

Review

- Consider random variables $X_1, X_2, \dots, X_n$, where $E(X_i) = \mu_i$ and $\text{Var}(X_i) = \sigma_i^2$.

Define $W_n \triangleq a_1 X_1 + a_2 X_2 + \dots + a_n X_n$. Then,

$$E(W_n) = a_1 \mu_1 + a_2 \mu_2 + \dots + a_n \mu_n.$$

If X_i 's are independent:

$$\text{Var}(W_n) = a_1^2 \sigma_1^2 + a_2^2 \sigma_2^2 + \dots + a_n^2 \sigma_n^2.$$

(* For the previous equation to be correct, it's enough that X_i 's are uncorrelated.)

Special case

Assume that X_i 's are i.i.d. (independent and identically distributed). Hence,

$$\forall i: \begin{cases} \mu_i = \mu, \\ \sigma_i^2 = \sigma^2. \end{cases}$$

Let $a_i = \frac{1}{n}$ in W_n , denote the resulting random variable by $\bar{X}_n$, i.e.,

$$\bar{X}_n = \frac{X_1 + \dots + X_n}{n}.$$

Then,

$$E(\bar{X}_n) = n \cdot \frac{\mu}{n} = \mu,$$

$$\text{Var}(\bar{X}_n) = n \cdot \frac{\sigma^2}{n^2} = \frac{\sigma^2}{n}.$$

* Notice that $\text{Var}(\bar{X}_n)$ decreases as n increases.

Law of Large Numbers

- For any positive ϵ ,

$$\lim_{n \rightarrow \infty} \Pr(|\bar{X}_n - \mu| > \epsilon) = 0.$$

Proof. To prove the result, we use Chebyshev inequality that for a random variable Y with $E(Y) = \mu_Y$ and $\text{Var}(Y) = \sigma_Y^2$, *

$$P(|Y - \mu_Y| \geq \epsilon) \leq \frac{\sigma_Y^2}{\epsilon^2}.$$

Now, using Chebyshev inequality for $\bar{X}_n$, we get:

$$P(|\bar{X}_n - \mu| \geq \epsilon) \leq \frac{\sigma^2/n}{\epsilon^2} = \frac{\sigma^2}{n\epsilon^2}.$$

Hence,

$$0 \leq \lim_{n \rightarrow \infty} P(|\bar{X}_n - \mu| \geq \epsilon) \leq \lim_{n \rightarrow \infty} \frac{\sigma^2}{n\epsilon^2} = 0 \Rightarrow \lim_{n \rightarrow \infty} P(|\bar{X}_n - \mu| \geq \epsilon) = 0. \quad \blacksquare$$

(* Here is a proof of Chebyshev inequality:

$$\begin{aligned} \sigma_Y^2 &= \int_{-\infty}^{+\infty} (y - \mu_Y)^2 f(y) dy \geq \int_{|y - \mu_Y| \geq \epsilon} (y - \mu_Y)^2 f(y) dy \geq \epsilon^2 \int_{|y - \mu_Y| \geq \epsilon} f(y) dy = P(|Y - \mu_Y| \geq \epsilon) \\ \Rightarrow P(|Y - \mu_Y| \geq \epsilon) &\leq \frac{\sigma_Y^2}{\epsilon^2}. \end{aligned}$$

More About the Law of Large Numbers (LLN)

The LLN justifies our intuition that the probability of a repeatable event A can be estimated by the relative frequency of its occurrence for a large number of independent repetitions. (Hence, it fills the gap between theory and the real world!)

To see this, assume that we want to estimate the probability of event A in practice. For that, introduce random variable

$$X_i = \begin{cases} 1 & \text{if } A \text{ occurs at the } i\text{-th trial} \\ 0 & \text{otherwise.} \end{cases}$$

Then,

$$E(X_i) = P(X_i=1) \times 1 + P(X_i=0) \times 0 = P(X_i=1)$$

Denote $P(X_i=1)$ by p . Using the LLN:

$$\Pr \left(\left| \frac{X_1 + X_2 + \dots + X_n}{n} - \overbrace{E\left(\frac{X_1 + \dots + X_n}{n}\right)}^{=p} \right| < \epsilon \right) \xrightarrow{n \rightarrow \infty} 1$$

$$\Rightarrow \Pr \left(\left| \frac{X_1 + \dots + X_n}{n} - p \right| < \epsilon \right) \xrightarrow{n \rightarrow \infty} 1$$

This means that if the number of successes of A in n trials equals k , then with probability one, $\frac{k}{n} \rightarrow p$ as $n \rightarrow \infty$.

