Probability and Stats Experiments with Python

by Thom Ives, Ph.D.

Find this on DagsHub too. On DagsHub, I am ThomIves, and this repo is "Probability_and_Statistics_with_Python".

Calculating (Sample) Mean and Standard Deviation

$$\mu = rac{\sum x_i}{n} \quad \sigma = \sqrt{rac{\sum (x_i - \mu)^2}{n}}$$

```
def mean(X):
    mu = sum(X) / len(X)

    return mu

def standard_deviation(X, mu=None):
    if not mu:
        mu = mean(X)
    sigma = (sum([(x - mu)**2 for x in X])/len(X))**0.5

    return sigma
```

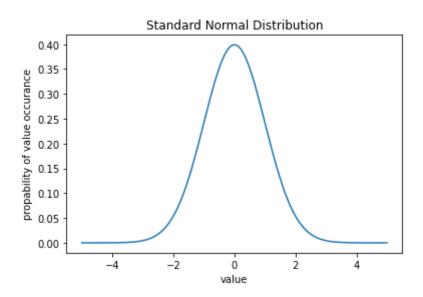
Normal Probability Distribution Function

$$p=rac{1}{\sigma\sqrt{2\pi}}e^{-rac{1}{2}\left(rac{x-\mu}{\sigma}
ight)^2}$$

```
def PDF(x, mean=0, std_dev=1):
    # define e and pi explicitly
    e = 2.718281828
    pi = 3.1415927
    # calculate in two steps
    p = 1.0 / (std_dev * ((2 * pi) ** 0.5))
    p *= e ** (-0.5 * ((x - mean)/std_dev)**2)

    return p

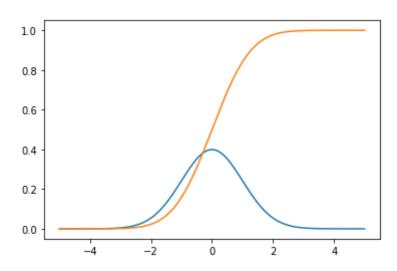
X = [(x - 1000)/200 for x in list(range(2001))]
P = [PDF(x) for x in X]
plt.plot(X, P)
plt.title(label="Standard Normal Distribution")
plt.xlabel(xlabel="value")
plt.ylabel(ylabel="propability of value occurance")
plt.show()
```



Cummulative Normal Distribution Function

$$cdf = \int_{x_{left}}^{x_{right}} rac{1}{\sigma \sqrt{2\pi}} e^{-rac{1}{2}\left(rac{x-\mu}{\sigma}
ight)^2}$$

```
import matplotlib.pyplot as plt
def PDF(x, mean=0, std_dev=1):
    # define e and pi explicitly
    e = 2.718281828
    pi = 3.1415927
    # calculate in two steps
    p = 1.0 / (std_dev * ((2 * pi) ** 0.5))
    p *= e ** (-0.5 * ((x - mean)/std_dev)**2)
    return p
def CDF(mean=0, std_dev=1, x_left=-5, x_right=5, width=0.0001):
    CDF = 0
    X = [] # for plotting only
    CDF_y = [] # for plotting only
    x = x_{left} + width / 2
    while x < x_right:
        X.append(x) # for plotting only
        panel = PDF(x, mean, std_dev) * width # panel under PDF
        CDF += panel # running sum of panels = integration
        CDF_y.append(CDF) # for plotting only
        x += width # current x value
    return CDF, X, CDF_y
total_integral, X, CDF_y = CDF()
P = [PDF(x) \text{ for } x \text{ in } X]
total_integral = round(total_integral, 5)
msg = f'Total integral of PDF = {total_integral}'
print(msg)
plt.plot(X, P)
plt.plot(X, CDF_y)
plt.show()
Total integral of PDF = 1.0
```

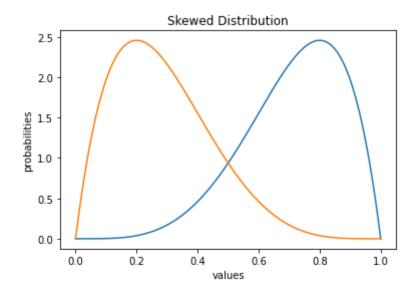


The Beta Distribution

$$f(x,lpha,eta)=rac{1}{B(lpha,eta)}\;x^{lpha-1}\;(1-x)^{eta-1}$$

$$B(lpha,eta)=\int_0^1 t^{lpha-1}(1-t)^{eta-1}dt$$

```
import matplotlib.pyplot as plt
class Beta_Distribution:
    def __init__(self, alpha, beta, panels=10000):
        self.alpha = alpha
        self.beta = beta
        self.panels = panels
        self.__Beta_Function__()
    def __Beta_Function__(self):
        width = 1 / self.panels
        X = [x/self.panels for x in range(self.panels)]
        # makes total integral of beta_PDF sum to 1
        self.B = sum(
            [(x^{**}(self.alpha - 1) * \setminus
             (1 - x)**(self.beta - 1)) * width
             for x in X])
    def beta_PDF(self, x):
        return x**(self.alpha - 1) * \
               (1 - x)**(self.beta - 1) / self.B
X = [x/1000 \text{ for } x \text{ in range}(1000+1)]
bd = Beta_Distribution(5, 2)
Y1 = [bd.beta_PDF(x) for x in X]
Y_{integral} = round(sum([y*0.001 for y in Y1]), 3)
bd = Beta_Distribution(2, 5)
Y2 = [bd.beta\_PDF(x) for x in X]
print(f"The total integral of beta_PDF is {Y_integral}")
plt.plot(X, Y1)
plt.plot(X, Y2)
plt.title(label="Skewed Distribution")
plt.xlabel(xlabel="values")
plt.ylabel(ylabel="probabilities")
plt.show()
The total integral of beta_PDF is 1.0
```



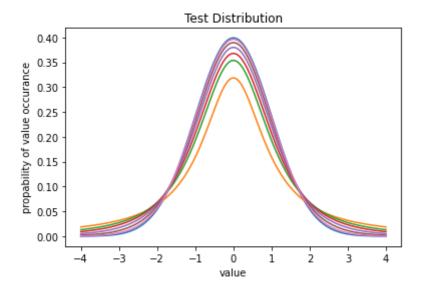
Student's T-Distribution

$$B(lpha,eta)=\int_0^1 t^{lpha-1}(1-t)^{eta-1}$$

$$PDF_t(t) = rac{1}{\sqrt{
u}B(rac{1}{2},rac{
u}{2})}\left(1+rac{t^2}{
u}
ight)^{-rac{
u+1}{2}}$$

```
class T_Distribution:
   def __init__(self, dof=9):
        self.beta = self.beta_function(0.5, dof/2)
        self.front = 1 / (dof ** 0.5 * self.beta)
        self.dof = dof
        self.power = -(dof + 1)/2
   def beta_function(self, x, y):
     pw = 1 / 1000000
     beta = 0
     t = pw / 2
     while t < 1.0:
          beta += t ** (x - 1) * (1 - t) ** (y - 1) * pw
      return beta
    def PDFt(self, t):
        # The t probability distribution method
        f_of_t = self.front * (1 + t**2/self.dof) ** self.power
        return f_of_t
    def CDFt(self, t_left, t_right):
        # The t cummulative distribution method
        # We simply numerically integrate under the PDFt curve
        panels = self.dof * 100
       width = (t_right - t_left) / panels
        cdf = 0
        t = t_left
       prob = self.PDFt(t)
       # print(panels, width, prob)
        for i in range(panels):
           t += i * width
            prob = self.PDFt(t)
            cdf += prob * width
        return cdf
```

```
import matplotlib.pyplot as plt
def PDF(x, mean=0, std_dev=1):
    # define e and pi explicitly
    e = 2.718281828
    pi = 3.1415927
    # calculate in two steps
    p = 1.0 / (std_dev * ((2 * pi) ** 0.5))
    p *= e ** (-0.5 * ((x - mean)/std_dev)**2)
    return p
X = [(x - 1000)/250 \text{ for } x \text{ in list(range(2001))}]
P = [PDF(x) \text{ for } x \text{ in } X]
plt.plot(X, P)
for dof in [1, 2, 3, 5, 10, 30]:
    t_dist = T_Distribution(dof=dof)
    TP = [t_dist.PDFt(x) for x in X]
    plt.plot(X, TP)
plt.title(label="Test Distribution")
plt.xlabel(xlabel="value")
plt.ylabel(ylabel="propability of value occurance")
plt.show()
```



Basic Determination Of Significance Value

A Khan Academy Problem

0.101

Basic Centerpoint Integration

We start t at $\frac{w}{2}$ to use centerpoints for each panel.

There are other methods of numerical integration.

