In [1]:
```
import numpy as np
import pandas as pd
from scipy.stats import norm,t
import matplotlib.pyplot as plt
```

Q1

1.1

In [2]:
```
def getClass1Prop(x, r):

    x = np.array(x)
    dist = np.zeros(len(x_train))
    for i in range(len(x_train)):
        dist[i] = np.linalg.norm(x-x_train[i])
    dist_label_1 = dist[y_train==1]
    dist_1r = dist_label_1[dist_label_1<=r]
    if len(dist[dist<=r]):
        return len(dist_1r)/len(dist[dist<=r])
    else:
        return np.nan
```

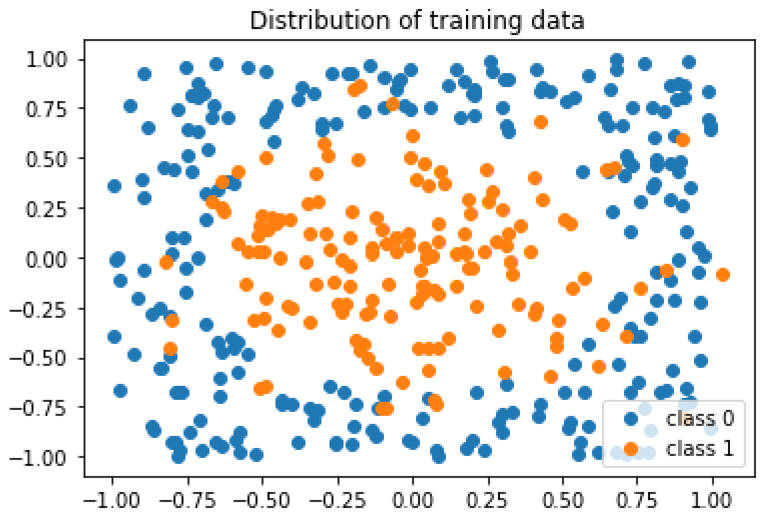
1.2

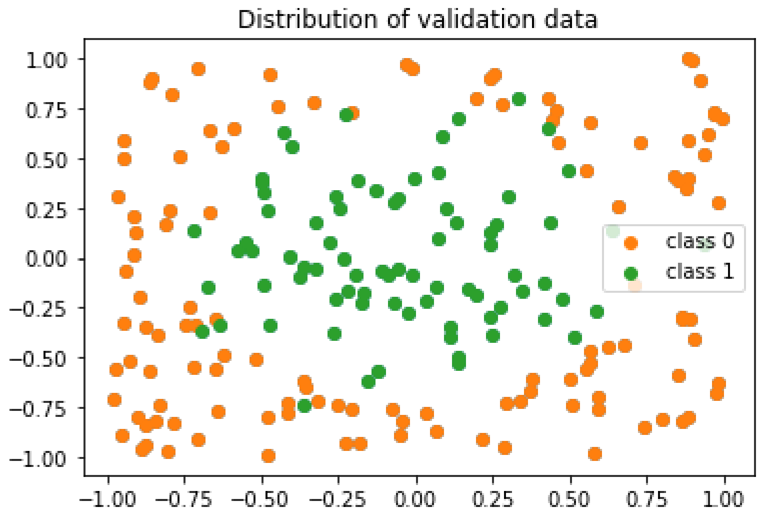
In [3]:
```
def computeMisVal(data_val, r):
    x_val = data_val.iloc[:,1:3].to_numpy()
    y_val = data_val['Y'].to_numpy()
    y_pred = np.zeros(len(y_val))
    for i in range(len(x_val)):
        p = getClass1Prop(x_val[i],r)
        y_pred[i] = 1 if p>=0.5 else 0

    mis = (len(y_val)-(y_pred==y_val).sum())/len(y_val)

    return mis
```

1.3

In [4]:
```
data = pd.read_csv('SML.NN.data.csv')
data_train = data[data['set']=='train']
data_val = data[data['set']=='valid']
data_test= data[data['set']=='test']
x_train = data_train.iloc[:,1:3].to_numpy()
y_train = data_train['Y'].to_numpy()
x_val = data_val.iloc[:,1:3].to_numpy()
y_val = data_val['Y'].to_numpy()
```

