## MATH 416/516 ASSIGNMENT 2 SOLUTIONS

Note: assume all Us are RVs from Uni(0,1) and the page references are to the textbook.

• Problem 4.1: Matlab

• Problem 4.2: Matlab

```
function X = myrand( p, n )
% Input p is pmf vector of length n
% Output is random integer 1, ..., n with pmf p.
js = [1:n]; F = cumsum(p); X = min( js( rand < F ) );
% end myrand</pre>
```

• Problem 4.4\*: Matlab

Mean and standard deviation should both be 1.

• Problem 4.7: Matlab code uses vector v with  $v_i$  as a T/F flag for dice sum = j:

Expected number of dice rolls is approximately 61.

- Problem 4.10
  - a) A negative binomial RV  $X = \sum_{i=1}^r X_i$ , if each  $X_i$  is a geometric RV with parameter p (see p.23), so  $X_i = 1 + \lfloor \frac{\ln(U_i)}{\ln(1-p)} \rfloor$  (p.54), and therefore  $X = r + \sum_{i=1}^r \lfloor \frac{\ln(U_i)}{\ln(1-p)} \rfloor$ .
  - b) Just check the algebra.
  - c) Given r and p, generate  $U \sim Uni(0,1)$ , initialize  $pj = p^r$ , F = pj, j = r, and then (p.50) use while U > F, j = j + 1; pj = (j 1)(1 p)pj/(j r); F = F + pj; end, X = j.
  - d) Initialize i = 0, j = 0, then, following the suggestion, use while i < r, j = j + 1, if Uni(0, 1) > p, i = i + 1 end, end, X = i.
- Problem 4.11; use a modified version of the permutation algorithm to generate random subsets of size r, until one of  $1, \ldots, k$  is present.

Algorithm (assuming each U is a new Uniform (0,1) RV):

**Do:** initialize  $P_i = i, i = 1, 2 ..., n$ 

for m = n : -1 : n-r+1, set  $j = \lceil mU \rceil$  and swap  $P_j$ ,  $P_m$  values; end Until  $\min(P_{n-r+1}, P_{n-r+2}, \dots, P_n) \leq k$ :

Note: for small r, k this might not be very efficient. Modified algorithm:

Initialize  $P_i = i, i = 1, 2 \dots, n$ ; set  $j = \lceil kU \rceil$  and swap  $P_j, P_n$  values;

for m = n-1 : -1 : n-r+1, set  $j = \lceil mU \rceil$  and swap  $P_j$ ,  $P_m$  values; end Output  $\{P_{n-r+1}, P_{n-r+2}, \dots, P_n\}$ .

• Problem 4.12\*

$$E(|Z|) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} |x| e^{-x^2/2} dx = \frac{2}{\sqrt{2\pi}} \int_{0}^{\infty} x e^{-x^2/2} dx = -\frac{2}{\sqrt{2\pi}} e^{-x^2/2} \Big|_{0}^{\infty} = \frac{2}{\sqrt{2\pi}} \approx 0.798.$$

• Problem 4.16: for composition there are 4 cases: 5x.06 = .3, 2x.15 = .3, 2x.13 = .26, and 1x.14, corresponding to respective X values (1, 2, 3, 4, 5), (6, 9), (7, 10), and (8).

Algorithm:

Generate  $U_1, U_2$ ;

If  $U_1 < .3$  then  $X = \lceil 5U_2 \rceil$ ; Elseif  $U_1 < .6$  then if  $U_2 < .5$ , X = 6, else X = 9; Elseif  $U_1 < .86$  then if  $U_2 < .5$ , X = 7, else X = 10; Else X = 8.

