

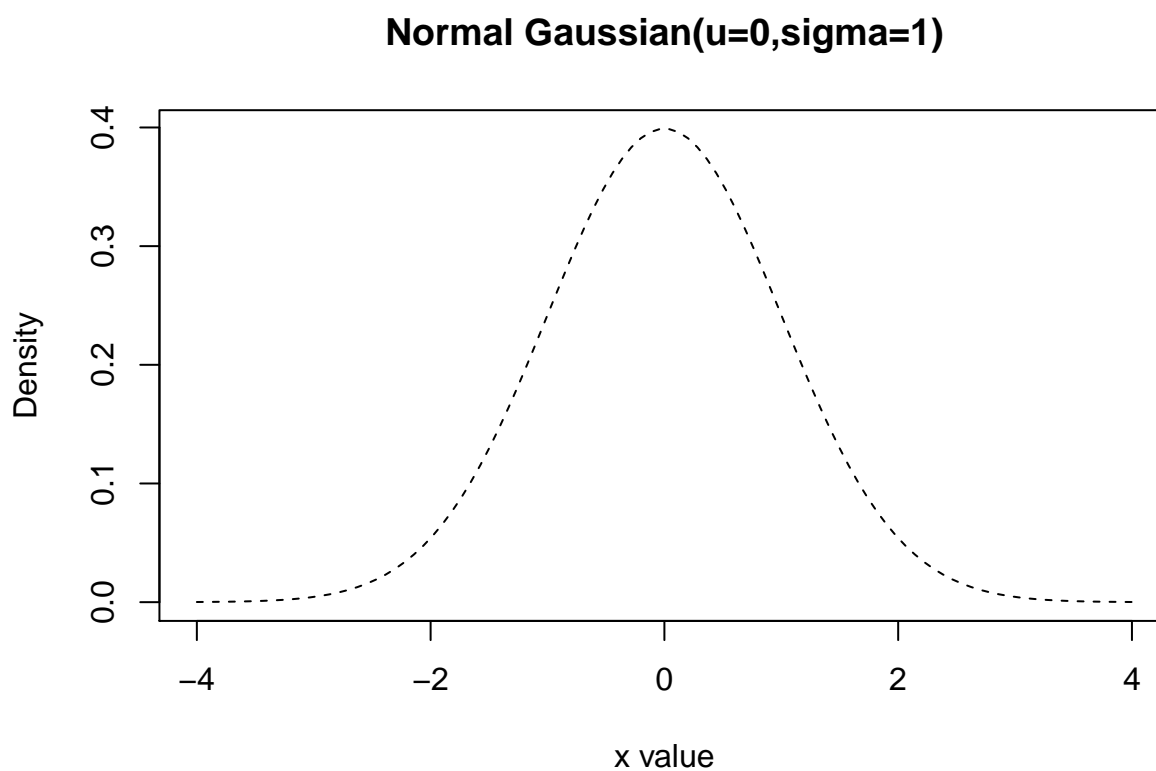
Maximum Likelihood

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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

