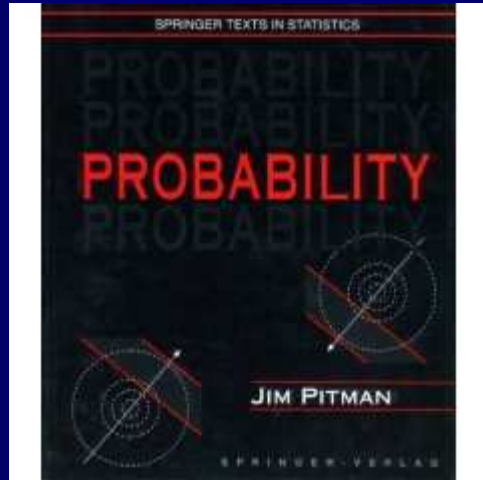


# Introduction to probability

Stat 134

FALL 2005

Berkeley



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Follows Jim Pitman's  
book:

Probability  
Section 2.2

## Recall: the Mean ( $\mu$ )

of a binomial( $n,p$ ) distribution  
is given by:

$$\mu = \# \text{Trials} \times P(\text{success}) = n p$$

- The Mean = Mode (most likely value).
- The Mean = "Center of gravity" of the distribution.

# Standard Deviation

The **Standard Deviation (SD)** of a distribution, denoted  $\sigma$  measures the spread of the distribution.

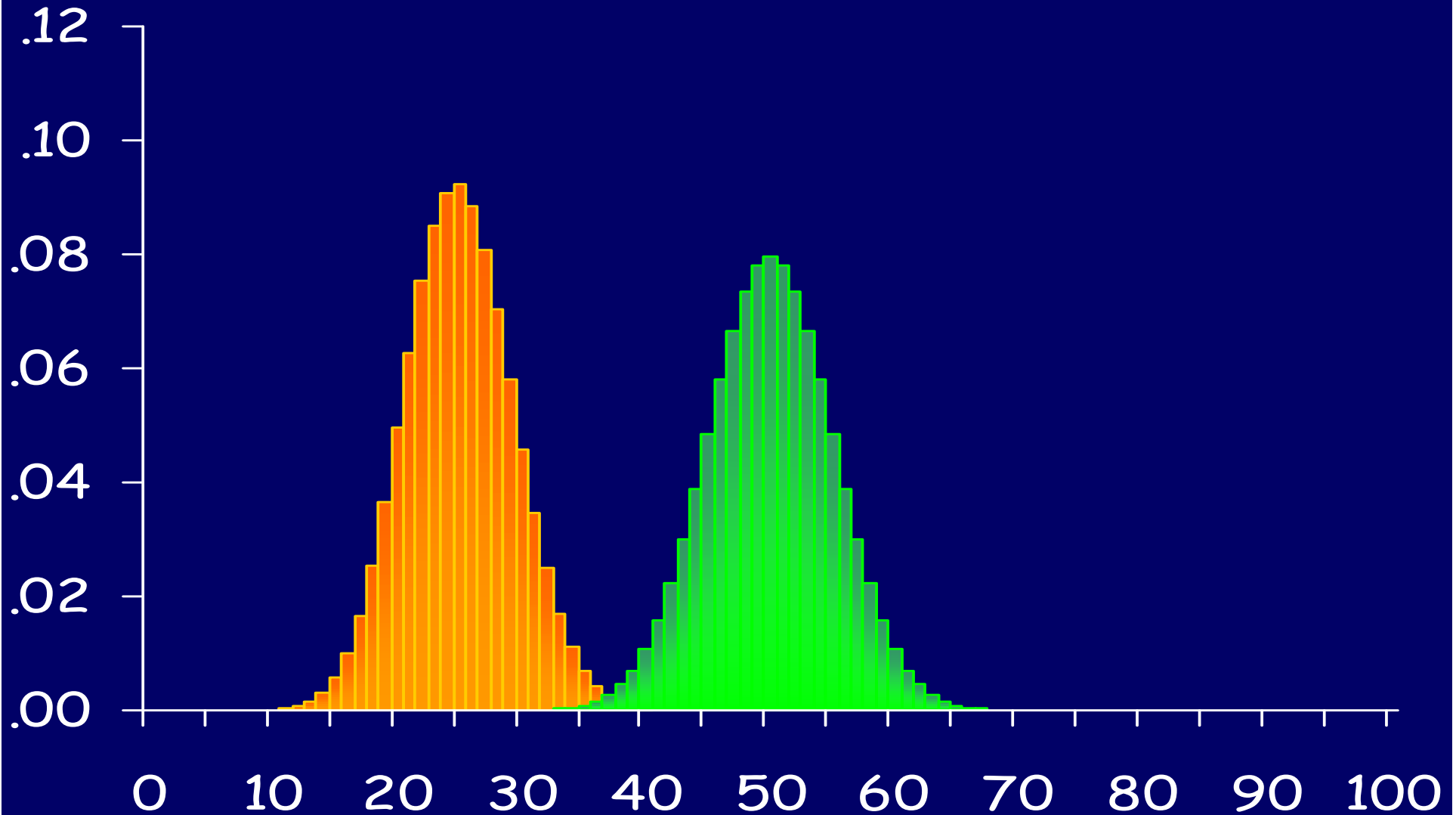
Def: The **Standard Deviation (SD)**  $\sigma$  of the binomial( $n,p$ ) distribution is given by:

$$\sigma = \sqrt{np(1 - p)}$$

## Example 1:

- Let's compare  $\text{Bin}(100, 1/4)$  to  $\text{Bin}(100, 1/2)$ .
- $\mu_1 = 25, \mu_2 = 50$
- $\sigma_1 = 4.33, \sigma_2 = 5$
- We expect  $\text{Bin}(100, 1/4)$  to be less spread than  $\text{Bin}(100, 1/2)$ .
- Indeed, you are more likely to guess the value of  $\text{Bin}(100, 1/4)$  distribution than of  $\text{Bin}(100, 1/2)$  since:
  - For  $p=1/2$  :  $P(50) \approx 0.079589237$ ;
  - For  $p=1/4$  :  $P(25) \approx 0.092132$ ;

Histograms for  $\text{binomial}(100, 1/4)$  &  
 $\text{binomial}(100, 1/2)$ ;



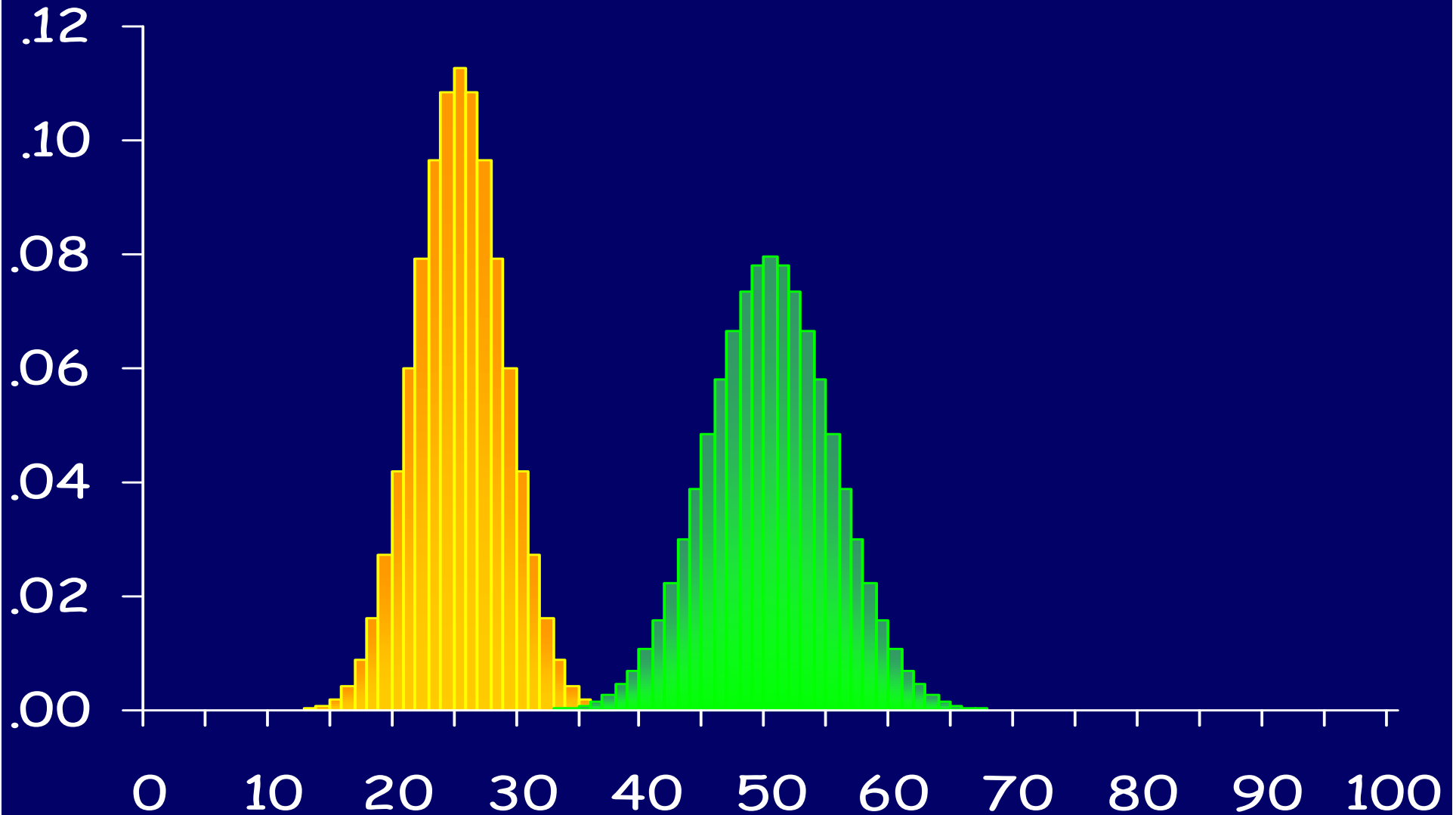
## Example 2:

