



# Channel coding

## Convolutional codes

Manuel A. Vázquez  
Jose Miguel Leiva  
Joaquín Míguez

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- 1 Codes with memory
- 2 Encoding
- 3 Decoding
- 4 Turbo codes

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# Linear block codes v. convolutional codes

A few (related) differences...

Convolutional codes

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- Encoding is *continuous*

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- Encoding is *blockwise*

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- System has **memory**

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# Linear block codes v. convolutional codes

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Convolutional codes	Linear block codes
<ul style="list-style-type: none"><li>● Encoding is <i>continuous</i></li><li>● System has <b>memory</b></li><li>● Sequence-to-sequence mapping</li></ul>	<ul style="list-style-type: none"><li>● Encoding is <i>blockwise</i></li><li>● System has <b>no memory</b></li><li>● Message-to-codeword mapping</li></ul>

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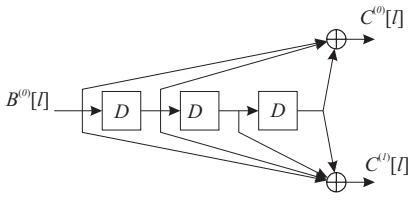
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In both schemes, every operation (e.g., convolution) is in  $GF(2)$ .



# Specification

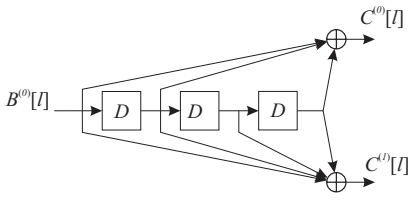
Codes are often specified through a block diagram that illustrates how the input is transformed into the output, e.g.



- $B^{(j)}[l]$  is the  $l$ -th bit of the  $j$ -th input
- $C^{(j)}[l]$  is the  $l$ -th bit of the  $j$ -th output
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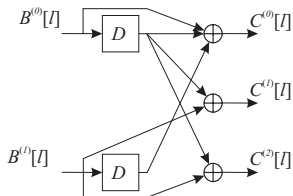
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## The system has memory

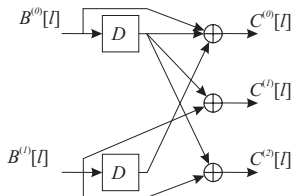
The output bits depend on previous (and current) inputs: this is a **state machine**

# Specification: equations



- Connection between the inputs and the outputs

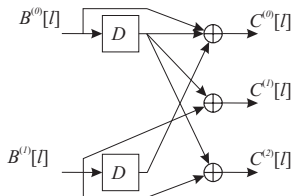
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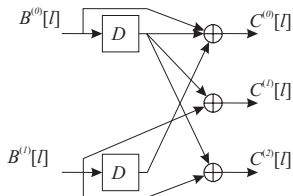


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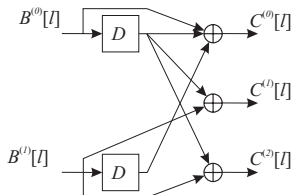
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- we express this relations in the  $D$  domain...

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## Convolution of discrete-time signals

$$x[n] * h[n] = h[n] * x[n] = \sum_{k=-\infty}^{\infty} h[k]x[n-k]$$

and assuming the impulse response,  $h[k]$ , is non-zero between time instants, e.g., 0 and 1

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**Every output is a sum of convolutions!!**

# D transform

## Definition: The $D$ transform...

...of a binary sequence  $B^{(i)}[l]$  is

$$\begin{aligned} B^{(i)}(D) &= \sum_u B^{(i)}[u] \cdot D^u \\ &= \dots B^{(i)}[-1] \cdot D^{-1} + B^{(i)}[0] + B^{(i)}[1] \cdot D^1 + \dots \end{aligned}$$

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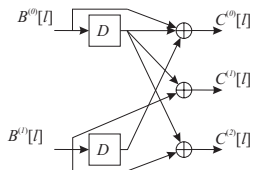
with the property

$$B^{(i)}[l - d] \leftrightarrow B^{(i)}(D) \cdot D^d$$

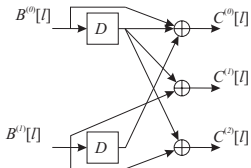
so that, e.g.,

$$B^{(i)}[l] + B^{(i)}[l - 1] + B^{(i)}[l - 2] + B^{(i)}[l - 3] \xleftrightarrow{D} B^{(i)}(D)(1 + D + D^2 + D^3).$$

