

# **CSSS/POLS 510 MLE Lab**

## **Lab 4. Prediction and Quantities of Interest**

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# Agenda

1. Review HW1
2. Last lab review
3. Quantities of Interest

# 1. Review HW1: simulation precision

```
dbinom(x=16, size=30, prob=0.49)

## [1] 0.1293457

set.seed(12345)

sims <- 100      # 100 simulations

nmen <- rep(NA,sims)
for (i in 1:sims) {
  nmen[i] <- sum(sample(c(0,1),
                        30,
                        replace = TRUE,
                        prob = c(0.51, 0.49) ))
}
sum(nmen==16)/length(nmen) # sum of trials with 16 males

## [1] 0.16
```

# 1. Review HW1: simulation precision

```
dbinom(x=16, size=30, prob=0.49)

## [1] 0.1293457

set.seed(12345)

sims <- 1000      # 1000 simulations

nmen <- rep(NA,sims)
for (i in 1:sims) {
  nmen[i] <- sum(sample(c(0,1),
                        30,
                        replace = TRUE,
                        prob = c(0.51, 0.49) ))
}
sum(nmen==16)/length(nmen) # sum of trials with 16 males

## [1] 0.131
```

# 1. Review HW1: simulation precision

```
dbinom(x=16, size=30, prob=0.49)

## [1] 0.1293457

set.seed(12345)

sims <- 10000      # 10000 simulations

nmen <- rep(NA,sims)
for (i in 1:sims) {
  nmen[i] <- sum(sample(c(0,1),
                        30,
                        replace = TRUE,
                        prob = c(0.51, 0.49) ))
}
sum(nmen==16)/length(nmen) # sum of trials with 16 males

## [1] 0.1285
```

# 1. Review HW1: simulation precision

```
dbinom(x=16, size=30, prob=0.49)

## [1] 0.1293457

set.seed(12345)

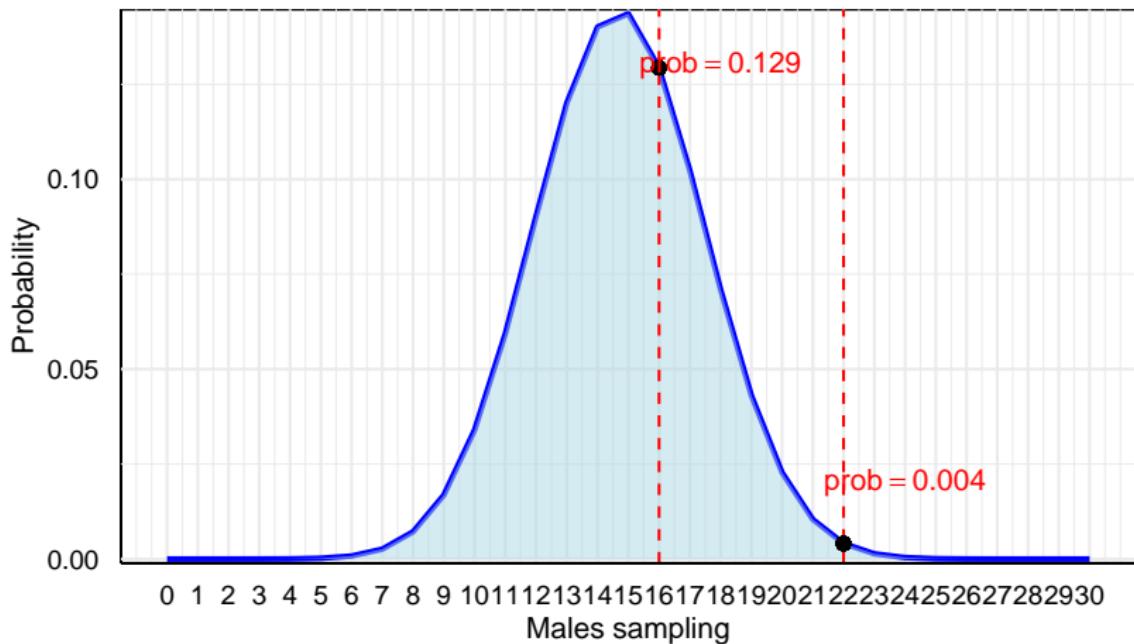
sims <- 100000      # 100000 simulations

nmen <- rep(NA,sims)
for (i in 1:sims) {
  nmen[i] <- sum(sample(c(0,1),
                        30,
                        replace = TRUE,
                        prob = c(0.51, 0.49) ))
}
sum(nmen==16)/length(nmen) # sum of trials with 16 males

## [1] 0.1294
```

