

Unit 10: Convolutional Codes

EL-GY 6013: DIGITAL COMMUNICATIONS

PROF. SUNDEEP RANGAN

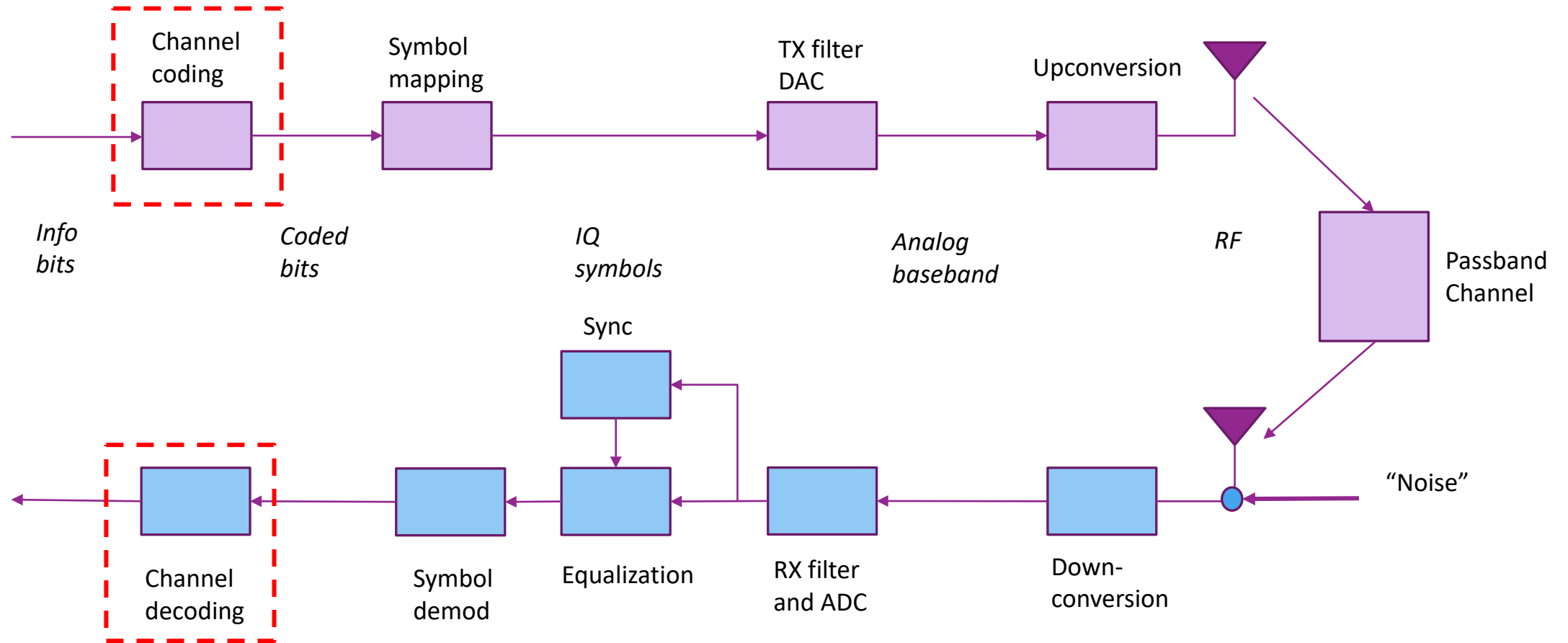
Learning Objectives

- ❑ Encode data using a convolutional code for given a generator polynomial
- ❑ Compute the rate of the code including tail bits
- ❑ Represent the code via a trellis diagram and finite state machine
- ❑ Compute the branch metrics of a code for a memoryless channel
- ❑ Decode the code via the Viterbi algorithm

Graduate vs. Undergraduate

- ❑ Unit 9 on basic codes is skipped for the graduate students
- ❑ However, a few of the Unit 9 slides are included here for completeness
- ❑ Grad students who would like a review are encouraged to look at Unit 9

This Unit



Outline

 Convolutional codes: encoding and representations

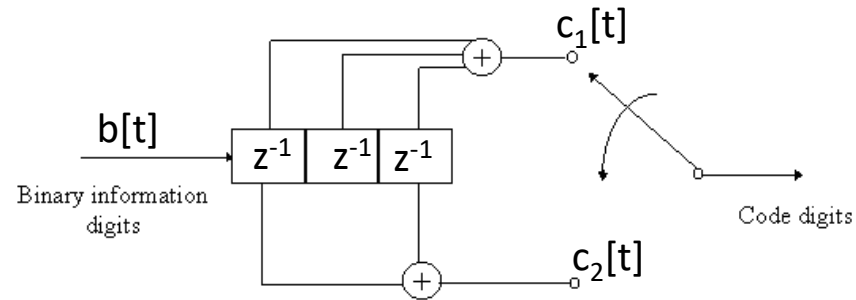
- ☐ Tree, trellis and state diagrams
- ☐ Decoding with branch metrics
- ☐ Viterbi decoding

Convolutional Codes History

- ❑ Generates a stream of coded bits from uncoded bits
 - Block codes form by terminating the stream
- ❑ Output stream created by binary FIR filters
- ❑ Developed originally by Elias (1955)
 - Key challenge was decoders. Much study in 1960s.
 - Practical, optimal decoders developed by Viterbi, 1967.
- ❑ Can perform within 2-3 dB of Shannon limit.
- ❑ Instrumental in Pioneer Space program (along with RS codes)
- ❑ Most widely-used code in industry today: WiFi, cellular
 - In the mid 1990s, longer block length cellular codes were replaced with Turbo codes,
 - But, these use convolutional codes as basis

Convolutional Codes

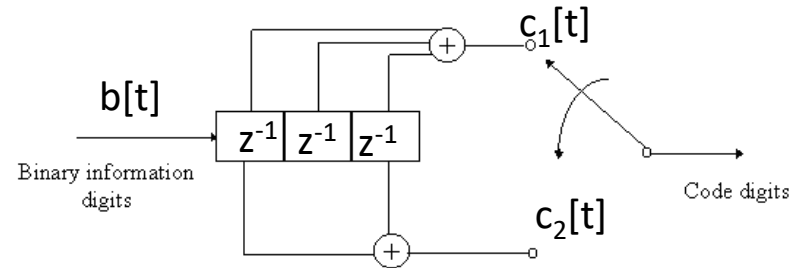
- ❑ Encode data through parallel binary (usu. FIR) filters
- ❑ Example convolutional code:
 - Rate = $\frac{1}{2}$ (two output bits ($c_1[t]$, $c_2[t]$) for each input bit $b[t]$).
 - **Constraint length** $K=3$ (size of shift register)



$$c_1[t] = b[t] + b[t-1] + b[t-2]$$
$$c_2[t] = b[t] + b[t-2]$$

Convolutional Codes

Block Implementation



$$c_1[t] = b[t] + b[t - 1] + b[t - 2]$$
$$c_2[t] = b[t] + b[t - 2]$$

□ To implement as block code:

- Start with L input bits $b[0], b[1], \dots, b[L-1]$
- Append $K-1$ zero $b[L]=b[L+1]=\dots=b[L+K-2]=0$ (called **tail bits**)
- Generate output bits from each branch
 - $c_j[0], c_j[1], \dots, c_j[L+K-2]$, $j=1, \dots, N$ where N = number of branches
- Final codeword is concatenation of branch output
 - $\mathbf{c} = (c_1[0], c_1[1], \dots, c_1[L+K-2], \dots, c_N[0], c_N[1], \dots, c_N[L+K-2])$

□ Effective rate: $R = \frac{L}{N(L+K-1)} \approx \frac{1}{N}$ for large L

Convolutional Codes

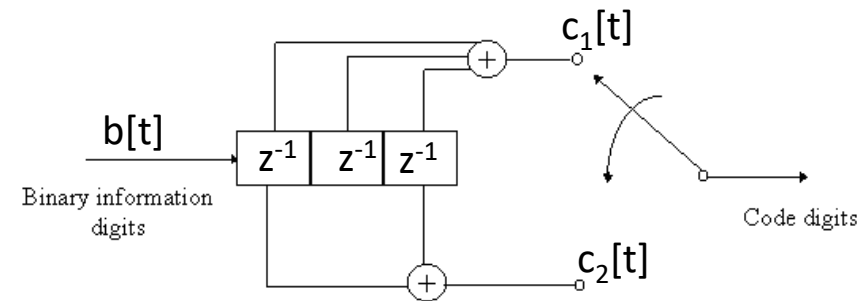
Encoding Example

- ❑ Encode message $\mathbf{b} = [1\ 0\ 1]$
- ❑ Branch outputs $\mathbf{c1}=[11011]$ $\mathbf{c2}=[11001]$
- ❑ Final output $\mathbf{c}=[11,10,00,10,11]$ (interleaved)
- ❑ Rate = 3/10

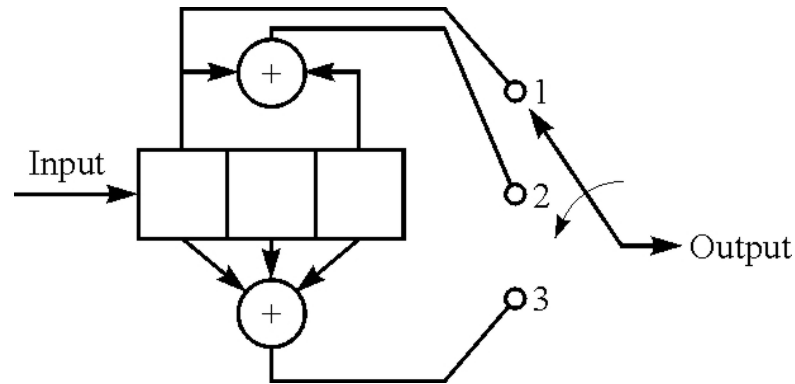
| t | b[t] | c1[t] | c2[t] |
|---|------|-------|-------|
| 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 0 |
| 2 | 1 | 0 | 0 |
| 3 | 0 | 1 | 0 |
| 4 | 0 | 1 | 1 |