# Generator matrix



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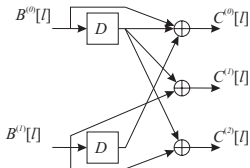
- In polynomial form

$$C^{(0)}(D) = (1 + D)B^{(0)}(D) + DB^{(1)}(D)$$

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- Using matrices:  $\mathbf{C}(D) = \mathbf{B}(D)\mathbf{G}(D)$ , with

$$\mathbf{C}(D) = [C^{(0)}(D) \quad C^{(1)}(D) \quad C^{(2)}(D)] \quad \mathbf{B}(D) = [B^{(0)}(D) \quad B^{(1)}(D)]$$

$$\mathbf{G}(D) = \begin{bmatrix} 1 + D & D & D \\ D & 1 & 1 \end{bmatrix}_{k \times n}$$

$\mathbf{G} \equiv$  generator matrix  
 $g_{ij} \equiv$  contribution of the  $i$ -th input  
 to the  $j$ -th output



# Definitions

## Definition: Overall memory...

...of the code,  $M_t$ , is the number of delay units in the coding scheme.

$$M_t = \sum_{i=0}^{k-1} M^{(i)}$$

with

$$M^{(i)} = \max_j \text{degree}(g_{ij}(D)) \equiv \text{memory } i\text{-th input}$$

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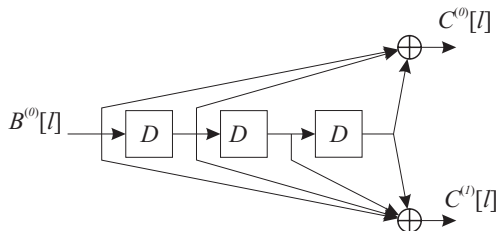
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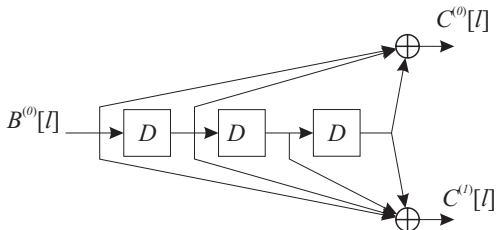
$$K = 1 + \max_{i,j} \text{degree}(g_{ij}(D))$$

A convolutional code can also be **systematic** (same definition).

# The encoder as a finite-state machine



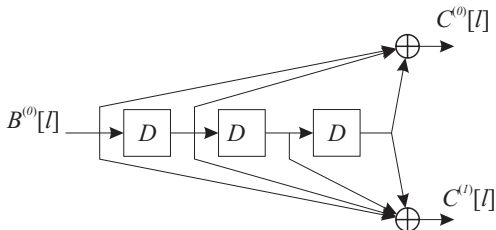
# The encoder as a finite-state machine



- The *state* of the encoder is given by the bits stored (yielded as output) in the delay elements, here

$$\psi \equiv (B^{(0)}[l-1], B^{(0)}[l-2], B^{(0)}[l-3]).$$

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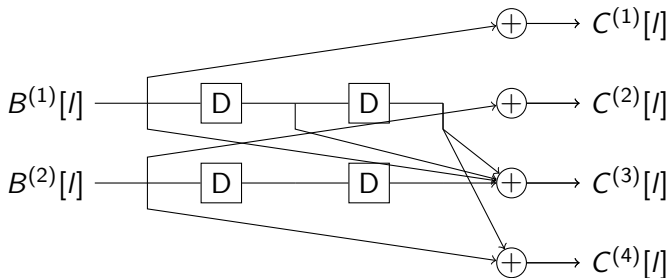
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- **In general there are  $2^{M_t}$  possible states** (bits from delay elements across all the inputs are stacked together). A possible mapping here:

$$\Psi_0 \rightarrow (0, 0, 0) \quad \Psi_1 \rightarrow (1, 0, 0) \quad \Psi_2 \rightarrow (0, 1, 0) \quad \Psi_3 \rightarrow (1, 1, 0)$$

$$\Psi_4 \rightarrow (0, 0, 1) \quad \Psi_5 \rightarrow (1, 0, 1) \quad \Psi_6 \rightarrow (0, 1, 1) \quad \Psi_7 \rightarrow (1, 1, 1)$$

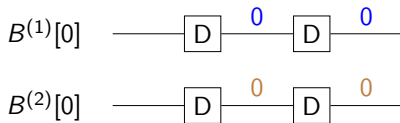
# State transition I



Let us take a look at the evolution of the state of the system for a simple example...

