

# Review

Note Title

2/20/2012

\* The factor graph representation of the convolutional code.

\* Each circle is a state variable that can take different values.

\* Each rectangle is a factor function that takes input of the variables that are connected to the rectangle.

\* The function  $f$  is usually decided by the underlying code structure & by the observation. & the objective function of interest.

\* The objective function is thus

$$\underset{S}{\operatorname{argmax}} f_0(s_0) \prod_{t=1}^T f_t(s_{t-1}, s_t) \quad \left| \begin{array}{c} \boxed{f_0} - \textcircled{s_0} - \boxed{f_1} - \textcircled{s_1} \\ \textcircled{s_2} - \boxed{f_3} - \textcircled{s_2} - \boxed{f_2} \end{array} \right.$$

$$\text{or } \underset{x}{\operatorname{argmax}} \sum_{S: S_i = x} f_0(s_0) \prod_{t=1}^T f_t(s_{t-1}, s_t)$$

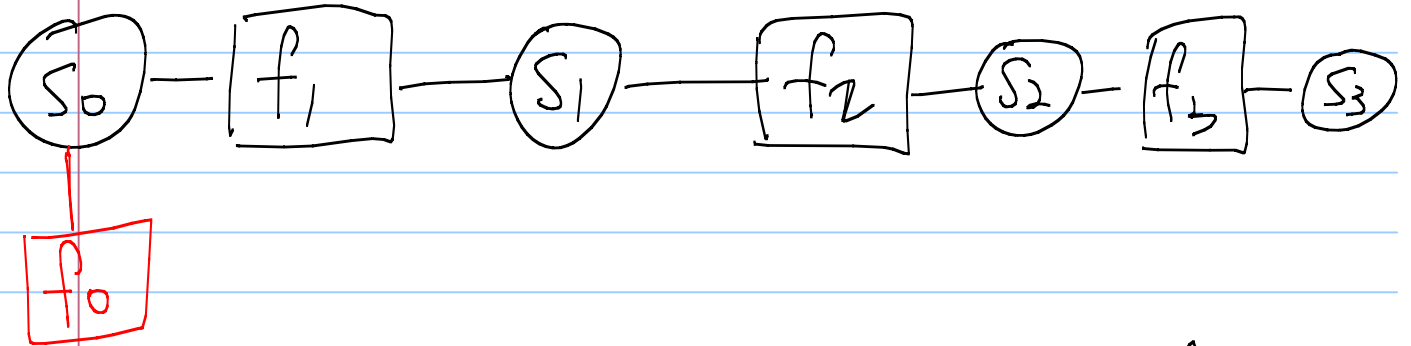
Note: Each  $f_t$  may be different due to different  $t$

# Lecture 12

Note Title

2/20/2012

Back to our discussion of the convolutional codes



Let us rederive the VA based on the factor graph representation

$$\text{Obj: } \max_{\mathbf{s}} f_0(s_0) \cdot \prod_{t=1}^T f_t(s_{t-1}, s_t)$$

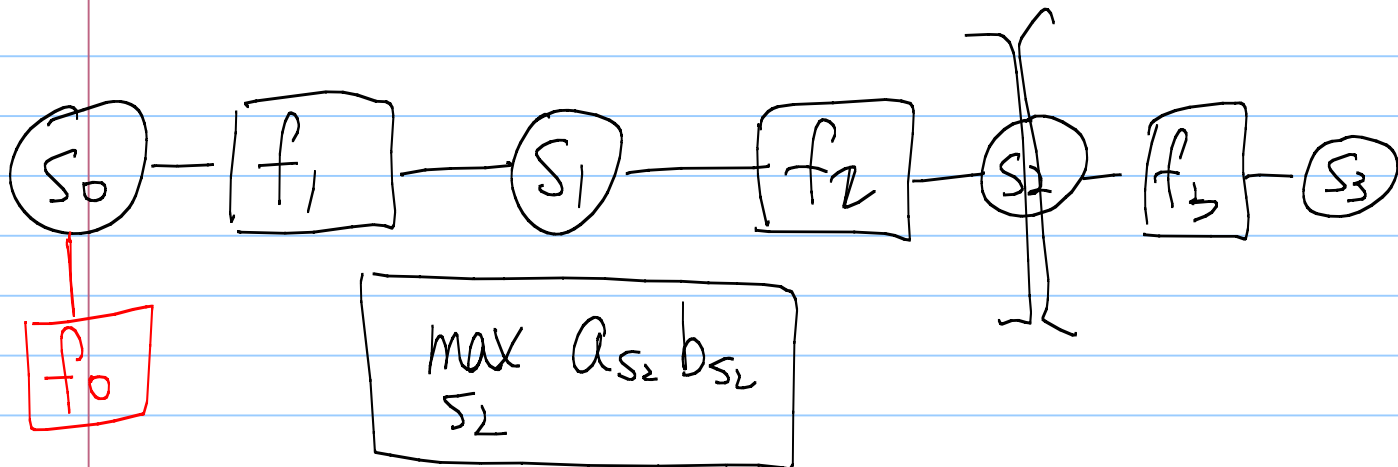
$$\text{Forward metrics } a_{s_t} = \max_{s_{t-1}} a_{s_{t-1}} f_t(s_{t-1}, s_t)$$

