

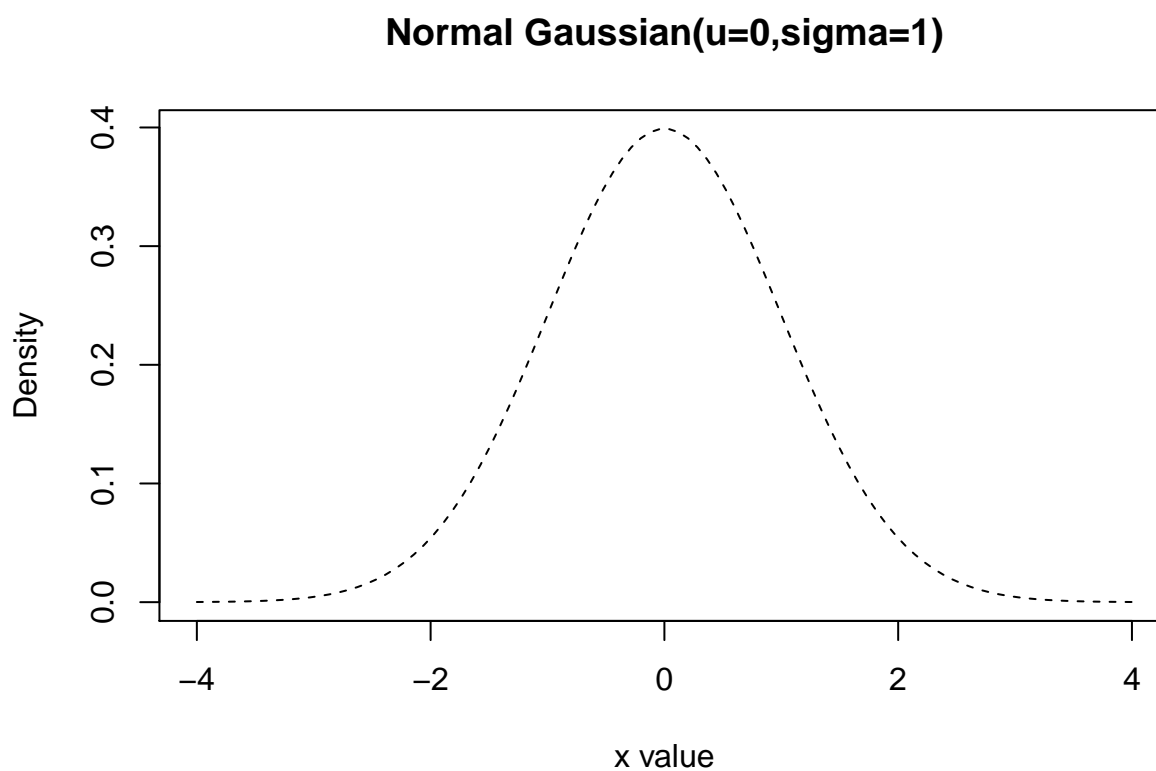
Maximum Likelihood

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Gaussian

```
x <- seq(-4, 4, length=100)
hx <- dnorm(x)
plot(x, hx, type="l", lty=2, xlab="x value", ylab="Density", main="Normal Gaussian(u=0,sigma=1)")
```



