Statistics 2 - Notes

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1 Estimation

1.1 Introduction

Definition 1.1 - *Probabiltiy Space,* $(\Omega, \mathcal{F}, \mathbb{P})$
A mathematical construct for modelling the real world. A *Probabilty Space* has three elements

i) Ω - Sample space.

ii) $\mathcal{F}$ - Set of events.

iii) $\mathbb{P}$ - Probability measure.

and most fulfil the following conditions

i) $\Omega \in \mathcal{F}$;

ii) $\forall\ A \in \mathcal{F} \implies A^c \in \mathcal{F}$;

iii) $\forall\ A_0, \dots, A_n \in \mathcal{F} \implies \left(\bigcup_i A_i\right) \in \mathcal{F}$;

iv) $\mathbb{P}(\Omega) = 1$; and,

v) $\mathbb{P}\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} \mathbb{P}(A_i)$ for disjoint $A_1, A_2, ...$ (Countable Additivity).

Definition 1.2 - *Random Variable*
A function which maps an event in the sample space to a value *e.g.* $X : \Omega \to \mathbb{R}$.

Remark 1.1 - *Probability Density Function for iid Random Variable Vector*
For $\mathbf{X} \sim f_n(\cdot; \theta)$ where each component of $\mathbf{X}$ is independent and identically distribution the probability density function of $\mathbf{X}$ is

$$f_n(\mathbf{x}; \theta) = \prod_{i=1}^{n} f(x_i; \theta)$$

Definition 1.3 - *Expectation*
The mean value for a random variable. For rv X

$$\mathbb{E}(X) := \sum_{x \in \chi} x f_X(x) \quad \& \quad \mathbb{E}(X) := \int_{\mathbb{R}} x f_X(x) dx$$

Theorem 1.1 - *Expection of a Function*
For a function $g : \mathbb{R} \to \mathbb{R}$ and rv X with pmf f_X

$$\mathbb{E}(g(X)) := \sum_{g(x) \in \chi} x f_X(x) \quad \& \quad \mathbb{E}(g(X)) := \int_{\mathbb{R}} g(x) f_X(x) dx$$

Theorem 1.2 - *Expectation of a Linear Operator*
For rv X with pmf f_X & $a, b \in \mathbb{R}$

$$\mathbb{E}(aX + b) = a\mathbb{E}(X) + b$$

Definition 1.4 - *Variance*
For rv X

$$\text{var}(X) := \mathbb{E}\big[(X - \mathbb{E}(X))^2\big] = \mathbb{E}(X^2) - \mathbb{E}(X)^2$$

Theorem 1.3 - *Variance of a Linear Operator*
For rv X and $a, b \in \mathbb{R}$

$$\text{var}(aX + b) = a^2\text{var}(X)$$

Definition 1.5 - *Moment of a Random Variable*
For rv X the n^{th} moment of X is defined as $\mathbb{E}(X^n)$.
N.B. - $\mathbb{E}(X^n) \neq \mathbb{E}(X)^n$.

Definition 1.6 - *Covariance*
For rv X & Y

$$\text{cov}(X, Y) := \mathbb{E}\big[(X - \mathbb{E}(X))(Y - \mathbb{E}(Y))\big] = \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y)$$

Theorem 1.4 - *Properties of Covaraince*
Let X & Y be independent random varaibles

i) $\text{cov}(X, X) = \text{var}(X)$;

ii) $\text{cov}(X, Y) = 0$

Theorem 1.5 - *Variance of two Random Variables with linear operators*

$$\text{var}(aX + bY) = a^2\text{var}(X) + b^2\text{var}(Y) + 2ab\text{cov}(X, Y)$$

Theorem 1.6 - *Independent Random Variables*
Random variables $X_1, \dots, X_n$ are independent iff

$$\mathbb{P}(X_1 \leq a_1, \dots, X_n \leq a_n) = \prod_{i=1}^n \mathbb{P}(X_i \leq a_i) \ \forall\ a_1, \dots, a_n \in \mathbb{R}$$

