ma414soln5.tex

MA414 SOLUTIONS 5. 13.2.2012

Q1. Proof (Doob's Submartingale Inequality). Let $F := \{\max_{k \le n} X_k \ge c\}, \quad F_k := \{X_0 < c\} \cap \{X_1 < c\} \cap \dots \{X_{k-1} < c\} \cap \{X_k \ge c\}.$

Then F is the disjoint union $F = F_0 \cup \ldots \cup F_n$. Also $F_k \in \mathcal{F}_k$, and $X_k \ge c$ on F_k . So

$$E[X_n I(F_k)] \geq E[X_k I(F_k)] \quad (X \text{ a submg})$$

$$\geq cE[I(F_k)] = P(F_k).$$

Sum over k:

$$E[X_n] \ge E[X_n I(F)] = \sum_k E[X_n I(F_k)]$$
$$\ge \sum_k cP(F_k)$$
$$= cP(F). //$$

Q2 (Second Borel-Cantelli Lemma for Pairwise Independence). If the events A_n are pairwise independent, then $\sum P(A_n)$ diverges implies $P(\limsup A_n) = P(A_n \ i.o.) = 1$.

Proof. For A_n pairwise independent, put $S_n := \sum_{i=1}^{n} I(A_i), S := \sum_{i=1}^{\infty} I(A_i),$ $m_n := E[S_n] = \sum_{i=1}^{n} P(A_i).$

$$var(S_n) = E[(S_n - m_n)^2] = E[(\sum_{i=1}^n (I(A_i) - EI(A_i))(\sum_{j=1}^n (I(A_j) - EI(A_j)))]$$
$$= E[\sum_i \sum_j (\dots)(\dots)] = \sum_i E[(\dots)^2] + \sum_{i \neq j} E(\dots)(\dots)] = \sum_i E[(\dots)^2]$$

(the sum over $i \neq j$ is 0, as there by pairwise independence and the Multiplication Theorem $E[(\ldots)(\ldots)] = E[(\ldots)]E[(\ldots)] = 0.0 = 0$ – variance of sum = sum of variances under pairwise independence). As $I(A_i)$ is Bernoulli with parameter $P(A_i)$, its variance is $P(A_i)[1 - P(A_i)] \leq P(A_i)$. So

$$E[(S_n - m_n)^2] \le \sum_{i=1}^{n} P(A_i) = m_n,$$

which increases to $+\infty$ as $\sum P(A_n)$ diverges, by assumption. But

$$P(S \le m_n/2) \le P(S_n \le m_n/2) \quad (S_n \le S)$$

= $P(S_n - m_n \le -m_n/2)$
 $\le P(|S_n - m_n| \ge m_n/2)$
 $\le \frac{4}{m_n^2} var(S_n) \quad \text{(by Tchebycheff's Inequality)}$
 $\le 4/m_n \quad \text{(by above)}$
 $\to 0 \quad (n \to \infty).$

But the LHS increases to $P(S < \infty)$, by continuity (= σ -additivity) of P(.). So $P(S < \infty) = 0$: $P(\sum I(A_n) < \infty) = 0$, i.e. $P(\sum I(A_n) = \infty) = 1$. This says that $P(A_n \ i.o.) = 1$: $P(\limsup A_n) = 1$. //

Q3. (i) For s < t, $M_s = E[M_t | \mathcal{F}_s]$ as M is a mg. So by the conditional Jensen inequality,

$$\phi(M_s) = \phi(E[M_t | \mathcal{F}_s]) \le E[\phi(M_t) | \mathcal{F}_s],$$

which says that $\phi(M)$ is a submg.

(ii) If M is a submg, $M_s \leq E[M_t | \mathcal{F}_s]$. As ϕ is non-decreasing on the range of M,

$$\phi(M_s) \le \phi(E[M_t|\mathcal{F}_s]) \le E[\phi(M_t)|\mathcal{F}_s]$$

(the second inequality by conditional Jensen as above), and again $\phi(M)$ is a submg.

Q4. For $S_n = \sum_{1}^{n} X_k$ with X_k independent with mean 0, $S = (S_n)$ is a mg. As $\phi(x) := x^2$ is convex, S^2 is a submg, and $E[S_n^2] = varS_n = \sum_{1}^{n} varX_k$. By Doob's Submg Inequality,

$$P(\max_{k \le n} |S_k| \ge c) = P(\max_{k \le n} S_k^2 \ge c^2) \le E[S_n^2]/c^2 = c^{-2} var S_n = c^{-2} \sum_{k \le n}^n var X_k,$$

giving Kolmogorov's Inequality. //

NHB