Assignment 2: CS215

Satyam Sinoliya, 23B0958
Vaibhav Singh, 23B1068
Shaik Awez Mehtab, 23B1080

Solution 1

Task A

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

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

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

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

$$G_{\text{Ber}}(z) = P[X = 0]z^0 + P[X = 1]z^1 \tag{3}$$
$$= (1 - p) + pz \tag{4}$$

Task B

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

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

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

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

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

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

$$= (1 - p + pz)^n. \tag{9}$$

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

Task C

By the definition of PGF,

$$G(z) = \sum_{n=0}^{\infty} P[X_1 = n]z^n \tag{10}$$

Let $(G(z))^k = \sum_{n=0}^{\infty} a_n z^n$. Now, $G_\Sigma(z)$ is

$$G_\Sigma(z) = \sum_{n=0}^{\infty} P[X = n]z^n \tag{11}$$

$$= \sum_{n=0}^{\infty} P[X_1 + \cdots + X_k = n]z^n \tag{12}$$

$$= \sum_{n=0}^{\infty} \sum P[X_1 = i_1, \ldots, X_k = i_k]z^n \tag{13}$$

where $i_1 + \cdots + i_k = n$.

$$= \sum_{n=0}^{\infty} \sum P(i_1) \ldots P(i_n)z^n \tag{14}$$

Now, $G(z) = \sum_{n=0}^{\infty} P(n)z^n$. And since a_n is coefficient of z^n in $(G(z))^k = (\sum_{n=0}^{\infty} P(n)z^n)^k$.

$$a_n = \sum P(i_1)P(i_2)\ldots P(i_k) \text{ where } i_1 + \cdots + i_k = n \tag{15}$$

By equation 14

$$G_\Sigma(z) = \sum_{n=0}^{\infty} a_n z^n = (G(z))^k \tag{16}$$

Hence Proved.

Task D

When $X \sim \text{Geo}(p)$, PMF of X,
$$P[X = k] = (1 - p)^{k-1}p \tag{17}$$

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

$$G_{\text{Geo}}(z) = \sum_{k=0}^{\infty} P[X = k]z^k \tag{18}$$

$$= \sum_{k=1}^{\infty} P[X = k]z^k \tag{19}$$

$$= \sum_{k=1}^{\infty} p(1 - p)^{k-1}z^k \tag{20}$$

$$= \sum_{k=1}^{\infty} pz(z - zp)^{k-1} \tag{21}$$

$$= pz \sum_{k=0}^{\infty} (z - zp)^k \tag{22}$$

$$= \frac{pz}{1 - z + pz} \tag{23}$$

Task E

By equation 9,

$$G_{\text{Bin}}(z) = (1 - p + pz)^n = G_X^{(n,p)}(z). \tag{24}$$

For $Y \sim \text{NegBin}(n, p)$, Y represents the number of independent coin throws required to get n heads of a coin. Let X_i represents the number of throws of coin required after getting $(i-1)^{\text{th}}$ head to get the ith head. Since all of the coin throws are independent, the outcome of a given throw doesn't depend on the previous coins' output. Thus, X_i is just the number of throws to get a head when a coin in thrown, where each $X_i \sim \text{Geo}(p)$ since each coin is same with probability of getting head as p.

Y can be written as $Y = X_1 + X_2 + \cdots + X_k$. Using equations 16 and 23,

$$G_Y^{(n,p)}(z) = (G_{\text{Geo}}(z))^n \tag{25}$$

$$= \left(\frac{pz}{1 - z + pz}\right)^n \tag{26}$$

$$\tag{27}$$

$$G_X^{(n,p^{-1})}(z^{-1}) = \left(1 - \frac{1}{p} + \frac{1}{pz}\right)^n \tag{28}$$

$$= \left(\frac{1 - z + pz}{pz}\right)^n \tag{29}$$

$$\left(G_X^{(n,p^{-1})}(z^{-1})\right)^{-1} = \left(\frac{pz}{1 - z + pz}\right)^n \tag{30}$$

$$= G_Y^{(n,p)}(z) \tag{31}$$

Hence Proved.

