

Assignment-01Part 1: Probability

1.1

(a) sample space (Ω) = $\{\text{HH}, \text{HT}, \text{TH}, \text{TT}\}$ (b) Event space (\mathcal{F}) = $P(\Omega) = \{\{\text{HH}\}, \{\text{HT}\}, \{\text{TH}\}, \{\text{TT}\}, \{\text{HH}, \text{HT}\}, \{\text{HH}, \text{TH}\}, \{\text{HH}, \text{TT}\}, \{\text{HT}, \text{TH}\}, \{\text{HT}, \text{TT}\}, \{\text{TH}, \text{TT}\}, \{\text{HT}, \text{TH}, \text{TT}\}, \{\text{HH}, \text{HT}, \text{TH}\}, \{\text{HH}, \text{HT}, \text{TT}\}, \{\text{HH}, \text{TH}, \text{TT}\}, \{\text{HT}, \text{TH}, \text{TT}\}, \emptyset, \Omega\}$

(c) Using the three axioms of probability:

(1) E be any event, i.e. $E \in \mathcal{F}$, then $P(E) \geq 0$ (2) w_i be any elementary events, i.e. $w_i \in \Omega \forall i$,
s.t. $\bigcup_i w_i = \Omega$, then $P(\bigcup_i w_i) = P(\Omega) = 1$ (3) for w_1, w_2, \dots, w_k mutually exclusive events,

$$P(w_1 \cup w_2 \cup \dots \cup w_k) = \sum_{i=1}^k P(w_i)$$

Also, it is known that all elementary events are mutually exclusive.
to each other.Now ~~$P(\Omega) = 1$~~ $P(\Omega) = 1$

$$\Rightarrow P(\{\text{HH}\} \cup \{\text{HT}\} \cup \{\text{TH}\} \cup \{\text{TT}\}) = 1$$

$$\Rightarrow P(\{\text{HH}\}) + \dots + P(\{\text{TT}\}) = 1$$

now, given that all elementary events are equiprobable,

let $P(w_i) = p \quad \forall w_i \in \Omega$

$$\Rightarrow p + p + p + p = 1 \Rightarrow (p = \frac{1}{4})$$

So, probability of occurrence of each elementary event is $\frac{1}{4}$ or 0.25.

