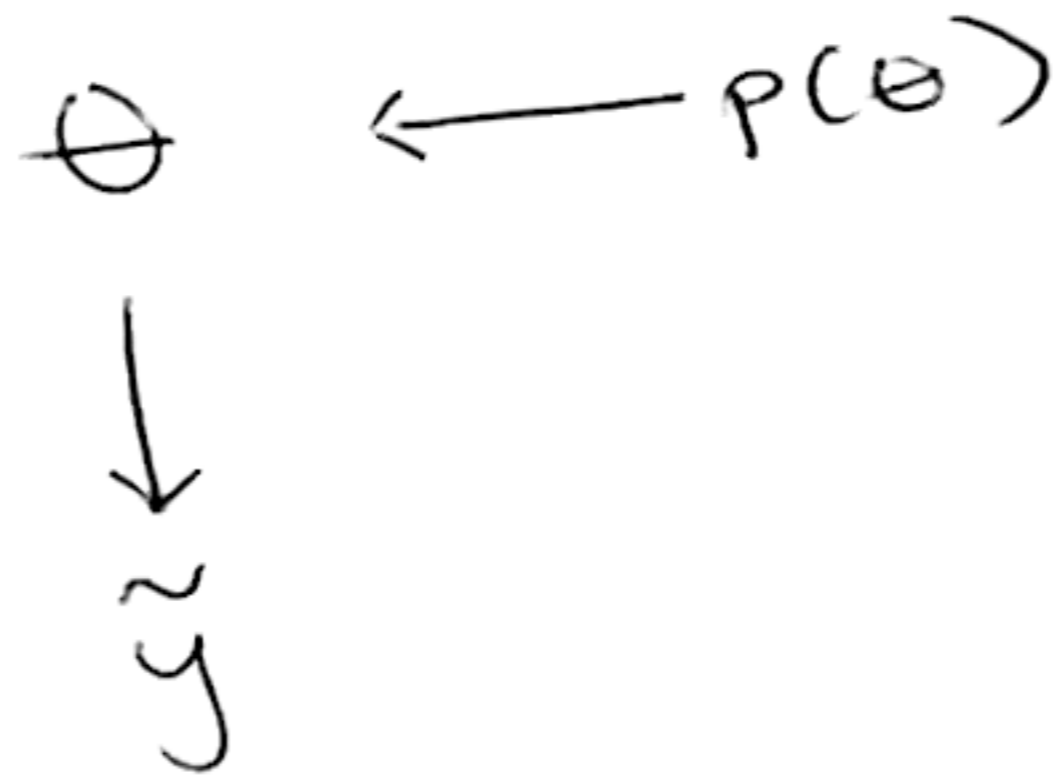


# PRIOR PREDICTIVE DISTRIBUTION

- tells us how a <sup>prior</sup> belief about  $\theta$ ,  $p(\theta)$  translates into beliefs about  $\tilde{y}$ , according to our sampling model. ①

PICTURE:



MATH:

$$p(\tilde{y}) = \int p(\tilde{y}|\theta) p(\theta) d\theta$$

PSEUDO-CODE:

```
Let S be large.
for (s in 1:S) {
  draw  $\theta^{(s)} \sim p(\theta)$ 
  draw  $\tilde{y}^{(s)} \sim p(\tilde{y}|\theta^{(s)})$ 
}
```

# POSTERIOR PREDICTIVE DISTRIBUTION

(2)

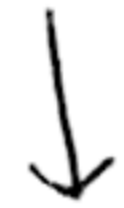
- tells us how our posterior beliefs about  $\theta$ ,  $p(\theta | \vec{y})$ , translate into beliefs about  $\tilde{y}$ .
- useful for evaluating our sampling model,  $p(y | \theta)$ .
- Does not "rule model in" but may help expose a flawed model. Note: this depends on many factors, e.g. the statistic of interest.

PICTURE:

$$y_1, \dots, y_n := \vec{y}$$



$$\theta$$



$$\tilde{y}$$

MATH:

$$p(\tilde{y} | y_1, \dots, y_n) = \int p(\tilde{y} | \theta) p(\theta | y_1, \dots, y_n) d\theta$$

To approximate  $p(\tilde{y} | y_1, \dots, y_n)$  w/ Monte Carlo:

Let  $S$  large.

for  $(s \text{ in } 1:S) \{$

$$\theta^{(s)} \sim p(\theta | \vec{y})$$

$$\tilde{y}^{(s)} \sim p(\tilde{y} | \theta)$$

}

PSEUDO-CODE:

