(u_2)}}{e^{L(u_1)} + e^{L(u_2)}} \approx \operatorname{sign}(L(u_1)) \cdot \operatorname{sign}(L(u_2)) \cdot \min(|L(u_1)|, |L(u_2)|)$$

(5)

From now on we will use a special algebra for the log-likelihood ratio values $L(u)$: We use the symbol \boxplus as the notation for the addition defined by

$$L(u_1) \boxplus L(u_2) \triangleq L(u_1 \oplus u_2)$$

(7)

with the additional rules

$$L(u) \boxplus \infty = L(u) \quad L(u) \boxplus -\infty = -L(u)$$

(8)

and

$$L(u) \boxplus 0 = 0$$

(9)

By induction one can further prove that

$$\sum_{j=1}^J \boxplus L(u_j) \triangleq L \left(\sum_{j=1}^J u_j \right)$$

$$= \log \frac{\prod_{j=1}^J (e^{L(u_j)} + 1) + \prod_{j=1}^J (e^{L(u_j)} - 1)}{\prod_{j=1}^J (e^{L(u_j)} + 1) - \prod_{j=1}^J (e^{L(u_j)} - 1)}$$

(10)

is true. Using the relation $\tanh(u/2) = (e^u - 1)/(e^u + 1)$ we obtain [3]

$$\sum_{j=1}^J L(u_j) = \log \frac{1 + \prod_{j=1}^J \tanh(L(u_j)/2)}{1 - \prod_{j=1}^J \tanh(L(u_j)/2)}$$

$$= 2 \operatorname{artanh} \left(\prod_{j=1}^J \tanh(L(u_j)/2) \right)$$

(11)

and finally approximate it as in (6) by

$$\sum_{j=1}^J L(u_j) = L \left(\sum_{j=1}^J u_j \right) \approx \left(\prod_{j=1}^J \operatorname{sign}(L(u_j)) \right) \cdot \min_j |L(u_j)|$$

(12)

The reliability of the sum \boxplus is therefore determined by the smallest reliability of the terms. From (11) we get the symmetrical relation

$$\tanh \left(\frac{1}{2} \sum_{j=1}^J L(u_j) \right) = \prod_{j=1}^J \tanh(L(u_j)/2)$$

(13)

to be used in the Appendix.

B. Soft Channel Outputs

Now, we will define more clearly what is meant by the "soft values" of a channel. If we encode the binary value u having a soft value $L(u)$ then we create coded bits x with soft values $L(x)$. For an (N, K) -systematic code, K of the bits x are equal to the information bits u . After transmission over a binary symmetric channel (BSC) or a Gaussian/fading channel we can calculate the log-likelihood ratio of x conditioned on the matched filter output y

$$L(x|y) = \log \frac{P(x=+1|y)}{P(x=-1|y)}$$

$$= \log \frac{p(y|x=+1)}{p(y|x=-1)} \cdot \frac{P(x=+1)}{P(x=-1)}$$

(14)

With our notation we obtain

$$L(x|y) = \log \frac{\exp(-\frac{\alpha}{2}(y-a)^2)}{\exp(-\frac{\alpha}{2}(y+a)^2)} + \log \frac{P(x=+1)}{P(x=-1)}$$

$$= L_c \cdot y + L(x)$$

(15)

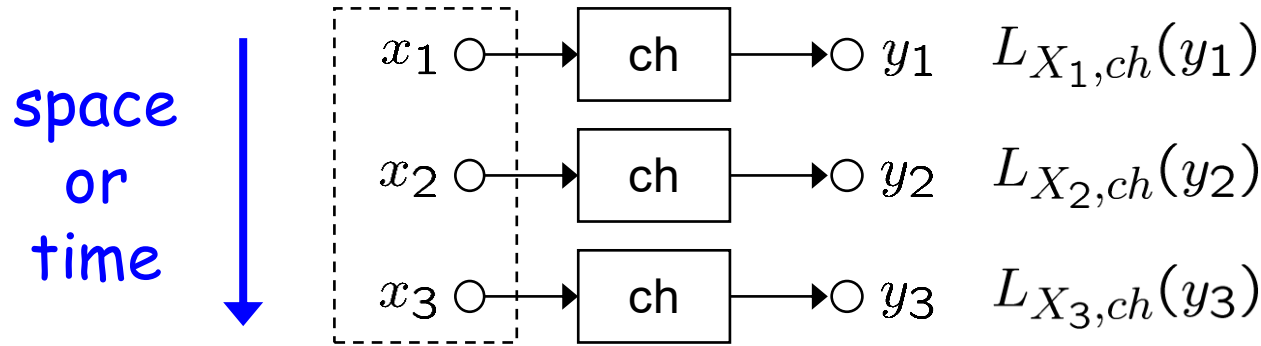
with $L_c = 4a \cdot E_s/N_0$. For a fading channel, a denotes the fading amplitude whereas for a Gaussian channel we set $a = 1$. For a BSC, L_c is the log-likelihood ratio of the crossover probabilities P_b , where $L_c = \log((1 - P_b)/P_b)$. L_c is called the reliability value of the channel.

