

# Lab1

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## Task 1

Let  $y_1, \dots, y_n | \theta \sim \text{Bern}(\theta)$ , and assume that you have obtained a sample with  $s = 14$  successes in  $n = 20$  trials. Assume a  $\text{Beta}(\alpha_0, \beta_0)$  prior for  $\theta$  and let  $\alpha_0 = \beta_0 = 2$ .

### a) Posterior $\theta | y \sim \text{Beta}(\alpha_0 + s, \beta_0 + f)$ .

Verify graphically that the posterior mean and standard deviation converges to the true values as the number of random draws grows large.

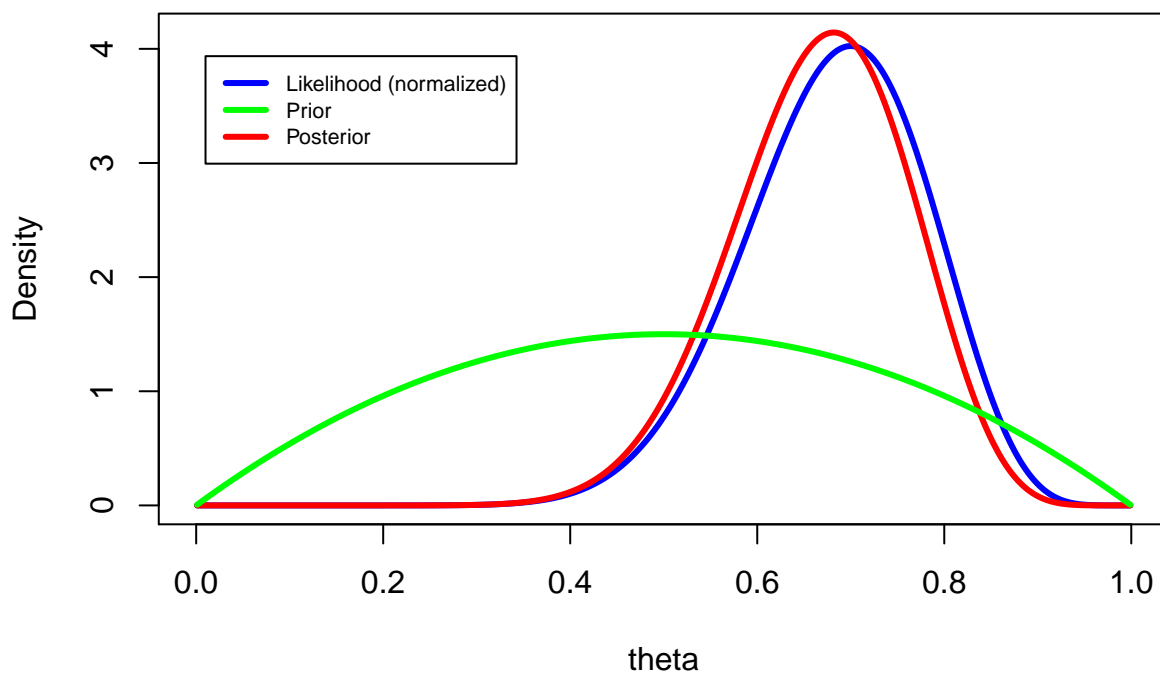
For 20 draws we get:

```
## [1] "Posterior Mean GT: 0.666666666666667"
## [1] "ground truth std: 0.0942809041582063"
## [1] "std: 0.0932218585926857"
## [1] "Mean: 0.672041764648697"
```

For 10 000 draws we get:

```
## [1] "Posterior Mean GT: 0.666666666666667"
## [1] "ground truth std: 0.0942809041582063"
## [1] "std: 0.0950053167839754"
## [1] "Mean: 0.66700827198354"
```

### Bernoulli model – Beta(a,b) prior



b)

Using 10 000 draws we seek to compute the posterior probability  $\Pr(\theta < 0.4|y)$ .

```
## [1] "probability condition with random: 0.0039"
```