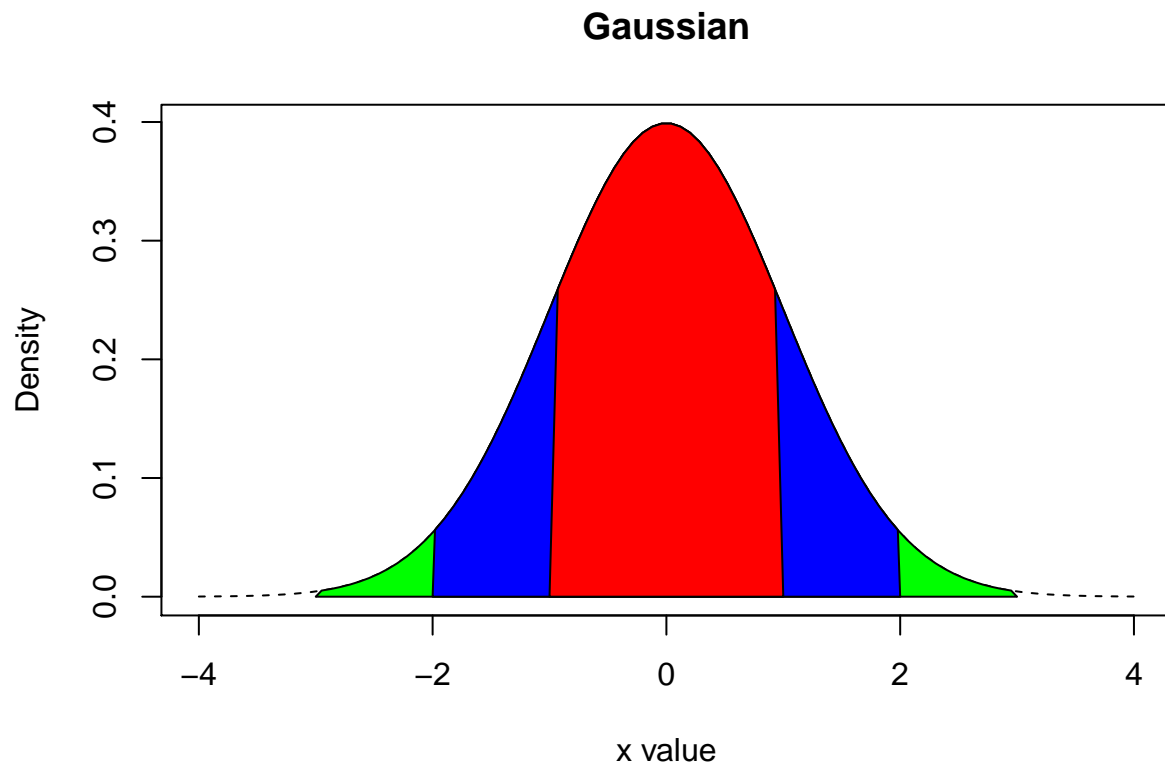
```
plotGaussian <- function(u, sigma, color = "black"){
  x <- seq(-4, 4, length=100)
  hx <- dnorm(x, mean = u, sd = sigma)
  plot(x, hx, type="l", lty=2, xlab="x value", ylab="Density", main="Gaussian", col = color)
}
plotArea <- function(u, sigma, sigmaSize, color){
  x <- seq(-4, 4, length=100)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

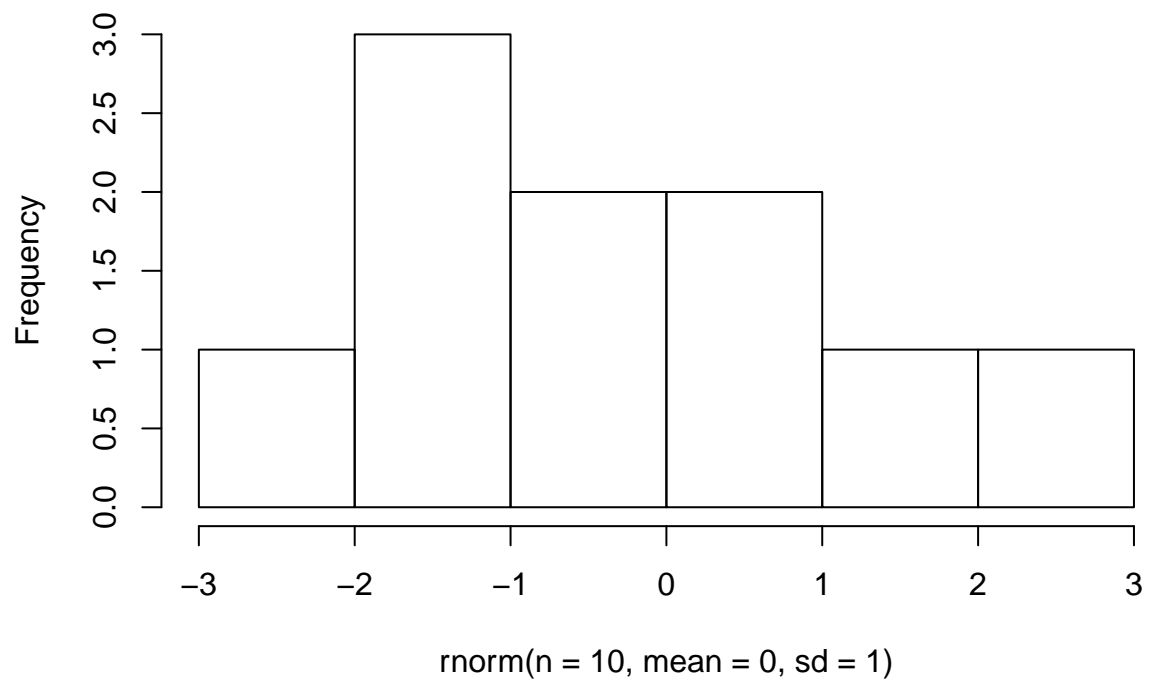
```