- Let's compare  $\text{Bin}(50, 1/2)$  to  $\text{Bin}(100, 1/2)$ .
- $\mu_1 = 25, \mu_2 = 50$
- $\sigma_1 = 3.54, \sigma_2 = 5$
- We expect  $\text{Bin}(50, 1/2)$  to be less spread than  $\text{Bin}(100, 1/2)$ .
- Indeed, you are more likely to guess the value of  $\text{Bin}(50, 1/2)$  distribution than of  $\text{Bin}(100, 1/2)$  since:

For  $n=100$  :  $P(50) \approx 0.079589237$ ;

For  $n=50$  :  $P(25) \approx 0.112556$ ;

# Histograms for $\text{binomial}(50, 1/2)$ & $\text{binomial}(100, 1/2)$

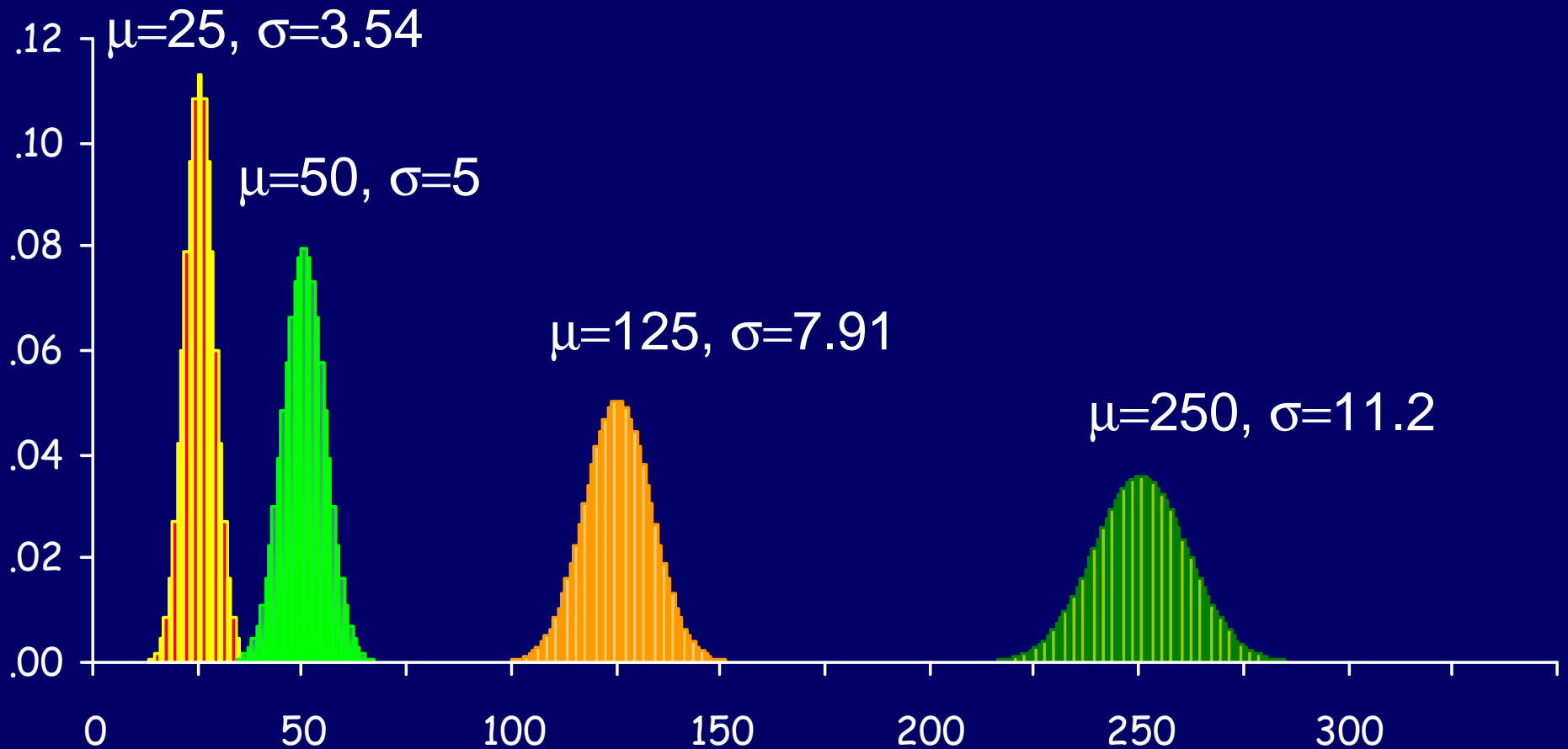


## $\mu$ , $\sigma$ and the normal curve

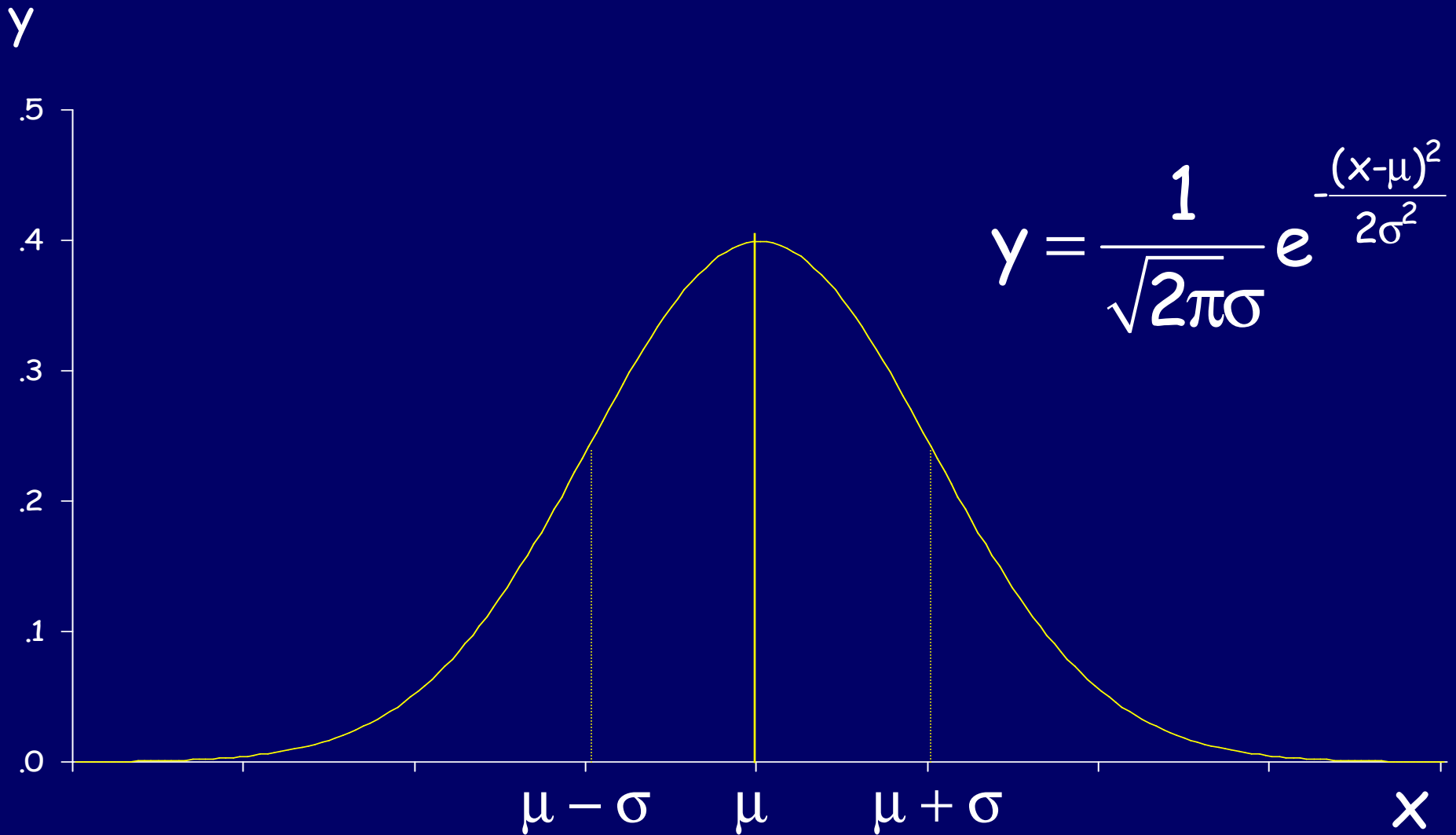
- We will see today that the
- Mean ( $\mu$ ) and the
- SD ( $\sigma$ ) give a very good summary of the  $\text{binom}(n,p)$  distribution via
- The Normal Curve with parameters  $\sigma$  and  $\mu$ .



