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ENGR131A-80

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Final Project (based on first Class Project upload)

1.

a.

```
t = 10 , p(odd number)=0.4000
t = 50 , p(odd number)=0.4600
t = 100 , p(odd number)=0.4700
t = 500 , p(odd number)=0.5280
t = 1000 , p(odd number)=0.5270
```

b.

$$S_x = \{1,2,3,4\}$$

$$P(X \text{ is odd}) = P\{X = 1 \text{ or } X = 3\} = \frac{1}{2}$$

c. The experimental result approaches the theoretical result as the number of coin tosses increases (and they are approximately equal as t goes to infinity due to law of large numbers).

d.

$$x + y = 1$$

$$x = 2y$$

$$2y + y = 1$$

$$y = \frac{1}{3}; x = \frac{2}{3}$$

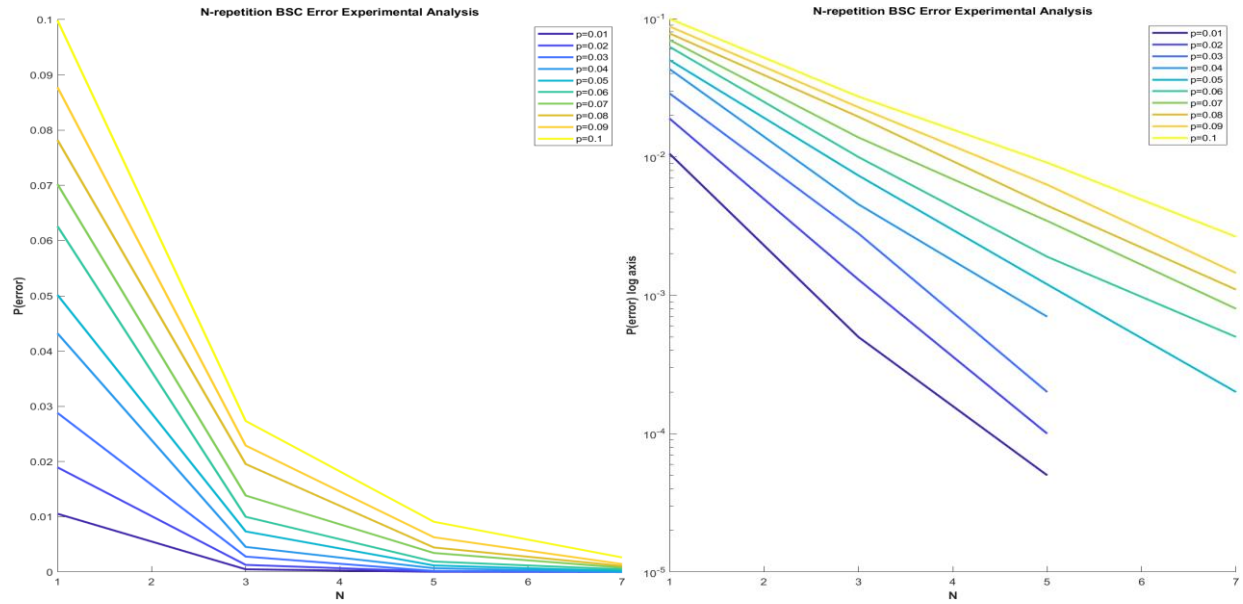
$$P(\text{odd}) = \frac{1}{3}; P(\text{even}) = \frac{2}{3}$$

```
t = 10 , p(odd number)=0.2000
t = 50 , p(odd number)=0.2400
t = 100 , p(odd number)=0.3100
t = 500 , p(odd number)=0.3080
t = 1000 , p(odd number)=0.3280
```

Similarly to part c, the experimental result approaches the theoretical result as the number of coin tosses increases (and they are approximately equal as t goes to infinity due to law of large numbers).

2.

a.



| | P=0.01 | P=0.02 | P=0.03 | P=0.04 | P=0.05 | P=0.06 | P=0.07 | P=0.08 | P=0.09 | P=0.1 |
|-----|---------|---------|--------|---------|---------|--------|---------|---------|---------|---------|
| N=1 | 0.01055 | 0.01895 | 0.0288 | 0.0432 | 0.05015 | 0.0626 | 0.0702 | 0.0782 | 0.08775 | 0.09985 |
| N=3 | 0.0005 | 0.0013 | 0.0028 | 0.00455 | 0.00735 | 0.01 | 0.01385 | 0.01955 | 0.0229 | 0.02735 |
| N=5 | 5e-05 | 0.0001 | 0.0002 | 0.0007 | 0.0012 | 0.0019 | 0.00345 | 0.00445 | 0.0063 | 0.0091 |
| N=7 | 0 | 0 | 0 | 0 | 0.0002 | 0.0005 | 0.0008 | 0.0011 | 0.00145 | 0.00265 |

b.

