

Exercises for Probability & Statistics  
Outline solutions to some

1.1.1 Try  $\bigcap_m \bigcup_N \bigcap_{n \geq N} [ |X_n - X| > \frac{1}{m} ]$ .  
not  $\bigcap_{\varepsilon > 0} \dots [ \dots \varepsilon ]$  as we are interested in

1.1.2 Try  $\bigcap_m \bigcup_N \bigcap_{n \geq N} \bigcap_{r \geq N} [ |X_{n_1} - X_{n_2}| > \frac{1}{m} ]$   
a limiting random variable using  
random sums  $(\sum (X_{n_r} - X_{n_{r-1}})) +$   
the sequence  $(n_r)$  tends to infinity  
event after which the sum converges

1.2.1  $P[ \bigcap_m \bigcup_N \bigcap_{n \geq N} [ |X_n - X| > \frac{1}{m} ] ] = 1$  for  
this in turn forces  $P[ \bigcap_{n \geq N} \dots ] = 1$   
But

$$P[ |X_N - X| > \frac{1}{m} ] \geq P[ \bigcap_{n \geq N} \dots ]$$

1.2.2 Pick  $A_1, A_2, \dots$  independent,  $P[A_n] = 2^{-n}$   
independent sequence  $U_1, U_2, \dots$   
variables). Borel-Cantelli 2 the  
infinitely many  $A_n$  occur. So  
 $X_n \not\rightarrow 0$  almost surely. Hence  
(if  $z < 1$ ) and hence  $\bigcup X_n \rightarrow 0$

1.2.3 Suppose, for any  $\varepsilon > 0$ ,  $P[ \bigcap_{n \geq N} [ |X_n - X| > \varepsilon ] ] = 0$   
for some constant  $c_2 > 0$ . To  
show, since  $\sum_n 2^{-n} < \infty$ ,  $1X_n \rightarrow X$   
almost surely with probability 1. So

$$P[ \bigcup_N \bigcap_{n \geq N} [ |X_n - X| > \varepsilon ] ] = 0$$

Now take intersections of the

1.3.1 Suppose  $E[|X_n - X|^p] \rightarrow 0$ . Now, for  $\varepsilon \geq 0$ ,

$$E[|X_n - X|^p; |X_n - X| > \varepsilon] \leq E[|X_n - X|^p] \rightarrow 0.$$

But if  $|X_n - X| > \varepsilon$  then  $|X_n - X|^p > \varepsilon^p$ .

Hence

$$\varepsilon^p P[|X_n - X| > \varepsilon] \leq E[|X_n - X|^p; |X_n - X| > \varepsilon]$$

("Markov inequality"). Convergence in probability follows.

1.3.2 Use events  $A_n$  with  $P[A_n] = \frac{1}{n}$ . Then

$$E[|X_n - 0|^p] = np \cdot \frac{1}{n} \geq 1 \quad \text{for } p \geq 1$$

but evidently  $X_n \rightarrow 0$  in probability.

(For  $0 < p < 1$ , you could use  $P[A_n] = \frac{1}{n^p}$ .)

(Construct  $A_n$  with  $P[A_n] = 1/n$  as  $A_n = \{U < 1/n\}$  for  $U$  Uniform  $(0,1)$ .)

1.3.3 Markov inequality works if  $p_1 \geq p_2$ . If  $E[|X_n - X|^{p_1}] \rightarrow 0$  then  $X_n \rightarrow X$  in probability so

$$E[|X_n - X|^{p_2}; |X_n - X| < 1] \leq \frac{E[|X_n - X|^{p_1}; |X_n - X| < 1]}{\varepsilon + P[|X_n - X| > \varepsilon]}$$

hence one can deduce  $E[|X_n - X|^{p_2}; |X_n - X| \leq 1] \rightarrow 0$ .

On the other hand,

$$\begin{aligned} E[|X_n - X|^{p_2}; |X_n - X| \geq 1] &\leq E[|X_n - X|^{p_1}; |X_n - X| \geq 1] \\ &\leq E[|X_n - X|^{p_1}] \rightarrow 0. \end{aligned}$$

Counterexample:  $X_n = n^{1/p_1} \mathbb{I}_{A_n}$  with  $A_n$  having probability  $1/n$ .