In [5]:
```
plt.figure()
plt.scatter(x_train[y_train==0][:,0],x_train[y_train==0][:,1],label = "class
 0")
plt.scatter(x_train[y_train==1][:,0],x_train[y_train==1][:,1],label = "class
 1")
plt.legend()
plt.title('Distribution of training data')
plt.show()
plt.figure()
plt.scatter(x_val[:,0],x_val[:,1])
plt.scatter(x_val[y_val==0][:,0],x_val[y_val==0][:,1],label = "class 0")
plt.scatter(x_val[y_val==1][:,0],x_val[y_val==1][:,1],label = "class 1")
plt.legend()
plt.title('Distribution of validation data')
plt.show()
```





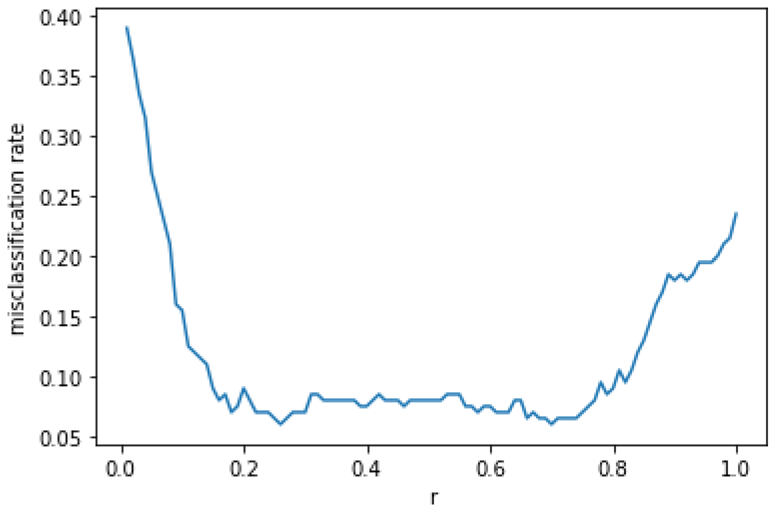
The distributions of training and validation set show that points in class 1 mainly locate at center while points in class 0 form the outer circle. A good value of r should be able to differentiate two classes. The radius of points in class 1 is roughly 0.25. So r = 0.25 would be my guess.

1.4

In [6]:
```
def computeMisTest(data_test, r):
    x_test = data_test.iloc[:,1:3].to_numpy()
    y_test = data_test['Y'].to_numpy()
    y_pred = np.zeros(len(y_test))
    for i in range(len(x_test)):
        p = getClass1Prop(x_test[i],r)
        y_pred[i] = 1 if p>=0.5 else 0

    mis = (len(y_test)-(y_pred==y_test).sum())/len(y_test)

    return mis
```

In [7]:
```
data = pd.read_csv('SML.NN.data.csv')
data_train = data[data['set']=='train']
data_val = data[data['set']=='valid']
data_test= data[data['set']=='test']
x_train = data_train.iloc[:,1:3].to_numpy()
y_train = data_train['Y'].to_numpy()
r_grid = np.arange(0.01,1.01,0.01)
mis_total = []
```

In [8]:
```
for i in r_grid:
    mis_total.append(computeMisVal(data_val, i))

plt.figure()
plt.plot(r_grid,mis_total)
plt.xlabel('r')
plt.ylabel('misclassification rate')
plt.show()
rs = r_grid[np.argmin(mis_total)]
print(f"When r = {rs}, the model achieves the lowest misclassification rate as
{mis_total[np.argmin(mis_total)]}")
```



```
When r = 0.26, the model achieves the lowest misclassification rate as 0.06
```

In [9]:
```
mis_test = computeMisTest(data_test, rs)
mis_test_gs = computeMisTest(data_test, 0.25)
print(f"When r = {rs}, the misclassification rate on test data is {mis_test}")
print(f"When r = {0.25}, the misclassification rate on test data is {mis_test_
gs}")
```

```
When r = 0.26, the misclassification rate on test data is 0.045
When r = 0.25, the misclassification rate on test data is 0.05
```