2 The Likelihood Function

Definition 2.1 - *Likelihood Function*
Define $\mathbf{X} \sim f_n(\cdot; \theta^*)$ for some unknown $\theta^* \in \Theta$ and let $\mathbf{x}$ be an observation of $\mathbf{X}$.
A *Likelihood Function* is any function, $L(\cdot; \mathbf{x}) : \Theta \to [0, \infty)$, which is proportional to the PMF/PDF of the obeserved realisation $\mathbf{x}$.

$$L(\theta; \mathbf{x}) := C f_b(\mathbf{x}; \theta) \ \forall\ C > 0$$

N.B. Sometimes this is called the *Observed* Likelihood Function since it is dependent on observed data.

Definition 2.2 - *Log-Likelihood Function*
Let $\mathbf{X} \sim f_n(\cdot; \theta^*)$ for some unknown $\theta^* \in \Theta$ and $\mathbf{x}$ be an observation of $\mathbf{X}$.
The *Log-Likelihood Function* is the natural log of a *Likelihood Function*

$$\ell(\theta; \mathbf{x}) := \ln f_n(\mathbf{x}; \theta) + C,\ C \in \mathbb{R}$$

Theorem 2.1 - *Multidiensional Transforms*
Let $\mathbf{X}$ be a continuous random vector in $\mathbb{R}^n$ with PDF $f_\mathbf{X}$; $g : \mathbb{R}^n \to \mathbb{R}^n$ be a continuous diferentiable bijection; and, $h := g^{-1}$.
Then $\mathbf{Y} = g(\mathbf{X})$ is a continuous random vector and its PDF is

$$f_\mathbf{Y}(\mathbf{y}) = f_\mathbf{X}(h(\mathbf{y})H_h(\mathbf{Y})$$

where
$$J_h := \left|\det\left(\frac{\partial h}{\partial \mathbf{y}}\right)\right|$$

Proposition 2.1 - *Invaraince of Likelihood Function by bijective transformation of the observations independent of θ*
Let $g : \mathbb{R}^n \to \mathbb{R}^n$ be a bijetive transformation which is independent of θ; and $\mathbf{Y} := g(\mathbf{X})$.
Then $\mathbf{Y}$ is a random variable with PDF/PMG
$$f_{\mathbf{Y}}(\mathbf{y};\theta) \propto f_{\mathbf{X}}(g^{-1}(\mathbf{y});\theta)$$
Hence, if $\mathbf{y} = g(\mathbf{x})$ then $L_{\mathbf{Y}}(\theta;\mathbf{y}) \propto L_{\mathbf{X}}(\theta;\mathbf{x})$

Proof 2.1 - *Proposition 2.1*
Let $g : \mathbb{R}^n \to \mathbb{R}^n$ be a bijective transformation which is independent of θ; $h := g^{-1}$; $\mathbf{X},\mathbf{Y}$ be a rvs st $\mathbf{Y} := g(\mathbf{X})$.

i) *Discrete Case* - Consider the case when $\mathbf{X}$ is a discrete rv. Then
$$\begin{aligned} f_{\mathbf{Y}}(y;\theta) &= \mathbb{P}(\mathbf{Y} = \mathbf{y};\theta) \\ &= \mathbb{P}(g^{-1}(\mathbf{Y}) = g^{-1}(\mathbf{y});\theta) \\ &= \mathbb{P}(h(\mathbf{Y}) = h(\mathbf{y});\theta) \\ &= \mathbb{P}(\mathbf{X} = h(\mathbf{y});\theta) \\ &= f_{\mathbf{X}}(g^{-1}(\mathbf{y});\theta) \end{aligned}$$

ii) *Continuous Case* - Consider the case when $\mathbf{X}$ is a continuous rv.
Then, by **Theorem 2.1**
$$f_{\mathbf{Y}}(\mathbf{y};\theta) = f_{\mathbf{X}}(g^{-1}(\mathbf{y});\theta)J_{g^{-1}}(\mathbf{y})$$
Since $J_{g^{-1}}$ does not depend on θ this case is solved.