- Problem 4.17: using a little algebra, rewrite the pmf as  $P\{X=j\} = \frac{1}{2}[(\frac{1}{2})(\frac{1}{2})^{j-1}] + \frac{1}{2}[(\frac{1}{3})(\frac{2}{3})^{j-1}],$  a composition of two equally weighted geometric distributions ( see p.53 with p=1/2,1/3). Algorithm for X: if  $U_1 < 1/2$ , set  $X = 1 + \lfloor \frac{\ln(U_2)}{\ln(1/2)} \rfloor$ , otherwise set  $X = 1 + \lfloor \frac{\ln(U_2)}{\ln(2/3)} \rfloor$ . The first two Us from p.48 are  $U_1 = .23$  and  $U_2 = .66$ , so  $X = 1 + \lfloor \frac{\ln(.66)}{\ln(1/2)} \rfloor = 1 + \lfloor .59946 \rfloor = 1$ .
- Problem 4.18\*:
  - a) we have  $p_1 = \lambda_1 (1 \sum_{j=1}^0 p_j) = \lambda_1$ ,  $p_2 = \lambda_2 (1 \sum_{j=1}^1 p_j) = \lambda_2 (1 p_1) = \lambda_2 (1 \lambda_1)$ ; Using induction, assume  $p_i = \lambda_i (1 - \sum_{j=1}^{i-1} p_j) = \lambda_i (1 - \lambda_1) \cdots (1 - \lambda_{i-1})$ , for  $i = 1, \dots, k$ ; then  $p_{k+1} = \lambda_{k+1} (1 - \sum_{j=1}^k p_j) = \lambda_{k+1} ((1 - \lambda_1) \cdots (1 - \lambda_{k-1}) - p_k)$  $= \lambda_{k+1} (((1 - \lambda_1) \cdots (1 - \lambda_{k-1}))(1 - \lambda_k))$ , so induction hypothesis is satisfied.
  - b) The algorithm generates Us, rejecting each j with probability  $(1 \lambda_j)$ , for  $j = 1, \ldots, n 1$ , until accepting j = n with probability  $\lambda_n$ , so probability of accepting n is  $\prod_{j=1}^{n-1} (1 \lambda_j) \lambda_n = p_n$ .
  - c) If X is geometric then  $p_j = pq^{j-1}$ , with q = 1 p so  $\sum_{j=1}^{n-1} p_j = p(1 + q + \dots + q^{n-2}) = p(1 q^{n-1})/(1 (1 p)) = (1 q^{n-1}),$ and therefore  $\lambda_n = p_n/(1 \sum_{j=1}^{n-1} p_j) = pq^{n-1}/q^{n-1} = p$ .

The algorithm rejects with probability q until n is accepted with correct probability  $p_n = pq^{n-1}$ .

- Problem 5.1: after integration  $F(X) = (e^X 1)/(e 1) = U$ ; solving for  $X, X = \ln(1 + (e 1)U)$ .
- Problem 5.2: after integration of the first part  $F(x) = (x-2)^2/4$  for  $2 \le x < 3$ , with F(3) = 1/4; the integral of second part is  $3/4 3(2 x/3)^2/4$ , so  $F(x) = 1/4 + 3/4 3(2 x/3)^2/4 = 1 3(2 x/3)^2/4$ , for  $3 \le x \le 6$ . If U < 1/4, invert first part, solving  $U = (X 2)^2/4$ , with  $X 2 = \sqrt{4U}$ , so  $X = 2 + 2\sqrt{U}$ ; otherwise solve  $U = 1 3(2 X/3)^2/4$ , with  $2 X/3 = \sqrt{4(1 U)/3}$ , so  $X = 6 6\sqrt{(1 U)/3}$ .
- Problem 5.3: inverting  $U = (X^2 + X)/2$ ,  $X = (\sqrt{1 + 8U} 1)/2$ .
- Problem 5.5\*:  $F(x) = e^{2x}/2$ , if x < 0, otherwise  $F(x) = 1 e^{-2x}/2$  with both parts easily inverted: if  $U_1 < .5$ ,  $X = \ln(2U_2)/2$ , otherwise  $X = -\ln(2(1 U_2))/2$ .
- Problem 5.7: the method is similar to the discrete composition method (p. 61): first generate a discrete RV J using the pmf  $P\{J=j\}=p_j$ ; then generate an  $X \sim F_J(x)$ .
- Problem 5.8:
  - a) This has  $p_1 = p_2 = p_3 = 1/3$ , with  $F_1 = x$ ,  $F_2 = x^3$ ,  $F_3 = x^5$ , so if  $U_1 < 1/3$ , set  $X = U_2$ ; if  $U_1 \ge 2/3$ , set  $X = U_2^{1/5}$ ; otherwise set  $X = U_2^{1/3}$ .
  - c) First use  $U_1$  to generate a discrete RV I using the pmf  $P\{I=i\}=\alpha_i$ ; then generate  $X=U_2^{1/I}$ .
- Problem 5.9\*: F(x) is a continuous composition of  $x^y$  cdfs, with exponential weight function  $e^{-y}$ . So first set  $Y = -\ln(U_1)$  to get a random  $F_Y(x) = x^Y$ , then invert this to get  $X = U_2^{1/Y}$ .
- Problem 5.10: The simulation should use binomial (1000,.05) RVs to determine the number N of claims each month, then use Exp(1/800) RVs to determine the amount of each claim. For each set of claims, determine if the total exceeds \$50000. Some Matlab for a simulation using K = 1000 months (with the binomial RV method from class lecture):