Percentage

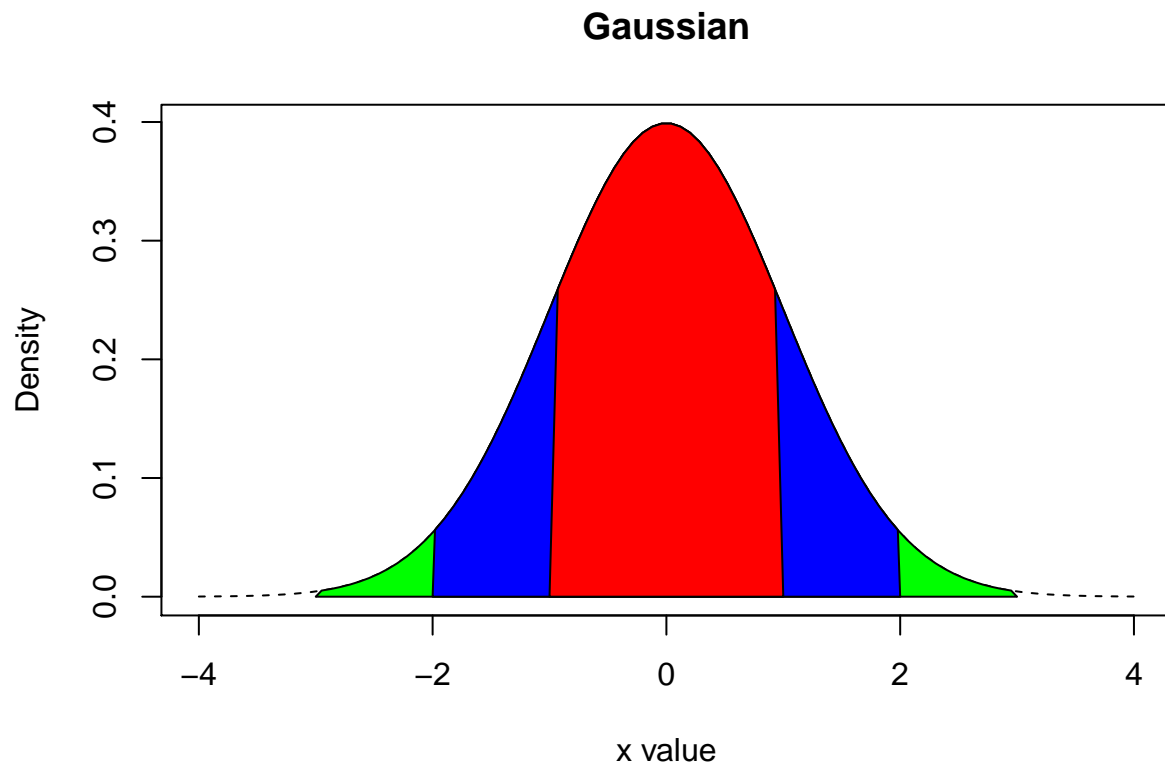
```
plotGaussian <- function(u, sigma, color = "black"){
  x <- seq(-4, 4, length=100)
  hx <- dnorm(x, mean = u, sd = sigma)
  plot(x, hx, type="l", lty=2, xlab="x value", ylab="Density", main="Gaussian", col = color)
}
plotArea <- function(u, sigma, sigmaSize, color){
  x <- seq(-4, 4, length=100)
  hx <- dnorm(x, mean = u, sd = sigma)
  l <- -(sigma*sigmaSize)
```

```

r <- (sigma*sigmaSize)
i <- x >= l & x <= r
polygon(c(l,x[i],r), c(0,hx[i],0), col=color)
}

plot.new()
plotGaussian(0,1)
plotArea(0,1,3,"green")
plotArea(0,1,2,"blue")
plotArea(0,1,1,"red")

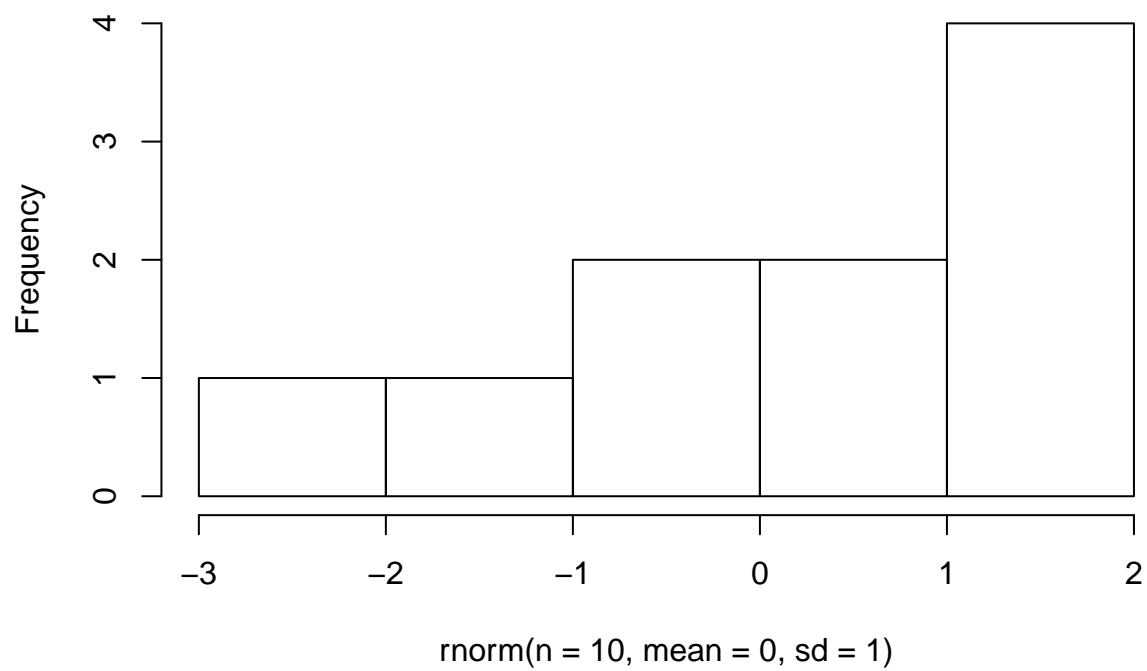
```



Density Simulation

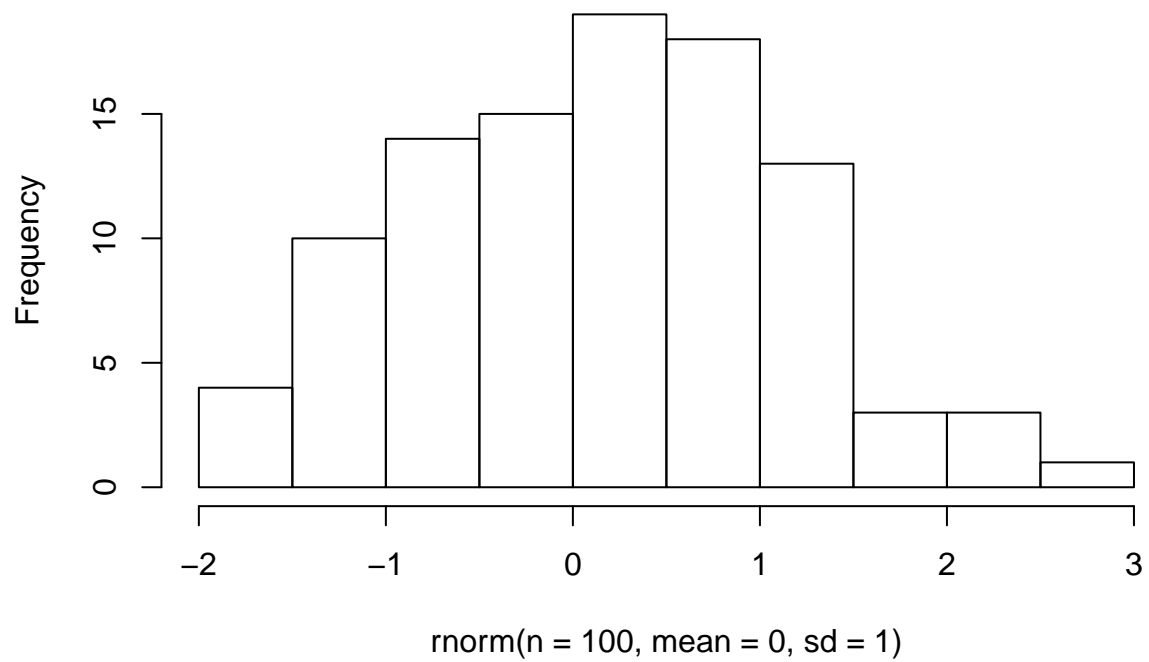
```
hist(rnorm(n = 10, mean = 0, sd = 1))
```