Thus in botoh cases $L_{\mathbf{Y}}(\theta;y) = f_{\mathbf{Y}}(y;\theta) \propto f_{\mathbf{X}}(g^{-1}(\mathbf{y});\theta) = L_{\mathbf{X}}(\theta;\mathbf{x})$.

3 Maximum Likelihood Estimates

Definition 3.1 - *Maximum Likelihood Estimate*
Let $\mathbf{X} \sim f_n(\cdot;\theta)$; and $\mathbf{x}$ be a realisation of $\mathbf{X}$.
The *Maximum Likelihood Estimate* is the value $\hat{\theta} \in \Theta$ st
$$\forall\ \theta \in \Theta\ f_n(\mathbf{x};\hat{\theta}) \geq f_n(\mathbf{x},\theta)$$
Equivalently
$$\forall\ \theta \in \Theta\ L(\hat{\theta};\mathbf{x}) \geq L(\theta;\mathbf{x}) \quad \text{or} \quad \ell(\hat{\theta};\mathbf{x}) \geq \ell(\theta;\mathbf{x})$$
i.e. $\hat{\theta}(\mathbf{x}) := \text{argmax}_\theta(L(\theta;\mathbf{x})$.

Remark 3.1 - *The Maximum Likelihood Estimate may <u>not</u> be unique*

Example 3.1 - *MLE for Uniform Distribution*
Consider $\mathbf{X} \overset{\text{iid}}{\sim} U[0,\theta]$ for $\theta > 0$.
Then
$$\begin{aligned} L(\theta;\mathbf{x}) &\propto f_n(\mathbf{x};\theta) \\ &= \prod_{i=1}^n \frac{1}{\theta}\mathbb{1}\{x_i \in [0,\theta] \\ &= \frac{1}{\theta^n}\prod_{i=1}^n \mathbb{1}\{x_i \in [0,\theta] \\ \implies \qquad \hat{\theta} &= \max\{x_i : x_i \in \mathbf{x}\} \end{aligned}$$

Remark 3.2 - *MLE of Reparameterisation*
Define $\tau(\theta):\mathbb{R}\to\mathbb{R}$. Then
$$\hat{\tau}=\tau(\hat{\theta})$$
N.B. We often write $\tilde{f}$ to represent the pmf when τ is taken as a parameter rateher than θ. *i.e.* $f(x;\theta)=\tilde{f}(x;\tau(\theta))$.

Theorem 3.1 - *Invariance of MLE under bijective Reparameterisation*
Let $g:\Theta\to G$ be a bijective transformation of the statisitcal parameter θ.
Let $\mathbf{X}\sim f(\cdot;\theta)=\tilde{f}(\cdot;g(\theta))$ for some θ, and let $\mathbf{x}$ be a realisation of $\mathbf{X}$.
$$\text{If } \hat{\theta} \text{ s an MLE of } \theta \text{ then } \hat{\tau}=g(\hat{\theta}) \text{ is an MLE of } \tau.$$

Proof 3.1 - *Theorem 3.1*
This is a proof by contradiction.
Suppose $\exists\ \tau^*\in Gst\tilde{f}(x;\tau^*)>\tilde{f}(x;\tau^*)$ We know that $\forall\ \theta\in\Theta,\ f(x;\theta)=\tilde{f}(x;g(\theta))$ and $\forall\ \tau\in G,\ f(x;g^{-1}(\tau))=\tilde{f}(x;\tau)$.
We deduce that
$$\begin{array}{rcl} f(x;g^{-1}(\tau^*)) &=& \tilde{f}(x;\tau^*)\\ &>& \tilde{f}(x;\hat{\tau}) \text{ by assumption}\\ &=& f(x;g^{-1}(\hat{\tau}))\\ &=& f(x;\hat{\theta}) \end{array}$$
This contradicts the assumption that $\hat{\theta}$ is an maximum likelihood estimate of θ.