Density Simulation

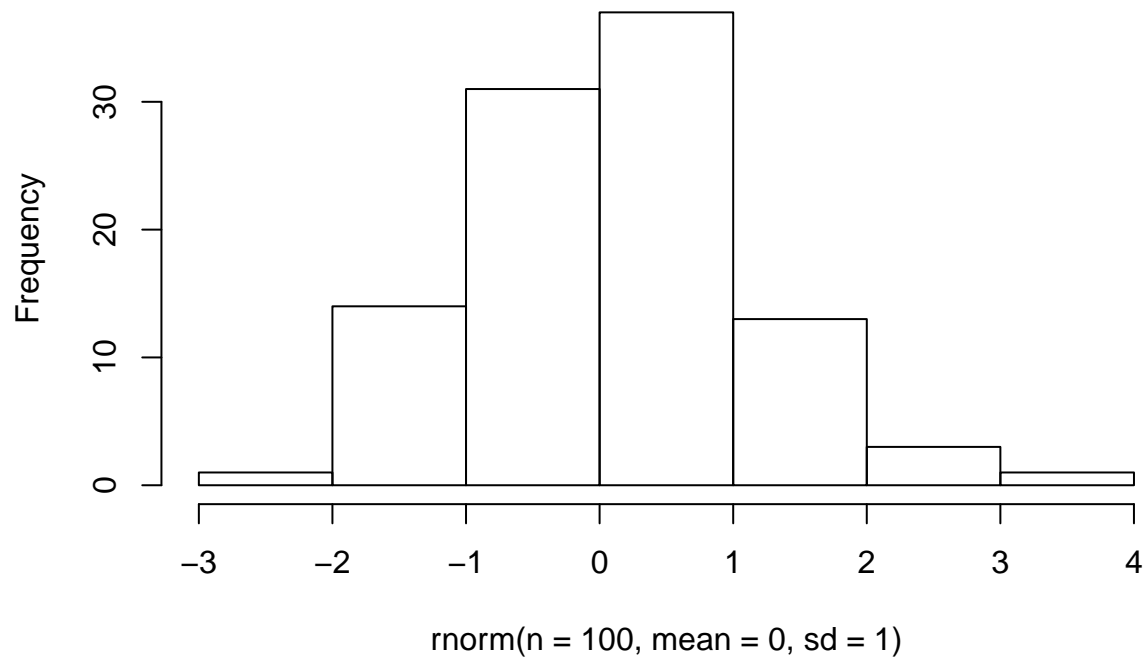
```
hist(rnorm(n = 10, mean = 0, sd = 1))
```

