

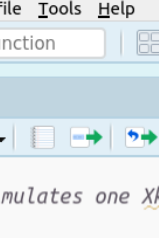



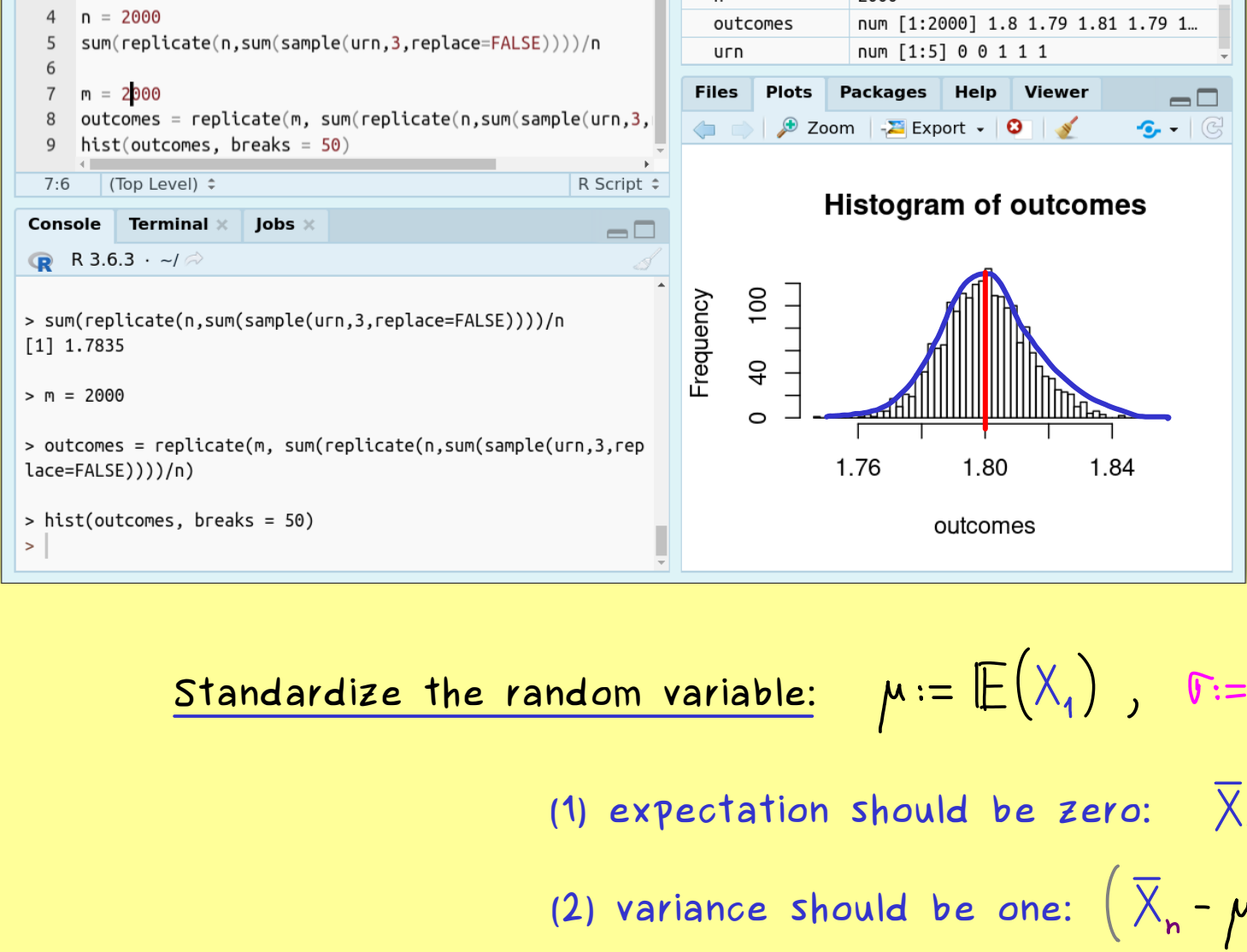
# The Bright Side of Mathematics

## Probability Theory - Part 31

Assumptions of the central limit theorem:  $(X_k)_{k \in \mathbb{N}}$  i.i.d. with  $\text{Var}(X_i) < \infty$ .

part 28  
 $\Rightarrow \bar{X}_n := \frac{1}{n} \sum_{k=1}^n X_k$  satisfies  $E(\bar{X}_n) = E(X_1)$ ,  $\text{Var}(\bar{X}_n) = \frac{\text{Var}(X_1)}{n}$

Example:  urn model without replacement = hypergeometric distribution (part 6)  
 $X_k$  picks 3 balls and counts numbers of 



$$E(X_1) = \frac{9}{5} = 1.8$$

$$\bar{X}_n := \frac{1}{n} \sum_{k=1}^n X_k$$

What is the distribution?  
 close to normal distribution!

$$\text{Var}(\bar{X}_n) = \frac{\text{Var}(X_1)}{n}$$

Standardize the random variable:  $\mu := E(X_1)$ ,  $\sigma := \sqrt{\text{Var}(X_1)}$

(1) expectation should be zero:  $\bar{X}_n - \mu$

(2) variance should be one:  $(\bar{X}_n - \mu) / \left(\frac{\sigma}{\sqrt{n}}\right)$

Central limit theorem: For  $(X_k)_{k \in \mathbb{N}}$  i.i.d. with  $\text{Var}(X_i) < \infty$ , define:

$$Y_n := \left( \frac{1}{n} \sum_{k=1}^n X_k - \mu \right) \cdot \left( \frac{\sigma}{\sqrt{n}} \right)^{-1} \quad \text{where } \mu := E(X_1), \quad \sigma := \sqrt{\text{Var}(X_1)}$$

Then the cdf of  $Y_n$  converges to the cdf of  $\text{Normal}(0, 1)$  :

$$\mathbb{P}(Y_n \leq x) \xrightarrow{n \rightarrow \infty} \Phi(x) \quad \text{for every } x \in \mathbb{R}$$

$$\stackrel{||}{=} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{1}{2}t^2} dt$$

