

Stochastic Optimisation - Problem Sheet 1

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Answer 3)

Let X_1, X_2, \dots be iid random variables with distribution $\text{Bern}(p)$ with $p \in [0, 1]$. Let $q \in [0, 1]$ with $q > p$.

The moment generating function of X is $\mathcal{M}_X(t) := \mathbb{E}[e^{tX}] = (p + e^t + (1 - p))$.

By applying *Chernoff Bounds* we have that

$$\begin{aligned}\mathbb{P}\left(\sum_{i=1}^n X_i > nq\right) &\leq \inf_{\theta > 0} e^{-nq\theta} (\mathbb{E}[e^{\theta X}])^n \\ &= \inf_{\theta > 0} e^{-nq\theta} (pe^{\theta} + (1 - p))^n\end{aligned}$$

Consider the natural log of the right hand side and define

$$f := -nq\theta + \ln(pe^{\theta} + 1 - p)$$

Since the natural log is a monotonically increasing function, $\inf_{\theta > 0} e^f$ is equal to the RHS of above.

We have

$$\begin{aligned}\text{Setting } \frac{\partial f}{\partial \theta} &= -nq + n \frac{pe^{\theta}}{pe^{\theta} + 1 - p} \\ \frac{\partial f}{\partial \theta} &= 0 \\ \implies 0 &= -nq + n \frac{pe^{\theta}}{pe^{\theta} + 1 - p} \\ \implies q &= \frac{pe^{\theta}}{pe^{\theta} + 1 - p} \\ \implies pe^{\theta} + 1 - p &= \frac{p}{e^{\theta}} \\ \implies e^{\theta} &= \frac{q}{\frac{p}{q} - p} \\ &= \frac{q}{q - qp} \\ \text{Since } q &> p \\ \implies q - qp &> p - qp \\ \implies \frac{q - qp}{p - qp} &> 1 \\ \implies \ln\left(\frac{q - qp}{p - qp}\right) &> 0\end{aligned}$$

Thus $\operatorname{argmin}_{\theta; \theta > 0}(f) = \ln\left(\frac{q - qp}{p - qp}\right)$. This means

$$\begin{aligned}
 \inf_{\theta > 0} f &= -nq \ln\left(\frac{q - qp}{p - qp}\right) + n \ln\left(p \cdot \frac{q - qp}{p - qp} + 1 - p\right) \\
 &= -n \left[q \ln\left(\frac{q(1-p)}{p(1-q)}\right) - \ln\left(p \cdot \frac{q(1-p)}{p(1-q)} + 1 - p\right) \right] \\
 &= -n \left[q \ln\left(\frac{q}{p}\right) + q \ln\left(\frac{1-p}{1-q}\right) - \ln\left(\frac{q(1-p)}{1-q} + 1 - p\right) \right] \\
 &= -n \left[q \ln\left(\frac{q}{p}\right) - q \ln\left(\frac{1-q}{1-p}\right) - \ln\left(\frac{1-p}{1-q}\right) \right] \\
 &= -n \left[q \ln\left(\frac{q}{p}\right) + (1-q) \ln\left(\frac{1-q}{1-p}\right) \right] \\
 &= -nK(q; p) \\
 \implies \inf_{\theta > 0} e^{-nq\theta} (pe^\theta + (1-p))^n &= \exp(-nK(q; p)) \\
 \implies \mathbb{P}\left(\sum_{i=1}^n X_i > nq\right) &\leq \exp(-nK(q; p))
 \end{aligned}$$

Answer 6a)

Let $Z \sim N(0, 1)$.

$$\begin{aligned}
 \mathbb{E}[e^{\theta Z}] &= \int_{-\infty}^{\infty} e^{\theta x} f_Z(x) dx \\
 &= \int_{-\infty}^{\infty} e^{\theta x} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx \\
 &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x^2 - 2x\theta)} dx \\
 &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x-\theta)^2 + \frac{1}{2}\theta^2} dx \\
 &= e^{\frac{1}{2}\theta^2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x-\theta)^2} dx \\
 &= e^{\frac{1}{2}\theta^2} \int_{-\infty}^{\infty} f_Y(x) dx \quad \text{where } Y \sim N(\theta, 1) \\
 &= e^{\frac{1}{2}\theta^2} \cdot 1 \\
 &= e^{\frac{1}{2}\theta^2}
 \end{aligned}$$

Answer 6b)

Let X_1, X_2, \dots be iid random variables with distribution $N(\mu, \sigma^2)$ for $\mu, \sigma \in \mathbb{R}$. Let $\gamma \in \mathbb{R}$ st $\gamma > \mu$.

The moment generating function of X is $\mathcal{M}_X(t) := \mathbb{E}[e^{tX}] = e^{\mu t + \frac{1}{2}\sigma^2 t^2}$.

By applying *Chernoff Bounds* we have that

$$\begin{aligned}
 \mathbb{P}\left(\sum_{i=1}^n X_i > n\gamma\right) &\leq \inf_{\theta > 0} e^{-n\gamma\theta} (\mathbb{E}[e^{X\theta}])^n \\
 &= \inf_{\theta > 0} e^{-n\theta(\gamma - \mu - \frac{1}{2}\sigma^2\theta)}
 \end{aligned}$$

Consider the natural log of the right hand side and define $f := -n\theta(\gamma - \mu - \frac{1}{2}\sigma^2\theta)$.

$$\begin{aligned}
 \frac{\partial f}{\partial \theta} &= -n(\gamma - \mu - \frac{1}{2}\sigma^2\theta) - n\theta(-\frac{1}{2}\sigma^2) \\
 &= -n(\gamma - \mu - \sigma^2\theta) \\
 \text{Setting } \frac{\partial f}{\partial \theta} &= 0 \\
 \implies \gamma - \mu - \sigma^2\theta &= 0 \\
 \implies \theta &= \frac{\gamma - \mu}{\sigma^2} \\
 \text{Since } \gamma > \mu \text{ \& } \sigma^2 > 0 \\
 \implies 0 &< \frac{\gamma - \mu}{\sigma^2} = \theta
 \end{aligned}$$

Thus $\operatorname{argmin}_{\theta; \theta > 0}(f) = \frac{\gamma - \mu}{\sigma^2}$. This means

$$\begin{aligned}
 \inf_{\theta > 0} f &= -n \left(\frac{\gamma - \mu}{\sigma^2} \right) \left(\gamma - \mu - \frac{1}{2}(\gamma - \mu) \right) \\
 &= -n \frac{(\gamma - \mu)^2}{2\sigma^2} \\
 \implies \inf_{\theta > 0} e^{-n\theta(\gamma - \mu - \frac{1}{2}\sigma^2\theta)} &= \exp \left(-n \frac{(\gamma - \mu)^2}{2\sigma^2} \right) \\
 \implies \mathbb{P} \left(\sum_{i=1}^n X_i > n\gamma \right) &\leq \exp \left(-n \frac{(\gamma - \mu)^2}{2\sigma^2} \right)
 \end{aligned}$$