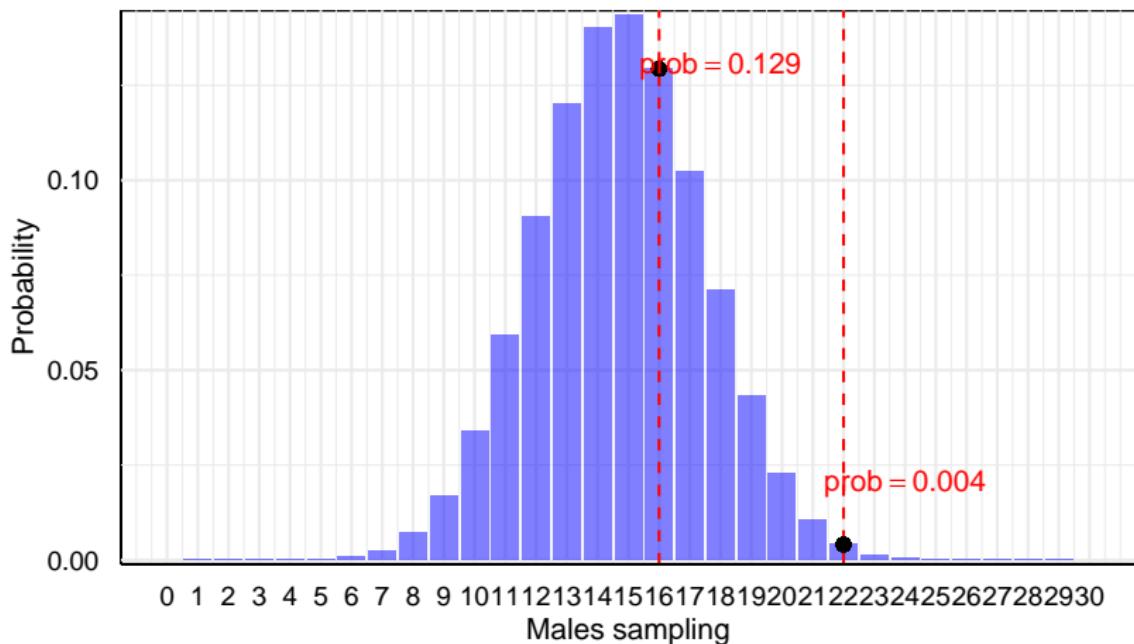
# 1. Review HW1: Probability Mass Functions

Q1 – Binomial distribution



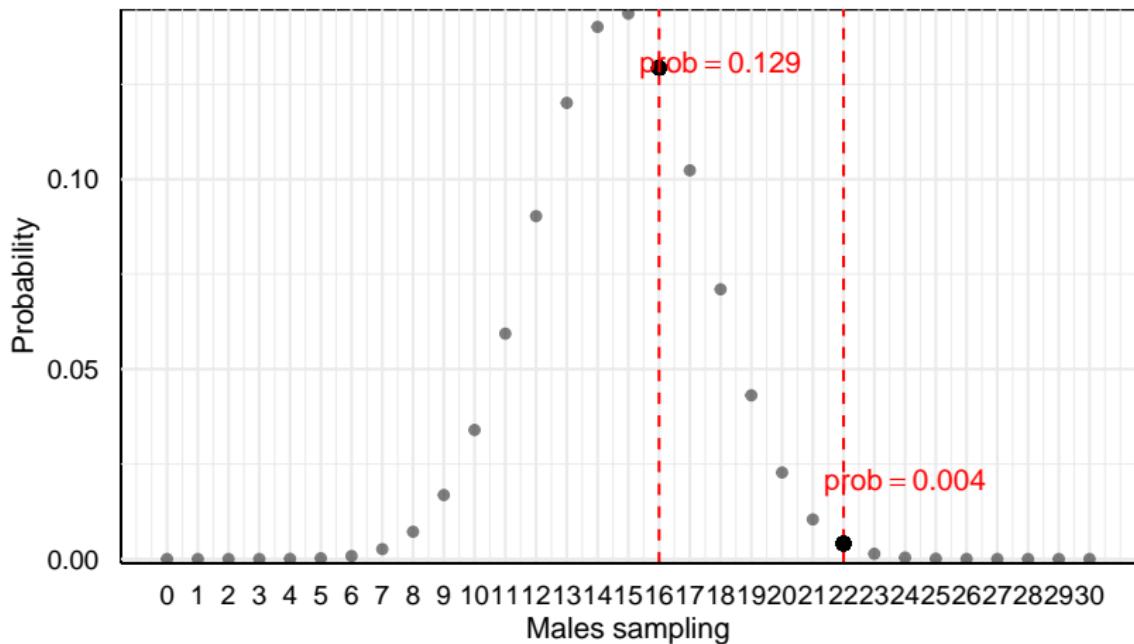
# 1. Review HW1: Probability Mass Functions