Remark 3.3 - *Not all Reparameterisations are Bijective*
When reparameterisations $g:\mathbb{R}\to\mathbb{R}$ is not bijective it is helpful to consider the *induced likelihood*
$$L^*(\tau;\mathbf{x}):=\max_{\theta\in G_\tau}L(\theta;\mathbf{x}) \text{ where } G_\tau:=\{\theta:g(\theta)=\tau\}$$
Since this reduces the domain to only where g is bijective.

3.1 Determinig MLEs - The Tractable Case

Proposition 3.1 - *Differentiable Likelihood in the continuous case - Multivariate*
When $L(\theta;\mathbf{x}$ is differentiable one can find MLEs by considering its extrema. This is done equating & solving the cases when the gradient is zero, *i.e.* $\nabla L(\theta;\mathbf{x})=0$, and then checking whether this is a maximum or minimum point.
A point is a local minimum if the Hessian at the point is *Negative Definite i.e.* $x^TAx<0\,\forall\,x\neq\mathbf{0}$.

Example 3.2 - *MLE of Normal Distribution*
Let $\mathbf{X}\overset{\text{iid}}{\sim}\mathcal{N}(\mu,\sigma^2)$
$$\begin{array}{lrcl} & L(\mu,\sigma^2;\mathbf{x}) &=& \prod_{i=1}^n\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x_i-\mu)^2}{2\sigma^2}}\\ \Longrightarrow & \ell(\mu,\sigma^2;\mathbf{x}) &=& C-\frac{n}{2}\ln(\sigma^2)-\frac{1}{2\sigma^2}\sum_{i=1}^n(x_i-\mu)^2\\ \Longrightarrow & \nabla\ell(\mu,\sigma^2;\mathbf{x}) &=& \left(\frac{-1}{\sigma^2}\sum_{i=1}^n(x_i-\mu),\quad -\frac{n}{2\sigma^2}+\frac{1}{2\sigma^4}\sum_{i=1}^n(x_i-\mu)^2\right)\\ \text{Setting} & \frac{-1}{\sigma^2}\sum_{i=1}^n(x_i-\mu) &=& 0\\ \Longrightarrow & \hat{\mu} &=& \frac{1}{n}\sum_{i=1}^n x_i=\bar{x}\\ \text{Setting} & -\frac{n}{2\sigma^2}+\frac{1}{2\sigma^4}\sum_{i=1}^n(x_i-\mu)^2 &=& 0\\ \Longrightarrow & \hat{\sigma}^2 &=& \frac{1}{n}\sum_{i=1}^n(x_i\hat{\mu})^2 \end{array}$$

We now want to check whether $(\hat{\mu}, \hat{\sigma^2})$ is a minimum.

$$\begin{aligned}\nabla^2\ell(\mu,\sigma^2;\mathbf{x}) &= \begin{pmatrix}\dfrac{\partial^2\ell(\mu,\sigma^2;\mathbf{x})}{\partial\mu^2} & \dfrac{\partial^2\ell(\mu,\sigma^2;\mathbf{x})}{\partial\mu\partial\sigma^2}\\ \dfrac{\partial^2\ell(\mu,\sigma^2;\mathbf{x})}{\partial\mu\sigma^2} & \dfrac{\partial^2\ell(\mu,\sigma^2;\mathbf{x})}{\partial(\sigma^2)^2}\end{pmatrix}\\ &= \begin{pmatrix}-\dfrac{n}{\hat{\sigma}^2} & 0\\ 0 & -\dfrac{n}{2\hat{\sigma}^4}\end{pmatrix}\end{aligned}$$

Since $\begin{pmatrix}z_1 & z_2\end{pmatrix}\begin{pmatrix}-a & 0\\ 0 & -b\end{pmatrix}\begin{pmatrix}z_1\\ z_2\end{pmatrix} = -az_1^2 - bz_2^2 < 0\ \forall\ a,b>0$ and we have $\frac{n}{\hat{\sigma}^2},\ \frac{n}{2\hat{\sigma}^4} > 0$ then we can conclude that $\nabla^2\ell$ is negative definite.
Thus $\hat{\mu} = \bar{x}$ & $\hat{\sigma}^2 = \dfrac{1}{n}\sum_{i=1}^{n}(x_i\hat{\mu})^2$ is an MLE for the normal distribution.