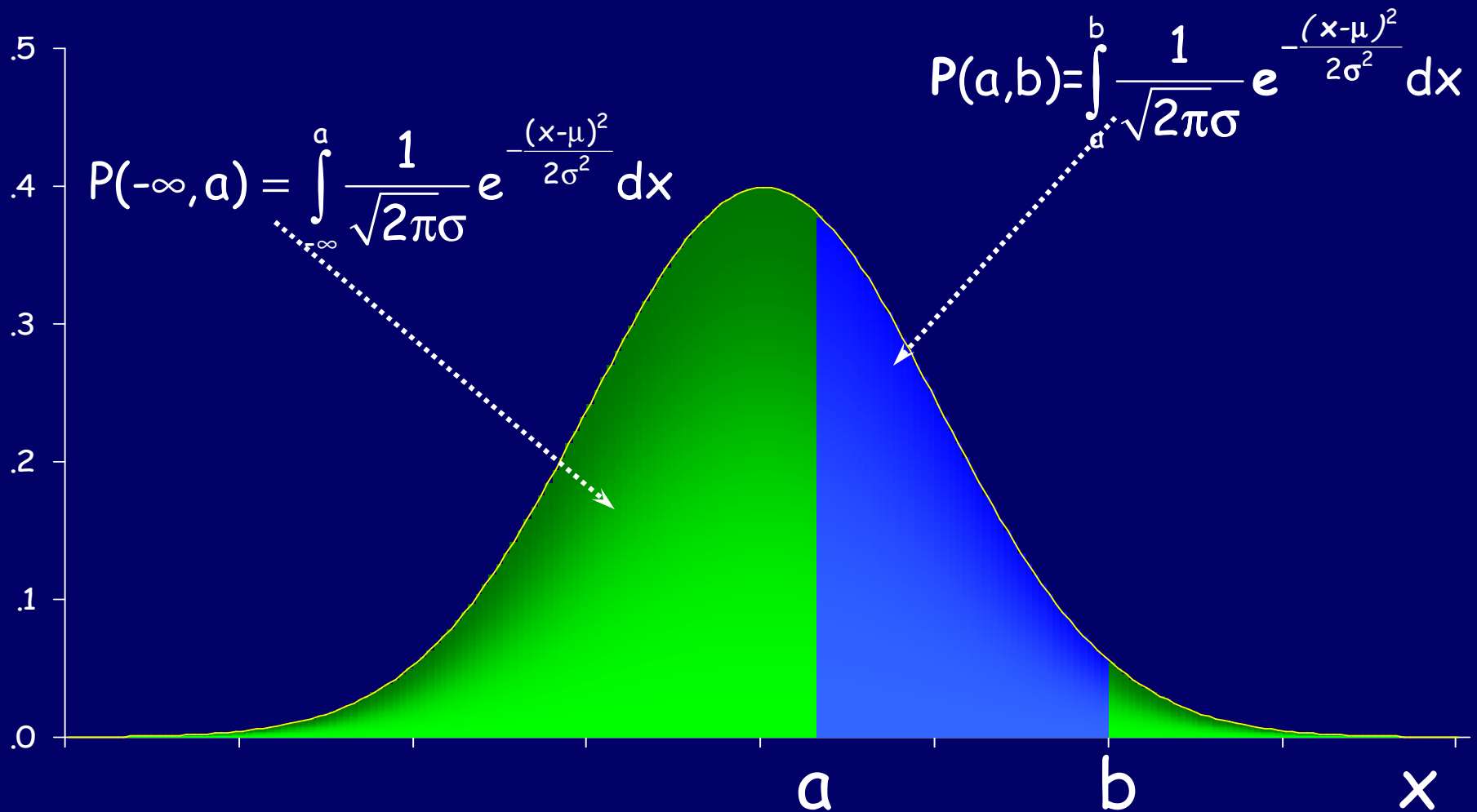
# binomial( $n, \frac{1}{2}$ ); $n=50, 100, 250, 500$



# Normal Curve

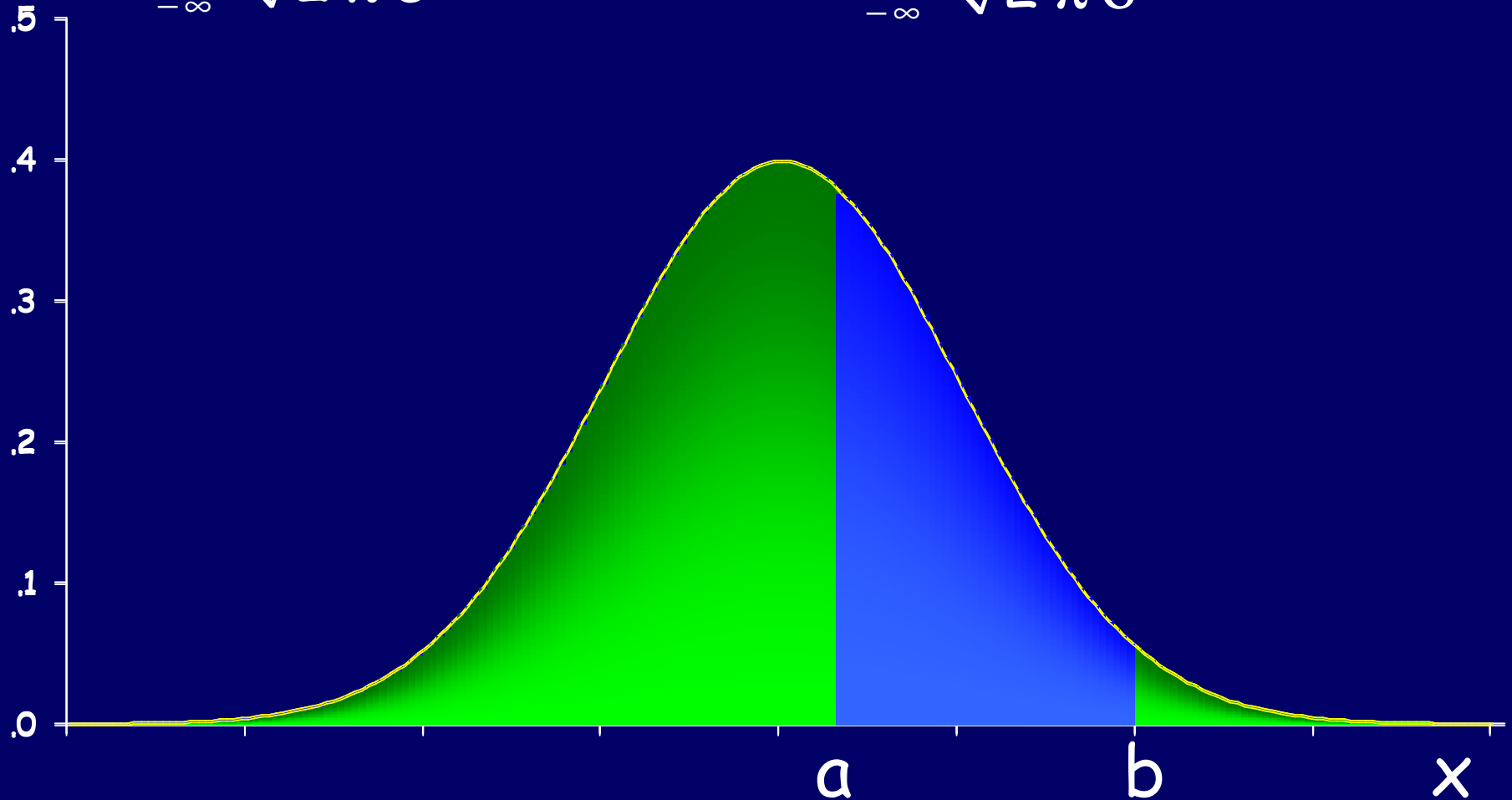


# The Normal Distribution



$$P(a,b) = \int_a^b \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

$$= \int_{-\infty}^b \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx - \int_{-\infty}^a \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$



