# HW1

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#### Problem 1 1

Because for  $\forall X, L_n(X) = \frac{q_n(X)}{p_n(X)} \ge 0$ , using Markov's Inequality,  $P(\frac{q_n(X)}{p_n(X)} > M) \le \frac{E(\frac{q_n(X)}{p_n(X)})}{M^2} = \frac{\int_{p_n(X)>0} \frac{q_n(X)}{p_n(X)} p_n(X) dx}{M^2} = \frac{\int_{p_n(X)>0} \frac{q_n(X)}{p_n(X)} dx}{M^2} = \frac{\int_{p_n(X)>0} \frac{q_n(X)}{p_n(X)} dx}{M^2} = \frac{\int_{p_n(X)>0} \frac{q_n(X)}{p_n(X)} dx}{M^2} = \frac{\int_{p_n(X)>0} \frac{q_n(X)}{p_n(X)} dx}{M^2}$  $\frac{\int_{p_n(X)>0}q_n(X)dx}{\frac{M^2}{M^2}} \leq \frac{1}{M^2}.$  So we have  $P(L_n(X)>M) \leq \frac{1}{M^2}$  for  $\forall n$ , implying that  $\sup_n P(L_n(X)>M) < \frac{2}{M^2}$ .

For  $\forall \epsilon > 0$ , take  $M^* = \sqrt{\frac{2}{\epsilon}}$ , Then  $\sup_n P(L_n(X) > M^*) < \epsilon$ , the sequence is uniformly tight.

#### $\mathbf{2}$ Problem 2

For  $Beta(\theta,1)$ ,  $\bar{X}_n = \frac{\theta}{1+\theta}$  and  $Var(X_n) = \frac{\theta}{(\theta+1)^2(\theta+2)}$ .

By Central Limit Theorem,  $\sqrt{n}(\bar{X}_n - \frac{\theta}{1+\theta}) \xrightarrow{d} N(0, Var(X_i))$ , so  $\sqrt{n}(\bar{X}_n(1+\theta) - \theta) = \sqrt{n}(\bar{X}_n - (1-\bar{X}_n)\theta) \xrightarrow{d} N(0, Var(X_i))$  $N(0, (1+\theta)^2 Var(X_i)).$ 

By Law of Large Numbers,  $\bar{X_n} \xrightarrow{p} \frac{\theta}{1+\theta}$ , so  $1 - \bar{X_n} \xrightarrow{p} \frac{1}{1+\theta}$ .

Then by Slutsky's Lemma,  $\sqrt{n}(\frac{\bar{X_n}}{1-\bar{X_n}}-\theta) \xrightarrow{d} N(0, Var(X_i)(1+\theta)^4)$ , which is equivalent to  $\sqrt{n}(\hat{\theta_n}-\theta) \xrightarrow{d} N(0, Var(X_i)(1+\theta)^4)$  $N(0, \frac{\theta(1+\theta)^2}{\theta+2})$ 

# Problem 3

Let U = X - E(X), and u be any non-negative number.

 $P(X - E(X) \ge t) = P(U + u \ge t + u) \le P((U + u)^2 \ge (t + u)^2). \text{ Using Markov inequality, we have } P((U + u)^2 \ge (t + u)^2) \le \frac{E((U + u)^2)}{(t + u)^2} = \frac{(E(U + u))^2 + Var(U)}{(t + u)^2} = \frac{u^2 + \sigma^2}{(t + u)^2} = f(u).$  Optimizing this over  $u \ge 0$ , set  $0 = f(u)' = 2u(t + u)^2 - (u^2 + \sigma^2)(2u + 2t) = ut^2 + u^2t - u\sigma^2 - \sigma^2t = (u + t)(tu - \sigma^2)$ . So f(u) achieves maximum at  $u = \frac{\sigma^2}{t}$ . Max  $f(u) = \frac{(\frac{\sigma^2}{t})^2 + \sigma^2}{t + (\frac{\sigma^2}{t})^2} = \frac{\sigma^2}{\sigma^2 + t^2}$ 