Example 3.3 - *MLE for Capture-Recapture Model*
Suppose you are wanting to calculate the unknown size of a population, n. The Capture-Recapture Model is one technique that can be used. You tag $t \leq n$ members of the population; wait for a while; then recapture $c \leq n$ members of which $x \leq \min\{t,c\} \leq n$ are tagged.
With t, c, x known produce a MLE for n.
We first work out the associated probability distribution for X, the population size. We have

i) $\binom{t}{x}$ ways of choosing x members among the tagged ones;

ii) $\binom{n-t}{c-x}$ ways of choosing the remaining members among the non-tagged ones;

iii) $\binom{n}{c}$ ways of choosing c members in a population of n individuals.

Thus
$$f_X(x;n) = \frac{\binom{t}{x}\binom{n-t}{c-x}}{\binom{n}{c}}$$

This means that $X \sim \text{Hypergeometric}(t,n,c)$ with t & c known.
Now we calculate the MLE for X

$$\begin{aligned}L(n;x) &= f_X(x;n)\\ &= \frac{\binom{t}{x}\binom{n-t}{c-x}}{\binom{n}{c}}\\ &= \frac{\dfrac{t!}{x!(t-x)!}\dfrac{(n-t)!}{(c-x)!(n-t-c+x)!}}{\dfrac{n!}{c!(n-c)!}}\end{aligned}$$

Now we consider $L(n;x) = 0$ when $x > \min\{t,c\}$. We want to indetify values of n for which $L(n;x) \geq L(n-1;x)$.

Consider $n-1 \geq \min\{t,c\} \implies L(n-1;x) > 0$

$$\begin{array}{rrcl} & \text{Let } r(n) & := & \frac{L(n;x)}{L(n-1;x)} \\ & & = & \frac{n-t}{n-t-c+x}\frac{n-c}{n} \\ \Rightarrow & 1 & \leq & r(n) \\ \Leftrightarrow & 1 & \leq & \frac{n-t}{n-t-c+x}\frac{n-c}{n} \\ \Leftrightarrow & n(n-t-c+x) & \leq & (n-t)(n-c) \\ \Leftrightarrow & n^2-nt-cn+xn & \leq & n^2-nt-cn+ct \\ \Leftrightarrow & xn & \leq & ct \\ \Leftrightarrow & x & \leq & \frac{ct}{n} \end{array}$$

So $L(n;x)$ is increasing for $n \leq \left\lfloor \frac{ct}{x} \right\rfloor$ & decreasing for $n > \left\lfloor \frac{ct}{x} \right\rfloor$.
Consequently $\hat{n}_{\text{MLE}}(x) = \left\lfloor \frac{tc}{x} \right\rfloor$

4 Statistics and Estimators

Definition 4.1 - *Statistic*
Given some data $\mathbf{x}$ a statistic is a fucntion of the data $T(\mathbf{x})$.
N.B. A statistic cannot depend on an unknown statistical parameter.

Definition 4.2 - *Estimate*
Let $\mathbf{X} \sim f_n(\cdot;\theta^*)$ with $\theta^* \in \Theta$ and $\mathbf{x}$ be a realisation of $\mathbf{X}$.
An *Estimate* θ^* is a statistic $\hat{\theta}(\mathbf{x}) = T(\mathbf{x})$ which is intended to approximate the real value of θ^*.
N.B. An *Estimate* is a real value & thus is hard to evaluate.