$l$	-2	-1	0	+1
$B^{(1)}[l]$	0	0	1	1
$B^{(2)}[l]$	0	0	0	1
	previous bits		<b>bits to be encoded</b>	

# State transition II



Initial state:

$$\Psi = [0, 0, 0, 0, ]$$



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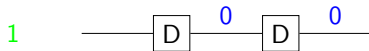
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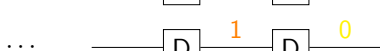


$$B^{(2)}[1] = 1$$



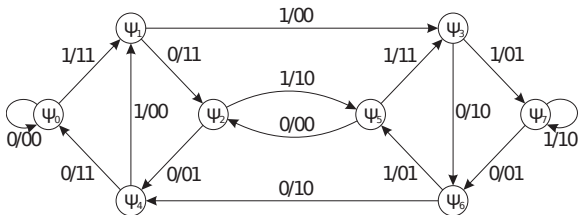
$$\Psi = [1, 1, 1, 0, ]$$

$$B^{(1)}[1] = \dots$$



$$B^{(2)}[1] = \dots$$

# State diagram



Every arrow is labeled with

- the input bits triggering that transition, and
- the output bits originating from that state given the corresponding input bits.

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# Encoding

Straightforward once we know

- the initial state
- the state diagram



## Example

Let us assume we start from state  $\Psi_0$  and we want to encode the sequence [001]. The result is

[00 00 11]

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## ★ Header

After the *information sequence*, a *header* is transmitted to force the encoder to go back to its initial state.

information

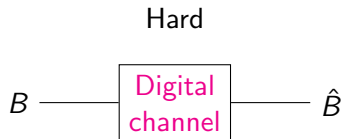
header

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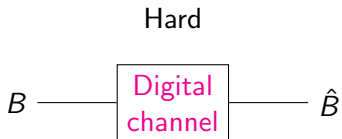


# Decoding

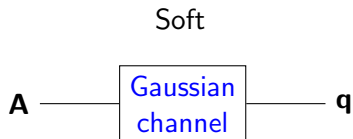


- Metric: **Hamming** distance

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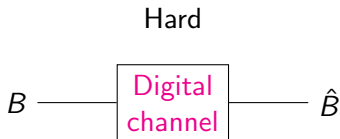


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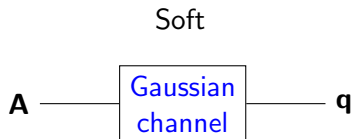


- Metric: **Euclidean** distance  
(at every step, squared difference)

# Decoding



- Metric: **Hamming** distance



- Metric: **Euclidean** distance  
(at every step, squared difference)

In both cases:

- the goal is to find the *full* sequence most likely transmitted
- the solution is given by the Viterbi algorithm

# Viterbi algorithm

Some keys

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- Whenever two paths reach the same state, we keep the one with the smallest *accumulated* cost.



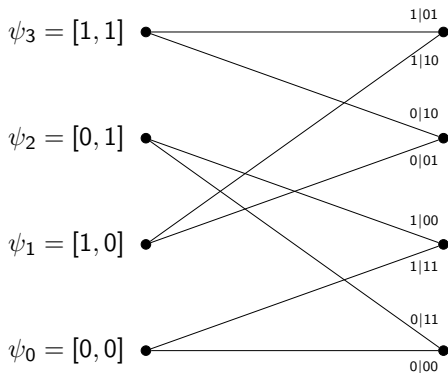
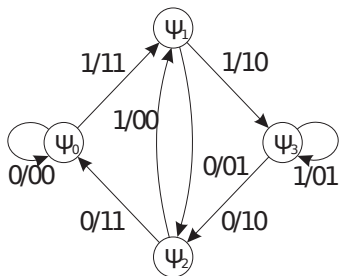
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- At every time instant, for every possible state, we need to find the path reaching it with the smallest accumulated cost.
- Whenever two paths reach the same state, we keep the one with the smallest *accumulated* cost.
- Decoding must end up in the initial state since a *header* is appended to every transmitted sequence in order to enforce this.