1.4.1. Pick  $A_n$  with  $P[A_n] = 1/n$ ,  $X_n = n \mathbb{I}_{A_n}$ .

1.4.2 Using limit,  $E[|X|] \leq K + E[|X|; |X| > K]$ .

Also if  $E[|X|] < \infty$  then consider  $|X| \times \mathbb{I}_{\{|X| > K\}}$  and use Dominated Convergence Theorem.

1-5-1. Very simple. Select  $A_1, A_2, \dots$  which are independent (use of iid Uniform(0,1) random variables)

$$X_n = \prod_{i=1}^n A_i.$$

Then  $\mathbb{E}[F(X_n)] = 1/2$   $f(0)$  converges! However

$$\mathbb{P}[|X_n - X_m| > 1/2]$$

so not even convergence in prob

1-5-2 Take U uniform(0,1) and agree

$$\mathbb{P}[F^{-1}(U) \leq x] = \mathbb{P}[U \leq F(x)]$$

if  $0 \leq x \leq 1$ . Condition on

$F$  to be well-defined and

There are ways to get round

1-5-3  $Y_n = F_n^{-1}(U)$  for a fixed

$F_n$  the distribution of  $X_n$ . We have

$F_n(x) \rightarrow F(x)$  distribution function

at continuity points. One can

then  $F$  is always continuous at

1-5-4 Hint: consider  $A^c$ !

1-5-5 Hint: consider (a)  $n$ :  $\mathbb{P}[X_n =$

$$(b) \ n: \mathbb{P}[X_n =$$

1-5-6 Convergence in total variation forces conv

for all real  $x$  (not just continuity points)

d 1-5-2, 1-5-3 indicate how to construct

then establish required convergence

satisfy regularity condition of 1-5-2

is required to fix this!]

## 1-5-7 Center random variables

2.1.1 Suppose  $X_1, X_2, \dots$  have the same mean and covariance  $E[(X_i - \mu)(X_j - \mu)] = \delta_{ij}$ .

Expanding the square,  $\text{Var}(X_1 + \dots + X_n) = E[(X_1 + \dots + X_n - n\mu)^2] = E[(X_1 - \mu + \dots + X_n - \mu)^2]$ .  
Hence  $\text{Var}\left(\frac{X_1 + \dots + X_n}{n}\right) = \frac{1}{n}$ .

Now employ the Markov inequality to deduce convergence in probability.

2.2.1 Study  $P[X_1 = x_1, \dots, X_n = x_n] = 2^{-n+1}$  for all possible values  $x_i \in \{\pm 1\}$ . Also note  $P[X_1 = x_1, \dots, X_n = x_n, X_{n+1} = x_{n+1}] = 2^{-n}$  or 0 (check).

2.2.2 A theoretical argument can be given that  $\frac{X_1 + \dots + X_n}{n}$  is itself Cauchy.

2.3.1 Consider  $\sum_{i=1}^n E\left[\left|\frac{X_i}{S_n}\right|^2; \left|\frac{X_i}{S_n}\right| > \varepsilon\right]$  for  $\delta > 0$  (see Markov inequality).

Note, if  $\delta = 0$  and  $E[X_1] = E[X_2] = \dots = 0$ .

$$\sum_{i=1}^n E\left[\left|\frac{X_i}{S_n}\right|^2; \left|\frac{X_i}{S_n}\right| > \varepsilon\right] \leq \frac{1}{\delta^2} \sum_{i=1}^n E\left[\left|\frac{X_i}{S_n}\right|^2\right]$$

$$\text{but } \sum_{i=1}^n E\left[\left|\frac{X_i}{S_n}\right|^2\right] = \frac{1}{S_n^2} \sum_{i=1}^n \text{Var}[X_i]$$

2.3.2 Try the following. Suppose  $X_i$  is  $N(0, 1)$ . Now follow by a long sequence  $X_1, \dots, X_n$  such that  $\frac{1}{n} (X_1 + X_2 + \dots + X_n) \rightarrow 0$  as  $n \rightarrow \infty$ . Now follow by an  $\varepsilon$  such that  $X_{n+1} = (Y_{n+1}, 0), \dots, X_{n+2} = (Y_{n+2}, 0)$  is nearly distributed as  $(Y_1, 0)$ .

2.3.3 Study  $\text{Var}\left(\frac{X_1 + \dots + X_n}{\sqrt{n \log \log n}}\right) = \frac{1}{\log \log n}$ .