$N = 1,3,5,7, \dots \text{odd number}$

$$n = \left\lfloor \frac{N}{2} \right\rfloor ; p(\text{bit} = 0) = \frac{1}{2} ; p(\text{bit} = 1) = \frac{1}{2}$$

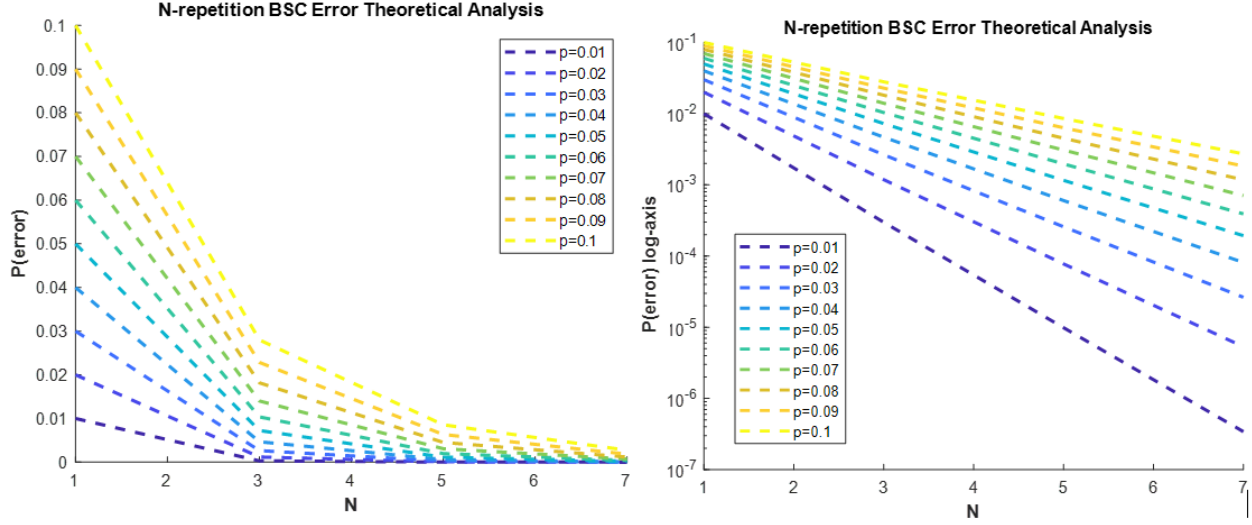
$$p(\text{error} | \text{bit} = 0) = \sum_{i=n}^N \binom{N}{i} (1-p)^{N-i} p^i$$

$$p(\text{error} | \text{bit} = 1) = \sum_{i=n}^N \binom{N}{i} (1-p)^{N-i} p^i$$

$$p(\text{error}) = p(\text{bit} = 0) * p(\text{error} | \text{bit} = 0) + p(\text{bit} = 1) * p(\text{error} | \text{bit} = 1)$$

$$= \sum_{i=n}^N \binom{N}{i} (1-p)^{N-i} p^i$$

| | P=0.01 | P=0.02 | P=0.03 | P=0.04 | P=0.05 | P=0.06 | P=0.07 | P=0.08 | P=0.09 | P=0.1 |
|-----|------------|------------|------------|------------|------------|------------|------------|-----------|-----------|----------|
| N=1 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.06 | 0.07 | 0.08 | 0.09 | 0.1 |
| N=3 | 0.000298 | 0.001184 | 0.002646 | 0.004672 | 0.00725 | 0.010368 | 0.014014 | 0.018176 | 0.022842 | 0.028 |
| N=5 | 9.8506e-06 | 7.7619e-05 | 0.000258 | 0.00060221 | 0.0011581 | 0.0019703 | 0.0030799 | 0.0045253 | 0.0063413 | 0.00856 |
| N=7 | 3.4167e-07 | 5.3357e-06 | 2.6359e-05 | 8.1282e-05 | 0.00019358 | 0.00039149 | 0.00070724 | 0.0011763 | 0.0018366 | 0.002728 |



c. If the BSC channel has the probability of flipping a bit equal to 0.5, then the BSC channel is uninterpretable (a random channel), as the user cannot determine what bit was sent. To show this, follow the proof below:

$N = 1, 3, 5, 7, \dots$ odd number

$$n = \left\lfloor \frac{N}{2} \right\rfloor ; p(\text{bit sent} = 0) = \frac{1}{2} ; p(\text{bit sent} = 1) = \frac{1}{2} ;$$

$$p(\text{bit 1 flipped}) = \frac{1}{2} ; p(\text{bit 0 flipped}) = \frac{1}{2} ;$$

$$1 - p(\text{bit 1 flipped}) = \frac{1}{2} = p(\text{bit 1 flipped}) ; 1 - p(\text{bit 0 flipped}) = \frac{1}{2} = p(\text{bit 0 flipped})$$

receive = R, sent = S

$$\begin{aligned} p(R = 0 | S = 0) &= \sum_{i=n}^N \binom{N}{i} (p(\text{bit 0 flipped}))^{N-i} (1 - p(\text{bit 0 flipped}))^i \\ &= \sum_{i=n}^N \binom{N}{i} (1 - p(\text{bit 0 flipped}))^{N-i} (p(\text{bit 0 flipped}))^i = p(R = 1 | S = 0) \end{aligned}$$

