

# Inference Cheatsheet

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## 1 Convergence in Probability

**Def 1.1** (Convergence in Probability).  $Y_n \xrightarrow{p} c$  if for every  $\epsilon > 0$  and  $\delta > 0$ ,  $\exists n_0(\epsilon, \delta)$  such that

$$P(|Y_n - c| > \epsilon) < \delta, \forall n > n_0(\epsilon, \delta)$$

**Thm 1.1** (Chebyshev Inequality). For random variable,  $Y$ ,  $a > 0$ , and  $c$ ,

$$P(|Y - c| \geq a) \leq \frac{\mathbf{E}(Y - c)^2}{a^2}$$

**Def 1.2** (Markov Inequality). If  $X$  is a non-negative random variable and  $a > 0$  then

$$P(X \geq a) \leq \frac{\mathbf{E}X}{a}$$

**Thm 1.2.** If  $\mathbf{E}(Y - c)^2 \rightarrow 0$ , then  $Y_n \xrightarrow{p} c$ .

**Thm 1.3.** If  $X_1, \dots, X_n$  iid,  $\mathbf{E}X_i = \mu$ ,  $\mathbf{Var}X_i = \sigma^2 < \infty$ , then

$$\bar{X} \xrightarrow{p} \mu$$

**Thm 1.4.** If  $A_n \xrightarrow{p} a$  and  $B_n \xrightarrow{p} b$ , then

1.  $A_n \pm B_n \xrightarrow{p} a \pm b$ ,
2.  $A_n \cdot B_n \xrightarrow{p} a \cdot b$ .

**Thm 1.5.** If  $Y_n \xrightarrow{p} c$  and  $f$  is continuous at  $c$ , then  $f(Y_n) \xrightarrow{p} f(c)$ .

**Def 1.3.** A sequence of estimators  $\delta_n$  of  $g(\theta)$  is *consistent* if

$$\delta_n \xrightarrow{p} g(\theta)$$

**Thm 1.6.** If bias and variance of  $\delta_n \rightarrow 0$  as  $n \rightarrow \infty$ ,  $\delta_n$  is consistent.

**Def 1.4.**  $A_n = o_p(B_n)$  if  $\frac{A_n}{B_n} \xrightarrow{p} 0$ .

## 2 Convergence in Law

**Def 2.1.**  $Y_n$  is *bounded in probability* if for any  $\epsilon > 0 \exists K$  and  $n_0(\epsilon)$  such that

$$P(|Y_n| > K) < \epsilon \text{ for all } n > n_0(\epsilon).$$

**Def 2.2.** Convergence in Law/Distribution  $Y_n \xrightarrow{L} Y$  if  $H_n(x) \rightarrow H(x)$  for all continuity points  $x$ .

**Thm 2.1.** If  $Y_n \xrightarrow{L} H$  then  $Y_n$  is bounded in probability.

**Thm 2.2.** Slutsky's Theorem If  $Y_n \xrightarrow{L} Y$ ,  $A_n \xrightarrow{p} a$ , and  $B_n \xrightarrow{p} b$ , then

$$A_n + B_n Y_n \xrightarrow{L} a + bY.$$

**Cor 2.1.** If  $Y_n \xrightarrow{L} Y$ ,  $R_n \xrightarrow{p} 0$ , and  $B_n \xrightarrow{p} 1$ , then

$$\begin{aligned} Y_n + R_n &\xrightarrow{L} Y \\ Y_n/B_n &\xrightarrow{L} Y. \end{aligned}$$

**Thm 2.3.** If  $k_n(Y_n - c) \xrightarrow{L} H$  and  $k_n \rightarrow \infty$  then  $Y_n \xrightarrow{p} c$ .

**Def 2.3.**  $Y_n \xrightarrow{p} Y$  if  $Y_n - Y \xrightarrow{p} 0$ .

**Thm 2.4.**  $Y_n \xrightarrow{p} Y \implies Y_n \xrightarrow{L} Y$

## 3 Central Limit Theorem

**Thm 3.1.** If  $X_1 \dots X_n$  iid,  $\mathbf{E}X_i = \xi$ ,  $\mathbf{Var}X_i = \sigma^2 < \infty$ , then

$$\sqrt{n}(\bar{X} - \xi) \xrightarrow{L} N(0, \sigma^2).$$

**Thm 3.2** (Berry-Esseen). If  $X_1 \dots X_n$  iid  $\sim F$  with finite 3rd moment, then  $\exists C$  that is independent of  $F$  such that for all  $x$ ,

$$|G_n(x) - \Phi| \leq \frac{C}{\sqrt{n}} \frac{\mathbf{E}|X_i - \xi|^3}{\sigma^3}$$

where  $G_n(x)$  is the CDF of  $\sqrt{n}(\bar{X} - \xi)/\sigma$ .

**Cor 3.1.** Under the assumptions of Berry-Esseen's theorem,

$$G_n(x) \rightarrow \Phi(x) \text{ as } n \rightarrow \infty$$

for any sequence  $F_n$  with mean  $\xi_n$  and  $\sigma_n^2$  for which

$$\frac{E_n|X_1 - \xi_n|^3}{\sigma_n^3} = o(\sqrt{n})$$

and in particular if it is bounded.

## 4 Delta Method

**Thm 4.1.** If  $\sqrt{n}(T_n - \theta) \xrightarrow{L} N(0, \tau^2)$  and  $f'(\theta) \neq 0$ , then

$$\sqrt{n}(f(T_n) - f(\theta)) \xrightarrow{L} N(0, \tau^2[f'(\theta)]^2).$$

## 5 Miscellaneous

**Thm 5.1** (Markov Inequality). If  $X$  is a non-negative RV and  $a > 0$  then  $\mathbf{P}(X \geq a) \leq \frac{\mathbf{E}X}{a}$ .

**Thm 5.2** (Binomial  $p_n$ ). If  $\frac{1}{n} = o_p(p_n)$  then

$$\frac{S_n - np_n}{\sqrt{np_n q_n}} \xrightarrow{L} N(0, 1).$$