Tail bits {

$$c_1[t] = b[t] + b[t-1] + b[t-2]$$
$$c_2[t] = b[t] + b[t-2]$$



Generator Polynomials: Binary Form



Rate 1/3, K=3 example:

$$c_1[t] = b[t]$$

$$c_2[t] = b[t] + b[t - 1]$$

$$c_3[t] = b[t] + b[t - 1] + b[t - 2]$$

□ Code polynomials: Binary vector of filter coefficients

$$g_1 = [100]$$

$$g_2 = [101]$$


$$g_3 = [111]$$

Generator Polynomials: Octal Form

❑ For large constraint lengths (large K), binary form is inefficient

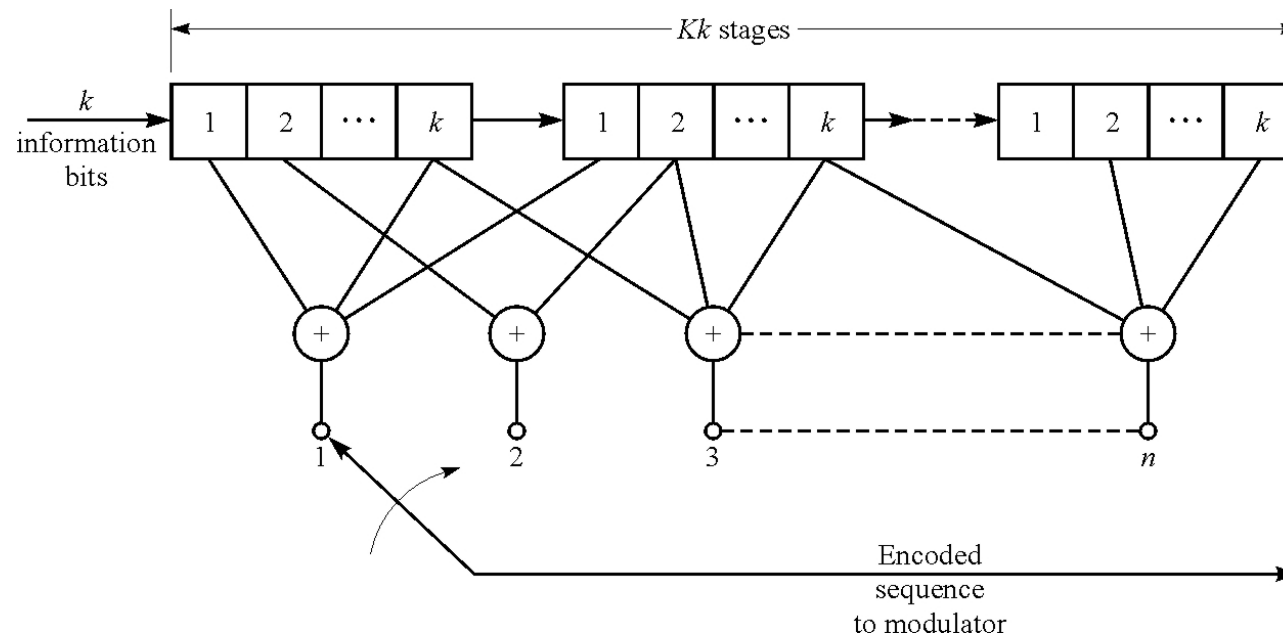
- Engineers often use octal form
- Base 8, each digit 0...7
- Each digit represents three bits

❑ Example:

| | | |
|------------------|---|--------------|
| $g_1 = [1\ 011]$ |  | $g_1 = [13]$ |
| $g_2 = [1\ 101]$ | | $g_2 = [15]$ |
| $g_3 = [1\ 010]$ | | $g_3 = [12]$ |
| Binary | | Octal |

Multiple Inputs

- ❑ Examples up to now are $R=1/n$
- ❑ Can extend to rate $R=k/n$
 - Add k bits at a time



In-Class Exercise

Convolution Code In-Class Exercises

Building an Encoder

We will look at a simple $R=1/2$ convolution code:

$$\begin{aligned}c(t,1) &= b(t) + b(t-1) + b(t-2) \\ c(t,2) &= b(t) + b(t-2)\end{aligned}$$

This encoder can be represented with a generator matrix G as shown.

```
G = [1 1 1; 1 0 1];  
nin = 1;           % number of input streams  
nout = size(G,1);  % number of output streams  
conLen = size(G,2); % constraint length
```

We will build a simple encoder using the convolution method. The convolution method in MATLAB uses real values, so we will use a modulo to convert back to .

Outline

☐ Convolutional codes: encoding and representations

 Tree, trellis and state diagrams

☐ Decoding with branch metrics

☐ Viterbi decoding

Convolutional Codes as State Machines

- ❑ Convolutional codes have memory
 - Stored in contents of shift registers
 - Each input bit changes memory contents
 - Output bits are a function of memory and input

- ❑ Three common ways to represent evolution of the memory:
 - Tree diagram
 - Trellis diagram
 - State diagram

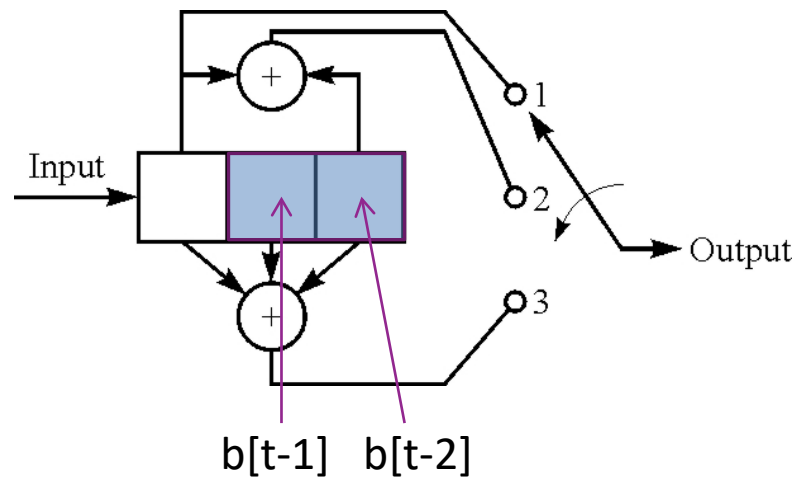
Encoder States

- State of the encoder determined by contents of shift register:

$$x[t] = (b[t - 1], \dots, b[t - K])$$

- Only need to look at most recent $K-1$ bits not including the current bit

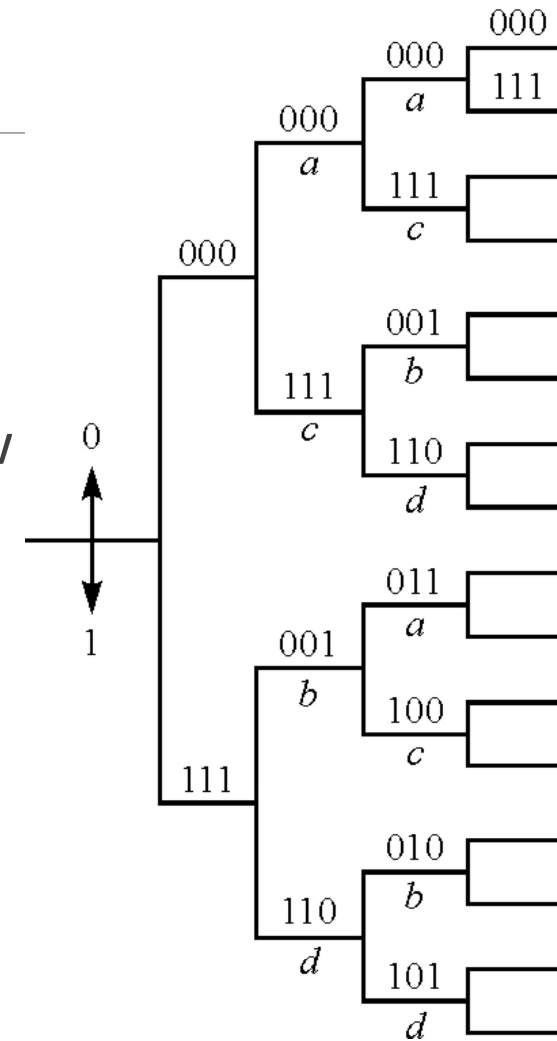
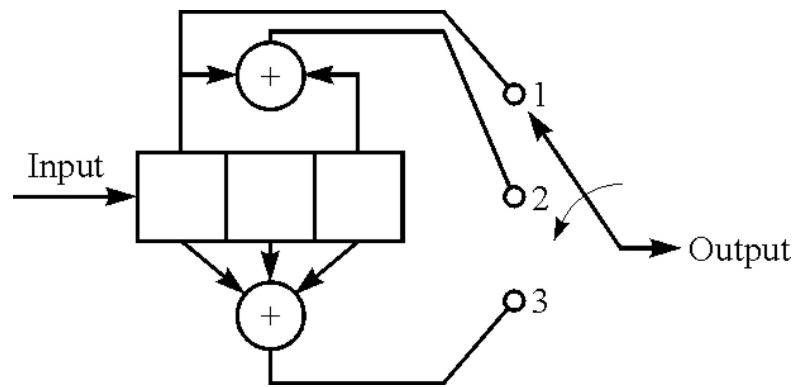
- Last bit will be shifted out
- There are 2^{K-1} states



| State label | $b[t - 1]$ | $b[t - 2]$ |
|-------------|------------|------------|
| a | 0 | 0 |
| b | 0 | 1 |
| c | 1 | 0 |
| d | 1 | 1 |

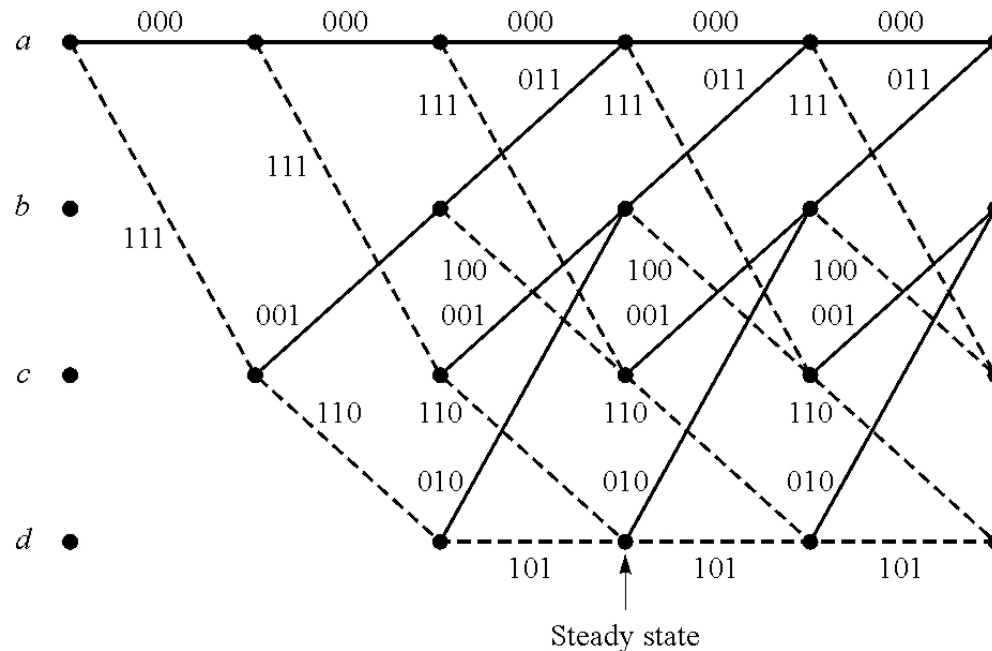
Tree Diagram

- ❑ Two branches for each input bit 0 or 1.
- ❑ Branches labeled by output bits (n bits)
- ❑ Difficult to use since branches infinitely grow



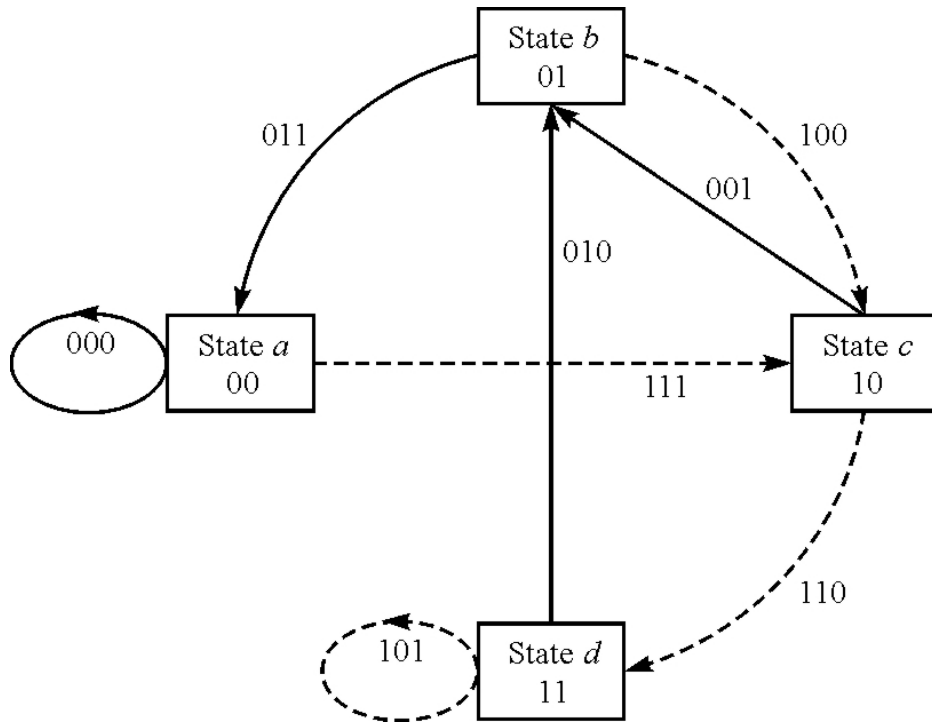
Trellis Diagram

- Show trajectory through the states
- Solid lines: paths with $b[t]=0$, Dash lines: $b[t]=1$