Then, by the same logic as the derivation above, $p(R=1 | S=1) = p(R=0 | S=1)$

$$p(R = 0 | S = 0) = P(R = 0 | S = 1) = P(R = 1 | S = 0) = P(R = 1 | S = 1)$$

$$P(S = 1) = P(S = 0)$$

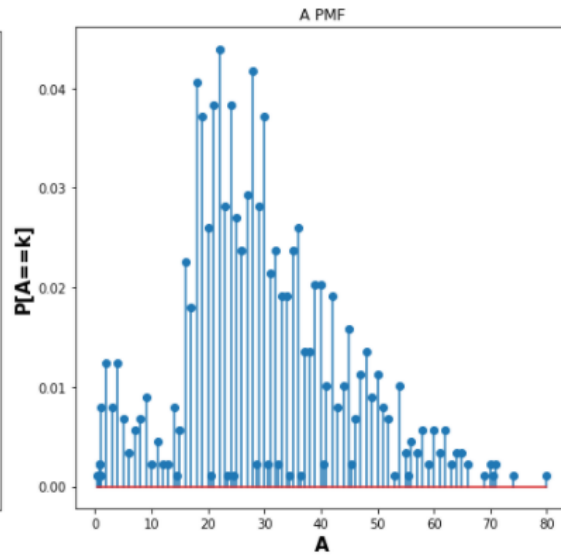
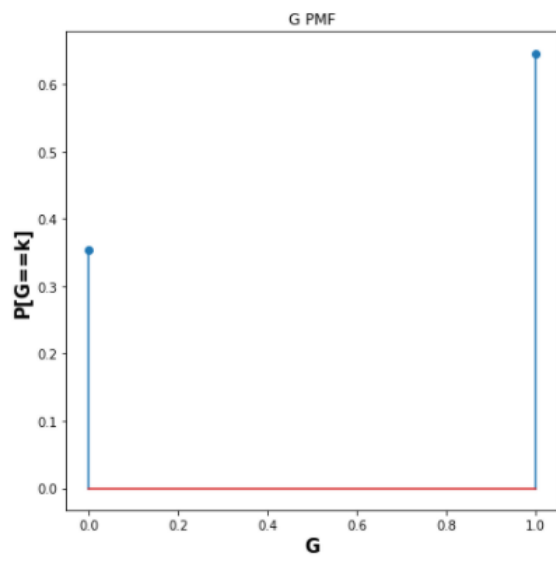
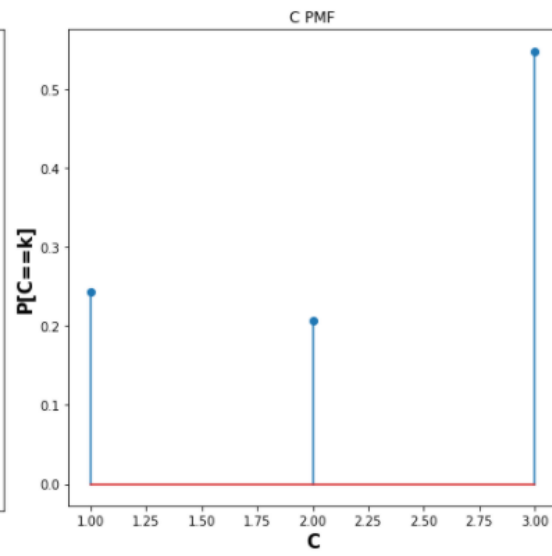
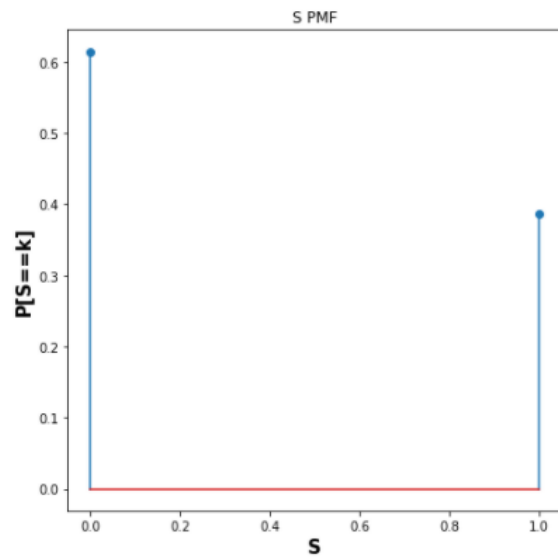
$$p(S = 1 | R = 0) = \frac{p(R = 0 | S = 1) * p(S = 1)}{\sum_{i=\{0,1\}} P(R = 0 | S = i) * P(S = i)} = \frac{p(R = 0 | S = 0) * p(S = 0)}{\sum_{i=\{0,1\}} P(R = 0 | S = i) * P(S = i)} = P(S = 0 | R = 0)$$

and the same logic holds for $p(S=0 | R = 1) = p(S=1 | R=1)$.