## Standard Normal Density Function:

$$\varphi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

Corresponds to  $\mu = 0$  and  $\sigma = 1$

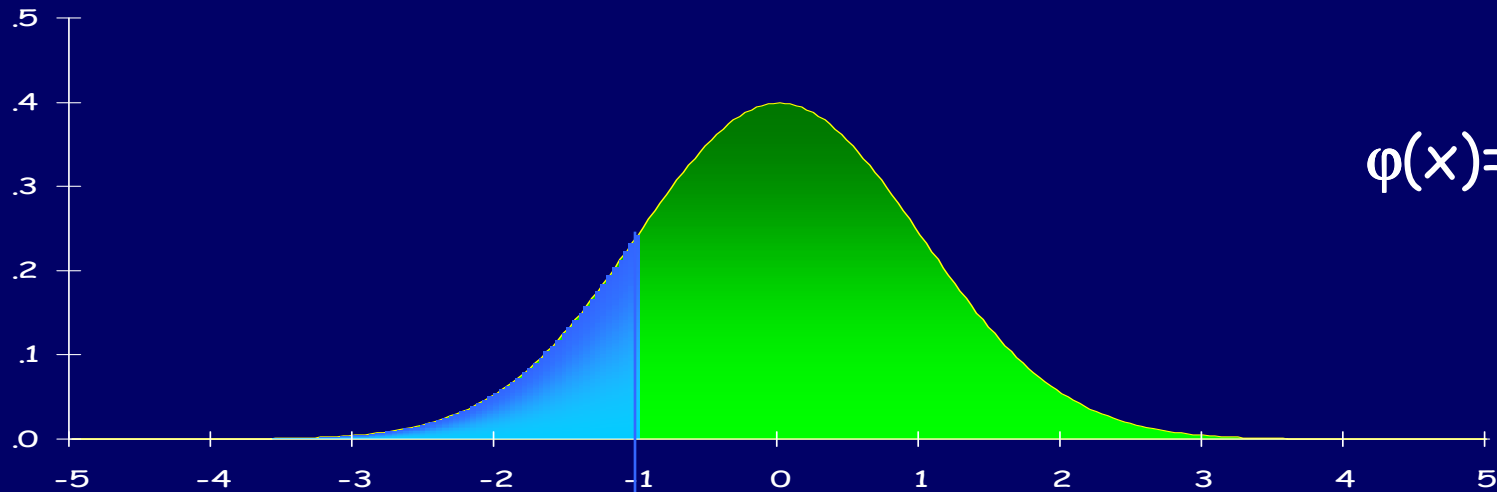
## Standard Normal Cumulative Distribution Function:

$$\Phi(z) = \int_{-\infty}^z \varphi(x) dx$$

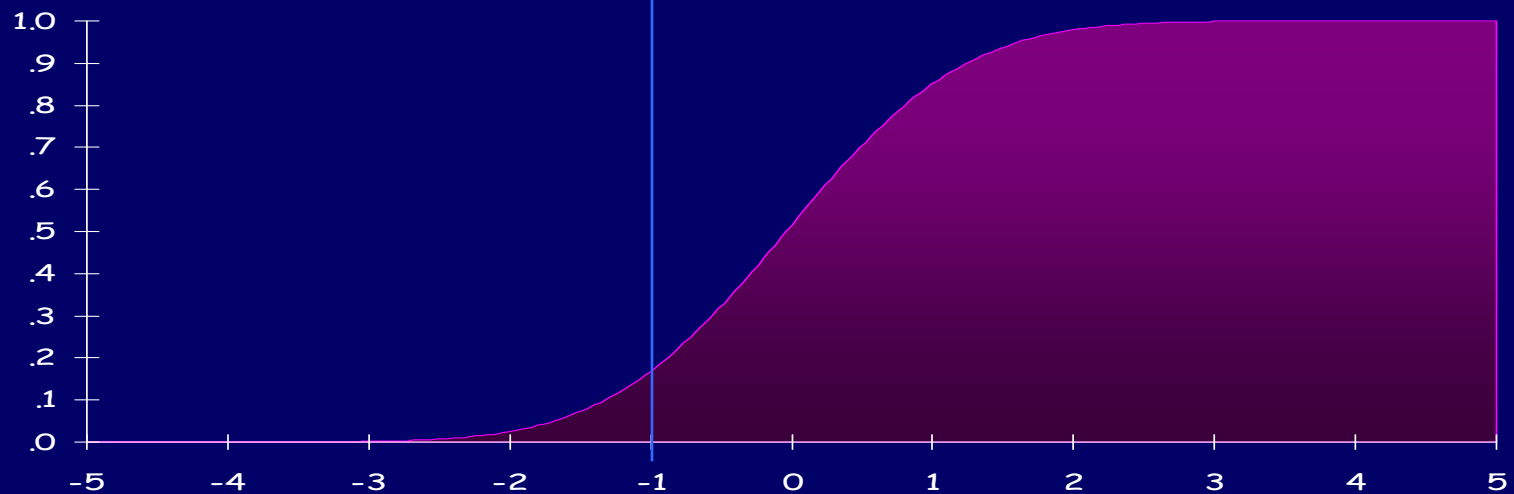
For the normal  $(\mu, \sigma)$  distribution:

$$P(a, b) = \Phi((b - \mu) / \sigma) - \Phi((a - \mu) / \sigma);$$

# Standard Normal

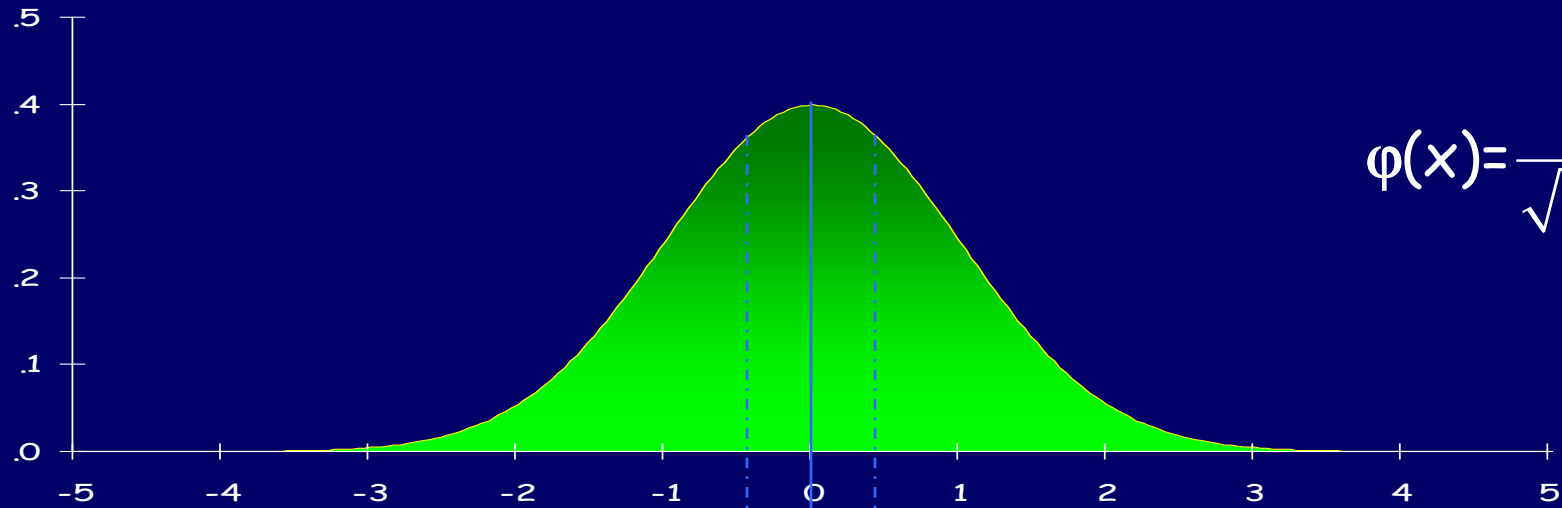


$$\varphi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

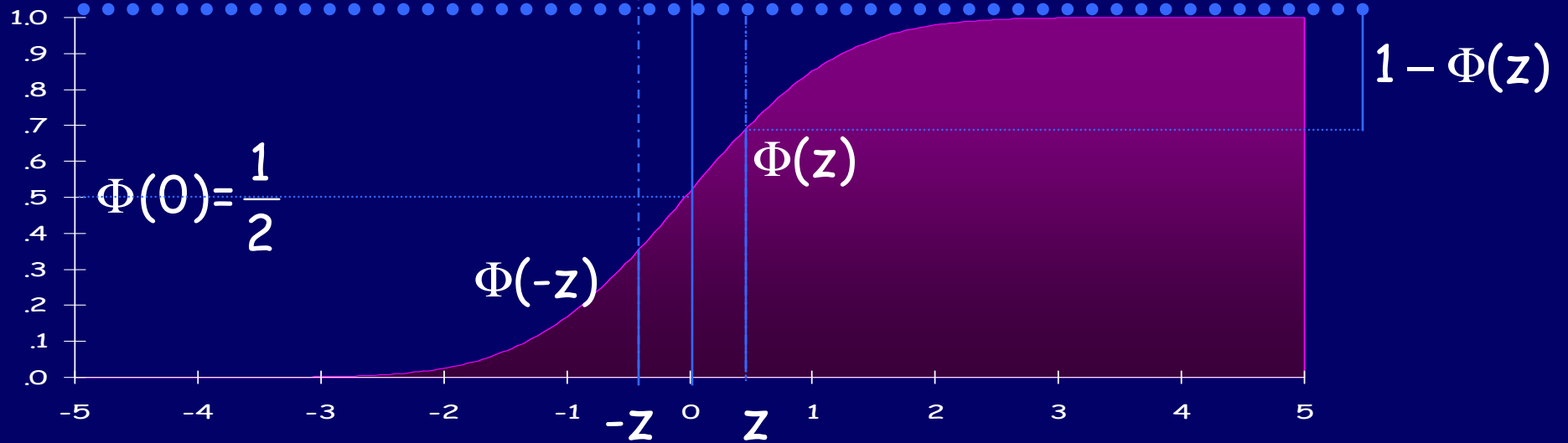


$$\Phi(z) = \int_{-\infty}^z \varphi(x) dx$$

# Standard Normal



$$\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$





## Standard Normal Cumulative Distribution Function:

For the normal  $(\mu, \sigma)$  distribution:

$$P(a, b) = \Phi((b - \mu) / \sigma) - \Phi((a - \mu) / \sigma);$$

In order to prove this, suffices to show:

$$P(-\infty, a) = \Phi((a - \mu) / \sigma);$$

$$\int_{-\infty}^a \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx = \int_{-\infty}^{\frac{a-\mu}{\sigma}} \frac{1}{\sqrt{2\pi}} e^{-\frac{s^2}{2}} ds$$

$$s = \frac{x-\mu}{\sigma}$$

$$ds = \frac{dx}{\sigma}$$

$$x = a \Rightarrow s = \frac{a-\mu}{\sigma}$$

$$= \int_{-\infty}^{\frac{a-\mu}{\sigma}} \varphi(s) ds$$

$$= \Phi\left(\frac{a-\mu}{\sigma}\right)$$

## Properties of $\Phi$ :

$$\Phi(0) = 1/2;$$

$$\Phi(-z) = 1 - \Phi(z);$$

$$\Phi(-\infty) = 0;$$

$$\Phi(\infty) = 1.$$

$\Phi$  does not have a closed form formula!

## Normal Approximation of a binomial

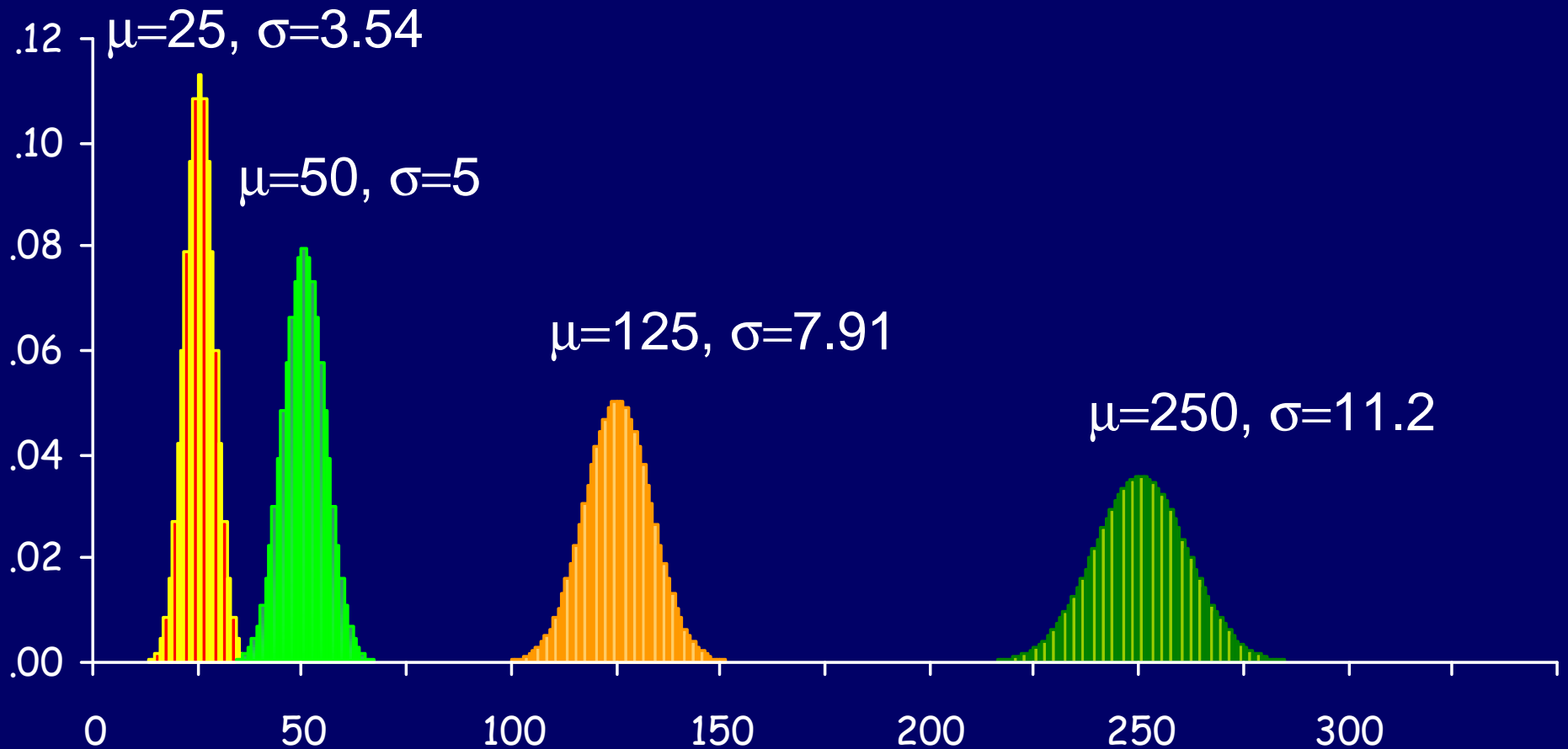
For  $n$  independent trials with success probability  $p$ :

$$P(a \leq \# \text{sucesses} \leq b) \sim \Phi\left(\frac{b + 0.5 - \mu}{\sigma}\right) - \Phi\left(\frac{a + 0.5 - \mu}{\sigma}\right)$$

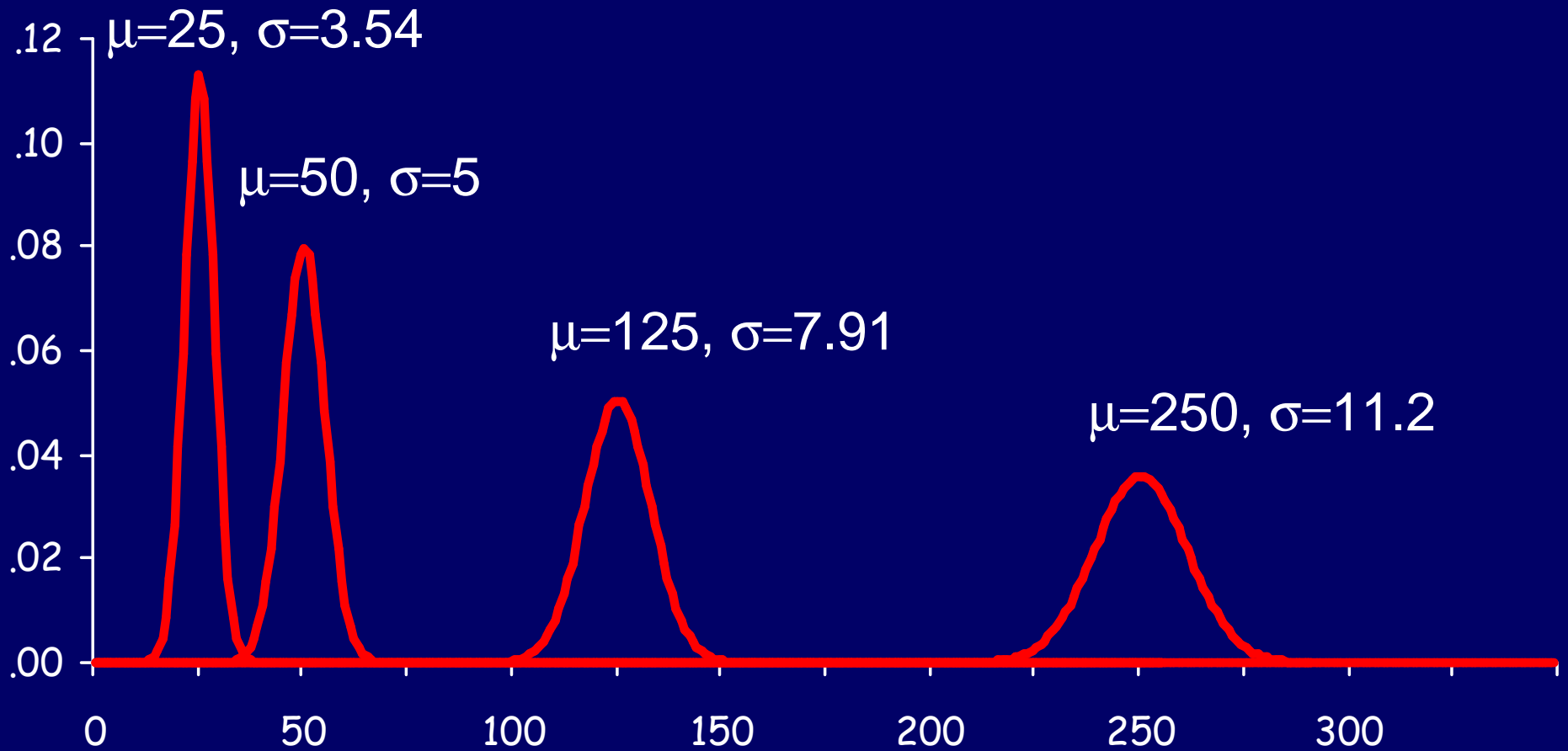
where:

$$\mu = np, \quad \sigma = \sqrt{np(1 - p)}$$

# binomial( $n, \frac{1}{2}$ ); $n=50, 100, 250, 500$



# Normal( $\mu, \sigma$ ):



# Normal Approximation of a binomial

For  $n$  independent trials with success probability  $p$ :

$$P(a \leq \# \text{sucesses} \leq b) \sim \Phi\left(\frac{b + 0.5 - \mu}{\sigma}\right) - \Phi\left(\frac{a - 0.5 - \mu}{\sigma}\right)$$