We further note that for statistically independent transmission, as in dual diversity or with a repetition code

$$L(x|y_1, y_2) = L_{c1} y_1 + L_{c2} y_2 + L(x)$$

(16)

Calculating with LLR



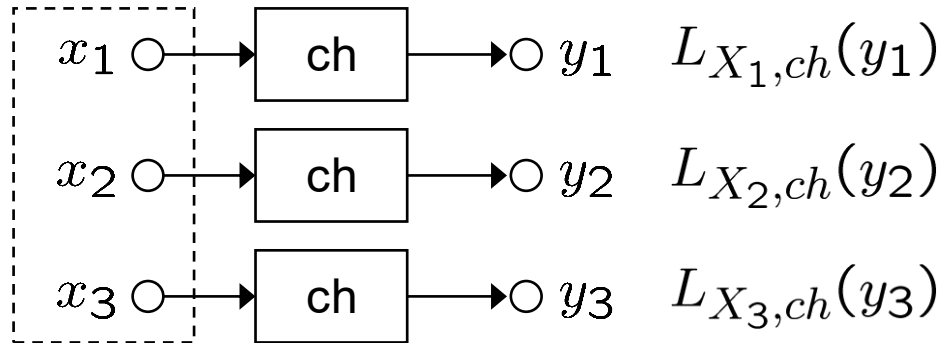
$$\begin{aligned}
 L(X_1 | \underline{Y} = \underline{y}) &= \log \frac{P(X_1 = +1 | \underline{Y} = \underline{y})}{P(X_1 = -1 | \underline{Y} = \underline{y})} = \log \frac{P(X_1 = +1)}{P(X_1 = -1)} + \log \frac{P(\underline{Y} = \underline{y} | X_1 = +1)}{P(\underline{Y} = \underline{y} | X_1 = -1)} \\
 &= \underbrace{\log \frac{P(X_1 = +1)}{P(X_1 = -1)}}_{\text{a-priori L-value}} + \underbrace{\log \frac{P(Y_1 = y_1 | X_1 = +1)}{P(Y_1 = y_1 | X_1 = -1)}}_{\text{channel L-value}} + \underbrace{\log \frac{P(\underline{Y}_{[1]} = \underline{y}_{[1]} | X_1 = +1)}{P(\underline{Y}_{[1]} = \underline{y}_{[1]} | X_1 = -1)}}_{\text{extrinsic L-value}}
 \end{aligned}$$

$$L_{X_1, app}(\underline{y}) = L_{X_1, apri} + L_{X_1, ch}(y_1) + L_{X_1, extr}(\underline{y}_{[1]})$$

For a vector \underline{y} with its i 'th element removed we write

$$\underline{y}_{[i]} = [y_1, \dots, y_{i-1}, y_{i+1}, \dots, y_n]$$

Repeat Code



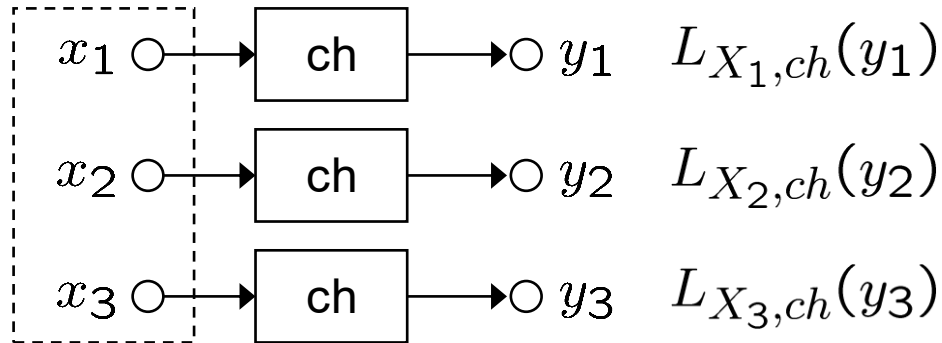
$$x_1 = x_2 = x_3$$

$$\begin{aligned} L_{X_1,extr}(\underline{y}_{[1]}) &= \log \frac{P(\underline{Y}_{[1]} = \underline{y}_{[1]} | X_1 = +1)}{P(\underline{Y}_{[1]} = \underline{y}_{[1]} | X_1 = -1)} \\ &= \log \frac{P(Y_2 = y_2, Y_3 = y_3 | X_2 = +1, X_3 = +1)}{P(Y_2 = y_2, Y_3 = y_3 | X_2 = -1, X_3 = -1)} \\ &= \log \frac{P(Y_2 = y_2 | X_2 = +1)}{P(Y_2 = y_2 | X_2 = -1)} + \log \frac{P(Y_3 = y_3 | X_3 = +1)}{P(Y_3 = y_3 | X_3 = -1)} \end{aligned}$$