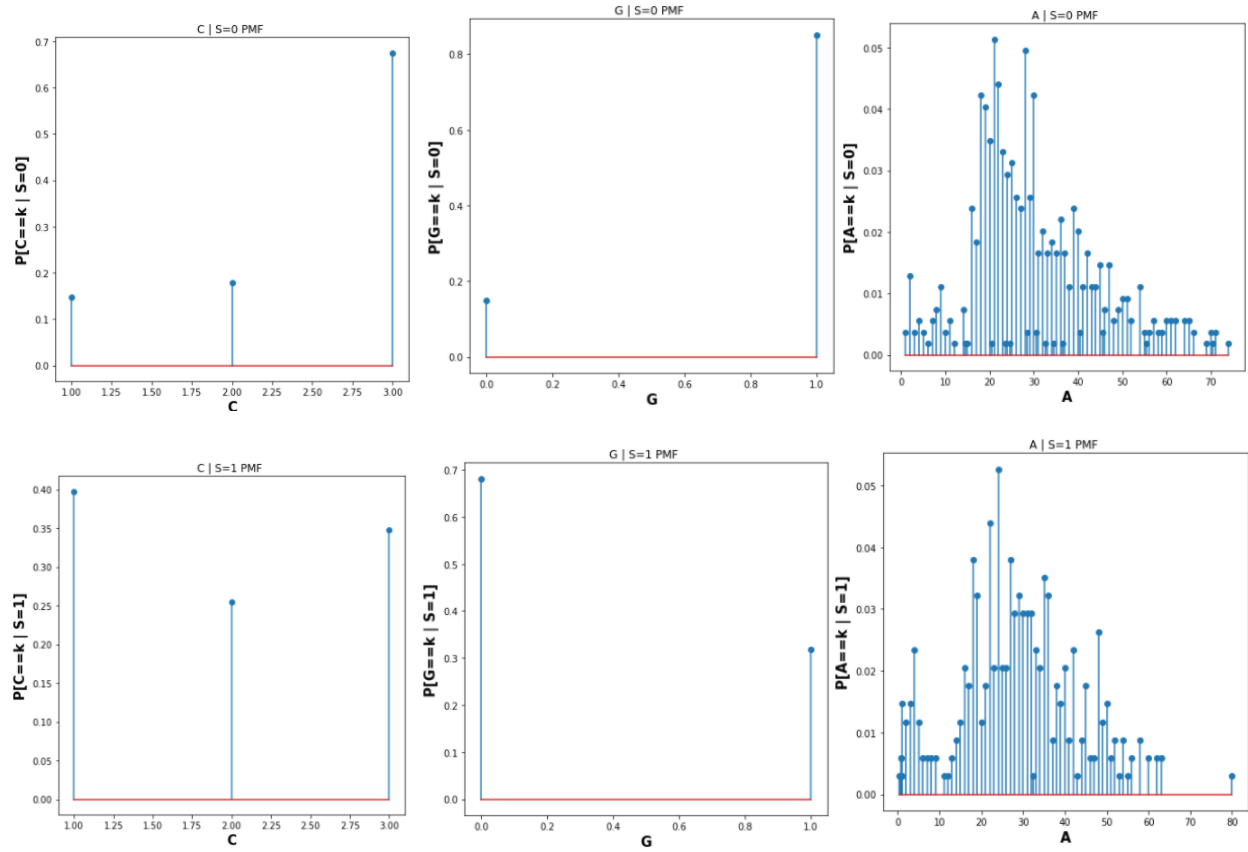
If I knew that $0.5 < p < 1$ then I would say that the receiver should swap the 1s with the 0s and vice versa to get an equivalent channel cross probability of $(1-p) < \frac{1}{2}$.

3.

a.



b.



c.

$$\begin{aligned}
 P(S = 0, C = 1, G = 0, A \leq 40) &= P(C = 1, G = 0, A \leq 40 | S = 0) * P(S = 0) \\
 &= P(C = 1 | S = 0) P(G = 0 | S = 0) P(A \leq 40 | S = 0) P(S = 0) \\
 &= 0.010625322687488965
 \end{aligned}$$

$$\begin{aligned}
 P(S = 1, C = 1, G = 0, A \leq 40) &= P(C = 1, G = 0, A \leq 40 | S = 1) * P(S = 1) \\
 &= P(C = 1 | S = 1) P(G = 0 | S = 1) P(A \leq 40 | S = 1) P(S = 1) \\
 &= 0.08460553314142813
 \end{aligned}$$

d.