Labels are the outputs along each path

State Diagram



❑ One node per state

❑ Solid lines:

- Transitions with $b[t]=0$

❑ Dashed lines:

- Transitions with $b[t]=1$

❑ Labels indicate outputs on each state

State Machine Functional Description

□ Finite state machine:

- $x[t]$: Sequence of **states**, $x[t] \in \{0, \dots, 2^{K-1} - 1\}$
- $b[t]$: Input sequence
- $c[t]$: Output sequence

□ Iterative generating sequence:

$$\begin{aligned} x[t+1] &= f(x[t], b[t]) && \leftarrow \text{State function} \\ c[t] &= h(x[t], b[t]) && \leftarrow \text{Output function} \end{aligned}$$

□ Initial condition: $x[0]$

In-Class Exercise

Representing the State Transition Function

We wish to represent the convolutional encoder as a finite state machine. To this end, we will represent the states by a single decimal number:

$$x(t) = 2*b(t-2) + b(t-1) + 1$$

This state runs from $x(t) = 1, \dots, nstate$ where $nstate = 2^{\{convLen-1\}}$

To represent the state transition, we create a matrix `xnextMat`

- `xnextMat(i,1)` = the value of $x(t+1)$ when $b(t)=0$ and $x(t)=i$
- `xnextMat(i,2)` = the value of $x(t+1)$ when $b(t)=1$ and $x(t)=i$

```
ninVal = 2^nin;           % number of input values per time step
nstate = 2^(conLen-1);    % number of states


% Intiialize matrix
xnextMat = zeros(nstate,ninVal);

% TODO: Write a for loop to fill in the xnextMat matrix
```

We next create a matrix to represent the output:

- `coutMat(k,i,j)` = output $c(t,k)$ when $x(t)=i$ and $b(t)=j+1$

Outline

- ☐ Convolutional codes: encoding and representations
- ☐ Tree, trellis and state diagrams
-  ☐ Decoding with branch metrics
- ☐ Viterbi decoding

ML Estimation

- ❑ Assume the following dimensions:
 - N outputs per time steps: $c[t] = (c_1[t], \dots, c_N[t])$
 - T time steps (including tail bits!)

- ❑ Channel model:
 - For each bit $c_i[t]$, we make some observation $r_i[t]$
 - Output is probabilistic $P(r_i[t]|c_i[t])$
 - Assume all outputs are independent:

$$P(\mathbf{r}|\mathbf{c}) = \prod_{t=0}^{T-1} \prod_{i=1}^N P(r_i[t]|c_i[t])$$

- ❑ Find ML estimate:

$$\hat{c} = \arg \max_c P(r|c)$$

- Maximum over all sequences

LLR Review

□ Before studying convolutional codes, consider simple code:

- Codeword has N output bits: $\mathbf{c} = (c_1, \dots, c_N)$
- Receive N symbols $\mathbf{r} = (r_1, \dots, r_N)$. Each r_i may be binary, discrete, real-valued or complex-valued
- Assume a memoryless channel:

$$P(\mathbf{r}|\mathbf{c}) = \prod_{i=1}^N P(r_i|c_i)$$

□ Define LLR: $L_i = \log \frac{P(r_i|c_i=1)}{P(r_i|c_i=0)}$

□ **Theorem**: The ML codeword maximizes the LLR sum **value function** (se Unit 9)

$$\hat{\mathbf{c}} = \arg \max_{\mathbf{c}} J(\mathbf{c}), \quad J(\mathbf{c}) = \sum_{i=0}^{N-1} c_i L_i$$

Example 1: Binary Symmetric Channel

□ Binary symmetric channel: Output $r_i = 0$ or 1

□ Error probability $p < 1/2$

$$P(r_i|c_i) = \begin{cases} 1-p & \text{if } c_i = r_i \text{ (no error)} \\ p & \text{if } c_i \neq r_i \text{ (error)} \end{cases}$$

□ Branch metric: $L_i = \begin{cases} A & \text{if } c_i = r_i \text{ (no error)} \\ -A & \text{if } c_i \neq r_i \text{ (error)} \end{cases}$, $A = \log \frac{1-p}{p} > 0$

□ Observe $c_i L_i = A(1_{\{r_i=c_i\}} + 1 - r_i)$

□ Hence maximizing value function:

$$\begin{aligned} \arg \max_c J(c) &= \arg \max_c \sum [1_{\{r_i=c_i\}} + 1 - r_i] = \arg \max_c \sum [1_{\{r_i=c_i\}}] \\ &= \arg \max_c \#(\text{correct bits}) \end{aligned}$$

Example 2: QPSK Channel

- Binary modulation (on a real or imaginary dimension):

$$r_i = s_i + w_i, \quad w_i \sim N(0, N_0/2), \quad s_i = \begin{cases} A & c_i = 1 \\ -A & c_i = 0 \end{cases}$$

- Gaussian distribution: $\log p(r_i | s_i) = -\frac{1}{N_0} (r_i - s_i)^2 - \frac{1}{2} \log \frac{N_0}{2}$

- LLR is: $L_i = \log p(r_i | s_i = A) - \log p(r_i | s_i = -A) = -\frac{1}{N_0} [(r_i - A)^2 - (r_i + A)^2] = \frac{4A}{N_0} r_i$

- LLR sum value function:

$$J(c) = \sum_i L_i c_i = \frac{4A}{N_0} \sum_i r_i c_i$$

Branch Metric

□ Log-likelihood ratio: $L_i[t] = \log \frac{P(r_i[t] | c_i[t] = 1)}{P(r_i[t] | c_i[t] = 0)}$

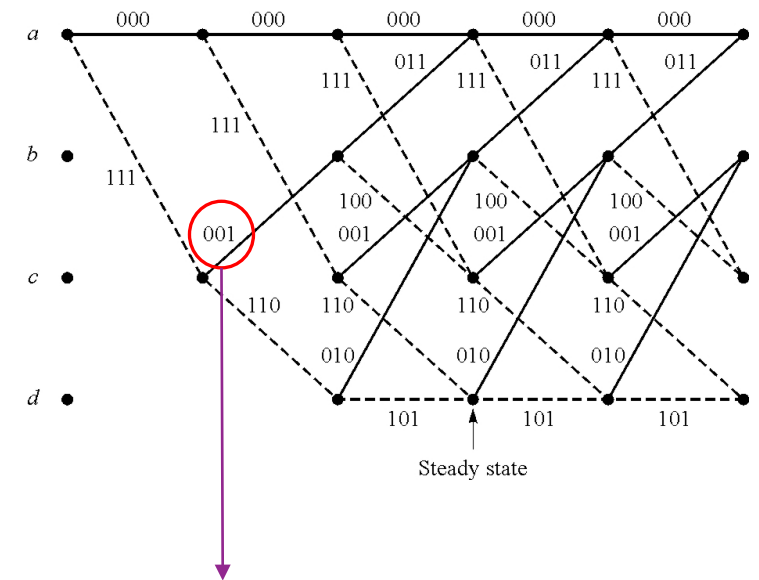
- Depends on received symbol $r_i[t]$

□ Each branch has an output set of bits $c[t] = (c_1[t], \dots, c_N[t])$

□ Define the **branch metric**:

$$\mu_t(x_{t+1}, x_t) = \sum_{i=1}^N c_i[t] L_i[t]$$

- $c_i[t]$ is the coded outputs on the branch
- Describes likelihood that sequence passed through the branch
 - Branches with higher branch metrics are more likely



$$c[t] = (0,0,1) \Rightarrow \mu_t = 0L_1[t] + 0L_2[t] + L_3[t] = L_3[t]$$

Branch Metric Maximization

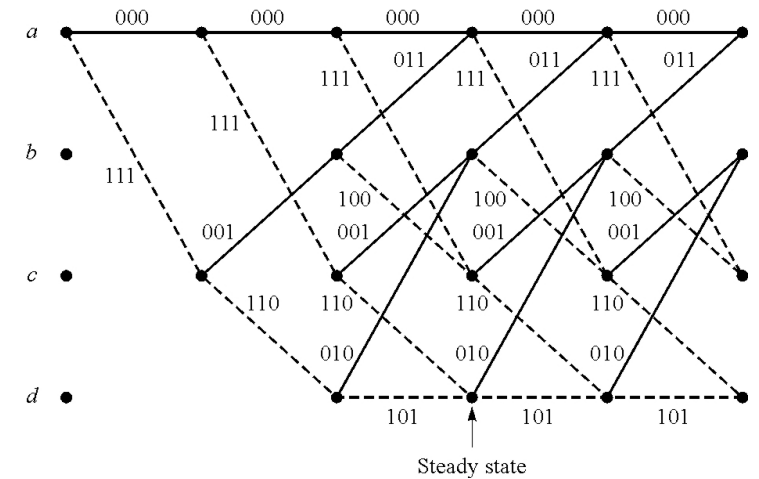
□ Each branch in trellis has a branch metric $\mu_t(x_{t+1}, x_t) = \sum_{i=1}^N c_i[t] L_i[t]$

□ We can write LLR sum value function as:

$$J(c) = \sum_{t=0}^{T-1} \sum_{i=1}^N c_i[t] L_i[t] = \sum_{t=0}^{T-1} \mu_t(x_{t+1}, x_t)$$

□ Interpretation:

- Each code sequence is a path in the trellis
- Value function is the sum of branch metrics on the path



Conclusion: ML estimate is the codeword with the highest total path

Example

❑ Consider toy Trellis (not a real conv code)