Histogram of `rnorm(n = 10, mean = 0, sd = 1)`



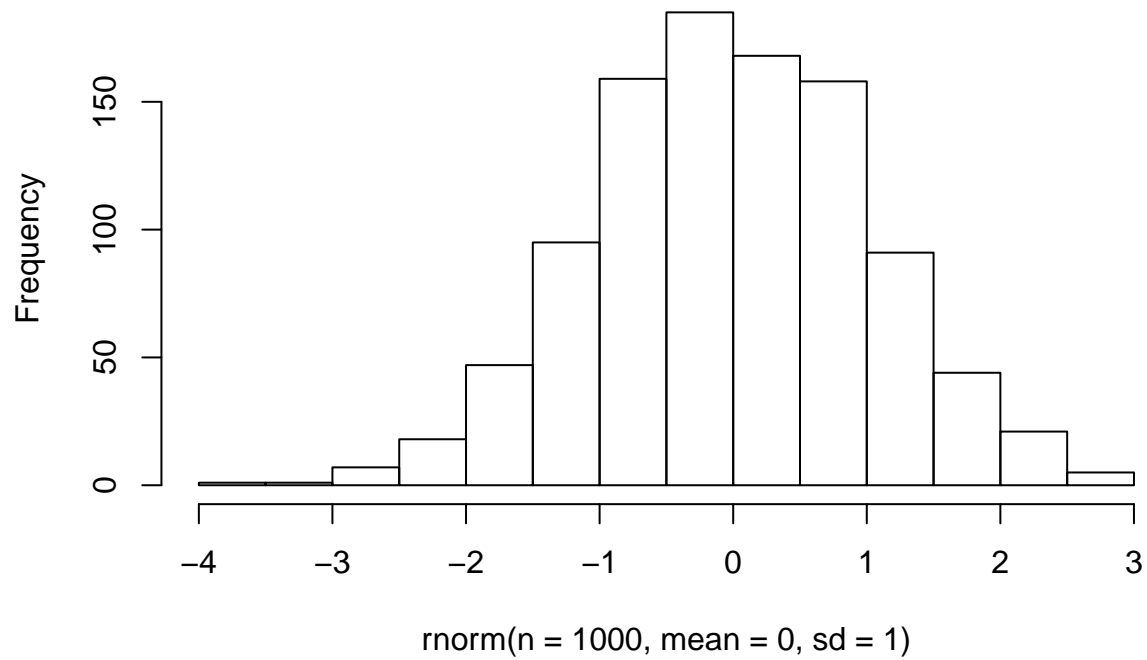
```
hist(rnorm(n = 100, mean = 0, sd = 1))
```

Histogram of $\text{rnorm}(n = 100, \text{mean} = 0, \text{sd} = 1)$

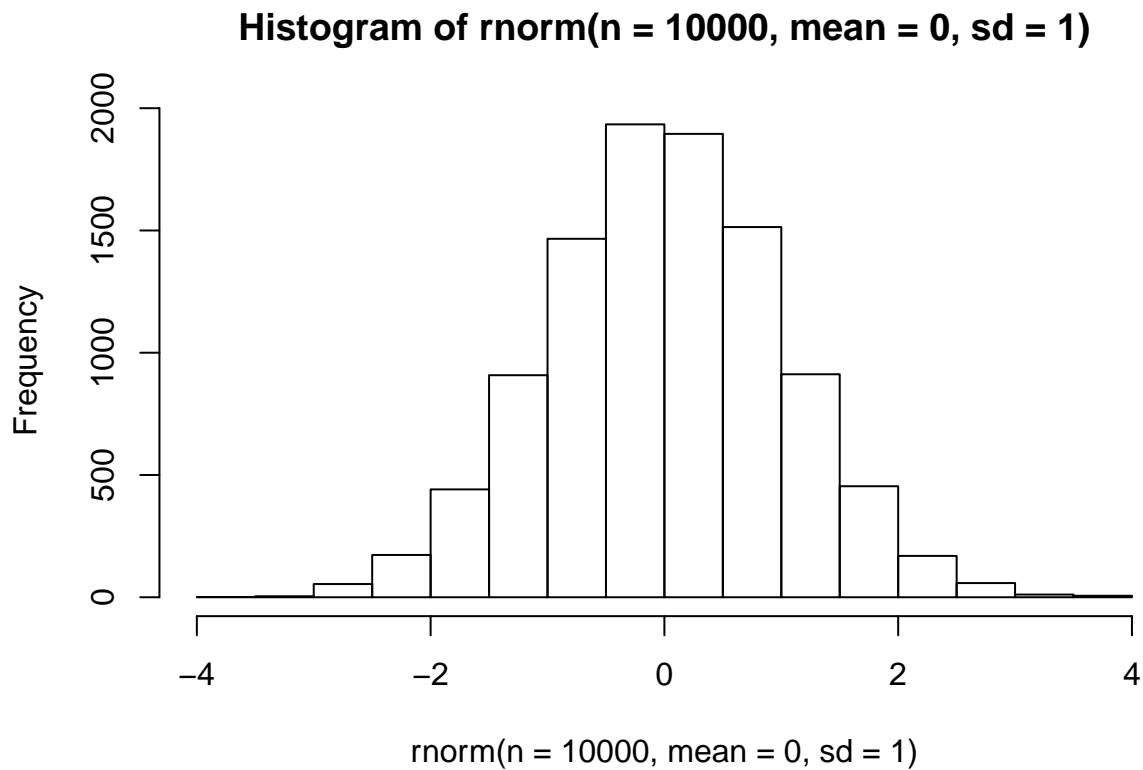


```
hist(rnorm(n = 1000, mean = 0, sd = 1))
```

Histogram of `rnorm(n = 1000, mean = 0, sd = 1)`



```
hist(rnorm(n = 10000, mean = 0, sd = 1))
```



Likelihood

Suppose we have an observation and two possible distributions that can be considered as the source distributions of this observations. We want to choose the best option: in this case the most probable source distribution.