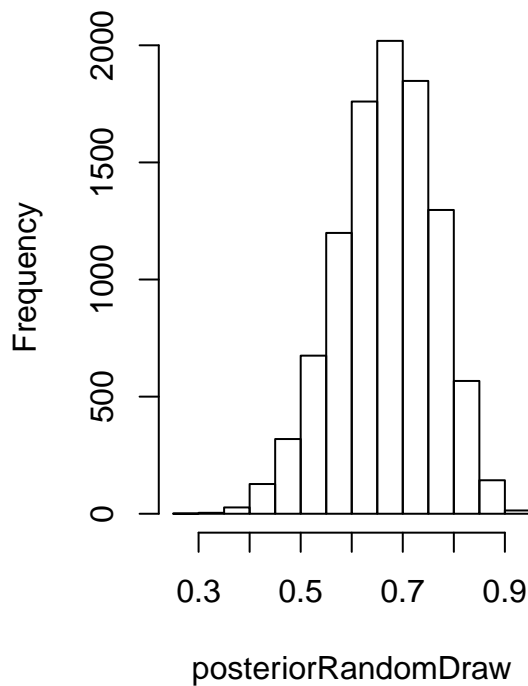
```
## [1] "ground truth probability: 0.00397268082810898"
```

Looking at the plot above, the probability for  $\theta < 0.5|y$  is very small. The simulated value is relatively close to the ground truth. (Note: The further to the left on the tail, the larger sample we will need as the data points become more sparse.)

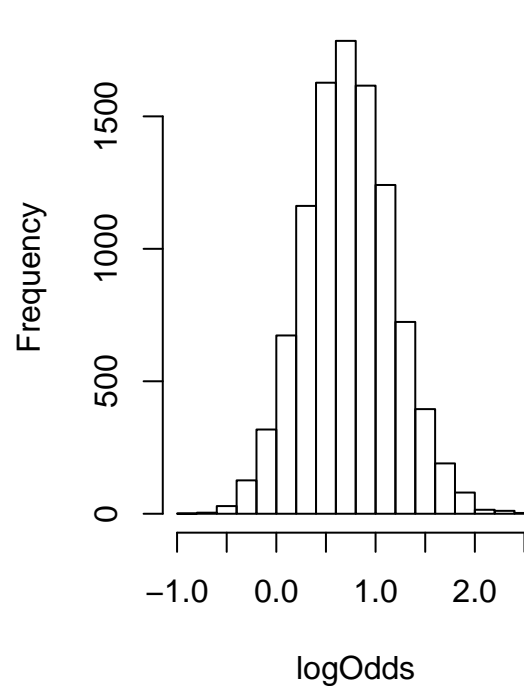
c)

Computing posterior distribution of the log-odds by simulating 10 000 random draws.

**Histogram of posteriorRandomDraw**



**Histogram of logOdds**

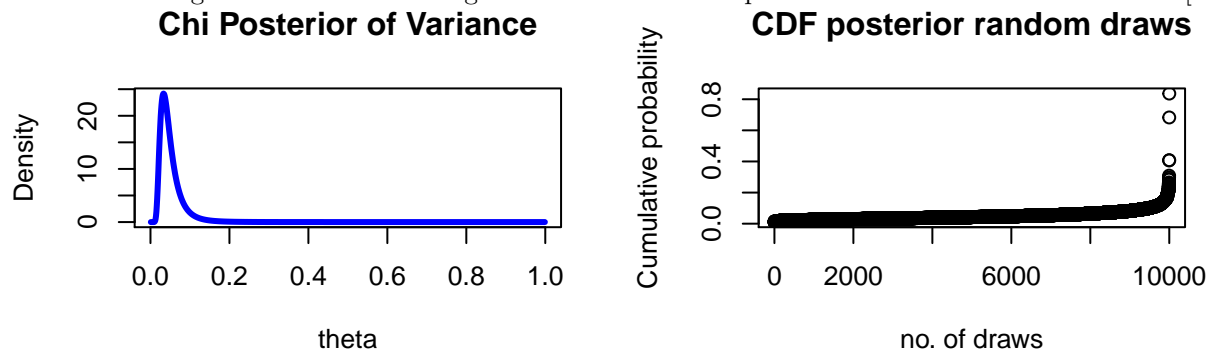


```
##  
## Call:  
## density.default(x = logOdds)  
##  
## Data: logOdds (10000 obs.); Bandwidth 'bw' = 0.06348  
##  
##      x      y  
## Min.  :-1.1368 Min.  :0.0000072  
## 1st Qu.: -0.1734 1st Qu.:0.0052186  
## Median : 0.7900 Median :0.0929175  
## Mean   : 0.7900 Mean   :0.2592487  
## 3rd Qu.: 1.7534 3rd Qu.:0.4970806  
## Max.   : 2.7168 Max.   :0.8973241
```