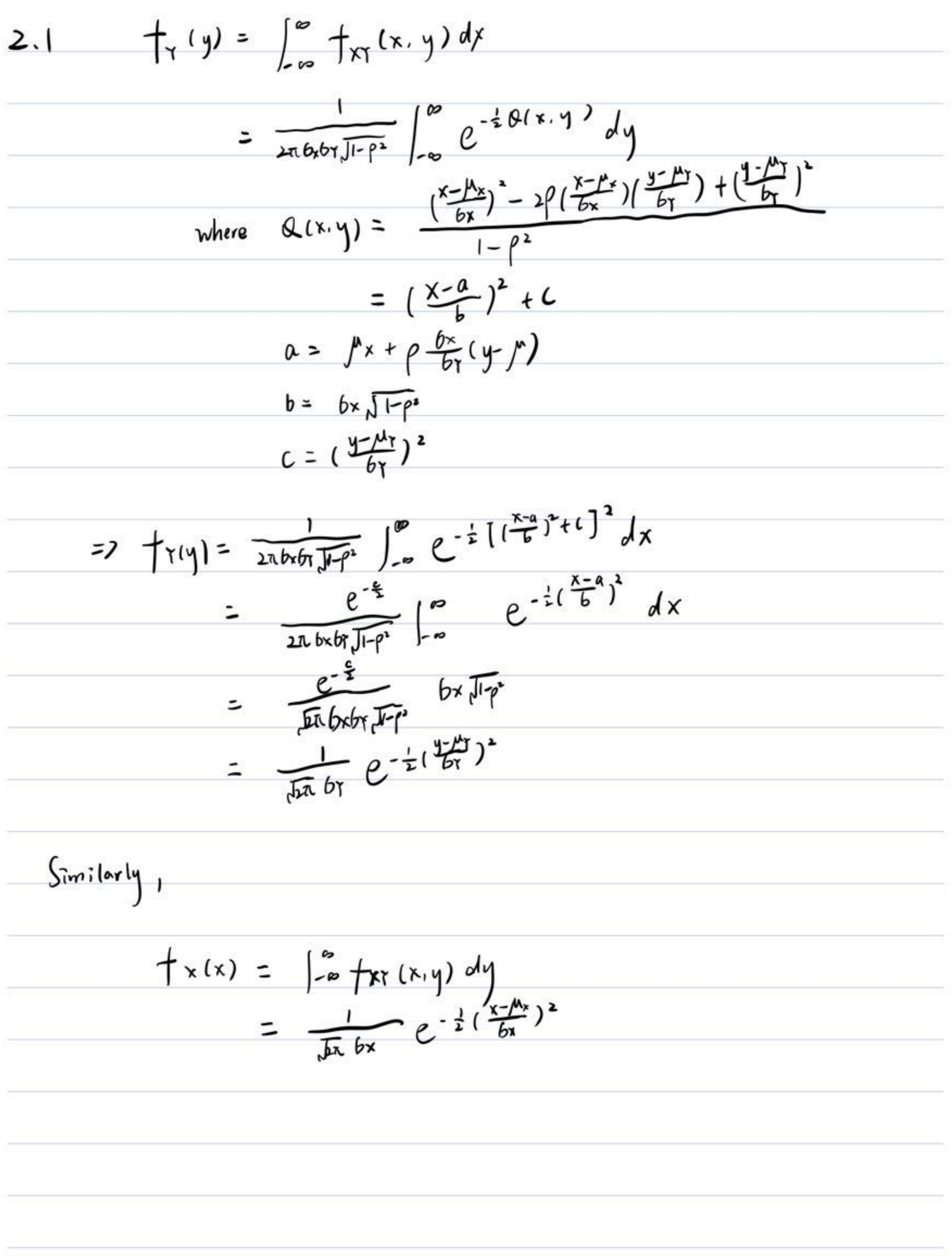
0.25 is our guess value of r, 0.26 is the value chosen based on experiments. The results show our guess is very close to the optimal value of r

Q2

2.1

In [10]:
```
from IPython.display import Image
Image('2_1.jpg')
```

Out[10]:



2.1 $f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x,y)\,dx$

$$= \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}}\int_{-\infty}^{\infty} e^{-\frac{1}{2}Q(x,y)}\,dy$$

where $Q(x,y) = \dfrac{\left(\frac{x-\mu_X}{\sigma_X}\right)^2 - 2\rho\left(\frac{x-\mu_X}{\sigma_X}\right)\left(\frac{y-\mu_Y}{\sigma_Y}\right) + \left(\frac{y-\mu_Y}{\sigma_Y}\right)^2}{1-\rho^2}$

$$= \left(\frac{x-a}{b}\right)^2 + c$$

$a = \mu_X + \rho\frac{\sigma_X}{\sigma_Y}(y-\mu)$

$b = \sigma_X\sqrt{1-\rho^2}$

$c = \left(\frac{y-\mu_Y}{\sigma_Y}\right)^2$

$$\Rightarrow f_Y(y) = \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}}\int_{-\infty}^{\infty} e^{-\frac{1}{2}\left[\left(\frac{x-a}{b}\right)^2+c\right]^2}dx$$

$$= \frac{e^{-\frac{c}{2}}}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}}\int_{-\infty}^{\infty} e^{-\frac{1}{2}\left(\frac{x-a}{b}\right)^2}dx$$

$$= \frac{e^{-\frac{c}{2}}}{\sqrt{2\pi}\sigma_X\sigma_Y\sqrt{1-\rho^2}}\sigma_X\sqrt{1-\rho^2}$$