$$\text{Backward metrics } a_{s_0} = f_0(s_0)$$

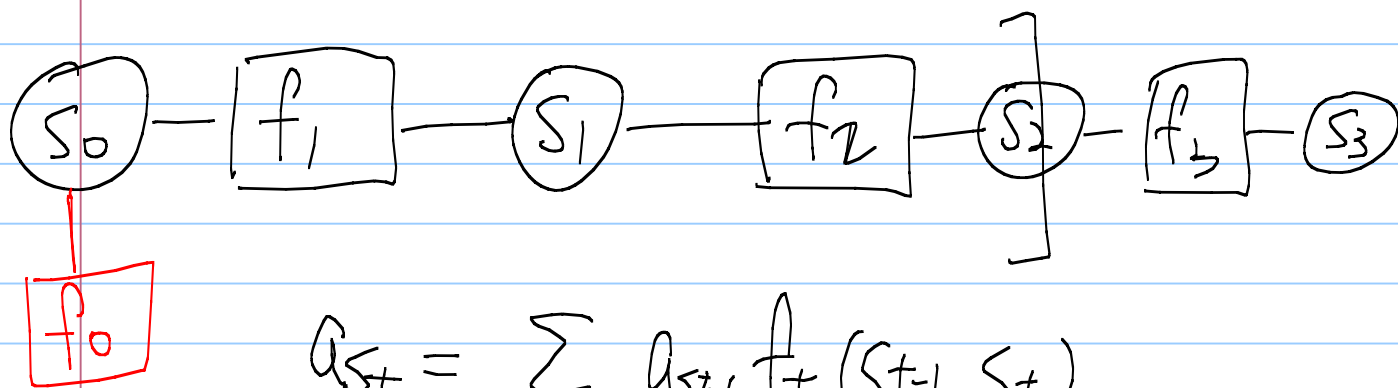
$$b_{s_t} = \max_{s_{t+1}} b_{s_{t+1}} f_{t+1}(s_t, s_{t+1})$$

$$b_{s_T} = 1 \text{ for all } s_t \text{ values.}$$

To combine the  $a_{st}$  &  $b_{st}$ .

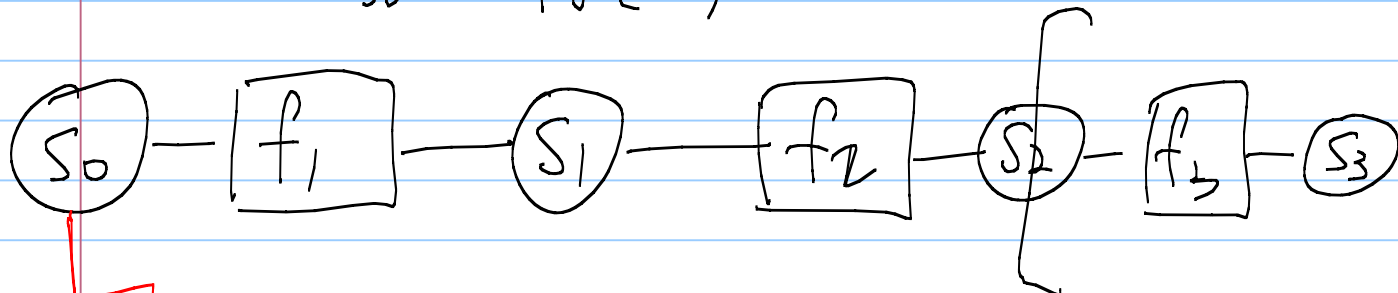


The BCJR algorithm can be derived similarly



$$a_{st} = \sum_{s_{t-1}} a_{s_{t-1}t} f_t(s_{t-1}, s_t)$$

$$a_{s_0} = f_0(s_0)$$



$$b_{st} = \sum_{s_{t+1}} f_{t+1}(s_t, s_{t+1}) b_{s_{t+1}}$$

This state based generation leads to new application of the VA & BCJR decoders.