Task F

For $Y \sim \text{NegBin}(n,p)$,

$$P[Y = k] = \binom{k-1}{n-1}p^n(1-p)^{k-n} \text{ for } k \geq n \tag{32}$$

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

$$G_Y^{(n,p)}(z) = \sum_{k=0}^{\infty} P[Y = k]z^k \tag{33}$$

$$= \sum_{k=n}^{\infty} \binom{k-1}{n-1}p^n(1-p)^{k-n}z^k \tag{34}$$

$$= \sum_{k=0}^{\infty} \binom{k+n-1}{n-1}p^n(1-p)^k z^{n+k} \tag{35}$$

$$= (pz)^n \sum_{k=0}^{\infty} \binom{k+n-1}{n-1}(z - pz)^k \tag{36}$$

Using equation 27,

$$\left(\frac{pz}{1 - z + pz}\right)^n = (pz)^n \sum_{k=0}^{\infty} \binom{k+n-1}{n-1}(z - pz)^k \tag{37}$$

$$(1 - (z - pz))^{-n} = \sum_{k=0}^{\infty} \binom{k+n-1}{n-1}(z - pz)^k \tag{38}$$

Since z, p are arbitrary, let $z - pz = x$.

$$(1 - x)^{-n} = \sum_{r=0}^{\infty} \binom{r+n-1}{n-1}x^r = \sum_{r=0}^{\infty} \binom{-n}{r}x^r \tag{39}$$

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:

$$G(z) = \mathbb{E}(z^X) = \sum_{k=0}^{\infty} P[X = k]z^k \tag{40}$$

$$G'(z) = \sum_{k=0}^{\infty} kP[X = k]z^{k-1} \tag{41}$$

$$G'(1) = \sum_{k=0}^{\infty} kP[X = k] \tag{42}$$

$$= \mathbb{E}[X] \tag{43}$$

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

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

$$G_{\text{Ber}}(z) = (1-p) + pz \tag{44}$$
$$G'_{\text{Ber}}(z) = p \tag{45}$$
$$G'_{\text{Ber}}(1) = p = \mathbb{E}[X] \tag{46}$$

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

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

$$G_{\text{Bin}}(z) = (1 - p + pz)^n \tag{47}$$
$$G'_{\text{Bin}}(z) = np(1 - p + pz)^{n-1} \tag{48}$$
$$G'_{\text{Bin}}(1) = np = \mathbb{E}[X] \tag{49}$$

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

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

$$G_{\text{Geo}}(z) = \frac{pz}{1 - z + pz} \tag{50}$$
$$G'_{\text{Geo}}(z) = \frac{p(1 - z + pz) - pz(p-1)}{(1 - z + pz)^2} \tag{51}$$
$$= \frac{p}{(1 - z + pz)^2} \tag{52}$$
$$G'_{\text{Geo}}(1) = \frac{p}{p^2} = \frac{1}{p} = \mathbb{E}[X] \tag{53}$$

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

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

$$G_{\text{NegBin}}(z) = \left(\frac{pz}{1 - z + pz}\right)^n \tag{54}$$
$$G'_{\text{NegBin}}(z) = n\left(\frac{pz}{1 - z + pz}\right)^{n-1}\left(\frac{p}{(1 - z + pz)^2}\right) \tag{55}$$
$$G'_{\text{NegBin}}(1) = \frac{n}{p} = \mathbb{E}[X] \tag{56}$$

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

Solution 2

Task A

To prove:
Let X be a continuous real-valued random variable with CDF : $\mathbb{R} \to [0, 1]$. 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

$$F_X(x) = P(X \leq x) \tag{57}$$

Define a new random variable Y,

$$Y = F_X(X) \tag{58}$$

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 probablity that $Y \leq y$ is:

$$P(Y \leq y) = P(F_X(X) \leq y) \tag{59}$$

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

$$P(Y \leq y) = P(X \leq F_X^{-1}(y)) \tag{60}$$

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

$$P(Y \leq y) = P(X \leq F_X^{-1}(y)) = F_X(F_X^{-1}(y)) = y \tag{61}$$

So,

$$P(Y \leq y) = y \tag{62}$$

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,

$$F_X(X) = Y \tag{63}$$
$$X = F_X^{-1}(Y) \tag{64}$$

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 $F_U(u)$,

$$P(U \leq u) = P(F_X^{-1}(Y) \leq u) \tag{65}$$
$$F_U(u) = P(Y \leq F_X(u)) \tag{66}$$
$$\tag{67}$$

Since, Y is a uniform random variable between 0 and 1,

$$F_U(u) = F_Y(F_X(u)) \tag{68}$$
$$F_U(u) = F_X(u) \tag{69}$$
$$\tag{70}$$

Since, for any uniform random variable P between 0 and 1,

$$F_P(x) = x$$

This proves that, U and X have the same CDF.