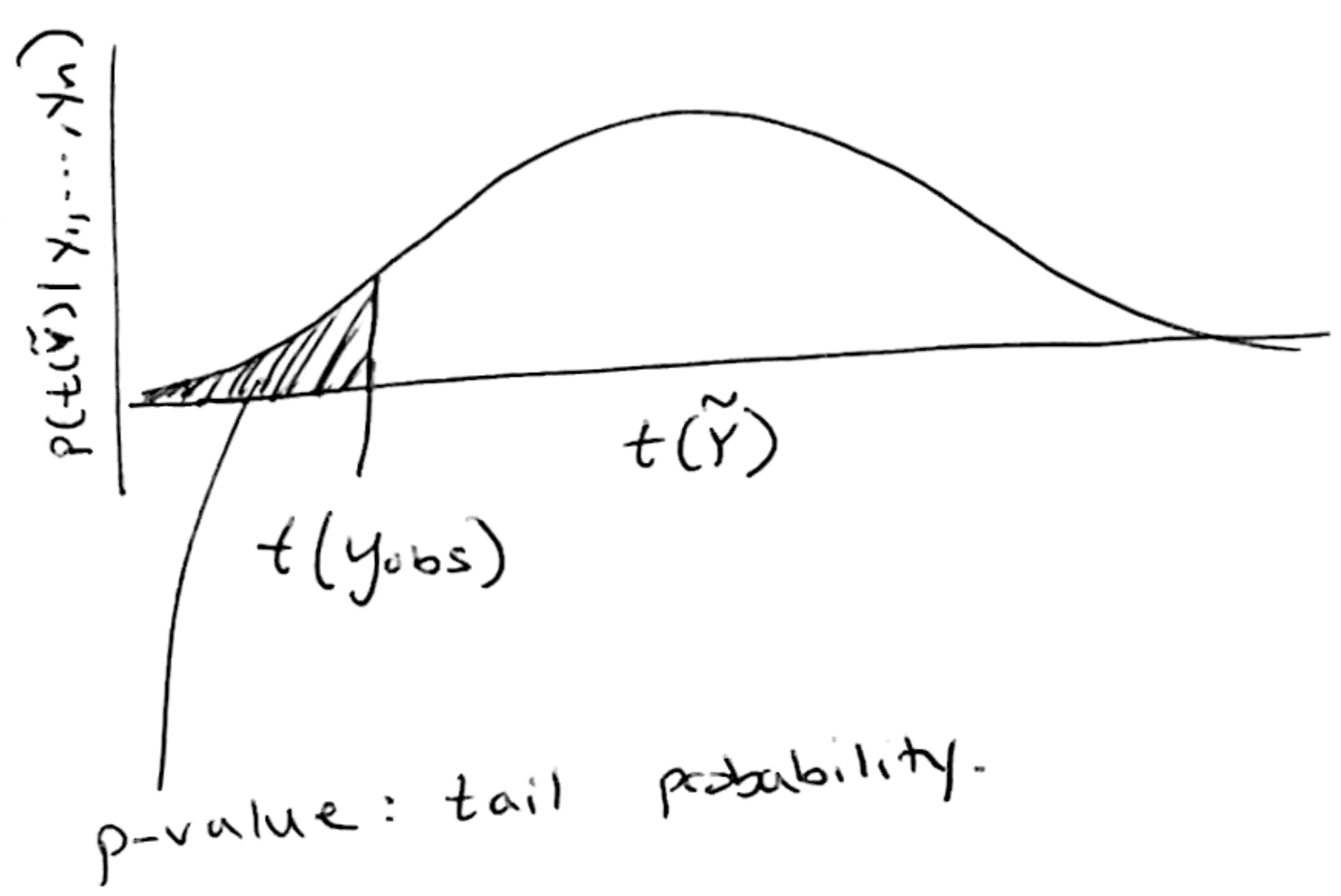
POSTERIOR PREDICTIVE CHECK

- Given the posterior predictive distr., compute the tail probability of some statistic.

Recall: definition of statistic  $t(Y)$ : a function of the data

ex:  $t(Y) = \frac{1}{n} \sum Y_i$   
ex:  $t(Y) = \max \{ Y_1, \dots, Y_n \}$

PICTURE:



More generally:  $p\text{-value} = P = \text{prob}(t(Y) \leq t(Y_{\text{obs}}) | \text{something})$

\* NOT distributed  $\text{unif}(0,1)$  like a traditional p-value!

$\{y_1, \dots, y_n\}$  "posterior predictive"

ex:  $\theta = \hat{\theta}_{MLE}$  "parametric bootstrap"

posterior predictive p-value:

$$P = \int_{-\infty}^{t(y_{\text{obs}})} p(t(\tilde{y}) | y_1, \dots, y_n) dt(\tilde{y})$$

$$\int_{\theta} p(t(\tilde{y}) | \theta) p(\theta | y_1, \dots, y_n) d\theta$$

# POSTERIOR PREDICTIVE P-VALUE PSEUDOCODE :

(4)

TO APPROXIMATE  $\text{prob}(t(y) \leq t(y_{\text{obs}}) \mid y_1, \dots, y_n)$  using Monte Carlo:

```
Let S large.  
for (s in 1:S) {  
  sample  $\theta^{(s)} \sim p(\theta \mid y_1, \dots, y_n)$   
  sample n  $\tilde{y} \sim p(\tilde{y} \mid \theta^{(s)})$   
  compute & save  $t(\tilde{y}_1^{(s)}, \dots, \tilde{y}_n^{(s)})$   
}  
Report + mean  $(t(\tilde{y}) < t(y_{\text{obs}}))$ .
```