❑ Input: $b[t], t = 0, 1, 2$

❑ Output: $c[t] = (c_1[t], c_2[t])$

- Shown on branches

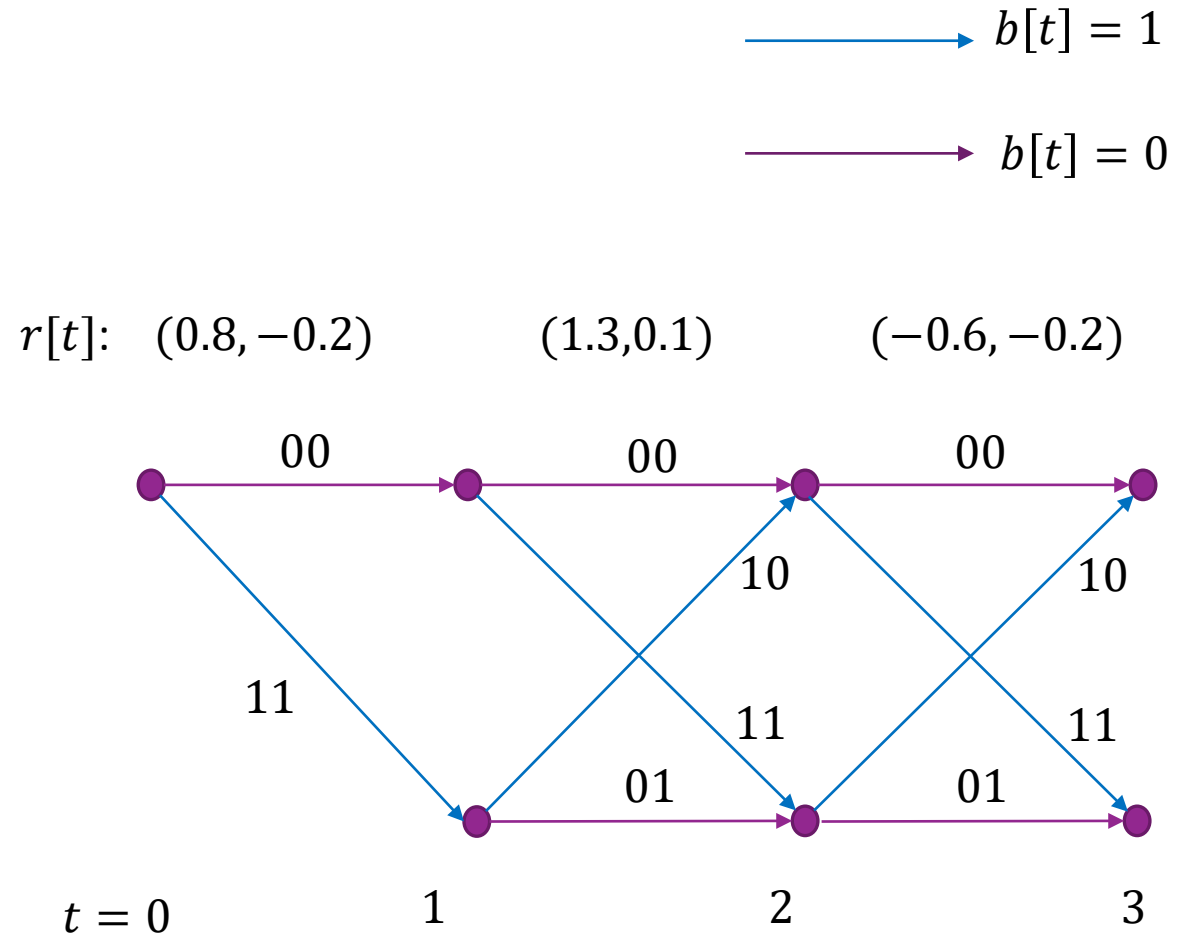
❑ RX symbols: $r[t] = (r_1[t], r_2[t])$

- Values shown above Trellis

❑ Assume QPSK channel value function:

$$J(c) = \sum_t \sum_i r_i c_i$$

- Constant is ignored

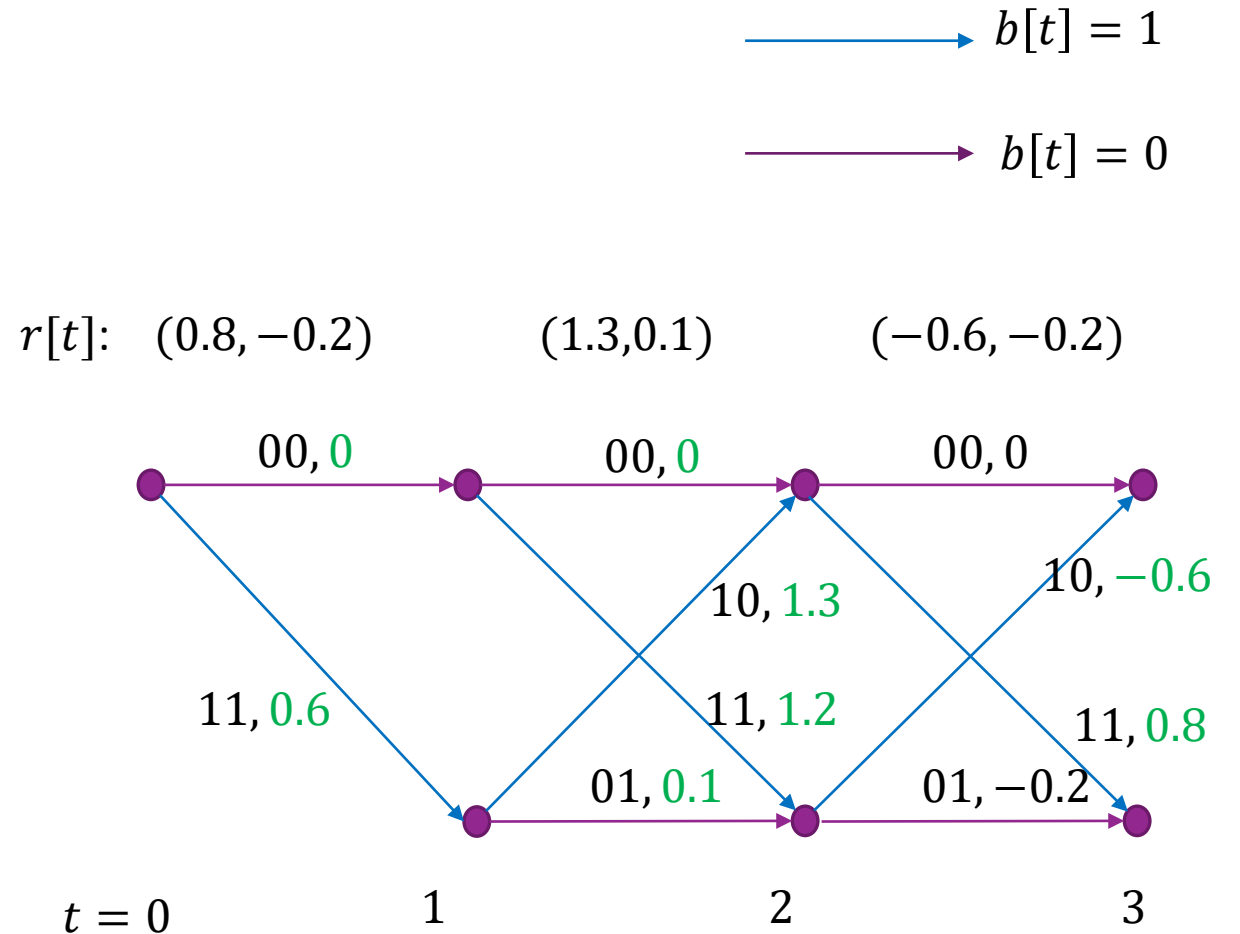


Step 1: Compute Branch Metrics

- For QPSK channel, branch metric is

$$\mu_t(x_{t+1}, x_t) = \sum_i r_i[t] c_i[t]$$

- On each branch we have labeled:
(Output Bits, **branch**) = $(c[t], \mu_t)$



Step 2: Find the Maximizing Path

□ For this simple Trellis, we can do this manually

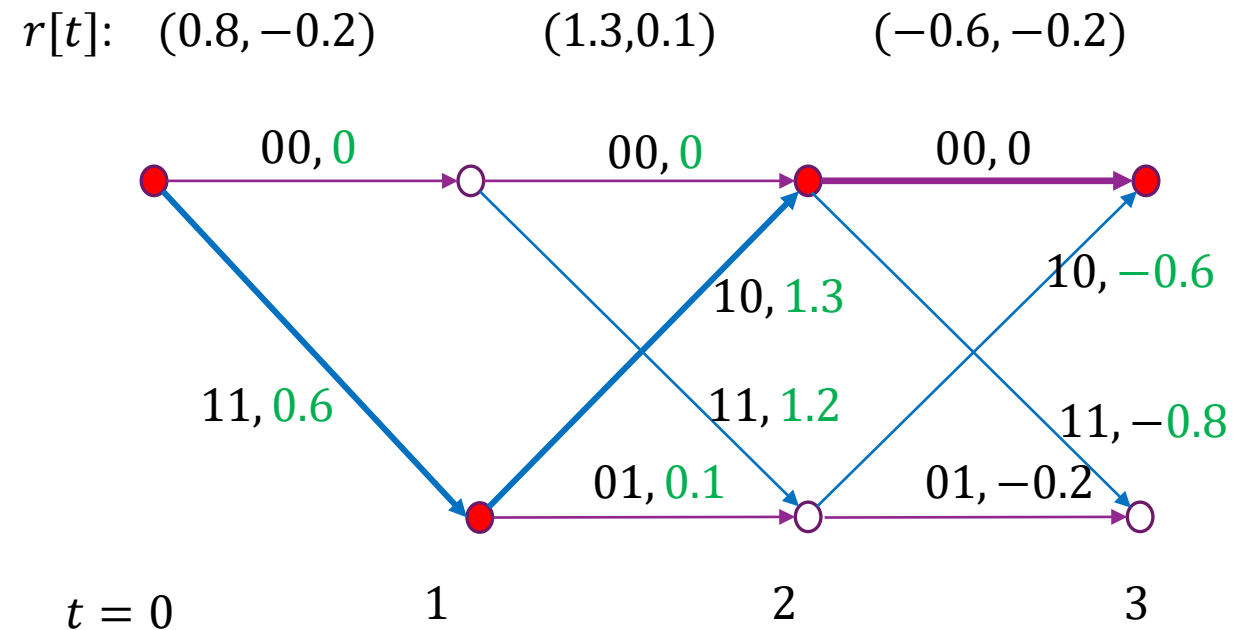
□ Path is shown with red nodes ●

□ Solution:


- Coded sequence: (11), (10), (00)
- Bits: (1,1,0)

→ $b[t] = 1$

→ $b[t] = 0$

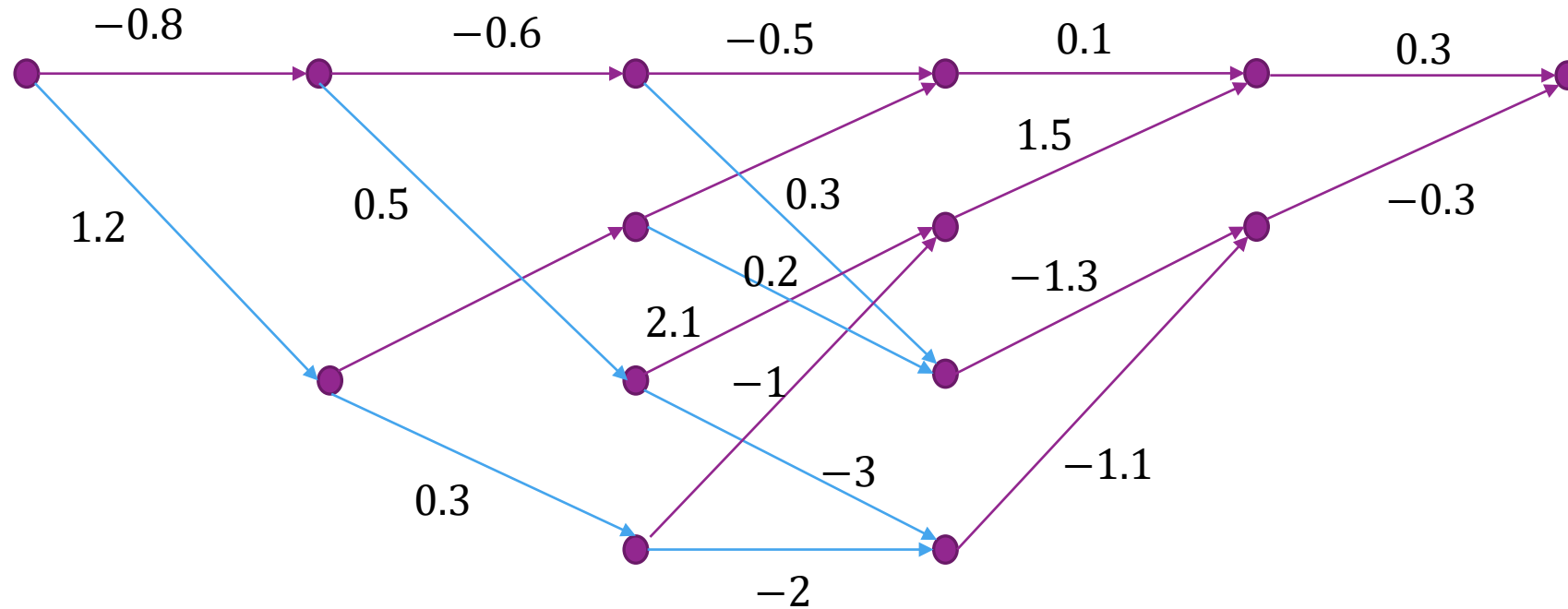


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- ☐ Convolutional codes: encoding and representations
- ☐ Tree, trellis and state diagrams
- ☐ Decoding with branch metrics
-  ☐ Viterbi decoding