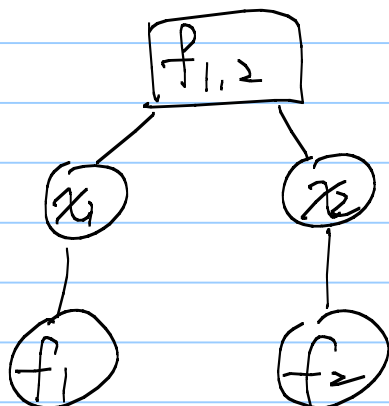
Example 1: Consider a simple linear code with codeword length 2, and parity-check matrix  $H = (1, 1)$ .

Both codewords are equally likely to be chosen.

Suppose we observe  $\vec{y}_{obs} = (1, 1)$  through a BSC with cross-over prob  $p$ .

$$\begin{aligned}
 & \bullet \bullet P_{\vec{x}, \vec{y}}((0, 0), (1, 1)) \\
 & = P_{\vec{x}}(0, 0) \cdot P_{\vec{y} | \vec{x}}((1, 1) | (0, 0)) \\
 & = P_{x_1}(x_1) \cdot P_{y_1 | x_1}(y_1 | x_1) \cdot P_{y_2 | x_2}(y_2 | x_2) \\
 & \quad \downarrow \quad \downarrow \\
 & \quad \text{2 variables} \\
 & \quad \underbrace{\hspace{15em}} \\
 & \quad \exists \text{ factors.}
 \end{aligned}$$

Ans. The factor graph is



$$f_1(x_1) = P_{Y_1|X_1}(y_1|x_1)$$

$$= \begin{cases} p & \text{if } x_1 = 0 \\ 1-p & \text{if } x_1 = 1 \end{cases}$$

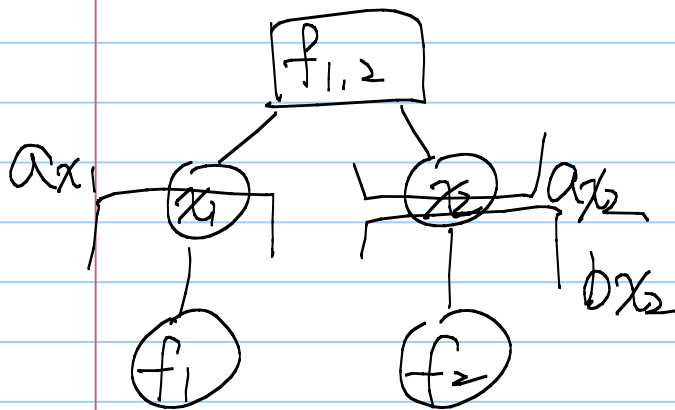
$$f_2(x_2) = P_{Y_2|X_2}(y_2|x_2) = \begin{cases} p & \text{if } x_2 = 0 \\ 1-p & \text{if } x_2 = 1 \end{cases}$$

$$f_{1,2}(x_1, x_2) = P_{X_1, X_2}(x_1, x_2) \\ = \begin{cases} \frac{1}{2} & \text{if } x_1 + x_2 = 0 \\ 0 & \text{otherwise} \end{cases}$$

Q: Use the VA to find the most likely codeword.

We use

The 2-WAY VA.



$$a_{x_1} = f_1(x_1)$$

$$= \begin{cases} p & \text{if } x_1 = 0 \\ 1-p & \text{if } x_1 = 1 \end{cases}$$

$$a_{x_2} = \max_{x_1} a_{x_1} f_{1,2}(x_1, x_2)$$

$$= \begin{cases} \max(p \times \frac{1}{2}, (1-p) \times 0) & \text{if } x_2 = 0 \\ = \frac{p}{2} \end{cases}$$

$$\begin{cases} \max(p \times 0, (1-p) \times \frac{1}{2}) & \text{if } x_2 = 1 \\ = \frac{1-p}{2} \end{cases}$$

$$b_{x_2} = f_2(x_2) = \begin{cases} p & \text{if } x_2 = 0 \\ 1-p & \text{if } x_2 = 1 \end{cases}$$