Q1 – Binomial distribution



# 1. Review HW1: Probability Mass Functions

Q1 – Binomial distribution



# 1. Review HW1: summary

- ▶ When displaying PMFs, provide visuals with a discrete sample space.
- ▶ **Sanity checks:**
  - ▶ Use R built-in or packages programs/functions to **double-check**.
  - ▶ Increase simulations/sample **size**.
    - ▶ Convergence in probability ( $N \rightarrow \infty$ )

## 2. Last lab review: MLE

- ▶ How do we estimate the MLE?
  1. Define a probability model (PDF):  $Y_i \sim N(\mu_i, \sigma^2)$ .
  2. Derive the log-likelihood function.
  3. Reduce to sufficient statistics and substitute systematic component.
  4. Use `optim()` or any other function to find the maxima.

## 2. Normal homoskedastic

Two **different** notations for the **same** model.

LS notation:

$$\varepsilon \sim N(0, \sigma^2) \quad (\text{stochastic})$$

$$Y_i = x_i\beta \quad (\text{systematic})$$

$$Y_i = x_i\beta + \varepsilon \quad (\text{stochastic} + \text{systematic})$$

MLE notation:

$$Y_i \sim N(\mu_i, \sigma^2) \quad (\text{stochastic})$$

$$\mu_i = x_i\beta \quad (\text{systematic})$$

$$Y_i \sim N(x_i\beta, \sigma^2) \quad (\text{stochastic} + \text{systematic})$$

## 2. MLE general notation

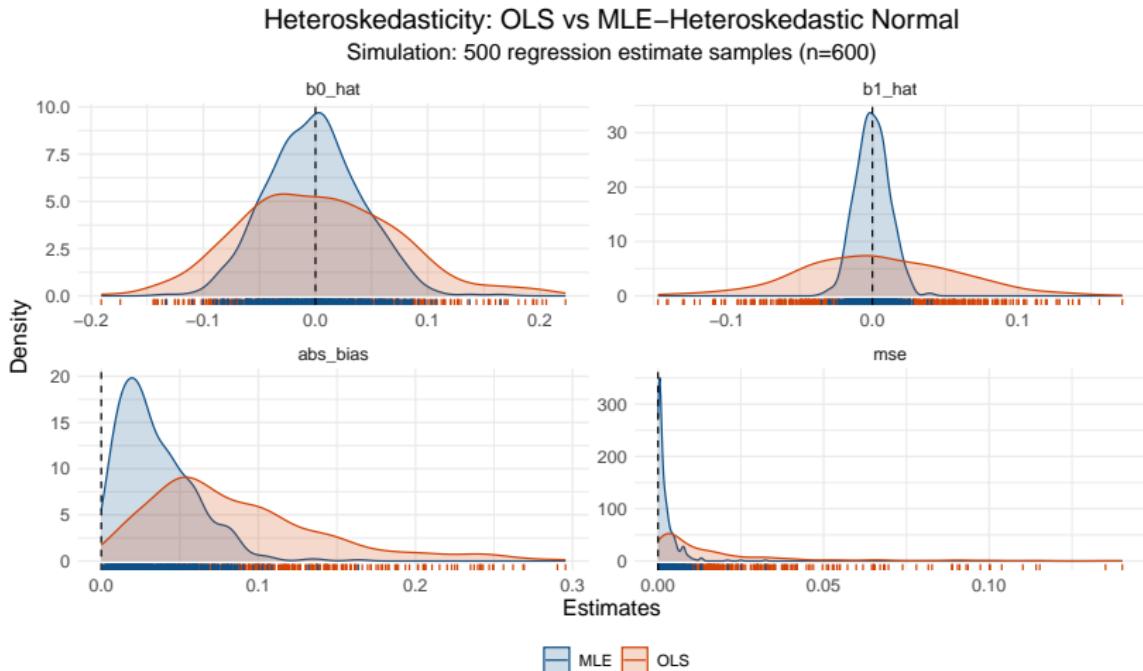
$$Y_i \sim f(\theta_i, \alpha) \quad (\text{stochastic})$$