Viterbi Algorithm by Example

- Iterative solution for finding maximum path in a graph
- Key idea: Find the max path one time step at a time
- We will illustrate by example: Shown are the branch metrics

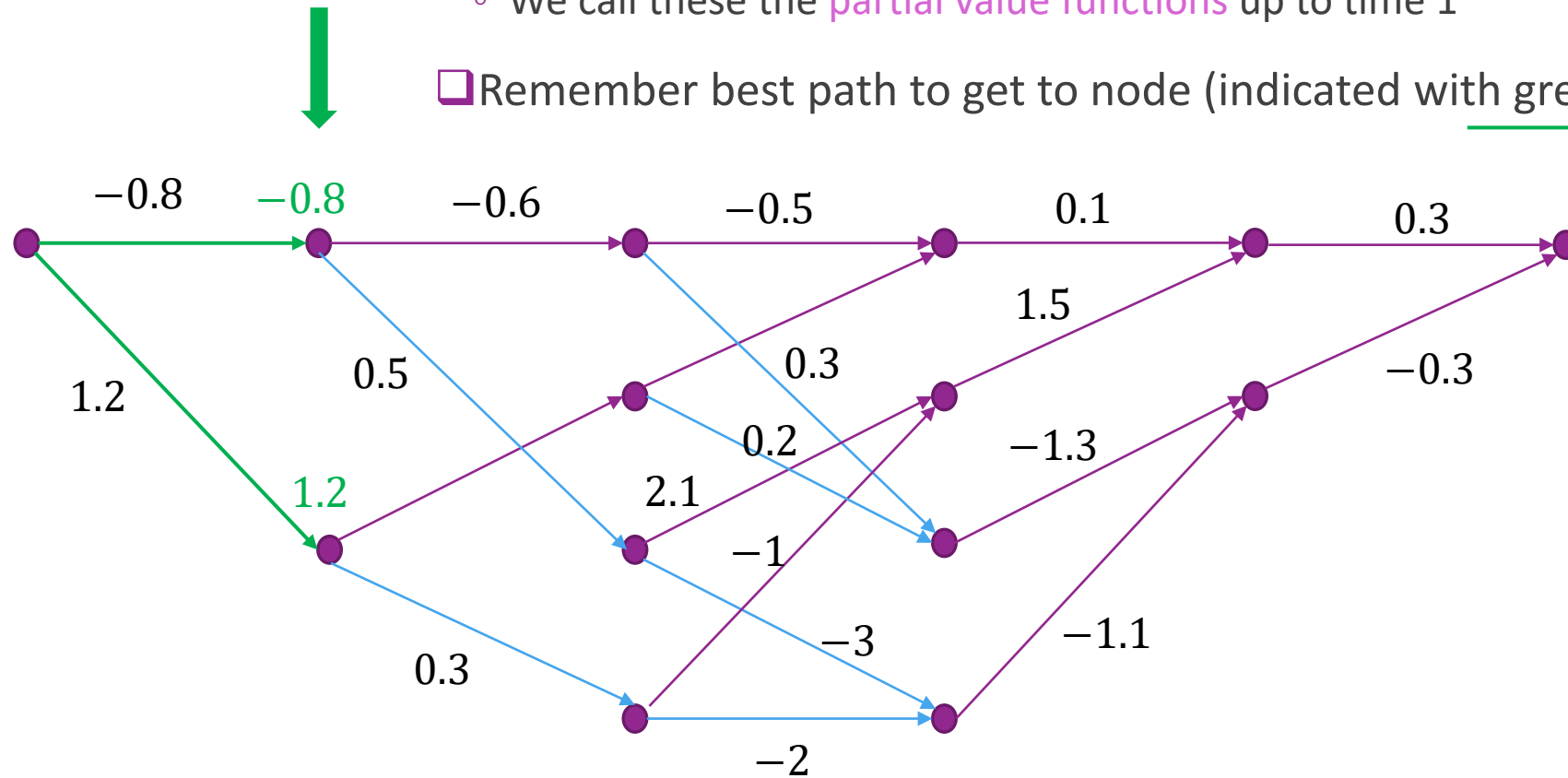


Ex: Time 1

Find total value to get to each node at time 1

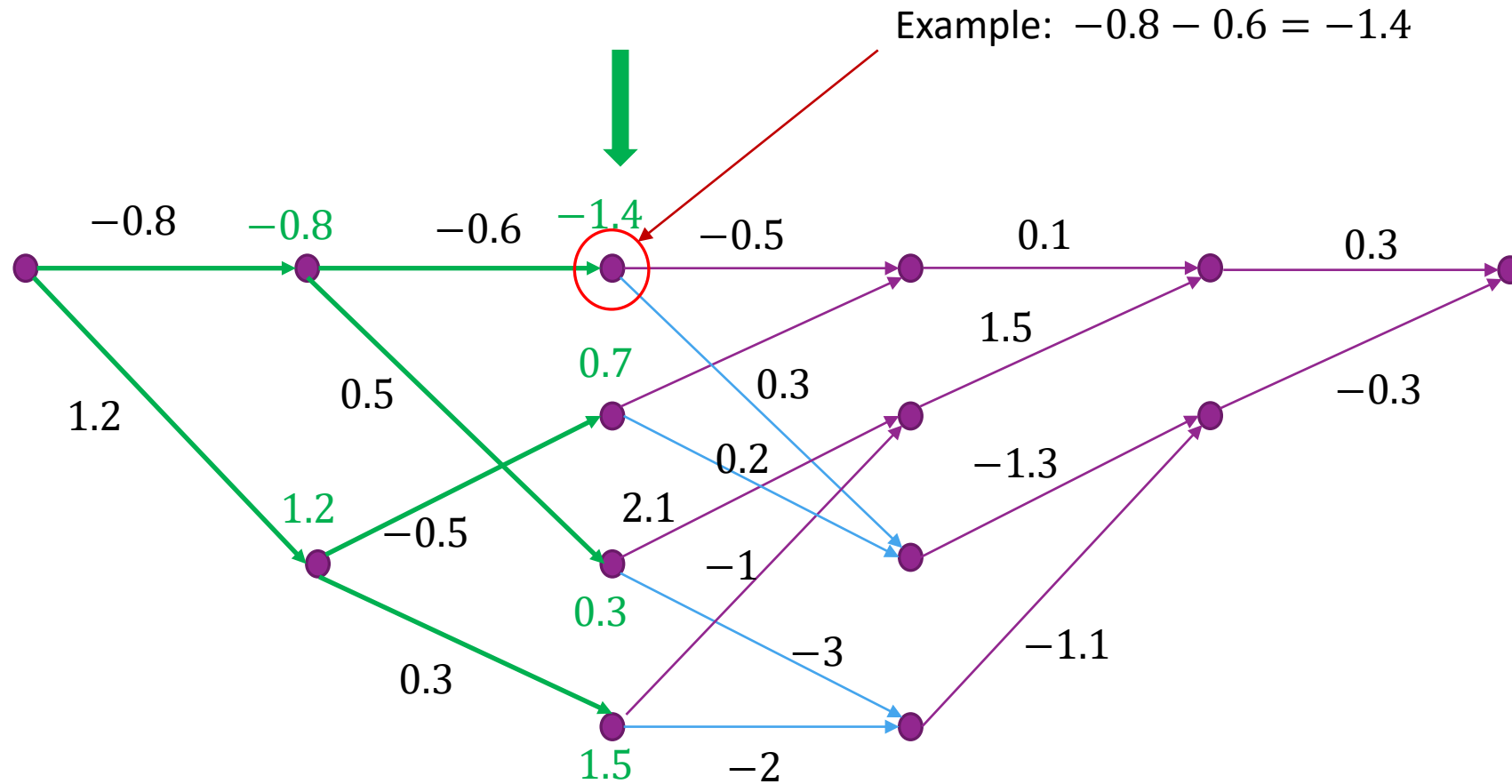
◦ We call these the **partial value functions** up to time 1

Remember best path to get to node (indicated with green line)