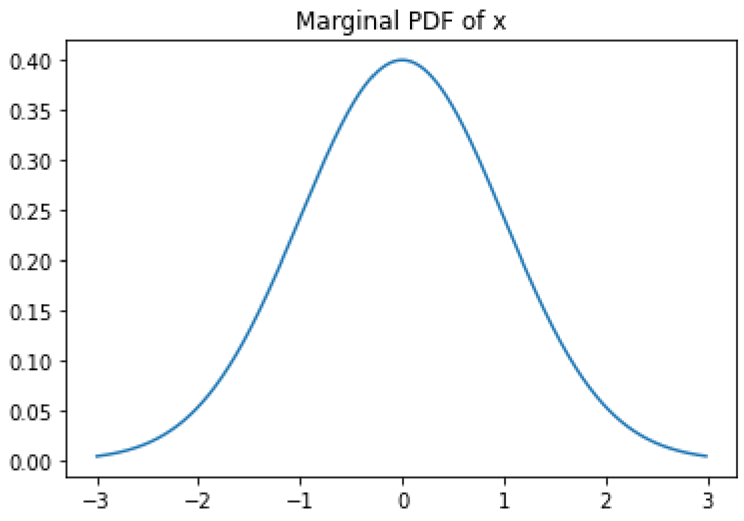
$$= \frac{1}{\sqrt{2\pi}\sigma_Y}e^{-\frac{1}{2}\left(\frac{y-\mu_Y}{\sigma_Y}\right)^2}$$

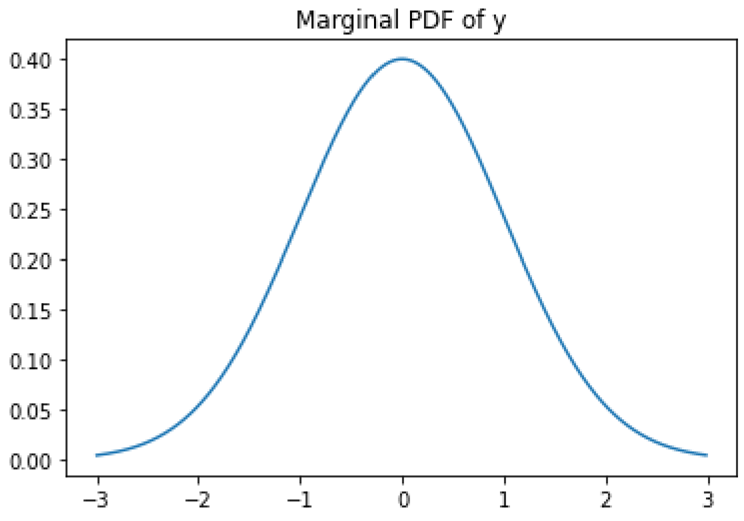
Similarly,

$$f_X(x) = \int_{-\infty}^{\infty} f_{XY}(x,y)\,dy$$

$$= \frac{1}{\sqrt{2\pi}\sigma_X}e^{-\frac{1}{2}\left(\frac{x-\mu_X}{\sigma_X}\right)^2}$$

In [11]:
```
x = np.arange(-3, 3, 0.01)
y = np.arange(-3, 3, 0.01)

# Calculating mean and standard deviation
mu_x,mu_y,sig_x,sig_y = 0,0,1,1

plt.figure()
plt.plot(x, norm.pdf(x, mu_x, sig_x))
plt.title('Marginal PDF of x')
plt.show()
plt.figure()
plt.plot(y, norm.pdf(y, mu_y, sig_y))
plt.title('Marginal PDF of y')
plt.show()
```