$$L_{X_1,extr}(\underline{y}_{[1]}) = L_{X_2,ch}(y_2) + L_{X_3,ch}(y_3)$$

$$L_{X_1,app}(\underline{y}) = L_{X_1,apri} + L_{X_1,ch}(y_1) + L_{X_2,ch}(y_2) + L_{X_3,ch}(y_3)$$

Single Parity-Check Code

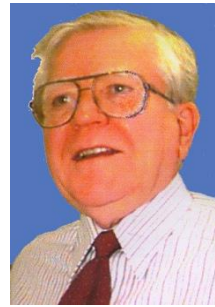


$$x_1 \cdot x_2 \cdot x_3 = +1$$

$$\begin{aligned} L(X_1 | \underline{Y} = \underline{y}) &= \log \frac{P(X_1 = +1)}{P(X_1 = -1)} + \log \frac{P(Y_1 = y_1 | X_1 = +1)}{P(Y_1 = y_1 | X_1 = -1)} + \log \frac{P(\underline{Y}_{[1]} = \underline{y}_{[1]} | X_1 = +1)}{P(\underline{Y}_{[1]} = \underline{y}_{[1]} | X_1 = -1)} \\ &= \log \frac{P(Y_1 = y_1 | X_1 = +1)}{P(Y_1 = y_1 | X_1 = -1)} + \log \frac{P(X_1 = +1 | \underline{Y}_{[1]} = \underline{y}_{[1]})}{P(X_1 = -1 | \underline{Y}_{[1]} = \underline{y}_{[1]})} \end{aligned}$$

$$L_{X_1,ch}(y_1) \quad L_{X_1,apri} + L_{X_1,extr}(\underline{y}_{[1]})$$

Gallager-Lemma



Consider a sequence of m independent binary digits in which the i 'th digit is 1 with probability P_i . Then the probability that an **even** number of digits are 1 is

$$\frac{1 + \prod_{i=1}^m (1 - 2P_i)}{2}$$

The probability that an **odd** number of digits are 1 is

$$1 - \frac{1 + \prod_{i=1}^m (1 - 2P_i)}{2} = \frac{1 - \prod_{i=1}^m (1 - 2P_i)}{2}$$

Single Parity-Check Code



$$\log \frac{P(X_1 = +1 | \underline{Y}_{[1]} = \underline{y}_{[1]})}{P(X_1 = -1 | \underline{Y}_{[1]} = \underline{y}_{[1]})}$$

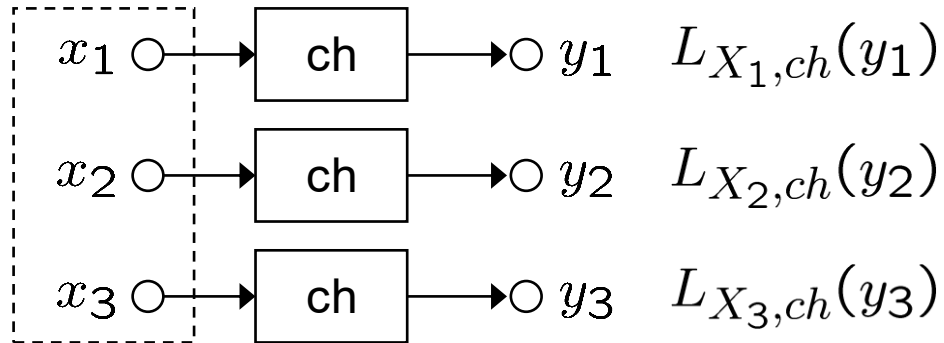
$$\begin{aligned} P(X_1 = -1 | \underline{Y}_{[1]} = \underline{y}_{[1]}) &= P(X_2 \cdot X_3 = -1 | \underline{Y}_{[1]} = \underline{y}_{[1]}) \\ &= \frac{1 - \prod_{i \neq 1} [1 - 2P(X_i = -1 | \underline{Y}_{[1]} = \underline{y}_{[1]})]}{2} \end{aligned}$$