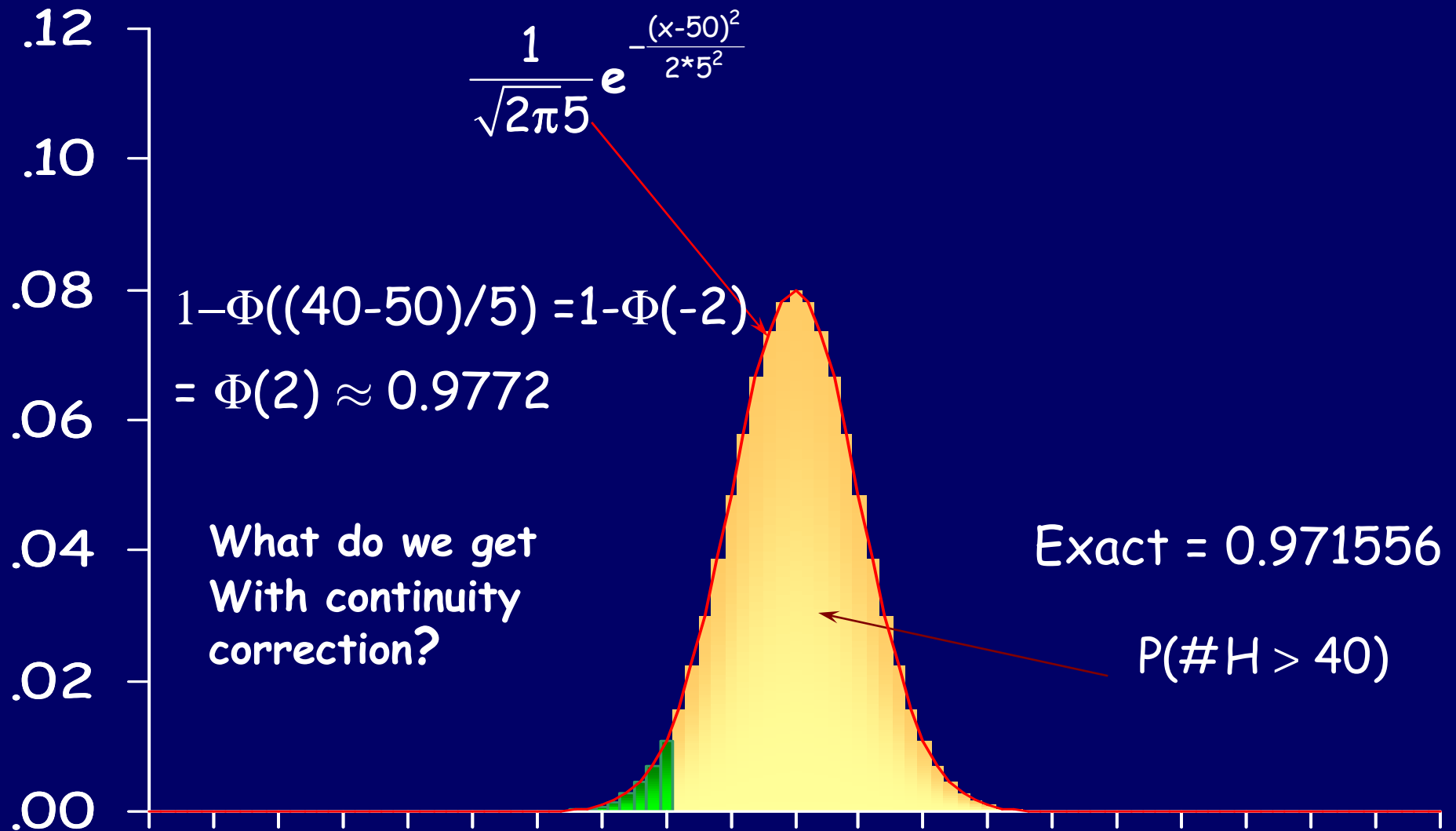
- The 0.5 correction is called the "continuity correction"
- It is important when  $\sigma$  is small or when  $a$  and  $b$  are close.

# Normal Approximation

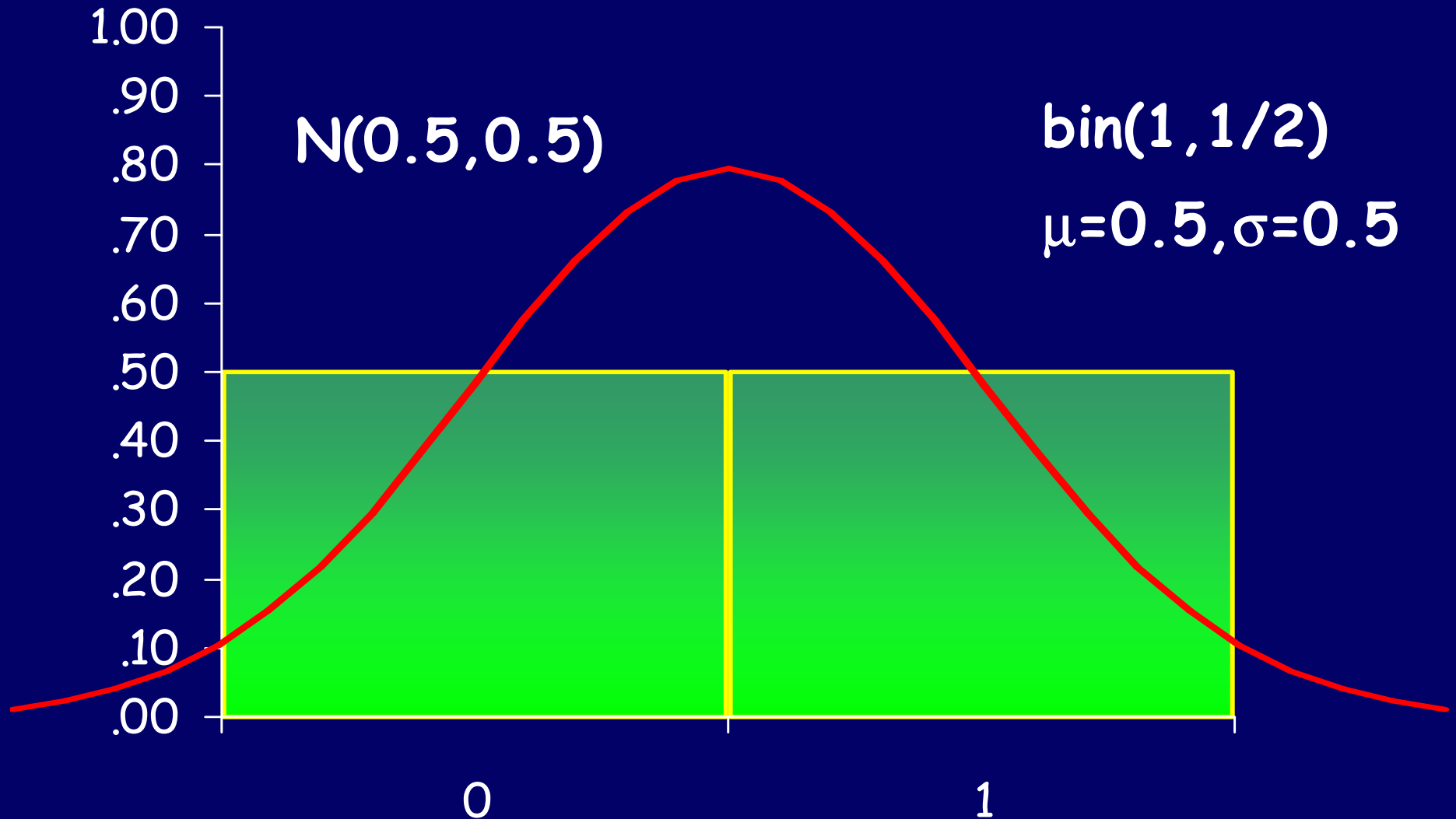
Question: Find  $P(H > 40)$  in 100 tosses.