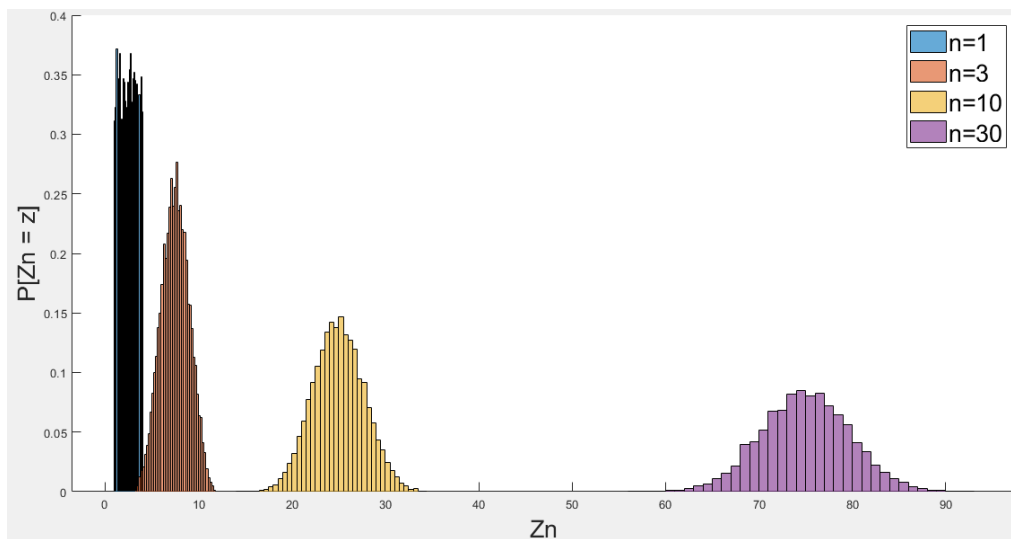
$$\begin{aligned}
 P(S = 0 | C = 1, G = 0, A \leq 40) &= \frac{P(C = 1, G = 0, A \leq 40 | S = 0) P(S = 0)}{P(C = 1, G = 0, A \leq 40)} \\
 &= \frac{P(C = 1, G = 0, A \leq 40 | S = 0) P(S = 0)}{\sum_{i=\{0,1\}} P(C = 1, G = 0, A \leq 40, S = i)} \\
 &= \frac{P(C = 1, G = 0, A \leq 40 | S = 0) P(S = 0)}{P(C = 1, G = 0, A \leq 40 | S = 1) P(S = 1) + P(C = 1, G = 0, A \leq 40 | S = 0) P(S = 0)} \\
 &= 0.11157436941003064
 \end{aligned}$$

$$\begin{aligned}
 P(S = 1 | C = 1, G = 0, A \leq 40) &= \frac{P(C = 1, G = 0, A \leq 40 | S = 1) P(S = 1)}{P(C = 1, G = 0, A \leq 40)} \\
 &= \frac{P(C = 1, G = 0, A \leq 40 | S = 1) P(S = 1)}{\sum_{i=\{0,1\}} P(C = 1, G = 0, A \leq 40, S = i)} \\
 &= \frac{P(C = 1, G = 0, A \leq 40 | S = 1) P(S = 1)}{P(C = 1, G = 0, A \leq 40 | S = 1) P(S = 1) + P(C = 1, G = 0, A \leq 40 | S = 0) P(S = 0)} \\
 &= 0.8884256305899694
 \end{aligned}$$

She will survive with probability of approximately 0.888 (most likely will survive...) .

4.

a.



As n increases (and approaches infinity) the distribution of Z_n becomes a Gaussian distribution. This is evident by looking at the difference between $n = 1$, and $n = 30$. At $n = 1$, the distribution of Z_n appears to still be a uniform distribution like the iid X_i , but when $n = 30$, the distribution of Z_n appears to be a Gaussian distribution. The tails become wider and wider as n increases, with the peak probability at the mean decreasing.

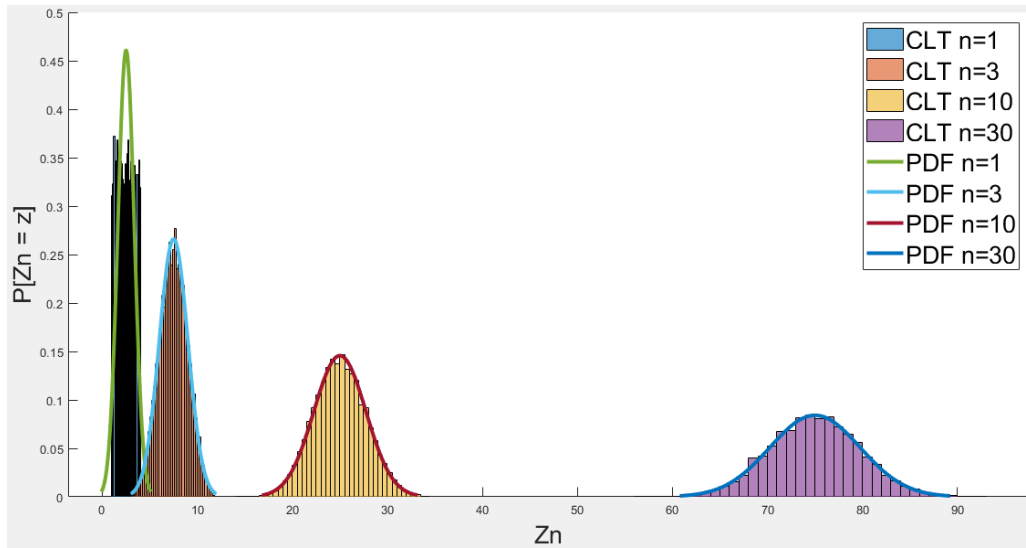
b.

$$E[X_i] = \frac{(a + b)}{2} = \frac{5}{2}; \text{Var}(X_i) = \frac{(b - a)^2}{12} = \frac{3}{4}$$