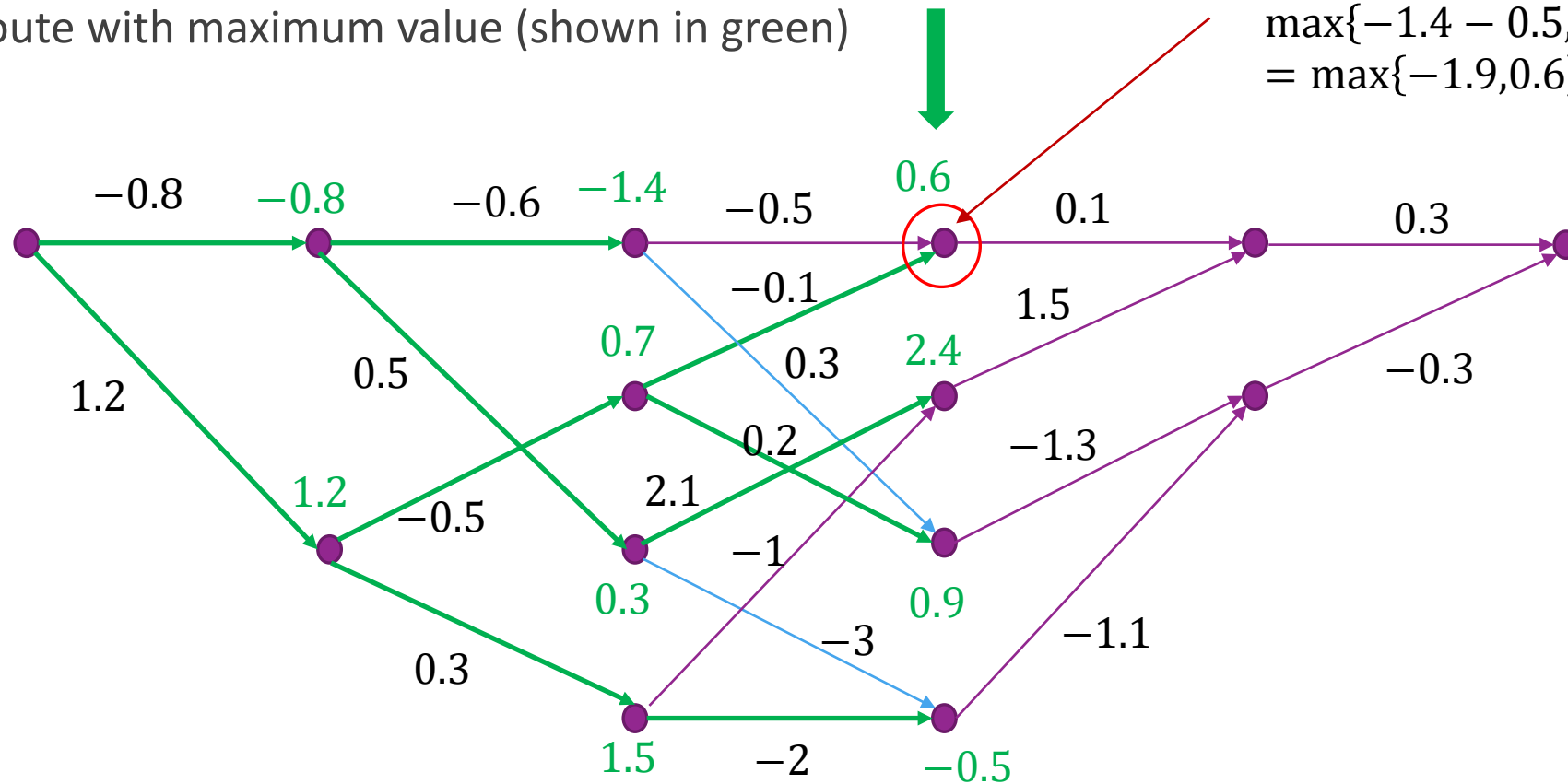
Ex: Time 2

□ Add value from Time 1 + branch



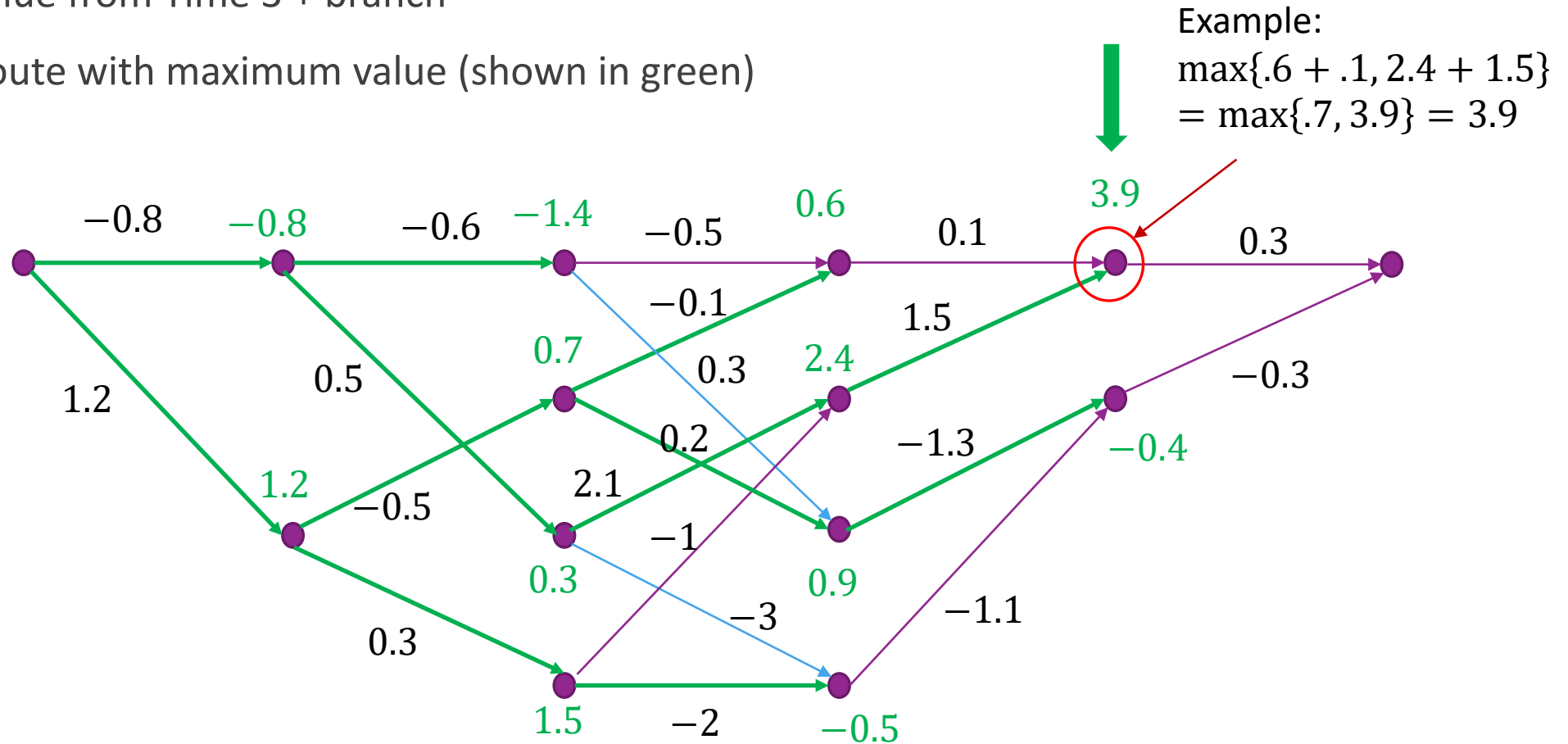
Ex: Time 3

- Add value from Time 2 + branch
- Take route with maximum value (shown in green)



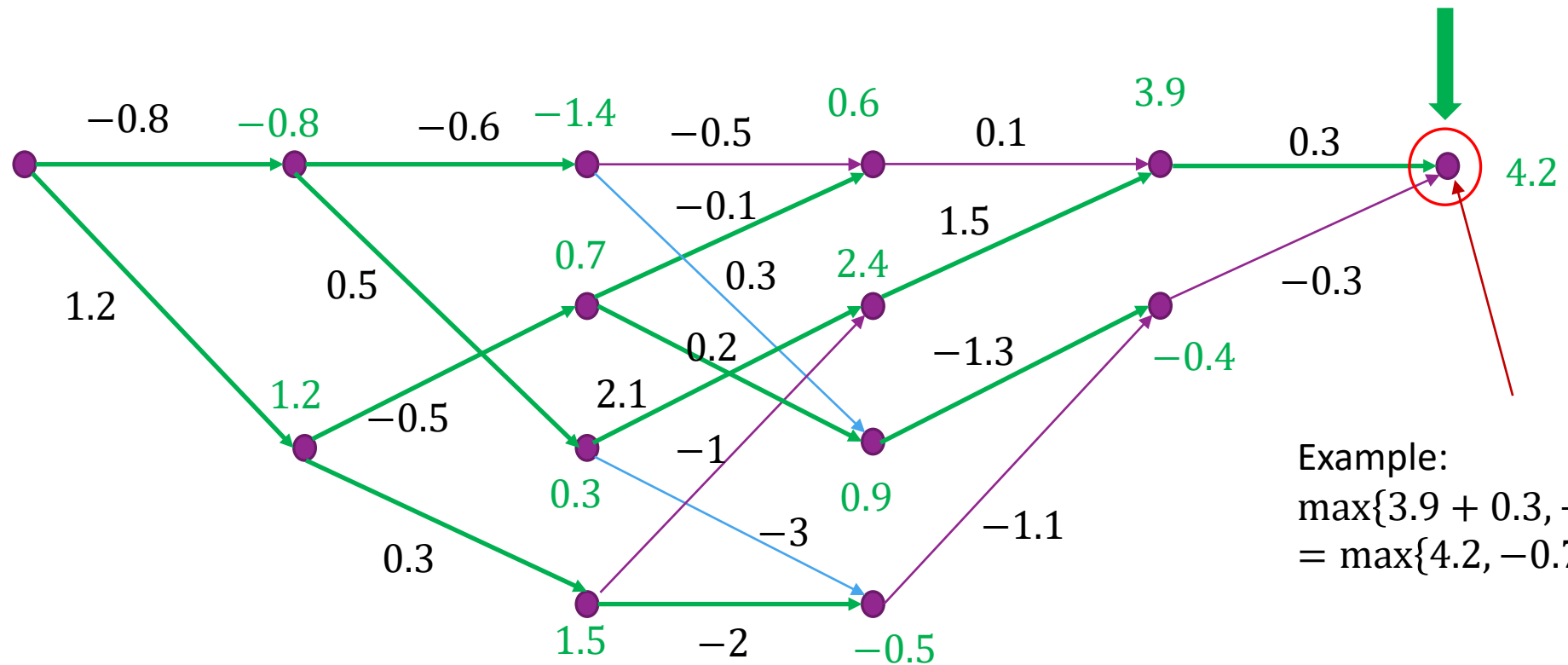
Ex: Time 4

- Add value from Time 3 + branch
- Take route with maximum value (shown in green)



Ex: Time 5

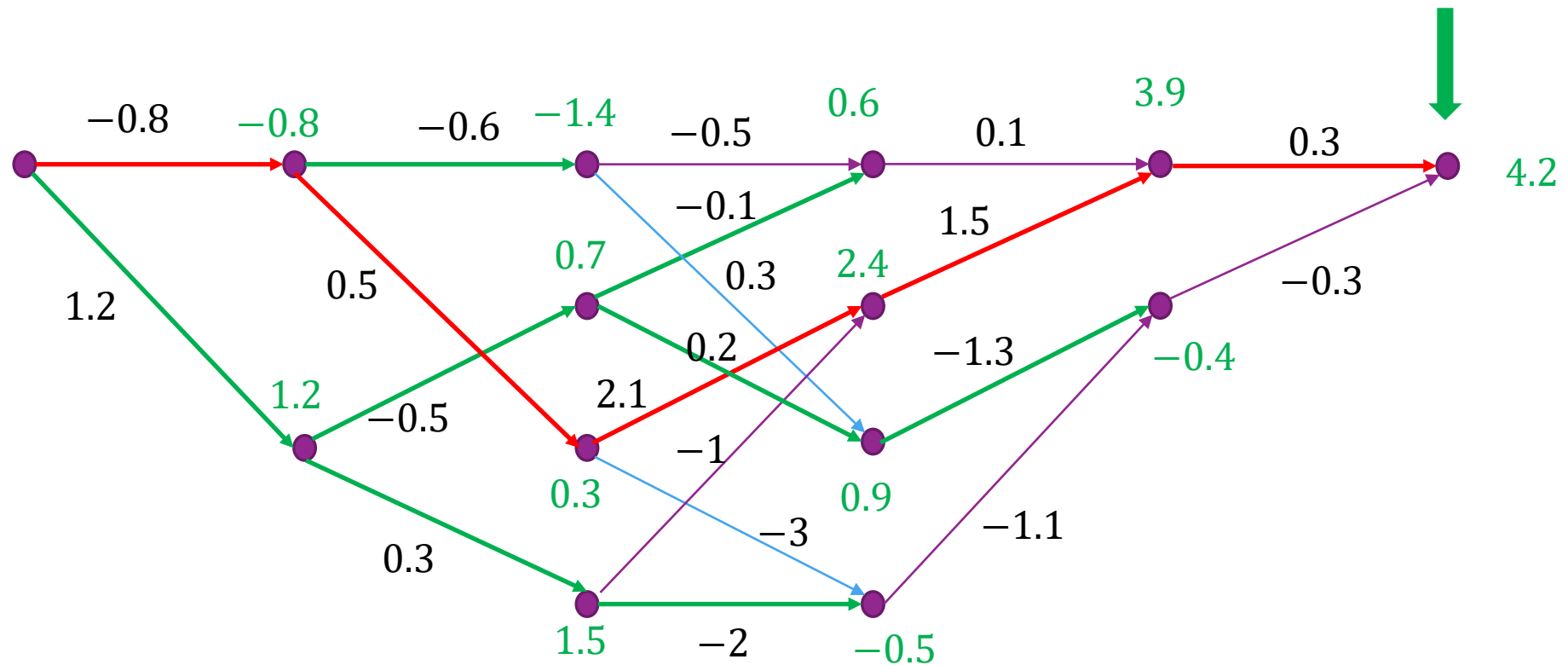
- Add value from Time 4 + branch
- Take route with maximum value (shown in green)