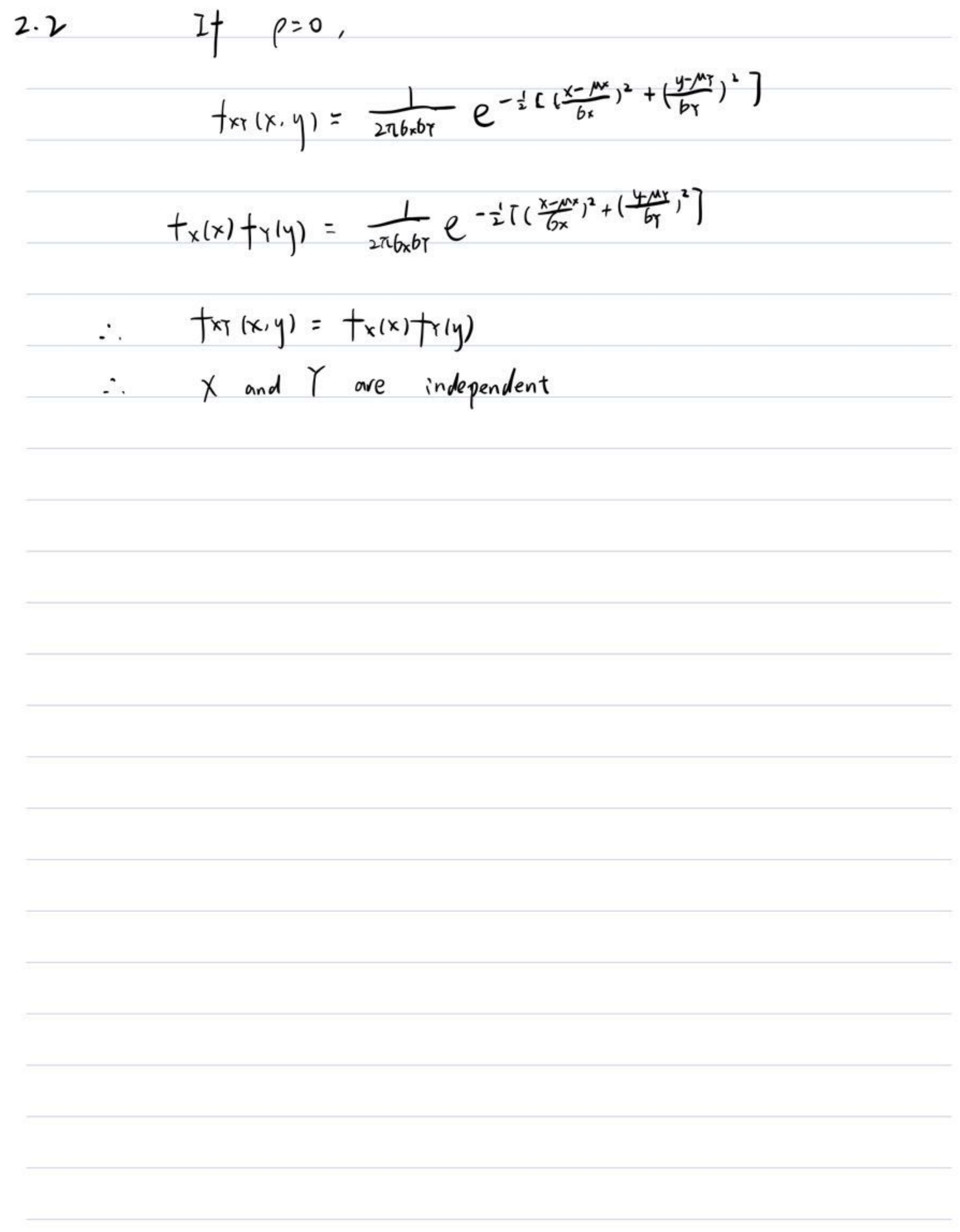


Those marginal pdfs are identical with Normal(0,1) pdf

2.2

```
In [12]: Image('2_2.jpg')
```

```
Out[12]:
```



2.2 If $\rho = 0$,

$$f_{XY}(x,y) = \frac{1}{2\pi\sigma_X\sigma_Y} e^{-\frac{1}{2}[(\frac{x-\mu_X}{\sigma_X})^2 + (\frac{y-\mu_Y}{\sigma_Y})^2]}$$

$$f_X(x) f_Y(y) = \frac{1}{2\pi\sigma_X\sigma_Y} e^{-\frac{1}{2}[(\frac{x-\mu_X}{\sigma_X})^2 + (\frac{y-\mu_Y}{\sigma_Y})^2]}$$