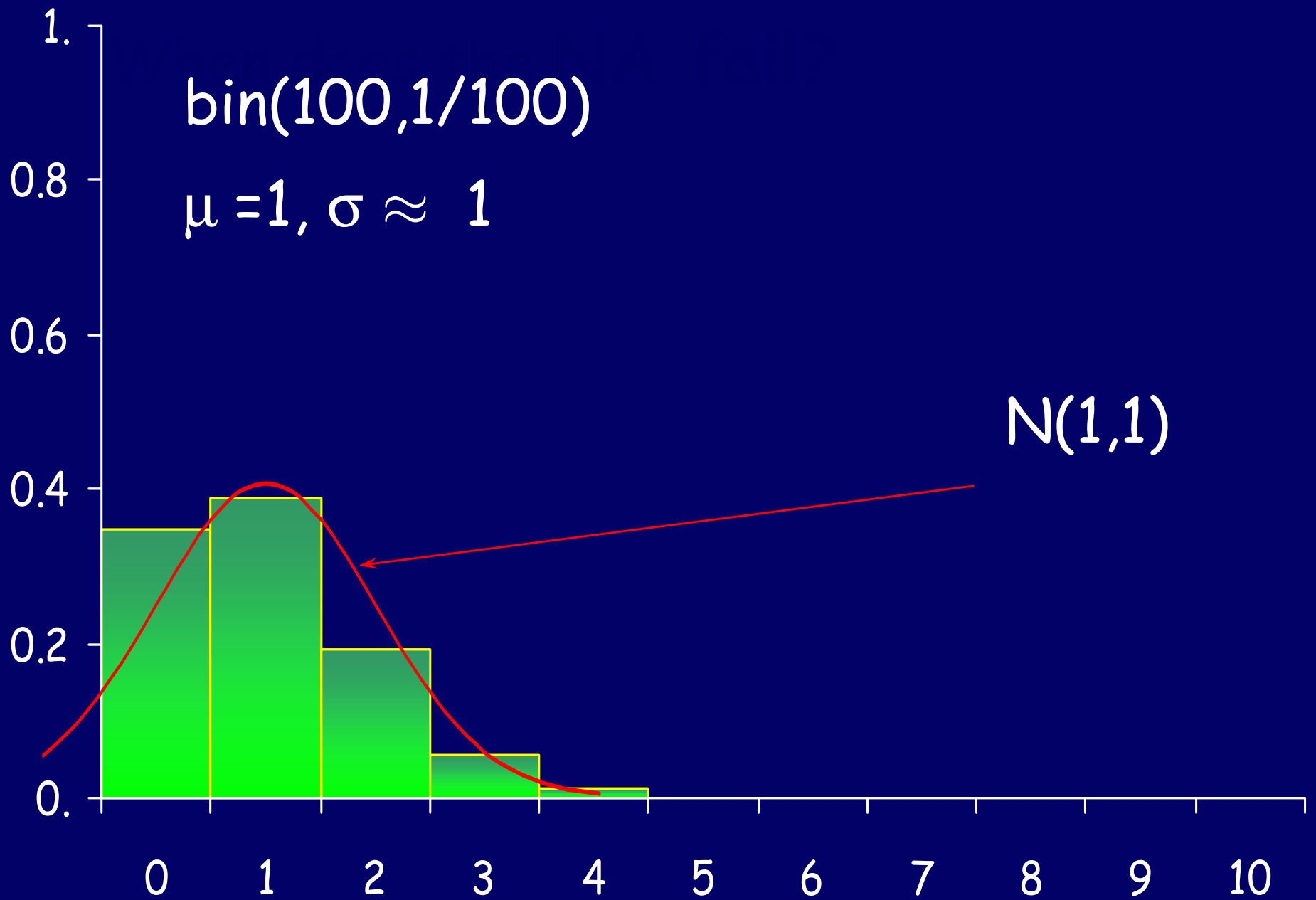


# Normal Approximation to bin(100,1/2).



# When does the **Normal** **Approximation** fail?





# Rule of Thumb

Normal works better:

- The larger  $\sigma$  is.
- The closer  $p$  is to  $\frac{1}{2}$ .

# Fluctuation in the number of successes.

From the normal approximation it follows that:

$P(\mu - \sigma \text{ to } \mu + \sigma \text{ successes in } n \text{ trials}) \approx 68\%$

$P(\mu - 2\sigma \text{ to } \mu + 2\sigma \text{ successes in } n \text{ trials}) \approx 95\%$

$P(\mu - 3\sigma \text{ to } \mu + 3\sigma \text{ successes in } n \text{ trials}) \approx 99.7\%$

$P(\mu - 4\sigma \text{ to } \mu + 4\sigma \text{ successes in } n \text{ trials}) \approx 99.99\%$

Typical size of fluctuation in the number of successes is:

$$\sigma = \sqrt{np(1-p)}$$

Typical size of fluctuation in the proportion of successes is:

$$\frac{\sigma}{n} = \sqrt{\frac{p(1-p)}{n}}$$

## Square Root Law

Let  $n$  be a large number of independent trials with probability of success  $p$  on each.

The number of successes will, with high probability, lie in an interval, centered on the mean  $np$ , with a width a moderate multiple of  $\sqrt{n}$ .

The proportion of successes, will lie in a small interval centered on  $p$ , with the width a moderate multiple of  $1/\sqrt{n}$ .

## Law of large numbers

Let  $n$  be a number of independent trials, with probability  $p$  of success on each.

For each  $\varepsilon > 0$ ;

$$P(|\#successes/n - p| < \varepsilon) \rightarrow 1, \text{ as } n \rightarrow \infty$$



# Confidence intervals

Suppose we observe the results of  $n$  trials with an **unknown** probability of success  $p$ .

The observed frequency of successes  $\hat{p} = \frac{\text{\#successes}}{n}$ .

The Normal Curve Approximation says that for any fixed  $p$  and  $n$  large enough, there is a 99.99% chance that the observed frequency  $\hat{p}$  will differ from  $p$  by

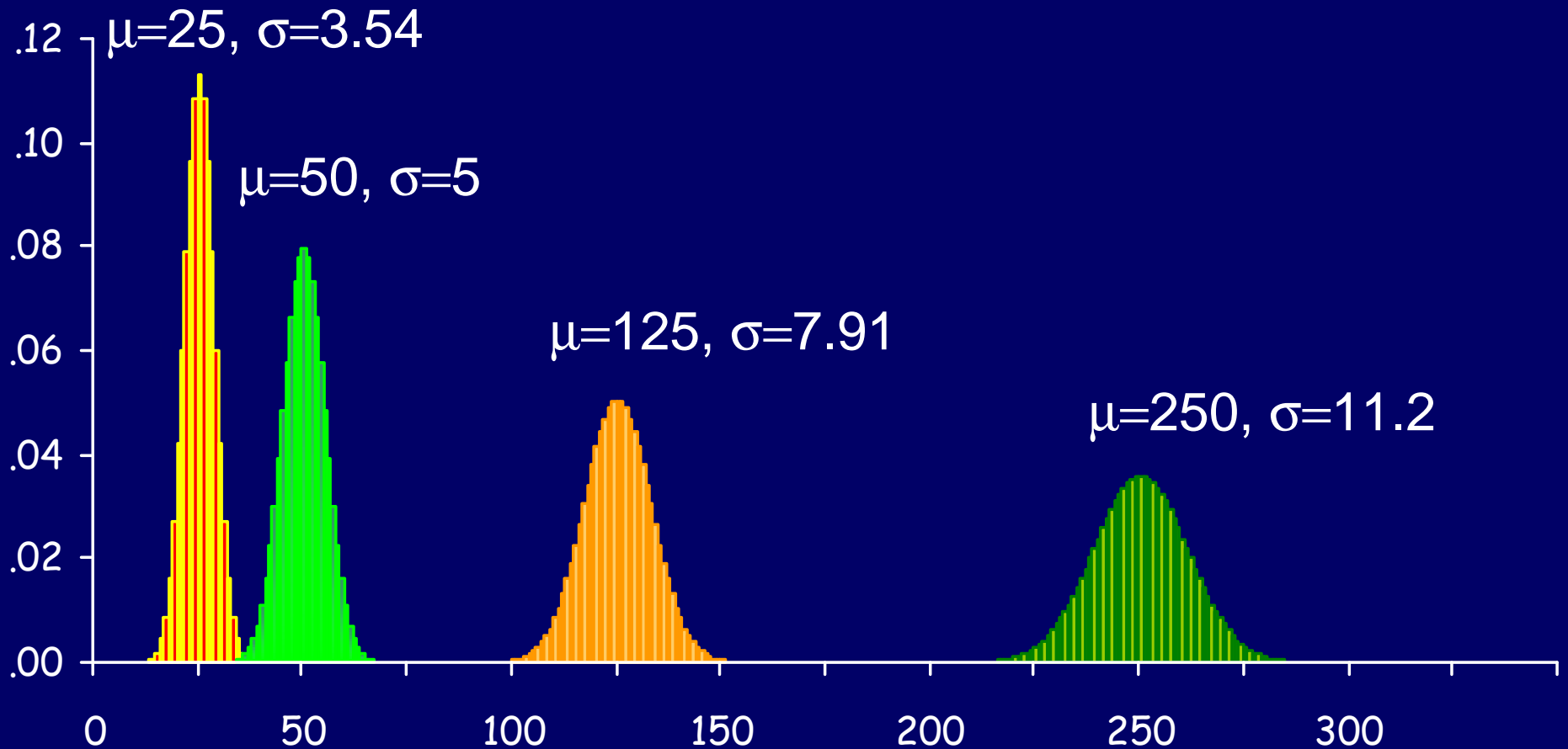
less than  $4\sqrt{\frac{p(1-p)}{n}}$ .