Options:

Gaussian #1

$\mu = -2$

$\sigma = 1$

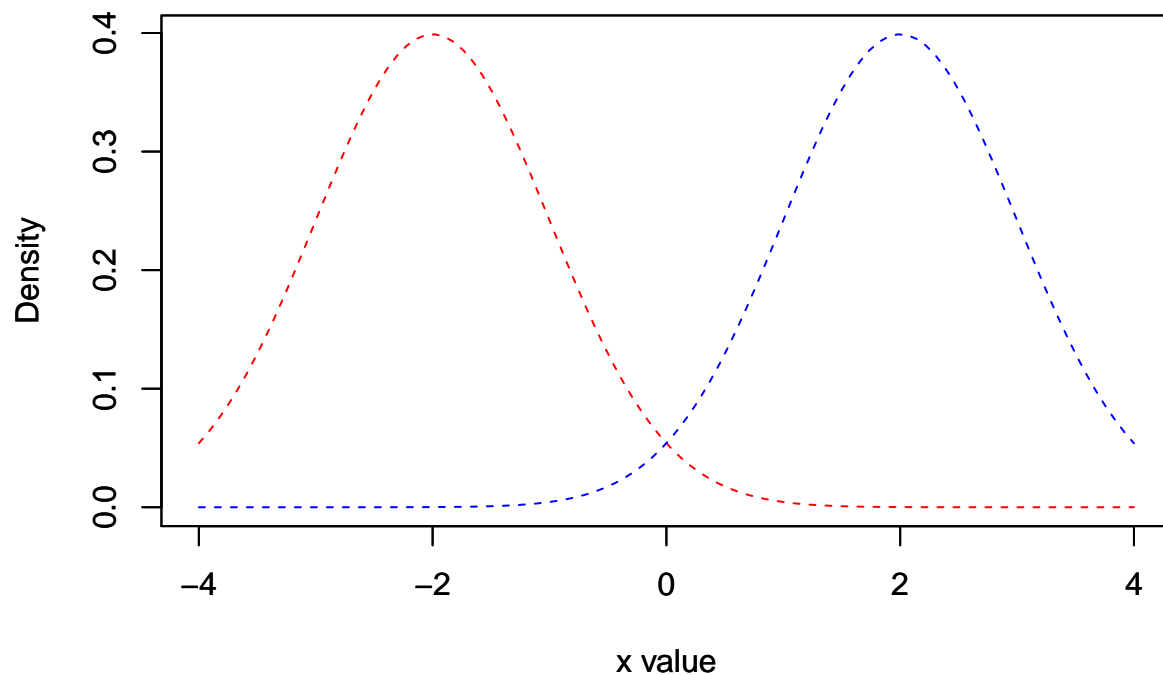
Gaussian #2

$\mu = 2$

$\sigma = 1$

```
plotGaussian(-2,1,"red")
par(new=TRUE)
plotGaussian(2,1, "blue")
```

Gaussian



Observations

A = -0.25

B = -1

C = 0.45

To choose the best distribution we will choose the distribution whose density is bigger in that particular point. For example, for observation A:

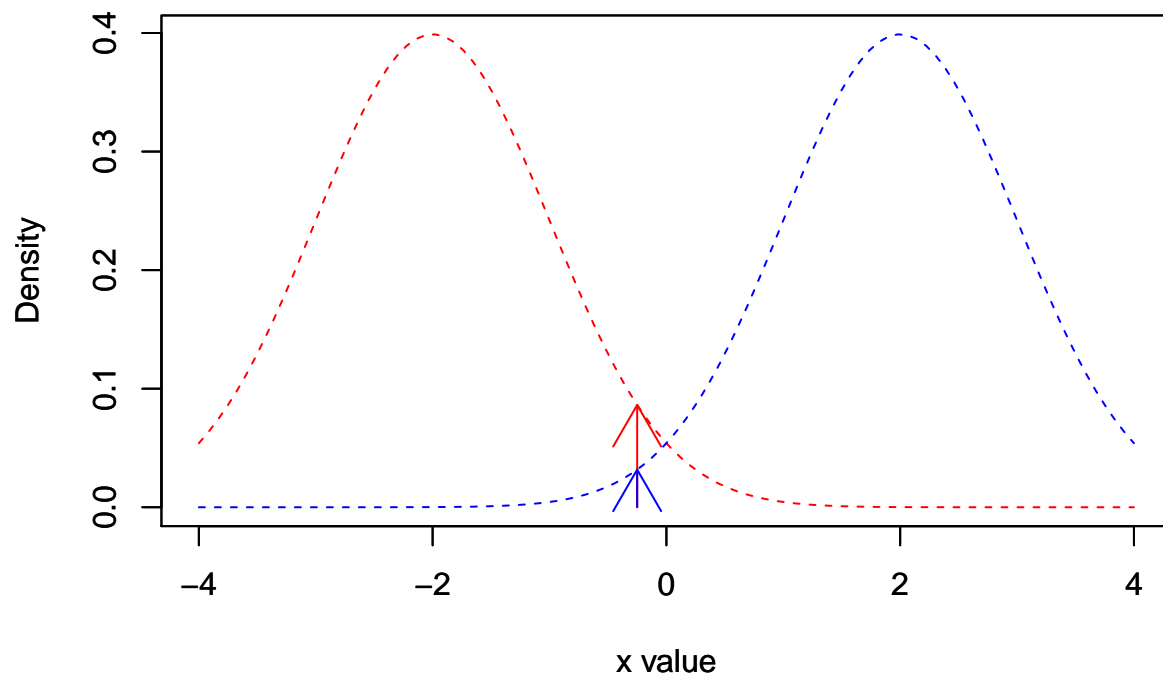
Probability of observing A from Gaussian #1 ($\mu=-2, \sigma=1$) = 0.0862773

Probability of observing A from Gaussian #2 ($\mu=2, \sigma=1$) = 0.0317397

In this case the best option is Gaussian #1. It is more likely/probable that the observation #A comes from Gaussian #1 than Gaussian #2.

```
plotGaussian(-2,1,"red")
arrows(-0.25,0,-0.25,dnorm(-0.25,-2,1), col = "red")
par(new=TRUE)
plotGaussian(2,1, "blue")
arrows(-0.25,0,-0.25,dnorm(-0.25,2,1), col = "blue")
```