(c) (ii) let event E_1 : at least one head occurs

$$\Rightarrow E_1 = \{HH\} \cup \{HT\} \cup \{TH\}$$

$$P(E_1) = P(\{HH\} \cup \{HT\} \cup \{TH\})$$

$$= P(HH) + P(HT) + P(TH) = 3p = \frac{3}{4}$$

$$\text{So, } P(E_1) = 0.75$$

(iii) let event E_2 : exactly one head appears

$$E_2 = \{HT\} \cup \{TH\}$$

$$\text{So, } P(E_2) = P(\{HT\} \cup \{TH\}) = 2p = \frac{1}{2}$$

$$\text{So, } P(E_2) = \frac{1}{2} \text{ or } 0.5.$$

Part 2: Discrete random variables

2.1

Given: probability assignment function

$$f(k, n, p) = \frac{n!}{k!(n-k)!} p^k (1-p)^{n-k}$$

* $k = \# \text{ correctly recognised words} = 45$

$n = \text{total } \# \text{ words} = 50$

$p = \text{probability of guessing correctly} = 0.9$

so, $P(\text{correctly recognising 45 out of 50 words})$

$$= f(45, 50, 0.9) = \frac{50!}{45! 5!} (0.9)^{45} (0.1)^5$$
$$\approx 0.185$$

2.2 Given: PMF: $f(k, \lambda) = \frac{\lambda^k e^{-\lambda}}{k!}$

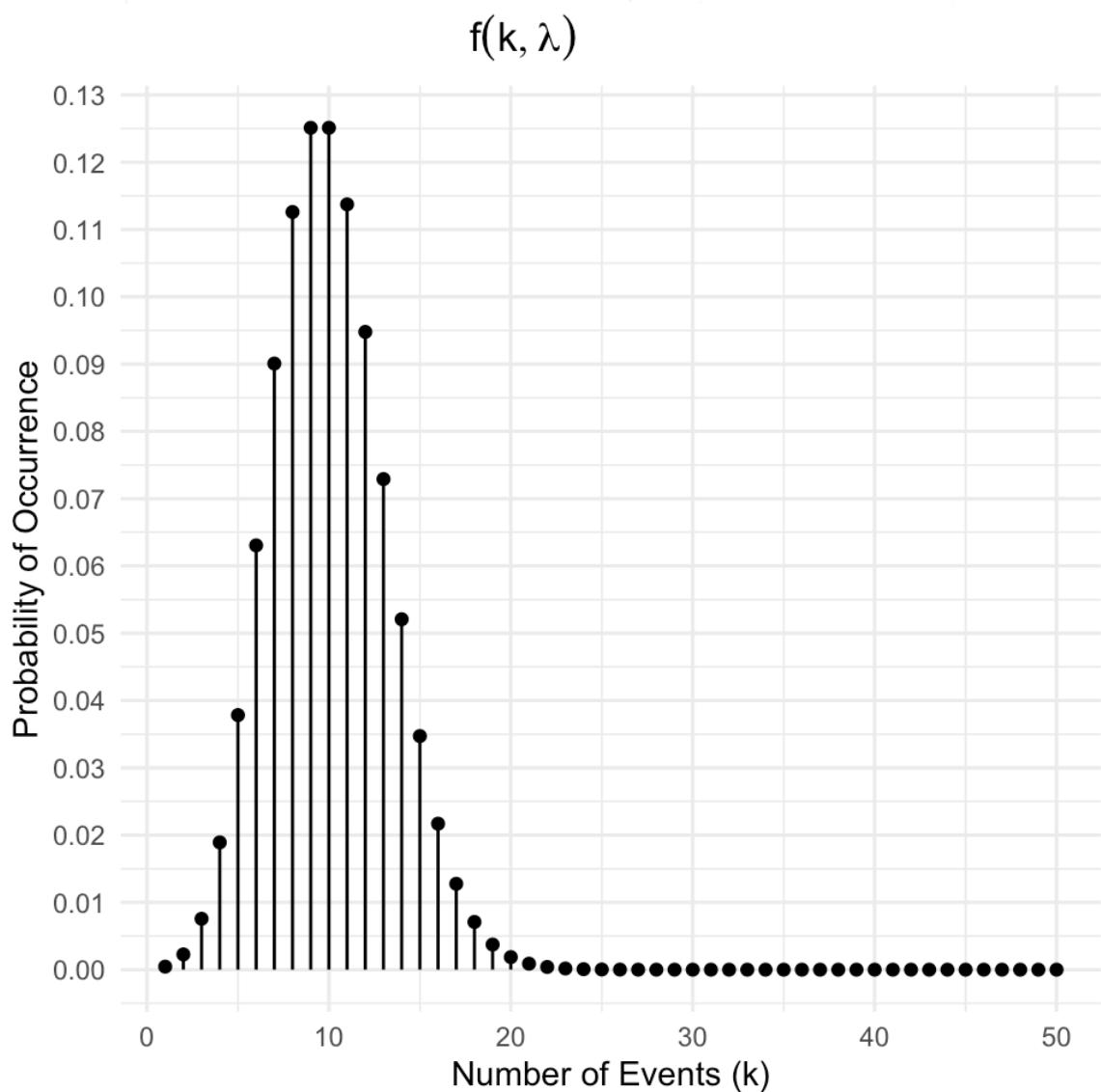
and $\lambda = 10$

(a) $P(\text{zero road accidents}) = P(K=0) = \frac{10^0 e^{-10}}{0!} = e^{-10} \approx 4.54 \times 10^{-5}$

(b) $P(\text{more than 7 but less than 10}) = P(8 \leq K < 10)$

$$= P(K=8) + P(K=9) = \frac{10^8 e^{-10}}{8!} + \frac{10^9 e^{-10}}{9!} \approx 0.24$$

(c) We calculate the values of $f(k, \lambda)$ for $k=1, 2, \dots, 50$ and plot the graph of PMF below. Graph is drawn using ggplot in R language (code added to the end of the PDF file).



Part 3 : Continuous Random Variables

3.1

given : pdf : $f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

$$(a) f(x=0; \mu=1, \sigma=1) = \frac{1}{(1)\sqrt{2\pi}} e^{-\frac{(0-1)^2}{2(1)}} = \frac{e^{-0.5}}{\sqrt{2\pi}} \approx$$

$$(b) f(x=1; \mu=0, \sigma=1) = \frac{1}{(1)\sqrt{2\pi}} e^{-\frac{(1-0)^2}{2(1)}} = \frac{e^{-0.5}}{\sqrt{2\pi}} \approx$$