As an example, consider a coin in which we do not know $P(\text{Head})$ for. We perform a large number of trials (tossing the coin) and see how many times it shows "Head". The relative frequency of "Head"s gives us an estimate $\hat{p}$ of $P(\text{Head})$.

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clear,close all
p = 0.4; %% set the probability of "head" to an arbitrary number in
[0,1]

% Simulation of a sample path for evolution of X_bar
N = 2000;    %% number of trials

S = zeros(1,N+1); %% initiate the number of successes vector
X_bar = zeros(1,N+1); %% initiate the success frequency vector
for n = 1 : N
    X_n = (rand(1) < p);    %% (just a way to) simulate a coin toss
    S(n+1) = S(n) + X_n;    %% update the number of success vector
    X_bar(n+1) = S(n+1)/n; %% update the success frequency vector

    % plot the results
    if mod(n,10) == 0
        figure(1)
        plot(1:n,X_bar(2:n+1)) %% plot the success frequency vs number
of trials
        xlim([1,N])            %% set limits for x-axis
        ylim([0,1])
        xlabel({'n'}, 'FontSize',14);
        ylabel({'$(X_1+X_2+...+X_n)/n$'}, 'Interpreter', 'latex', 'FontSize',14)
        grid on
        pause(.001)            %% pause so we can see the evolution
of the output graph
    end
end
hold on
plot(1:N,p*ones(1,N), 'r--') % plot the line for the actual p used
title({'A sample path of $\bar{X}$ (n)$'}, 'Interpreter', 'latex', 'FontSize',14)
pause(2)

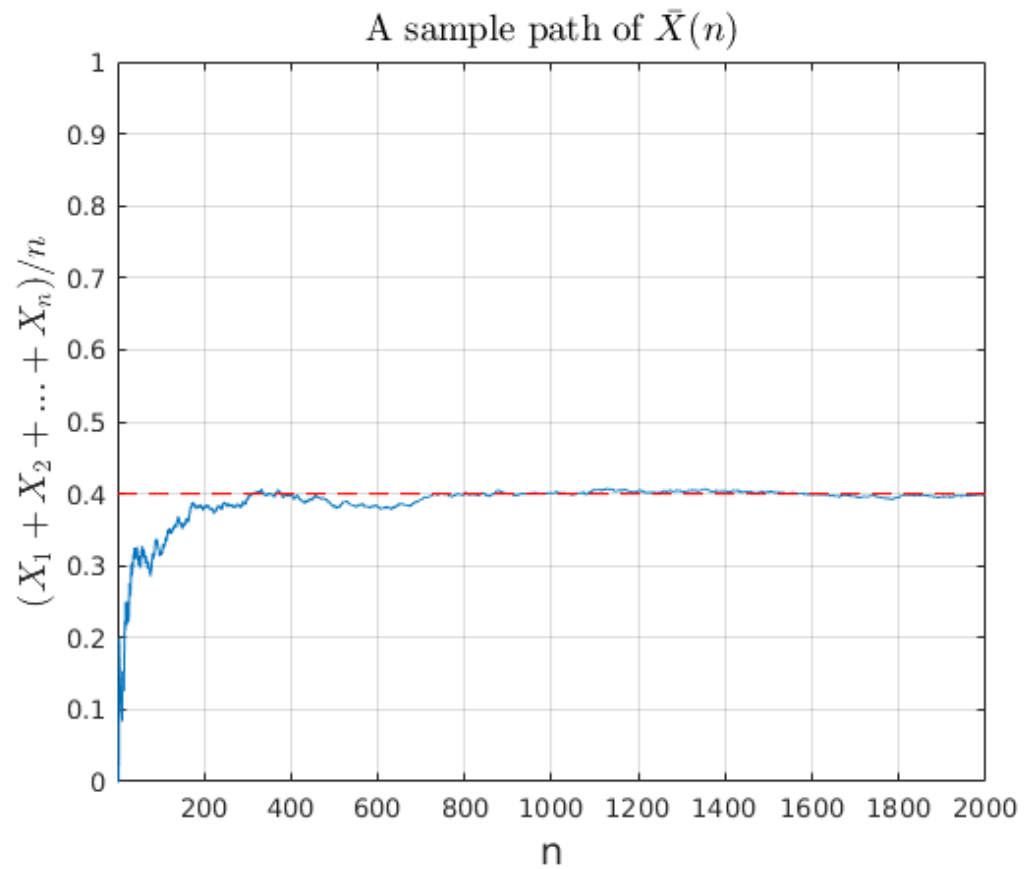
% Sample paths of X_bar for several different realizations
figure(2)
N = 2500;
for m = 1:25 % iterate for different realizations
    S = zeros(1,N+1); %% initiate the number of successes vector
    X_bar = zeros(1,N+1); %% initiate the success frequency vector
    for n = 1 : N
        X_n = (rand(1) < p);    %% (just a way to) simulate a coin
toss
        S(n+1) = S(n) + X_n;    %% update the number of success vector
        X_bar(n+1) = S(n+1)/n; %% update the success frequency vector
    end
    % plot the results
    figure(2)
    plot(1:N,X_bar(2:end), 'Color', rand(1,3)) %% plot the success
frequency vs number of trials
    hold on