Gaussian

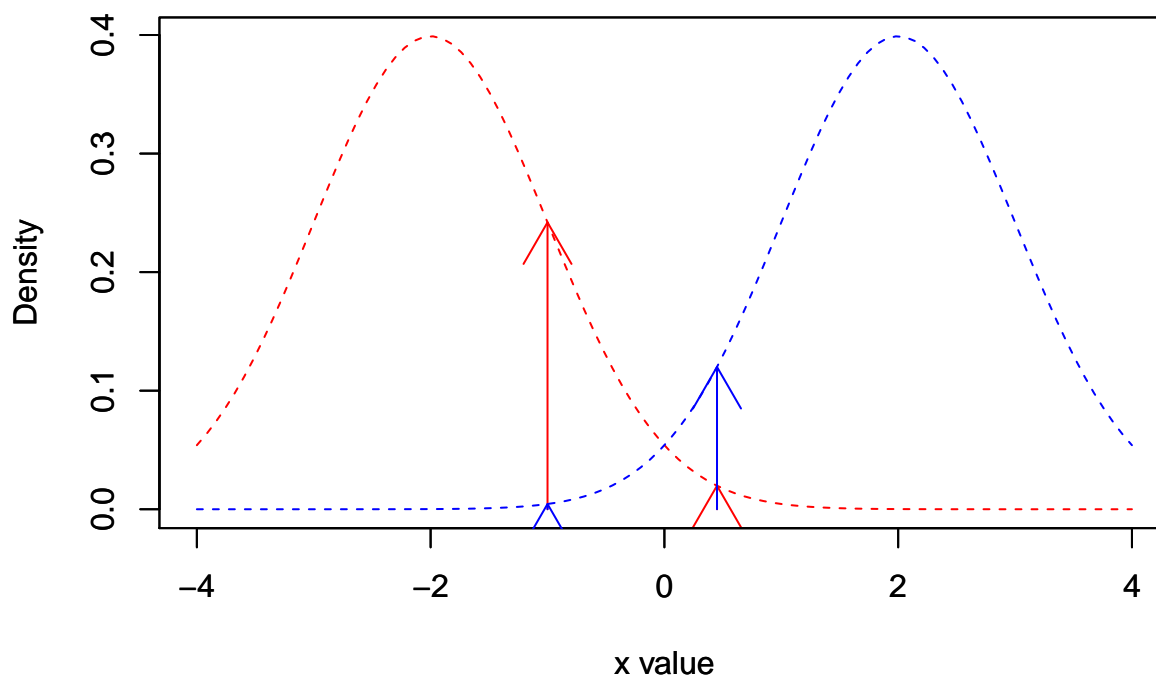


We can use the same calculations to the others observations.

Probability of observing B from Gaussian #1 ($\mu=-2, \sigma=1$) = 0.2419707
Probability of observing B from Gaussian #2 ($\mu=2, \sigma=1$) = 0.0044318
Probability of observing C from Gaussian #1 ($\mu=-2, \sigma=1$) = 0.0198374
Probability of observing C from Gaussian #2 ($\mu=2, \sigma=1$) = 0.120009

```
plotGaussian(-2,1,"red")
arrows(-1,0,-1,dnorm(-1,-2,1), col = "red")
arrows(0.45,0,0.45,dnorm(0.45,-2,1), col = "red")
par(new=TRUE)
plotGaussian(2,1, "blue")
arrows(-1,0,-1,dnorm(-1,2,1), col = "blue")
arrows(0.45,0,0.45,dnorm(0.45,2,1), col = "blue")
```


Gaussian



So we can say that:

The likelihood of $\mu = -2$ and $\sigma^2 = 1$ for an observation -1 is 0.2419707 because the probability of seeing a value -1 from a Gaussian with $\mu = -2$ and $\sigma^2 = 1$ is 0.2419707 .

In other words:

The likelihood of θ , the Gaussian parameters, given x is 0.2419707 because the probability of x given θ is 0.2419707 .

Or:

$$L(\theta|x) = p(x|\theta)$$

Maximum Likelihood

Maximum Likelihood of just one point

Imagine now that we do not have two options predetermined. We have all possible Gaussians and we want to find the best Gaussian to each observation, first one-by-one, and then as a set. The best Gaussian for observation A is the Gaussian with the maximum likelihood. So our problem can be described as:

$$\text{maximize } \theta \text{ in } L(\theta|x)$$

We saw that this is the same as

$$\text{maximize } \theta \text{ in } p(x | \theta)$$

So given x , which is a known value, we must find the θ that maximizes the function. θ in this particular case is the set $\{\mu, \sigma^2\}$. So given X , we must find μ and σ^2 that will maximize $p(x|\mu, \sigma^2)$.

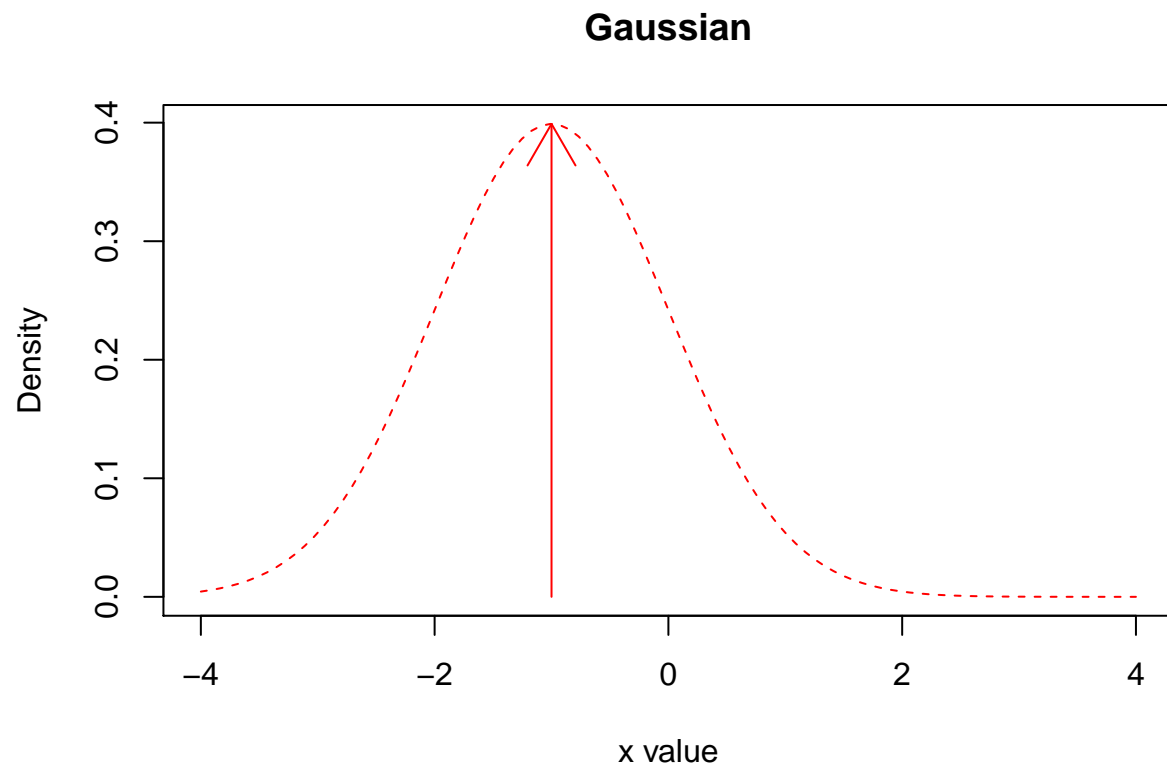
For this trivial case we will have a problem, that will be shown later. For now let's fix $\sigma^2 = 1$ and try to maximize just for μ . So we have:

maximize u in $p(x | u, sd = 1)$

Well... looking again to the Gaussian distribution we see that the maximum value is at u . So if we want to maximize $p(x | u, sd = 1)$, we just have to make $u = x$.

