

Last lecture

Gaussian (normal) Distribution ([Ch 3.6.2](#))

- Motivation and Definition
- Examples

The Central Limit Theorem and Gaussian Approximation ([Ch 3.6.3](#))

- Definition
- CDF Approximation
- Examples

Agenda

Gaussian (normal) Distribution ([Ch 3.6.2](#))

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ML estimation for continuous RVs ([Ch 3.7](#))

- Definition
- Examples

Examples

Suppose $\mu_X = 10$ and $\sigma_X^2 = 3$. Compute $P\{X < 10 - \sqrt{3}\}$ if

- X is a Gaussian RV in terms of Q
- X is a uniform RV

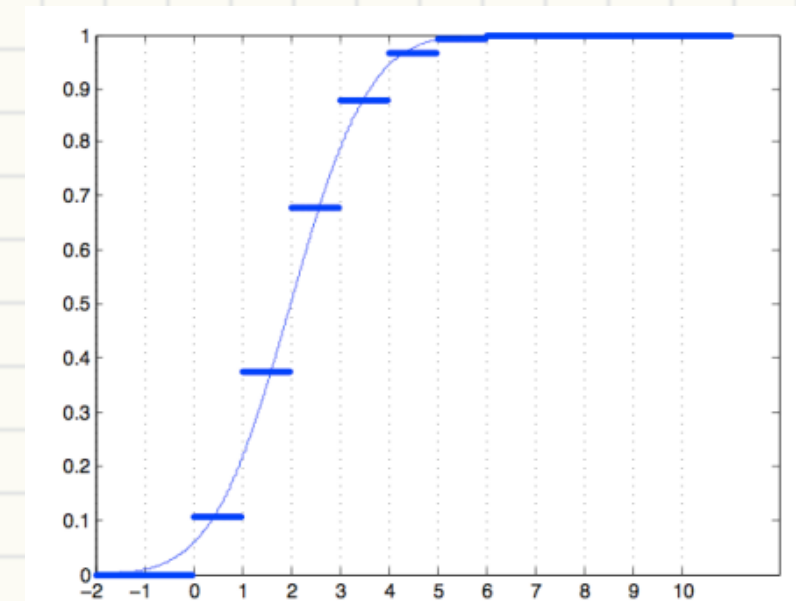
(Hint: $10 - \sqrt{3} \approx 8.27$)

Central Limit Theorem and Gaussian Approximation

Central Limit Theorem (CLT)

If many **independent** random variables are added together, and if each of them is **small** in magnitude compared to the sum, then the **sum** X has an approximately **Gaussian** distribution $\tilde{X}$.

- $P\{X \leq v\} \approx P\{\tilde{X} \leq v\}$
- E.g., $X \sim \text{Binomial}(n, p)$ when np and $n(1 - p)$ are not small
 - $(n, p) = (10, 0.2)$
 - $\mu_X =$
 - $\sigma_X^2 =$
- What if np is small?