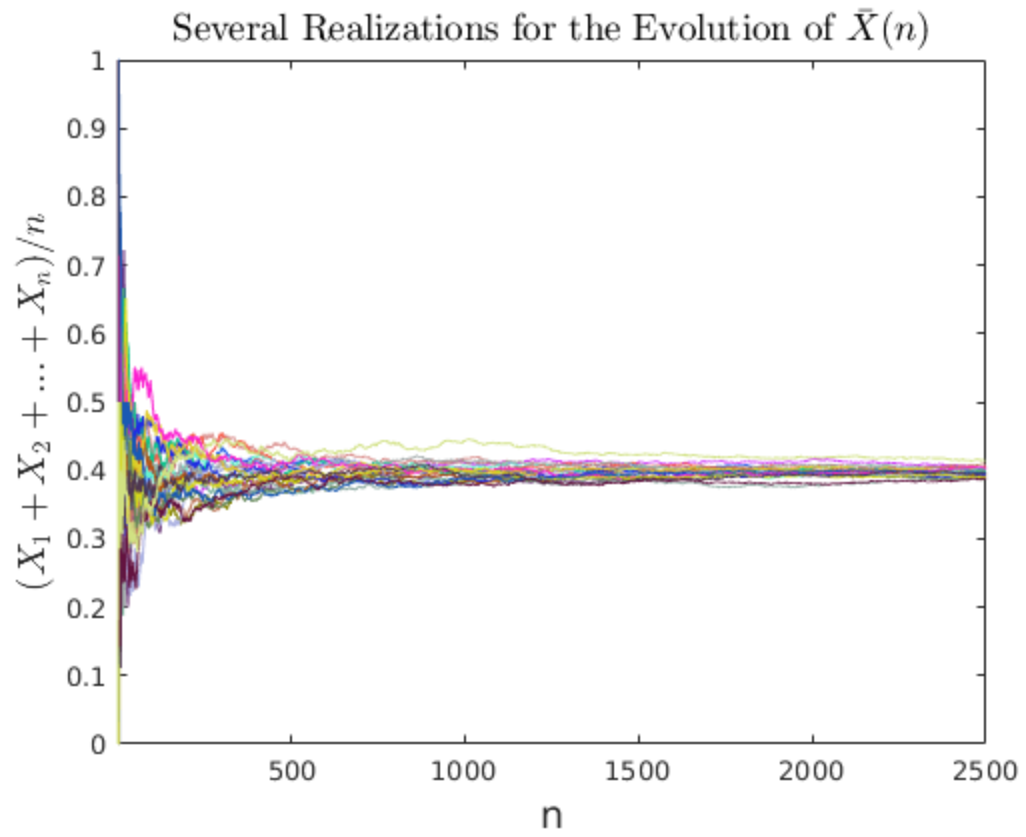
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    pause(0.025)
end
xlim([1,N])           %% set limits for x-axis
ylim([0,1])
xlabel({'n'}, 'FontSize',14);
ylabel({'$(X_1+X_2+\dots+X_n)/n$'}, 'Interpreter','latex','FontSize',14)
title({'Several Realizations for the Evolution of $\bar{X}(n)$'}, 'Interpreter','latex','FontSize',14)