$\therefore$ $f_{XY}(x,y) = f_X(x) f_Y(y)$

$\therefore$ X and Y are independent

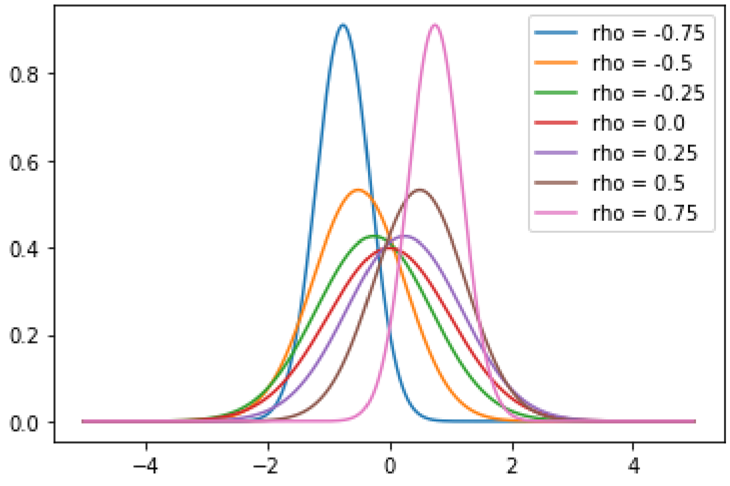
2.3

Given $Y = 1$:

$E[X|Y=1]=\mu_x+\rho\sigma_x\frac{1-\mu_y}{\sigma_y}$

$Var[X|Y = 1] = (1 - \rho^2)\sigma_x^2$

In [13]:
```
rho_grid = np.arange(-0.75,1,0.25)
x = np.arange(-5, 5, 0.01)
mu_x,mu_y,sig_x,sig_y = 0,0,1,1
plt.figure()
for rho in rho_grid:
    mu = mu_x+rho*sig_x*(1-mu_y)/sig_y
    sig = (1-rho**2)*sig_x**2
    plt.plot(x, norm.pdf(x, mu, sig),label=f'rho = {rho}')
plt.legend()
plt.show()
```



The negative and positive ρ both help to predict X since they indicate a linear relation bwtween X and Y. Larger ρ implies a stronger linearity. It is hard to predict X if X and Y are independent, i.e. $\rho = 0$.

Q3

3.1

In [14]:
```
np.random.seed(0)
lam = 10
x = np.random.exponential(1/lam,100)
```

$L = \lambda e^{(-\lambda x_1)} \lambda e^{(-\lambda x_1)} \ldots \lambda e^{(-\lambda x_1 00)} = \lambda^{100} e^{(-\lambda(x_1 + x_2 + \ldots + x_{100}))}$

$L' = \ln L = 100 \ln \lambda - \lambda \sum_{i=0}^{100} x_i$

$\frac{\partial L'}{partial \lambda} = \frac{100}{\lambda} - \sum_{i=0}^{100} x_i = 0$