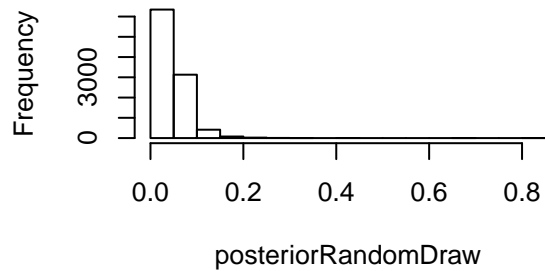
## Task 2

Log-normal distribution and the Gini coefficient ####a) Simualtion 10 000 draws from posterior of variance, assuming mean = 3.5 and comparing with the theoretical Inv Chi square posterior distribution.

“Chi posterior of variance” plot is the basis for comparison. The posterior CDF of the random draws together with the histogram of the random posterior shows that the ..... [TBD]

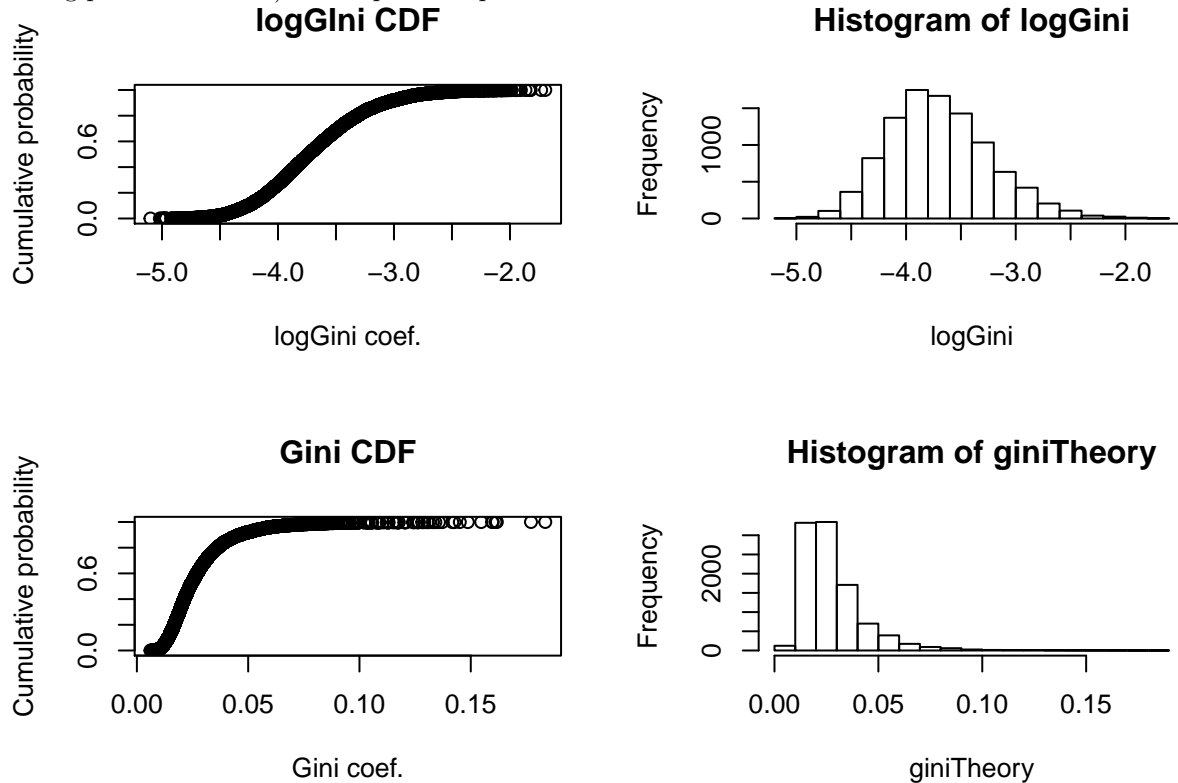


### Histogram of posteriorRandomDraw



b)

Using posterior from a) to compute the posterior distribution of the Gini coefficient for the current dataset.



c)

Using posterior draws from b) to calculate a 95% equal tail credible interval for the Gini coefficient  $G$ . In addition a kernel density estimate of the posterior of  $G$  to use that kernel density to compute a 95% HPD interval for  $G$ .