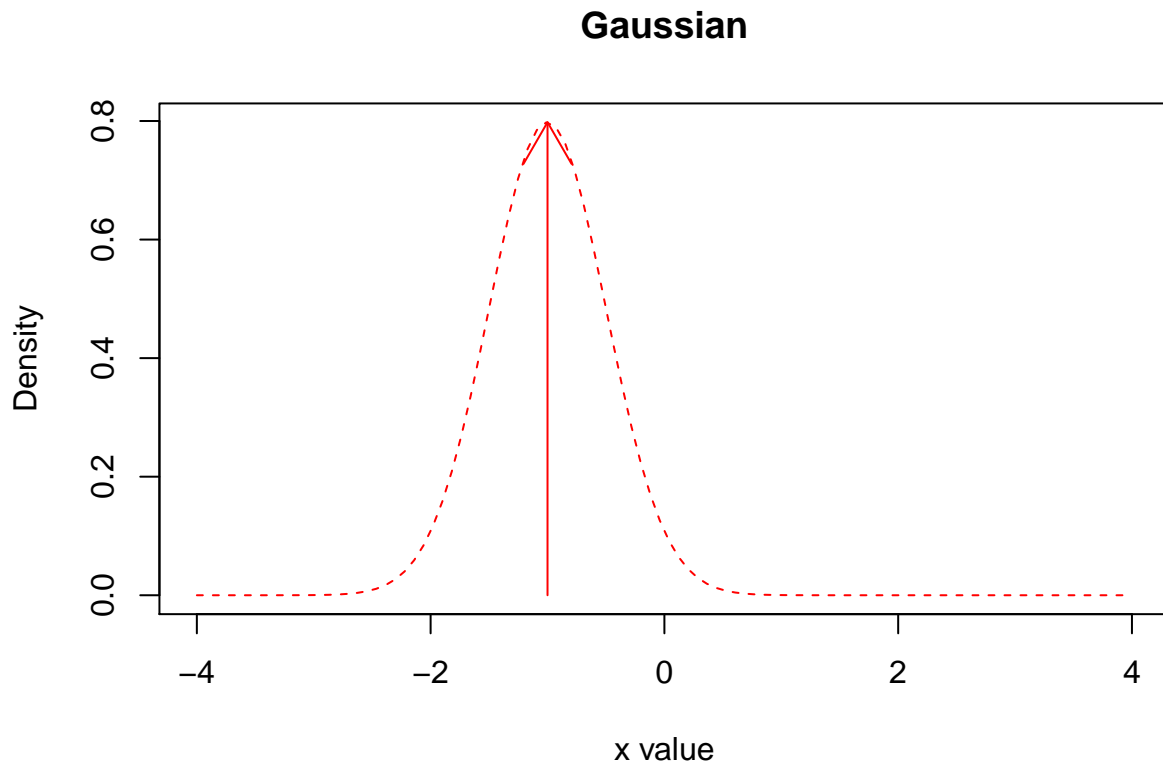
So in this case we have:

```
plotGaussian(-1,1,"red")  
arrows(-1,0,-1,dnorm(-1,-1,1), col = "red")
```



But we still have one problem. We can improve the likelihood in this case decreasing the sd. If we chose a $sd = 0.5$, for example, we will have:

```
plotGaussian(-1,0.5,"red")  
arrows(-1,0,-1,dnorm(-1,-1,0.5), col = "red")
```



Actually we can always improve the likelihood by decreasing the sd in this particular case, because we just have one point.

Likelihood of two points

For the likelihood of two points we are going to use the same method to find the best Gaussian distribution to explain both observations together.

This means:

$$L(\theta|x) = L(\theta|x_1, x_2) = p(x_1, x_2|\theta)$$

To simplify let start optimizing this function for μ first. So we have:

$$p(x_1, x_2|\mu) = p(x_1|x_2)p(x_2) = p(x_2|x_1)p(x_1)$$

We generally assume that both observations are independent because in this way we have that

$$p(x_2|x_1) = p(x_2)$$

$$p(x_1|x_2) = p(x_1)$$

so

$$p(x_1, x_2|\mu) = p(x_1)p(x_2)$$

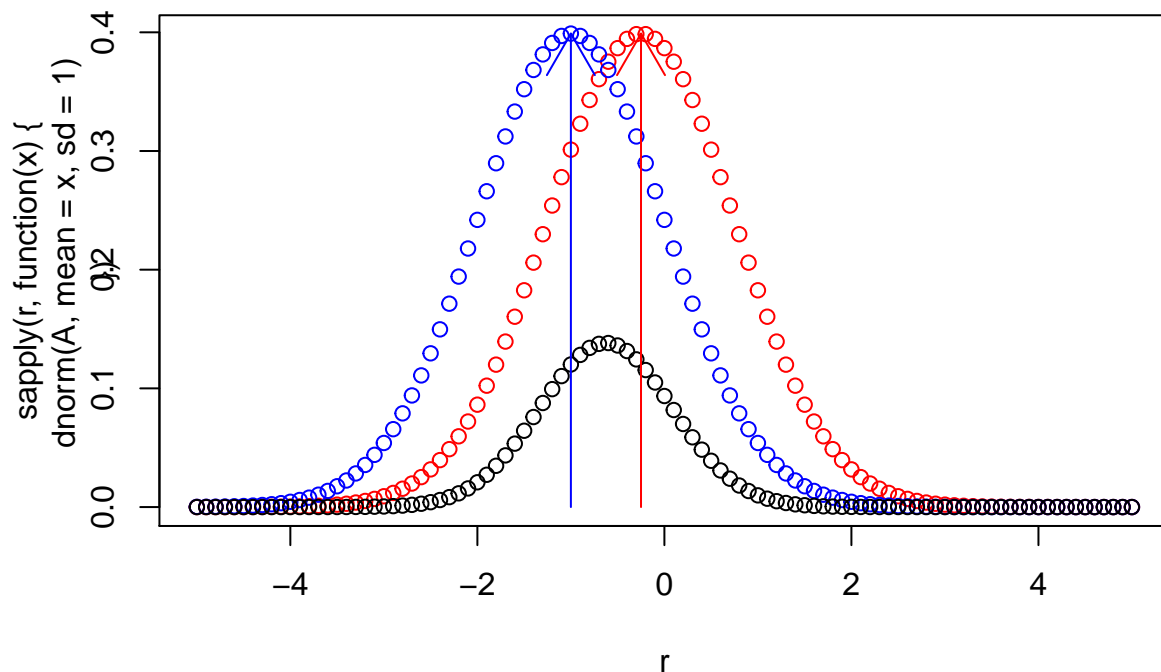
This means that we must optimize the product of the probability density function.