Centerpoint is pretty good at balancing areas above

and below the function being integrated.

```
import matplotlib.pyplot as plt
import math
W = 1/1000
f_of_t = math.sin
T = \lceil w/2 \rceil
S = [0]
C = [-1]
for t in range(10000):
    T.append(T[-1] + w) # Our time step
    S.append(f_of_t(t^*w)) # Our Function
    C.append(f_of_t(t^*w)^*w + C[-1]) # Integrating
plt.plot(T, S)
plt.plot(T, C)
plt.show()
 1.00
 0.75
 0.50
 0.25
 0.00
-0.25
-0.50
```

Null And Alternate Hypotheses Distributions With Dynamic Significance Level

For the LaTeX in MatPlotLib Inside Colab, See:

https://stackoverflow.com/a/62075348/996205

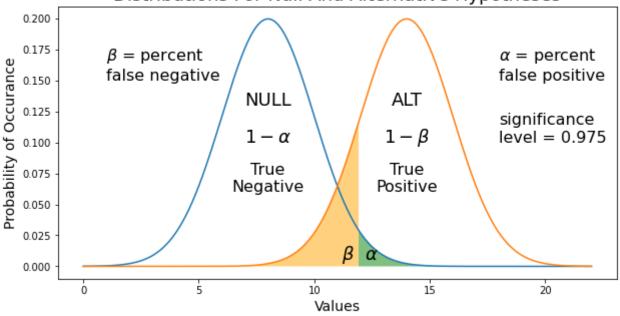
-0.75 -1.00

```
import matplotlib
from matplotlib import rc
import matplotlib.pyplot as plt
%matplotlib inline

rc('text', usetex=True)
matplotlib.rcParams['text.latex.preamble'] = [r'\usepackage{amsmath}']
!apt install texlive-fonts-recommended texlive-fonts-extra cm-super dvipng
```

```
import matplotlib.pyplot as plt
import math
import time
def PDF(x, mean=0, std_dev=1):
    p = 1.0 / (std_dev * ((2 * math.pi) ** 0.5))
    p = math.e ** (-0.5 * ((x - mean)/std_dev)**2)
    return p
pw = 1/1000
X = [(x + 0.5)*pw for x in range(22000)]
P1 = [PDF(x, 8, 2) \text{ for } x \text{ in } X]
P2 = [PDF(x, 14, 2) \text{ for } x \text{ in } X]
C1 = [] # C2 = []
sum1 = 0 # sum2 = 0
for i in range(len(X)):
    sum1 += P1[i]*pw # sum2 += P2[i]*pw
    C1.append(sum1) # C2.append(sum2)
SigLevels = [(v/2 + 90)/100 \text{ for } v \text{ in range}(17)]
SigLevels = [0.975]
for sl in SigLevels:
    for i in range(len(X)):
        if C1[i] > sl:
            siq i = i
            break
    plt.figure(figsize = (10,5))
    plt.plot(X, P1)
    plt.plot(X, P2)
    plt.title(
        label="Distributions For Null And Alternative Hypotheses", fontsize=18)
    plt.xlabel(xlabel="Values", fontsize=14)
    plt.ylabel(ylabel="Probability of Occurance", fontsize=14)
    plt.fill_between(X[sig_i:], 0, P1[sig_i:], facecolor='green', alpha=0.5)
    plt.fill_between(X[:sig_i], 0, P2[:sig_i], facecolor='orange', alpha=0.5)
    plt.text(8, 0.13, 'NULL', fontsize=18, ha='center')
    plt.text(14, 0.13, 'ALT', fontsize=18, ha='center')
    plt.text(8, 0.06, 'True\nNegative', fontsize=16, ha='center')
    plt.text(14, 0.06, 'True\nPositive', fontsize=16, ha='center')
    plt.text(1, 0.15, r'$\beta$ = percent'+'\nfalse negative',
            fontsize=16, ha='left')
    plt.text(18, 0.15, r'$\alpha$ = percent'+'\nfalse positive',
```

Distributions For Null And Alternative Hypotheses



<Figure size 432x288 with 0 Axes>

Null And Alternate Hypotheses Distributions With Dynamic Alternative Mean

```
import matplotlib.pyplot as plt
import math
import time
def PDF(x, mean_=0, std_dev_=1):
    p = 1.0 / (std_dev_* ((2 * math.pi) ** 0.5))
    p *= math.e ** (-0.5 * ((x - mean_)/std_dev_)**2)
    return p
pw = 1/1000
X = [(x + 0.5)*pw for x in range(22000)]
P1 = [PDF(x, 8, 2) \text{ for } x \text{ in } X]
C1 = [] # C2 = []
sum1 = 0
for i in range(len(X)):
    sum1 += P1[i]*pw
    C1.append(sum1)
sig_level = 0.975
for i in range(len(X)):
    if C1[i] > sig_level:
        sig_i = i
        break
for i in range(19):
    mu_alt = 12.4 + i * 0.2
    mu_alt = round(mu_alt, 1)
    P2 = [PDF(x, mu\_alt, 2) \text{ for } x \text{ in } X]
    plt.figure(figsize = (10,5))
    plt.plot(X, P1)
    plt.plot(X, P2)
    plt.title(
        label="Distributions For Null And Alternative Hypotheses", fontsize=18)
    plt.xlabel(xlabel="Values", fontsize=14)
    plt.ylabel(ylabel="Probability of Occurance", fontsize=14)
    plt.fill_between(X[sig_i:], 0, P1[sig_i:], facecolor='green', alpha=0.5)
    plt.fill_between(X[:sig_i], 0, P2[:sig_i], facecolor='orange', alpha=0.5)
    plt.text(8, 0.13, 'NULL', fontsize=16, ha='center')
    plt.text(mu_alt, 0.13, 'ALT', fontsize=16, ha='center')
    plt.text(8, 0.06, 'True\nNegative', fontsize=14, ha='center')
    plt.text(mu_alt, 0.06, 'True\nPositive', fontsize=14, ha='center')
    plt.text(1, 0.15, r'$\beta$ = percent'+'\nfalse negative',
             fontsize=14, ha='left')
```

```
plt.text(20, 0.15, r'$\alpha$ = percent'+'\nfalse positive',
         fontsize=14, ha='left')
this_text = f'significance\nlevel = {round(sig_level, 3)}'
plt.text(20, 0.10, this_text,
         fontsize=14, ha='left')
plt.text(20, 0.06, r'\$\mu_{alt}) + f' = \{\mu_{alt}\}',
         fontsize=16, ha='left')
plt.text(8, 0.1, r'$1 - \alpha$', fontsize=16, ha='center')
plt.text(mu_alt, 0.1, r'$1 - \beta$', fontsize=16, ha='center')
plt.text(X[sig_i] + 0.25, 0.005, r'$\alpha$', fontsize=18)
plt.text(X[sig_i] - 0.75, 0.005, r'$\beta$', fontsize=18)
plt.xlim([0, 26])
plt.savefig(f'hypos_{round(mu_alt, 1)}.png')
plt.show()
time.sleep(1)
plt.figure().clear()
```

ROC Curve From Dynamic Significance Level

ROC = True Positive Rate vs. False Positive Rate

```
import matplotlib.pyplot as plt
import math
import time
def PDF(x, mean=0, std_dev=1):
    p = 1.0 / (std_dev * ((2 * math.pi) ** 0.5))
    p *= math.e ** (-0.5 * ((x - mean)/std_dev)**2)
    return p
pw = 1/1000
X = [(x + 0.5)*pw for x in range(22000)]
P1 = [PDF(x, 8, 2) \text{ for } x \text{ in } X]
P2 = [PDF(x, 11, 2) \text{ for } x \text{ in } X]
C1 = []
C2 = []
sum1 = 0
sum2 = 0
for i in range(len(X)):
    sum1 += P1[i]*pw
    sum2 += P2[i]*pw
    C1.append(sum1)
    C2.append(sum2)
ROC_X = []
ROC_Y = []
pts = 41
Sig_Levels = [(v * 100/(pts-1))/100 \text{ for } v \text{ in } range(0, pts)]
for sig_lev in Sig_Levels:
    if sig_lev == 1:
        sig_lev = 0.999
    for i in range(len(X)):
        if C1[i] > sig_lev:
             sig_i = i
             break
    if sig_lev == 0.999:
        sig_lev = 1
    TP_Rate = 1 - C2[sig_i]
    FP_Rate = 1 - C1[sig_i]
    ROC_X.append(FP_Rate)
    ROC_Y.append(TP_Rate)
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 5))
    ax1.plot(X, P1)
    ax1.plot(X, P2)
```

```
msg = "Receiver Operator Curve (ROC) From Sweeping Significance Level"
fig.suptitle(msg, fontsize=18)
msg = "Significance Level On Null & Alt Distributions"
ax1.set_title(label=msg)
ax1.set_xlabel(xlabel="Values", fontsize=14)
ax1.set_ylabel(ylabel="Probability of Occurance", fontsize=14)
ax1.fill_between(X[sig_i:], 0, P1[sig_i:], facecolor='green', alpha=0.5)
ax1.fill_between(X[:sig_i], 0, P2[:sig_i], facecolor='orange', alpha=0.5)
ax1.text(1, 0.15, r'\$\beta = percent'+'\nfalse neg',
        fontsize=16, ha='left')
ax1.text(14, 0.15, r'\$\alpha = percent'+'\nfalse pos',
        fontsize=16, ha='left')
this_text = f'significance\nlevel = {round(sig_lev, 3)}'
ax1.text(14, 0.10, this_text,
        fontsize=16, ha='left')
ax1.text(X[sig_i] + 0.25, 0.005, r'$\alpha$', fontsize=18)
ax1.text(X[sig_i] - 0.75, 0.005, r'$\beta$', fontsize=18)
ax1.set_xlim([0, 21])
ax2.plot([0, 1], [0, 1])
ax2.plot(ROC_X, ROC_Y)
ax2.set_title(label="Receiver Operator Curve (ROC)")
ax2.set_xlabel(xlabel="False Positive Rate", fontsize=14)
ax2.set_ylabel(ylabel="True Positive Rate", fontsize=14)
ax2.set_xlim(0, 1)
ax2.set_ylim(0, 1)
plt.show()
fig.savefig(f'hypo_{round(sig_lev, 3)}.png')
time.sleep(0.2)
```