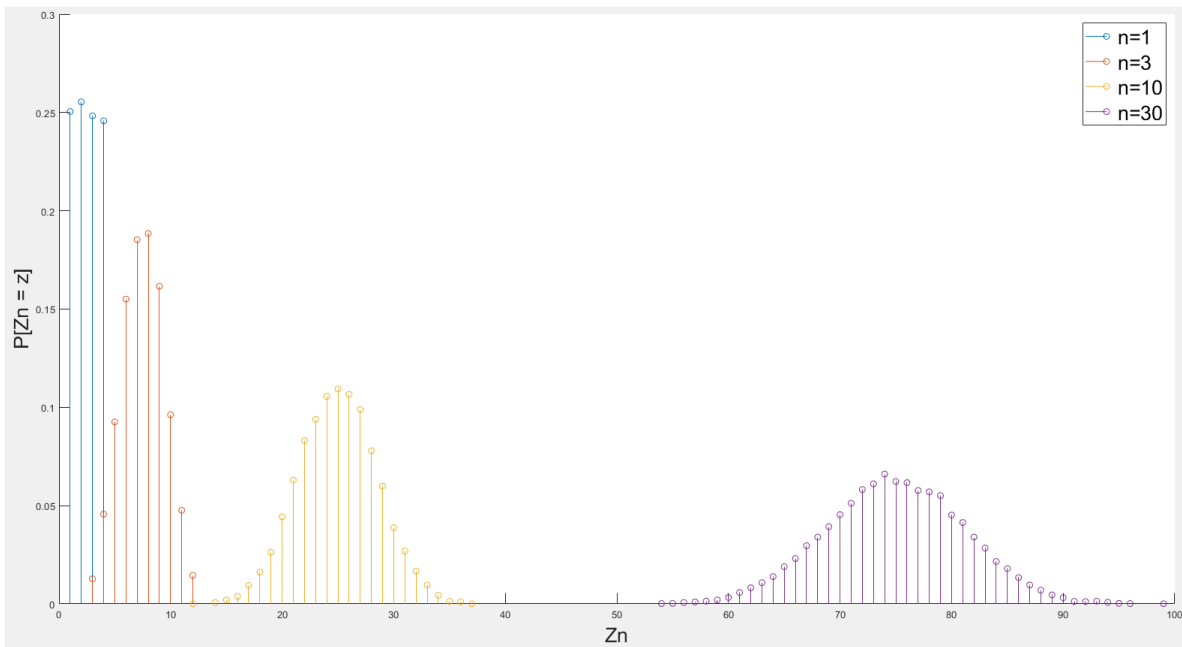
$$E[Z_n] = n * E[X_i] = \frac{5n}{2}; \text{Var}(Z_n) = \frac{n * (b - a)^2}{12} = \frac{3n}{4}$$

| n | E[Z_n] | Var(Z_n) |
|----------|-------------------------|---------------------------|
| 1 | 2.5 | 0.75 |
| 3 | 7.5 | 2.25 |
| 10 | 25.0 | 7.50 |
| 30 | 75.0 | 22.5 |

c.



d.

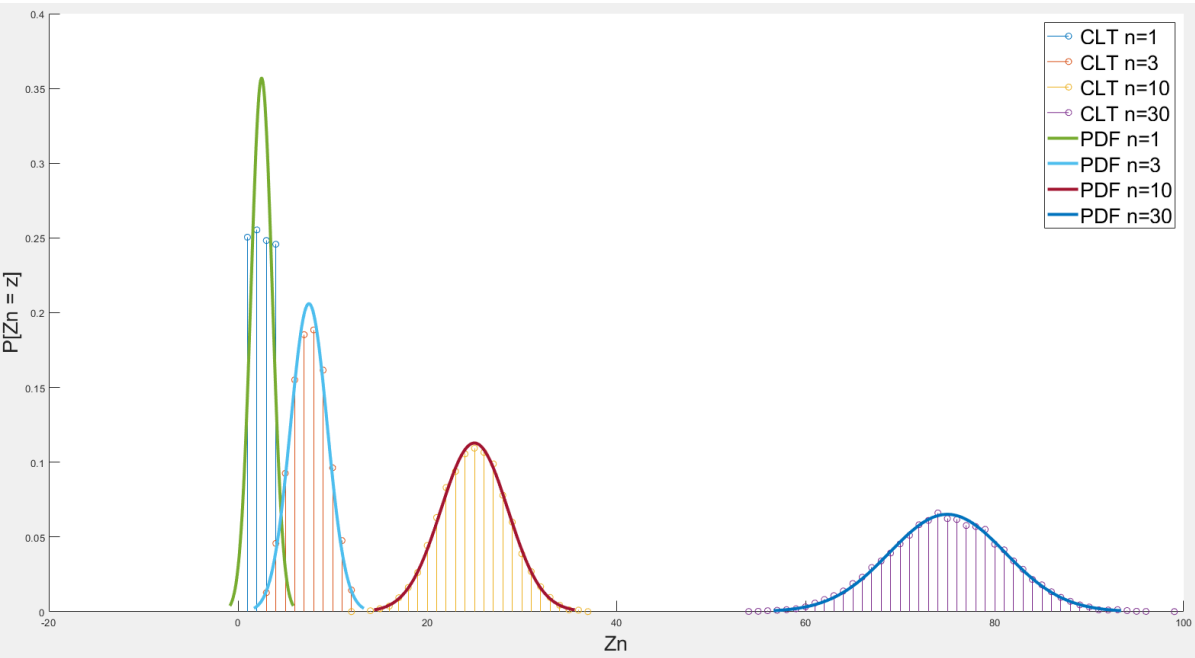


As n increases (and approaches infinity) the distribution of Z_n becomes a Gaussian distribution. This is evident by looking at the difference between $n = 1$, and $n = 30$. At $n = 1$, the distribution of Z_n appears to still be a uniform distribution like the iid X_i , but when $n = 30$, the distribution of Z_n appears to be a Gaussian distribution. The tails become wider and wider as n increases, with the peak decreasing. A difference between part (a) is that Z_n is discrete random variable.