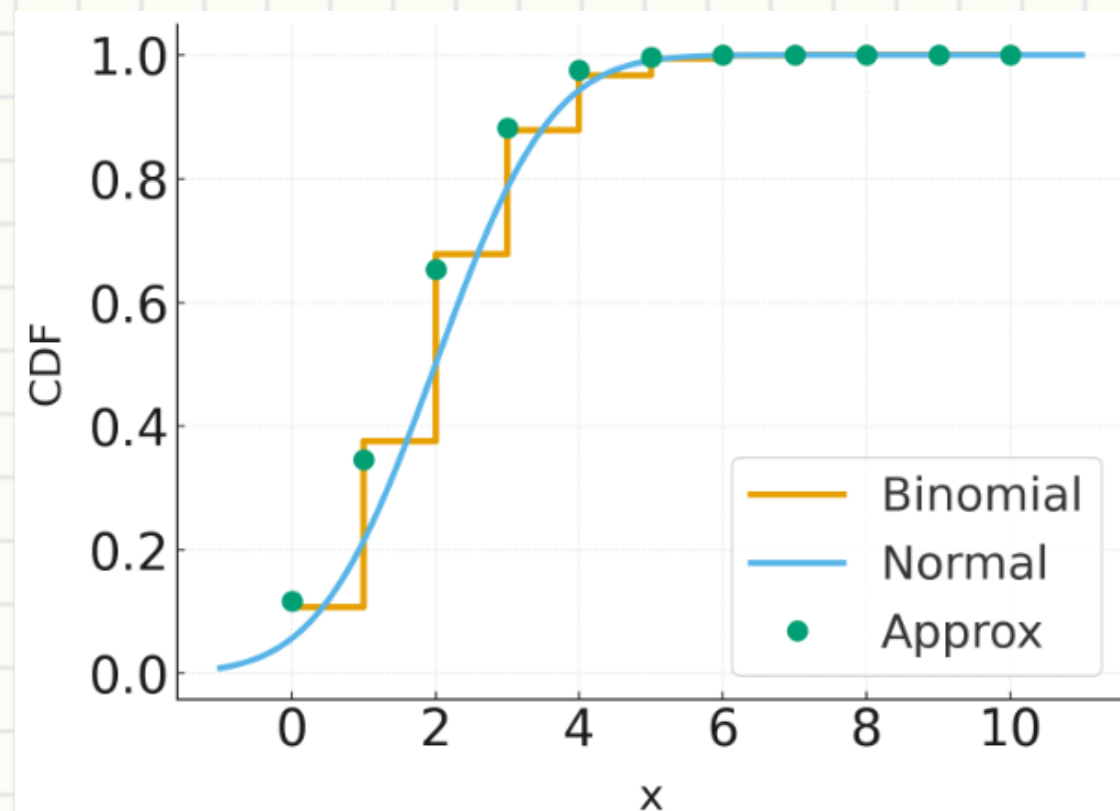


Gaussian Approximation

Approximate $X \sim \text{Bin}(10, 0.2)$ with $\tilde{X} \sim N(2, 1.6)$

- $F_X(2) = F_X(2.1) = F_X(2.9)$
- $F_{\tilde{X}}(2) \neq F_{\tilde{X}}(2.9)$
- How should we approximate?

- $P\{X \leq k\} \approx$
- $P\{X < k\} \approx$
- $P\{X \geq k\} \approx$
- $P\{X > k\} \approx$



Standardized Binomials

Standardized $S_{n,p} \sim \text{Bin}(n, p)$

- $X = \frac{S_{n,p} - np}{\sqrt{np(1-p)}}$

DeMoivre-Laplace limit theorem (First CLT version)

$$\lim_{n \rightarrow \infty} P \left\{ \frac{S_{n,p} - np}{\sqrt{np(1-p)}} \leq c \right\} = \Phi(c)$$

Example

$X \sim \text{Bin}(n = 1000, p = 0.5)$, Using Gaussian approximation, find K s.t. $P\{X \geq K\} \approx 0.01 = Q(2.325)$

- $\mu_X =$, $\sigma_X = \sqrt{np(1-p)} = \sqrt{250} \approx 15.8$
- $P\{X \geq K\} =$
- What if $n = 1000000$?

Example

We want to estimate p with $\hat{p} = \frac{X}{n}$

- Find $P\{|\hat{p} - p| < \delta\}$ in terms of n , p , δ , and Φ
- Find δ w/ 99% confidence if $p = 0.5$. Given that $\Phi(2.58) \approx 0.995$
- What if $p = 0.1$?

ML estimation

Definition

Recall for discrete RV X , given observation u , ML is to find θ maximizing $p_{\theta}(u)$

- But for continuous RV, $p_{\theta}(u) = 0$
- Instead, ML maximize $f_{\theta}(u)$ because
 - $f_{\theta}(u) \approx \frac{1}{\epsilon} P\{u - \frac{\epsilon}{2} < X < u + \frac{\epsilon}{2}\}$
 - $\hat{\theta}_{ML}(u) \triangleq \operatorname{argmax}_{\theta} f_{\theta}(u)$

Example

$T \sim \text{Exp}(\lambda)$ where λ is unknown. We want to estimate λ with observation t

- $f_T(t) =$
- Extrema happens at $\frac{df_T(t)}{d\lambda} = 0$