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



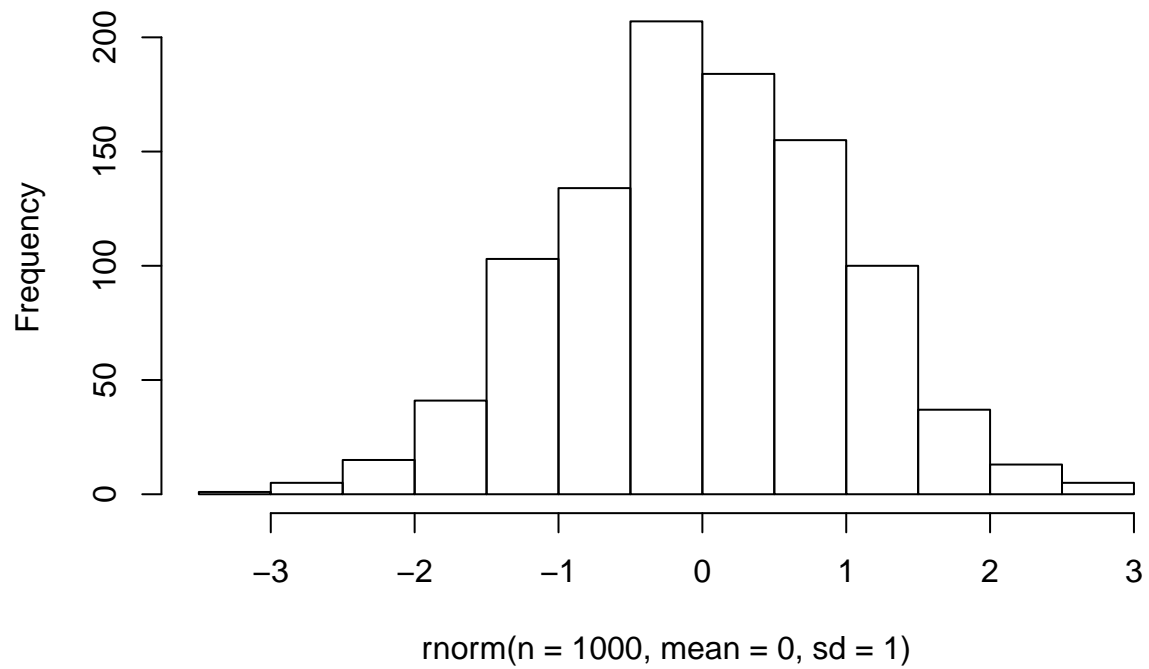
```
hist(rnorm(n = 100, mean = 0, sd = 1))
```

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



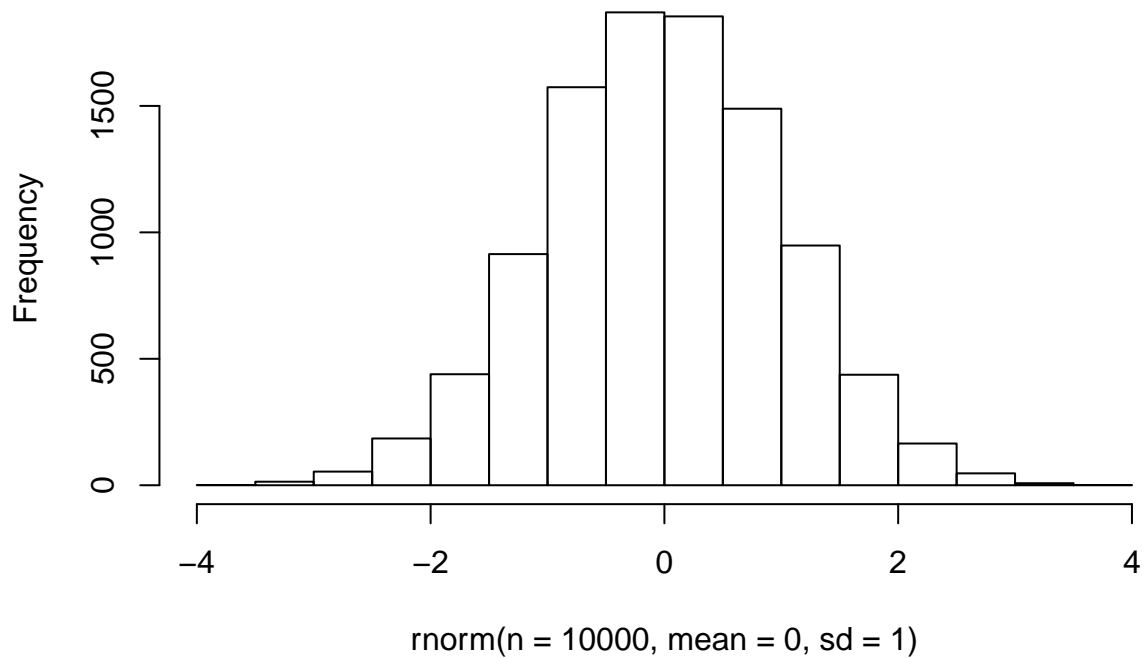
```
hist(rnorm(n = 1000, mean = 0, sd = 1))
```