ROC Curve Changes Due To Separation Of NULL And ALT Distributions' Means

ROC = True Positive Rate vs. False Positive Rate

```
import matplotlib.pyplot as plt
import math
import time
def PDF(x, mean=0, std_dev=1):
    p = 1.0 / (std_dev * ((2 * math.pi) ** 0.5))
    p *= math.e ** (-0.5 * ((x - mean)/std_dev)**2)
    return p
pw = 1/1000
X = [(x + 0.5)*pw for x in range(22000)]
P1 = [PDF(x, 8, 2) \text{ for } x \text{ in } X]
C1 = []
sum1 = 0
for i in range(len(X)):
    sum1 += P1[i]*pw
    C1.append(sum1)
pts = 101
Sig_Levels = [(v * 100/(pts-1))/100 \text{ for } v \text{ in } range(0, pts)]
for i in range(71):
    mu_alt = 8 + 0.1 * i
    mu_alt = round(mu_alt, 1)
    P2 = [PDF(x, mu\_alt, 2) \text{ for } x \text{ in } X]
    C2 = []
    sum2 = 0
    for i in range(len(X)):
        sum2 += P2[i]*pw
        C2.append(sum2)
    ROC_X = []
    ROC_Y = []
    for sig_lev in Sig_Levels:
        if sig_lev == 1:
             sig_lev = 0.999
        for i in range(len(X)):
             if C1[i] > sig_lev:
                 sig_i = i
                 break
        if sig_lev == 0.999:
             sig_{ev} = 1
        TP_Rate = 1 - C2[sig_i]
        FP_Rate = 1 - C1[sig_i]
        ROC_X.append(FP_Rate)
```

```
ROC_Y.append(TP_Rate)
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 5))
ax1.plot(X, P1)
ax1.plot(X, P2)
msg = "Receiver Operator Curve (ROC) From Sweeping Significance Level"
fig.suptitle(msg, fontsize=18)
msg = "Significance Level On Null & Alt Distributions"
ax1.set_title(label=msg)
ax1.set_xlabel(xlabel="Values", fontsize=14)
ax1.set_ylabel(ylabel="Probability of Occurance", fontsize=14)
ax1.text(8, 0.09, 'NULL\nHypothesis',
        fontsize=14, ha='center')
ax1.text(mu_alt, 0.04, 'ALT\nHypothesis',
        fontsize=14, ha='center')
ax1.set_xlim([0, 21])
ax2.plot([0, 1], [0, 1])
ax2.plot(ROC_X, ROC_Y)
ax2.set_title(label="Receiver Operator Curve (ROC)")
ax2.set_xlabel(xlabel="False Positive Rate", fontsize=14)
ax2.set_ylabel(ylabel="True Positive Rate", fontsize=14)
ax2.set_xlim(0, 1)
ax2.set_ylim(0, 1)
plt.show()
fig.savefig(f'hypo_{round(mu_alt, 3)}.png')
# time.sleep(0.05)
```

ROC Curve Changes Due To Changes In NULL And ALT Distributions' Standard Deviations

ROC = True Positive Rate vs. False Positive Rate

```
import matplotlib.pyplot as plt
import math
import time
def PDF(x, mean=0, std_dev=1):
    p = 1.0 / (std_dev * ((2 * math.pi) ** 0.5))
    p *= math.e ** (-0.5 * ((x - mean)/std_dev)**2)
    return p
pw = 1/1000
X = [(x + 0.5)*pw for x in range(22000)]
pts = 101
Sig_Levels = [(v * 100/(pts-1))/100 \text{ for } v \text{ in range}(0, pts)]
for i in range(26):
    std_alt = 3.5 - 0.1 * i
    std_alt = round(std_alt, 1)
    P1 = [PDF(x, 8, std_alt) for x in X]
    C1 = []
    sum1 = 0
    for i in range(len(X)):
        sum1 += P1[i]*pw
        C1.append(sum1)
    P2 = [PDF(x, 12, std_alt) for x in X]
    C2 = []
    sum2 = 0
    for i in range(len(X)):
        sum2 += P2[i]*pw
        C2.append(sum2)
    ROC_X = []
    ROC_Y = []
    for sig_lev in Sig_Levels:
        if sig_lev == 1:
            sig_lev = 0.999
        for i in range(len(X)):
            if C1[i] > sig_lev:
                sig_i = i
                break
        if sig_lev == 0.999:
            sig_{lev} = 1
        TP_Rate = 1 - C2[sig_i]
        FP_Rate = 1 - C1[sig_i]
        ROC_X.append(FP_Rate)
```

```
ROC_Y.append(TP_Rate)
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 5))
ax1.plot(X, P1)
ax1.plot(X, P2)
msg = "Receiver Operator Curve (ROC) From Sweeping Significance Level"
fig.suptitle(msg, fontsize=18)
msg = "Significance Level On Null & Alt Distributions"
ax1.set_title(label=msg)
ax1.set_xlabel(xlabel="Values", fontsize=14)
ax1.set_ylabel(ylabel="Probability of Occurance", fontsize=14)
ax1.text(8, 0.09, 'NULL\nHypothesis',
        fontsize=14, ha='center')
ax1.text(12, 0.04, 'ALT\nHypothesis',
        fontsize=14, ha='center')
ax1.set_xlim([0, 21])
ax2.plot([0, 1], [0, 1])
ax2.plot(ROC_X, ROC_Y)
ax2.set_title(label="Receiver Operator Curve (ROC)")
ax2.set_xlabel(xlabel="False Positive Rate", fontsize=14)
ax2.set_ylabel(ylabel="True Positive Rate", fontsize=14)
ax2.set_xlim(0, 1)
ax2.set_ylim(0, 1)
plt.show()
fig.savefig(f'hypo_{round(sig_lev, 3)}.png')
# time.sleep(0.05)
```

F1 Score

```
F_1 = \frac{2}{\frac{1}{Recall} + \frac{1}{Precision}}
```

Accuracy, Recall, Precision

 $\protect\$ \$\protection = \frac{TP}{TP + FP} = \frac {\protections}\$\$

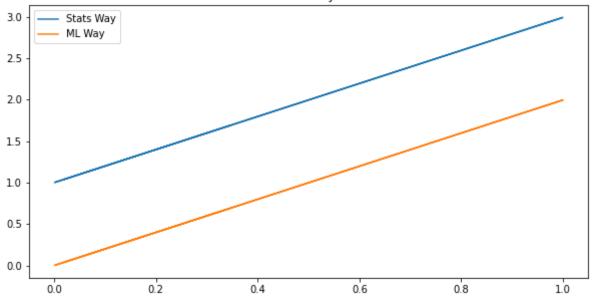
LASSO In Logistic Regression to Compare with Statistics Version