Task C

The code can be found in `2c.py`. In this script, we generate random samples from a Gaussian distribution using the inverse transform sampling method. The function `sample(loc, scale)` begins by creating a sample, `x`, which consists of uniformly distributed random variables between 0 and 1, with a sample size of `N` (where `N` = 10^5 or 100,000).

These uniform samples, `x`, are then transformed into samples from a Gaussian (normal) distribution by passing them through the inverse cumulative distribution function (CDF) of the normal distribution, implemented via `norm.ppf`. The arguments `loc` and `scale` represent the mean and standard deviation of the Gaussian distribution, respectively. This transformation effectively maps the uniform samples to samples drawn from the specified Gaussian distribution, as demonstrated theoretically in previous sections.

We then define the list `params`, which contains tuples of means and variances for the Gaussian distributions we wish to sample from and plot. For each set of parameters, the `sample()` function is called, and the resulting samples are stored in the `samples` list.

Finally, we loop over the pairs of parameters (`params`) and their corresponding samples (`samples`) to create a histogram for each distribution. The histograms are plotted with 500 bins, and the density is normalized. A legend is included to indicate the mean (μ) and standard deviation (σ) for each distribution.

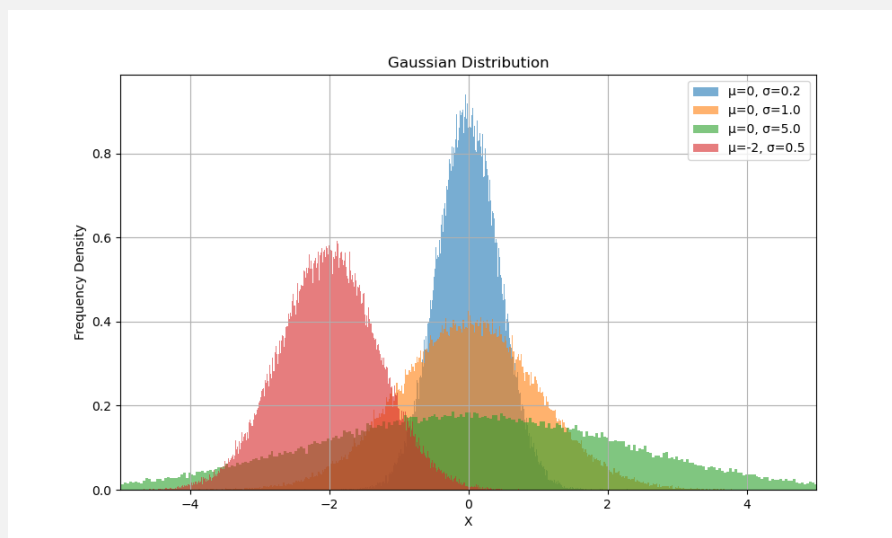Below is the resulting histogram:

Figure 1: Histograms of Gaussian distributions for different means and variances

Task D

The code for simulating the Galton board is found in `2d.py`. We implemented a function called `galton_board`, which takes two parameters: `h`, representing the depth of the Galton board (number of pegs the ball hits), and `N`, the number of balls dropped.

Inside the function, the variable `steps` is a matrix with `N` rows and `h` columns. Each row corresponds to a ball, and each column represents a decision the ball makes at a peg. At each step, the ball either moves left, represented by -1, or right, represented by 1. The final position of each ball is determined by summing all its steps, which is stored in the 1-D array `positions`. This array records the final pocket into which each ball falls.

For the simulation, 1000 balls are dropped for different values of h (the depth of the board). The resulting distributions for each value of h are visualized as histograms, with the x-axis representing the final positions (pockets) and the y-axis showing the probability of balls falling into each pocket. The results for different values of h are shown below.
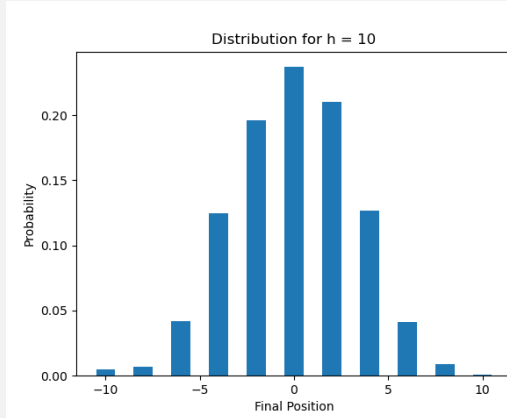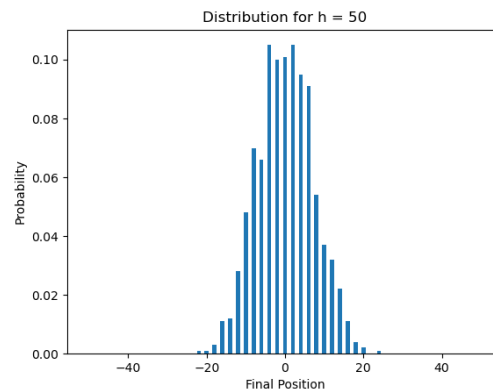