K = 1000; n = 1000; p = .05; q = 1-p; r(1) = q^n; js = [1:n+1]; % binomial RV setup
for j = 1 : n, r(j+1) = r(j)\*p\*(n-j+1)/(j\*q); end, F = cumsum(r); % binomial RV setup
for i = 1 : K % determine claim total for each month
 N = min( js(F>=rand) ) - 1; % binomial(1000, .05) RV

X(i) = sum( -800\*log(rand(1,N)) ); % total claims

end, disp( sum(  $\rm X > 50000$  )/K ) % display proportion > 50000 0.109

Approximately 11% of the months had total claims exceeding \$50000.

- Problem 5.16: you need the pdf  $f(x) = e^{-x}(1 + 2e^{-x} 3e^{-2x})$ .
  - a) the easiest algorithm uses AR with  $g(x) = e^{-x}$ , so  $h(x) = f/g = (1 + 2e^{-x} 3e^{-2x})$ . Then  $h' = e^{-x}(-2 + 6e^{-x}) = 0$  when  $x^* = \ln(3)$ , so rejection constant is  $h(x^*) = 4/3 = c$ .

AR Algorithm:

- 1) Generate  $U_1, U_2, \text{ set } X = -\ln(U_2);$
- 2) If  $U_1 > \frac{f(X)}{cg(X)}$  goto 1), otherwise accept X.
- b) another algorithm could use AR with  $g(x) = e^{-x/2}/2$ , so  $h(x) = f/g = 2e^{-x/2}(1+2e^{-x}-3e^{-2x})$ . A graphical solution shows maximum  $c \approx 1.77$  at  $x^* \approx .64$ , not as efficient as a).

AR Algorithm:

- 1) Generate  $U_1, U_2$ , set  $X = -2 \ln(U_2)$ ;
- 2) If  $U_1 > \frac{f(X)}{cg(X)}$  goto 1), otherwise accept X.

Note:  $F(r) = 1 - r - r^2 + r^3$ , with  $r = e^{-x}$ , so an inversion algorithm could solve the cubic F(r) = U for r and then use  $X = -\ln(r)$ .

- Problem 5.17:
  - a) this is composition of  $\frac{1}{4}(1)$ ,  $\frac{1}{2}4x^3$  and  $\frac{1}{4}5x^4$  with cdf's  $x, x^4, x^5$ . Algorithm:

Generate  $U_1, U_2$ 

If  $U_1 < .25$  then  $X = U_2$ ;

Elseif  $U_1 < .75$  then  $X = U_2^{\frac{1}{4}}$ ;

Else  $X = U_2^{\frac{1}{5}}$ .