Definition 4.3 - *Estimator*
Let $\mathbf{X} \sim f_n(\cdot;\theta^*)$ with $\theta^* \in \Theta$ and $\mathbf{x}$ be a realisation of $\mathbf{X}$.
An *Estimator* of θ^* is $\hat{\theta}$ where $\hat{\theta}(\mathbf{x})$ is an *estimate.*
N.B. We call $T(\mathbf{X})$ an estimator. This is a random variable.

Definition 4.4 - *Distribution of an Estimator*
Let $\mathbf{X}|sim f_n(\cdot;\theta^*)$ with $\theta^* \in \Theta \subseteq \mathbb{R}$.
If $\hat{\theta}(\mathbf{X})$ is a real-valued random variable, we can write its CDF as

$$\begin{array}{rcl} F_{\hat{\theta}(\mathbf{X})}(t;\theta^*) & = & \mathbb{P}(\hat{\theta}(\mathbf{X}) \leq t;\theta^*) \\ & = & \int_{\mathcal{X}^n} \mathbb{1}\{\hat{\theta}(\mathbf{x}) \leq t\} f_n(\mathbf{x};\theta^*)d\mathbf{x} \end{array}$$

Remark 4.1 - *Estimator dependends upon true value*
The distribution of $\hat{theta}(\mathbf{X})$ depends on the distribution of $\mathbf{X}$ which in turn depends upon the distribution of θ^*.
Thus the distribution of an estimator depends on the true parameter of the variable it is estimating.

Remark 4.2 - *Estimator Distribution & Sample Size*
As sample size increasesthe distribution of an estimator may converge to a more standard distribution (*e.g.* Normal, Poisson).

Definition 4.5 - *Bias*
Bias is a measure of how much an estimator deviates from the true value, on average.

$$\begin{aligned}\text{Bias}(\hat{\theta};\theta^*) &:= \mathbb{E}(\hat{\theta}(\mathbf{X})-\theta^*;\theta^*)\\ &= \mathbb{E}(\hat{\theta};\theta^*)-\mathbb{E}(\theta^*;\theta^*)\\ &= \mathbb{E}(\hat{\theta};\theta^*)-\theta^*\end{aligned}$$

Definition 4.6 - *Unbiased Estimator*
An *Estimator*, $\hat{\theta}$, is said to be *Unbiased* if $\forall\ \theta\in\Theta,\ \text{Bias}(\hat{\theta};\theta)=0$.
Equivalently $\mathbb{E}(\hat{\theta};\theta)=\theta$.

Definition 4.7 - *Mean Square Error*
The *Mean Square Error* of an estimator is the mean of the squared error associated with rv $\hat{\theta}$.

$$MSE(\hat{\theta};\theta^*):=\mathbb{E}\left[(\hat{\theta}(\mathbf{X})-\theta^*)^2;\theta^2\right]$$

Proposition 4.1 - *Simplifcation of MSE Formula*
The MSE is a combination of variance & bias.

$$\begin{aligned}MSE(\hat{\theta};\theta^*) &= \mathbb{E}\left[(\hat{\theta}(\mathbf{X})-\theta^*)^2;\theta^2\right]\\ &= \mathbb{E}\left[\left\{\hat{\theta}-\mathbb{E}(\hat{\theta};\theta^*)\right\}^2;\theta^*\right]+\left(\mathbb{E}(\hat{\theta}-\theta^*;\theta^*\right)^2\\ &= \text{Var}(\hat{\theta};\theta^*)+\text{Bias}(\hat{\theta};\theta^*)^2\end{aligned}$$

Example 4.1 - *Sample mean as an Estimator*
Let $\mathbf{X}\overset{\text{iid}}{\sim}\text{Poisson}(\lambda^*)$.
Suppose we are using the sample mean, $\hat{\lambda}(\mathbf{x}):=\frac{1}{n}\sum_{i=1}^n x_i$, as an estimate of λ^*. We first want to show this estimator is *Unbiased*

$$\begin{aligned}\mathbb{E}(\hat{\lambda};\lambda) &= \mathbb{E}\left(\frac{1}{n}\sum_{i=1}^n X_i;\lambda\right)\\ &= d\frac{1}{n}\sum_{i=1}^n\mathbb{E}(X_i;\lambda)\\ &= \frac{1}{n}n\lambda\\ &= \lambda\end{aligned}$$