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Problem A.12

a) We solve this problem for $N=2$ and $p=0.8$. (Instead of $N=2$ and $p=0.2$)

$$\begin{aligned} P(\text{correct decoding}) &= P(\text{majority of identical digits decoded correctly on their own}) \\ &= \sum_{i=N+1}^{2N+1} \binom{2N+1}{i} p^i (1-p)^{2N+1-i}. \end{aligned}$$

For $N=2$ and $p=0.8$: $P(\text{correct decoding}) = 0.942$.

b) $2N+1=3 \Rightarrow N=1$.

$$\sum_{i=2}^3 \binom{3}{i} p^i (1-p)^{3-i} \geq 0.942 \xrightarrow[\text{solve for } p]{} p \geq 0.8537.$$

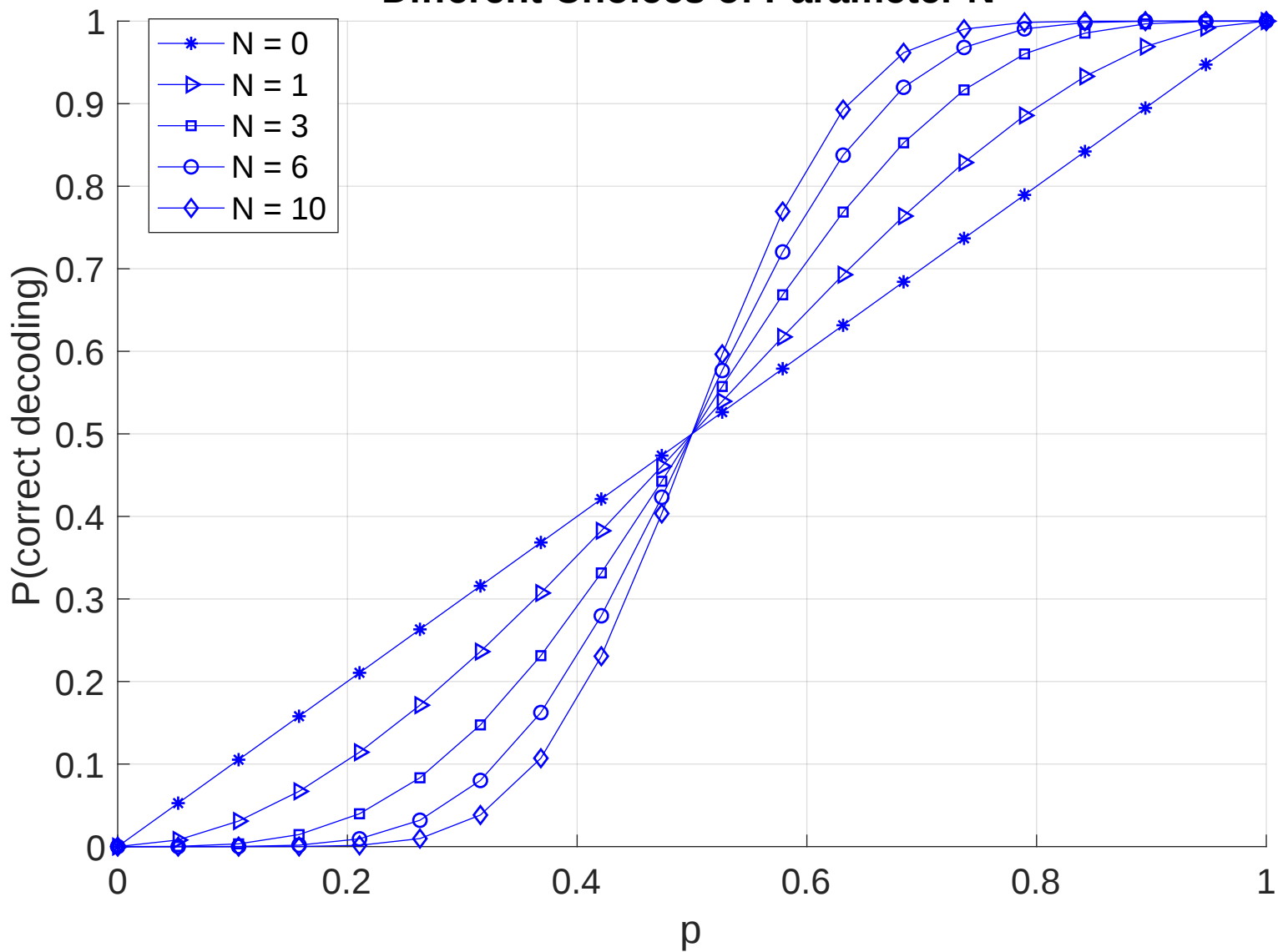
So, to get the same performance with adding less redundancy, we must have a better channel (higher p).