# Error-free example

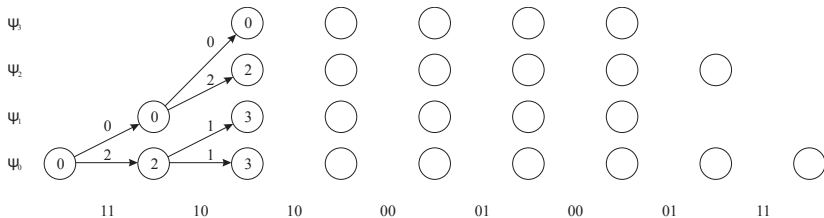
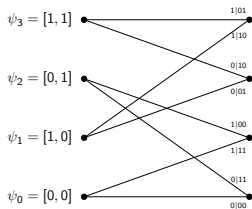
- Input sequence: 1 1 0 1 0 1 0 0
- Received sequence: 11 10 10 00 01 00 01 11



( **Trellis** representation )

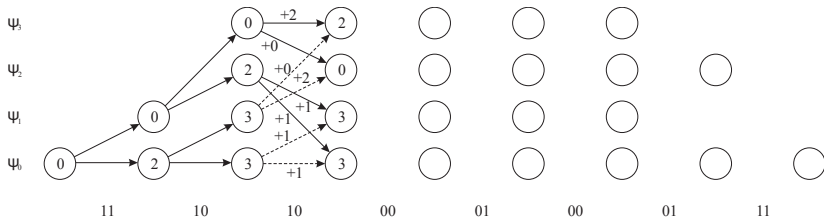
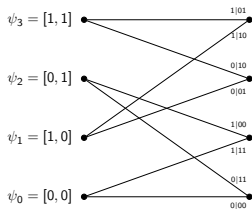
# Error-free example

- Two first iterations



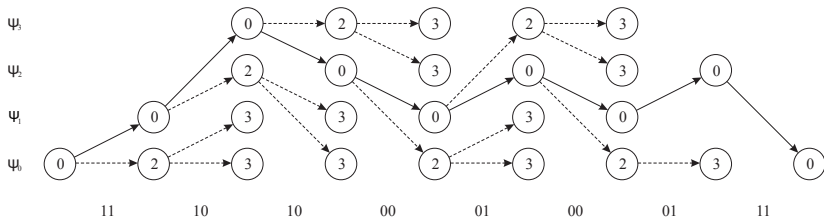
# Error-free example

- Third iteration



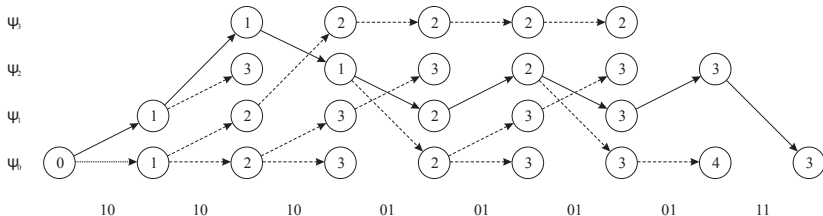
# Error-free example

- Final result



# Example with errors

- Received sequence: 10 10 10 01 01 01 01 11
- Final result



- The states sequence  $\psi_0 \psi_1 \psi_3 \psi_2 \psi_1 \psi_2 \psi_1 \psi_2 \psi_0$  is associated with the input sequence 11010100

# Performance

- Soft decoding

$$P_e \approx \kappa_2 Q \left( \sqrt{\frac{2D_{min}E_s}{N_0}} \right)$$

where  $\kappa_2$  is the number of bit errors (in the decoded sequence) caused by the sequence associated with  $D_{min}$ .

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- Hard decoding

$$P_e \approx \kappa_2 \sum_{i=\lfloor (D_{min}-1)/2 \rfloor + 1}^{nz} \binom{nz}{i} \epsilon^i (1 - \epsilon)^{nz-i}$$

where  $z$  is the length of the trajectory associated with  $D_{min}$  and  $\epsilon$  is the bit error probability.



## Finding the minimum distance $D_{min}$

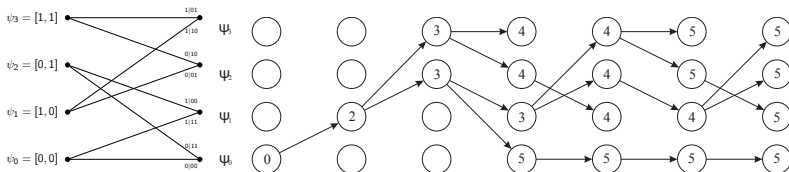
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## Goal

We seek the sequence of states (path) that starts at the all-zeros sequence and goes back to it with the smallest accumulated cost.