Thus $\hat{\lambda}$ is unbiased.
Now we consider the MSE of $\hat{\lambda}$

$$\begin{aligned}MSE(\hat{\lambda};\lambda) &= \text{Var}(\hat{\lambda};\lambda)\\ &= \text{Var}\left(\frac{1}{n}\sum_{i=1}^n X_i;\lambda\right)\\ &= \frac{1}{n^2}\sum_{i=1}^n\text{Var}(X_i;\lambda)\\ &= \frac{1}{n^2}n\lambda\\ &= \frac{\lambda}{n}\end{aligned}$$

This shows that as the sample size increases the MSE of $\hat{\lambda}$ converges to 0.

5 Probabilistic Convergence

Remark 5.1 - *Motivation*
Here we consider the properties of a maximum likelihood estimators as the sample size increases.

Theorem 5.1 - *Markov's Inequality*
For a *non-negative* random variable X and a constant $a > 0$

$$\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}(X)}{a}$$

Proof 5.1 - *Markov's Inequality*
Consider continuous X. We have

$$\begin{array}{rrcl} & a\mathbb{P}(X \geq a) & = & a\int_a^\infty f_X(x)dx \\ & & \leq & \int_a^\infty xf_X(x)dx \\ & & \leq & \int_0^\infty xf_X(x)dx \\ & & = & \mathbb{E}(X) \\ \implies & a\mathbb{P}(X \geq a) & = & \mathbb{E}(X) \\ \implies & \mathbb{P}(X \geq a) & \leq & \frac{\mathbb{E}(X)}{a} \end{array}$$

$\square$

Theorem 5.2 - *Chebyshev's Inequality*
Let $\mu = \mathbb{E}(X)$ and $\sigma^2 = \text{Var}(X)$. Then

$$\forall\ a > 0,\ \mathbb{P}(|X - \mu| \geq a) \leq \frac{\sigma^2}{a^2}$$

Proof 5.2 - *Chebyshev's Inequality*
We have

$$\begin{array}{rcl} \mathbb{P}(|X - \mu| \geq a) & = & \mathbb{P}(|X - \mu|^2 \geq a^2) \\ & \leq & \frac{\mathbb{E}\left((X-\mu)^2\right)}{a^2} \text{ By Markov's Inequality} \\ & = & \frac{\sigma^2}{a^2} \end{array}$$

$\square$

0 Appendix

Definition 0.1 - *Gradient*

$$\nabla f(\boldsymbol{\theta};\mathbf{x}) := \left(\frac{\partial f(\boldsymbol{\theta};\mathbf{x})}{\partial\theta_1},\dots,\frac{\partial f(\boldsymbol{\theta};\mathbf{x})}{\partial\theta_n}\right)$$

Definition 0.2 - *Hessian*

$$\nabla f(\boldsymbol{\theta};\mathbf{x}) := \begin{pmatrix} \frac{\partial^2 f(\boldsymbol{\theta};\mathbf{x})}{\partial\theta_1^2} & \frac{\partial^2 f(\boldsymbol{\theta};\mathbf{x})}{\partial\theta_1\partial\theta_2} & \dots & \frac{\partial^2 f(\boldsymbol{\theta};\mathbf{x})}{\partial\theta_n\theta_1} \\ \frac{\partial^2 f(\boldsymbol{\theta};\mathbf{x})}{\partial\theta_1^2} & \frac{\partial^2 f(\boldsymbol{\theta};\mathbf{x})}{\partial\theta_1\theta_2} & \dots & \frac{\partial^2 f(\boldsymbol{\theta};\mathbf{x})}{\partial\theta_n\theta_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f(\boldsymbol{\theta};\mathbf{x})}{\partial\theta_1\partial\theta_n} & \frac{\partial^2 f(\boldsymbol{\theta};\mathbf{x})}{\partial\theta_2\theta_n} & \dots & \frac{\partial^2 f(\boldsymbol{\theta};\mathbf{x})}{\partial\theta_n^2} \end{pmatrix}$$