Regressor Coefficient From Statistics Vs. Machine Learning Methods

```
import matplotlib.pyplot as plt
import numpy as np
# Synthesize some data (i.e. create fake data)
X = np.random.uniform(0, 1, 1000)
Y = 2.0 * X
Y_noise = np.max(Y) * 0.073
Y += np.random.normal(0, 0.073, 1000)
# Statistics Way To Create Model
X_{std} = np.std(X)
Y_std = np.std(Y)
r = np.corrcoef(X, Y)
Cs = Y_std / X_std * r[0, 1]
print(Cs)
# Machine Learning
mod_LR = LinearRegression(fit_intercept=False, copy_X=True)
mod_LR.fit(X.reshape(-1, 1), Y.reshape(-1, 1))
Cml = mod_LR.coef_[0, 0]
print(Cml)
# Visualize
plt.figure(figsize=(10, 5))
plt.plot(X, Cs*X+1) # + 1 separates the two exact plots
plt.plot(X, Cml*X)
plt.title('Models Determined By Stats And ML')
plt.legend(('Stats Way', 'ML Way'))
plt.show()
1.9918506427390517
```

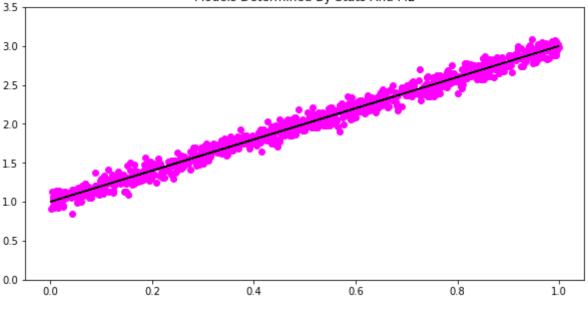
1.9957689952415045





Regressor Coefficient AND "Intercept" FROM Statistics

```
import matplotlib.pyplot as plt
import numpy as np
# Synthesize some data (i.e. create fake data)
X = np.random.uniform(0, 1, 1000)
Y = 2.0 * X + 1
Y_{noise} = np.max(Y) * 0.073
Y += np.random.normal(0, 0.073, 1000)
# Statistics Way To Fit Model Coefficient
X_{std} = np.std(X)
Y_std = np.std(Y)
r = np.corrcoef(X, Y)
Cs = Y_std / X_std * r[0, 1]
print(Cs)
# Statistics Way To Calculate Intercept
X_{mean} = np.mean(X)
Y_{mean} = np.mean(Y)
b = Y_mean - Cs*X_mean
print(b)
1.9992493711567196
1.001206029449972
```

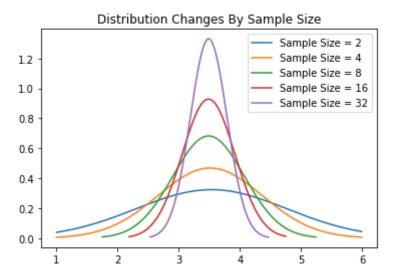


```
# Visualize
plt.figure(figsize=(10, 5))
plt.scatter(X, Y, color='magenta')
plt.plot(X, Cs*X+b, color='black')
plt.ylim((0, 3.5))
plt.title('Models Determined By Stats And ML')
plt.show()
```

Central Limit Theorem Principles

Sample Means Distribtion For Increasing Sample Sizes

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
die_values = [1, 2, 3, 4, 5, 6]
sample\_sizes = [2, 4, 8, 16, 32]
for experiment in range(1):
    for sample_size in sample_sizes:
        sample_means = []
        for num_samples in range(1000):
            die_cast = np.random.choice(
            die_values, size=sample_size)
            sample_mean = np.mean(die_cast)
            sample_means.append(sample_mean)
        experiment_mean = np.mean(sample_means)
        experiment_std = np.std(sample_means)
        x_{min} = min(sample_means)
        x_max = max(sample_means)
        x = np.arange(x_min, x_max, 0.01)
        y = norm.pdf(x, experiment_mean, experiment_std)
        plt.plot(x, y)
    legend_texts = [f'Sample Size = {v}' for v in sample_sizes]
    plt.legend(legend_texts)
    plt.title("Distribution Changes By Sample Size")
    plt.show()
```



Approaching The Central Limit Theorem

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
import os
cwd = os.getcwd()
if not os.path.isdir(f"{cwd}/images"):
    os.mkdir(f"{cwd}/images")
no_images = True
image_num = 0
if no_images:
    die_values = [1, 2, 3, 4, 5, 6]
    sample\_sizes = [2, 4, 8, 16, 32]
    num_add_samples_list = [2] + [1]*8 + [2]*5 + [10]*8 + [100]*9
    sample_means_D = {k: [] for k in sample_sizes}
    total\_samples = 0
    for num_samples in num_add_samples_list:
        total_samples += num_samples
        plt.figure(figsize=(12, 6))
        for sample_size in sample_sizes:
            for sample_num in range(num_samples):
                die_cast = np.random.choice(
                die_values, size=sample_size)
                sample_mean = np.mean(die_cast)
                sample_means_D[sample_size].append(sample_mean)
            experiment_mean = np.mean(sample_means_D[sample_size])
            experiment_std = np.std(sample_means_D[sample_size])
            x_min = min(sample_means_D[sample_size])
            x_max = max(sample_means_D[sample_size])
            x = np.arange(x_min, x_max, 0.001)
            y = norm.pdf(x, experiment_mean, experiment_std)
            plt.plot(x, y)
        legend_texts = [f'Sample Size = {v}' for v in sample_sizes]
        plt.legend(legend_texts)
        title = f"Distribution Of Means For {total_samples} "
        title += "Samples For Various Sample Sizes"
        plt.title(title)
        plt.xlim([1, 6])
        if total_samples == 2:
            for i in range(5):
                plt.savefig(f"{cwd}/images/{image_num:02d}.png")
                image_num += 1
        elif total_samples == 1000:
            for i in range(5):
                plt.savefig(f"{cwd}/images/{image_num:02d}.png")
                image_num += 1
```

```
else:
    plt.savefig(f"{cwd}/images/{image_num:02d}.png")
    image_num += 1

plt.close()

# Run below on command line to create movie - needs ffmpeg
# ffmpeg -framerate 4 -pattern_type glob -i "*.png" output.avi
```

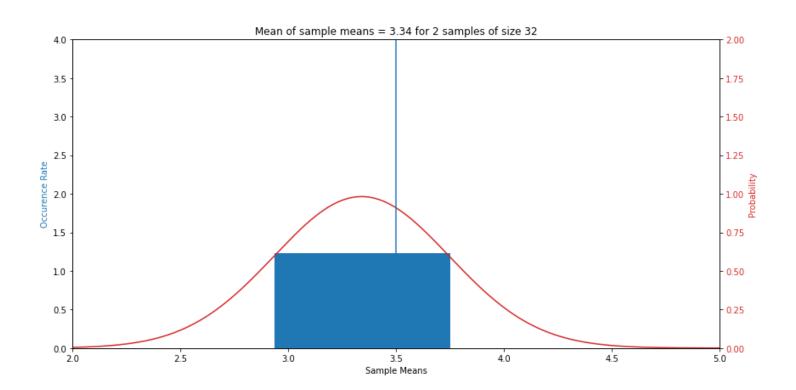
Sample From Huge Population To See When Central Limit Theorem Is Reached

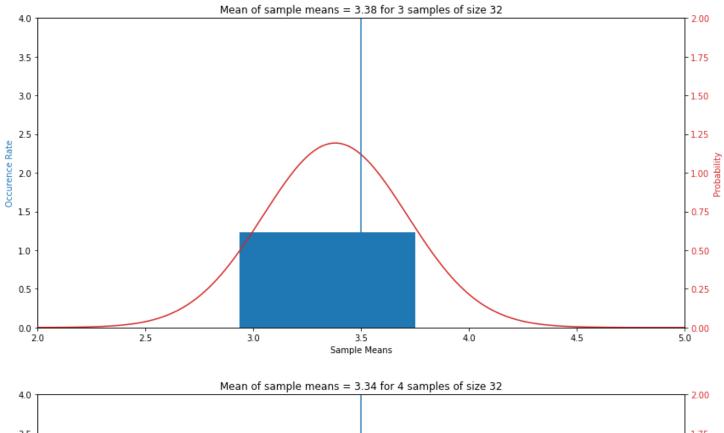
```
import numpy as np
import matplotlib.pyplot as plt
die_values = [1, 2, 3, 4, 5, 6]
die_roles = [np.random.choice(die_values, size=1)[0] for _ in range(int(1e6))]
# plt.hist(die_roles, bins=6, width=0.73)
# plt.show();
mean = round(np.mean(die_roles), 1)
print(f'Population mean is {mean}')
for sample_size in [2, 4, 8, 16, 32, 64]:
    sample\_means = []
    samples = 0
    while True:
        samples += 1
        roles = np.random.choice(die_roles, size=sample_size)
        sample\_mean = np.mean(roles)
        sample_means.append(sample_mean)
        running_mean = round(np.mean(sample_means), 2)
        if running_mean == 3.50:
            break
    title = f'Mean sample means = {running_mean} for {samples} samples of {sample_size}'
    running_std = np.std(sample_means)
    x = np.arange(1, 6, 0.001)
    y = norm.pdf(x, running_mean, running_std)
    plt.xlim([1, 6])
    plt.plot(x, y)
    plt.title(title)
    plt.axvline(3.5)
    plt.show();
```

