#### Massachusetts Institute of Technology

Department of Electrical Engineering & Computer Science

## 6.041/6.431: Probabilistic Systems Analysis

(Fall 2010)

#### Recitation 20 Solutions: November 18, 2010

1. (a) Let  $X_i$  be a random variable indicating the quality of the *i*th bulb ("1" for good bulbs, "0" for bad ones).  $X_i$ 's are independent Bernoulli random variables. Let  $Z_n$  be

$$Z_n = \frac{X_1 + X_2 + \dots + X_n}{n}.$$
  
$$\mathbf{E}[Z_n] = p \qquad \operatorname{var}(Z_n) = \frac{n \operatorname{var}(X_i)}{n^2} = \frac{\sigma^2}{n},$$

where  $\sigma^2$  is the variance of  $X_i$ .

Applying Chebyshev's inequality yields,

$$\mathbf{P}(|Z_n - p| \ge \epsilon) \le \frac{\sigma^2}{n\epsilon^2},$$

As  $n \to \infty$ ,  $\frac{\sigma^2}{n\epsilon^2} \to 0$  and  $\mathbf{P}(|Z_n - p| \ge \epsilon) \to 0$ . Hence,  $Z_n$  converges to p in probability.

(b) By Chebychev's inequality,

$$\mathbf{P}(|Z_{50} - p| \ge 0.1) \le \frac{\sigma^2}{50(0.1)^2},$$

Since  $X_i$  is a Bernoulli random variable, its variance  $\sigma^2$  is p(1-p), which is less than or equal to  $\frac{1}{4}$ . Thus,

$$\mathbf{P}(|Z_{50} - p| \ge 0.1) \le \frac{1/4}{50(0.1)^2} = 0.5$$

(c) By Chebychev's inequality,

$$\mathbf{P}(|Z_n - p| \ge 0.1) \le \frac{\sigma^2}{n\epsilon^2} \le \frac{1/4}{n(0.1^2)}$$

To guarantee a probability 0.95 of falling in the desired range,

$$\frac{1/4}{n(0.1)^2} < 0.05,$$

which yields  $n \ge 500$ . Note that  $n \ge 500$  guarantees the accuracy specification even for the highest variance, namely 1/4. For smaller variances, we need smaller values of n to guarantee the desired accuracy. For example, if  $\sigma^2 = 1/16$ ,  $n \ge 125$  would suffice.

2. (a) 
$$\mathbf{E}[X_n] = 0 \cdot \left(1 - \frac{1}{n}\right) + 1 \cdot \frac{1}{n} = \frac{1}{n}$$

$$\operatorname{var}(X_n) = \left(0 - \frac{1}{n}\right)^2 \cdot \left(1 - \frac{1}{n}\right) + \left(1 - \frac{1}{n}\right)^2 \cdot \left(\frac{1}{n}\right) = \frac{n-1}{n^2}$$

$$\mathbf{E}[Y_n] = 0 \cdot \left(1 - \frac{1}{n}\right) + n \cdot \frac{1}{n} = 1$$

$$\operatorname{var}(Y_n) = (0 - 1)^2 \cdot \left(1 - \frac{1}{n}\right) + (n - 1)^2 \cdot \left(\frac{1}{n}\right) = n - 1$$

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(b) Using Chebyshev's inequality, we have

$$\lim_{n \to \infty} \mathbf{P}(|X_n - \frac{1}{n}| \ge \epsilon) \le \lim_{n \to \infty} \frac{n-1}{n^2 \epsilon^2} = 0$$

Moreover,  $\lim_{n \to \infty} \frac{1}{n} = 0$ .

It follows that  $X_n$  converges to 0 in probability. For  $Y_n$ , Chebyshev suggests that,

$$\lim_{n \to \infty} \mathbf{P}(|Y_n - 1| \ge \epsilon) \le \lim_{n \to \infty} \frac{n - 1}{\epsilon^2} = \infty,$$

Thus, we cannot conclude anything about the convergence of  $Y_n$  through Chebychev's inequality.

(c) For every  $\epsilon > 0$ ,

$$\lim_{n \to \infty} \mathbf{P}(|Y_n| \ge \epsilon) \le \lim_{n \to \infty} \frac{1}{n} = 0,$$

Thus,  $Y_n$  converges to zero in probability.

- (d) The statement is false. A counter example is  $Y_n$ . It converges in probability to 0 yet its expected value is 1 for all n.
- (e) Using the Markov bound, we have

$$\mathbf{P}(|X_n - c| \ge \epsilon) = P(|X_n - c|^2 \ge \epsilon^2) \le \frac{\mathbf{E}\left[(X_n - c)^2\right]}{c^2}.$$

Taking the limit as  $n \to \infty$ , we obtain

$$\lim_{n \to \infty} \mathbf{P}\left(|X_n - c| \ge \epsilon\right) = 0,$$

which establishes convergence in probability.

(f) A counter example is  $Y_n$ .  $Y_n$  converges to 0 in probability, but

$$\mathbf{E}\left[ (Y_n - 0)^2 \right] = 0 \cdot \left( 1 - \frac{1}{n} \right) + (n^2) \cdot \frac{1}{n} = n$$

Thus,

$$\lim_{n\to\infty} \mathbf{E}\left[ (Y_n - 0)^2 \right] = \infty,$$

and  $Y_n$  does not converge to 0 in the mean square.

- 3. (a) No. Since  $X_i$  for any  $i \geq 1$  is uniformly distributed between -1.0 and 1.0.
  - (b) Yes, to 0. Since for  $\epsilon > 0$ ,

$$\lim_{i \to \infty} \mathbf{P}(|Y_i - 0| > \epsilon) = \lim_{i \to \infty} \mathbf{P}\left(\left|\frac{X_i}{i} - 0\right| > \epsilon\right)$$
$$= \lim_{i \to \infty} \left[\mathbf{P}(X_i > i\epsilon) + \mathbf{P}(X_i < -i\epsilon)\right] = 0.$$

(c) Yes, to 0. Since for  $\epsilon > 0$ ,

$$\lim_{i \to \infty} \mathbf{P}(|Z_i - 0| > \epsilon) = \lim_{i \to \infty} \mathbf{P}(|(X_i)^i - 0| > \epsilon)$$

$$= \lim_{i \to \infty} \left[ \mathbf{P}(X_i > \epsilon^{\frac{1}{i}}) + \mathbf{P}(X_i < -(\epsilon)^{\frac{1}{i}}) \right]$$

$$= \lim_{i \to \infty} \left[ \frac{1}{2} (1 - \epsilon^{\frac{1}{i}}) + \frac{1}{2} (1 - \epsilon^{\frac{1}{i}}) \right] = \lim_{i \to \infty} \left( 1 - \sqrt[i]{\epsilon} \right)$$

$$= 0.$$

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