0.1 Notation

Notation	Denotes
$\theta \in \Theta \subseteq \mathbb{R}^{d_\theta}$	Scalar or vector parameter characterising a probability distribution
$\hat{\theta}$	Estimation for the value of the parameter θ
θ^*	True value of the paramter θ
$\mathbb{P}$	Probability measure $\mathbb{P} : \mathcal{F} \to [0,1]$
Ω	Sample space
X	Scalar random variable
$\mathcal{F}$	Sigma field (Set of events)
χ	Support of rv XX. A set set X is definitely in it *i.e.* $\mathbb{P}(X \in \chi;\theta) = 1$
$\mathbf{X}$	Vector consiting of scalar random variables

0.2 R

Command	Result
hist(a)	Plots a histogram of the values in array a
mean(a)	Returns the mean value of array a
rbinom(s,n,p)	Samples n of $Bi(n,p)$ random variables
rep(v,n)	Produces an array of size n where each entry has value v
$x \leftarrow v$	Maps value v to variable x

0.3 Probability Distributions

Definition 0.3 - *Binomial Distribution*
Let X be a discrete random variable modelled by a *Binomial Distribution* with n events and rate of success p.

$$\begin{array}{rcl} p_X(k) & = & \binom{n}{k}p^k(1-p)^{n-k} \\ \mathbb{E}(X)np = & \& & Var(X) = np(1-p) \end{array}$$

Definition 0.4 - *Gamma Distribution*
Let T be a continuous randmo variable modelled by a *Gamma Distribution* with shape parameter α & scale parameter λ. Then

$$\begin{array}{rcl} f_T(x) & = & \frac{\lambda^\alpha x^{\alpha-1}e^{-\lambda x}}{\Gamma(\alpha)} \quad \text{for } x > 0 \\ \mathbb{E}(T) = \frac{\alpha}{\lambda} & \& & Var(T) = \frac{\alpha}{\lambda^2} \end{array}$$

N.B. $\alpha, \lambda > 0$.

Definition 0.5 - *Exponential Distribution*
Let T be a continuous random variable modelled by a *Exponential Distribution* with parameter λ. Then

$$\begin{array}{rcl} f_T(t) & = & \mathbb{1}\{t \geq 0\}.\lambda e^{-\lambda t} \\ F_T(t) & = & \mathbb{1}\{t \geq 0\}.\left(1 - e^{-\lambda t}\right) \\ \mathbb{E}(X) = \frac{1}{\lambda} & \& & Var(X) = \frac{1}{\lambda^2} \end{array}$$

N.B. Exponential Distribution is used to model the wait time between decays of a radioactive source.

Definition 0.6 - *Normal Distribution*
Let X be a continuous random variable modelled by a *Normal Distribution* with mean μ & variance σ^2.
Then

$$\begin{array}{rcl} f_X(x) & = & \dfrac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \\ F_X(x) & = & \dfrac{1}{\sqrt{2\pi\sigma^2}} \int\limits_{-\infty}^{x} e^{-\frac{(y-\mu)^2}{2\sigma^2}} dy \\ M_X(\theta) & = & e^{\mu\theta + \sigma^2\theta^2(1/2)} \\ \mathbb{E}(X) = \mu & \& & Var(X) = \sigma^2 \end{array}$$

Definition 0.7 - *Poisson Distribution*
Let X be a discrete random variable modelled by a *Poisson Distribution* with parameter λ. Then

$$\begin{array}{rcl} p_X(k) & = & \dfrac{e^{-\lambda}\lambda^k}{k!} \qquad \text{For } k \in \mathbb{N}_0 \\ \mathbb{E}(X) = \lambda & \& & Var(X) = \lambda \end{array}$$

N.B. Poisson Distribution is used to model the number of radioactive decays in a time period.