Example:
 $\max\{3.9 + 0.3, -0.4 - 0.3\}$
 $= \max\{4.2, -0.7\} = 4.2$

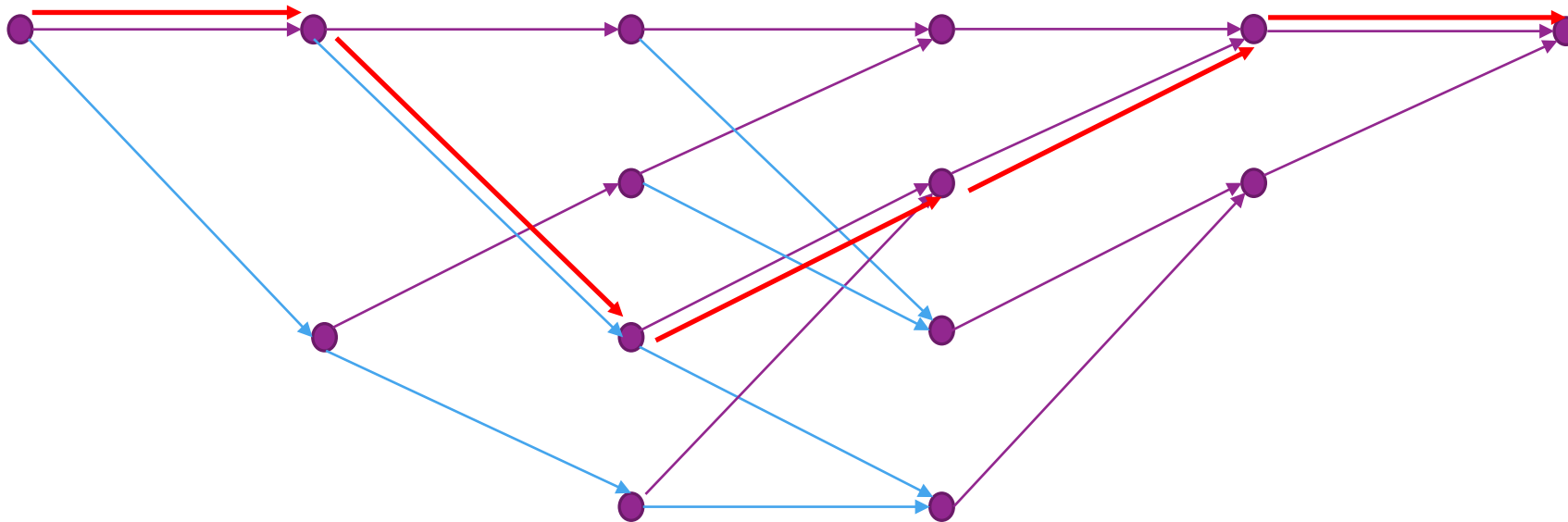
Ex: Trace back path

Trace back maximum path. Shown in red



Ex: Read off bits

- Read off the bits from the maximum path
- ML input bits = (0,1,0,0,0)



Complexity

- ❑ Update of each node requires maxima over 2^k branches
- ❑ There are $2^{k(K-1)}$ states, so complexity / time is $O(2^{kK})$
- ❑ Total complexity is $O(T2^{kK})$
- ❑ Storage is also $O(T2^{kK})$. (From the paths)
- ❑ Summary:
 - Viterbi algorithm is **linear** in block length.
 - Can have very long block lengths (often T in the 1000s)
 - But, complexity is **exponential** in constraint length
 - Practical decoders limited to $K = 7$ or $K = 9$.

Terminating the Trellis

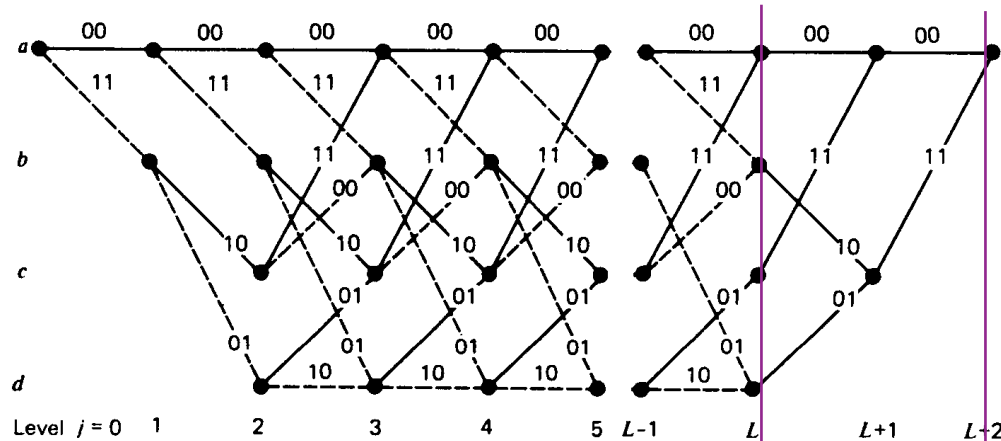


Figure 11.15 Trellis for the convolutional encoder of Fig. 11.13a.

During tail bits
only paths with
zero bit inputs.

- Recall tail bits are zero:
 $\mathbf{b}(L) = \dots = \mathbf{b}(L + K - 2) = 0$.
- Limits the paths at the end of the trellis
- Viterbi algorithm should only be done on the zero path.
- Very important to not forget the bits at the end.
- Otherwise, final bits are not protected.

Pruning the Path Memory

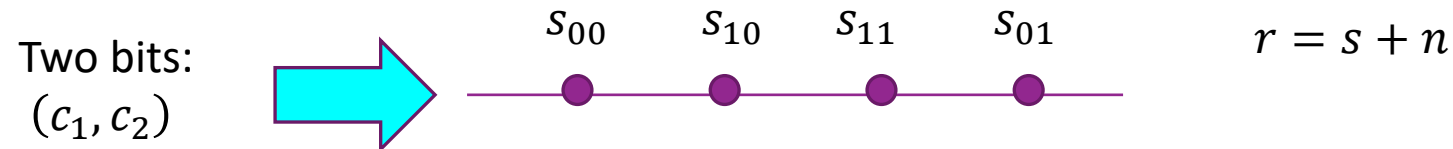
- ❑ In current algorithm, path $P_t(x_t)$ grows to full block length.
- ❑ Adds storage: Storage is $O(T2^{kK})$. Linear in T
- ❑ Adds delay. No bits can be determined until code is fully decoded.
- ❑ Many practical implementations:
 - Store some finite length δ of each surviving path.
 - Can make decision on bit input $\mathbf{b}(t)$ after $\mathbf{r}(t + \delta)$.
 - Rule of thumb: Good performance if $\delta \geq 5K$.

Rate Matching Convolutional Codes

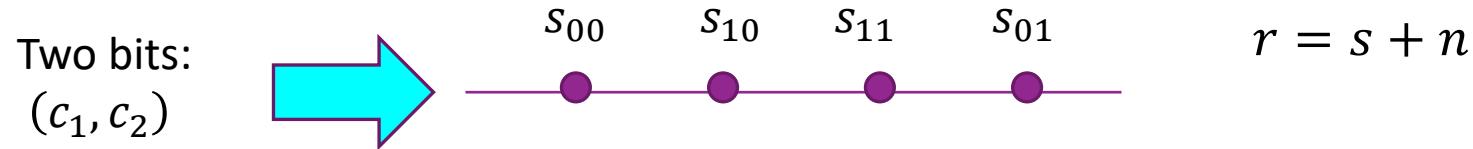
- ❑ Convolutional codes have limited rates, usu. $\frac{1}{2}$ or $\frac{1}{3}$.
- ❑ Obtain other rates through
 - **Puncturing**: Remove coded bits to increase rate
 - **Repetition**: Repeat coded bits to decrease rate
- ❑ Puncture / repeat pattern is important (see Proakis)
 - Try to spread out modified bits
- ❑ For punctured bits, set corresponding LLRs to zero
 - Viterbi decoder just ignores those bits
- ❑ For repeated bits, add the corresponding LLRs
 - Viterbi decoder will increase confidence on that branch

High Order Constellations

- ❑ Higher order constellations (eg. 16- or 64-QAM)
- ❑ Each constellation point is a function of multiple bits.
- ❑ Likelihood does not factorize
 - Each symbol $r(t)$ depends on multiple bits
- ❑ Example 4-PAM (or one dimension of 16-QAM):
 - Each symbol likelihood depends on two bits: $p(r|c_1, c_2)$



High Order Constellations



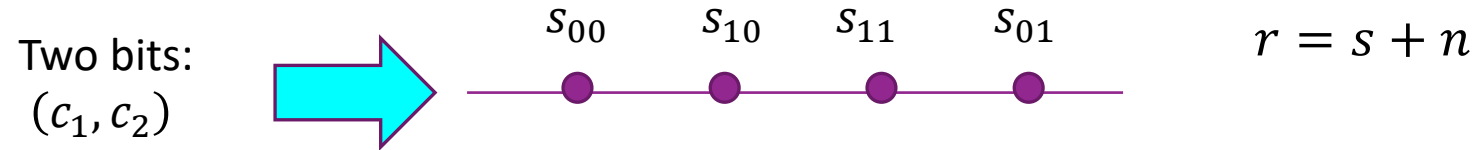
- To create LLRs for individual bits use total probability rule:

$$p(r|c_1) = \frac{1}{2} (p(r|c_1, c_2 = 0) + p(r|c_1, c_2 = 1))$$

- Resulting bitwise LLR:

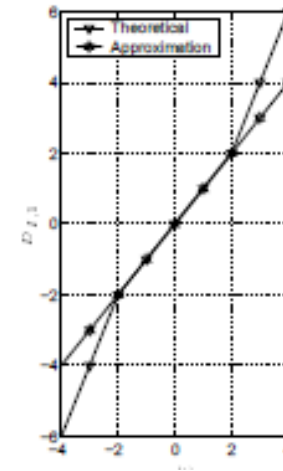
$$LLR \text{ for } c_1 = \log \frac{p(r|c_1, c_2 = 1, 0) + p(r|c_1, c_2 = 1, 1)}{p(r|c_1, c_2 = 0, 0) + p(r|c_1, c_2 = 0, 1)}$$

High Order Constellations

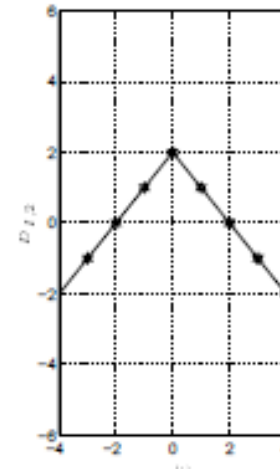


- ❑ LLRs can have irregular shapes
- ❑ Not simple linear function as in BPSK / QPSK case
- ❑ Often use approximations
- ❑ More info: Caire, Taricco and Biglieri, "Bit-Interleaved Coded Modulation," 1998.