Figure 2: Height = 10
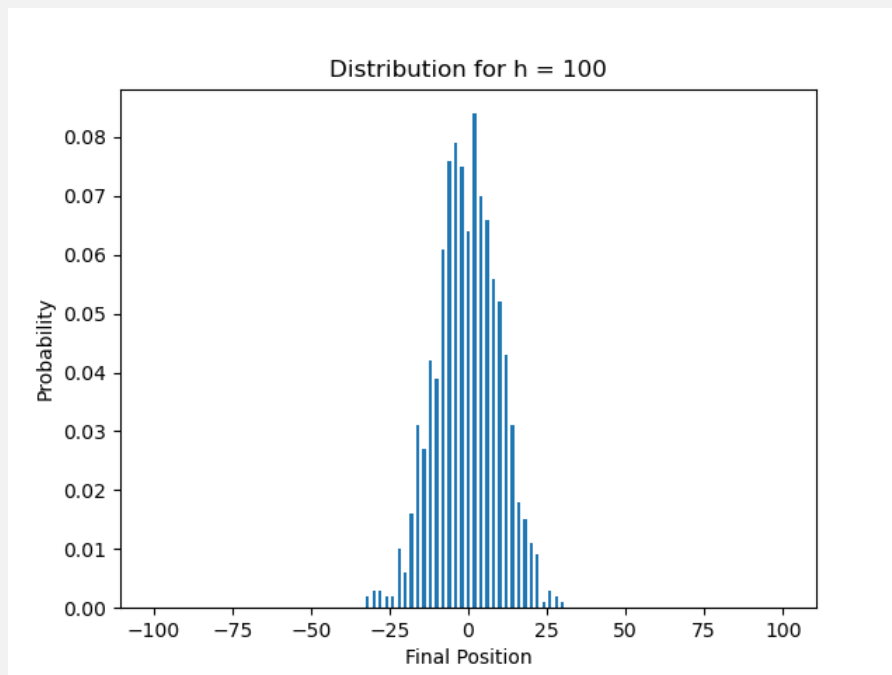

Figure 3: Height = 50

Figure 4: Height = 100

The shape of the tops of the histogram closely resembles a Gaussian distribution. As the height (h) of the Galton board increases, the distribution becomes smoother and more bell-shaped, indicating that most balls tend to fall around the center pockets.

Task E(B)

We have a random variable X which can take values from $\{-h, -h+2, \ldots, h-2, h\}$. Each ball makes h random binary decisions(left or right) as it descends. If we let Y be the number of

times the ball moves right, the final position of the ball will be given by,

$$X = -h + 2Y \tag{71}$$

where Y is a **binomial variable** because in simple terms it is the summation of h bernoulli decisions each with probability $\frac{1}{2}$.

$$Y \sim \text{Bin}(h, \frac{1}{2}) \tag{72}$$

For a particular pocket $X = 2i$, the corresponding value of Y is:

$$Y = \frac{h + 2i}{2} \tag{73}$$

Thus, the probability that the ball lands in the pocket $X = 2i$ is the probability that $Y = \frac{h+2i}{2}$. Using Binmial distribution, this is:

$$P_h[X = 2i] = P_h\left[Y = \frac{h+2i}{2}\right] = \binom{h}{\frac{h+2i}{2}}\left(\frac{1}{2}\right)^h \tag{74}$$