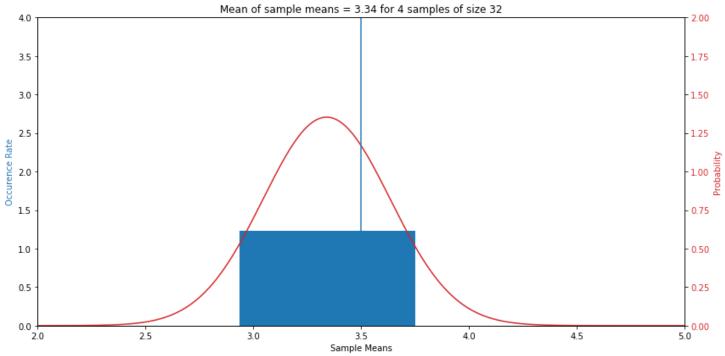


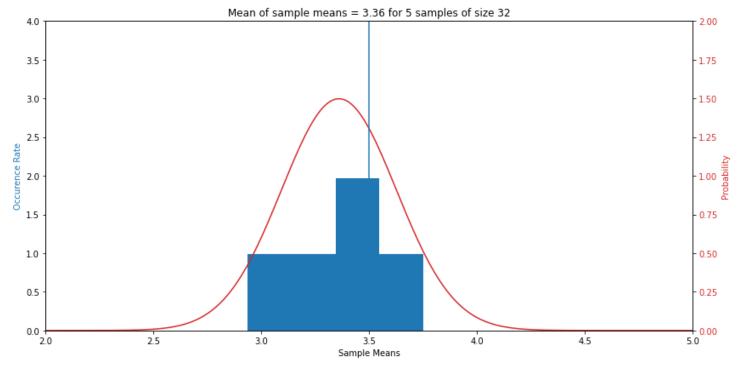
```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
import os
cwd = os.getcwd()
if not os.path.isdir(f"{cwd}/images"):
    os.mkdir(f"{cwd}/images")
no_images = True
image_num = 0
if no_images:
    die_values = [1, 2, 3, 4, 5, 6]
    num_add_samples_list = [2] + [1]*8 + [2]*5 + [10]*8 + [100]*9
    num_add_samples_list += [9000] + [900000] + [900000] + [10000000]
    sample_means = []
    total\_samples = 0
    for num_samples in num_add_samples_list:
        total_samples += num_samples
        for sample_num in range(num_samples):
            die_casts = np.random.choice(
                die_values, size=32)
            sample_mean = np.mean(die_casts)
            sample_means.append(sample_mean)
        fig, ax1 = plt.subplots()
        fig.set_figheight(6)
        fig.set_figwidth(12)
        color = 'tab:blue'
        ax1.set_xlabel('Sample Means')
        ax1.set_ylabel('Occurence Rate', color=color)
        bins = len(set(sample_means))
        ax1.hist(sample_means, bins=bins, density=True, stacked=True)
        ax1.set_xlim([2, 5])
        ax1.set_ylim([0, 4])
        ax2 = ax1.twinx()
        color = 'tab:red'
        ax2.set_ylabel('Probability', color=color)
        ax2.tick_params(axis='y', labelcolor=color)
        running_mean = round(np.mean(sample_means), 2)
        title = f'Mean of sample means = {running_mean} '
        title += f'for {total_samples} samples of size 32'
        running_std = np.std(sample_means)
        x = np.arange(2, 5, 0.001)
        y = norm.pdf(x, running_mean, running_std)
        ax2.plot(x, y, color=color)
```

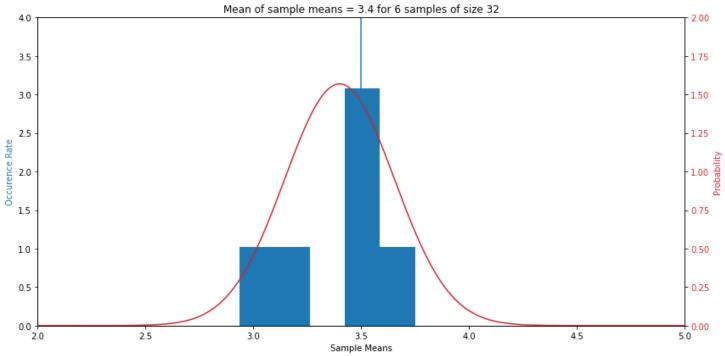
```
ax2.set_ylim([0, 2])
        plt.title(title)
        plt.axvline(3.5)
        fig.tight_layout()
        # if total_samples == 2:
              for i in range(5):
                  plt.savefig(f"{cwd}/images/{image_num:02d}.png")
        #
                  image_num += 1
        # elif total_samples > 1000000:
              for i in range(5):
        #
                  plt.savefig(f"{cwd}/images/{image_num:02d}.png")
        #
                  image_num += 1
        #
        # else:
              plt.savefig(f"{cwd}/images/{image_num:02d}.png")
              image_num += 1
        plt.show();
        # plt.close()
# Run below on command line to create movie - needs ffmpeg
# ffmpeg -framerate 4 -pattern_type glob -i "*.png" output.avi
```

