

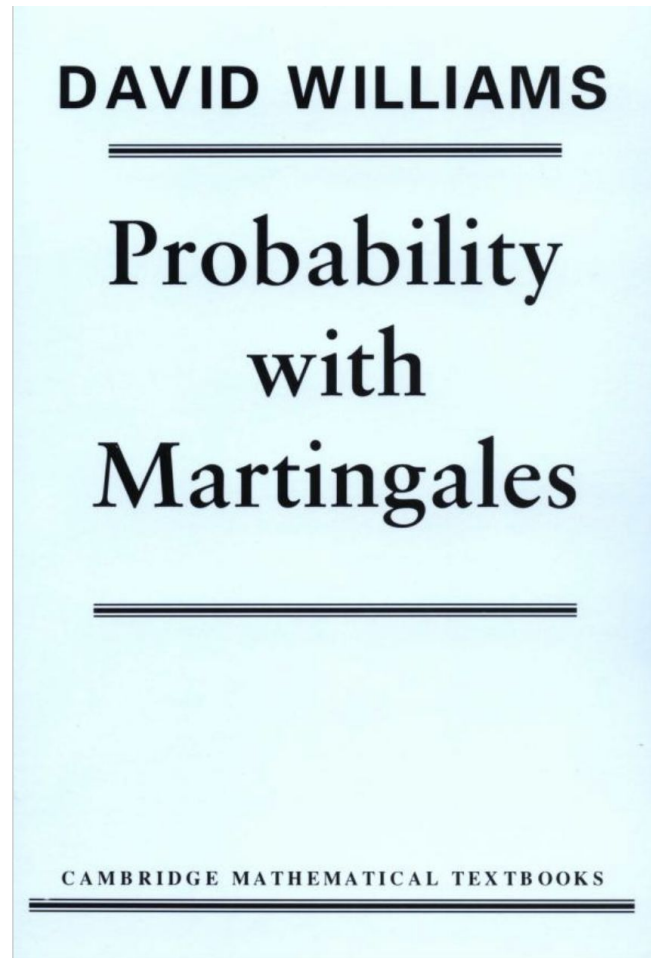
# High-Dimensional Probability and Statistics

MATH/STAT/ECE 888: Topics in Mathematical Data Science  
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**Lecture 3 (09/13/21)**

Course website

Today's slides based on Williams (but results can be found in any graduate-level probability textbook)



See e.g. <https://people.math.wisc.edu/~roch/grad-prob/>

# Important Probability Facts

# Markov's inequality

## 6.4. Markov's inequality

*Suppose that  $Z \in \mathfrak{m}\mathcal{F}$  and that  $g : \mathbf{R} \rightarrow [0, \infty]$  is  $\mathcal{B}$ -measurable and non-decreasing. (We know that  $g(Z) = g \circ Z \in (\mathfrak{m}\mathcal{F})^+$ .) Then*

$$\blacktriangleright \quad \mathbf{E}g(Z) \geq \mathbf{E}(g(Z); Z \geq c) \geq g(c)\mathbf{P}(Z \geq c).$$

**Examples:** for  $Z \in (\mathfrak{m}\mathcal{F})^+$ ,  $c\mathbf{P}(Z \geq c) \leq \mathbf{E}(Z)$ ,  $(c > 0)$ ,

for  $X \in \mathcal{L}^1$ ,  $c\mathbf{P}(|X| \geq c) \leq \mathbf{E}(|X|)$   $(c > 0)$ .

$\blacktriangleright$  *Considerable strength can often be obtained by choosing the optimum  $\theta$  for  $c$  in*

$$\blacktriangleright \quad \mathbf{P}(Y > c) \leq e^{-\theta c}\mathbf{E}(e^{\theta Y}), \quad (\theta > 0, \quad c \in \mathbf{R}).$$

## 7.3. Chebyshev's inequality

As you know this says that for  $c \geq 0$ , and  $X \in \mathcal{L}^2$ ,

$$c^2\mathbf{P}(|X - \mu| > c) \leq \text{Var}(X), \quad \mu := \mathbf{E}(X);$$

and it is obvious.

# Convergence in probability

## A13.1. Modes of convergence: definitions

Let  $(X_n : n \in \mathbf{N})$  be a sequence of RVs and let  $X$  be a RV, all carried by our triple  $(\Omega, \mathcal{F}, \mathbf{P})$ . Let us collect together definitions known to us.

### Convergence in probability

We say that  $X_n \rightarrow X$  **in probability** if, for every  $\varepsilon > 0$ ,

$$\mathbf{P}(|X_n - X| > \varepsilon) \rightarrow 0 \quad \text{as} \quad n \rightarrow \infty.$$

# Lp norm

## 6.7. Monotonicity of $\mathcal{L}^p$ norms

►► For  $1 \leq p < \infty$ , we say that  $X \in \mathcal{L}^p = \mathcal{L}^p(\Omega, \mathcal{F}, \mathbf{P})$  if

$$\mathbf{E}(|X|^p) < \infty,$$

and then we define

► 
$$\|X\|_p := \{\mathbf{E}(|X|^p)\}^{\frac{1}{p}}.$$

The monotonicity property referred to in the section title is the following:

►(a) *if  $1 \leq p \leq r < \infty$  and  $Y \in \mathcal{L}^r$ , then  $Y \in \mathcal{L}^p$  and*

$$\|Y\|_p \leq \|Y\|_r.$$

# Cauchy-Schwarz inequality

## 6.8. The Schwarz inequality

►(a) *If  $X$  and  $Y$  are in  $\mathcal{L}^2$ , then  $XY \in \mathcal{L}^1$ , and*

$$|\mathbf{E}(XY)| \leq \mathbf{E}(|XY|) \leq \|X\|_2 \|Y\|_2.$$

The following is an immediate consequence of (a):

(b) *if  $X$  and  $Y$  are in  $\mathcal{L}^2$ , then so is  $X + Y$ , and we have the triangle law.*

$$\|X + Y\|_2 \leq \|X\|_2 + \|Y\|_2.$$