LLR for c_2

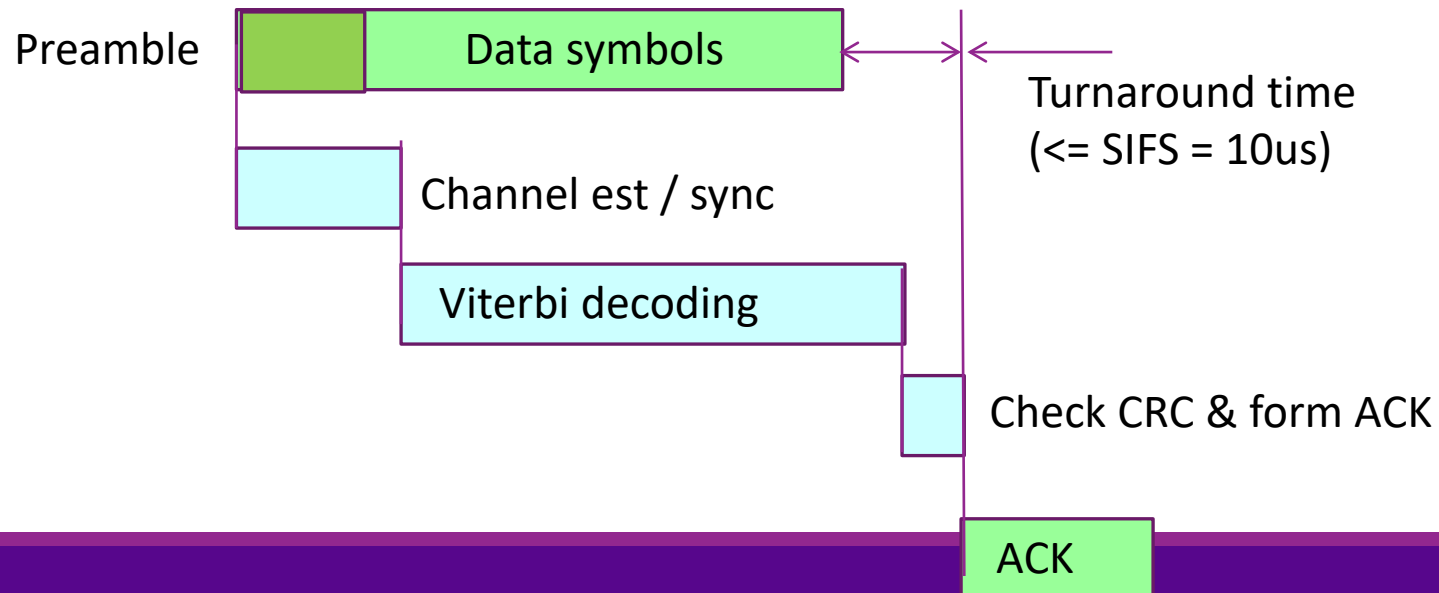


LLR for c_1



Convolutional Codes in WiFi

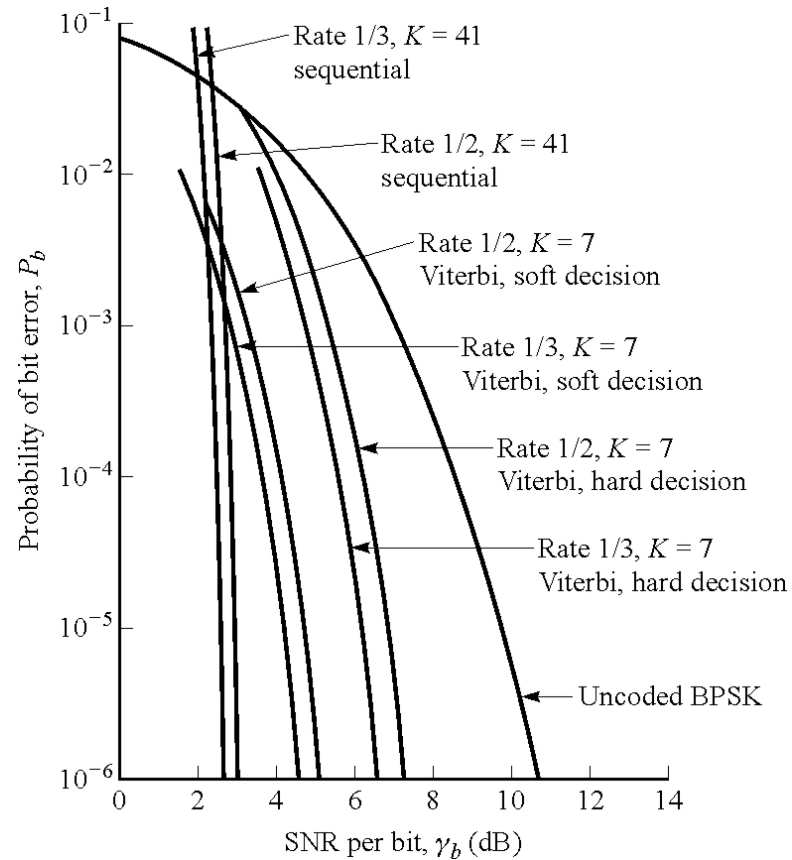
- ❑ 802.11 uses $R=1/2$ $K=7$ code.
- ❑ Length adjusted to packet size
- ❑ Higher rates ($R=2/3$ and $3/4$) achieved through puncturing
- ❑ Enables decoding as data arrives for ACK fast turnaround



Convolutional Codes in LTE

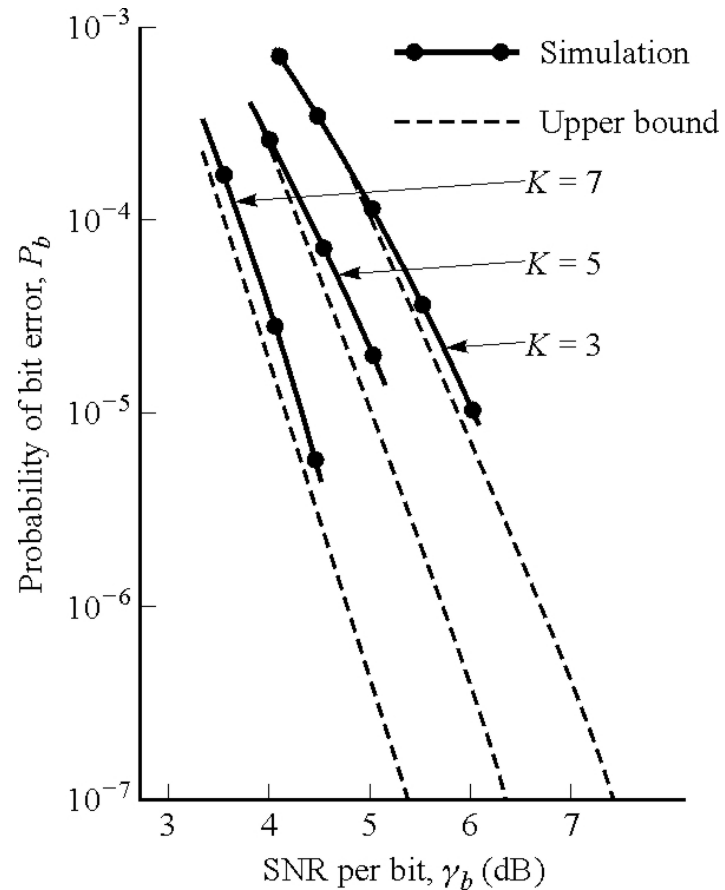
- ❑ Convolutional codes in LTE used for:
 - Control channels (payload typ 20-40 bits +CRC), and
 - Short (< 128 bit) data frames
- ❑ Larger payloads encoded with turbo codes (discussed later)
- ❑ Uses rate=1/3 base convolutional code with K=7.
- ❑ Higher rates achieved via puncturing
- ❑ Control channels use a sophisticated technique called **tail biting** to reduce loss on the tail bits

Decoding Performance



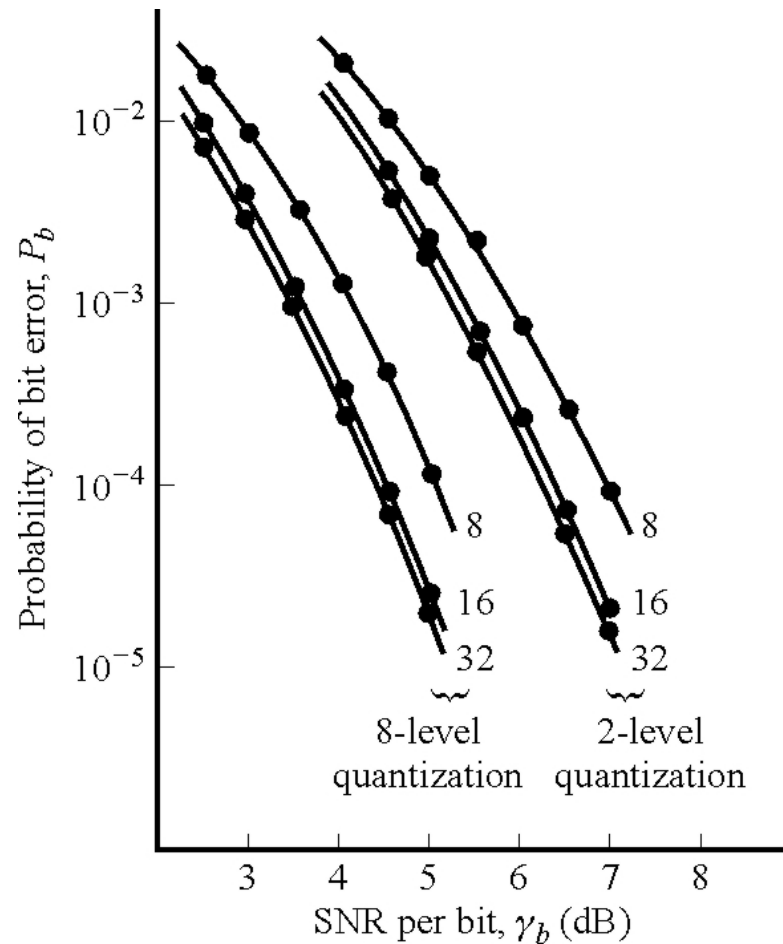
- ❑ Hard decision loses approximately 1.5 to 2 dB
- ❑ Constraint length $K=7$ is sufficient for very sharp error performance

Different Constraint Lengths



- Approximate 1 dB improvement between $K=3, 5$ and 7
- Higher constraint lengths become computationally intractable
- Recall decoding complexity is exponential in K

LLR Quantization



- Minimal gains after 16 bit quantization of branch metrics
- Recall HD is equivalent to 1 bit quantization
- Most commercial implementations use 6-bit LLRs

MATLAB Convolution Tools

Demo Convolutional Code

The Viterbi decoder built in the in-class exercise is very slow. Fortunately, MATLAB has excellent tools for encoding and decoding

- Perform convolutional encoding with the MATLAB comm toolbox commands
- Extract LLRs from the qamdemod command
- Perform convolution decoding from the soft LLRs
- Measure the block error rate as a function of the SNR
-

We illustrate with a simple convolutional coder over an AWGN channel. We use a standard constraint length $K=7$ code:

```
% Create the convolutional encoder and decoder with constraint length K=7
trellis = poly2trellis(7,[171 133]);
convEnc = comm.ConvolutionalEncoder('TrellisStructure', trellis, 'TerminationMethod','Terminated');
convDec = comm.ViterbiDecoder('TrellisStructure', trellis, 'TerminationMethod','Terminated');

% Modulation
bitsPerSym = 2; % QPSK
M = 2^bitsPerSym;

% Number of information bits per block
nbits = 1000;
```

❑ MATLAB comm toolbox

- General convolution encoders & decoders
- Efficient implementation
- Excellent for testing

❑ See demo

In-Class Exercise

Building a Simple Viterbi Decoder

We conclude with building a simple decoder. This decoder is slow but illustrates the ideas.

To start, let's encode some random data.

```
% Number of bits
nbits = 100;

% TODO: Generate random bits
%   b = ...

% TODO: Create output bits.
%   c = ...
```