(c) we know that

$$P(x_1 \leq X \leq x_2) = \int_{x_1}^{x_2} f(x) dx \quad \text{where } f(x) \text{ is the p.d.f. of random var. } X.$$

$$\text{so, given } P(x_1 \leq X \leq x_2) = \int_{x_1}^{x_2} f(x) dx = 0.3 \quad \dots \quad (1)$$

$$P(x_1 \leq X \leq x_3) = \int_{x_1}^{x_3} f(x) dx = 0.45 \quad \dots \quad (2)$$

subtract (1) from (2)

$$\Rightarrow \int_{x_1}^{x_3} f(x) dx - \int_{x_1}^{x_2} f(x) dx = 0.15$$

$$\Rightarrow \int_{x_2}^{x_3} f(x) dx + \int_{x_1}^{x_2} f(x) dx - \int_{x_1}^{x_2} f(x) dx = 0.15$$

$$\Rightarrow \int_{x_2}^{x_3} f(x) dx = 0.15 = P(x_2 \leq X \leq x_3)$$

Part 4: The Likelihood function

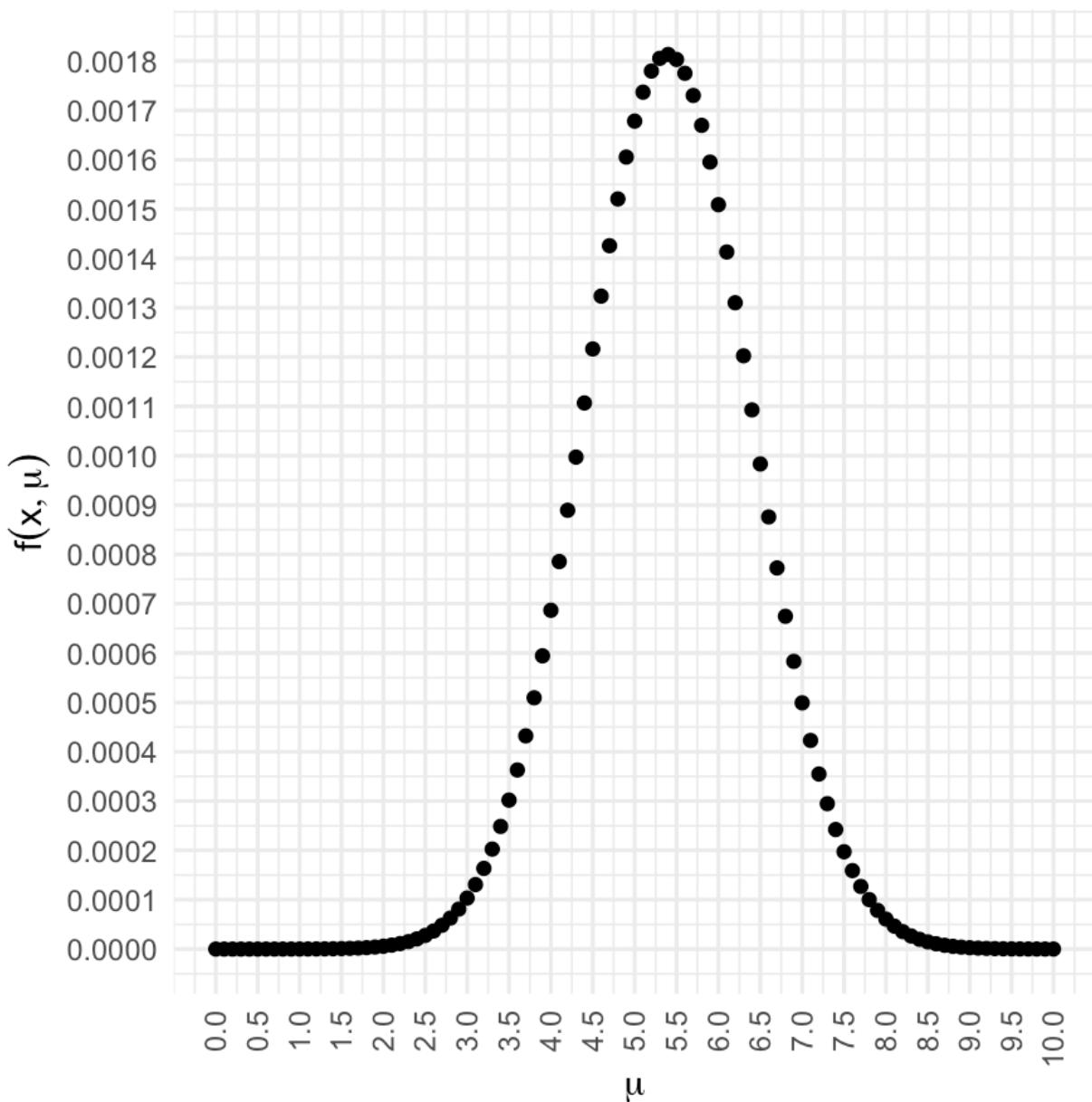
4.1:

$$\text{given: } f(x, \mu) = \frac{1}{x\sqrt{2\pi}} e^{-\frac{(\log x - \mu)^2}{2}}$$

$$(a) \text{ when you fix } x \text{ to } 220, f(220, \mu) = \frac{1}{220\sqrt{2\pi}} e^{-\frac{(\log 220 - \mu)^2}{2}}$$

Again using this function and R-language, the graph of the likelihood function is plotted below and code is attached at the end of the pdf.

Likelihood Function: $f(x, \mu)$



(b) let ~~g(x)~~ $f(x, \mu)$ be the likelihood fn at fixed $x = x_0$

then likelihood fn. for observing x_1, x_2, \dots, x_k is

$$g(x, \mu) = f(x_1, \mu) \cdot f(x_2, \mu) \cdots f(x_k, \mu)$$

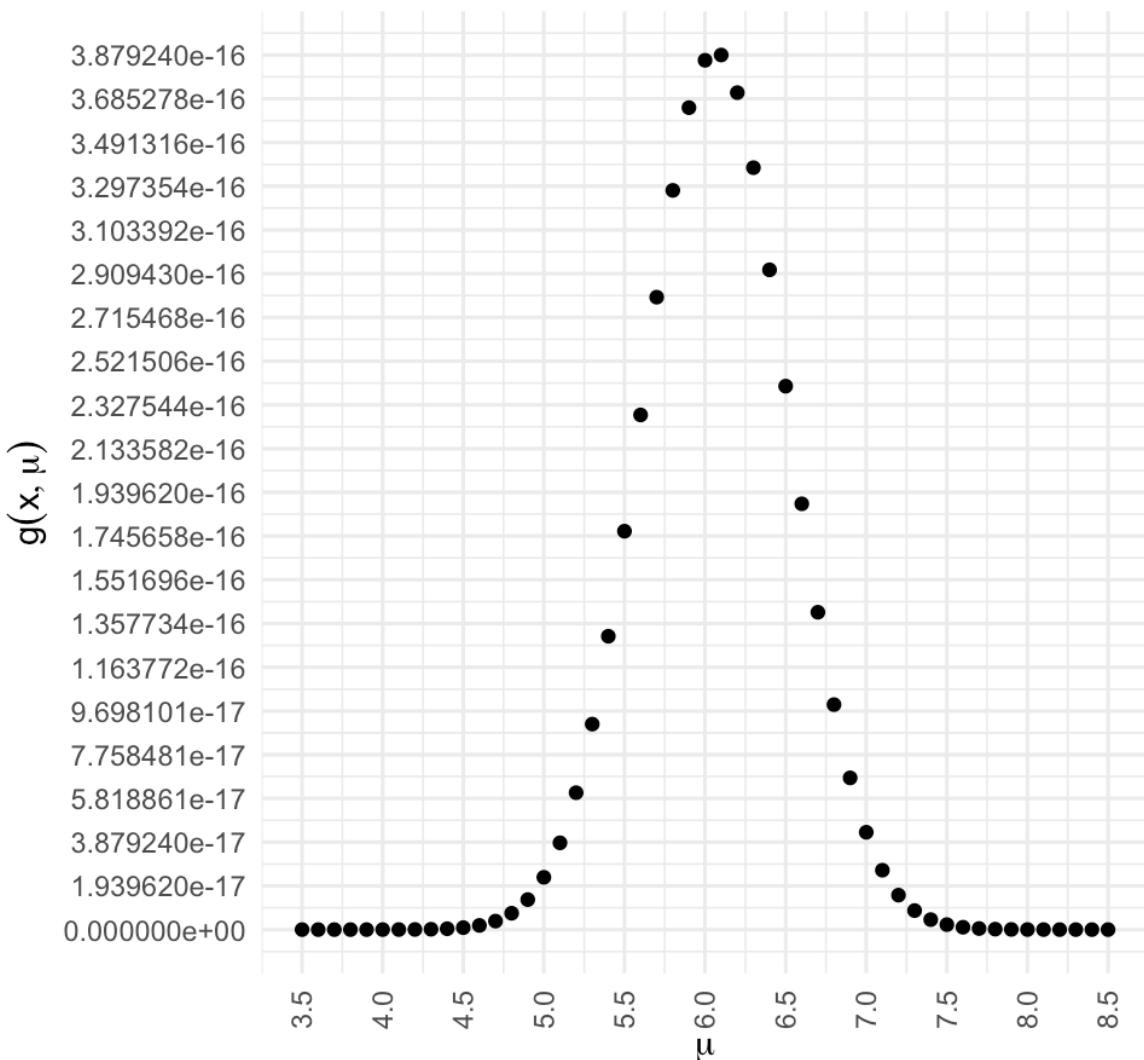
$$\Rightarrow g(x, \mu) = \frac{1}{(\prod_i^n x_i) \sqrt{2\pi}} e^{-\left(\sum_i^k (\log x_i - \mu)^2\right)}$$