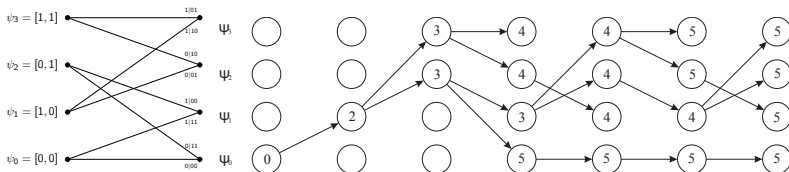


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$D_{min}$  allows computing the remaining parameters that have an impact on the performance

$$D_{min} = 5 \Rightarrow \begin{cases} \kappa_2 = 1 \\ z = 3 \end{cases}$$

# Soft decoding

For the sake of simplicity, let us assume antipodal modulation i.e.,  $A[l] = \pm A$ .

## Notation

$$B_{0,:} = \{B[0], B[1], B[2], \dots\} \equiv \text{input bits}$$
$$q_{0,:} = \{q[0], q[1], q[2], \dots\} \equiv \text{soft estimates}$$

2 possibilities

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$B_{0,:} = \{B[0], B[1], B[2], \dots\} \equiv$  input bits

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2 possibilities

- **Sequence** soft decoding: it minimizes the sequence error probability

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- **Sequence** soft decoding: it minimizes the sequence error probability

$$\hat{B}_{0,:} = \arg \max_{B_{0,:}} p(q_{0,:} | B_{0,:})$$

- **Bitwise** soft decoding: it minimizes the bit error probability

$$\hat{B}[i] = \arg \max_{B[i]} p(B[i] | q_{0,:}), i = 0, 1, \dots$$

# Sequence soft decoding

ML rule  $\equiv$  MAP rule

$$\begin{aligned}\hat{B}_{0,:} &= \arg \max_{B_{0,:}} p(q_{0,:} | B_{0,:}) = \arg \max_{B_{0,:}} \prod_l p(q[l] | B[l]) \\ &= \arg \min_{B_{0,:}} \sum_l -\log p(q[l] | B[l])\end{aligned}$$

where

$$p(q[l] | B[l]) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(q[l] - A[l])^2}{2\sigma^2}\right).$$

Implemented by means of the Viterbi algorithm

# Bitwise soft decoding

## MAP rule

We apply the maximum a posteriori (MAP) rule at the bit level to compute

$$P(B[l] = 1|q_{0,:})$$

and we decide

$$\hat{B}[l] = \begin{cases} 1 & \text{if } p(B[l] = 1|q_{0,:}) > p(B[l] = 0|q_{0,:}) \\ 0 & \text{otherwise} \end{cases}$$

Implemented by means of **BCJR** (Bahl, Cocke, Jelinek and Raviv) algorithm



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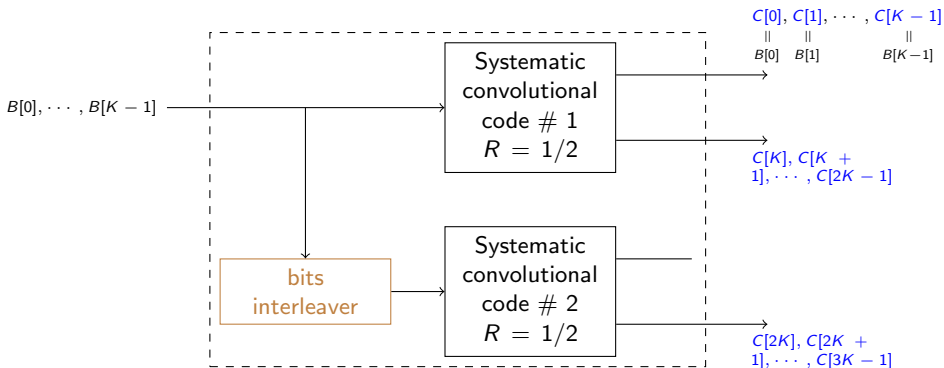
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# Turbo codes

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- They are built by composing two convolutional codes that operate over bits ordered differently.
- Main elements:
  - 2 convolutional codes
  - bit interleaver



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- The interleaver is used to increase the memory of the system without increasing the decoding complexity.
- Good performance in the low-SNR region (at about 0.7 dBs from Shannon limit).
- Regarding decoding...
  - It is iterative since the decoding of the original sequence and the *shuffled* one must agree.
  - Relies on BCJR algorithm.