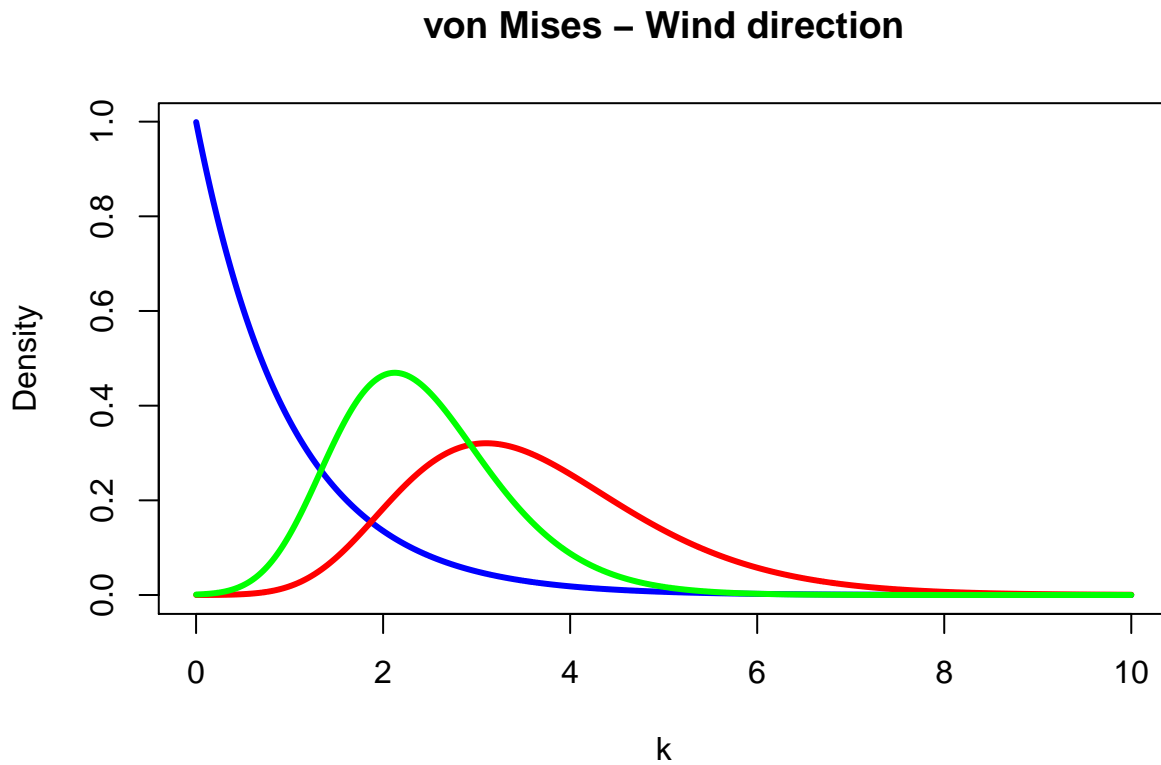
```
##
## Call:
## density.default(x = middleData)
##
## Data: middleData (9501 obs.); Bandwidth 'bw' = 0.001601
##
##      x      y
## Min. :0.006348 Min. : 0.00228
## 1st Qu.:0.023458 1st Qu.: 2.38529
## Median :0.040569 Median : 7.84956
## Mean :0.040569 Mean :14.59648
## 3rd Qu.:0.057679 3rd Qu.:25.01183
## Max. :0.074790 Max. :44.38201
## [1] 0.01114952
## [1] 0.06998829
```

### Task 3

Bayesian inference for the concentration parameter in the von Mises distribution.

a)

Plot the posterior distribution of  $k$  (concentration parameter) for the wind direction.



b)

Approximate poosterior mode of the concentration parameter  $k$  given the information in a).

```
## [1] 2.125
```

Output above shows the approximate mode of  $k$ .