

Assignment 2: CS215

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Solution 1

Task A

When $X \sim \text{Ber}(p)$, PGF of X is

$$G_{\text{Ber}}(z) = \mathbb{E}(z^X) \quad (1)$$

$$= \sum_{n=0}^{\infty} P[X = n]z^n \quad (2)$$

Since $P[X = 0] = (1 - p)$, $P[X = 1] = p$, $P[X = n] = 0$ when $n > 1$,

$$G_{\text{Ber}}(z) = P[X = 0]z^0 + P[X = 1]z^1 \quad (3)$$

$$= (1 - p) + pz \quad (4)$$

Task B

When $X \sim \text{Bin}(n, p)$, PMF of X is

$$P[X = k] = \binom{n}{k} p^k (1 - p)^{n-k} \text{ for } k \leq n. \quad (5)$$

and $P[X = k] = 0$ for $k > n$.

$$G_{\text{Bin}}(z) = \sum_{k=0}^{\infty} P[X = k]z^k \quad (6)$$

$$= \sum_{k=0}^n \binom{n}{k} p^k (1 - p)^{n-k} z^k \quad (7)$$

$$= \sum_{k=0}^n \binom{n}{k} (pz)^k (1 - p)^{n-k} \quad (8)$$

$$= (1 - p + pz)^n. \quad (9)$$

By equation 4, $G_{\text{Bin}}(z) = (1 - p + pz)^n = (G_{\text{Ber}}(z))^n$. Hence proved.

Task D

When $X \sim \text{Geo}(p)$, PMF of X ,

$$P[X = k] = (1 - p)^{k-1} p \quad (10)$$

for $k > 0$. $P[X = 0] = 0$. Now, PGF of X ,

$$G_{\text{Geo}}(z) = \sum_{k=0}^{\infty} P[X = k]z^k \quad (11)$$

$$= \sum_{k=1}^{\infty} P[X = k]z^k \quad (12)$$

$$= \sum_{k=1}^{\infty} p(1 - p)^{k-1} z^k \quad (13)$$

$$= \sum_{k=1}^{\infty} pz(z - zp)^{k-1} \quad (14)$$

$$= pz \sum_{k=0}^{\infty} (z - zp)^k \quad (15)$$

$$= \frac{pz}{1 - z + pz} \quad (16)$$

Task E

By equation 9, $G_{\text{Bin}}(z) = (1 - p + pz)^n = G_X^{(n,p)}(z)$. For $Y \sim \text{NegBin}(n, p)$

$$P[Y = k] = \binom{k-1}{n-1} p^n (1-p)^{k-n} \text{ for } k \geq n \quad (17)$$

Otherwise, $P[Y = k] = 0$. PGF of Y is

$$G_Y^{(n,p)}(z) = \sum_{k=0}^{\infty} P[Y = k] z^k \quad (18)$$

$$= \sum_{k=n}^{\infty} \binom{k-1}{n-1} p^n (1-p)^{k-n} z^k \quad (19)$$

$$= \sum_{k=0}^{\infty} \binom{k+n-1}{n-1} p^n (1-p)^k z^{n+k} \quad (20)$$

$$= (pz)^n \sum_{k=0}^{\infty} \binom{k+n-1}{n-1} (z-pz)^k \quad (21)$$

We know $\sum_{k=0}^{\infty} \binom{k+n-1}{n-1} x^k = (1-x)^{-n}$. Thus

$$G_Y^{(n,p)}(z) = (pz)^n (1 - z + pz)^{-n} \quad (22)$$

$$= \left((1 - p^{-1} + p^{-1}z^{-1})^n \right)^{-1} \quad (23)$$

$$= (G_X^{(n,p^{-1})}(z^{-1}))^{-1}. \quad (24)$$

Hence Proved.

Task G

To prove: Given PGF of a random variable X is $G(z)$, expectation of X i.e $\mathbb{E}(x) = G'(1)$

Proof:

$$G(z) = \mathbb{E}(z^X) = \sum_{k=0}^{\infty} P[X = k] z^k \quad (25)$$

$$G'(z) = \sum_{k=0}^{\infty} k P[X = k] z^{k-1} \quad (26)$$

$$G'(1) = \sum_{k=0}^{\infty} k P[X = k] \quad (27)$$

$$= \mathbb{E}[X] \quad (28)$$

Hence Proved. Now, Let's derive means of Bernoulli, Binomial, Geometric and Negative Binomial distributions using this:

1. **Bernoulli Distribution:** Let $X \sim \text{Ber}(p)$,

$$G_{\text{Ber}}(z) = (1 - p) + pz \quad (29)$$

$$G'_{\text{Ber}}(z) = p \quad (30)$$

$$G'_{\text{Ber}}(1) = p = \mathbb{E}[X] \quad (31)$$

Thus, $\mathbb{E}[X] = p$.