using this function and R language for

$$x_1 = 303.5, x_2 = 443, x_3 = 220, x_4 = 560, x_5 = 880$$

the following plot is generated, code is attached at
the end of the pdf file.

Combined Likelihood Function: $g(x, \mu)$



(c) $g(\mu) = \text{likelihood fn for } 303, 443, 220, 560, 880$

$$g(\mu) = \frac{e^{-\sum_i (\log x_i - \mu)^2 / 2}}{\prod_i (\sqrt{2\pi})}$$

is greatest when

e^y is greatest i.e. y is lowest

$$\Rightarrow y=0$$

$\Rightarrow g(\mu)$ is greatest when $\sum_i (\log x_i - \mu)^2 = 0$

$$\Rightarrow 5\mu^2 - 2\mu \sum_i \log(x_i) + \sum_i \log^2(x_i) = 0 \Rightarrow 5\mu^2 - 26.325\mu + 34.87 = 0$$

$$\Rightarrow \boxed{\mu \approx 6.062}$$

Code for 2.2 (c)

```
1 library(ggplot2)
2
3 poisson_pmf <- function(k, lambda) {
4   (lambda^k * exp(-lambda)) / factorial(k)
5 }
6
7 lambda <- 10
8 k_values <- 1:50
9
10 # Compute PMF values for each k
11 pmf_values <- sapply(k_values, poisson_pmf, lambda = lambda)
12
13 # Create a data frame for plotting
14 data <- data.frame(k = k_values, PMF = pmf_values)
15
16 # Plot the PMF using ggplot2 with vertical lines and detailed axis labels
17 ggplot(data, aes(x = k, y = PMF)) +
18   geom_point() +
19   geom_segment(aes(x = k, xend = k, y = 0, yend = PMF)) +
20   labs(title = expression(paste("Poisson PMF: ", f(k, lambda))), 
21        x = "Number of Events (k)", 
22        y = "Probability of Occurrence") +
23   scale_y_continuous(breaks = seq(0, 0.5, by = 0.01)) +
24   theme_minimal()
```

Code for 4.1 (a)

```
library(ggplot2)

f <- function(x, mu) {
  return (1/(x * sqrt(2*pi))) * exp(-((log(x) - mu)^2)/2)
}

x_fixed <- 220
mu_values <- seq(3.5, 8.5, length.out = 100) # Range of mu values

data <- data.frame(mu = mu_values, fx_mu = sapply(mu_values, function(mu) f(x_fixed, mu)))

# Plot the function using ggplot2
ggplot(data, aes(x = mu, y = fx_mu)) +
  geom_line() +
  labs(title = "Plot of f(x, mu) for x = 220",
       x = "Value of mu",
       y = "f(x, mu)") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5))
```

Code for 4.1 (b)

```
library(ggplot2)

f <- function(x, mu) {
  return (1/(x * sqrt(2*pi))) * exp(-((log(x) - mu)^2)/2)
}

x_values <- c(303.5, 443, 220, 560, 880)
mu_values <- seq(3.5, 8.5, length.out = 100) # Range of mu values

# Calculate likelihood for each x and mu
likelihoods <- sapply(x_values, function(x) sapply(mu_values, function(mu) f(x, mu)))

# Calculate the combined likelihood (product of likelihoods for each x)
combined_likelihood <- apply(likelihoods, 2, prod)

# Create data frame for plotting
data <- data.frame(mu = mu_values, combined_likelihood = combined_likelihood)

# Plot the combined likelihood using ggplot2
ggplot(data, aes(x = mu, y = combined_likelihood)) +
  geom_line() +
  labs(title = "Combined Likelihood for Fixed Values of x",
       x = "Value of mu",
       y = "Combined Likelihood") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5))
```