This is the **closed form expression for $P_h[X = 2i]$**
Now, we need to show $P_h[X = 2i]$ approximates to normal distribution for very large h.
Using **stiriling's approximation** for large n, which states that:

$$n! \approx \sqrt{2\pi n}\left(\frac{n}{2}\right)^n \tag{75}$$

We can convert the factorials in the binomial coefficient:

$$\binom{h}{r} \approx \frac{h!}{r!(h-r)!} \tag{76}$$

Using stirlings approximation, we have,

$$\binom{h}{y} = \frac{\sqrt{2\pi h}\left(\frac{h}{e}\right)^h}{\sqrt{2\pi y}\left(\frac{y}{e}\right)^y \cdot \sqrt{2\pi(h-y)}\left(\frac{h-y}{e}\right)^{h-y}} \tag{77}$$

where $y = \frac{h+2i}{2}$ For large h, we can simplify this assuming small i (relative to h). In particular, $\frac{h+2i}{2}$ can be written as $\frac{h}{2}$, leading to:

$$\binom{h}{\frac{h+2i}{2}} \approx \frac{2^h}{\sqrt{\pi h}}e^{-\frac{2i^2}{h}} \tag{78}$$

Substituting it back in P_h gives:

$$P_h[X = 2i] \approx \frac{2^h}{\sqrt{\pi h}}e^{-\frac{2i^2}{h}}\left(\frac{1}{2}\right)^h \tag{79}$$

Simplifying the powers of 2 gives:

$$P_h[X = 2i] \approx \frac{1}{\sqrt{\pi h}}e^{-\frac{2i^2}{h}} \tag{80}$$

which is basically normal distribution with $\mu = 0$ and $\sigma^2 = h/2$

Solution 3

Task D

Given, PDF of Gamma-distribution $\text{Gamma}(k,\theta)$ is $f(x;k,\theta) = \frac{1}{\theta^k\Gamma(k)}x^{k-1}e^{-\frac{x}{\theta}}$. First moment of it is

$$\mu_1^{\text{Gamma}} = \mathbb{E}[X] \tag{81}$$

$$= \int_{-\infty}^{\infty} x\frac{1}{\theta^k\Gamma(k)}x^{k-1}e^{-\frac{x}{\theta}}dx \tag{82}$$

$$= \frac{1}{\theta^k\Gamma(k)}\int_{-\infty}^{\infty} x^k e^{-\frac{x}{\theta}}dx \tag{83}$$

Let $u = \frac{x}{\theta}$, then $\theta du = dx$

$$= \frac{\theta}{\Gamma(k)}\int_{-\infty}^{\infty} u^k e^{-u}du \tag{84}$$

$$= \frac{\theta\Gamma(k+1)}{\Gamma(k)} \tag{85}$$

Since $\Gamma(k+1) = k\Gamma(k)$

$$= k\theta \tag{86}$$

Second moment of it is

$$\mu_2^{\text{Gamma}} = \mathbb{E}[X^2] \tag{87}$$

$$= \int_{-\infty}^{\infty} x^2\frac{1}{\theta^k\Gamma(k)}x^{k-1}e^{-\frac{x}{\theta}}dx \tag{88}$$

$$= \frac{1}{\theta^k\Gamma(k)}\int_{-\infty}^{\infty} x^{k+1} e^{-\frac{x}{\theta}}dx \tag{89}$$

Let $u = \frac{x}{\theta}$, then $\theta du = dx$

$$= \frac{\theta^2}{\Gamma(k)}\int_{-\infty}^{\infty} u^{k+1} e^{-u}du \tag{90}$$

$$= \frac{\theta^2\Gamma(k+2)}{\Gamma(k)} \tag{91}$$

$$= (k+1)k\theta^2 \tag{92}$$

Thus, $\mu_1^{\text{Gamma}} = k\theta$, $\mu_2^{\text{Gamma}} = (k+1)k\theta^2$.
Estimate the best gamma distribution approximation to the given data by equating first and second moments. For $X \sim \text{Gamma}(n,p)$, density function is

$$f(x;k,\theta) = \frac{1}{\theta^k\Gamma(k)}x^{k-1}e^{-\frac{x}{\theta}} \tag{93}$$

$\mu_1 = k\theta$ and $\mu_2 = k(k+1)\theta^2$.

Task E

- Log likelihood for binomimal distribution ≈ -2.157

- Log likelihood for gamma distribution $= -\texttt{inf}$

Awez **Vaibhav** **Satyam**

Thus binomial distribution is a better fit for the data.

Task F

- Log likelihood for two-component Gaussian mixture is -2.183

Thus, binomial distribution is slightly better fit than the given two-component gaussian mixture (whose variance is assumed to be 1).