2. **Binomial Distribution:** Let $X \sim \text{Bin}(n, p)$,

$$G_{\text{Bin}}(z) = (1 - p + pz)^n \quad (32)$$

$$G'_{\text{Bin}}(z) = np(1 - p + pz)^{n-1} \quad (33)$$

$$G'_{\text{Bin}}(1) = np = \mathbb{E}[X] \quad (34)$$

Thus, $\mathbb{E}[X] = np$.

3. **Geometric Distribution:** Let $X \sim \text{Geo}(p)$,

$$G_{\text{Geo}}(z) = \frac{pz}{1 - z + pz} \quad (35)$$

$$G'_{\text{Geo}}(z) = \frac{p(1 - z + pz) - pz(p - 1)}{(1 - z + pz)^2} \quad (36)$$

$$= \frac{p}{(1 - z + pz)^2} \quad (37)$$

$$G'_{\text{Geo}}(1) = \frac{p}{p^2} = \frac{1}{p} = \mathbb{E}[X] \quad (38)$$

Thus, $\mathbb{E}[X] = \frac{1}{p}$.

4. **Negative Binomial Distribution:** Let $X \sim \text{NegBin}(n, p)$,

$$G_{\text{NegBin}}(z) = \left(\frac{pz}{1 - z + pz} \right)^n \quad (39)$$

$$G'_{\text{NegBin}}(z) = n \left(\frac{pz}{1 - z + pz} \right)^{n-1} \left(\frac{p}{(1 - z + pz)^2} \right) \quad (40)$$

$$G'_{\text{NegBin}}(1) = \frac{n}{p} = \mathbb{E}[X] \quad (41)$$

Thus, $\mathbb{E}[X] = \frac{n}{p}$.

Solution 2

Task A

To prove:

Let X be a continuous real-valued random variable with CDF $F_X : \mathbb{R} \rightarrow [0, 1]$. Assume that F_X is invertible. Then the random variable $Y := F_X(X) \in [0, 1]$ is uniformly distributed in $[0, 1]$

Proof:

F_X by definition can also be written as

$$F_X(x) = P(X \leq x)$$

Define a new random variable Y ,

$$Y = F_X(X)$$

Y is the result of applying CDF F_X to the random variable X . To prove the theorem, assume $y \in [0, 1]$. So, the probability that $Y \leq y$ is:

$$P(Y \leq y) = P(F_X(X) \leq y)$$

It is assumed that $F_X(x)$ is invertible, so,

$$P(Y \leq y) = P(X \leq F_X^{-1}(y))$$

which is basically, probability that X is less than or equal to $F_X^{-1}(y)$. This can be written in the CDF form, which is $F_X(F_X^{-1}(y))$. So,

$$P(Y \leq y) = P(X \leq F_X^{-1}(y)) = F_X(F_X^{-1}(y)) = y$$

So,

$$P(Y \leq y) = y$$

where $y \in [0, 1]$, which is the CDF of uniform distribution in $[0, 1]$. So, Y is a uniform distribution in $[0, 1]$ regardless of X .

Task B

According to the theorem proved above, CDF of any random variable X mapped with itself gives a uniform random variable Y in $[0, 1]$. So, let $Y \sim \text{Uniform}(0, 1)$. Then for any random variable X ,

$$F_X(X) = Y \quad (42)$$

$$X = F_X^{-1}(Y) \quad (43)$$

Algorithm \mathcal{A} :

1. Input: A sample y from the uniform distribution on $[0, 1]$.
2. Transformation:
 - Apply the inverse CDF to y to compute a sample u .
 - Define $\mathcal{A}(u) = u = F_X^{-1}(y)$
3. Output: The random variable $U = F_X^{-1}(Y)$

This gives us the correct required random variables as, CDF of U is $F_U(u)$,

$$P(U \leq u) = P(F_X(Y) \leq u) \quad (44)$$

$$F_U(u) = P(F_X(F_X^{-1}(X)) \leq u) \quad (45)$$

$$F_U(u) = P(X \leq u) \quad (46)$$

$$F_U(u) = F_X(u) \quad (47)$$

$$(48)$$

U and X have the same CDF, which was initially required.