Hence,  $P(X - E(X) \ge t) \le \frac{\sigma^2}{\sigma^2 + t^2}$ 

#### Problem 4 4

#### 4.1

Expectation does not converge. Let  $X_n = X + \frac{1}{n}$ .  $E(g(X)) = \sum_{k=1}^9 \frac{\lambda^k e^{-\lambda}}{k!}$  and  $E(g(X_n)) = \sum_{k=0}^9 \frac{\lambda^{k+\frac{1}{n}} e^{-\lambda}}{(k+\frac{1}{n})!}$  $E(g(X_n))$  does not converge to E(g(X)) because at x = 0,  $g(x_n) * f(x_n) = \frac{\lambda^{\frac{1}{n}} e^{-\lambda}}{\frac{1}{n}!} \to e^{-\lambda}$ 

### 4.2

 $0 \le g(x) = e^{-x^2} \le 1$  is continuous everywhere. By Portmanteau theorem, convergence in distribution guarantees convergence in expectation.

#### 4.3

g(x) is clearly bounded. Pormanteau theorem states that if g(x) is continuous everywhere, then  $\sum_i g(X_n) f(X_n) \to \sum_i g(X) f(X)$ .  $\sum_i g(X_n) f(X_n) = \sum_{f(X_n) \neq 0} g(X_n) f(X_n) + \sum_{f(X_n) = 0} h(X_n) f(X_n)$ , where h(X) could be any arbitrary function. This means that Pormanteau theorem works as long as g(x) is continuous at the points where  $f(x) \neq 0$ . g(x) = sgn(cos(x)) is only noncontinuous at non-integers points, where f(x) = 0 under Poisson distribution. Hence expectation converges.

#### 4.4

Expectation does not converge. Construct  $X_n$  in the following way:

$$P(X_n = k) = \begin{cases} \frac{1}{n} + (1 - \frac{1}{n}) \frac{\lambda^n e^{-\lambda}}{n!} & \text{if } k = n\\ (1 - \frac{1}{n}) \frac{\lambda^k e^{-\lambda}}{k!} & \text{if } k \in N, k \neq n \end{cases}$$

It's easy to check  $f(X_n)$  is a valid density as  $\sum_k P(X_n = k) = \frac{1}{n} + (1 - \frac{1}{n}) \sum_k \frac{\lambda^k e^{-\lambda}}{k!} = \frac{1}{n} + 1 + \frac{1}{n} = 1$ . And  $X_n \xrightarrow{d} X$ .  $E(X) = \lambda$  but  $E(X_n) = n\frac{1}{n} + (1 - \frac{1}{n}) \sum_k \frac{\lambda^k e^{-\lambda}}{k!} k \to 1 + \lambda \neq \lambda$  as  $n \to \infty$ 

# 5 Problem 5

### 5.1

$$P(X \le x) = \begin{cases} x & \text{if } 0 \le x \le 1\\ 0, & \text{if } x < 0\\ 1, & \text{otherwise} \end{cases}$$

$$P(X_n \le x) = \begin{cases} \frac{\lfloor xn \rfloor}{n} & \text{if } 0 \le x \le 1\\ 0, & \text{if } x < 0\\ 1, & \text{otherwise} \end{cases}$$

Clearly,  $\frac{xn-1}{n} \leq \frac{\lfloor xn \rfloor}{n} \leq \frac{xn}{n} = x$ . As  $n \to \infty$ ,  $\frac{xn-1}{n} \to x$ . Hence  $\frac{\lfloor xn \rfloor}{n} \to x$ .  $P(X_n \leq x) \to P(X \leq x)$  as  $n \to \infty$ . We have  $X_n \stackrel{d}{\to} X$ .

### 5.2

For  $\forall \epsilon > 0$ ,  $P(|X_n - X| > \epsilon) \ge P(X_n > \epsilon + X) = \int_0^1 P(X_n > x + \epsilon) dx \ge \int_0^1 (1 - x - \epsilon) dx = x - x\epsilon - \frac{x^2}{2}|_0^1 = \frac{1}{2} - \epsilon$ . This does not converge to 0 for  $\epsilon < \frac{1}{2}$ . Hence  $X_n$  does not converge to X in probability.