$$\begin{aligned} 1 - 2P(X_1 = -1 | \underline{Y}_{[1]} = \underline{y}_{[1]}) &= \prod_{i \neq 1} [1 - 2P(X_i = -1 | \underline{Y}_{[1]} = \underline{y}_{[1]})] \\ &= \prod_{i \neq 1} [1 - 2P(X_i = -1 | Y_i = y_i)] \end{aligned}$$

$$\tanh \frac{L_{X_1, \text{apri}} + L_{X_1, \text{extr}}(y_{[1]})}{2} = \prod_{i \neq 1} \tanh \frac{L_{X_i, \text{intr}}(y_i)}{2}$$

$$L_{X_1, \text{apri}} + L_{X_1, \text{extr}}(y_{[1]}) = 2 \cdot \tanh^{-1} \prod_{i \neq 1} \tanh \frac{L_{X_i, \text{intr}}(y_i)}{2}$$

Single Parity-Check Code



$$x_1 \cdot x_2 \cdot x_3 = +1$$

$$L(X_1 | \underline{Y} = \underline{y}) = L_{X_1, ch}(y_1) + 2 \cdot \tanh^{-1} \left[\prod_{i \neq 1} \tanh \frac{L_{X_i, intr}(y_i)}{2} \right]$$

$$L_{X_1, ch}(y_1) \quad L_{X_1, apri} + L_{X_1, extr}(\underline{y}_{[1]})$$

If we receive independent noisy observations of the same binary random variable, we can add their channel L-values.

The L-value of a binary random variable that is the XOR of other random variables can be calculated using the tanh-rule.

Single Parity-Check Code Example



Parity-Check code $x_1 \oplus x_2 \oplus x_3 = +1$

Assumption: no a-priori information ($L_{ch} = L_{intr}$)

$$L_{intr} = [+1.50 \quad -2.00 \quad +2.00]$$

$$L(X_1 | \underline{Y} = \underline{y}) = L_{X_1, ch}(y_1) + 2 \cdot \tanh^{-1} \left[\prod_{i \neq 1} \tanh \frac{L_{X_i, intr}(y_i)}{2} \right]$$

$$L_{app} = [+0.18 \quad -0.94 \quad +0.94]$$

Decoder output: +1 -1 +1

This is not a codeword!!!

Single Parity-Check Code Sequence Probability



$$\begin{aligned}P(\underline{X} = \underline{x} | \underline{Y} = \underline{y}) &= P(\underline{Y} = \underline{y} | \underline{X} = \underline{x}) \cdot \frac{P(\underline{X} = \underline{x})}{P(\underline{Y} = \underline{y})} \\&= \frac{P(\underline{X} = \underline{x})}{P(\underline{Y} = \underline{y})} \cdot \prod_i P(Y_i = y_i | X_i = x_i) \\&= \frac{P(\underline{X} = \underline{x})}{P(\underline{Y} = \underline{y})} \cdot \prod_i P(X_i = x_i | Y_i = y_i) \cdot \frac{P(Y_i = y_i)}{P(X_i = x_i)}\end{aligned}$$

$$P(X = +1 | Y = y) = \frac{e^{L_{ch}(y)}}{1 + e^{L_{ch}(y)}} = \frac{e^{\frac{L_{ch}(y)}{2}}}{e^{-\frac{L_{ch}(y)}{2}} + e^{\frac{L_{ch}(y)}{2}}}$$

$$P(X = -1 | Y = y) = \frac{1}{1 + e^{L_{ch}(y)}} = \frac{e^{-\frac{L_{ch}(y)}{2}}}{e^{-\frac{L_{ch}(y)}{2}} + e^{\frac{L_{ch}(y)}{2}}}$$

$$\operatorname{argmax}_{\underline{x} \in \mathcal{C}} \{P(\underline{X} = \underline{x} | \underline{Y} = \underline{y})\} = \operatorname{argmax}_{\underline{x} \in \mathcal{C}} \left\{ \sum_i L_{X_i, ch} \cdot X_i \right\}$$

Single Parity-Check Code Sequence Probability - Example



$$L_{\text{intr}} = [+1.50 \quad -2.00 \quad +2.00]$$

\underline{x}	$\sum_i L_{X_i, \text{intr}} \cdot X_i$
+1 +1 +1	+1.50
+1 -1 -1	+1.50
-1 -1 +1	+2.50
-1 +1 -1	-5.50

- If the decoder uses **a-priori** information it is called maximum a-posteriori (MAP) decoder.
- If the decoder uses **no a-priori** information it is called maximum likelihood (ML) decoder.
- The decoder can be designed to find the most likely **symbol** or the most likely **sequence**. This is independent of the use of a-priori information!