First let plot this product value for various μ values. With this plot we can clearly see that the function is optimized when the product is maximized.

```

A <- -0.25
B <- -1
obs <- c(A,B)
r <- seq(-5,5, by = 0.1)
plot(r,sapply(r, function(x) {dnorm(A, mean = x, sd = 1)}), col = "red")
points(r,sapply(r, function(x) {dnorm(B, mean = x, sd = 1)}), col = "blue")
points(r,sapply(r, function(x) {dnorm(A, mean = x, sd = 1)*dnorm(B, mean = x, sd = 1)}))
arrows(A,0,A,dnorm(A,A,1), col = "red")
arrows(B,0,B,dnorm(B,B,1), col = "blue")

```



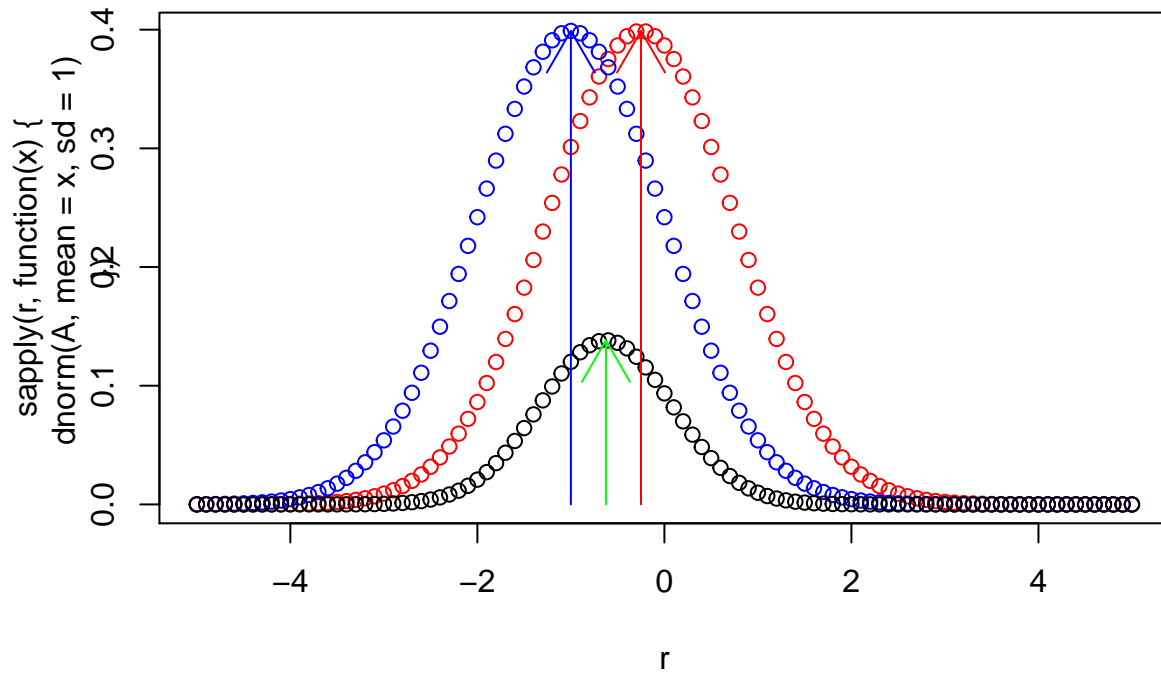
So, first lets try to optimize the function numeracally:

```

A <- -0.25
B <- -1
f <- function (x) {dnorm(A, mean = x, sd = 1)*dnorm(B, mean = x, sd = 1)}
xmax <- optimize(f, c(-5, 5), tol = 0.0001, maximum = TRUE)

A <- -0.25
B <- -1
obs <- c(A,B)
r <- seq(-5,5, by = 0.1)
plot(r,sapply(r, function(x) {dnorm(A, mean = x, sd = 1)}), col = "red")
points(r,sapply(r, function(x) {dnorm(B, mean = x, sd = 1)}), col = "blue")
points(r,sapply(r, function(x) {dnorm(A, mean = x, sd = 1)*dnorm(B, mean = x, sd = 1)}))
arrows(A,0,A,dnorm(A,A,1), col = "red")
arrows(B,0,B,dnorm(B,B,1), col = "blue")
arrows(xmax$maximum,0,xmax$maximum,xmax$objective, col = "green")

```



So now we know that: $L(\theta|x)$

$= L(\theta|x_1, x_2)$

$= p(x_1, x_2|\theta)$ (for simplicity $\theta = \{u\}$)

$= p(x_1|x_2)p(x_2)$ for $\text{Gaussian}(u, \text{sd} = 1)$

$= p(x_1)p(x_2)$ for $\text{Gaussian}(u, \text{sd} = 1)$

$\text{argmax}(u)$ in $p(x_1)p(x_2)$ for $\text{Gaussian}(u, \text{sd} = 1)$

maximum at -0.6249842

$L(u = -0.6249842, \text{sd} = 1) = 0.1382762$

so the best distribution is: $\text{Gaussian}(u = -0.6249842, \text{sd} = 1)$

But we have more than one parameter to optimize. Maybe it is possible to optimize even further the function by using other values of sd.