It's easy to see that  $\sqrt{p(1-p)} \leq \frac{1}{2}$ , so  $4\sqrt{\frac{p(1-p)}{n}} \leq \frac{2}{\sqrt{n}}$ .

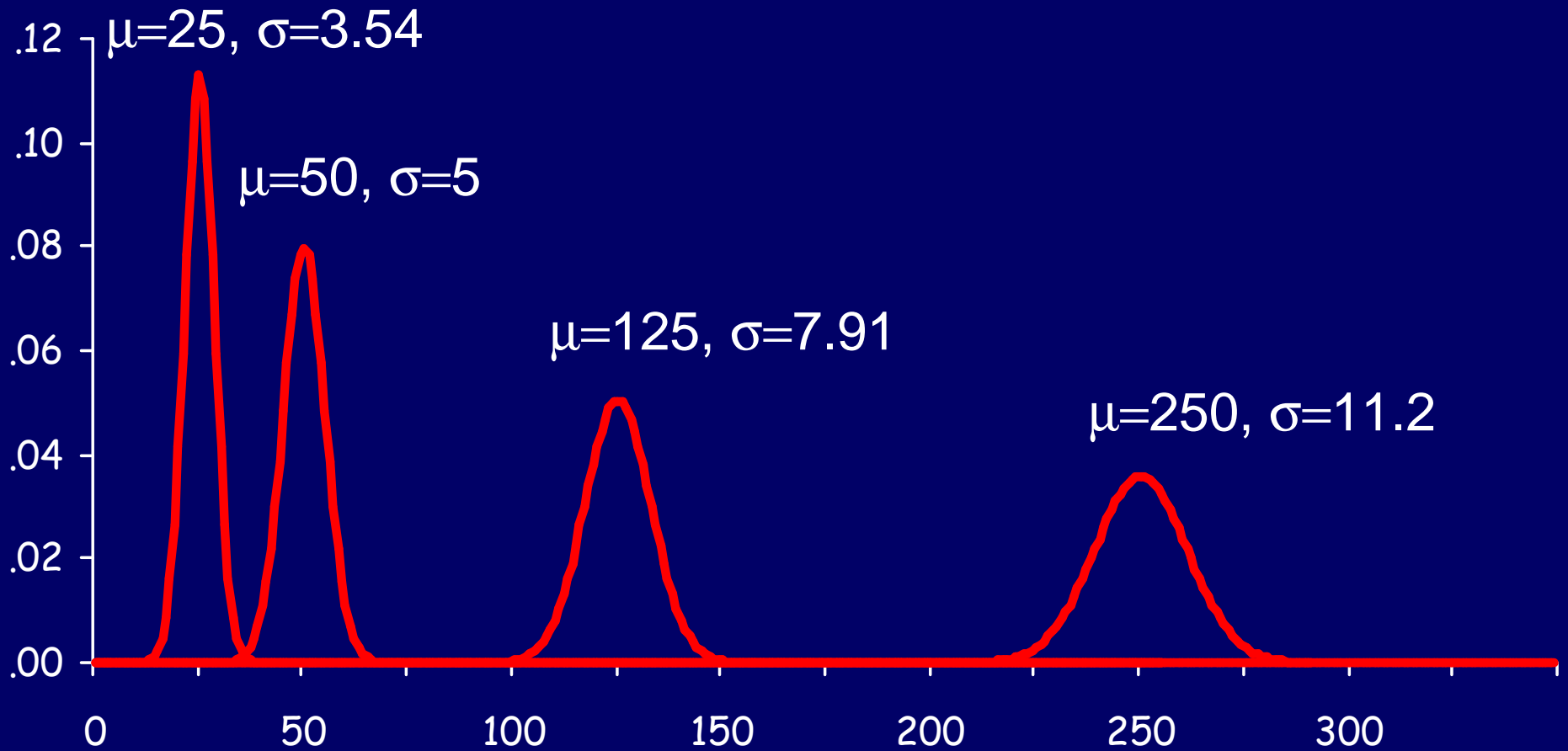
$$\left( \hat{p} - \frac{2}{\sqrt{n}}, \hat{p} + \frac{2}{\sqrt{n}} \right)$$

is called a **99.99% confidence interval**.

# binomial( $n, \frac{1}{2}$ ); $n=50, 100, 250, 500$

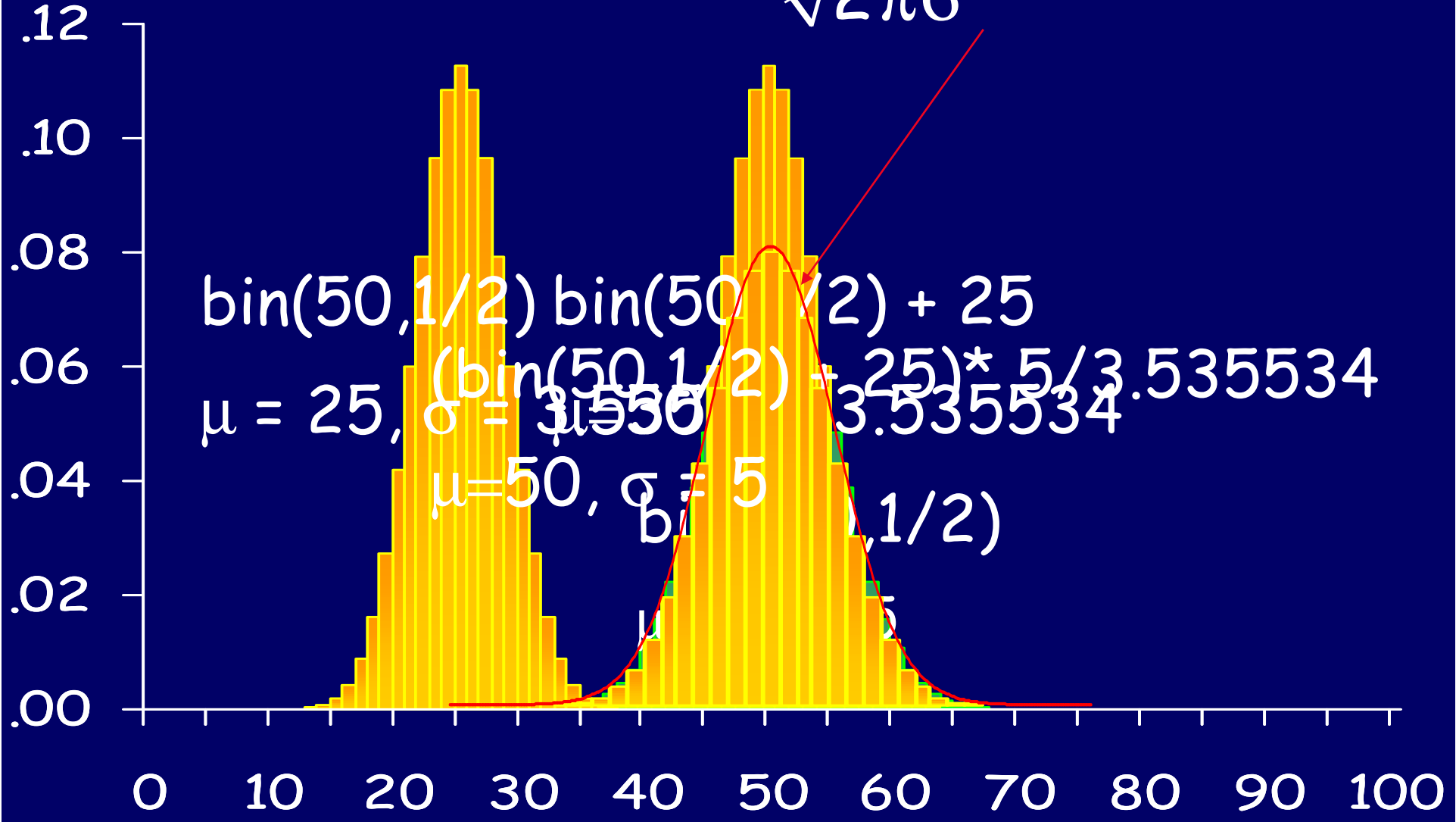


# Normal( $\mu, \sigma$ ):



$\mu=50, \sigma=5$

$$\frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$





Bientôt je pus montrer quelques esquisses. Personne n'y comprit rien. Même ceux qui furent favorables à ma perception des vérités que je voulais ensuite graver dans le temple, me félicitèrent de les avoir découvertes au « microscope », quand je m'étais au contraire servi d'un télescope pour apercevoir des choses, très petites en effet, mais parce qu'elles étaient situées à une grande distance [...]. Là où je cherchais les grandes lois, on m'appelait fouilleur de détails. (TR, p.346)