Discrete Response Model
Lecture 1

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Maximum Likelihood Estimation (1)

Maximum Likelihood Estimation

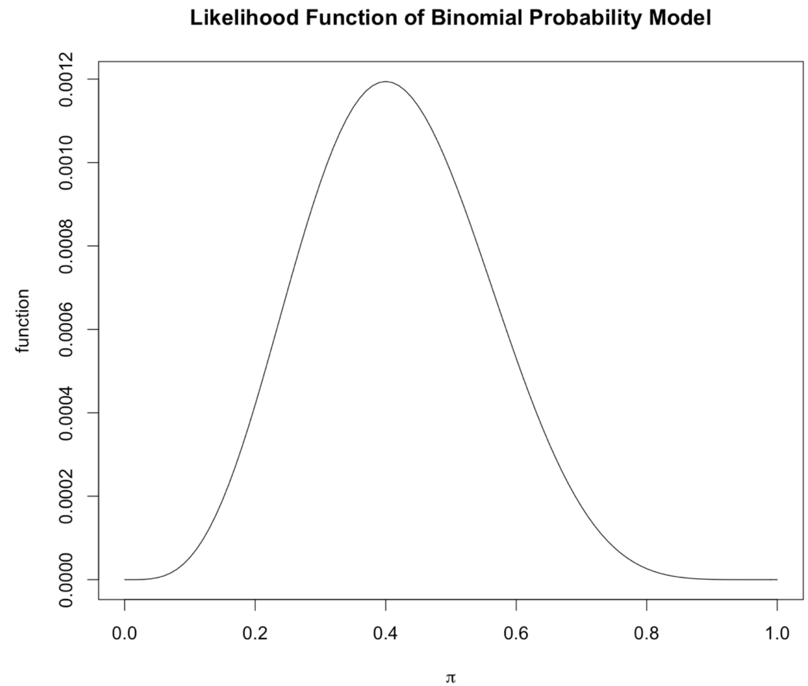
Suppose w = 4 and n = 10. Given this observed information, we would like to find the corresponding parameter value for π that produces the largest probability of obtaining this particular sample.

The following table can be formed to help find this parameter value:

π	$L(\pi \mid y_1,\ldots,y_n)$
0.2	0.000419
0.3	0.000953
0.35	0.001132
0.39	0.001192
0.4	0.001194
0.41	0.001192
0.5	0.000977

Maximum Likelihood Estimation (in R)

```
> sum.y<-4
> n<-10
> # Try different values of pi
> pi<-c(0.2, 0.3, 0.35, 0.39, 0.4, 0.41, 0.5)
> Lik<-pi^sum.y*(1-pi)^(n-sum.y)
> data.frame(pi, Lik)
    pi          Lik
1 0.20 0.0004194304
2 0.30 0.0009529569
3 0.35 0.0011317547
4 0.39 0.0011918935
5 0.40 0.0011943936
6 0.41 0.0011919211
7 0.50 0.0009765625
```




```
#Likelihood function plot
curve(expr = x^sum.y*(1-x)^(n-sum.y), xlim = c(0,1),
    xlab = expression(pi), ylab = "Likelihood
    function", main="Likelihood Function of Binomial Probability Model")
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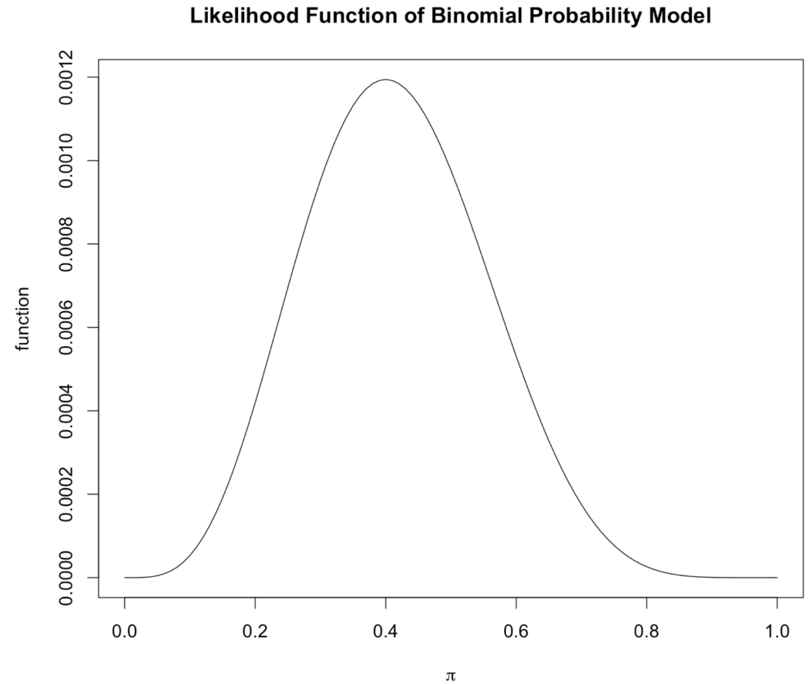


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Note that $\pi = 0.4$ is the "most plausible" value of π for the observed data because this maximizes the likelihood function. Therefore, 0.4 is the <u>maximum likelihood estimate (MLE)</u>.

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