The final decision

$$\max_{x_2} a_{x_2} b_{x_2} = \max_{x_2} \left( \frac{p^2}{2}, \frac{(1-p)^2}{2} \right)$$

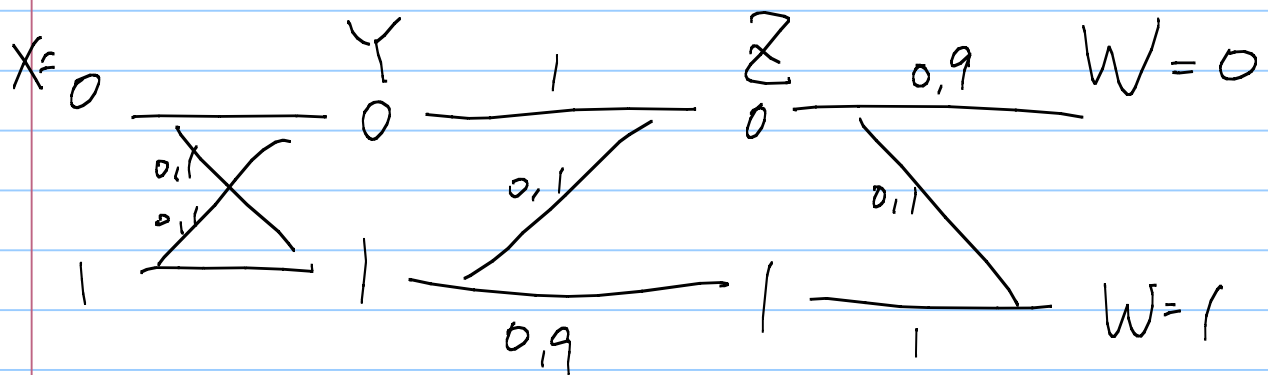
+ backward tracking for both directions.

Q: Does the answer make sense?

A: Yes. it is indeed the MAP decoder

## Example 2: A Markov chain example

The channel model:

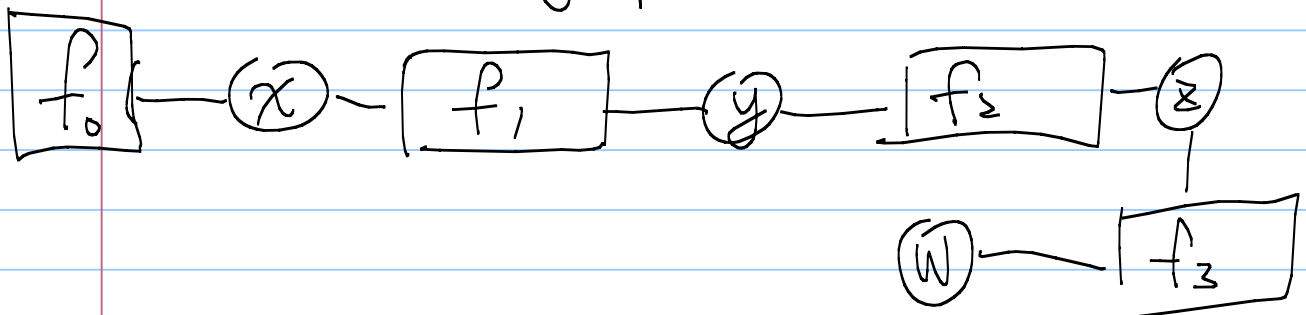


Q: Suppose we know  $X=0$ , what is the most likely value of  $W$ ?

Ans: Let us use the factor graph + BCJR to solve this problem

Obj:  $P_{XYZW} = \underbrace{P_X}_{f_0} \cdot \underbrace{P_{Y|X}}_{f_1} \cdot \underbrace{P_{Z|Y}}_{f_2} \cdot \underbrace{P_{W|Z}}_{f_3}$   
factors.