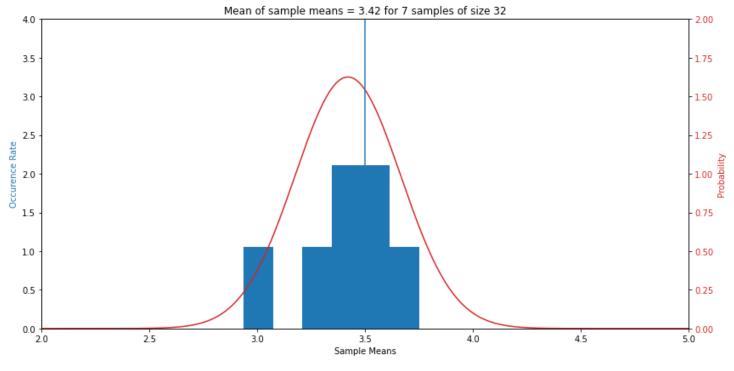


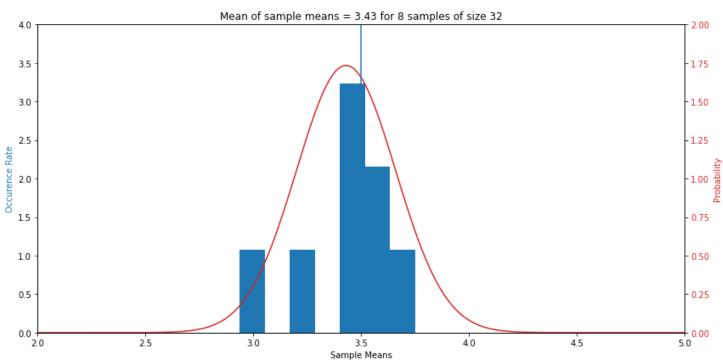


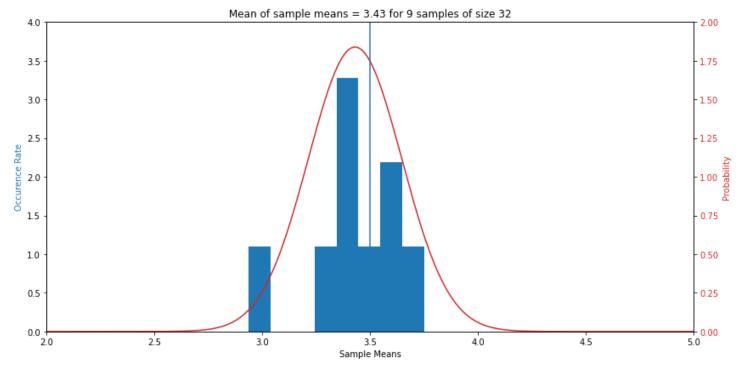


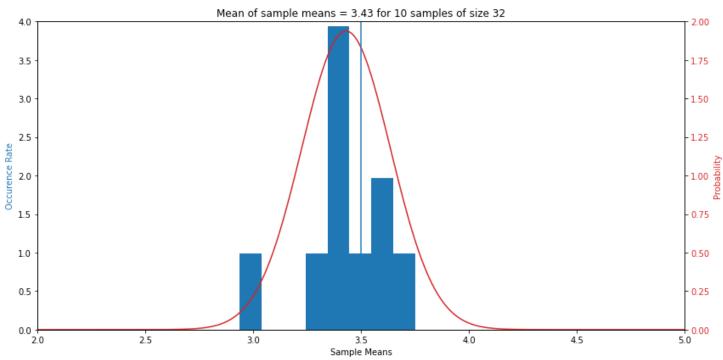


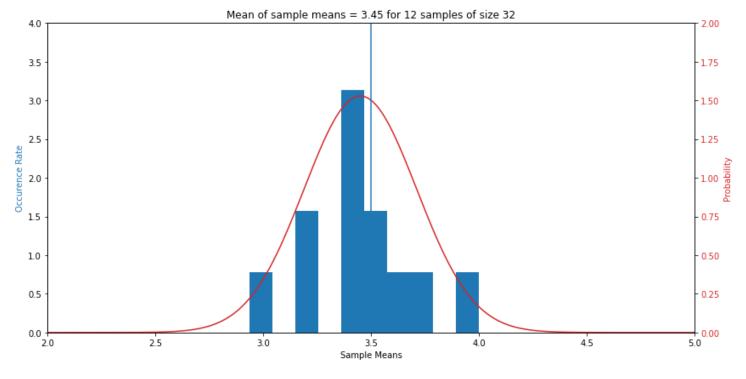


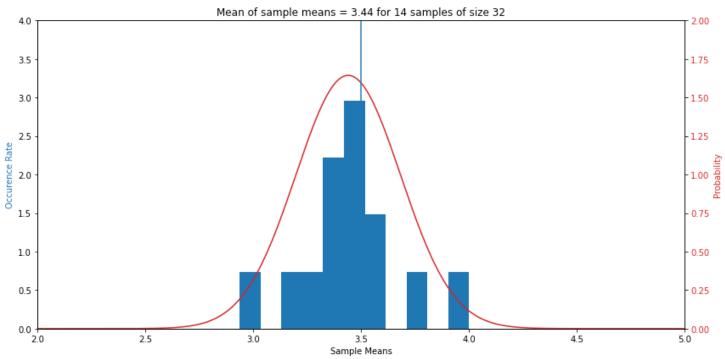


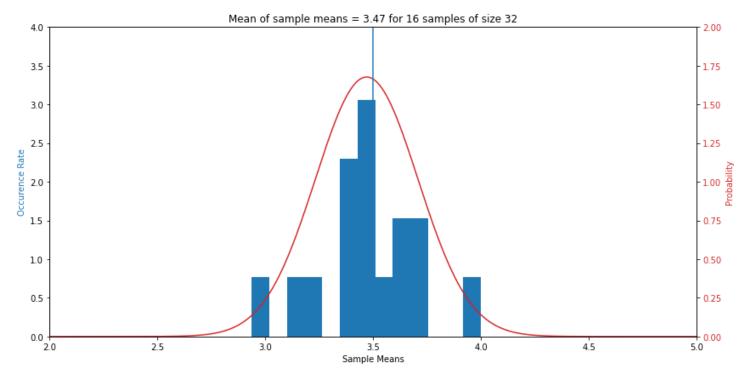


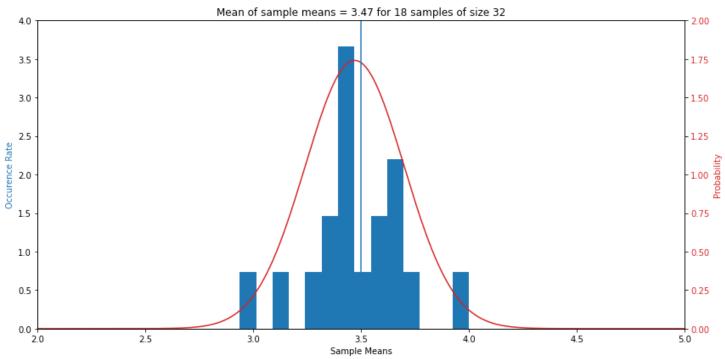


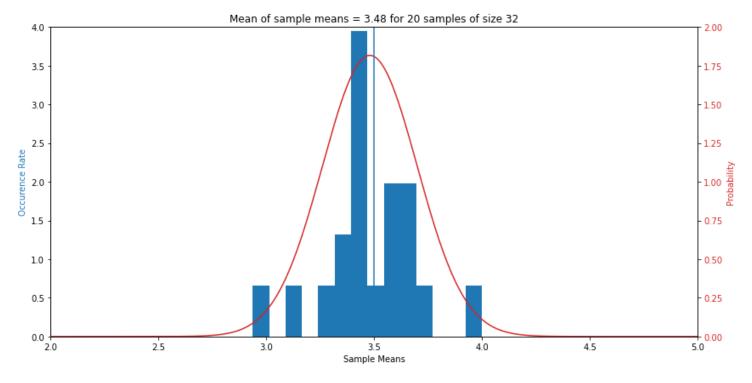


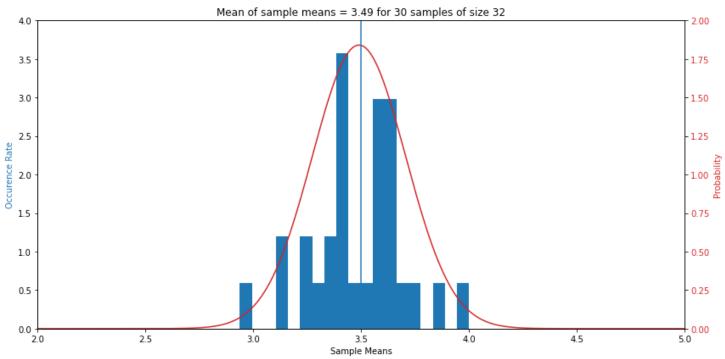


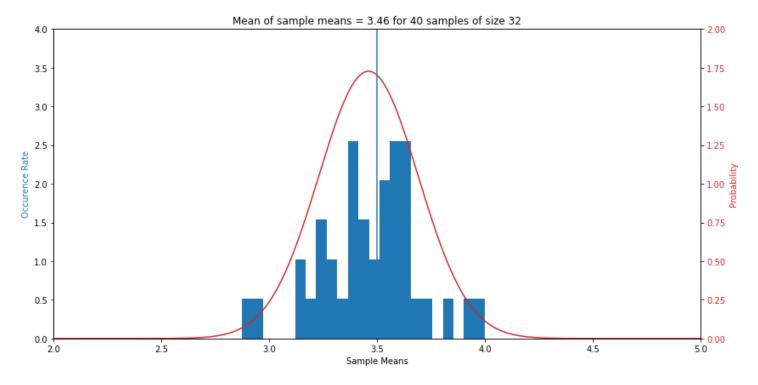


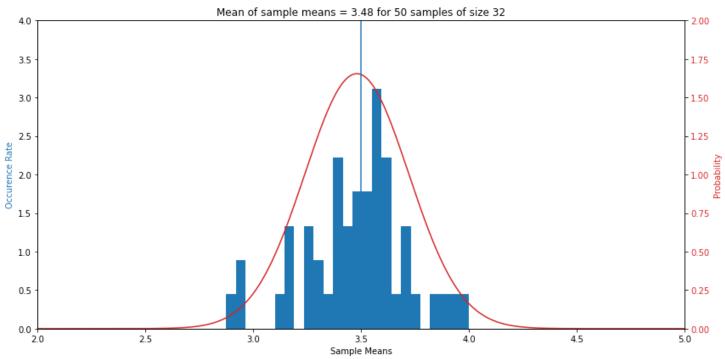


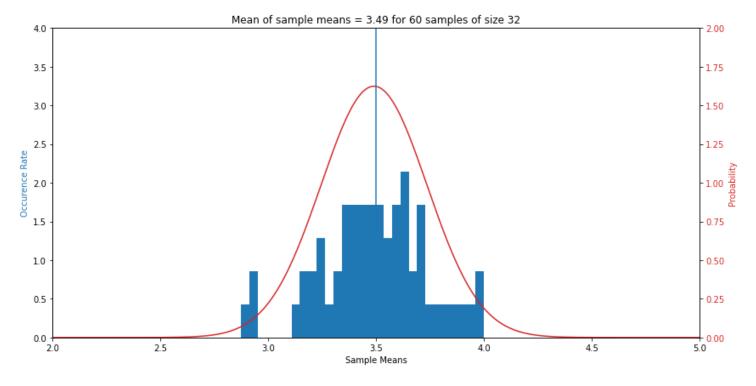


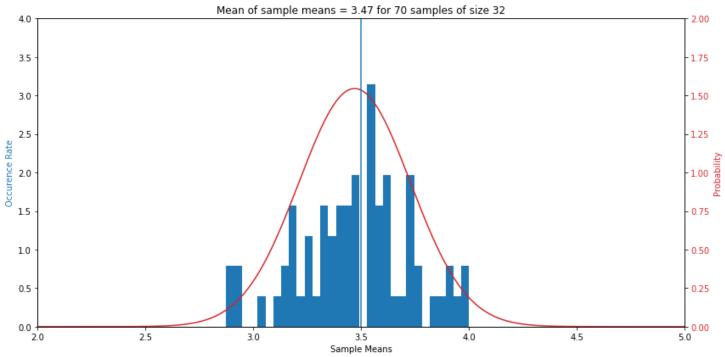


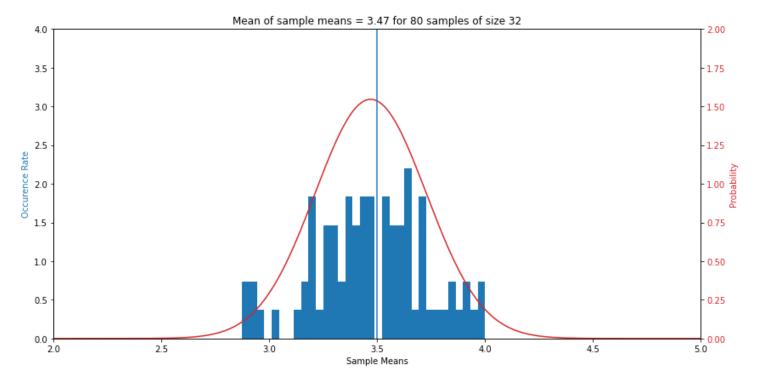


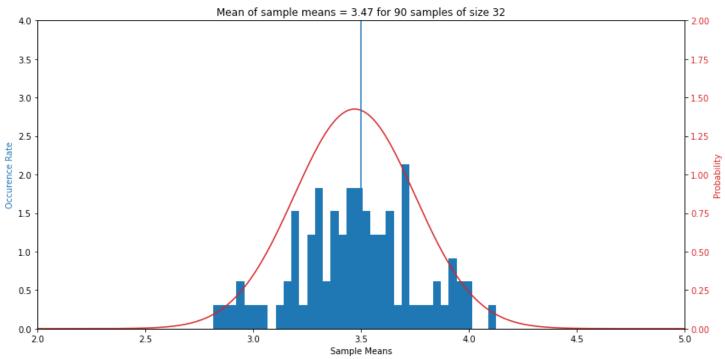


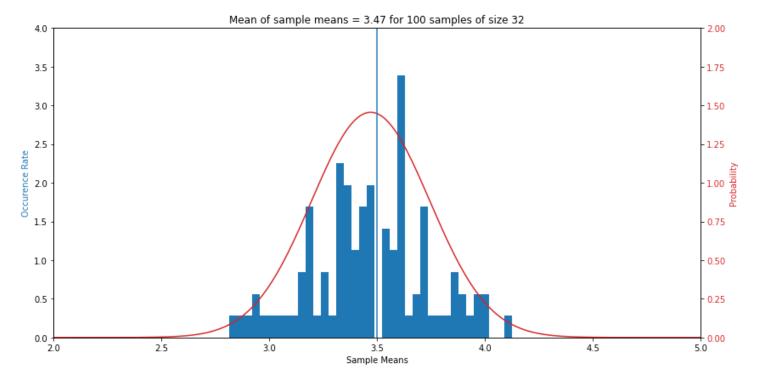


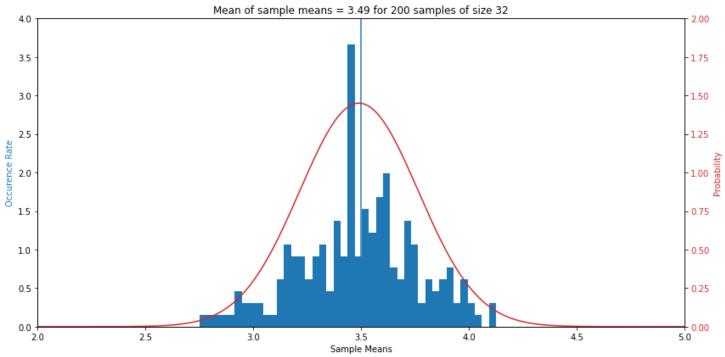


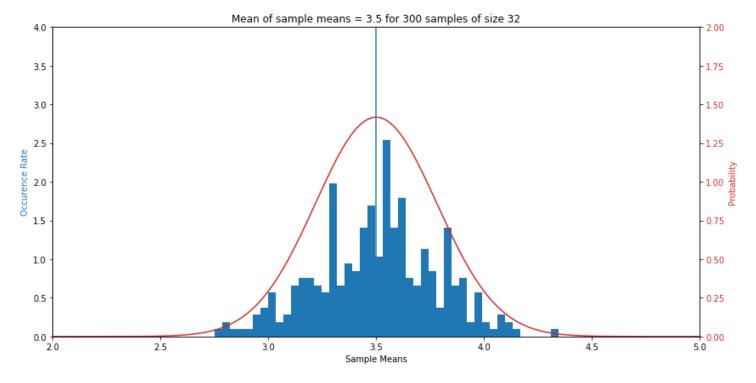


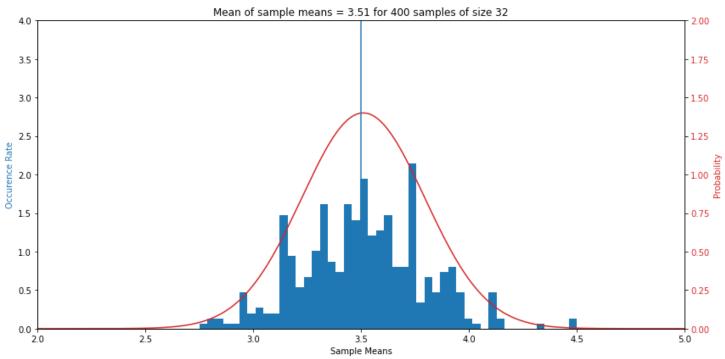


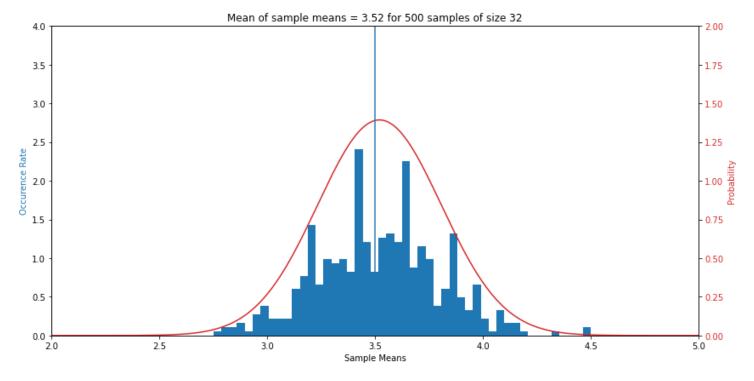


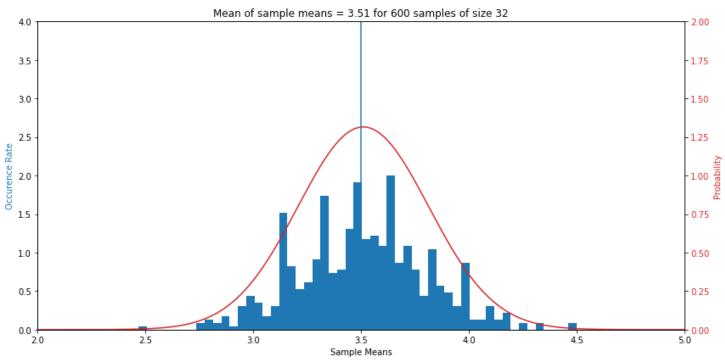


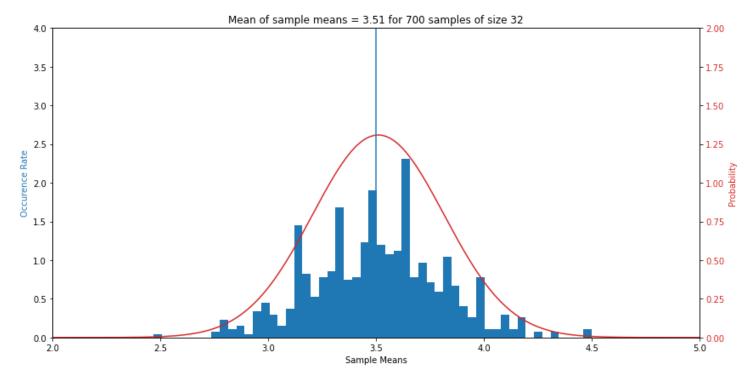