Solution 4

Task D

We are given $Y = \sum_{i=1}^{n} X_i$, where each X_i is an independent Bernoulli random variable with $\mathbb{E}[X_i] = p_i$

1. Expectation of Y

The new random variable Y is given by:

$$Y = \sum_{i=1}^{n} X_i$$

Using the liniearity of expectation, the expectation of Y is:

$$\mathbb{E}[X_i] = \mathbb{E}\left[\sum_{i=1}^{n}\right] = \sum_{i=1}^{n} \mathbb{E}[X_i] = \sum_{i=1}^{n} p_i$$

Let $\mu = \sum_{i=1}^{n} p_i$, So $\mathbb{E}[Y] = \mu$

2. Proof

From previous subparts, we know

$$P[X \geq x] \leq e^{-tx} M_X(t) \text{ for all } t > 0$$

where $M_X(t)$ is the MGF.

$$M_Y(t) = \mathbb{E}[e^{tY}] \tag{94}$$
$$= \mathbb{E}[e^{t \sum_{i=1}^{n} X_i}] \tag{95}$$
$$= \mathbb{E}\left[\prod_{i=1}^{n} e^{tX_i}\right] \tag{96}$$

Using the independence of each X_i, we can write the expecatation of product as product of expectation,

$$M_Y(t) = \prod_{i=1}^{n} \mathbb{E}[e^{tX_i}] \tag{97}$$
$$= \prod_{i=1}^{n} M_{X_i} \tag{98}$$

MGF of a Bernoulli random variable is

$$M_{X_i} = p_i e^t + (1 - p_i)$$

So,

$$M_Y(t) = \prod_{i=1}^{n} (p_i e^t + (1 - p_i))$$

Putting it back into the inequality,

$$P[X \geq (1 + \delta)\mu] \leq \frac{\prod_{i=1}^{n}(p_i e^t + (1 - p_i))}{e^{t(1+\delta)\mu}}$$

We know that, $1 + x \leq e^x$. Substituting x with $p_i(e^t - 1)$, we get:

$$1 + p_i(e^t - 1) \leq e^{p_i(e^t - 1)}$$

Rearranging terms,

$$p_i e^t + (1 - p_i) \leq e^{p_i(e^t - 1)}$$

So,

$$P[X \geq (1 + \delta)\mu] \leq \frac{\prod_{i=1}^{n} e^{p_i(e^t - 1)}}{e^{t(1+\delta)\mu}} \tag{99}$$

$$P[X \geq (1 + \delta)\mu] \leq \frac{e^{\sum_{i=1}^{n} p_i(e^t - 1)}}{e^{t(1+\delta)\mu}} \tag{100}$$

$$P[X \geq (1 + \delta)\mu] \leq \frac{e^{(e^t - 1)\sum_{i=1}^{n} p_i}}{e^{(1+\delta)t\mu}} \tag{101}$$

$$P[X \geq (1 + \delta)\mu] \leq \frac{e^{(e^t - 1)\mu}}{e^{(1+\delta)t\mu}} \tag{102}$$

This completes the proof

3. Improving bound

To improve bound, we have to minimise the right hand term in 102. As it is a continuous functions, we can differentiate it to get a minima. Let the RHS be $f(t)$

$$\frac{\mathrm{d}f}{\mathrm{d}t} = \frac{\mathrm{d}\frac{e^{(e^t-1)\mu}}{e^{(1+\delta)t\mu}}}{\mathrm{d}t}$$

For minima, $\frac{\mathrm{d}f}{\mathrm{d}t}$ should be 0.

$$\frac{\mathrm{d}\frac{e^{(e^t-1)\mu}}{e^{(1+\delta)t\mu}}}{\mathrm{d}t} = 0 \tag{103}$$

$$\frac{(e^{(1+\delta)t\mu})\frac{\mathrm{d}e^{(e^t-1)\mu}}{\mathrm{d}t} - e^{(e^t-1)\mu}\frac{\mathrm{d}e^{(1+\delta)t\mu}}{\mathrm{d}t}}{(e^{(1+\delta)t\mu})^2} = 0 \tag{104}$$

$$(e^{(1+\delta)t\mu})(e^{(e^t-1)\mu})(\mu e^t) - (e^{(e^t-1)\mu})((e^{(1+\delta)t\mu}))(1 + \delta)\mu = 0 \tag{105}$$

$$e^t - (1 + \delta) = 0 \tag{106}$$

$$t = \ln(1 + \delta) \tag{107}$$

The improved bound will be,

$$f(\ln(1 + \delta)) = \frac{e^{(e^{\ln(1+\delta)} - 1)\mu}}{e^{(1+\delta)\ln(1+\delta)\mu}}$$