The factor graph becomes



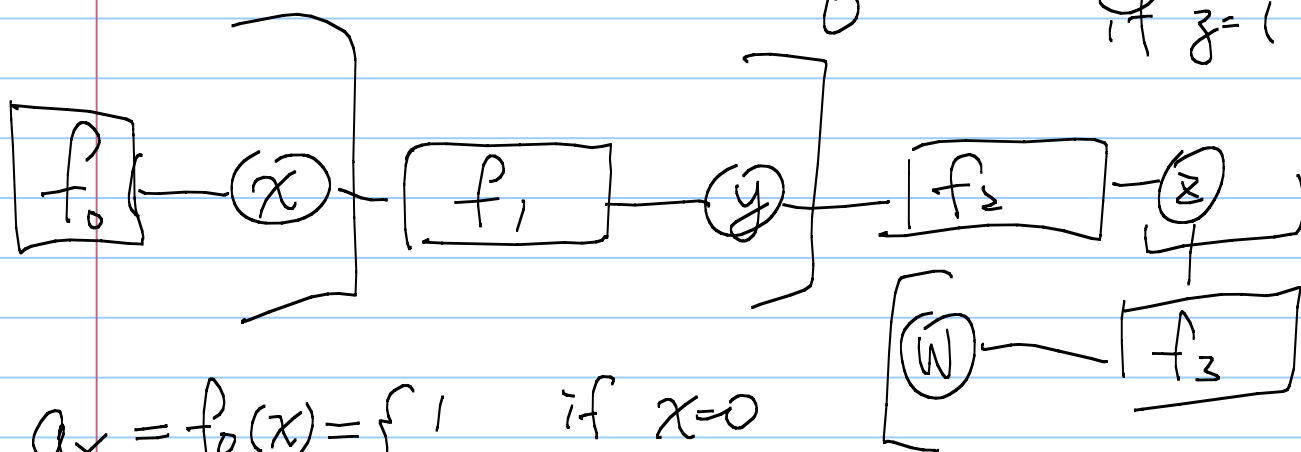


$$f_0(x) = P_X(x) = \begin{cases} 1 & \text{if } x=0 \\ 0 & \text{otherwise} \end{cases}$$

$$f_1(x, y) = P_{Y|X}(y|x) = \begin{cases} 0.9 & \text{if } x=y \\ 0.1 & \text{if } x \neq y \end{cases}$$

$$f_2(y, z) = P_{Z|Y}(z|y) = \begin{cases} 1 & \text{if } y=z=0 \\ 0.9 & \text{if } y=z=1 \\ 0.1 & \text{if } y=1, z=0 \\ 0 & \text{if } y=0, z=1 \end{cases}$$

$$f_3(z, w) = P_{W|Z}(w|z) = \begin{cases} 1 & \text{if } z, w=1 \\ 0.9 & \text{if } z=0, w=0 \\ 0.1 & \text{if } z=0, w=1 \\ 0 & \text{if } z=1, w=0 \end{cases}$$



$$a_x = f_0(x) = \begin{cases} 1 & \text{if } x=0 \\ 0 & \text{if } x=1 \end{cases}$$

$$a_y = \sum_x a_x f_1(x, y) = \begin{cases} 0.9 & \text{if } y=0 \\ 0.1 & \text{if } y=1 \end{cases}$$

$$a_z = \sum_y a_y f_2(y, z) = \begin{cases} 0.9 \times 1 + 0.1 \times 0.1 & \text{if } z=0 \\ 0.9 \times 0 + 0.1 \times 0.9 & \text{if } z=1 \end{cases}$$

$= 0.91$   $= 0.09$

$$a_w = \sum_z a_z f_3(z, w) = \begin{cases} 0.91 \times 0.9 + 0.09 \times 0 & \text{if } w=0 \\ 0.91 \times 0.1 + 0.09 \times 1 & \text{if } w=1 \end{cases}$$

