Principles of Statistics

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These notes are based on lectures given (virtually) by Dr P-L Loh in Michaelmas term 2021. Credit is also due to Evan Chen for the style file for these notes¹.

Contents

1	Introduction	1
2	Convergence	1

§1 Introduction

(skip if not interested in meta notes)

This course follows naturally on from IB Statistics. It also borrows some technology from II Probability and Measure. I haven't currently decided what emphasis to add to these notes: a focus on intuitions or rigour or something else entirely.

§2 Convergence

Since we're in a non-deterministic setting, we need new defintions of convergence. Let $X, X_1, X_2, ... : \mathcal{X} \to \mathbb{R}$ be random variables, where $\mathcal{X} \subseteq \mathbb{R}^p$. The first and weakest notion of convergence is *convergence in distribution*.

Definition 2.1 (Convergence in distribution). $X_n \stackrel{d}{\rightarrow} X$ if

$$\mathbb{P}\left[X_n \le t\right] \to \mathbb{P}\left[X \le t\right] \tag{1}$$

for all $t \in \mathbb{R}^p$ for which $t \to \mathbb{P}[X \le t]$ is continuous.

Here, \leq means $x_i \leq y_i$ in all components.

A stronger notion is convergence is convergence in probability.

Definition 2.2 (Convergence in probability). $X_n \stackrel{P}{\to} X$ if

$$\lim_{n \to \infty} \mathbb{P}\left[||X_n - X|| > \varepsilon\right] = 0. \tag{2}$$

The proof that convergence in probability implies convergence in distribution is omitted.

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¹Available here: https://github.com/vEnhance/dotfiles/blob/master/texmf/tex/latex/evan/evan.sty.

Example 2.3 (Convergence in distribution *⇒* convergence in probability)

Consider $X, X_1, X_2, ...$ independent and identically distributed $\mathcal{N}(0,1)$ random variables. Then all these have identical distribution function, but certainly $X_n \overset{P}{\nrightarrow} X$.

The strongest notion of convergence is convergence almost surely. This is closely related to null sets from measure theory, i.e not necessarily empty $A \in \mathfrak{B}$ with $\mu(A) = 0$.

Definition 2.4 (Convergence almost surely). $X_n \stackrel{a.s}{\to} X$ if

$$\mathbb{P}[||X_n - X|| \to 0] = 1. \tag{3}$$

Example 2.5 (Convergence in probability ≠ convergence in distribution)

Consider independent $X_1, X_2, ...$ with $X_n \sim \operatorname{Ber}(\frac{n-1}{n})^a$, and X the constant random variable 1 (equivalently $X_n \sim \operatorname{Ber}(1)$). Then (check!) $X_n \stackrel{P}{\to} X$ but $X_n \stackrel{a_{r}s}{\to} X$.

References

- [1] Rajen D. Shah (2021), Mathematics of Machine Learning, http://www.statslab.cam.ac.uk/~rds37/teaching/machine_learning/notes.pdf.
- [2] Philippe Rigollet, 18.657: Mathematics of Machine Learning, https://ocw.mit.edu/courses/mathematics/18-657-mathematics-of-machine-learning-fall-2015/lecture-notes/MIT18_657F15_LecNote.pdf.

 $^{^{}a}$ These random variables can be interpreted as the boolean outcomes of whether an ever-improving skeleton archer hits a bullseye on the nth shot at a target.