$\lambda = \frac{100}{\sum_{i=0}^{100} x_i}$

In [15]:
```
lam = 100/x.sum()
print(f'extimated lambda is {lam}')
```

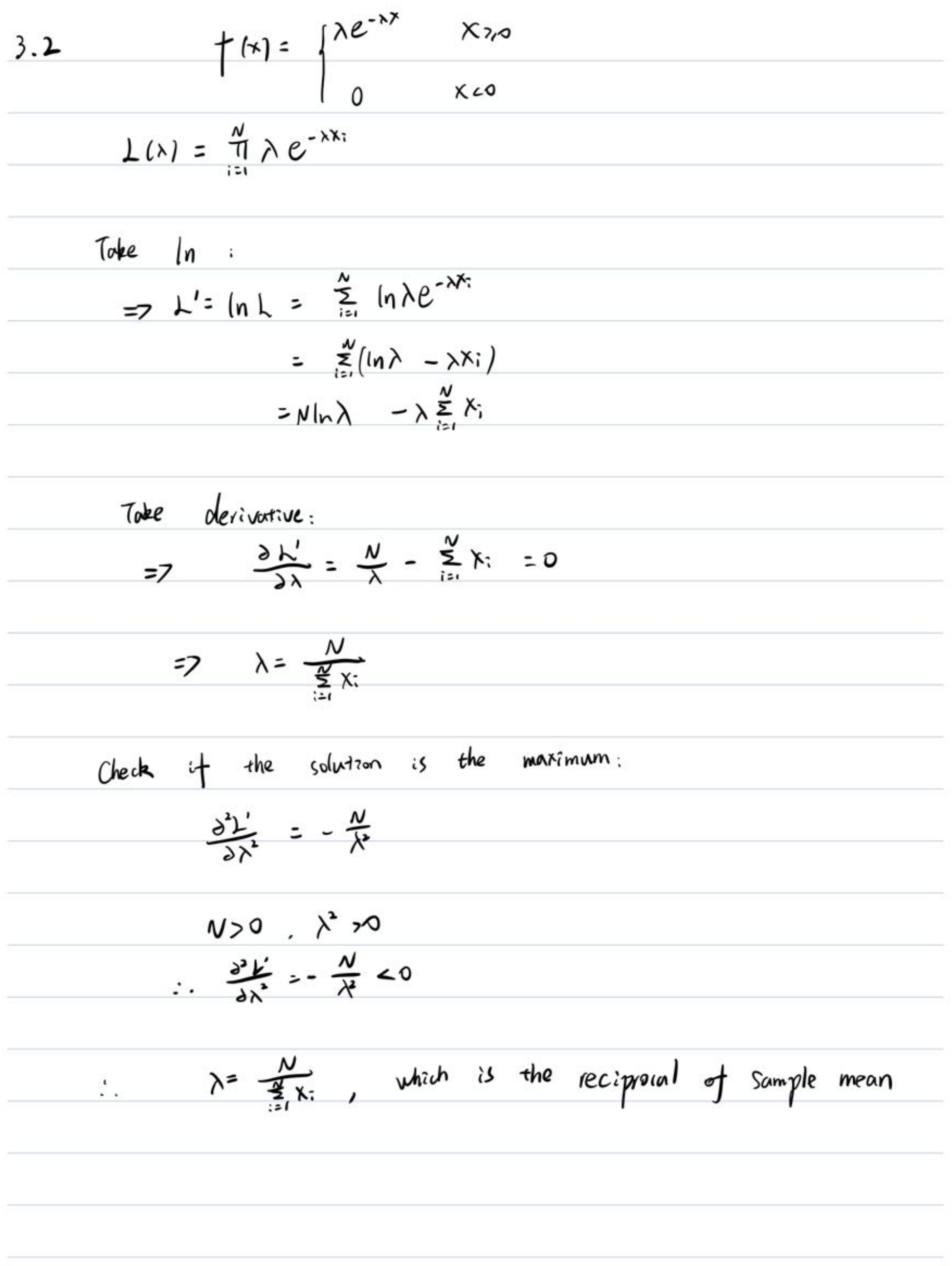
```
extimated lambda is 10.885557365453474
```

The estimated value of λ (10.89) is close to true λ (10)

3.2

```
In [16]: Image('3_2.jpg')
```

Out[16]:



3.2 $f(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$

$L(\lambda) = \prod_{i=1}^{N} \lambda e^{-\lambda x_i}$

Take ln :

$\Rightarrow L' = \ln L = \sum_{i=1}^{N} \ln \lambda e^{-\lambda x_i}$

$= \sum_{i=1}^{N} (\ln \lambda - \lambda x_i)$

$= N \ln \lambda - \lambda \sum_{i=1}^{N} x_i$

Take derivative:

$\Rightarrow \frac{\partial L'}{\partial \lambda} = \frac{N}{\lambda} - \sum_{i=1}^{N} x_i = 0$

$\Rightarrow \lambda = \frac{N}{\sum_{i=1}^{N} x_i}$

Check if the solution is the maximum:

$\frac{\partial^2 L'}{\partial \lambda^2} = -\frac{N}{\lambda^2}$

$N > 0$, $\lambda^2 > 0$

$\therefore \frac{\partial^2 L'}{\partial \lambda^2} = -\frac{N}{\lambda^2} < 0$

$\therefore$ $\lambda = \frac{N}{\sum_{i=1}^{N} x_i}$, which is the reciprocal of sample mean

Q4

Case 1

In [17]:
```
seed_grid = np.arange(1,1001)
coverage = 0

for i in seed_grid:
    np.random.seed(i)
    x = np.random.normal(0,1,4)
    mu = x.mean()
    std = x.std()
    up = mu+1.6449*std/np.sqrt(4)
    lower = mu-1.6449*std/np.sqrt(4)
    if up>=0 and lower<=0:
        coverage += 1
    else:
        pass
ef = coverage/len(seed_grid)
print(f'The empirical frequency of coverage is {ef}')
```