$= 0.819$   $= 0.181$

$$\arg \max_w a_w = 0 = \text{a MAP decision}$$

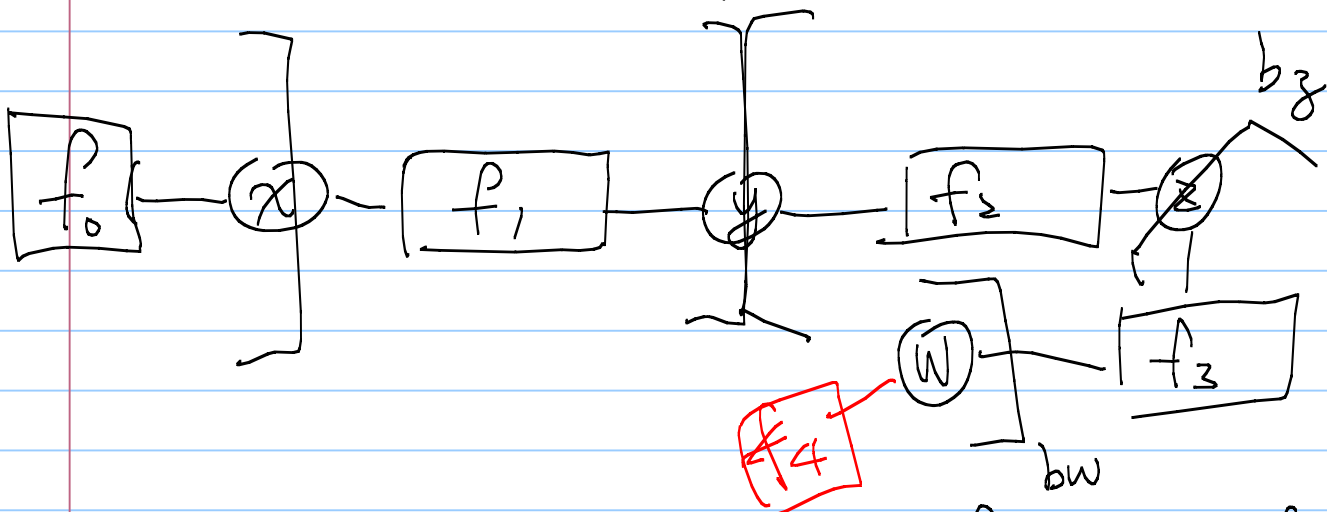
\* If you trace the computation in terms of probability, we are <sup>actually</sup> computing the marginals of  $X, Y, Z, W$  respectively.

Q: Suppose we know  $X=0$ , and  $W=1$ .  
What is the MAP decision of  $Y$ .

A: We need to modify the factor graph to take into account that  $W=1$  is given.

The new FG.  
 $a_x$

$a_y$  by.



$$a_x = \begin{cases} 1 & \text{if } x=0 \\ 0 & \text{if } x=1 \end{cases}$$

$$b_w = f_4(w) = \begin{cases} 0 & \text{if } w=0 \\ 1 & \text{if } w=1 \end{cases}$$

$$a_y = \begin{cases} 0,9 & \text{if } y=0 \\ 0,1 & \text{if } y=1 \end{cases}$$

$$b_z = \sum_w f_3(z, w) b_w$$

$$= \begin{cases} 0,9 \times 0 + 0,1 \times 1 & \text{if } z=0 \\ 0 \times 0 + 1 \times 1 & \text{if } z=1 \end{cases}$$