Let try some values:

```
A <- -0.25
B <- -1
x = seq(-2, 1, length= 20)
y = seq(-1, 2, length= 20)
f = function(x, y) { dnorm(A, mean = x, sd = y)*dnorm(B, mean = x, sd = y) }
z = outer(x, y, f)
```

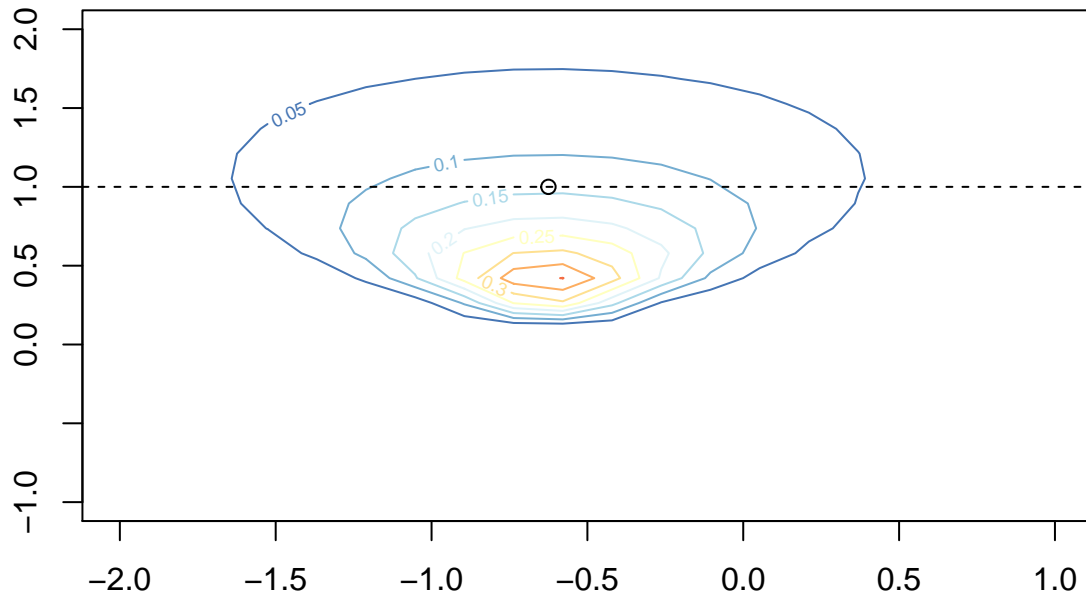
```
## Warning in dnorm(A, mean = x, sd = y): NaNs produced
```

```
## Warning in dnorm(B, mean = x, sd = y): NaNs produced
```

```

z[is.na(z)] = 0
library(RColorBrewer)
contour(x,y,z,col=rev(brewer.pal(11, "RdYlBu")), nlevels = 11)
abline(h=1, lty=2)
points(xmax$maximum, 1)

```



We have analyzed the problem with sd fixed as 1, and searched for the maximum likelihood in this scenario. If we analyze the above plot we will see that we searched the maximum following the dashed line and found it on the circled point.

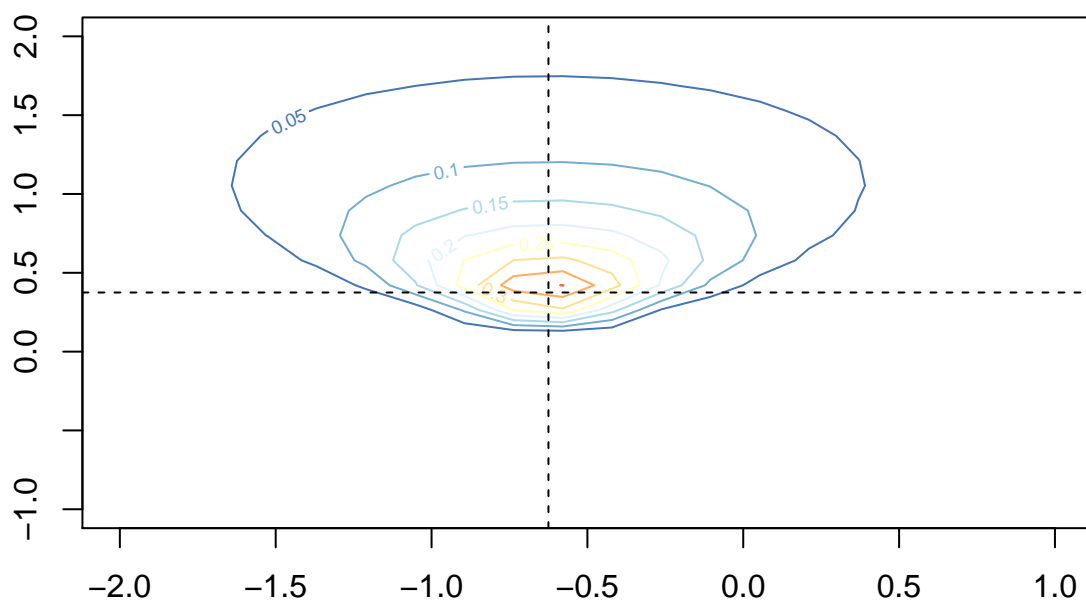
Now it is clear that we have now actually found the best solution to the problem.

```

A <- -0.25
B <- -1
f = function(x) { dnorm(A, mean = x[1], sd = x[2])*dnorm(B, mean = x[1], sd = x[2]) }
max = optim( c(xmax$maximum,1), f ,control=list(fnscale=-1))

contour(x,y,z,col=rev(brewer.pal(11, "RdYlBu")), nlevels = 11)
abline(h=max$par[2], v = max$par[1], lty=2)

```



OK! So now we have the best Gaussian distribution for our two observations.

Gaussian

$L(\theta|x)$

$= L(\theta|x_1, x_2)$

$= p(x_1, x_2|\theta)$ ($\theta = \{u, sd\}$)

$= p(x_1|x_2)p(x_2)$ for Gaussian(u, sd)

$= p(x_1)p(x_2)$ for Gaussian(u, sd)

$\text{argmax}(u, sd)$ in $p(x_1)p(x_2)$ for Gaussian(u, sd)

maximum at ($u = -0.6250109$, $sd = 0.375003$)

$L(u = -0.6250109, sd = 0.375003) = 0.4163544$

So taking sd into consideration we improved our likelihood from 0.1382762 to 0.4163544