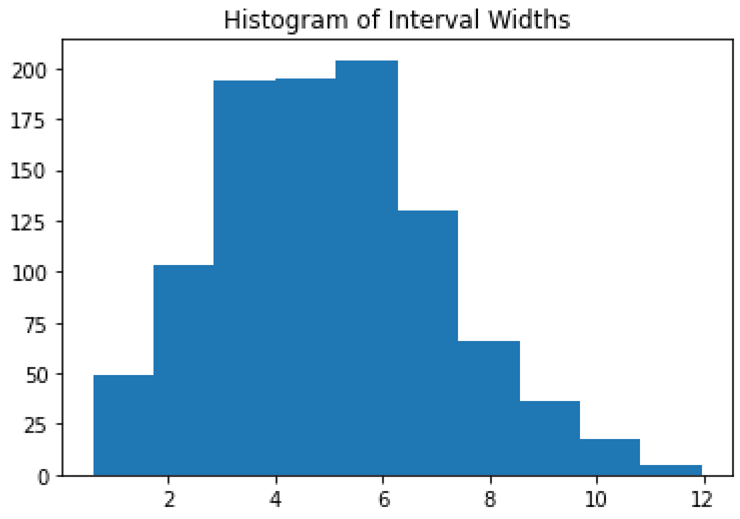
```
The empirical frequency of coverage is 0.749
```

Case 2

In [18]:
```
seed_grid = np.arange(1,1001)
coverage = 0
width = []

for i in seed_grid:
    np.random.seed(i)
    x = np.random.normal(0,1,4)
    mu = x.mean()
    std = x.std()
    interval = t.interval(alpha=0.95, df=3, loc=mu, scale=std)
    if interval[1]>=0 and interval[0]<=0:
        coverage += 1
    else:
        pass
    width.append(interval[1]-interval[0])
ef = coverage/len(seed_grid)
print(f'The empirical frequency of coverage is {ef}')
```

```
The empirical frequency of coverage is 0.988
```

In [19]:
```
plt.figure()
plt.hist(width)
plt.title('Histogram of Interval Widths')
plt.show()
```

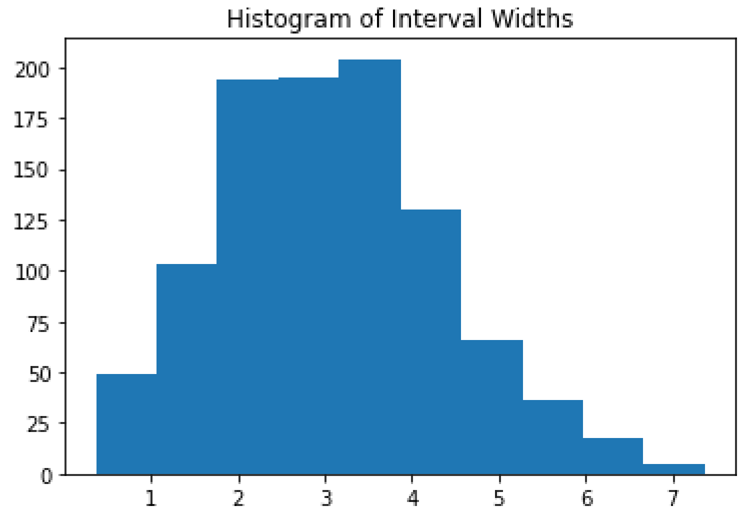


Case 3

In [20]:
```
seed_grid = np.arange(1,1001)
coverage = 0
width = []

for i in seed_grid:
    np.random.seed(i)
    x = np.random.normal(0,1,4)
    mu = x.mean()
    std = x.std()
    interval = norm.interval(alpha=0.95, loc=mu, scale=std)
    if interval[1]>=0 and interval[0]<=0:
        coverage += 1
    else:
        pass
    width.append(interval[1]-interval[0])
ef = coverage/len(seed_grid)
print(f'The empirical frequency of coverage is {ef}')
```

```
The empirical frequency of coverage is 0.957
```

In [21]:
```
plt.figure()
plt.hist(width)
plt.title('Histogram of Interval Widths')
plt.show()
```



Case 2 has the highest empirical frequency of coverage when exact small sample CI is computed using t-distribution. That makes sense since the sample is very small (N=4). When using approximate large-sample CI in case 3, the empirical frequency decreases.

In [ ]:
```

```