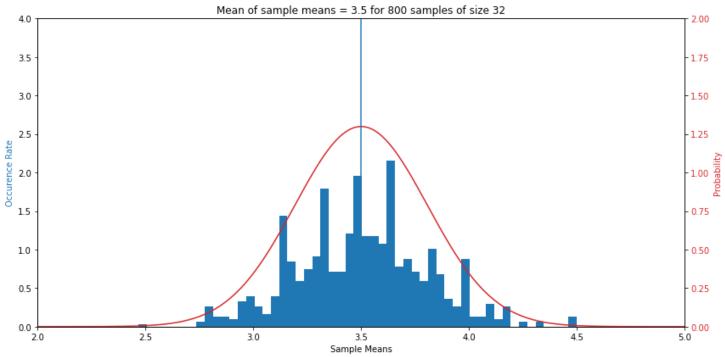


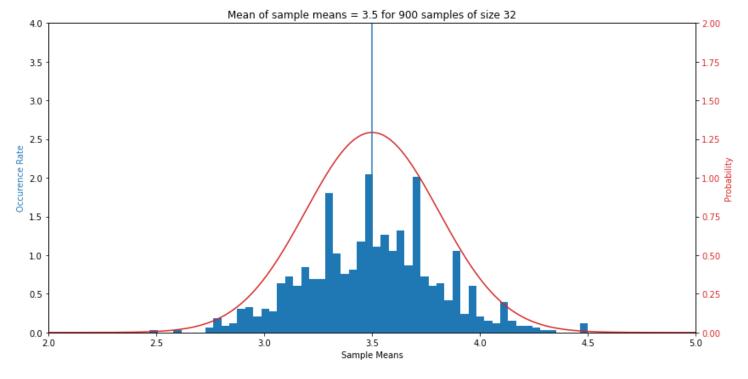


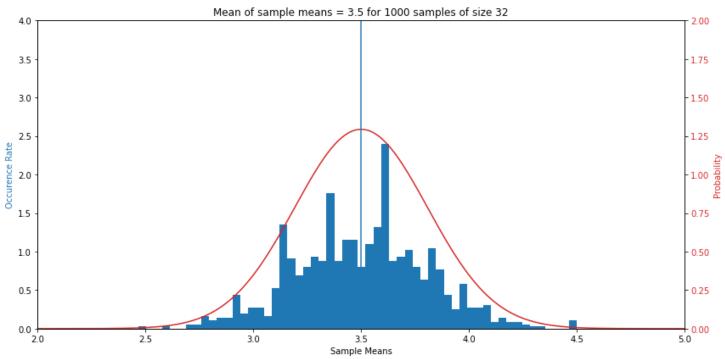


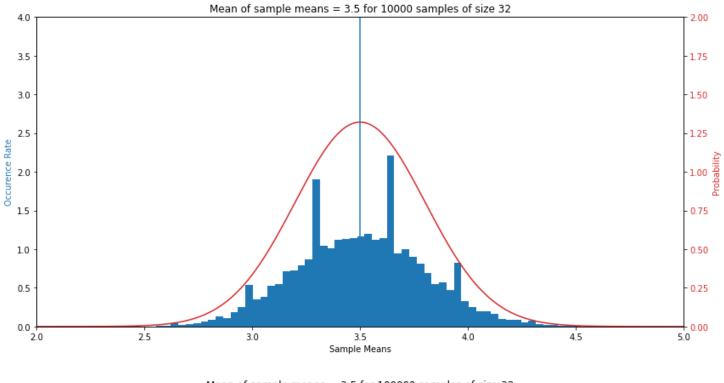


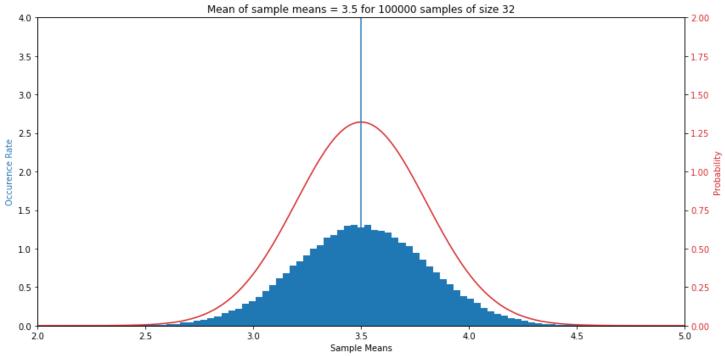


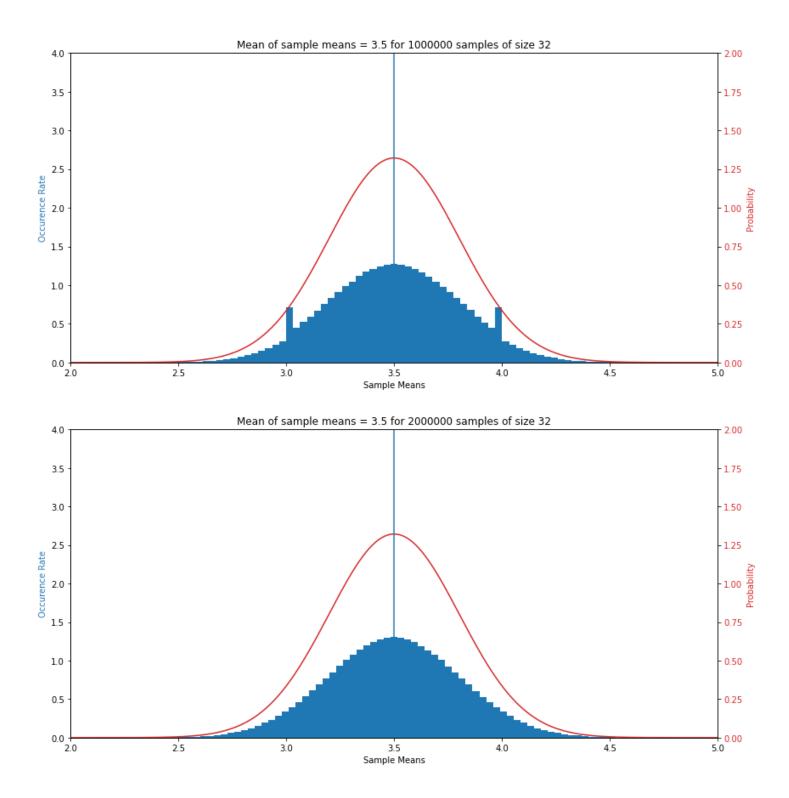












Two Y Axes

```
import numpy as np
import matplotlib.pyplot as plt
# Create some mock data
t = np.arange(0.01, 10.0, 0.01)
data1 = np.exp(t)
data2 = np.sin(2 * np.pi * t)
fig, ax1 = plt.subplots()
color = 'tab:red'
ax1.set_xlabel('time (s)')
ax1.set_ylabel('exp', color=color)
ax1.plot(t, data1, color=color)
ax1.tick_params(axis='y', labelcolor=color)
ax2 = ax1.twinx() # instantiate a second axes that shares the same x-axis
color = 'tab:blue'
ax2.set_ylabel('sin', color=color) # we already handled the x-label with ax1
ax2.plot(t, data2, color=color)
ax2.tick_params(axis='y', labelcolor=color)
fig.tight_layout() # otherwise the right y-label is slightly clipped
plt.show()
```