$$E[X_i] = \frac{(a + b)}{2} = \frac{5}{2}; Var(X_i) = \frac{(b - a + 1)^2 - 1}{12} = \frac{15}{12}$$

$$E[Z_n] = n * E[X_i] = \frac{5n}{2}; Var(Z_n) = \frac{n * [(b - a + 1)^2 - 1]}{12} = \frac{15n}{12}$$

| n | $E[Z_n]$ | $Var(Z_n)$ |
|----|----------|------------|
| 1 | 2.5 | 1.25 |
| 3 | 7.5 | 3.75 |
| 10 | 25.0 | 12.5 |
| 30 | 75.0 | 37.5 |



Appendix (Code)

1.

```
%% 1a
close all; clear all; clc;
tosses = [10,50,100,500,1000];
for t = tosses
    p_odd = mean(mod(randi(4,1,t),2));
    fprintf("t =%5d , p(odd number)=%.4f\n",t,p_odd)
end
%% 1d
close all; clear all; clc;
tosses = [10,50,100,500,1000];
s = RandStream('mlfg6331_64');
for t = tosses
    p_odd = mean(mod(datasample(s,1:4,t,'Weights',[1/6,2/6,1/6,2/6]),2));
    fprintf("t =%5d , p(odd number)=%.4f\n",t,p_odd)
end
```

2.

```
close all; clear all; clc;
%%
p = 0.01:0.01:.1;
N = 1:2:7;

for i = 1:length(N)
    for j = 1:length(p)
        [bits_sent, bits_encoded] = transmitted(p(j), N(i));
        p_error(i, j) = mean(decoder(bits_sent, N(i)) ~= bits_encoded);
        theoretical_error(i, j) = p_error_theor(p(j), N(i));
    end
end
subplot(1, 2, 1)
hold on
cmap = colormap(parula(length(p)));
for i = 1:length(p)
    plot(N, p_error(:, i), 'Color', cmap(i, :), 'LineWidth', 2)
end
legend("p="+string(p))
title("N-repetition BSC Error Experimental Analysis")
xlabel("N", 'FontWeight', 'bold')
ylabel("P(error)", 'FontWeight', 'bold')

figure(1)
subplot(1, 2, 2)
hold on
cmap = colormap(parula(length(p)));
for i = 1:length(p)
    plot(N, p_error(:, i), 'Color', cmap(i, :), 'LineWidth', 2)
end
set(gca, 'yscale', 'log')
legend("p="+string(p))
title("N-repetition BSC Error Experimental Analysis")
xlabel("N", 'FontWeight', 'bold')
ylabel("P(error) log axis", 'FontWeight', 'bold')

array2table(p_error, 'RowNames', "N="+string(N), 'VariableNames', "P="+string(p))

%%
figure(2)
subplot(1, 2, 2)
hold on
for i = 1:length(p)
    plot(N, theoretical_error(:, i), 'Color', cmap(i, :), 'LineStyle', '--', 'LineWidth', 2)
end
legend("p="+string(p))
set(gca, 'yscale', 'log')
legend("p="+string(p))
title("N-repetition BSC Error Theoretical Analysis")
xlabel("N", 'FontWeight', 'bold')
ylabel("P(error) log axis", 'FontWeight', 'bold')

subplot(1, 2, 1)
```

```

hold on
for i = 1:length(p)
    plot(N,theoretical_error(:,i),'Color',cmap(i,:), 'LineStyle','--', 'LineWidth',2)
end
legend("p="+string(p))
legend("p="+string(p))
title("N-repetition BSC Error Theoretical Analysis")
xlabel("N", 'FontWeight', 'bold')
ylabel("P(error)", 'FontWeight', 'bold')

array2table(theoretical_error, 'RowNames', "N="+string(N), 'VariableNames', "P="+
string(p))

%%
function [bits_sent, bits_encoded] = transmitted(p, N)
    bits_encoded = rand(20000, 1) < .5; % <.5 is 1, >= .5 is 0 transmitted
    bits_sent = rand(20000, N);
    bits_sent = (bits_sent < p) .* (1-bits_encoded) + (1-(bits_sent < p)) .*
bits_encoded;
end

function bits_received = decoder(transmission, N)
    bits_received = sum(transmission, 2) > N/2;
end

function theoretical_error = p_error_theor(p, N)
    n = ceil(N/2);
    theoretical_error = 0;
    for i = n:N
        theoretical_error = theoretical_error + nchoosek(N, i) * p^i * (1-p)^(N-
i);
    end
end

```

3. (in python)