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



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

Histogram of $\text{rnorm}(n = 10000, \text{mean} = 0, \text{sd} = 1)$



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

$\mu = -2$

$\sigma = 1$

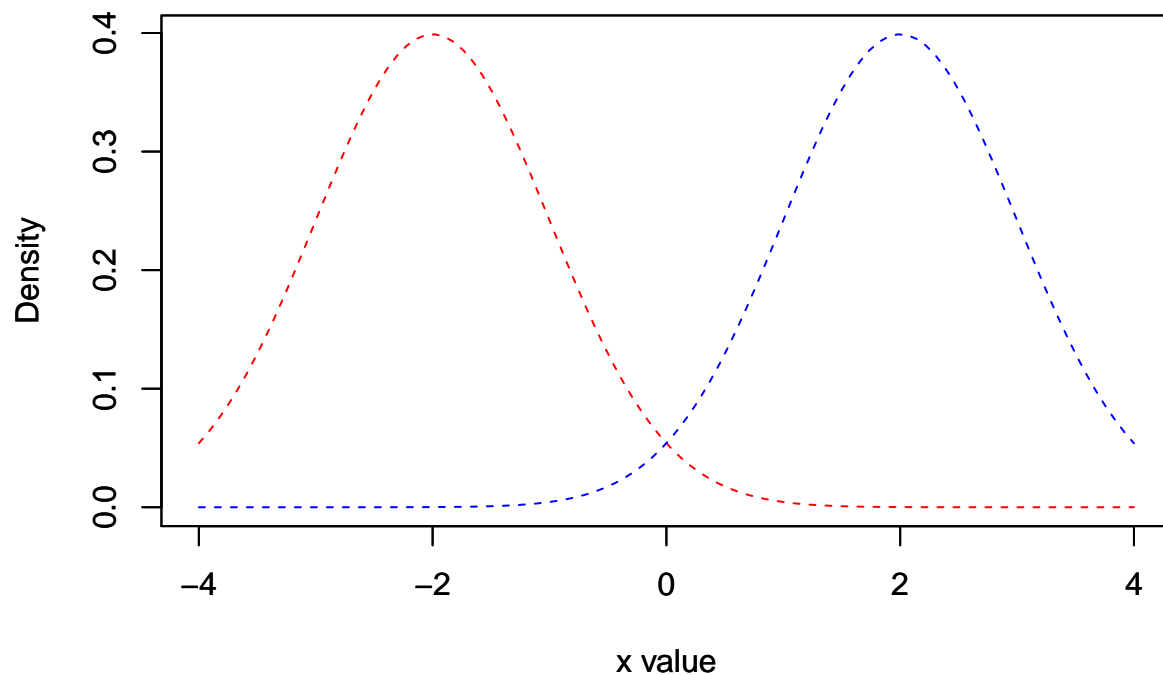
Gaussian #2

$\mu = 2$

$\sigma = 1$

```
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:

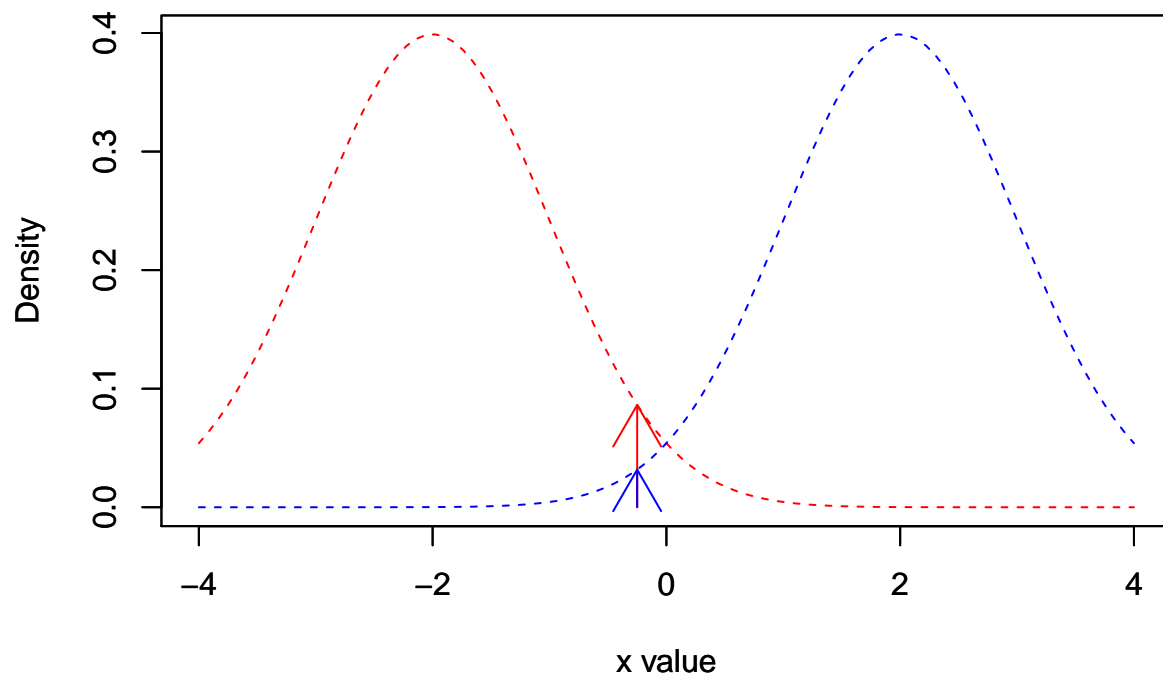
Probability of observing A from Gaussian #1 ($\mu=-2, \sigma=1$) = 0.0862773

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

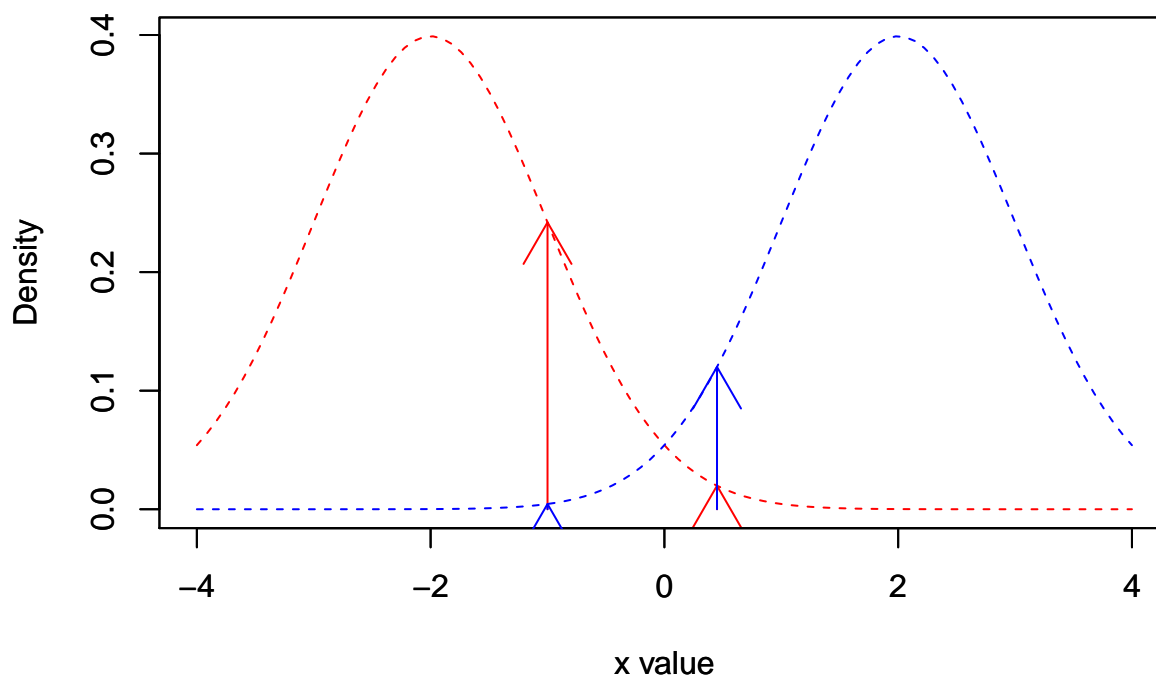