Solution 3

Solution 4

Solution 5

Task A

Given, PDF of GMM variable X is $f_X = \sum_{i=1}^K p_i P[X_i = x]$. Let its CDF be F_X . Then $F_X(x)$ is given by

$$F_X(x) = P[X \leq x] \quad (49)$$

$$= \int_{-\infty}^x f_X(t) dt \quad (50)$$

$$= \int_{-\infty}^x \sum_{i=1}^K p_i P[X_i = t] dt \quad (51)$$

$$= \sum_{i=1}^K p_i \int_{-\infty}^x P[X_i = t] dt \quad (52)$$

$$= \sum_{i=1}^K p_i P[X_i \leq x] \quad (53)$$

$$= \sum_{i=1}^K p_i F_{X_i}(x) \quad (54)$$

Where $F_{X_i}(x) = P[X_i \leq x]$ is CDF of X_i .

Now, let CDF of output of the given algorithm be $F_A(x) = P[\mathcal{A} \leq x]$. Since the events that we choose \mathcal{A} to be from the distribution i (say E_i) are disjoint for $i = 1, \dots, k$.

$$F_A(x) = P[\mathcal{A} \leq x] \quad (55)$$

$$= \sum_{i=1}^K P[E_i] \cdot P[\mathcal{A} \leq x | E_i] \quad (56)$$

$$= \sum_{i=1}^K p_i F_{X_i}(x) \quad (57)$$

$$= F_X(x) \quad (58)$$

We know that PDF of a random variable X with CDF $F_X(x)$ is $\frac{\partial F_X}{\partial x}$. Thus,

$$f_A(x) = \frac{\partial F_A}{\partial x} \quad (59)$$

$$= \frac{\partial F_X}{\partial x} \quad (60)$$

$$= f_X \quad (61)$$

Since x was arbitrary, for every $u \in \mathbb{R}$, $f_A(u) = f_X(u)$. i.e the algorithm indeed samples from the GMM variable's distribution.

Task B

Since

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} t \cdot P[X = t] dt \quad (62)$$

$$= \int_{-\infty}^{\infty} t \cdot \sum_{i=1}^K p_i P[X_i = t] dt \quad (63)$$

$$= \sum_{i=1}^K p_i \int_{-\infty}^{\infty} P[X_i = t] dt \quad (64)$$

$$= \sum_{i=1}^K p_i \mathbb{E}[X_i] \quad (65)$$

$$= \sum_{i=1}^K p_i \mu_i \quad (66)$$

Let $\mu = \mathbb{E}[X]$.

$$\text{Var}[X] = \int_{-\infty}^{\infty} (t - \mu)^2 P[X = t] dt \quad (67)$$

$$= \int_{-\infty}^{\infty} (t - \mu)^2 \sum_{i=1}^K p_i P[X_i = t] dt \quad (68)$$

$$= \sum_{i=1}^K p_i \int_{-\infty}^{\infty} (t - \mu)^2 P[X_i = t] dt \quad (69)$$

$$= \sum_{i=1}^K p_i \text{Var}[X_i] \quad (70)$$

$$= \sum_{i=1}^K p_i \sigma_i^2 \quad (71)$$

Let $\sigma^2 = \text{Var}[X]$.

$$\text{MGF}_X(t) = \int_{-\infty}^{\infty} e^{tX} P[X = x] dx \quad (72)$$

$$= \int_{-\infty}^{\infty} e^{tX} \sum_{i=1}^K p_i P[X_i = x] dx \quad (73)$$

$$= \sum_{i=1}^K p_i \int_{-\infty}^{\infty} e^{tX} P[X_i = x] dx \quad (74)$$

$$= \sum_{i=1}^K p_i \text{MGF}_{X_i}(t) \quad (75)$$

$$= \sum_{i=1}^K p_i e^{t\mu_i + \frac{1}{2}t^2\sigma_i^2} \quad (76)$$

Task C

Given $Z = \sum_{i=1}^K p_i X_i$, where $X_i \sim \mathcal{N}(\mu_i, \sigma_i^2)$

$$\mathbb{E}[Z] = \mathbb{E}\left[\sum_{i=1}^K p_i X_i\right] \quad (77)$$

$$= \sum_{i=1}^K p_i \mathbb{E}[X_i] \quad (78)$$

$$= \sum_{i=1}^K p_i \mu_i \quad (79)$$