c) $2N+1=7 \Rightarrow N=3$.

$$\sum_{i=4}^7 \binom{7}{i} p^i (1-p)^{7-i} \geq 0.942 \Rightarrow p \geq 0.7645.$$

Hence, if we use a worse channel, we need to add more redundancy to get the same performance.

**Performance of Majority Decoding Algorithm for
Different Choices of Parameter N**



Problem A.14

For Binomial distribution:

$$P(X=k) = \binom{n}{k} p^k (1-p)^{n-k}, \quad 0 \leq p \leq 1$$

To find p^* that maximizes $P(X=k)$, we differentiate $P(X=k)$ w.r.t. p .

Since $P(X=k)$ and $\ln(P(X=k))$ have their maximum at the same point, we find p^* by setting the derivative of $\ln P(X=k)$ equal to 0:

$$\frac{\partial}{\partial p} \ln P(X=k) = \frac{\partial (k \ln p + (n-k) \ln(1-p))}{\partial p} = \frac{k}{p} - \frac{n-k}{1-p} = 0 \Rightarrow \boxed{p^* = \frac{k}{n}, 0 < k < n} \quad (1)$$

$$\left[\frac{\partial^2 \ln P(X=k)}{\partial p^2} = -\frac{k}{p^2} - \frac{n-k}{(1-p)^2} \leq 0 \Rightarrow p^* \text{ is maximizer} \right]$$

$$\text{For } k=0, P(X=k) = (1-p)^n \Rightarrow \boxed{p^* = 0} \quad ((1-p)^n \text{ decreasing in } [0,1]) \quad (2)$$

$$\text{For } k=n, P(X=k) = p^n \Rightarrow \boxed{p^* = 1} \quad (p^n \text{ increasing in } [0,1]) \quad (3)$$

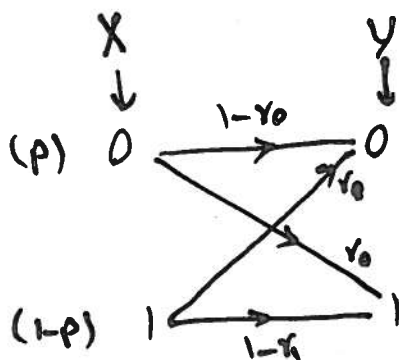
$$(1), (2), (3) \Rightarrow \boxed{p^* = \frac{k}{n}, k=0,1,\dots,n}$$

*What we did here is the Maximum Likelihood estimation of parameter p , given an observation of the model.

Maximum Likelihood is a method to estimate the parameters of a statistical model given observations. In particular, it chooses the parameter that most likely caused the observed data to occur.