- b) simplest algorithm is AR with g(x) = 1, but  $\max(f/g) = f(1) = 7/2$ ; not very efficient.
- Problem 5.19: a) use problem 5.4  $X = (\sqrt{1+8U} 1)/2$ ;
  - b) could use AR g(x) = 1,  $f(x) = \frac{1}{2} + x$ , with  $c = \max(f/g) = f(1) = 3/2$ ;
  - c) this is a composition of  $\frac{1}{2}(x)$  and  $\frac{1}{2}(x^2)$ .

Algorithm: Generate  $U_1, U_2$ ; if  $U_1 < .5$ ,  $X = U_2$ , otherwise  $X = U_2^{\frac{1}{2}}$ .

- b) might be fastest; on average all you need are 3 U's, and no sqrt's.
- Problem 5.20: for AR you need a g(x) with a thicker tail, try  $g(x) = e^{-x/2}/2$ . Then  $h(x) = f(x)/q(x) = e^{-x/2}(1+x)$ ;  $h'(x) = e^{-x/2}(1-x)/2$ , so maximum at x = 1, with  $c = 2/\sqrt{e} \approx 1.21$ , fairly efficient.

AR Algorithm:

- 1) Generate  $U_1, U_2$ , set  $X = -2\ln(U_2)$ ;
- 2) If  $U_1 > \frac{f(X)}{cq(X)}$  goto 1), otherwise accept X.
- Problem 5.21\*: a  $[c, \infty)$  truncated Gamma has pdf  $f(x) = Ax^{\alpha-1}e^{-x}$  for some constant A. A  $[c, \infty)$  truncated Exp pdf is  $g(x) = \lambda e^{-\lambda(x-c)}$ , with  $0 < \lambda \le 1$  so that g decays less rapidily. Now consider  $h(x) = \frac{f}{g} = Ax^{\alpha-1}e^{-c\lambda}e^{-x(1-\lambda)}/\lambda$ . This is a decreasing function for x > c, because  $0 < \alpha < 1$  and  $1 - \lambda \ge 0$ , so the maximum is at  $x^* = c$ .

Given  $x^* = c$  you need to minimize h(c) as function of  $\lambda$ . But  $h(c) = B/\lambda$  for constant B, with minimum at  $\lambda = 1$ . So rejection constant  $C = h(c) = Ac^{\alpha-1}e^{-c\lambda}$ , and rejection function is just  $h(x)/C = (x/c)^{\alpha-1}$ .

This q(x) does not usually have mean  $\alpha$ .

- Problem 5.22: following the example 5d use AR with g(x) = 1,  $h(x) = f(x)/g(x) = 30x^2(1-x)^2$ . with h'(x) = 30x(1-x)(2-4x) = 0 when  $x^* = 1/2$ ; rejection constant  $c = h(x^*) = 15/8 = 1.875$ . This method, with  $\approx 2$  steps for each accept, is moderately efficient.
- Problem 5.23\*: if you use AR with truncated uniform g(x) = 5,  $h(x) = \frac{f}{g} = \frac{x(1-x)^3}{.00168}$ , with max  $\approx 19$  at x = .8, so not efficient.

So try to better match f with easily invertible  $g = K(1-x)^3$ ;  $\int_{.8}^{1} g(x)dx = 1$  gives  $\frac{1}{K} = .0004$ .

Now  $h(x) = \frac{f}{g} = \frac{4x}{3.36}$ , with maximum value  $c = 4/3.36 \approx 1.19$  at x = 1, so AR is very efficient.

To set up the AR algorithm you need  $G(x) = \int_{.8}^{x} \frac{(1-x)^3}{.0004} dx = 1 - \frac{(1-x)^4}{.0016} dx$ , with the inversion formula  $X = 1 - (.0016(1-U))^{\frac{1}{4}}$ ; also notice  $\frac{f}{cg} = x$ .

AR Algorithm:

- 1) Generate  $U_1, U_2$ , and set  $X = 1 (.0016(1 U_2))^{\frac{1}{4}}$ ;
- 2) If  $U_1 > X$  goto 1), otherwise accept X.