Remark: The connection to the traditional prob computation is not clear

$$b_y = \sum_z f_2(y, z) b_z$$

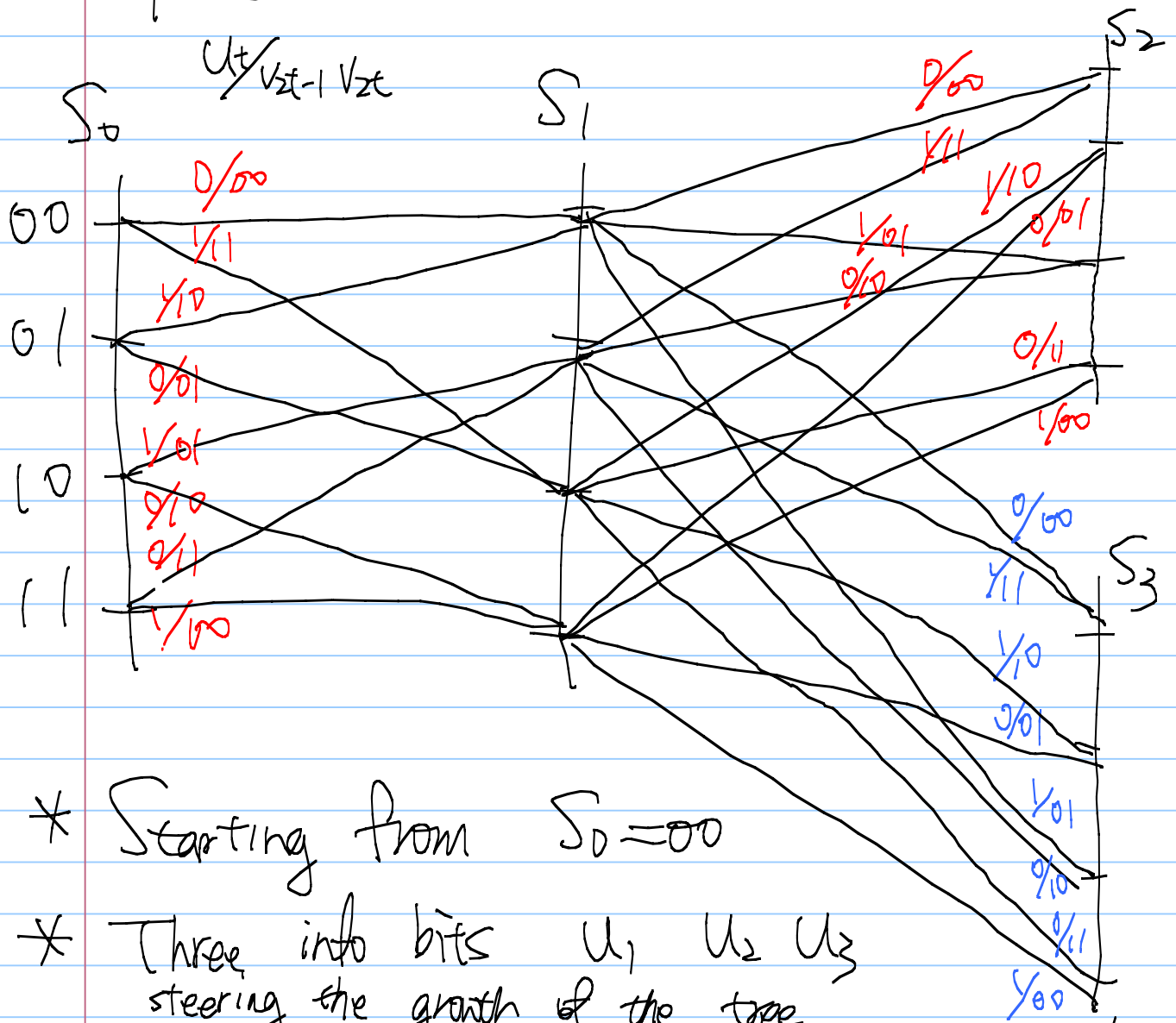
$$= \begin{cases} 1 \times 0,1 + 0 \times 1 & y=0 \\ 0,1 \times 0,1 + 0,9 \times 1 & y=1 \end{cases}$$

decision:

$$\max_y a_y b_y = \max_y \begin{cases} 0,09 & y=0 \\ 0,91 & y=1 \end{cases}$$

$\Rightarrow$  MAP decision of  $y$  is 1

# Example 3: A tree-based convolution code



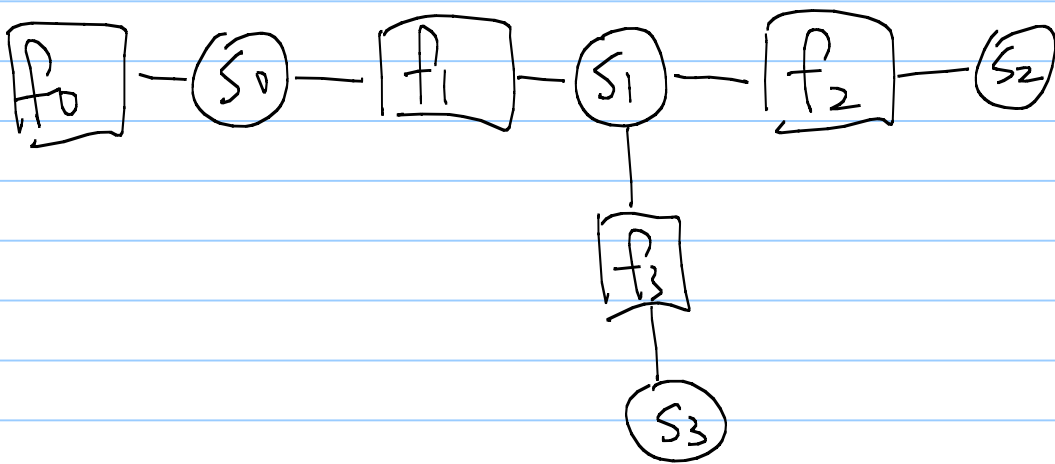
- \* Starting from  $S_0 = 00$
- \* Three info bits  $u_1, u_2, u_3$  steering the growth of the tree
- \* Six coded bits  $v_1 v_2 v_3 v_4 v_5 v_6$  (rate  $\frac{1}{2}$ )
- \* Encoding is straightforward.