We can use the same calculations to the others observations.

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 $u = -2$ and $sd = 1$ for a observation -1 is 0.2419707 because the probability of seeing a value -1 from a Gaussian with $u = -2$ and $sd = 1$ is 0.2419707 .

In others words:

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

Or:

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

Maximun Likelihood

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:

maximize θ in $L(\theta|x)$

We saw that this is the same as

maximize θ in $p(x | \theta)$

Se given x , which is a known value, we must find the θ that maximize the function. θ in this particular case is the set $\{u, sd\}$. So given X , we must find u and sd that will maximize $p(x|u, sd)$.

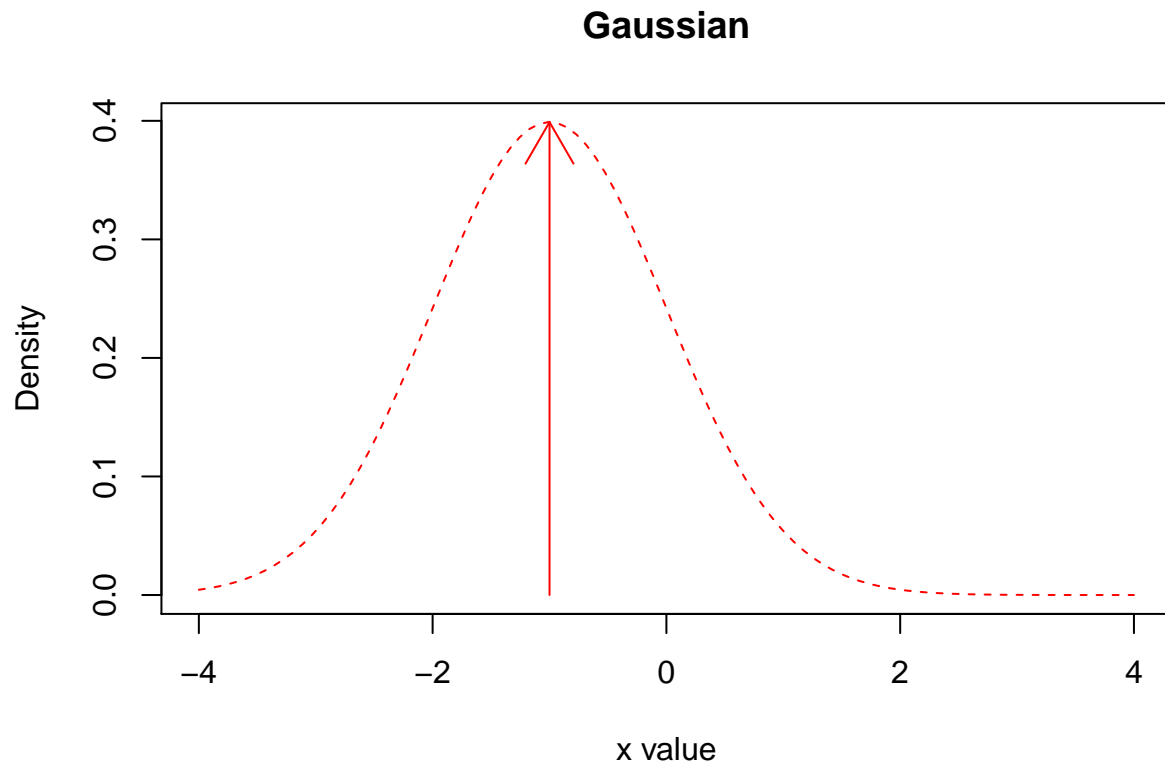
For this trivial case we will have a problem, that will be shown later. For now let fix $sd = 1$ and try to maximize just for u . So we have:

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 $p(x | u, \text{sd} = 1)$, 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 $\text{sd} = 0.5$, for example, we will have:

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

Gaussian