Problem A.17

$$\begin{aligned}
 \text{a) } P(\text{correct decoding}) &= P(Y=1, X=1) + P(Y=0, X=0) \\
 &= P(Y=1|X=1)P(X=1) + P(Y=0|X=0)P(X=0) \\
 &= (1-r_0)(1-p) + (1-r_0)p
 \end{aligned}$$



$$\begin{aligned}
 \text{b) } P(Y_1=1, Y_2=0, Y_3=1, Y_4=1 | X_1=1, X_2=0, X_3=1, X_4=1) \\
 &= P(Y_1=1 | X_1=1, X_2=0, X_3=1, X_4=1) P(Y_2=0 | X_1=1, X_2=0, X_3=1, X_4=1) \\
 &\quad P(Y_3=1 | X_1=1, X_2=0, X_3=1, X_4=1) P(Y_4=1 | X_1=1, X_2=0, X_3=1, X_4=1) \\
 &= P(Y_1=1 | X_1=1) P(Y_2=0 | X_2=0) P(Y_3=1 | X_3=1) P(Y_4=1 | X_4=1) \\
 &= (1-r_0)^3 (1-r_0)
 \end{aligned}$$

c) $(X_1, X_2, X_3) = (0, 0, 0)$ transmitted

Correct decoding when all Y_1, Y_2, Y_3 are '0' or one of them is '1' and the two others are '0':

$$\begin{aligned}
 P_{\text{maj}}(\text{correct decoding}) &= P(Y_1, Y_2, Y_3 \text{ are all '0'} | X_1=X_2=X_3=0) \\
 &\quad + P(\text{one of } Y_1, Y_2, Y_3 \text{ is '1' \& others are '0'} | X_1=X_2=X_3=0) \\
 &= (1-r_0)^3 + \binom{3}{1} r_0 (1-r_0)^2
 \end{aligned}$$

d) Find r_0 such that $(1-r_0)^3 + 3r_0(1-r_0)^2 \geq (1-r_0)$:

$$\Leftrightarrow \begin{aligned} & (1-r_0)^3 + 3r_0(1-r_0)^2 \geq (1-r_0) \\ & \Leftrightarrow (1-r_0)^2 (1-r_0 + 3r_0) \geq (1-r_0) \end{aligned}$$

Since $0 \leq r_0 \leq 1$, we can divide both sides by $(1-r_0)$ (assuming $r_0 \neq 1$):

$$1 - r_0 + 3r_0 \geq 1 \Rightarrow 2r_0 \geq 0 \Rightarrow r_0 \geq 0$$

Alternatively, solving the inequality directly:

$$(1-r_0)^2 (1+2r_0) \geq 1$$

$$\Rightarrow (1-r_0)^2 \geq \frac{1}{1+2r_0}$$

$$\Rightarrow 1-r_0 \geq \frac{1}{\sqrt{1+2r_0}}$$

$$\Rightarrow r_0 \leq 1 - \frac{1}{\sqrt{1+2r_0}}$$

The solution set is $0 \leq r_0 \leq 1 - \frac{1}{\sqrt{1+2r_0}}$.

Problem A.17 (Cont'd)

e) Let $P(x_1=0, x_2=0, x_3=0 | y_1=1, y_2=0, y_3=1)$

$$= \frac{P(y_1=1, y_2=0, y_3=1 | x_1=0, x_2=0, x_3=0) P(x_1=0, x_2=0, x_3=0)}{P(y_1=1, y_2=0, y_3=1)}$$

$$= \frac{r_0^2 (1-r_0) P}{P(y_1=1, y_2=0, y_3=1)} \quad (1)$$

Since, there are only two options for the transmitted sequence:

$$\begin{aligned} P(y_1=1, y_2=0, y_3=1) &= P(y_1=1, y_2=0, y_3=1 | x_1=0, x_2=0, x_3=0) P(x_1=0, x_2=0, x_3=0) \\ &\quad + P(y_1=1, y_2=0, y_3=1 | x_1=1, x_2=1, x_3=1) P(x_1=1, x_2=1, x_3=1) \\ &= r_0^2 (1-r_0) P + (1-r_1)^2 r_1 (1-P) \quad (2) \end{aligned}$$

$$(1), (2) \Rightarrow P(x_1=0, x_2=0, x_3=0 | y_1=1, y_2=0, y_3=1) = \frac{r_0^2 (1-r_0) P}{r_0^2 (1-r_0) P + (1-r_1)^2 r_1 (1-P)}$$