Binomial Variables

Rules Binomial Variables

- 1. Comprised Of Independent Trials
- 2. Each Trial Can Be Regarded As A Success Or Failure
- 3. There Are A FIXED Number Of Trials
- 4. Probability Of Success On Each Trial Is Constant (i.e. Rule 1 Repeats)

NOTE: Use The 10% Rule For Approximate Independence Of Trials When Resampling Is Not Possible

Binomial Combinametrics

$$p(k \ of \ n) = inom{n}{k} p^k (1-p)^{n-k}$$

$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$

$$\binom{n}{k} = \binom{n+k-1}{k} = \frac{(n+k-1)!}{k! \, (n-1)!} = \frac{n(n+1)(n+2)\cdots(n+k-1)}{k!},$$

$$p(k \ of \ n) = \frac{n!}{k!(n-k)!} p^k (1-p)^{n-k}$$

```
# Independent Trials Success Probability = 0.73
import math
import matplotlib.pyplot as plt

fact = math.factorial

Ps = 0.73
p_D = {}
n = 7
for k in range(n+1):
    nCk = fact(n) / (fact(k) * fact(n-k))
    p = nCk * Ps**k * (1 - Ps)**(n - k)
    p_D[k] = round(p, 2)

plt.bar(p_D.keys(), p_D.values())
plt.show()
```