- Problem 5.24:  $h(x) = f/g = 2e^{-x^2/2 + \lambda x}/(\sqrt{2\pi}\lambda)$ . h is maxmized when  $h' = (-x + \lambda)h = 0$  at  $x = \lambda$ , so  $c(\lambda) = 2e^{\lambda^2/2}/(\sqrt{2\pi}\lambda)$ .  $c' = (\lambda 1/\lambda)c = 0$  when  $\lambda = \pm 1$  with minimum at  $\lambda = 1$ .
- Problem 5.29: interarrival times are  $\sim Exp(5)$ , and bus sizes are uniform 20-40; Matlab:

• Problem 6.5\*: the covariance matrix Cholesky decomposition is (p.100)

$$\Sigma = \left[ \begin{array}{cc} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{array} \right] = \left[ \begin{array}{cc} \sigma_1 & 0 \\ \rho \sigma_2 & \sigma_2 \sqrt{1 - \rho^2} \end{array} \right] \left[ \begin{array}{cc} \sigma_1 & \rho \sigma_2 \\ 0 & \sigma_2 \sqrt{1 - \rho^2} \end{array} \right] = AA'.$$

If you let  $\mathbf{x} = (x_1, x_2)'$ , with  $\mu = (\mu_1, \mu_2)'$ , the bivariate Normal cdf is

$$B(X_1, X_2) = \int_{-\infty}^{X_1} \int_{-\infty}^{X_2} \frac{e^{-(\mathbf{x} - \mu)' \Sigma^{-1} (\mathbf{x} - \mu)/2}}{2\pi \sqrt{|\Sigma|}} dx_2 dx_1.$$

Then make the change of variables  $\mathbf{x} = A\mathbf{y} + \mu$ , so that  $y_1 = (x_1 - \mu_1)/\sigma_1$ ,  $y_2 = (x_2 - \mu_2 - \rho\sigma_2 y_1)/(\sigma_2 \sqrt{1 - \rho^2})$ , with

$$B(X_1, X_2) = \int_{-\infty}^{(X_1 - \mu_1)/\sigma_1} \frac{e^{-y_1^2/2}}{\sqrt{2\pi}} \int_{-\infty}^{(X_2 - \mu_2 - \rho\sigma_2 y_1)/(\sigma_2 \sqrt{1 - \rho^2})} \frac{e^{-y_2^2/2}}{\sqrt{2\pi}} dy_2 dy_1.$$

Scaling and shifting  $y_2$  produces the required result.

• Problem 6.6: first find Cholesky decomposition of

$$C = \begin{bmatrix} 3 & -2 & 1 \\ -2 & 5 & 3 \\ 1 & 3 & 4 \end{bmatrix} = \begin{bmatrix} a & 0 & 0 \\ b & c & 0 \\ d & e & f \end{bmatrix} \begin{bmatrix} a & b & d \\ 0 & c & e \\ 0 & 0 & f \end{bmatrix} = AA'.$$

So 
$$a = \sqrt{3}$$
,  $b = \frac{-2}{\sqrt{3}}$ ,  $d = \frac{1}{\sqrt{3}}$ ,  $c = \sqrt{5 - b^2} = \frac{\sqrt{11}}{3}$ ,  $e = \frac{3 - bd}{c} = \sqrt{\frac{11}{3}}$ ,  $f = \sqrt{4 - d^2 - e^2} = 0$ .  
Algorithm computes  $X = AZ + \mu$ , with  $\mu = (1, 2, 3)'$  and  $Z = (Z_1, Z_2, Z_3)'$  with  $Z_i \sim Normal(0, 1)$ , but you only need  $Z_1, Z_2$  for each  $X$  because  $f = 0$ .

• Problem 6.7: this is not very clear. If you assume the bivariate joint distribution is H(X,Y), with marginals F(X), G(Y), then  $C_{X,X}$  could mean  $C_{X,X}(x,x) = P(F(X) \le x, F(X) \le x) = G(F^{-1}(X), F^{-1}(X))$ .