On further calculation, we get,

$$f(\ln(1 + \delta)) = \frac{e^{\delta \mu}}{(1 + \delta)^{(1+\delta)\mu}}$$

Finally,

$$P[X \geq (1 + \delta)\mu] \leq \frac{e^{\delta \mu}}{(1 + \delta)^{(1+\delta)\mu}}$$

Solution 5

Task A

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

$$F_X(x) = P[X \leq x] \tag{108}$$

$$= \int_{-\infty}^{x} f_X(t)dt \tag{109}$$

$$= \int_{-\infty}^{x} \sum_{i=1}^{K} p_i P[X_i = t]dt \tag{110}$$

$$= \sum_{i=1}^{K} p_i \int_{-\infty}^{x} P[X_i = t]dt \tag{111}$$

$$= \sum_{i=1}^{K} p_i P[X_i \leq x] \tag{112}$$

$$= \sum_{i=1}^{K} p_i F_{X_i}(x) \tag{113}$$

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 $F_{\mathcal{A}}(x) = P[\mathcal{A} \leq x]$. Since the events that we choose $\mathcal{A}$ to be from the distribution i (say E_i) are disjoint for $i = 1, \ldots, k$.

$$F_{\mathcal{A}}(x) = P[\mathcal{A} \leq x] \tag{114}$$

$$= \sum_{i=1}^{K} P[E_i] \cdot P[\mathcal{A} \leq x | E_i] \tag{115}$$

$$= \sum_{i=1}^{K} p_i F_{X_i}(x) \tag{116}$$

$$= F_X(x) \tag{117}$$

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

$$f_{\mathcal{A}}(x) = \frac{\partial F_{\mathcal{A}}}{\partial x} \tag{118}$$

$$= \frac{\partial F_X}{\partial x} \tag{119}$$

$$= f_X \tag{120}$$

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

Task B

Since

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} t \cdot P[X = t] dt \tag{121}$$

$$= \int_{-\infty}^{\infty} t \cdot \sum_{i=1}^{K} p_i P[X_i = t] dt \tag{122}$$

$$= \sum_{i=1}^{K} p_i \int_{-\infty}^{\infty} P[X_i = t] dt \tag{123}$$

$$= \sum_{i=1}^{K} p_i \mathbb{E}[X_i] \tag{124}$$

$$= \sum_{i=1}^{K} p_i \mu_i \tag{125}$$

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

$$\text{Var}[X] = \int_{-\infty}^{\infty} (t - \mu)^2 P[X = t] dt \tag{126}$$

$$= \int_{-\infty}^{\infty} (t - \mu)^2 \sum_{i=1}^{K} p_i P[X_i = t] dt \tag{127}$$

$$= \sum_{i=1}^{K} p_i \int_{-\infty}^{\infty} (t - \mu)^2 P[X_i = t] dt \tag{128}$$

$$= \sum_{i=1}^{K} p_i \text{Var}[X_i] \tag{129}$$

$$= \sum_{i=1}^{K} p_i \sigma_i^2 \tag{130}$$

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

$$\text{MGF}_X(t) = \int_{-\infty}^{\infty} e^{tX} P[X = x] dx \tag{131}$$

$$= \int_{-\infty}^{\infty} e^{tX} \sum_{i=1}^{K} p_i P[X_i = x] dx \tag{132}$$

$$= \sum_{i=1}^{K} p_i \int_{-\infty}^{\infty} e^{tX} P[X_i = x] dx \tag{133}$$

$$= \sum_{i=1}^{K} p_i \text{MGF}_{X_i}(t) \tag{134}$$

$$= \sum_{i=1}^{K} p_i e^{t\mu_i + \frac{1}{2} t^2 \sigma_i^2} \tag{135}$$

Task C

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

$$\mathbb{E}[Z] = \mathbb{E}\left[\sum_{i=1}^{K} p_i X_i\right] \tag{136}$$

$$= \sum_{i=1}^{K} p_i \mathbb{E}[X_i] \tag{137}$$

$$= \sum_{i=1}^{K} p_i \mu_i \tag{138}$$