$$\theta_i = g(x_i \beta) \quad (\text{systematic})$$

where

- ▶  $Y_i$  is a random outcome variable.
- ▶  $f(\cdot)$  is a probability density function.
- ▶  $\theta_i$  is a systematic feature of the PDF that varies over  $i$ .
- ▶  $\alpha$  is an ancillary parameter (feature of  $f$  that we treat as constant).
- ▶  $g(\cdot)$  functional form for reparametrization of the data model.
- ▶  $x_i$  explanatory variables vector.
- ▶  $\beta$  vector of effect parameters.

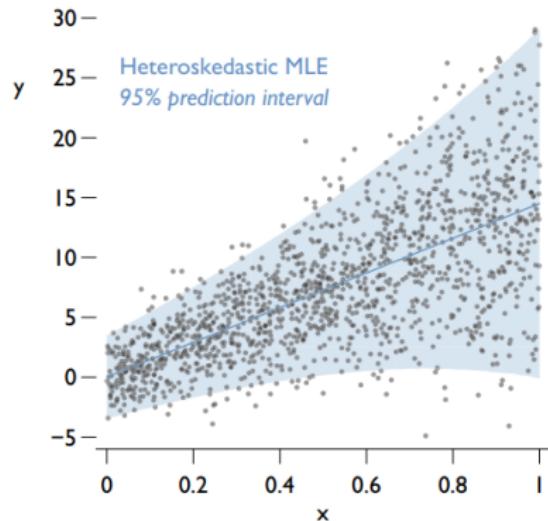
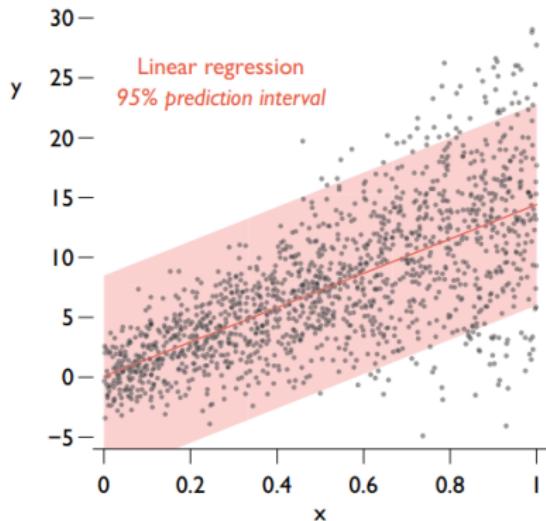
## 2. Last lab review: MLE - Heteroskedastic normal



Note: Estimates distributions are mean-centered on the true parameters. Each facet's axes are free to vary.

### 3. Quantities of Interest: prediction

Once we have estimated the model, we can compare the predictive performance of each model. Refer to Chris's MLE lecture ([slide 80](#)) for more details.



### 3. Quantities of Interest

**Motivation:** We want to study how the change in a particular explanatory variable affects the outcome variable, *all else being equal.*

We will focus on how to simulate predictions from *estimands* or **quantities of interest**.

Let's open RStudio and [Lab4.html](#) file jointly with the [Lab4.Rmd](#) file with the code and contents of today's lab!

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