\* The channel is BSC with crossover prob 0.1

\* Observation:  $\vec{y} = 001110$

Q: Use the VA to decide the ML codeword.

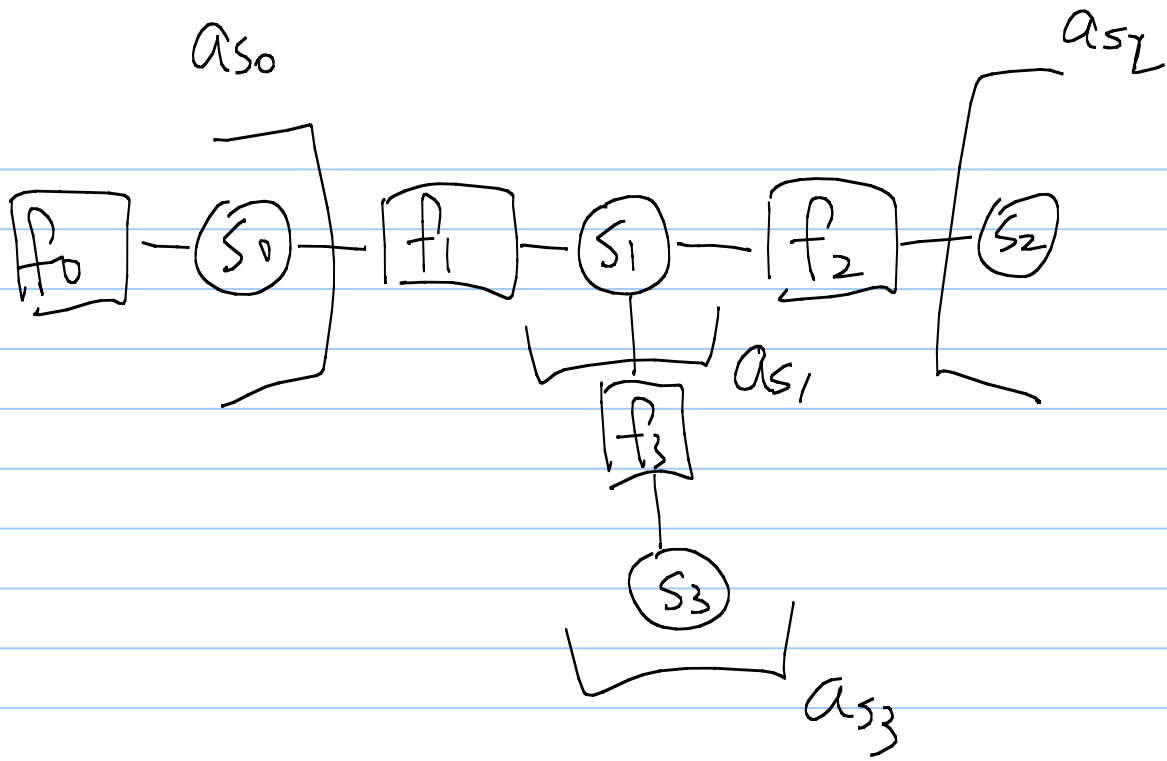
Ans: ① Convert it to the factor graph representation:



② Initialize the  $f_0 \dots f_3$  functions by the trellis structure  $\mathcal{T}$  by the observation  $\vec{y}$

$$f_0(s_0) = \begin{cases} 1 & \text{if } s_0 = 00 \\ 0 & \text{otherwise} \end{cases}$$

$f_1 \dots f_3$  are initialized in the same way as the prev. example



Each  $a_s$  is a summarizing "function" with respect to  $S$ .

$$a_{s_0} = f_0(s_0)$$

$$a_{s_2} = 1$$

$$a_{s_1} = \max_{S_0, S_2} a_{s_0} f_1(s_0, s_1) a_{s_2} f_2(s_1, s_2)$$

4x4=16 choices.

$$a_{s_3} = \max_{S_1} a_{s_1} f_3(s_1, s_3)$$

Final decision:  $S_1$

$\max_{S_3} a_{s_3}$  + backward tracking