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os

titanic = pd.read_csv("titanic.csv").rename(columns={'Survived':'S','Pclass':'C','Sex':'G','Age':'A'})
titanic.head()
titanic.describe()
titanic.isna().sum()

# a
N = titanic.shape[0]
PMF = {}
for col in titanic.columns:
    plt.figure(figsize=(7,7))
    ps = titanic[col].value_counts()/N
    plt.stem(ps.index,ps)
    plt.title("{} PMF".format(col))
    plt.xlabel(col,fontsize=15,weight='bold')
    plt.ylabel("P[{}==k]".format(col),fontsize=15,weight='bold')
    PMF[col] = ps

# b
survived = titanic.pop("S")
survived.unique()
PMF_Conditioned = {}
for survival in survived.unique():
    for col in titanic.columns:
        plt.figure(figsize=(7,7))
        N = (survived==survival).sum()
        ps = (titanic[col][survived==survival]).value_counts() / N
```

```

plt.stem(ps.index,ps)

plt.title("{} | S={} PMF ".format(col,survival))

plt.xlabel(col,fontsize=15,weight='bold')

plt.ylabel("P[{}]=k | S={}".format(col,survival),fontsize=15,weight='bold')

PMF_Conditioned["{}|S={}".format(col,survival)] = ps

# c

p0 =
PMF['S'][0]*((PMF_Conditioned["A|S=0"][(PMF_Conditioned["A|S=0"].index<=40)].sum()))*(PMF_Conditioned["C|S=0"][1])*(PMF_Conditioned["G|S=0"][0])

p1 =
PMF['S'][1]*((PMF_Conditioned["A|S=1"][(PMF_Conditioned["A|S=1"].index<=40)].sum()))*(PMF_Conditioned["C|S=1"][1])*(PMF_Conditioned["G|S=1"][0])

# d (she will survive)

p0 / (p0 + p1)

p1 / (p0 + p1)

```

```

%% a
close all; clc; clear all;
samples = [1,3,10,30];

i = 1;
for n = samples
    xs = rand(10000,n)*3 + 1;
    Z = sum(xs,2);
    fprintf("Z @ n =%3d = %4.5f ; =%4.5f\n",n,mean(Z),var(Z))
    z(i,:) = Z;
    i = i + 1;
end

figure(1)
hold on
for i = 1:length(samples)
    histogram(z(i,:), 'Normalization', 'pdf')
end
legend("n="+string(samples), 'FontSize', 20)
fprintf("\n\n")
ylabel("P[Zn = z]", 'FontSize', 20)
xlabel("Zn", 'FontSize', 20)
%% b
clearvars -except samples

i = 1;
for n = samples
    mu = (4+1)/2;
    var = (4-1)^2 / 12;
    z_mu(i) = (mu*n);
    z_var(i) = (var*n);
    fprintf("Z_mu @ n = %3d = %4.5f\n",n,z_mu(i))
    fprintf("Z_var @ n = %3d = %4.5f\n\n",n,z_var(i))
    i = i + 1;
end
%% c
figure(1)
hold on
for i = 1:length(samples)
    x = linspace(z_mu(i) - sqrt(z_var(i))*3, z_mu(i) + sqrt(z_var(i))*3, 1000);
    y = normpdf(x, z_mu(i), sqrt(z_var(i)));
    plot(x, y, 'linewidth', 3)
end
legend('CLT n=1', 'CLT n=3', 'CLT n=10', 'CLT n=30', 'PDF n=1', 'PDF n=3', 'PDF
n=10', 'PDF n=30')

%% a
close all; clc; clear all;
samples = [1,3,10,30];

i = 1;
for n = samples
    xs = randi([1,4], 10000, n);
    Z = sum(xs,2);
    fprintf("Z @ n =%3d = %4.5f ; =%4.5f\n",n,mean(Z),var(Z))

```

```

        z(i,:) = Z;
        i = i + 1;
end
%%
figure(1)
hold on
for i = 1:length(samples)
    [C,ia,ic] = unique(z(i,:));
    a_counts = accumarray(ic,1);
    value_counts = [C', a_counts];
    stem(C',a_counts/sum(a_counts));
end
legend("n="+string(samples),'FontSize',20)
fprintf("\n\n")
ylabel("P[Zn = z]","FontSize",20)
xlabel("Zn","FontSize",20)
%% b
clearvars -except samples

i = 1;
for n = samples
    mu = (4+1)/2;
    var = ((4-1+1)^2 - 1) / 12;
    z_mu(i) = (mu*n);
    z_var(i) = (var*n);
    fprintf("Z_mu @ n = %3d = %4.5f\n",n,z_mu(i))
    fprintf("Z_var @ n = %3d = %4.5f\n\n",n,z_var(i))
    i = i + 1;
end
%% c
figure(1)
hold on
for i = 1:length(samples)
    x = linspace(z_mu(i) - sqrt(z_var(i))*3,z_mu(i) + sqrt(z_var(i))*3,1000);
    y = normpdf(x,z_mu(i),sqrt(z_var(i)));
    plot(x,y,'linewidth',3)
end
legend('CLT n=1','CLT n=3','CLT n=10','CLT n=30','PDF n=1','PDF n=3','PDF
n=10','PDF n=30')

```